Measuring Liquidity Provision by Customers in Corporate Bond Markets: Evidence from 54 Million Transactions*

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Abstract

This paper measures the role of liquidity provision by buy-side customers in corporate bond markets via a structural vector autoregression (SVAR). Unobservable shocks to the willingness of customers and bond dealers to provide liquidity affect the choice of bond dealers, in opposite directions, between market-making (principal) and matchmaking (riskless principal) transactions. Exploiting this distinction, the SVAR disentangles these two shocks and reveals two episodes of high level of liquidity provision by customers in corporate bond markets: (i) the 2008 "flight-to-safety" and (ii) the 2014–2015 "requests for quotations" technology developments. Furthermore, yield spreads for bonds of different credit ratings respond differentially to shocks in liquidity provision by dealers and customers. My empirical identification strategy for the SVAR is motivated using a theoretical model of decentralized liquidity provision.

Keywords: corporate bond; customer liquidity provision; structural vector autoregression; sign restrictions
JEL Classification Codes: G12; G14; G24

1 Introduction

US corporate bond markets have long been a focal point of both academics and regulators in their search for liquidity providers in this (largely) over-the-counter (OTC) market, the size of which has grown to over \$9.2tn in 2018, compared to \$5.5tn in 2008.[1] Furthermore, the structure of bond market trading has been substantially affected by regulatory and technology developments since the financial crisis, including the Volcker Rule, the Basel banking accords, and the emergence of electronic trading platforms. These developments raise the questions of who provides liquidity in this market sector and how such liquidity provision changes during market stress events. Liquidity provision by customers has attracted considerable attention, as bond dealers might have become increasingly reluctant to provide liquidity due to regulatory changes.

This paper provides a structural vector autoregression (SVAR) to measure the willingness of buy-side customers to provide liquidity in corporate bond markets. My SVAR associates the willingness of customers to provide liquidity to the amount of riskless principal transactions conducted by bond dealers. In riskless principal transactions, dealers buy from customers and immediately sell to other customers who are the ultimate liquidity providers,[2] whereas in inventory transactions, dealers provide liquidity and hold the resulting inventory.

The amount of riskless principal transactions, however, reflects the competing willingness of customers versus dealers to provide liquidity. A separation of these two potential influences relies on an investigation of the movements of bid-ask spreads charged by bond dealers. A decrease in the risk-taking willingness of both dealers and customer liquidity providers weakly increases the bid-ask spreads for inventory transactions, but they affect the amount of riskless principal transactions in opposite directions.

At the core of the SVAR are the following three time series: (i) the bid-ask spreads implied by inventory transactions, (ii) the bid-ask spreads implied by riskless principal transactions, and (iii) the fraction of riskless principal transaction volume over total trading volume. These observable trading activities are among the popular quantities that have been studied by the literature about liquidity in corporate bond markets.[3]

The SVAR is governed by shocks to three structural variables, which are the risk-taking willingness of (i) customers who demand liquidity (hereafter "hedgers"), (ii) customer liq-

[1] See https://www.sifma.org/resources/research/fixed-income-chart/.

[2] Dealers help customers search for potential customer liquidity providers and get compensated for their efforts in the searching process.

[3] See, for example, Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018), Harris (2015), Trebbi and Xiao (2019), Goldstein and Hotchkiss (2019), Choi and Huh (2019), and Anderson and Stulz (2017).

uidity providers, and (iii) bond dealers. Structural shocks to the risk-taking willingness of dealers and customer liquidity providers are taken to be my new measures of liquidity.

What is the rationale to include these variables in the SVAR, and what are the economic connections between the structural shocks and the observed trading activities? First, the market-making willingness of bank-affiliated broker dealers might have been compromised by the above-noted regulatory changes, resulting in lowered capital commitments (Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018)); this is a shock lowering their risk-taking willingness. Another example is the run on the repo market in 2008 and the deterioration of the securitized banking system (Gorton and Metrick (2012)). When the required return on capital is high due to capital constrains, bond dealers tend to conduct riskless principal transactions and charge higher bid-ask spreads for inventory transactions.

Second, the risk-taking willingness of customer liquidity providers is my measure of customer liquidity. What distinct insights can this measure provide? The empirical literature has focused on post-crisis regulatory shocks to bank-affiliated bond dealers and the resulting high demand for liquidity provision by buy-side customers (Choi and Huh (2019)). Distinct from this perspective, my measure captures the supply side dynamics. One important example of supply side dynamics is capital inflows into fixed income mutual funds, which may lead to an increased willingness to buy distressed bonds at favorable prices. In such cases, more riskless principal transactions will be conducted.

Third, the risk-taking willingness of hedgers approximates their eagerness to liquidate the bond. For instance, unexpected losses due to natural disasters force insurance companies to liquidate their positions (Chaderina, Mürmann, and Scheuch (2019)). Shocks that lower the risk-taking willingness of hedgers lower their reservation prices and, thus, increase the bid-ask spreads due to the market power of bond dealers.

I separately estimate the SVAR for investment-grade bond markets and high-yield bond markets. The derived patterns of the structural shocks are sensible and instructive about important historic events. Bond dealers aggressively built inventory before the 2008 crisis when "too big to fail" guarantees incentivized dealers toward excessive risk-taking activities (Bessembinder, Spatt, and Venkataraman (2019)). Conversely, bond dealers were much less willing to provide liquidity during the collapse of Lehman Brothers and the post-regulation periods.

In sharp contrast, customer liquidity provision increases for investment-grade bond markets during the post-regulation period, consistent with the view that recently launched alternative trading systems (ATSs), a new but growing mechanism that is parallel to the classic OTC market-making mechanism, manage to locate more customer liquidity providers. The assets traded in ATSs tend to be liquid bonds with investment-grade ratings. My measure also uncovers an increase in customer liquidity provision during the 2008 financial crisis, especially for investment-grade bonds. Evidence suggests that customer liquidity providers crowd into corporate bond markets during the crisis. This is a "flight-to-safety" phenomenon, as documented by Dick-Nielsen, Feldhütter, and Lando (2012).

Measuring customer liquidity provision has potentially significant welfare implications. Theoretically, bank-affiliated dealers who face stringent regulations tend to increase investments on matchmaking technology (Saar, Sun, Yang, and Zhu (2019)). Improved matchmaking technology could reach more customer liquidity providers such that bond dealers can fulfill more orders from customers who have hedging demands but otherwise would not trade. Complementary to this theory, my contribution is to provide empirical evidence that developments in matchmaking technology, indeed, attract more customer liquidity providers.

Customer liquidity provision could potentially supplement aggregate liquidity when the willingness of bond dealers to provide liquidity contracts. In contrast, aggregate market liquidity could be largely suppressed if the willingness of both dealers and customers to provide liquidity decreases. Therefore, measuring the supply of liquidity provision by customers is important from the perspective of regulators and investors. Overall, my proposed SVAR approach can be utilized as a tool in understanding and evaluating market conditions and the associated impact on the tendency of dealers versus customers to provide liquidity.

Furthermore, I study the pricing implications of my derived liquidity measures. The question asked is whether my measures are related to time-series changes in yield spreads of corporate bonds. My analysis reveals that changes in yield spreads for bonds of different credit ratings respond differentially to my measures of liquidity. High quality (above A-rated) corporate bonds are more exposed to my measure of customer liquidity, whereas lower quality bonds (below A-rated) are mostly subject to my measure of dealer liquidity.

The differential impact of shocks to dealers versus customer liquidity providers also translates into different exposures of yield spreads in response to recent regulations (decrease in liquidity provision by dealers) and technology developments (increase in liquidity provision by buy-side customers). Raising concerns for regulators, the mixed consequence of stringent regulations and technology improvements could point to an outcome that safer bonds become more liquid, whereas markets are even thinner for bonds that are riskier and, likely, already illiquid. For example, Bao, O'Hara, and Zhou (2018) document that illiquidity of downgraded bonds is even more severe after the implementation of the Volcker Rule. Acharya, Amihud, and Bharath (2013) show that prices of investment-grade bonds increase, while prices of speculative-grade bonds fall during illiquidity periods. My paper attributes such effects to the conflicting exposures of corporate bonds to my measures of customer liquidity providers and bond dealers.

Empirically, the identification of a SVAR requires certain restrictions that need to be justified by economic theory. To motivate my identification strategy, I present a theoretical model of segmented markets. In each market, there is a market maker and two types of customers (hedgers and customer liquidity providers). Customers can trade *only* with the local market maker, and all market makers strategically trade in a centralized system. A market maker may buy from hedgers, sell a fraction to customer liquidity providers (riskless principal transactions), sell in the interdealer market, and keep the remaining as inventory.

This model sheds light on the three identification restrictions required in the SVAR. The risk-taking willingness of neither dealers nor customer liquidity providers will affect the bid-ask spreads for riskless principal transactions. The intuition is that dealers' own capital is not involved. In addition, an increase in customer liquidity provision improves both the bid and the ask prices in parallel, but not the bid-ask spreads. The third restriction is that the fraction of riskless principal transaction volume responds only to the relative changes in the risk-taking willingness among customers and dealers. In other words, this fraction remains stagnant when the risk-taking willingness of all market participants increases in proportion.

In addition, I exploit an alternative empirical method to identify the SVAR, which imposes sign restrictions on the impulse response functions (Uhlig (2005)), called the "agnostic method." The method focuses on the shock of interest (either hedgers, dealers, or customer liquidity providers) but remains agnostic about other shocks; only partial identification is achieved under this method. The advantage is that the imposed restrictions exploit relatively weak prior beliefs on the impulse response functions, and there restrictions are independent from the three equality restrictions. This agnostic method, as a safeguard, yields similar outcomes, compared with the full identification approach.

2 An SVAR approach

This section discusses the SVAR approach. This approach can help explain the source of shocks that affect the observed market trading patterns. My design of the SVAR separately yields measures of shocks to customer liquidity providers and shocks to bond dealers.

The SVAR incorporates three market-wide aggregate time series: (i) bid-ask spreads from riskless principal transactions (denoted by $\mathbf{Spread_t^{RPT}}$), (ii) bid-ask spreads from inventory transactions (denoted by $\mathbf{Spread_t^{IVT}}$), and (iii) fraction of customer-dealer-customer riskless principal transaction volume over total customer-dealer volume (denoted by $\mathbf{\%RPT}$).

Let the vector $\mathbf{y_t}$ contain the three series: $\mathbf{y_t} = \left[\log\left(\text{Spread}_{\text{t}}^{\text{RPT}}\right), \log\left(\text{Spread}_{\text{t}}^{\text{IVT}}\right), \%\text{RPT}_{\text{t}}\right]^T$. The SVAR specification[4] reads as

$$\mathbf{y_t} = \mathbf{A_0} + \sum_i \mathbf{A_i}\mathbf{y_{t-i}} + \underbrace{\begin{bmatrix} b_1 & b_{1,2} & b_{1,3} \\ b_{2,1} & b_2 & b_{2,3} \\ b_{3,1} & b_{3,2} & b_3 \end{bmatrix}}_{\mathbf{B}} \underbrace{\begin{bmatrix} \epsilon_t^H \\ \epsilon_t^L \\ \epsilon_t^d \end{bmatrix}}_{\boldsymbol{\epsilon}_\mathbf{t}}, \tag{1}$$

where $\boldsymbol{\epsilon}_\mathbf{t} = \left[\epsilon_t^H, \epsilon_t^L, \epsilon_t^d\right]^T$ is a vector of unit variance orthogonal shocks to hedgers (ϵ_t^H), customer liquidity providers (ϵ_t^L), and dealers (ϵ_t^d). A positive innovation in any element in $\boldsymbol{\epsilon}_\mathbf{t}$ means that the corresponding group of participants in aggregation becomes more risk averse and less willing to provide liquidity.

I assume the orthogonality conditions in my main analysis. Internet Appendix D presents a case in which the orthogonality conditions are violated. In that case, the recovered structural shocks can be interpreted as shocks to hedgers, shocks to dealers that are orthogonal to the shocks to the hedgers, and shocks to customer liquidity providers that are orthogonal to the other two types of shocks.

The SVAR does not incorporate proxies for the dynamics of information asymmetry, which could be a potential concern for market makers to charge bid-ask spreads. Empirical literature, however, shows that adverse selection is not a significant component for the effective bid-ask spreads in corporate bond markets.[5]

2.1 What is the expected impact of structural shocks?

The specification in equation (1) links the dynamics of unobserved structural shocks to various market participants ($\boldsymbol{\epsilon}_\mathbf{t}$) to the observable market trading patterns of interest ($\mathbf{y_t}$) to academics and regulators. The matrix $\mathbf{B}$ governs these links and determines the direction and the magnitude of the impact of each shock. My hypotheses on the directions of the elements in $\mathbf{B}$ are summarized below.

$$\mathbf{y_t} = \mathbf{A_0} + \sum_i \mathbf{A_i}\mathbf{y_{t-i}} + \underbrace{\begin{bmatrix} + & 0 & 0 \\ + & ? & + \\ ? & - & + \end{bmatrix}}_{\mathbf{B}} \underbrace{\begin{bmatrix} \epsilon_t^H \\ \epsilon_t^L \\ \epsilon_t^d \end{bmatrix}}_{\boldsymbol{\epsilon}_\mathbf{t}}, \tag{2}$$

[4]Logarithmic transformation is applied in order to be consistent with the conclusions drawn from the model in Section 5. Empirical results are economically similar without the logarithmic transformation.

[5]See Bessembinder, Maxwell, and Venkataraman (2006), Friewald and Nagler (2019), and Lu, Lai, and Ma (2017).

There are five priors (marked as "+" or "−") and two zero restrictions (marked as "0"); the associated economic intuitions are discussed below. The directions of the remaining two elements (marked as "?") are undetermined. I solicit answers based on the empirical data.

ϵ_t^H captures the eagerness of hedgers to liquidate a bond position due to certain exogenous liquidity shocks or changes in the desired inventory level. Positive shocks enlarge the gap of the reservation prices between hedgers and (both dealer and customer) liquidity providers.[6] Thus, profit-optimizing bond dealers charge higher $\mathbf{Spread_t^{RPT}}$, when conducting offsetting transactions between two customers; that is, $b_1 > 0$. Besides, this widened gap entices bond dealers to charge higher $\mathbf{Spread_t^{IVT}}$ because risk-averse dealers take more inventory and require higher compensation: $b_{2,1} > 0$.

A positive ϵ_t^d captures increased cost of market-making during the 2008 financial crisis and the post-regulation period. Facing such shocks, bond dealers conduct more riskless principal transactions ($\mathbf{\%RPT_t}$) and request more compensations for market-making ($\mathbf{Spread_t^{IVT}}$). Therefore, I hypothesize $b_3 > 0$ and $b_{2,3} > 0$. Choi and Huh (2019) show economically insignificant difference between $\mathbf{Spread_t^{RPT}}$ in the pre-crisis period (when market-making cost is low) and that in the post-regulation period. The cost of market-making (ϵ_t^d), thus, does not directly relate to $\mathbf{Spread_t^{RPT}}$, namely, $b_{1,3} = 0$.

The shock ϵ_t^L is considered as a parallel shift of the supply curve of aggregate customer liquidity due to various reasons. For instance, cash flows shift between equity markets and fixed income markets. Another reason is that bond dealers invest in matchmaking technology so that they can easily find a customer liquidity provider and conduct more riskless principal transactions. Higher ϵ_t^L, or less customer liquidity provision, is expected to lower $\mathbf{\%RPT_t}$: $b_{3,2} < 0$. Note that such an impact is distinct from a shock to dealers who choose the optimal quantities along the supply curve of customer liquidity.

The shock ϵ_t^L does not affect $\mathbf{Spread_t^{RPT}}$, specifically $b_{1,2} = 0$. Customer liquidity providers trade (indirectly) with hedgers because of their differential reservation prices. ϵ_t^L affects neither of the two reservation prices. Hence, it is optimal for a dealer to charge the same $\mathbf{Spread_t^{RPT}}$, despite the shifts of both the bid and the ask prices.

The two zero restrictions are important in estimating the SVAR. The other priors are not used in the estimation procedure, but they serve the purpose of testing the soundness of the SVAR, as predicted by economic intuitions and my theoretical model.

[6] A reservation price is the marginal price at which a participant would be optimal if she does not trade. Reservation prices for bond dealers and customer liquidity providers are not impacted by the structural shocks because they enter the market without initial endowment.

2.2 Estimation procedure for the SVAR

The following three restrictions on $\mathbf{B}$ are imposed to identify the SVAR:

$$b_{1,2} = 0, \qquad b_{1,3} = 0, \qquad \text{and} \qquad b_{3,1} + b_{3,2} + b_3 = 0. \tag{3}$$

I restrict that $b_{1,2} = b_{1,3} = 0$ because ϵ_t^d and ϵ_t^L have no impact on $\text{Spread}_t^{\text{RPT}}$. The third restriction ($b_{3,1}+b_{3,2}+b_3 = 0$) obeys the intuition that $\%\text{RPT}_\text{t}$ depends on the relative change in shocks between dealers and customers. If the risk-taking willingness of hedgers, dealers, and customer liquidity providers were all halved, the equilibrium prices would improve, but all volumes would remain the same. When every participant becomes proportionally less willing to hold this bond,[7] hedgers are more eager to sell, and dealers and customer liquidity providers become reluctant to hold this bond. Dealers and customer liquidity providers will still buy the same units of the bond from hedgers since the change is proportional. In Section 5, I show that $\frac{\partial \%\text{RPT}_\text{t}}{\partial \log(\delta_L)} + \frac{\partial \%\text{RPT}_\text{t}}{\partial \log(\delta_H)} + \frac{\partial \%\text{RPT}_\text{t}}{\partial \log(\delta_d)} = 0$, where δ_H, δ_L, and δ_d are the inverse of risk-taking willingness of the corresponding market participants, and logarithms of the δs represent $\boldsymbol{\epsilon}_\mathbf{t}$ in the SVAR.

Assuming the restrictions stated in equation (3), the SVAR is estimated in two steps (Lütkepohl, 2005, p. 372). In the first step, loadings on the lagged $\mathbf{y_t}$ terms, $\hat{\mathbf{A}} = [\hat{\mathbf{A}}_\mathbf{0} \dots \hat{\mathbf{A}}_\mathbf{I}]$, are estimated via ordinary least squares (OLS). The optimal number of lags I is determined by the Schwarz-Bayesian information criterion (SBIC). Next, loadings on the structural shocks, $\hat{\mathbf{B}}$, are estimated by maximizing the log-likelihood,

$$\log \mathscr{L}_c(\mathbf{B}) = \text{constant} - \frac{T}{2}\log|\mathbf{B}| - \frac{T}{2}\text{trace}\left(\mathbf{B}'^{-1}\mathbf{B}^{-1}\tilde{\Sigma}_u\right), \tag{4}$$

where $\tilde{\Sigma}_u$ is the covariance matrix estimated from the residuals in the first step.

In closing, I present the design of a SVAR in analyzing trading activities in corporate bond markets. In doing so, I outline my priors for coefficients in matrix $\mathbf{B}$ and the procedure for estimation.

3 Data

This section introduces the academia TRACE data and the steps to clean the database. I describe the method that I use to classify each customer-dealer transaction in TRACE as a riskless principal transaction or an inventory transaction. My focus is on aggregating the transaction level data into (i) the bid-ask spreads from riskless principal transactions

[7] Assume a positive net supply of the asset.

($\mathbf{Spread_t^{RPT}}$), (ii) the bid-ask spreads from inventory transactions ($\mathbf{Spread_t^{IVT}}$), and (iii) the vratio of riskless principal transaction volume over total customer-dealer volume ($\mathbf{\%RPT_t}$). These time-series are inputs into the SVAR.

3.1 Academia TRACE

The Trade Reporting and Compliance Engine (TRACE) is a FINRA-developed vehicle for mandatory reporting in OTC markets. It collects all the secondary market transactions conducted by FINRA registered broker-dealers in the U.S. corporate bond markets. The standard TRACE contains a limited set of information for each transaction, including capped transaction quantity, transaction price, execution date and time, indicator for dealer/client buy and sell, among others.

In addtion to that information, the academia TRACE provides uncapped transaction quantity and, importantly, masked identifications of the dealers that facilitate the transactions. Those fields allow me to identify riskless principal transactions conducted by the same dealers within a short time period.

The academia TRACE provides two fields: (a) **Reporting Market Participant Identifier** is the dealer who reports the transaction and likely the dealer who executes the transaction. (b) **Contra Identifier** could be either the contra-party dealer, if the field is populated by a masked dealer ID, or a customer denoted by a letter C. According to these two fields I can find riskless principal transactions, provided that the buyer in one transaction is the seller in the other transaction and that other transactional information matches.

I take care of the exceptions that the reporting party is not the party that executes the transaction, that is, "locked in" and "give up" transactions. In those cases, the additional fields **Reporting Side Give Up Participant Identifier** and/or **Contra Give Up Identifier** are populated.[8]

Table 1 lists the main steps that I implement for data cleaning. The database contains more than 159 million transactions for 106,873 distinct issues facilitated by 3,815 unique dealers over the entire sample period from 2002 to 2015. I apply the procedure from Dick-Nielsen (2014) to clean duplicated records in TRACE when a dealer attempts to cancel or modify a reported transaction, resulting in a total of 113 million transaction records.

[8] One example is that Dealer A hires Dealer B to report transactions conducted by Dealer A. In the example, Reporting Side Give Up Participant Identifier is Dealer A, and Reporting Market Participant Identifier is Dealer B. Another example is that two dealers transact in an alternative trading system (ATS). The ATS, on behalf of two dealers, reports the transaction to TRACE. Overall, the dealers in the Give Up fields should be treated as the actual buyer or seller in the transactions whenever the Give Up fields are populated.

I focus on non-puttable US Corporate Debentures and US Corporate Bank Notes as identified by FISD bond type (CDEB or USBN) after the end of phase-in period (Dec 31, 2005). Here I adopt two exclusionary criteria. First, I exclude transactions that occur within 30 days of the offering date. Second, I eliminate affiliated transactions in which a FINRA member dealer transfers its inventory to an affiliated party for bookkeeping purposes. Affiliated transactions are identified as those offsetting transactions conducted by a dealer at the exact same prices for both legs, and the dealer makes zero profits.[9]

The cleaned sample consists of 24,754 unique Cusips and approximately 54 million transactions conducted by 3,389 unique dealers. The cleaned TRACE data is merged with Mergent Fixed Income Securities Database (FISD) for information of bond characteristics and credit ratings.

3.2 Classifying riskless principal transactions

I follow the "last in, first out" (LIFO) method in Choi and Huh (2019) to classify riskless principal transactions. In general, a set of transactions on a single Cusip are considered as riskless principal transactions if the following conditions are satisfied:

- The transactions are conducted by the same dealer.
- The dealer buys and sells within a small time interval.
- The total volumes of buys and sells are approximately equal.

Internet Appendix E lists the detailed steps in identifying riskless principal transactions.

Based on the outcome of this algorithm, every customer-dealer transaction is classified based on the identity of the counterparty in the offsetting transaction. I focus on two types of transactions: (i) customer-dealer-customer riskless principal transactions (RPTs) and (ii) customer-dealer-customer inventory transactions (IVTs).

In a pair of RPTs, a customer sells to a dealer and the dealer sells to another customer within 15 minutes. In IVTs, a customer sells to a dealer and this dealer takes no selling action in the next 15 minutes. Transactions in which a dealer buys from a customer and sells to another dealer immediately are not considered. If a transaction partially follows the categories above, the classification is based on the largest portion. For instance, if a customer sells to a dealer 1,000 shares, and the dealer sells 800 shares to another customer immediately, it is considered an RPT.

[9] The detailed identification procedure is described in Internet Appendix A of Choi and Huh (2019). TRACE started to require reporting dealers to indicate affiliated transactions on 11/02/2015. This affiliated transaction indicator only covers the last two months of the data, so that I opted not to use it.

3.3 Computation of bid-ask spreads and trading volume

This subsection describes my method of computing the bid-ask spreads and presents the summary statistics of the monthly average bid-ask spreads and trading volume for RPTs and IVTs. Bid-ask spreads are computed for transactions with par value greater than (inclusive) \$100K. The full bid-ask spread is twice the difference between the traded price and the reference price, which is the volume-weighted average interdealer prices for the same bond on the same day.

I focus on the largest dealers, which tend to be bank-affiliated dealers, selected based on a $\boldsymbol{K}$-mean clustering method. The number of selected dealers per month is between 10 and 15 during the sample period of 2006 to 2015. Figure A-3 in Internet Appendix demonstrates the resulted clusters. These numbers are consistent with the top 70% sample in Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018).

$\boldsymbol{K}$-mean clustering is an algorithm to partition observations into $\boldsymbol{K}$ clusters so that the total distance between each observation and the mean of the belonged cluster is minimized. The advantage of the $\boldsymbol{K}$-mean clustering method is to jointly consider multidimensional activities of each dealer, including the customer-dealer trading volume, the interdealer trading volume, and the amount of offsetting transactions. It is better than a fixed threshold because there are large banks that enter and exit the market, and the aggregate trading volume is time-varying. The method excludes interdealer brokers that arrange agency trades only for dealers.

Table 2 presents the summary statistics for the trading activities. I first average the bid-ask spreads and volumes for all transactions over a given month and then report the mean, standard deviation and percentiles for these monthly aggregated quantities.

In investment-grade (IG) bond markets, the mean of $\mathbf{Spread_t^{IVT}}$ is 47.46bps, while the average of $\mathbf{Spread_t^{RPT}}$ is 22.12bps. In an average month, there are \$16.8 billion par value and 1,588 distinct Cusips transacted for IVTs and \$1.3 billion par value and 252 distinct Cusips transacted for RPTs. The average number of transactions per month with par value above (inclusive) \$1MM is 2,674 for IVTs and 173 for RPTs.

The number of transactions used to compute $\mathbf{Spread_t^{RPT}}$ is limited. Note that the level of reference price, which is hard to accurately pinned down, is not important in the computation of $\mathbf{Spread_t^{RPT}}$. It does not necessarily require a large number of transactions to infer an aggregate $\mathbf{Spread_t^{RPT}}$. To further reduce noise, especially for $\mathbf{Spread_t^{IVT}}$, I also include more transactions, that is, those with par value between \$100K and \$1MM. Transactions with a size smaller than \$100K tend to incur significantly higher bid-ask spreads, so they are excluded from my aggregations.

Similar patterns are observed for high-yield (HY) bonds. HY bonds are more likely to be transacted in RPT and dealers tend to charge higher bid-ask spreads for HY bonds.

Figure 1 plots the time series used for the SVAR. Presented are the monthly average $\mathbf{Spread}_{\mathrm{t}}^{\mathrm{RPT}}$ and $\mathbf{Spread}_{\mathrm{t}}^{\mathrm{IVT}}$ for IG and HY bonds, based on Moody's Corporation. Both spreads reach the peak during the 2008 financial crisis. $\mathbf{Spread}_{\mathrm{t}}^{\mathrm{IVT}}$ are always greater than $\mathbf{Spread}_{\mathrm{t}}^{\mathrm{RPT}}$. The differences between $\mathbf{Spread}_{\mathrm{t}}^{\mathrm{IVT}}$ and $\mathbf{Spread}_{\mathrm{t}}^{\mathrm{RPT}}$ are widened during the post-regulation period, relative to the pre-crisis period. Also presented is the ratio of riskless principal transaction volume over total customer-dealer volume ($\mathbf{\%RPT_t}$). $\mathbf{\%RPT_t}$ is higher during the post-regulation periods. These patterns are consistent with the observations in Choi and Huh (2019).

4 Customer liquidity provision: Empirical results

To streamline my discussion, recall that my notation for the structural shocks is the following: ϵ_t^H is the shock to hedgers, ϵ_t^L is the shock to customer liquidity providers, and ϵ_t^D is the shock to dealers. A positive shock represents a decrease in the risk-taking willingness of the corresponding party.

This section implements the SVAR, introduces the estimates of $\hat{\mathbf{B}}$, and provides economic interpretations. Then, I construct my measures of liquidity from the SVAR, which allows me to address the following questions:

- How do my measures of liquidity, especially the measure of customer liquidity provision, behave during significant historic events?
- What are the economic connections between my measures of liquidity and the prices of corporate bonds?

These questions are asked in light of the fact that dealers are subject to post-crisis regulations and the demand for liquidity provided by customers is heightened. As I show, my approach is supportive of the view that dealers have started to improve their matchmaking technology in the hope of luring more customer liquidity providers (actions that improve social welfare). Finally, I use my empirical setting to explore the asset pricing implications of my new dealer and customer liquidity measures.

4.1 Estimates of $\hat{\mathbf{B}}$ and economic interpretation

The SVAR in equation (1) is estimated using the three series presented in Figure 1 for IG bonds and HY bonds, respectively. Selected based on the SBIC, the optimal number of lagged terms is one for IG bonds and two for HY bonds. Table 3 reports the estimated $\hat{\mathbf{B}}$s. The sign of each estimated coefficient is allied with my hypotheses in Section 2.1 and is consistent with economic intuition.

First, $\mathbf{Spread}_t^{\mathrm{RPT}}$ are only affected by ϵ_t^H via b_1. The estimates of $\hat{b}_1$ are 0.23 and 0.14 for IG and HY bonds, suggesting that a positive ϵ_t^H increases $\mathbf{Spread}_t^{\mathrm{RPT}}$. They are both statistically significant at the 1% level. Note that $\mathbf{Spread}_t^{\mathrm{RPT}}$ enters into the SVAR in the logarithm format. The magnitudes of 23% and 14% movements of $\mathbf{Spread}_t^{\mathrm{RPT}}$ for a standard deviation change in ϵ_t^H are economically relevant.

Second, the impacts of ϵ_t^H, ϵ_t^L, and ϵ_t^D on $\mathbf{Spread}_t^{\mathrm{IVT}}$ are not restricted in the SVAR. The actual impacts are reflected in the second row ($[\hat{b}_{2,1}, \hat{b}_2, \hat{b}_{2,3}]$) of $\hat{\mathbf{B}}$. For IG bonds, the corresponding estimated coefficients are $[0.08, 0.01, 0.12]$. $\hat{b}_{2,1}$ and $\hat{b}_{2,3}$ are statistically significant at the $p = 1\%$ level, whereas $\hat{b}_2$ is insignificant. One standard deviation of a positive ϵ_t^H (ϵ_t^D) will increase $\mathbf{Spread}_t^{\mathrm{IVT}}$ by 8% (12%).

In contrast, for HY bonds, the corresponding estimated coefficients are $[0.05, 0.05, 0.09]$. All the coefficients are statistically significant at the $p = 1\%$ level. Interpreting the estimates in the HY market, a positive shock to the risk-taking willingness for any of the three market participants will increase $\mathbf{Spread}_t^{\mathrm{IVT}}$. Among the three structural shocks, ϵ_t^d exhibits the highest impact. A one standard deviation of increase in ϵ_t^d leads to 9% increase in $\mathbf{Spread}_t^{\mathrm{IVT}}$, while ϵ_t^H and ϵ_t^l have a marginal impact of 5% on $\mathbf{Spread}_t^{\mathrm{IVT}}$.

Finally, the third rows in $\hat{\mathbf{B}}$s demonstrate the impact of structural shocks on the fraction of riskless principal trading volume (i.e., $\%\mathbf{RPT}_t$). For the IG bond market, the estimates are $[0.31, -1.26, 0.95]$. My estimates imply that ϵ_t^L and ϵ_t^d are the important drivers of $\%\mathbf{RPT}_t$.

Building further on the economic insights, when customer liquidity providers receive a one standard deviation positive shock, they are expected to provide less liquidity; that is, $\%\mathbf{RPT}_t$ decreases by -1.26%. The impact is sizable, considering the average of $\%\mathbf{RPT}_t$ is 8.67% over the sample period. Providing complementary evidence, when dealers receive a one standard deviation positive shock, $\%\mathbf{RPT}_t$ increases by 0.95%.

This finding is consistent with the literature that shows that dealers conduct more riskless principal transactions both during the financial crisis and over the post-regulation periods (e.g., Choi and Huh (2019)). Similar intuition can be garnered when considering the impact of structural shocks on $\%\mathbf{RPT_t}$ for the HY market. Overall, my estimates of $\hat{\mathbf{B}}$s are aligned with theory and economic intuition.

4.2 What drives $\mathbf{Spread_t^{IVT}}$?

Recall that the second row in $\hat{\mathbf{B}}$ reflects the relationship between the three structural shocks and $\mathbf{Spread_t^{IVT}}$. $\mathbf{Spread_t^{IVT}}$ is an important object because it approximates the cost for immediacy in an OTC market, i.e., the marginal cost that hedgers pay, compared with the interdealer price. Since the structural shocks are orthogonal to each other, the fluctuation in $\mathbf{Spread_t^{IVT}}$ can be attributed to the variation of each shock. The impact of customer liquidity provisions on $\mathbf{Spread_t^{IVT}}$ can be determined in this setting.

In IG markets, my results suggest that most of the fluctuation (about 67%)[10] in $\mathbf{Spread_t^{IVT}}$ is driven by ϵ_t^d, while the remaining 33% results from ϵ_t^H. In contrast, the total fluctuation of $\mathbf{Spread_t^{IVT}}$ in HY markets can be decomposed into shocks to the three market participants such that 20% of the fluctuation is due to ϵ_t^H, 21% is resulted from ϵ_t^L, and the rest 59% is explained by ϵ_t^d.

The markets of IG and HY bonds exhibit some commonalities. The majority of the fluctuations of $\mathbf{Spread_t^{IVT}}$ for both markets is driven by ϵ_t^d. The direction of such an impact is consistent with the view that decreased dealers' risk-taking willingness leads to higher $\mathbf{Spread_t^{IVT}}$ (Duffie (2012)). I quantify the fraction of fluctuations in $\mathbf{Spread_t^{IVT}}$ with regard to this type of shock.

The two markets are distinct, when considering the impact of ϵ_t^L on $\mathbf{Spread_t^{IVT}}$. Only in HY markets, a positive ϵ_t^L significantly increases $\mathbf{Spread_t^{IVT}}$, and ϵ_t^L explains a meaningful amount of fluctuations in $\mathbf{Spread_t^{IVT}}$. The results answer the question that shocks to customer liquidity provision affect the $\mathbf{Spread_t^{IVT}}$. However, it suggests that the magnitude of impact differs between IG and HY bond sectors.

In Section 5, my theoretical model provides an explanation to this divergence in results in the two different bond sectors. In the model, I show that the marginal impact of ϵ_t^L on $\mathbf{Spread_t^{IVT}}$ is nonlinear. It depends on the relative amount of liquidity provision between dealers and customer liquidity providers. Change in customer liquidity provision exhibits a stronger marginal impact on $\mathbf{Spread_t^{IVT}}$, when there is relatively more customer liquidity provision on the market.

[10]Under the assumption that structural shocks are orthogonal, one can attribute the total variation of the unexpected change in $\mathbf{y_t}$ into three components. For this specific case, 67% is computed by $\frac{\hat{b}_{2,3}^2}{\hat{b}_{2,1}^2+\hat{b}_2^2+\hat{b}_{2,3}^2}$

The intuition is the following. Dealers charge $\mathbf{Spread}_t^{\mathbf{IVT}}$ for compensation for taking inventory risk. The $\mathbf{Spread}_t^{\mathbf{IVT}}$ charged by a dealer is linear in the ultimate absolute inventory level, which is nonlinear in the amount of customer liquidity provision. Interpreting this nonlinearity in inventory level is the key to understanding the explanation of the nonlinear impact of customer liquidity provision on $\mathbf{Spread}_t^{\mathbf{IVT}}$.

If the aggregate level of customer liquidity provision is high, dealers' relative inventory level is low. When a shock hits customer liquidity providers, dealers quickly step in to provide liquidity. Dealers' inventory level moves significantly, as does $\mathbf{Spread}_t^{\mathbf{IVT}}$. In contrast, if dealers are responsible for most of the liquidity provision, incremental changes in customer liquidity provision result in small changes in dealers' inventory level and $\mathbf{Spread}_t^{\mathbf{IVT}}$. Thus, the relative level of liquidity provision, between dealers and customers, plays a large role in the relative impact of liquidity shocks to dealers versus customers in a certain bond market sector.

Empirically, the marginal impact of shocks to customer liquidity on $\mathbf{Spread}_t^{\mathbf{IVT}}$ is much stronger in HY markets. In other words, dealers rely on customer liquidity provision to a much greater degree in HY markets. As shown in Figure 1, the percentage of riskless principal transaction volume ($\mathbf{\%RPT}_t$) is consistently higher in the HY market (15%–33%) than that in IG markets (3%–17%). Evidence supporting the empirical fact is documented in Goldstein and Hotchkiss (2019), who find that the tendency of overnight holdings for dealers are lower for HY bonds.

4.3 Evolution of historical structural shocks

Analyzing realized structural shocks yields insights on the conditions of corporate bond markets. The SVAR yields two separated liquidity measures for dealers and customer liquidity providers. To demonstrate their usefulness, this subsection discusses the linkages between the structural shocks and the most known historic events that affect corporate bond markets.

Figure 2 presents the backward accumulated structural shocks using a rolling window of twelve months.[11] Facilitating detected patters in Figure 2, Table 4 presents statistical evidences, in which inferences are drawn based on a bootstrap method described in Internet Appendix G.

I divide the sample into the following subperiods: pre-crisis period (Jan 2006 to Jun 2007), the 2008 financial crisis (Jul 2007 to Apr 2009), the post crisis period (May 2009 to May 2012), the Basel 2.5 period (Jun 2012 to Jun 2013), the Basel III period (Jul 2013 to Mar 2014), and

[11] For example, the data point labeled 2009 captures the cumulative sum of $\{\hat{\boldsymbol{\varepsilon}}_t\}$ from Jan 2008 to Dec 2008.

the Volcker Rule period (post Apr 2014). The selected dates follow Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018) and Bao, O'Hara, and Zhou (2018). I also include a period of the collapse of Lehman Brothers (Aug 2008 to Dec 2008) which is nested in the 2008 financial crisis period.

A. During the pre-crisis period, negative ϵ_t^ds are observed (i.e., expansion of dealer liquidity provision). It reflects the aggressive market-making strategies for bond dealers. Primary dealers accumulated up to \$225B inventory in corporate assets at the end of Aug 2007, compared with a net position of \$155B in Dec 2005.[12] Bessembinder, Spatt, and Venkataraman (2019) characterize this period with implicit "too big to fail" guarantees and low costs for market-making, which may not be socially optimal.

B. In the 2008 financial crisis, no significant ϵ_t^ds are observed during the overall period of Aug 2007 to Dec 2008. The evidence shows that dealers were not reluctant to provide liquidity, at least during the initial stage of the 2008 financial crisis.

Instead, positive ϵ_t^ds and negative ϵ_t^Ls are observed. The evidence suggests that some investors are eager to sell, whereas other customers are willing to provide liquidity, possibly due to capitals from other markets that are riskier than corporate bond markets. These two shocks drive the increase of bid-ask spreads and the amount of riskless principal transactions during late 2007 and early 2008.

The findings of increased customer liquidity provision during the crisis are called "flight-to-safety." Friewald, Jankowitsch, and Subrahmanyam (2012) document this phenomenon for IG bonds only. To interpret the distinction of customer liquidity provision between IG and HY markets, it requires further investigation into the months following the collapse of Lehman Brothers.

C. It was not until the collapse of Lehman Brothers that dealers become extremely cautious in liquidity provision. The nested dummy of Lehman Brothers is significantly positive for dealers. The aggregate net position for primary dealers on corporate securities with time-to-maturity over one year dropped from \$155B in May 2008 to \$73B in December 2008. One explanation is that increased haircut in repo transactions and the resulting run on repo limited the bond dealers' ability to market the market.

At the peak of the crisis, ϵ_t^L for HY turns significantly positive, while ϵ_t^L for IG does not. The evidence shows that although customer liquidity providers tend to participate in the riskier HY markets at the beginning of the crisis, they quickly flee away and shift toward the higher quality IG markets.

[12] Data of the > 1 year holdings are from the Federal Reserve Bank of New York: https://www.newyorkfed.org/markets/gsds/search.

Overall, the results suggest that customers facilitate liquidity provision during the 2008 financial crisis, complementing the findings in Di Maggio, Kermani, and Song (2017) that dealers are unwilling to expand their inventory, especially for those bonds that clients were selling the most at that moment.

D. In the periods of Basel Accords, positive ϵ_t^ds for HY bonds are detected in Figure 2 and Table 4. The effect is concentrated in the period of the Basel 2.5. There are two plausible explanations. First, banks start to comply with Basel III before the actual implementation date. Second, this finding agrees with the survey evidence in CGFS (2016): *For the corporate bond... ("Basel 2.5") were seen to have had the largest impact ... the Basel III requirements, in turn, was expected to have only a minor impact.*

Note that significant impacts are only detected for HY bonds. Basel 2.5 and Basel III aim at mitigating the risk of banks' portfolios, and thus lead to a stronger effect in the riskier HY markets. For example, Basel 2.5 introduces an incremental risk capital charge, which accounts for default and migration risk (Adrian, Fleming, Shachar, and Vogt (2017)). Basel III requires banks to maintain a minimum liquidity coverage ratio, which differentially treats IG and HY bonds.[13]

E. The Volcker Rule, which went into effect on April 1, 2014, requires banks to report inventory turnover as well as other statistics to ensure that banks do not engage in proprietary trading. The initial purpose of the Volcker Rule is to prevent bank holding companies from risky activities that take regulatory advantages, such as the FDIC insurance and "too big to fail" guarantees. However, Duffie (2012) observes that the nature of market-making activities is a form of proprietary trading and predicts that the implementation of the Volcker Rule could potentially disincentivize liquidity provision by bond dealers. Consistent with this prediction, it is shown that ϵ_t^ds in my SVAR are positive; that is, dealers receive positive shocks and become less willing to make the market.

The aftermath of the stringent regulations is also a period when dealers invest more in matchmaking technology for more customer liquidity providers. Many electronic trading systems emerge in corporate bond markets, mostly using a method called "requests for quotations" (RFQs). Those platforms aim to attract more customer liquidity providers into corporate bond markets. My contribution is to explicitly display this increase in the supply of customer liquidity provision.

[13] The liquidity coverage ratio is calculated by dividing the high quality liquid asset amount (HQLA) by the total net cash flows of the bank over a 30-day stress period. All HY bonds are not considered HQLA, while IG corporate debt securities issued by non-financial sector corporations are considered as Level 2 HQLA. See Bank for International Supervision (2013) for more details.

In IG markets, the measure ϵ_t^L exhibits a sharp decrease since July 2014. Note that the plot presents a cumulative backward 12-month shock, and that data point captures the raising of trading volume in the electronic platform in the second half of 2013 and early 2014. Electronic trading of IG corporate bonds constitutes 8% of total market volume in 2013 and 16% in 2014 (SIFMA, 2016, p. 5). As the market share of electronic trading platforms grows, ϵ_t^L keeps at a negative level (i.e., plentiful customer liquidity provision) until the end of my sample.

In contrast, movements of ϵ_t^L in HY markets are mild and insignificant. In Panel C of Figure 2, ϵ_t^L in HY markets does not increase until late 2015. This evidence is consistent with the documentation in Hendershott and Madhavan (2015) that RFQs in MarketAxess are more suitable for large size IG bonds.[14]

In short, this subsection discusses the movements of the derived measures of liquidity for both customers and dealers over the last decade. The behavior of these generated series are consistent with the expected directions in the literature. My SVAR could be used to measure future market conditions for regulators when data is available. For example, what is the consequence of the undergoing back push that proposes to loosen the restrictions around the Volcker Rule?

4.4 How do my measures relate to stress indicators?

It has been well documented that illiquidity of corporate bonds comoves with the aggregate market conditions. In this subsection, I investigate the relation between the stress indicators and my measures of liquidity. I show that ϵ_t^H and ϵ_t^d are positively correlated with the stress indicators, whereas ϵ_t^L is not, due to other driving forces such as the "flight-to-quality" phenomenon and the improvement of matchmaking technology.

Bao, Pan, and Wang (2011) approximate the aggregate market condition using the Chicago Board Options Exchange Volatility Index (VIX).[15] In addition to the VIX, I relate my measures to a volatility index for 30-year US Treasury bonds, called TVIX. Compared to the VIX, the TVIX is more specific to the corporate bond markets. The volatility of the Treasury bond prices has a larger exposure to the volatility of interest rates (Collin-Dufresne, Goldstein, and Martin (2001)), which is also an important factor in corporate bond mar-

[14] MarketAxess reports a 85% market share in electronically facilitated corporate bond trading (Bessembinder, Spatt, and Venkataraman (2019). MarketAxess is a dominating electronic platform that accounts for 20% (12%) of total TRACE trading volume for IG bonds in Dec 2015 (Jan 2014).

[15] Also see Di Maggio, Kermani, and Song (2017), Collin-Dufresne, Goldstein, and Martin (2001), amd Friewald and Nagler (2019).

kets. Furthermore, most primary dealers in the Treasury bond market also make markets in corporate bond markets. The risk-taking attitudes for dealers in the two markets are tied closely.

Specifically, I consider the price of a volatility contract whose payoff is the squared return of holding a fully collateralized 30-year Treasury bond futures for one period (approximately a month) under the risk-neutral measure,

$$\text{TVIX}_t^2 = R_{f,t+1}^{-1}\mathbb{E}_t^Q\left(\log\left\{\frac{F_{t+1}}{F_t}\right\}^2\right), \tag{5}$$

where F_t is the 30-year Treasury bond futures price at period t. The derivation of the TVIX exploits the spanning engine in Bakshi and Madan (2000) and Bakshi, Kapadia, and Madan (2003). A detailed description is available in Internet Appendix F.

Figure 3 plots the time series of my TVIX; also plotted is the VIX at the corresponding dates. Although the correlation between the TVIX and the VIX is high (0.81), the two indexes reflect different stress events. For instance, on Aug 24, 2015, world stock markets plunged due to the drop in commodity prices. This global equity market disaster, which caused a spike in the VIX, did not propagate any fear in fixed income markets. In contrast, the TVIX increased from 6.6 in Jun 2014 to 14.3 in Feb 2015, while the VIX did not change much in the same period. This period corresponds to Federal Reserve's decision to halt the quantitative easing (QE) purchases.[16] Hence, it is necessary to investigate the relation between the shocks from SVAR and the two indexes, respectively.

I investigate the relation between $\hat{\boldsymbol{\epsilon}}_{\mathbf{t}}$ and the volatility indexes. Table 5 presents the results from the following regression:

$$\text{y}_{t+1} = \textbf{Constant} + \beta_1 \sum_{s=t-l-1}^{t} \hat{\epsilon}^H_{s-1\to s} + \beta_2 \sum_{s=t-l-1}^{t} \hat{\epsilon}^L_{t-1\to t} + \beta_3 \sum_{s=t-l-1}^{t} \hat{\epsilon}^d_{t-1\to t} + u_t, \tag{6}$$

where y_{t+1} is $\textbf{VIX}_{\textbf{t+1}}$ or $\textbf{TVIX}_{\textbf{t+1}}$ and $l = \mathbf{1, 3, 6,}\, \text{or}\, \mathbf{12}$ is the length of the backward rolling window.[17]

Overall, evidence suggests that ϵ_t^d and ϵ_t^H are significantly correlated with VIX, whereas ϵ_t^L is not. My measure of customer liquidity provision is orthogonal to the commonly used stress indicators. It adds incremental value for the purpose of monitoring market conditions.

[16] The amount of outright holdings of Treasury bills and mortgage-backed securities approached the peak of $\$4.2$ trillion around October 2014 and remained stagnant afterwards. See data from https://fred.stlouisfed.org/graph/?g=qHw.

[17] Time subscripts are properly aligned so that y_{t+1} is the next available $\textbf{VIX}_{\textbf{t+1}}$ or $\textbf{TVIX}_{\textbf{t+1}}$ following the $\{\hat{\boldsymbol{\epsilon}}_{\mathbf{t}}\}$ up to time t. For instance, when $l = 3$, I use $\{\hat{\boldsymbol{\epsilon}}_{\mathbf{t}}\}$ for the month of May, June, and July 2015 to predict the VIX on August 31, 2015 and the TVIX on August 24, 2015.

Panel A in Table 5 exhibits the results for IG bonds when the regressand is the VIX. Jointly, the three ϵ_ts are able to explain a significant portion of the variation in VIX. The R^2_{adj} is 0.31 (0.40) for a rolling window of three (six) months. When $l = 3$, one standard deviation increase in $\sum\hat{\epsilon}^H$ ($\sum\hat{\epsilon}^d$) is related to an increase of 3.17 (3.61) in VIX. In contrast, $\sum\hat{\epsilon}^L$ always fails to provide incremental explanatory power in the fluctuations of the VIX.

Evidence from Panel B in Table 5, where the regressand is the TVIX, reinforces these findings. The proposed measure of customer liquidity provision is not correlated with the TVIX as well. One distinction is that the TVIX exhibits a stronger relation to $\sum\hat{\epsilon}^d$. When $l = 6$, the coefficients of $\sum\hat{\epsilon}^d$ and $\sum\hat{\epsilon}^H$ for the TVIX (VIX) are 2.43 (3.91) and 1.68 (4.62). One explanation is that government policies impact dealers' market-making behavior in both corporate bond markets and Treasury markets. Hence, the stress indicator in the Treasury market is more relevant to my measure of shocks to dealers.

Panels C and D provide results for the HY market. Patterns are mostly consistent with those in the IG market. Closing this section, evidence suggests that the derived shocks to dealers and hedgers are relevant to the stress indicators. My measure of customer liquidity provision, however, is orthogonal to the stress indicators. In the next section, I present the usefulness of the information contained in my measure of customer liquidity provision.

4.5 Liquidities and corporate bond yields

The willingness of market participants to provide liquidity affects not only market microstructure measures, but also equilibrium asset prices (Amihud and Mendelson (1986), Chen, Lesmond, and Wei (2007), and Friewald and Nagler (2019)). In this subsection, I examine the asset pricing implications of my liquidity measures of both customer liquidity providers and dealers. The variable of interest is the yield spread of corporate bonds, denoted as $\mathbf{YS}_{i,t}$, which is the difference between the yield of a corporate bond i and the yield of a corresponding Treasury bond of the same maturity. My prediction is that a decrease in risk-taking willingness (or an increase in my measure of structural shocks) could potentially decrease equilibrium asset prices and increase yield spreads.

To compute $\mathbf{YS}_{i,t}$, I use all transactions of a Cusip i that are executed during the second half of the month t.[18] To relieve market microstructure noises, I focus on transactions in which the par value is greater than or equal to \$100K and the maturity is greater than one

[18]The results are similar if using all transactions during the entire month, or the last ten transactions in the month.

month. The computation of yields is extremely sensitive to small change in prices when a bond is close to maturity.[19]

My analysis exploits the following panel regression:

$$\Delta\text{YS}_{i,t} = \alpha_i + \beta_1\textbf{Customer Liquidity}_t + \beta_2\text{Dealer}_t + \beta_3\text{Hedger}_t + \boldsymbol{\beta_4}\Delta\mathbf{X_{i,t}} + \boldsymbol{\beta_5}\Delta\mathbf{X_t} + u_{i,t}, \quad (7)$$

where $\textbf{Customer Liquidity}_\text{t}$, $\textbf{Dealer}_t$, and $\textbf{Hedger}_t$ are my SVAR-based measures of the willingness of liquidity provision for customer liquidity providers, dealers and hedgers. In my analysis, I use the three-month rolling sum of structural shocks and standardize the three-month measures to zero mean and unit variance for better interpretation of the economic consequences. $\Delta\text{YS}_{i,t}$ is measured in basis points (bps). α_i is the Cusip fixed effect. $\Delta\mathbf{X_{i,t}}$ and $\Delta\mathbf{X_t}$ are systematic and firm level factors that explain yield spread changes, following Collin-Dufresne, Goldstein, and Martin (2001). $\Delta\mathbf{X_{i,t}}$ includes the market return of the issuers' common equity.[20] $\Delta\mathbf{X_t}$ includes the change in risk-free rate (10-year Treasure), the squared change in risk-free rate, the change in the slope of the yield curve (10-year Treasure minus 2-year Treasure), the change in the VIX, the S&P 500 return, and the jump factor that captures the tail risks.

The aim is to evaluate the impact of my SVAR-based measures of dealers and customer liquidity providers on changes in yield spreads. Table 6 reports the results for bonds in different rating categories. Statistical inferences for the results are double-clustered at Cusip and year-month level. Clustering at year-month level is crucial because it takes care of the plausible comovements of the residuals between different bonds in the same month; that is, $cov(u_{i,t}, u_{j,t}) \neq 0$ for bonds i and j. The literature has shown that a large fraction of the change in yield spreads of corporate bonds is driven by a single component (Friewald and Nagler (2019)).

Consistent with my prediction, the coefficients in front of the structural shocks are all positive whenever they are statistically significant. However, the changes in yield spreads for bonds of different credit ratings differentially respond to the measures of liquidity, featuring the economic importance of customer liquidity provision, especially for high quality corporate bonds.

For high quality bonds, I find that the coefficient in front of the customer liquidity measure is 2.30 (2.15), with a p-value of 0.055 (0.065) for Aaa-rated (Aa-rated) bonds. One

[19] Also excluded are erroneous transactions in which the reported yield is 200% higher or 80% lower than both the preceding and subsequent transactions for this Cusip. For instance, the reported transaction yields (in percentages) are 5, 30, 5.1 for the first, second and third transactions. In this case, the second transaction will be excluded.

[20] I use the change in the leverage of the issuers produces similar results. Most of the fluctuations in the change in leverage are due to the change in the market value of equities.

standard deviation increase in customer liquidity provision decreases the yield spreads by approximately 2.3bps. The economic significance is meaningful, considering that the median of the absolute change in yield spread for both Aaa and Aa-rated bonds is 11bps.

For lower quality bonds (Baa-rated and below), the impact of customer liquidity measure is still positive but lacks statistical power. In contrast, for A-rated bonds, my measures of both dealers and customer liquidity providers are able to explain the movements of yield spreads. When considering A-rated bonds and high-yield bonds, I find that both the measure of dealers and the shock to hedgers are able to explain yield spread changes.

The coefficients in front of the control variables are all consistent with Friewald and Nagler (2019). A negative stock return ($\mathbf{R}_{i,t}$) leads to a higher probability of default and increases the yield spreads, especially for lower quality bonds. Increases in the risk-free rate ($\Delta\mathbf{RF}_t$) also lower the yield spreads. The static effect of increased spot rate is to increase the drift term of the stochastic process for the firm value and thus decreases the probability of default (Longstaff and Schwartz (1995)). Other variables ($\mathbf{RM}_t$, $\Delta\mathbf{VIX}_t$, $\Delta\mathbf{Jump}_t$) are not statistically significant, thanks to the robust standard errors.

Table 7 shows that the observed patterns are the same for bonds of different maturity groups. The explanatory power of the model in equation (7) is stronger for bonds with longer maturities. For Aa-rated bonds, the Adjusted-$\boldsymbol{R}^2$ is 54% for bonds with maturity over eight years and 18% for bonds with maturity less than eight years. Yield spreads for shorter maturity bonds are more sensitive to market microstructure noises, so that the changes in yield spreads are harder to explain.

One standard deviation of my measure of customer liquidity will impact the yield spreads of long-term IG bonds by 2.5bps. Considering a bond with a duration of 10 years, a change of 2.5bps implies a price movement of 25bps, which is sizable for a transaction over $100K. The magnitude is similar across bonds of lower ratings. In contrast, one standard deviation of my measure of dealers will impact the price of a 10-year Aaa-rated (Baa-rated) bond by 14bps (64bps). Note that the focus is the monthly changes in yield spreads. Events that introduce shocks over several months will lead to additive effects on the prices of corporate bonds.

Overall, the messages conveyed in the results are that high quality (Aaa and Aa) bonds are more exposed to my measure of customer liquidity, whereas lower quality bonds (below Aa) are mostly subject to liquidity provision of dealers. The results are consistent with the findings in Dick-Nielsen, Feldhütter, and Lando (2012). They find that flight-to-quality is confined to AAA-rated bonds during the subprime crisis. I explicitly attribute this effect to customer liquidity providers, rather than to dealers.

This differential impact of shocks to dealers versus customer liquidity providers translates into different exposures of yield spreads in response to recent regulations (i.e., decrease in liquidity provision from dealers) and technological developments (i.e., increase in liquidity provision from buy-side customers). Regulations imposed on bank-afflicted dealers and recent launches of ATSs could yield disproportional impact on bonds of different qualities. ATSs tend to include more frequently traded bonds (potentially high quality), and further enhance the liquidity of assets. In contrast, dealers who are restricted from market-making activities become even more reluctant to trade illiquid assets.

Hence, the impact of recent regulations on the corporate bond market could be misunderstood if one only examines the aggregate conditions of corporate markets because data on available transactions are biased even more toward liquid assets. The mixed consequence of stringent regulations and technological improvements could point to an outcome that safe bonds become more liquid, whereas the markets are even thinner for those bonds that are riskier and, likely, already illiquid.

4.6 An alternative method: sign restrictions

The full identification of the SVAR relies on the equality restrictions specified in equation (3). The restrictions are motivated by economic intuitions and my theoretical model, but they cannot be empirically tested.

To examine the robustness of my full identification strategy, I consider an alternative approach that imposes only sign restrictions, using the "pure-sign-restriction approach" in Uhlig (2005). The advantage is that theories and economic intuitions can provide clearer guidance for sign restrictions, compared with zero restrictions. For example, when considering the impact of shocks to customer liquidity providers, imposed restrictions are that an increase in ϵ_t^L (i) decreases $\%\mathrm{RPT}_\mathrm{t}$ (i.e., $b_{3,2} \leq 0$) and (ii) weakly increases $\log\left(\mathrm{Spread}_\mathrm{t}^{\mathrm{IVT}}\right)$ (i.e., $b_2 \geq 0$).

The limitation is that the procedure only achieves partial identification for the shock of interest and remains agnostic about the impact of other structural shocks. In the rest of this subsection, I briefly discuss this "agnostic" method,[21] and show that the obtained shocks are similar to my main results.

Recall that the object of interest in the SVAR, as stated in equation (1), is $\mathbf{B}$, which satisfies $\mathbf{B}\mathbb{E}\left[\boldsymbol{\epsilon_t}\boldsymbol{\epsilon_t'}\right]\mathbf{B}' = \Sigma_u$, where Σ_u is the covariance matrix from the associated reduced form VAR. The idea is to find an impulse vector $\boldsymbol{b}$, which is a column element in $\mathbf{B}$, such

[21] See Uhlig (2005) and Danne (2015) for a more detailed description.

that the resulting impulse response functions, up to certain horizon, obey all prespecified inequality restrictions. Specifically, the method can be summarized in the following steps.

1. Specify restrictions on the impulse response functions (for example, my shock of interest has positive impact on y_1 and negative impact on y_2 up to horizon 3).
2. Run the SVAR using a Cholesky decomposition and denote the result as $\tilde{\mathbf{B}}$, such that $\tilde{\mathbf{B}}\tilde{\mathbf{B}}' = \Sigma_u$. This Cholesky decomposition has no economic meaning but is used as elementary building blocks.
3. Randomly generate an impulse vector b, defined as $b = \tilde{\mathbf{B}}\beta$, where β is a vector randomly drawn from the unit sphere. Use this b to generate the impulse response functions.
4. Check whether the impulse response functions satisfy the sign restrictions in step (1). If yes, keep this b, drop otherwise.
5. Repeat steps (3) and (4) until a desired number of satisfying impulse vectors is obtained. Use each impulse vector to compute the impulse response functions and infer the structural shocks.
6. Report the median and other percentiles of the posterior distribution of the impulse response functions and structural shocks.

Bringing this method to my SVAR, I separately apply two inequality restrictions for each of the three structural shocks to be recovered. To recover the shocks to hedgers, I impose the restrictions that an increase in ϵ_t^H increases $\log\left(\mathrm{Spread}_t^{\mathrm{RPT}}\right)$ (i.e., $b_1 \geq 0$) and $\log\left(\mathrm{Spread}_t^{\mathrm{IVT}}\right)$ (i.e., $b_{2,1} \geq 0$). To obtain the shocks to dealers, I apply the restrictions that an increase in ϵ_t^d increases $\%\mathrm{RPT}_t$ (i.e., $b_3 \geq 0$) and $\log\left(\mathrm{Spread}_t^{\mathrm{IVT}}\right)$ (i.e., $b_{2,3} \geq 0$). Finally, to derive the shocks to customer liquidity providers, I use the restrictions that an increase in ϵ_t^d decreases $\%\mathrm{RPT}_t$ (i.e., $b_2 \leq 0$) and increases $\log\left(\mathrm{Spread}_t^{\mathrm{IVT}}\right)$ (i.e., $b_{3,2} \geq 0$).

Figure 4 presents the obtained impulse response functions with sign restrictions for IG bond markets. Figure 5 exhibits the histograms of the initial impulse response functions ($t = 0$). The directions of these initial impulse response functions all agree with the estimates based on my main results using equality restrictions (i.e., Table 3), providing robust evidence that the restrictions I impose in equation (3) are effective.

ϵ_t^d and ϵ_t^L are positively associated with $\mathrm{Spread}_t^{\mathrm{RPT}}$ for the median estimates, although the 2.5th and 97.5th percentiles straddle zero. One explanation is that these two shocks are positively correlated with ϵ_t^H, which will affect $\mathrm{Spread}_t^{\mathrm{RPT}}$. Internet Appendix D shows that my main SVAR is valid. The difference is that my main results recover the part of shocks that are orthogonal to ϵ_t^H, whereas the agnostic method generates full shocks. Another explanation is that, facing shocks to dealers or customer liquidity providers, bond dealers endogenously adjust their matchmaking costs, which is a determinant of $\mathbf{Spread}_t^{\mathrm{RPT}}$, for example, they put more effects to exploit their network to search for potential buyers.[22]

The left panel of Figure 6 compares the obtained monthly structural shocks from the full identification strategy versus the same shocks from the agnostic approach in IG markets. All the spots in the scatter plots are close to the diagonal line $y = x$, suggesting that the shocks from the two methods are quantitatively the same. The correlation coefficients of the shocks derived from the two methods are 0.86, 0.86, and 0.82 for ϵ_t^H, ϵ_t^L and ϵ_t^d, respectively.

Plots in the right panel exhibit the 12-month rolling sum time series for each shock. All the described features over historic events are preserved for shocks recovered based on a SVAR using inequality restrictions.

Therefore, I show that my liquidity measures of customer liquidity providers and dealers are robust under the agnostic method with the least controversial restrictions. Using the agnostic method, the analysis for HY markets in Figures A-4 and A-6 also yields similar results, compared to the full identification method.

5 A model of dealer and customer liquidity supply

Frictions and searching in OTC markets render dealers market power to charge bid-ask spreads. Empirical literature also documents the importance of network structure and relationship.[23] In this section, I present a simple setting, which sheds light on my empirical treatment in this paper.

My model relates to the setup in Liu and Wang (2016), who model the behavior of a monopoly market maker who deals with customer hedgers and customer liquidity providers. Malamud and Rostek (2017) develop a decentralized exchange model in which privately informed institutional investors strategically trade with each other under a generic network structure. One can trade in certain clubs that consist of a subset of investors.

5.1 My setup

Consider K segmented markets and one tradable risky asset whose payoff is normally distributed $\tilde{V} \sim N(\bar{V}, \sigma_v^2)$. All participants have the same information regarding the probability

[22] I thank Charles Calomiris for suggesting this point.

[23] See Hugonnier, Lesterz, and Weill (2016), Duffie, Gârleanu, and Pedersen (2005), Li and Schürhoff (2019), Di Maggio, Kermani, and Song (2017), Hollifield, Neklyudov, and Spatt (2017), Hendershott, Li, Livdan, and Schürhoff (2017), among others.

distribution of payoff for the tradable asset. They trade the risky asset with *accessible* counterparties in the first period and the payoff realizes in the second period.

In each segmented market, there are three types of participants: a continuum of mass N_L atomistic customer liquidity providers, a continuum of mass N_H atomistic customers (called hedgers) who suffer an exogenous shock and demand liquidity, and $N_M = 1$ designated market maker. Customer liquidity providers and hedgers can only trade with this market maker. This assumption attempts to capture the real-world customer-dealer relationship in which a customer may only obtain favorable prices from a set of dealers with whom she has a strong business tie, especially in the short run. For simplicity, it is assumed that customers can trade only with one market maker.

Dealers and customer liquidity providers are endowed with zero unit of the asset before trading occurs. Assume CARA utility functions for all participants and the risk aversions for market makers, hedgers, and customer liquidity providers are δ_d , δ_H and δ_L, respectively. Figure 7 demonstrates the market structure with three market makers.

Hedgers in the k-th market are subject to a liquidity shock by receiving X_k units of another non-tradable risky asset,[24] which has a per-unit payoff of $\tilde{L} \sim N\left(0,\sigma_l^2\right)$, and the payoff has a covariance of $\sigma_{lv} > 0$ (w.l.o.g) with the tradable asset.

All K market makers can trade in a centralized system by submitting their demand schedules. Hence, hedgers can indirectly hedge across markets via the local market maker and the interdealer network. The segmented dealer-customer markets and the interdealer market are cleared simultaneously.

The k-th market maker observes atomistic customer demand schedule, denoted as $\Theta_{L,k}\left(P_k^L\right)$ and $\Theta_{H,k}\left(X_k,P_k^H\right)$, and sets the optimal quantities (prices). These demand schedules imply that market makers can trade with customers at different prices P_k^L and P_k^H. Interpreting this setup, the market maker knows the identity of customers or she can infer the type of customers by observing their submitted demand schedules. In practice, dealers can differentiate customers by whether the customer or the dealer initiates the transaction.[25]

[24] The underlying data-generating process for $\{X_k\}_{k=1}^K$ is not crucial. Only the actual realizations of $\{X_k\}_{k=1}^K$ matter. It is equivalent if hedgers are assumed to receive heterogeneous shocks and the market maker cannot price discriminate these atomistic hedgers.

[25] Since the total number of outstanding issues is large, uninformed investors who do not hold the particular issue pay little attention to this issue until being contacted by their dealers. For instance, Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik (2008) consider this type of customer liquidity as latent: *"if a buy order comes in to a dealer ... the dealer could 'work the order' by contacting customers to ... convince someone to sell her the bond."*

The market maker sets P_k^L and P_k^H to clear the k-th market, resulting in an inventory level $\beta_k - \alpha_k$, where $\alpha_k\left(P_k^L, P_k^H\right) = \sum_{i=H,L} N_i \Theta_{i,k}^+$ and $\beta_k\left(P_k^L, P_k^H\right) = \sum_{i=H,L} N_i \Theta_{i,k}^-$, denoting the aggregate amount, which the market maker transacts with the hedgers and the liquidity providers in this market. If both β_k and α_k are strictly positive, the market maker conducts a typical customer-dealer-customer riskless principal transaction for the volume $\min\left(\beta_k, \alpha_k\right)$, generating a bid-ask spread for riskless principal transactions.

The market maker can hold a fraction of the resulted inventory for one period and trade the rest in the interdealer market to exchange excessive inventory or provide liquidity to other market makers. Assume symmetricity and conjecture the following demand curve for each market maker:

$$M_k\left(X_k, P^D\right) = \nu - \eta X_k - \gamma P^D, \tag{8}$$

where P^D is the price in the interdealer market. The demand for the k-th market maker is negatively related to the interdealer price P^D and the local hedgers' shock X_k.

Apply the market clearing condition in the interdealer market $\sum_{k=1}^K M_k = 0$, or

$$M_k\left(X_k, P^D\right) + \sum_{l \neq k}\left(\nu - \eta X_l - \gamma P^D\right) = 0. \tag{9}$$

The residual supply schedule is $P^D(m_k) = \frac{\nu}{\gamma} - \frac{\eta}{\gamma}\bar{X}_{-k} + \frac{1}{(K-1)\gamma} m_k$, where $\bar{X}_{-k} = \frac{1}{K-1}\sum_{l \neq k} X_l$ is the average liquidity shock from other segmented markets.

In each market, denote the reservation prices for CARA hedgers and customer liquidity providers as

$$P_{H,k}^R = \bar{V} - \delta_H \sigma_{lv} X_k \qquad \text{and} \qquad P_{L,k}^R = P_L^R = \bar{V}. \tag{10}$$

Individual customers maximize their utilities as prices (P_k^H, P_k^L) are given. Their demand schedules are denoted as

$$\Theta_{H,k} = \frac{1}{\delta_H \sigma_v^2}\left(P_k^{R,H} - P_k^H\right) \qquad \text{and} \qquad \Theta_{L,k} = \frac{1}{\delta_L \sigma_v^2}\left(P^{R,L} - P_k^L\right). \tag{11}$$

The market maker's problem is

$$\max_{P_k^L, P_k^H, m_k} E\left[-e^{-\delta_d \tilde{w}_k}\right], \tag{12}$$

subject to

$$\begin{aligned} \tilde{w}_k \quad = \quad & \underbrace{N_H \Theta_{H,k} P_k^H + N_L \Theta_{L,k} P_k^L}_{\text{Proceeds from sales to customers}} - \underbrace{m_k\left(\frac{\nu}{\gamma} - \frac{\eta}{\gamma} X_{-k} + \frac{1}{(K-1)\gamma} m_k\right)}_{\text{Payments for purcahses from other dealers}} \\ & + \underbrace{\left(-N_H \Theta_{H,k} - N_L \Theta_{L,k} + m_k\right)\tilde{V}}_{\text{Realized portfolio value}}. \end{aligned} \tag{13}$$

5.2 Equilibrium

Denote the quantity $\mathscr{D}^{-1} = \left(\frac{2}{\delta_d} + \frac{N_H}{\delta_H} + \frac{N_L}{\delta_L}\right)$. $\mathscr{D}^{-1}$ captures the total risk-bearing capacity in the economy. The equilibrium transaction prices are as follows:

$$P_k^L = \bar{V} - \frac{1}{2}\mathscr{D}\sigma_{lv}N_H\left(\frac{K-2}{K}\bar{X}_{-k} + \frac{2}{K}X_k\right), \tag{14}$$

$$P_k^H = \bar{V} - \frac{1}{2}\mathscr{D}\sigma_{lv}N_H\left(\frac{K-2}{K}\bar{X}_{-k} + \frac{2}{K}X_k\right) - \frac{\sigma_{lv}\delta_H}{2}X_k, \quad \text{and} \tag{15}$$

$$P^D = \bar{V} - \mathscr{D}\sigma_{lv}N_H\bar{X}, \tag{16}$$

where $\bar{X} = \frac{1}{K}\sum X_k$ is the average liquidity shock for all K markets. The equilibrium trading quantities are as follows:

$$\Theta_{L,k} = \frac{1}{2}\frac{\mathscr{D}}{\delta_L}\frac{\sigma_{lv}N_H}{\sigma_v^2}\left(\frac{K-2}{K}\bar{X}_{-k} + \frac{2}{K}X_k\right), \tag{17}$$

$$\Theta_{H,k} = \frac{1}{2}\frac{\mathscr{D}}{\delta_H}\frac{\sigma_{lv}N_H}{\sigma_v^2}\left(\frac{K-2}{K}\bar{X}_{-k} + \frac{2}{K}X_k\right) - \frac{\sigma_{lv}}{2\sigma_v^2}X_k, \quad \text{and} \tag{18}$$

$$m_k = \frac{1}{2}\frac{K-2}{K}\frac{\sigma_{lv}N_H}{\sigma_v^2}\left(\bar{X}_{-k} - X_k\right). \tag{19}$$

The inventory level of the k-th dealer is

$$-\underbrace{N_H\Theta_{H,k}}_{\substack{\text{Units to}\\\text{hedgers}}} - \underbrace{N_I\Theta_{I,k}}_{\substack{\text{Units to}\\\text{liquidity providers}}} + \underbrace{m_k}_{\substack{\text{Units from}\\\text{interdealer market}}} = \frac{\mathscr{D}}{\delta_d}\frac{\sigma_{lv}N_H}{\sigma_v^2}\left(\frac{K-2}{K}\bar{X}_{-k} + \frac{2}{K}X_k\right). \tag{20}$$

Internet Appendix A provides the proof.

Equation (14) presents the equilibrium price that a market maker charges the customer liquidity providers. This price is equal to the reservation value of customer liquidity providers $\bar{V}$ discounted by a quantity proportional to the size of liquidity shocks $\left(\frac{K-2}{K}\bar{X}_{-k} + \frac{2}{K}X_k\right)$. Since interdealer transactions propagate shocks across markets, the amount of discount relates to the local shock X_k and the average of shocks from other markets $\bar{X}_{-k}$. Price impact of dealers in the interdealer market prevents them from perfect risk sharing, resulting in an extra weight on X_k.

The amount of discount depends on the size of covariance σ_{lv}, the mass of hedgers who receive the shocks, and the total risk-bearing capacity in the market. If any of the participants in the market are risk-neutral, $\mathscr{D}$ is zero, and there is no discount in P_k^L.

The price that the market maker charges hedgers P_k^H is shown in equation (15). The difference between P_k^H and P_k^L is $\frac{\sigma_{lv}\delta_H}{2}X_k$. The market maker maximizes profits by setting the bid-ask spread as half of the gap in the reservation prices of hedgers and customer liquidity providers. Equations (14) and (15) show that bid-ask spreads from customer-dealer-customer riskless principal transactions are mainly driven by δ_H, but neither δ_d nor δ_L. The result supports my empirical identification strategy in the SVAR.

The interdealer price in equation (16) is equal to reservation price of market makers, discounted by the average of shocks $\bar{X}$ multiplied by $\mathscr{D}\sigma_{lv}N_H$. Equations (17) to (20) show the equilibrium trading quantities and the inventory level of dealers. Equation (17) shows that customer liquidity providers are buyers when the weighted average shock $\left(\frac{K-2}{K}\bar{X}_{-k} + \frac{2}{K}X_k\right)$ is positive. In such cases, the local market is hit by a positive shock X_k, and/or other segmented markets receive an average positive shock $\bar{X}_{-k}$.

The amount that hedgers trade are shown in equation (18). As indirect participants in the global markets, hedgers play an additional role in absorbing global shocks, constituting the first term in equation (18), which resembles the term for customer liquidity providers. The second term in equation (18) shows that, as the actual receivers of the local shock, competitive hedgers liquidate half of the shocks.

Equation (19) shows that market makers will buy in the interdealer market when the local shock X_k is less than the average global shocks $\bar{X}_{-k}$ (and vice versa). Dealers absorb the market average shocks but are biased toward the local market.

In the following subsections, I demonstrate the intuition of the model by a numerical example and provide comparative statics under the parameters chosen as below, unless otherwise stated. The choice of parameters is harmless for most of the implications.

Parameter	K	N_H	N_L	$\bar{V}$	σ_v^2	σ_{lv}	δ_d	δ_H	δ_L
Value	3	1	1	100	1	1	2	2	2

5.3 A numerical example

Figure 7 presents an OTC market incorporated by three segmented markets. Hedgers in the market of Dealer A receive a positive shock $X_A = 7$, which is greater than the shocks $X_B = 4$ and $X_C = -9$. For hedging purposes, the hedgers in the markets of Dealers A and B would like to sell and the hedgers in the market of Dealer C would like to buy. Customer liquidity providers transact against their local hedgers.

All prices and volumes shown in Figure 7 are equilibrium quantities computed from equations (14) to (19). Dealer A buys three units from hedgers at a price of 92 and then sells 0.5 (1.6) units at a price of 99 (99.7) to customer liquidity providers in the local market (other dealers in the interdealer market), resulting in a net inventory of 0.9 units.

The market for Dealer A experiences a relatively severer positive shock so that the dealer has to rely on both her own customer liquidity pool, where she works the orders with potential customer buyers without liquidity shocks and trades with other dealers in the interdealer market. In this example, Dealer A conducts 0.5 units of customer-dealer-customer riskless principal transactions, and the spread for this transaction is 7.[26]

Hedgers with Dealer B receive a moderate shock. Therefore, they transact fewer quantities at a better price. Hedgers with Dealer C receive a negative shock, and they buy 4.3 units from Dealer C at the price of 110.8, whereas customer liquidity providers partially provide 0.6 units liquidity to Dealer C at the price of 101.1. Dealer C purchases 2.5 units from the interdealer market, leaving a net balance of negative 1.2 units on her own book.

The aggregate global shock is positive, whereas perfect risk-sharing is not achieved. Market makers have monopoly power in local markets and face price impact in the interdealer market. Dealers and customer liquidity providers, considered as a whole, provide liquidity to hedgers and hold positive inventory. However, dealers and customer liquidity providers in market C remain with negative inventory.

Due to the positive aggregate shock, the interdealer price is 99.7, providing a positive expected return. Since markets are segmented, difference transaction prices are observed from different counterparties. Next, I discuss how to infer bid-ask spreads for riskless principal transactions and inventory transactions from the model. The interdealer price is regarded as the fundamental value of the asset at the first period. Note that the expected payoff of the asset $\bar{V} = 100$ is not a good candidate of fair price in this model.

5.4 Customer-dealer-customer riskless principal transactions

RPTs are empirically defined as a set of transactions in which a dealer buys from some customers and sells to other customers for appropriately equal quantities within a short period. Bringing the context into my model, I define RPT volume as the smaller one of the two absolute amounts that a dealer transacts with the two types of customers as follows:

$$\min(N_H|\Theta_{H,k}|, N_L|\Theta_{L,k}|)1_{\Theta_{H,k}\times\Theta_{L,k}<0}. \tag{21}$$

[26] For illustration purposes, the absolute level of spread 7 in the example is large, relative to the expected payoff of the asset $\bar{V} = 100$. Ceteris paribus, increase in $\bar{V}$ would not impact the equilibrium spreads and volumes. For instance, let $\bar{V} = 10{,}000$ and the spread of 7 could be interpreted as approximately 7bps, within a reasonable ballpark from empirical observations.

The amount in excess of the RPT volume is considered inventory transactions. In the numerical example, Dealer A conducts 2.5 units[27] of inventory transactions (IVT) with hedgers. In both RPT and IVT, hedgers sell at the price of 92.

This outcome, at first glance, seems counterintuitive. In fact, RPTs are traded at lower spreads because dealers opt to offer favorable prices to customer liquidity providers. In this example, the distance between interdealer price and liquidity provider price is smaller than the distance between interdealer price and hedger price. The consequence is a wider spread of 15.4 for IVT trades,[28] compared with a RPT spread of 7. In the RPT, the dealer offers the customer liquidity provider a negative half spread of -0.7.

The framework agrees with the intuition in Choi and Huh (2019): *... dealer might find a non-dealer (C2) who is willing to provide liquidity for a fee (i.e., buying at a lower price than the fundamental value of the bond) ... C2 pays an even smaller spread (a negative spread in this scenario)....* Evidence in their Table 2 supports my formulation of RPTs. They document that the leg of a customer buy in pairs of RPTs is more likely to cross the interdealer price. Customer buyers in corporate bond markets are usually viewed as liquidity providers.

This framework differs from Grossman and Miller (1988), in which hedgers can either trade immediately with the dealer for an inventory transaction at a higher spread or wait until the dealer finds another potential buyer and trades as an RPT at a lower spread. Alternatively, Grossman and Miller (1988) benchmark the transaction price with the expected payoff. The delay of trading is not modeled in my paper. Equivalently, if the hedgers decide to wait, my model implies that hedgers sell less to the dealer. My model emphasizes that market makers do not price discriminate hedgers.

5.5 Comparative statics

Figure 8 provides comparative statics for the expectation of bid-ask spreads and transaction volumes using a numerical method, in which liquidity shocks $\{X_k\}_{k=1}^{K}$ are randomly and independently drawn from identical and independent normal distributions. Computed are the bid-ask spread for RPTs, the bid-ask spread for IVTs, the ratio of RPT volume over total customer-dealer volume, and the average dealer inventory level. Internet Appendix B describes the details in computing these quantities.[29]

[27] $3.0-0.5=2.5$

[28] $(99.7-92)\times 2=15.4$

[29] I exclude the realizations of $\{X_k\}_{k=1}^{K}$ in which local hedgers and customer liquidity providers trade in the same direction. It occurs when the absolute level of X_k is small and hedgers effectively become liquidity

Panel A of Figure 8 exhibits comparative statics when δ_d increases. It mimics the scenarios both during the 2008 financial crisis and the post-regulation periods, when dealer capital is constrained. The left plot in Panel A of Figure 8 shows that the bid-ask spreads for RPTs remain flat when δ_d increases, whereas the spreads for IVTs increase. The increase of δ_d leads to a higher risk aversion for the economy, that is, $\mathscr{D}$ in equations (14) and (15). Thus, customer-dealer prices P_k^Hs for different markets become more diverged. Since hedgers in high X_k markets (e.g., P_A^H in Figure 7) conduct IVT sell, and hedgers in low X_k markets conduct IVT buy (e.g., P_C^H in Figure 7), the IVT spread (e.g., gap between P_A^H and P_C^H) becomes wider.

Dealers conduct more RPTs and hold less inventory when they become more risk averse, as shown in the right plot in Panel A of Figure 8. It explains the findings in Choi and Huh (2019) that the average bid-ask spreads do not increase due to higher RPT volume during the post-regulation period.

Panel B of Figure 8 presents the comparative statics when δ_H increases and hedgers are more eager to sell, for instance, the 2008 financial crisis and the Eurozone crisis. The left plot in Panel B of Figure 8 demonstrates that δ_H is an important determinant for both types of bid-ask spreads.

One may not conclude that δ_H drives most of the fluctuations in the spreads for IVTs, because the variations of δ_H and δ_d are of different scales. Dealers sometimes could be extremely risk averse. For instance, Chen and Wang (2018) let δ_d be infinite in their model.

The message in Panel C of Figure 8 is that δ_L does not impact the RPT spread. It may impact the IVT spread, but the magnitude largely depends on selected parameters. The right plot in Panel C of Figure 8 shows that fewer customer liquidity providers, or, equivalently, an increase of δ_L, result in less riskless principal transactions and higher dealer inventory.

Overall, the predictions from my model are consistent with the empirical findings in the SVAR, as stated in equation 2.

6 Conclusion

This paper provides a measure of customer liquidity provision in corporate bond markets. This measure incorporates the information contained in the trading activities when bond

providers. This exclusion is sensible, especially considering large dealers, who conduct much more dealer-customer transactions than interdealer transactions. Figures A-2 in the Internet Appendix show that the main results are the same without this exclusion.

dealers conduct inventory transactions and make markets versus arrange riskless principal transactions and match customer liquidity demanders and providers.

To infer this measure, I exploit a SVAR approach and decompose the changes in bid-ask spreads in corporate bond market into structural shocks to the risk-taking willingness of various market participants. This decomposition could be useful in monitoring conditions of different market participants in the corporate bond market and understanding the actual impact from regulatory events or market crises.

The obtained measures contain important information about the aggregate market conditions. Customer liquidity provisions are shown to increase during the post-regulation period, as suggested by Saar, Sun, Yang, and Zhu (2019), because dealers improve their technology in matchmaking.

I employ my new measures of both customer liquidity providers and dealers to explain the change in yield spreads for corporate bonds of different credit ratings. I show that yield spreads of high quality bonds respond more to the measure of customer liquidity provision, whereas yield spreads of riskier bonds are more exposed to the measure of dealers. It suggests that the decrease of liquidity due to stringent regulation and the increase of liquidity due to matchmaking technology might not be simply offset.

References

Acharya, V., Y. Amihud, and S. Bharath, 2013, "Liquidity Risk of Corporate Bond Returns: Conditional Approach," *Journal of Financial Economics*, 110(2), 358–386.

Adrian, T., M. Fleming, O. Shachar, and E. Vogt, 2017, "Market Liquidity after the Financial Crisis," *Annual Review of Financial Economics*, 9(1), 43–83.

Amihud, Y., and H. Mendelson, 1986, "Asset Pricing and the Bid-Ask Spread," *Journal of Financial Economics*, 17(2), 223–249.

Anderson, M., and R. Stulz, 2017, "Is Post-Crisis Bond Liquidity Lower?," No. w23317. National Bureau of Economic Research.

Bakshi, G., N. Kapadia, and D. Madan, 2003, "Stock Return Characteristics, Skew Laws, and the Differential Pricing," *The Review of Financial Studies*, 16(1), 101–143.

Bakshi, G., and D. Madan, 2000, "Spanning and Derivative-Security Valuation," *Journal of Financial Economics*, 55(2), 205–238.

Bank for International Supervision, 2013, "Basel III: The Liquidity Coverage Ratio and Liquidity Risk Monitoring Tools," *Basel Committee on Banking Supervision*, pp. 1–75.

Bao, J., M. O'Hara, and X. Zhou, 2018, "The Volcker Rule and Corporate Bond Market Making in Times of Stress," *Journal of Financial Economics*, 130(1), 95–113.

Bao, J., J. Pan, and J. Wang, 2011, "The Illiquidity of Corporate Bonds," *The Journal of Finance*, 66(3), 911–946.

Bessembinder, H., S. Jacobsen, W. Maxwell, and K. Venkataraman, 2018, "Capital Commitment and Illiquidity in Corporate Bonds," *The Journal of Fiannce*, 73(4), 1615–1661.

Bessembinder, H., W. Maxwell, and K. Venkataraman, 2006, "Market Transparency, Liquidity Externalities, and Institutional Trading Costs in Corporate Bonds," *Journal of Financial Economics*, 82(2), 251–288.

Bessembinder, H., C. Spatt, and K. Venkataraman, 2019, "A Survey of the Microstructure of Fixed-Income Markets," *Journal of Financial and Quantitative Analysis*, Forthcoming.

CGFS, 2016, "Fixed Income Market Liquidity," available at https://www.bis.org/publ/cgfs55.pdf.

Chaderina, M., A. Mürmann, and C. Scheuch, 2019, "The Dark Side of Liquid Bonds in Fire Sales," available at SSRN 2995544.

Chen, L., D. Lesmond, and J. Wei, 2007, "Corporate Yield Spreads and Bond Liquidity," *Journal of Finance*, 62(1), 119–149.

Chen, W., and Y. Wang, 2018, "Dynamic Market Making and Asset Pricing," available at SSRN 3224495.

Choi, J., and Y. Huh, 2019, "Customer Liquidity Provision: Implications for Corporate Bond Transaction Costs," available at SSRN 2848344.

Collin-Dufresne, P., R. Goldstein, and S. Martin, 2001, "The Determinants of Credit Spread Changes," *Journal of Finance*, 56(6), 2177–2207.

Danne, C., 2015, "The VARsignR Package," available at https://cran.r-project.org/web/packages/VARsignR/vignettes/VARsignR-vignette.html.

Di Maggio, M., A. Kermani, and Z. Song, 2017, "The Value of Trading Relations in Turbulent Times," *Journal of Financial Economics*, 124(2), 266–284.

Dick-Nielsen, J., 2014, "How to Clean Enhanced TRACE Data," available at SSRN 2337908.

Dick-Nielsen, J., P. Feldhütter, and D. Lando, 2012, "Corporate Bond Liquidity before and after the Onset of the Subprime Crisis," *Journal of Financial Economics*, 103(3), 471–492.

Duffie, D., 2012, "Market Making under the Proposed Volcker Rule," Rock Center for Corporate Governance at Stanford University Working Paper 106.

Duffie, D., N. Gârleanu, and L. Pedersen, 2005, "Over-the-Counter Markets," *Econometrica*, 73(6), 1815–1847.

Friewald, N., R. Jankowitsch, and M. Subrahmanyam, 2012, "Illiquidity or Credit Deterioration: A Study of Liquidity in the US Corporate Bond Market during Financial Crises," *Journal of Financial Economics*, 105(1), 18–36.

Friewald, N., and F. Nagler, 2019, "Over-the-Counter Market Frictions and Yield Spread Changes," *The Journal of Finance*.

Goldstein, M., and E. Hotchkiss, 2019, "Providing Liquidity in an Illiquid Market: Dealer Behavior in US Corporate Bonds," *Journal of Financial Economics*.

Gorton, G., and A. Metrick, 2012, “Securitized Banking and the Run on Repo,” *Journal of Financial Economics*, 104(3), 425–451.

Grossman, S., and M. Miller, 1988, “Liquidity and Market Structure,” *The Journal of Finance*, 43(3), 617–633.

Harris, L., 2015, “Transaction Costs, Trade Throughs, and Riskless Principal Trading in Corporate Bond Markets,” *Trade Throughs, and Riskless Principal Trading in Corporate Bond Markets (October 22, 2015).*

Hendershott, T., D. Li, D. Livdan, and N. Schürhoff, 2017, “Relationship Trading in OTC Markets,” Swiss Finance Institute Research Paper No. 17-30.

Hendershott, T., and A. Madhavan, 2015, “Click or Call? Auction versus Search in the Over-the-Counter Market,” *Journal of Finance*, 70(1), 419–447.

Hollifield, B., A. Neklyudov, and C. Spatt, 2017, “Bid-Ask Spreads, Trading Networks, and the Pricing of Securitizations,” *The Review of Financial Studies*, 30(9), 3048–3085.

Hugonnier, J., B. Lesterz, and P.-O. Weill, 2016, “Heterogeneity in Decentralized Asset Markets,” No. w20746. National Bureau of Economic Research.

Li, D., and N. Schürhoff, 2019, “Dealer Networks,” *The Journal of Finance*, 74(1), 91–144.

Liu, H., and Y. Wang, 2016, “Market Making with Asymmetric Information and Inventory Risk,” *Journal of Economic Theory*, 163, 73–109.

Longstaff, F., and E. Schwartz, 1995, “A Simple Approach to Valuing Risky Fixed and Floating Rate Debt,” *The Journal of Finance*, 50(3), 789–819.

Lu, E., G. Lai, and Q. Ma, 2017, “Organizational Structure, Risk-Based Capital Requirements, and the Sales of Downgraded Bonds,” *Journal of Banking and Finance*, 74, 51–68.

Lütkepohl, H., 2005, *New Introduction to Multiple Time Series Analysis*. Springer Science & Business Media.

Mahanti, S., A. Nashikkar, M. Subrahmanyam, G. Chacko, and G. Mallik, 2008, “Latent Liquidity: A New Measure of Liquidity, with an Application to Corporate Bonds,” *Journal of Financial Economics*, 88(2), 272–298.

Malamud, S., and M. Rostek, 2017, “Decentralized Exchange,” *American Economic Review*, 107(11), 3320–3362.

Newey, W., and K. West, 1987, "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55(3), 703–708.

Saar, G., J. Sun, R. Yang, and H. Zhu, 2019, "From Market Making to Matchmaking: Does Bank Regulation Harm Market Liquidity?," available at SSRN 3399063.

SIFMA, 2016, "SIFMA Electronic Bond Trading Report: US Corporate & Municipal Securities," available at https://www.sifma.org/wp-content/uploads/2017/05/sifma-electronic-bond-trading-report-us-corporate-and-municipal-securities.pdf.

Trebbi, F., and K. Xiao, 2019, "Regulation and Market Liquidity," *Management Science*, 65(5), 1949–1968.

Uhlig, H., 2005, "What are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure," *Journal of Monetary Economics*, 52(2), 381–419.

Table 1: Main steps in data cleaning
This table documents the steps in cleaning and filtering the academia TRACE data. Reported are the number of unique issues (Cusips), the number of total transactions, and the number of distinct dealers after each step.

	Issues #	Trades #	Dealers #
Corporate bonds in TRACE (2002–2015)	106,873	159,307,893	3,815
Remove cancellations and correct corrections based on Dick-Nielsen (2014)	104,857	112,303,179	3,611
Keep only straight bonds (FISD bond type=CDEB or USBN)	30,755	77,146,341	3,441
Exclude transactions in which execution date is before 12/31/2005	24,999	62,552,200	3,441
Exclude transactions in which execution date is within 30 days of offering date	24,796	60,006,571	3,389
Exclude transactions in which dealers trade with affiliated counterparties	24,754	54,731,492	3,389

Table 2: **Summary statistics for monthly average trading activities**
This table reports the summary statistics for inventory transactions (IVT) and riskless principal transactions (RPT) for investment-grade bonds and high-yield bonds. In each month, I compute average bid-ask spreads, total trading volume, total number of unique traded Cusips, and total number of transactions. Reported are mean, standard deviation, and percentiles of these monthly quantities. Only customer-dealer transactions are considered. Average spreads are computed using transactions in which the par value exceeds \$100K. The sample period is January 2006 to December 2015.

Ratings	Variables	Trade type	mean	std	5%	50%	95%
Investment-grade	Average bid-ask spread (bps)	IVT	47.46	24.24	22.54	40.83	100.36
		RPT	22.12	11.30	10.61	19.69	44.78
	Volume (\$M)	IVT	16,857	4,986	8,981	17,794	23,506
		RPT	1,304	574	531	1,311	2,308
	Total number of issues	IVT	1,588	475	842	1,695	2,191
		RPT	252	159	77	215	584
	Total number of trades:						
	Volume >= \$1M	IVT	2,674	867	1,250	2,865	3,903
		RPT	173	87	63	166	322
	\$100K <= Volume < \$1M	IVT	2,401	1,027	764	2,712	3,887
		RPT	115	150	11	54	490
	Volume < \$100K	IVT	5,907	2,722	1,905	6,281	9,702
		RPT	302	367	33	162	1,182
High-yield	Average bid-ask spread (bps)	IVT	58.36	11.44	44.29	56.26	80.50
		RPT	28.97	8.71	18.67	27.54	48.44
	Volume (\$M)	IVT	9,036	2,637	4,936	9,110	13,347
		RPT	2,664	1,183	1,266	2,376	4,903
	Total number of issues	IVT	752	220	408	736	1112
		RPT	283	104	158	253	463
	Total number of trades:						
	Volume >= \$1M	IVT	2,405	709	1,363	2,376	3,570
		RPT	553	226	280	528	976
	\$100K <= Volume < \$1M	IVT	1,187	663	451	961	2,324
		RPT	57	37	23	47	129
	Volume < \$100K	IVT	2,482	1,696	675	1,628	5,250
		RPT	121	96	31	71	294

Table 3: **Estimates of the B matrix**

This table presents estimates for the $\mathbf{B}$ matrix in the system $\mathbf{y_t} = \mathbf{A_0} + \sum_i \mathbf{A_i}\mathbf{y_{t-i}} + \mathbf{B}\boldsymbol{\epsilon}_\mathbf{t}$ for investment-grade bonds and high-yield bonds, respectively, where $\mathbf{y_t}$ is a vector that contains three variables: $\log\left(\text{Spread}_\text{t}^\text{RPT}\right)$, $\log\left(\text{Spread}_\text{t}^\text{IVT}\right)$, and $\%\text{RPT}_\text{t}$. $\log\left(\text{Spread}_\text{t}^\text{RPT}\right)$ is the monthly average bid-ask spread computed based on riskless principal transactions. $\log\left(\text{Spread}_\text{t}^\text{IVT}\right)$ is the monthly average bid-ask spread computed based on inventory transactions. $\%\text{RPT}_\text{t}$ is the ratio of customer-dealer-customer riskless principal transaction volume over total customer-dealer volume. I impose the following three restrictions: $b_{1,2} = 0$, $b_{1,3} = 0$, and $b_{3,1} + b_{3,2} + b_3 = 0$. Data from 2006 to 2015 are used to estimate the system. b_{ij} is expressed as b_i when $i = j$. Associated standard errors are reported in parentheses. Asterisks denote significance levels (*** = 1%, ** = 5%, and * = 10%).

Panel A: Investment-Grade

$b_{ij}(b_i)$	$j=1$	2	3
$i=1$	.23***		
	(.02)		
2	.08***	.01	.12***
	(.01)	(.01)	(.01)
3	.31**	-1.26^{***}	.95***
	(.15)	(.10)	(.11)

Panel B: High-Yield

$b_{ij}(b_i)$	$j=1$	2	3
$i=1$	.14***		
	(.01)		
2	.05***	.05***	.09***
	(.01)	(.01)	(.01)
3	.40**	-1.61^{***}	1.20***
	(.19)	(.12)	(.14)

Table 4: **Historical evolution of structural shocks**
This table presents the analysis for movements of structural shocks during the stressed periods. I regress each series of structural shocks $\hat{\epsilon}_t^H$, $\hat{\epsilon}_t^L$, and $\hat{\epsilon}_t^D$ (accumulated over three months) on a set of dummies variables indicating the pre-crisis period, the 2008 financial crisis, a nested period of Lehman Brothers bankruptcy during the financial crisis, the post-crisis period, the implementation of Basel Accords 2.5 and III, and the Volcker Rule. Reported are the coefficients in front of the dummies, total number of observations, and adjusted-$\boldsymbol{R}^2$s. Constant term is omitted in these regressions. In squared brackets are bootstrapped $\boldsymbol{P}$-values. Asterisks denote significance levels (*** = 1%, ** = 5%, and * = 10%).

	Panel A: IG			Panel B: HY		
	$\hat{\epsilon}_t^H$	$\hat{\epsilon}_t^L$	$\hat{\epsilon}_t^D$	$\hat{\epsilon}_t^H$	$\hat{\epsilon}_t^L$	$\hat{\epsilon}_t^D$
Pre-Crisis	0.17	-0.21	-0.77***	-0.20	-0.15	-1.04*
Jan 2006–Jun 2007	[0.47]	[0.18]	[0.01]	[0.41]	[0.53]	[0.07]
2008 Crisis	0.87*	-0.93*	0.12	0.79***	-0.76***	-0.22
Jul 2007–Apr 2009	[0.08]	[0.09]	[0.77]	[0.01]	[0.01]	[0.30]
Lehman Brothers	0.74	0.76	1.90**	0.94***	1.48***	2.03***
Aug 2008–Dec 2008	[0.13]	[0.15]	[0.03]	[0.01]	[0.00]	[0.00]
Post-Crisis	0.05	0.49**	-0.31*	-0.26	0.45	0.15
May 2009–May 2012	[0.84]	[0.01]	[0.09]	[0.18]	[0.16]	[0.45]
Basel Accords 2.5	-0.11	0.50*	-0.17	-0.19	0.31	0.46*
Jun 2012–Jun 2013	[0.76]	[0.06]	[0.37]	[0.38]	[0.49]	[0.08]
Basel Accords III	-0.34**	0.47	-0.13	-0.60*	-0.33	-0.04
Jul 2013–Mar 2014	[0.04]	[0.11]	[0.60]	[0.09]	[0.27]	[0.90]
Volcker Rule	-1.08***	-0.44***	0.65***	-0.10	-0.31	-0.14
Apr 2014–Dec 2015	[0.00]	[0.01]	[0.00]	[0.72]	[0.39]	[0.58]
N	116	116	116	115	115	115
$\boldsymbol{R}_{adj}^2$	0.46	0.29	0.36	0.28	0.22	0.31

Table 5: **How do structural shocks relate to market conditions?**

This table reports the results from the following regressions:

$$\mathbf{y_{t+1}} = \mathbf{Constant} + \beta_1 \sum_{s=t-l-1}^{t} \hat{\epsilon}^{H}_{s-1\to s} + \beta_2 \sum_{s=t-l-1}^{t} \hat{\epsilon}^{L}_{t-1\to t} + \beta_3 \sum_{s=t-l-1}^{t} \hat{\epsilon}^{D}_{t-1\to t} + u_t,$$

where y_{t+1} is $\mathbf{VIX_{t+1}}$ and $\mathbf{TVIX_{t+1}}$. Regressors are the rolling sums of estimated structural shocks obtained from the system $\mathbf{y_t} = \mathbf{A_0} + \sum_i \mathbf{A_i y_{t-i}} + \mathbf{B}\boldsymbol{\epsilon}_\mathbf{t}$. The backward rolling window is $l = \mathbf{1}$, $\mathbf{3}$, $\mathbf{6}$, and $\mathbf{12}$ months. The three regressors are normalized to zero mean and unit standard deviation. Sample period is from 2006 to 2015. Standard errors are based on Newey and West (1987) with 12 lags. Asterisks denote significance levels (*** = 1%, ** = 5%, and * = 10%).

Panel A: IG & VIX

	$l=1$	$l=3$	$l=6$	$l=12$
Const	20.81***	20.93***	21.13***	21.65***
	(2.03)	(1.78)	(1.52)	(1.35)
$\sum_{t-l+1}^{t} \hat{\epsilon}^{H}_{s-1\to s}$	2.32***	3.17***	4.62***	5.11***
	(0.79)	(0.99)	(1.20)	(1.35)
$\sum_{t-l+1}^{t} \hat{\epsilon}^{L}_{s-1\to s}$	0.72	1.05	1.61	0.29
	(0.45)	(0.79)	(0.99)	(1.38)
$\sum_{t-l+1}^{t} \hat{\epsilon}^{D}_{s-1\to s}$	2.77***	3.61***	3.91***	2.66**
	(0.84)	(0.89)	(1.04)	(1.26)
N	118	116	113	107
R^2_{adj}	0.16	0.31	0.40	0.37

Panel B: IG & TVIX

	$l=1$	$l=3$	$l=6$	$l=12$
Const	11.51***	11.58***	11.72***	11.98***
	(1.01)	(0.88)	(0.73)	(0.66)
$\sum_{t-l+1}^{t} \hat{\epsilon}^{H}_{s-1\to s}$	0.43	0.96**	1.68***	2.08***
	(0.28)	(0.48)	(0.56)	(0.60)
$\sum_{t-l+1}^{t} \hat{\epsilon}^{L}_{s-1\to s}$	0.12	0.46	0.73*	0.20
	(0.26)	(0.35)	(0.39)	(0.74)
$\sum_{t-l+1}^{t} \hat{\epsilon}^{D}_{s-1\to s}$	0.95***	1.85***	2.43***	1.90***
	(0.25)	(0.35)	(0.54)	(0.62)
N	117	115	112	106
R^2_{adj}	0.06	0.25	0.42	0.38

Panel C: HY & VIX

	$l=1$	$l=3$	$l=6$	$l=12$
Const	20.89***	21.00***	21.21***	21.71***
	(2.02)	(1.60)	(1.29)	(1.11)
$\sum_{t-l+1}^{t} \hat{\epsilon}^{H}_{s-1\to s}$	2.46*	4.02**	4.89***	6.11***
	(1.41)	(1.65)	(1.57)	(1.34)
$\sum_{t-l+1}^{t} \hat{\epsilon}^{L}_{s-1\to s}$	-0.63	1.10	2.74***	2.20***
	(0.47)	(0.75)	(1.03)	(0.69)
$\sum_{t-l+1}^{t} \hat{\epsilon}^{D}_{s-1\to s}$	1.88*	2.83**	1.89**	-0.41
	(1.03)	(1.26)	(0.85)	(0.92)
N	117	115	112	106
R^2_{adj}	0.12	0.30	0.41	0.37

Panel D: HY & TVIX

	$l=1$	$l=3$	$l=6$	$l=12$
Const	11.54***	11.62***	11.76***	12.03***
	(0.98)	(0.75)	(0.61)	(0.62)
$\sum_{t-l+1}^{t} \hat{\epsilon}^{H}_{s-1\to s}$	0.87	2.08***	2.40***	2.55***
	(0.53)	(0.69)	(0.68)	(0.56)
$\sum_{t-l+1}^{t} \hat{\epsilon}^{L}_{s-1\to s}$	-0.25	0.37	0.78*	0.70
	(0.21)	(0.34)	(0.46)	(0.53)
$\sum_{t-l+1}^{t} \hat{\epsilon}^{D}_{s-1\to s}$	0.65	1.34**	1.31***	0.49
	(0.49)	(0.58)	(0.51)	(0.62)
N	116	114	111	105
R^2_{adj}	0.06	0.32	0.47	0.35

Table 6: **Yield spread changes and measures of liquidity**

This table reports the results of the regression: $\Delta \mathrm{YS}_{i,t} = \alpha_i + \beta_1 \textbf{Customer Liquidity}_t + \beta_2 \textbf{Dealer}_t + \beta_3 \textbf{Hedger}_t + \boldsymbol{\beta_4 \Delta X_{i,t}} + \boldsymbol{\beta_5 \Delta X_t} + u_{i,t}$, where $\textbf{Customer Liquidity}_t$, $\textbf{Dealer}_t$, and $\textbf{Hedger}_t$ are measures capturing the willingness of liquidity provision for customer liquidity providers, dealers, and hedgers. $\boldsymbol{\Delta X_{i,t}}$ includes the change in the leverage of the issuers and the market return of the issuers' common equity. $\boldsymbol{\Delta X_t}$ includes the change in risk-free rate, the squared change in risk-free rate, the change in the slope of the yield curve, the change in the VIX, and the S&P 500 return. Reported in parentheses are standard errors double-clustered at Cusip and year-month level. The sample starts in 2006 and ends in 2015. Asterisks denote significance levels (*** = 1%, ** = 5%, and * = 10%).

Dep Var: Δ Yield Spread (bps)	(1) Aaa	(2) Aaa	(3) Aa	(4) Aa	(5) A	(6) A	(7) Baa	(8) Baa	(9) Ba	(10) Ba	(11) B	(12) B
$\textbf{Hedgers}_t$		-1.10		-0.70		1.38		4.62**		11.26*		13.06*
		(1.32)		(1.21)		(1.61)		(2.32)		(5.74)		(7.46)
$\textbf{Customer Liquidity}_t$		2.30*		1.98*		2.33*		1.70		4.31		5.02
		(1.16)		(1.06)		(1.38)		(1.93)		(4.66)		(6.17)
$\textbf{Dealers}_t$		1.71		1.87		4.62**		8.42***		14.93**		24.44***
		(1.34)		(1.34)		(1.84)		(2.72)		(6.20)		(8.61)
$\mathbf{R}_{i,t}$	0.05	0.08	0.09	0.09	-0.08	-0.08	-0.62***	-0.60***	-1.56***	-1.50***	-2.41***	-2.34***
	(0.17)	(0.17)	(0.13)	(0.13)	(0.07)	(0.06)	(0.13)	(0.14)	(0.33)	(0.30)	(0.37)	(0.35)
$\Delta\mathbf{RF}_t$	-0.58***	-0.56***	-0.51***	-0.48***	-0.59***	-0.50***	-0.80***	-0.61***	-1.54***	-1.17***	-1.63***	-1.09**
	(0.09)	(0.09)	(0.08)	(0.08)	(0.13)	(0.11)	(0.18)	(0.14)	(0.44)	(0.35)	(0.51)	(0.42)
$\Delta\mathbf{RF}_t^2$	-4.79***	-5.27***	-4.32**	-4.85***	-4.84*	-5.85**	-3.83	-5.15	-1.67	-4.61	7.16	2.65
	(1.76)	(1.75)	(1.71)	(1.74)	(2.73)	(2.59)	(4.19)	(3.74)	(10.06)	(9.52)	(12.88)	(11.45)
$\Delta\mathbf{SLOPE}_t$	0.98***	0.95***	0.91***	0.87***	0.99***	0.87***	1.15***	0.94***	1.47***	1.04***	1.70***	1.04**
	(0.11)	(0.11)	(0.10)	(0.10)	(0.15)	(0.13)	(0.23)	(0.17)	(0.40)	(0.31)	(0.55)	(0.42)
$\mathbf{RM}_t$	-0.40	-0.54	-0.88	-0.97	-1.03	-0.94	-1.67	-1.16	-1.57	-0.87	-6.39	-5.17
	(0.58)	(0.59)	(0.70)	(0.69)	(1.00)	(0.91)	(1.42)	(1.23)	(2.91)	(2.64)	(4.10)	(3.68)
$\Delta\mathbf{VIX}_t$	0.44	0.33	0.49	0.37	0.78	0.68	0.43	0.48	1.55	1.34	-0.87	-1.04
	(0.39)	(0.37)	(0.44)	(0.43)	(0.52)	(0.49)	(0.55)	(0.53)	(0.95)	(1.14)	(1.58)	(1.93)
$\Delta\mathbf{Jump}_t$	-0.53	-0.52	-0.20	-0.23	0.16	-0.09	1.49	0.90	4.42	3.29	6.86	5.09
	(0.61)	(0.59)	(0.75)	(0.72)	(1.03)	(0.93)	(1.51)	(1.27)	(3.03)	(2.53)	(4.41)	(3.74)
Observations	2086	2086	8748	8748	47176	47176	67633	67633	23078	23078	20294	20294
Adjusted R^2	0.269	0.278	0.296	0.303	0.288	0.306	0.251	0.279	0.233	0.259	0.230	0.251
Cusip FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: **Yield spread changes and measures of liquidity: Different maturity**

This table reports the results of the regression: $\Delta \text{YS}_{i,t} = \alpha_i + \beta_1 \textbf{Customer Liquidity}_t + \beta_2 \textbf{Dealer}_t + \beta_3 \textbf{Hedger}_t + \boldsymbol{\beta_4} \Delta \mathbf{X_{i,t}} + \boldsymbol{\beta_5} \Delta \mathbf{X_t} + u_{i,t}$, where $\textbf{Customer Liquidity}_t$, $\textbf{Dealer}_t$, and $\textbf{Hedger}_t$ are measures capturing the willingness of liquidity provision for customer liquidity providers, dealers, and hedgers. $\Delta \mathbf{X_{i,t}}$ includes the change in the leverage of the issuers and the market return of the issuers' common equity. $\Delta \mathbf{X_t}$ includes the change in risk-free rate, the squared change in risk-free rate, the change in the slope of the yield curve, the change in the VIX, and the S&P 500 return. Reported in parentheses are standard errors double-clustered at Cusip and year-month level. The sample starts in 2006 and ends in 2015. Asterisks denote significance levels (*** = 1%, ** = 5%, and * = 10%).

Panel A: Maturity: Long (over eight years)

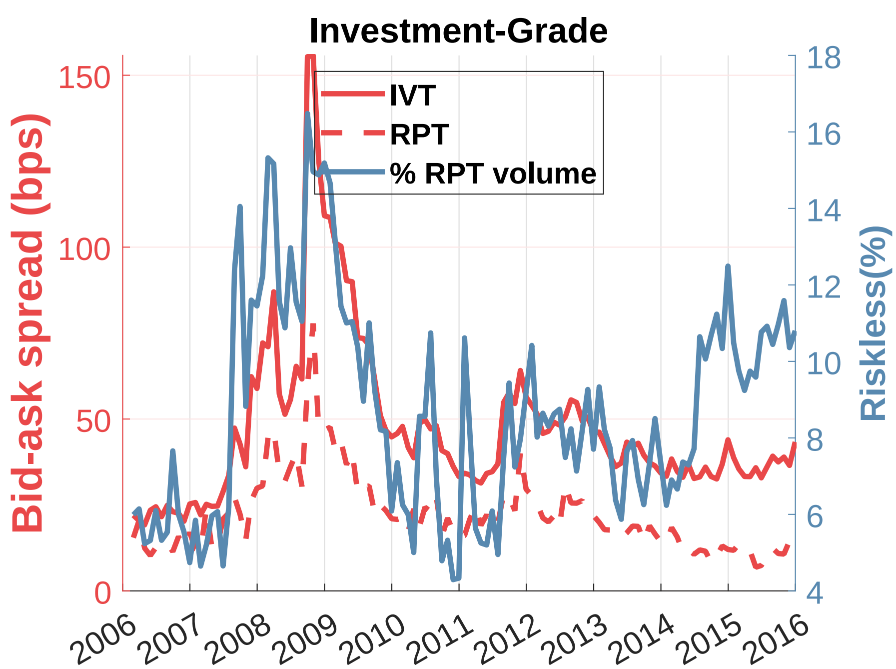
	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var: Δ Yield Spread (bps)	Aaa	Aa	A	Baa	Ba	B
Hedgers$_t$	-1.07	-0.90	0.91	3.15	6.88	8.33
	(1.68)	(1.48)	(1.83)	(2.25)	(4.32)	(5.37)
Customer Liquidity$_t$	2.49*	2.31**	2.57*	2.27	5.05	4.67
	(1.21)	(1.14)	(1.37)	(1.75)	(3.38)	(4.01)
Dealers$_t$	1.44	1.55	3.41*	6.37**	9.03**	14.06**
	(1.58)	(1.56)	(2.04)	(2.46)	(4.06)	(5.69)
Observations	1144	3533	20388	27108	6530	4342
Adjusted R^2	0.519	0.542	0.465	0.393	0.327	0.324
Cusip FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Maturity: Short (less than eight years)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var: Δ Yield Spread (bps)	Aaa	Aa	A	Baa	Ba	B
Hedgers$_t$	-1.31	-0.69	1.42	5.65**	14.01**	15.49*
	(1.47)	(1.19)	(1.63)	(2.55)	(6.59)	(8.31)
Customer Liquidity$_t$	1.87	1.94*	2.29	1.59	4.75	5.93
	(1.30)	(1.15)	(1.51)	(2.13)	(5.32)	(6.77)
Dealers$_t$	1.65	1.99	5.30***	9.71***	16.55**	26.15***
	(1.60)	(1.30)	(1.85)	(2.97)	(7.03)	(9.55)
Observations	933	5160	26584	40259	16512	15924
Adjusted R^2	0.092	0.184	0.218	0.229	0.257	0.253
Cusip FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Figure 1: **Monthly average bid-ask spreads and fractions of riskless principal trading volumes**

These figures plot the bid-ask spreads for inventory transactions, the bid-ask spreads for riskless principal transactions, and the ratio of customer-dealer-customer riskless principal transaction volume over total customer-dealer volume for investment-grade bonds and high-yield bonds, respectively. The detailed algorithm to classify riskless principal transactions is documented in Internet Appendix E. The bid-ask spread charged for every customer-dealer transaction is twice the difference between the dealer-customer price and the benchmark interdealer price. Bid-ask spreads of each type are computed by averaging the spreads for all transactions of each type with par value above (inclusive) $100K.



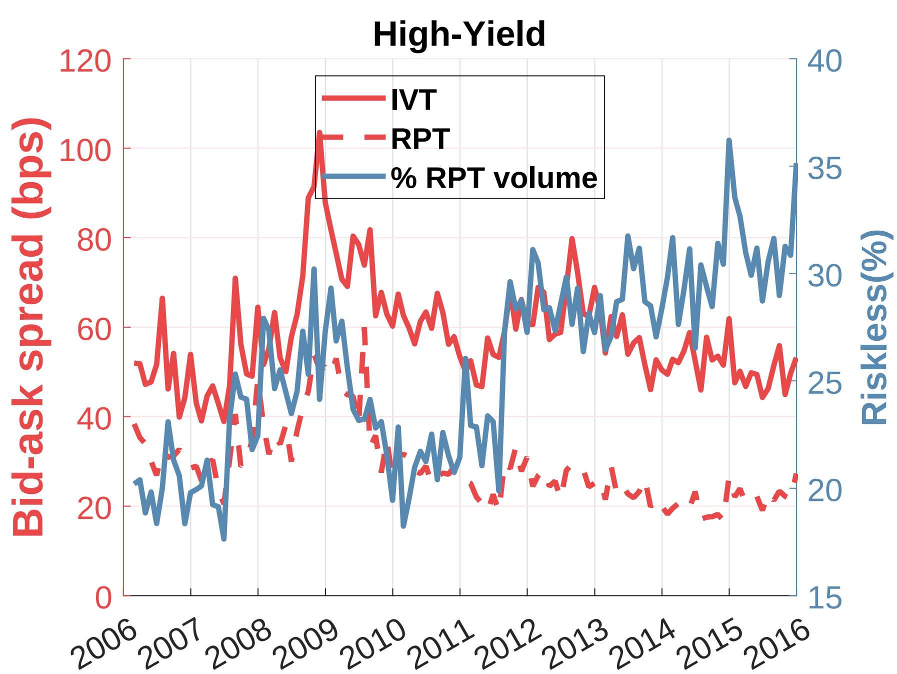


Figure 2: Historical evolution of structural shocks

These figures present the forward cumulated structural shocks using a rolling window of 12 months $\sum_{t}^{t+11} \hat{\boldsymbol{\epsilon}}_{\mathbf{t}}$. $\boldsymbol{\epsilon}_{\mathbf{t}} = \left[\epsilon_t^H \, \epsilon_t^L \, \epsilon_t^d\right]^T$ is a vector of unit variance orthogonal shocks to hedgers (ϵ_t^H), customer liquidity providers (ϵ_t^L), and dealers (ϵ_t^d). Each panel highlights the shocks to one of the three market participants. They are estimated from the system $\mathbf{y_t} = \mathbf{A_0} + \sum_i \mathbf{A_i} \mathbf{y_{t-i}} + \mathbf{B}\boldsymbol{\epsilon}_{\mathbf{t}}$ for investment-grade bonds and high-yield bonds, respectively. $\mathbf{y_t}$ is a vector that contains three variables: $\log\left(\mathrm{Spread}_\mathrm{t}^{\mathrm{RPT}}\right)$, $\log\left(\mathrm{Spread}_\mathrm{t}^{\mathrm{IVT}}\right)$, and $\%\mathrm{RPT}_\mathrm{t}$. $\log\left(\mathrm{Spread}_\mathrm{t}^{\mathrm{RPT}}\right)$ is the monthly average bid-ask spread computed based on riskless principal transactions. $\log\left(\mathrm{Spread}_\mathrm{t}^{\mathrm{IVT}}\right)$ is the monthly average bid-ask spread computed based on inventory transactions. $\%\mathrm{RPT}_\mathrm{t}$ is the ratio of customer-dealer-customer riskless principal transaction volume over total customer-dealer volume. I impose the following three restrictions: $b_{1,2} = 0$, $b_{1,3} = 0$, and $b_{3,1} + b_{3,2} + b_3 = 0$. Data from 2006 to 2015 are used to estimate the system.

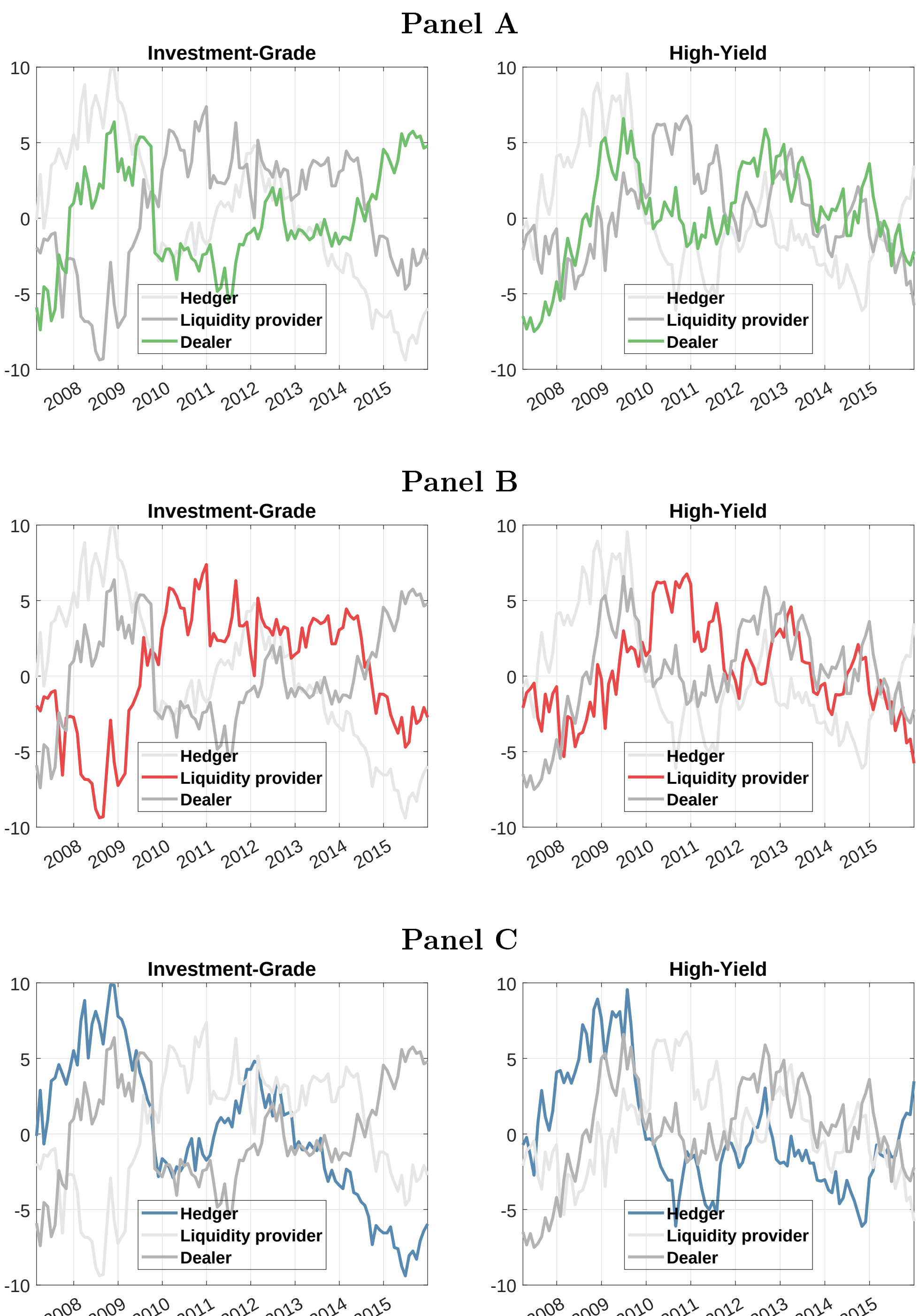


Figure 3: **Volatility index for equity and 30-year Treasury bond futures**
This table presents the time series of CBOE VIX and the volatility index for the 30-year Treasury bond futures (TVIX). VIX is obtained from yahoo.com. TVIX is computed based on options on the 30-year Treasury bond futures. Options data are obtained from the CME group. Sample begins in 2006 and ends in 2015.

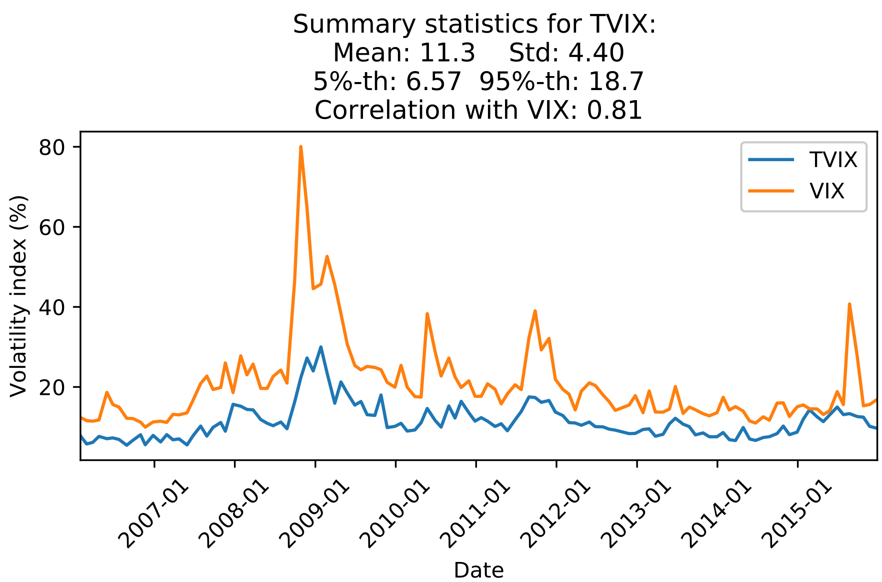


Figure 4: Impulse response functions based on the agnostic method for investment-grade bond markets
These figures present the impulse response functions of the SVAR model in equation (1) for investment-grade bond markets, using the agnostic method. The total number of lags selected is one. For each of the shocks to be recovered, I separately apply two inequality restrictions, up to a horizon of three periods, on candidate impulse response functions. To recover the shocks to hedgers, I impose the restrictions that an increase in ϵ_t^H increases $\log\left(\mathbf{Spread}_t^{\mathrm{RPT}}\right)$ (i.e., $b_1 \geq 0$) and $\log\left(\mathbf{Spread}_t^{\mathrm{IVT}}\right)$ (i.e., $b_{2,1} \geq 0$). To obtain the shocks to dealers, I apply the restrictions that an increase in ϵ_t^d increases $\%\mathbf{RPT}_t$ (i.e., $b_3 \geq 0$) and $\log\left(\mathbf{Spread}_t^{\mathrm{IVT}}\right)$ (i.e., $b_{2,3} \geq 0$). Finally, to derive the shocks to customer liquidity providers, I use the restrictions that an increase in ϵ_t^d decreases $\%\mathbf{RPT}_t$ (i.e., $b_2 \leq 0$) and increases $\log\left(\mathbf{Spread}_t^{\mathrm{IVT}}\right)$ (i.e., $b_{3,2} \geq 0$). Plotted are the median (in red) and 5-th and 95-th percentiles (in blue) of all feasible impulse response functions that satisfy the inequality constrains.

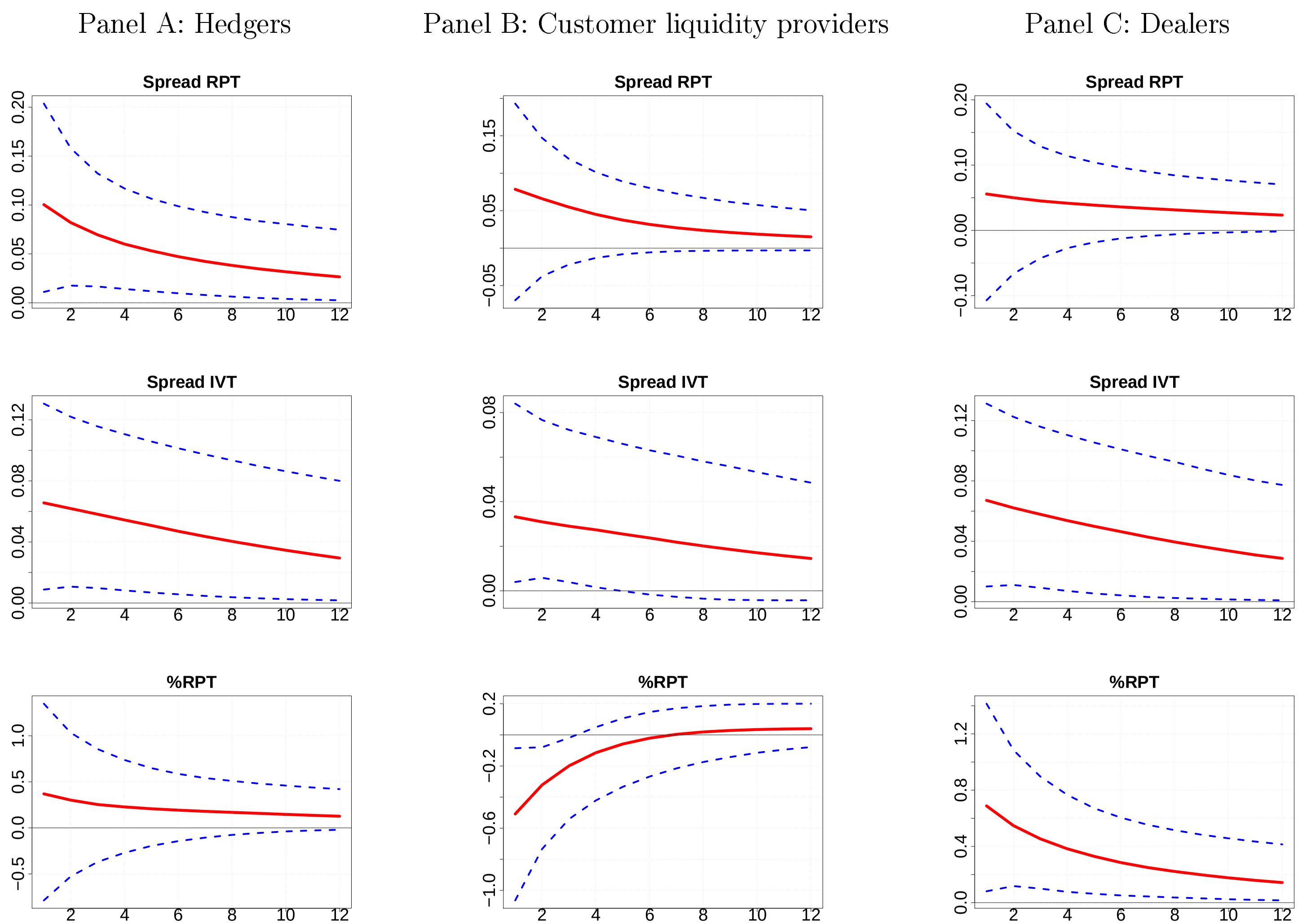


Figure 5: **Histograms of the initial impulse responses**

These figures plots the posterior distribution of the initial impulse responses for investment-grade bond markets, using the agnostic method. The total number of lags selected is one. For each of the shocks to be recovered, I separately apply two inequality restrictions, up to a horizon of three periods, on candidate impulse response functions. To recover the shocks to hedgers, I impose the restrictions that an increase in ϵ_t^H increases $\mathbf{log}\left(\mathbf{Spread}_t^{\mathrm{RPT}}\right)$ (i.e., $b_1 \geq 0$) and $\mathbf{log}\left(\mathbf{Spread}_t^{\mathrm{IVT}}\right)$ (i.e., $b_{2,1} \geq 0$). To obtain the shocks to dealers, I apply the restrictions that an increase in ϵ_t^d increases $\%\mathbf{RPT}_t$ (i.e., $b_3 \geq 0$) and $\mathbf{log}\left(\mathbf{Spread}_t^{\mathrm{IVT}}\right)$ (i.e., $b_{2,3} \geq 0$). Finally, to derive the shocks to customer liquidity providers, I use the restrictions that an increase in ϵ_t^d decreases $\%\mathbf{RPT}_t$ (i.e., $b_2 \leq 0$) and increases $\mathbf{log}\left(\mathbf{Spread}_t^{\mathrm{IVT}}\right)$ (i.e., $b_{3,2} \geq 0$). Red lines in the plots indicate the 2.5th, 16th, 50th, 84th, and 97.5th percentiles.

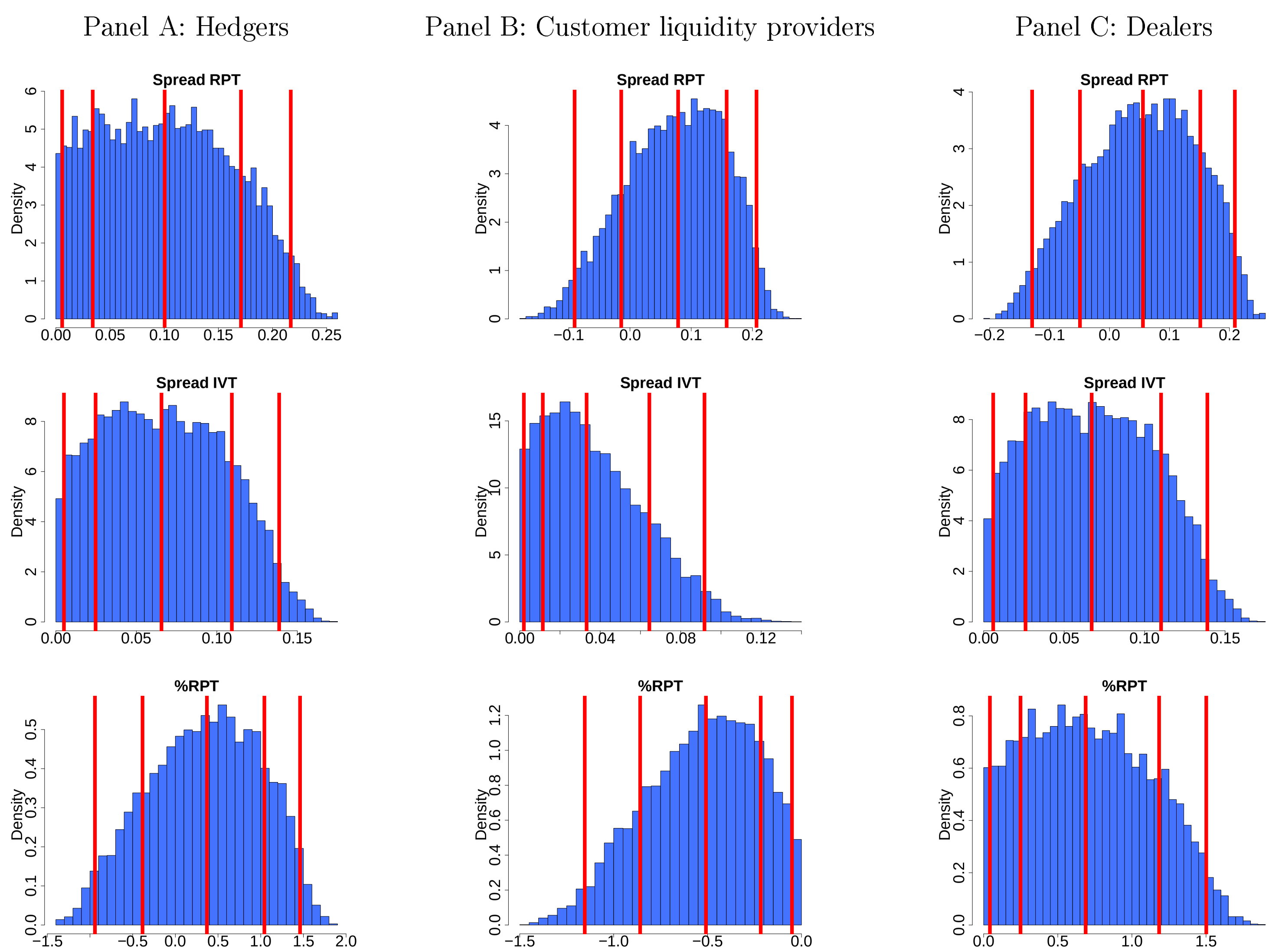


Figure 6: **Structural shocks from the agnostic method for investment-grade markets**
These plots compare the obtained structural shocks based on the full identification method versus the agnostic method. Panel A presents the scatter plots where each spot represents a pair of the shocks based on the two methods in the same month. Also reported are the correlation coefficients of the shocks generated by the two methods. Panel B exhibits the time series of 12-month rolling sum of the structural shocks. Colored and solid lines are based on the sign restrictions, while gray and dashed lines are based on the equality restrictions.

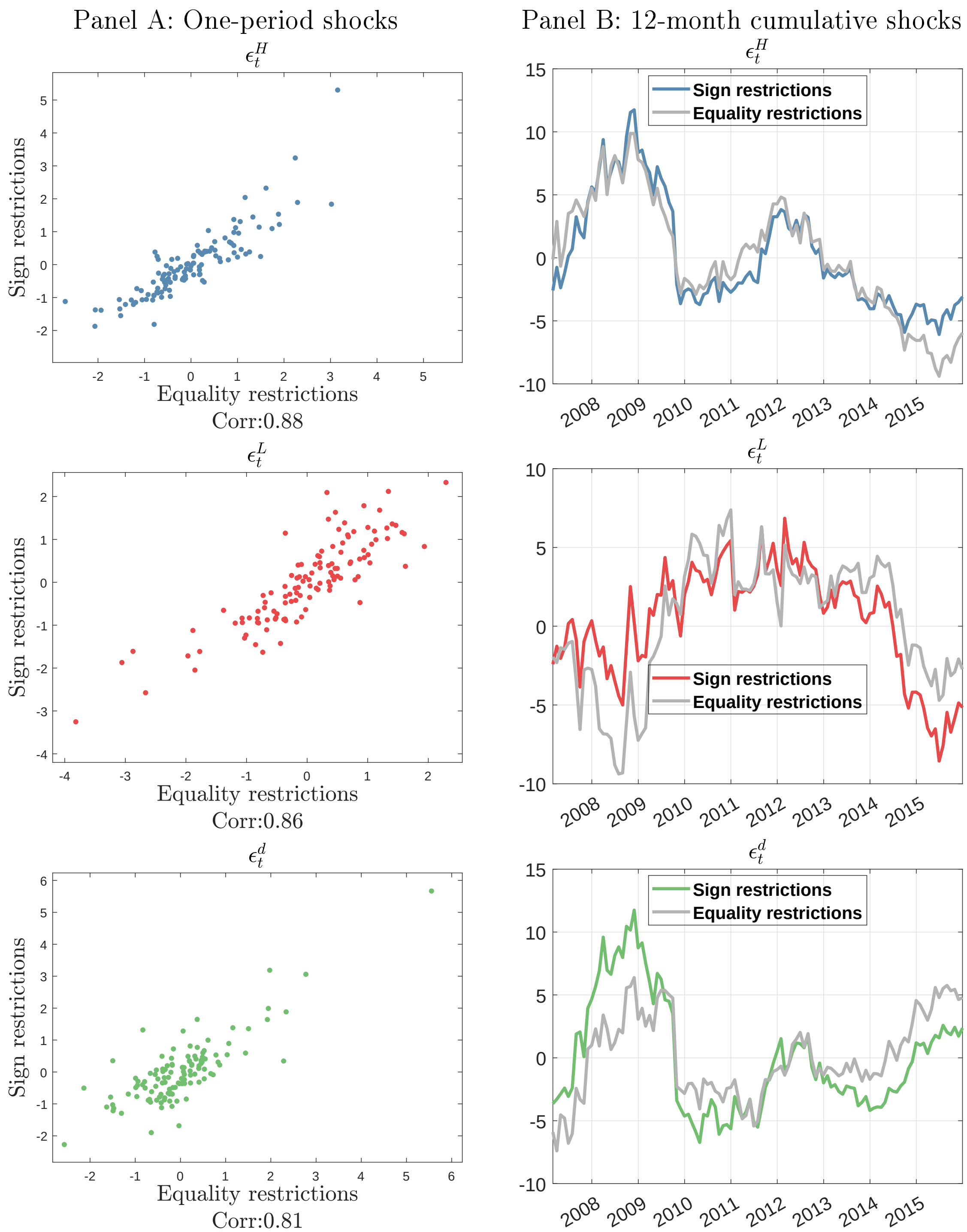


Figure 7: **A numerical illustration of the market for three local dealers**
This figure illustrates the modeled market structure. In this example, there are three local dealers. Each dealer has her own customers. Dealers can also trade in the interdealer market. Each dealer has two types of customers: hedgers who receive a liquidity shock from a correlated non-tradable asset of size X. The rectangles named Liquidity stand for customers who do not suffer from liquidity shocks, that is, customer liquidity providers. The arrows indicate the direction of transaction of the asset in equilibrium. For example, Dealer A buys from hedgers, sells to customer liquidity providers, and sells in the interdealer market. Numbers of equilibrium prices (P) and volumes (V) are presented on the side of the arrows, which represents the direction of transactions. Also reported are the total volume and average spreads for inventory trades and riskless principal transactions.

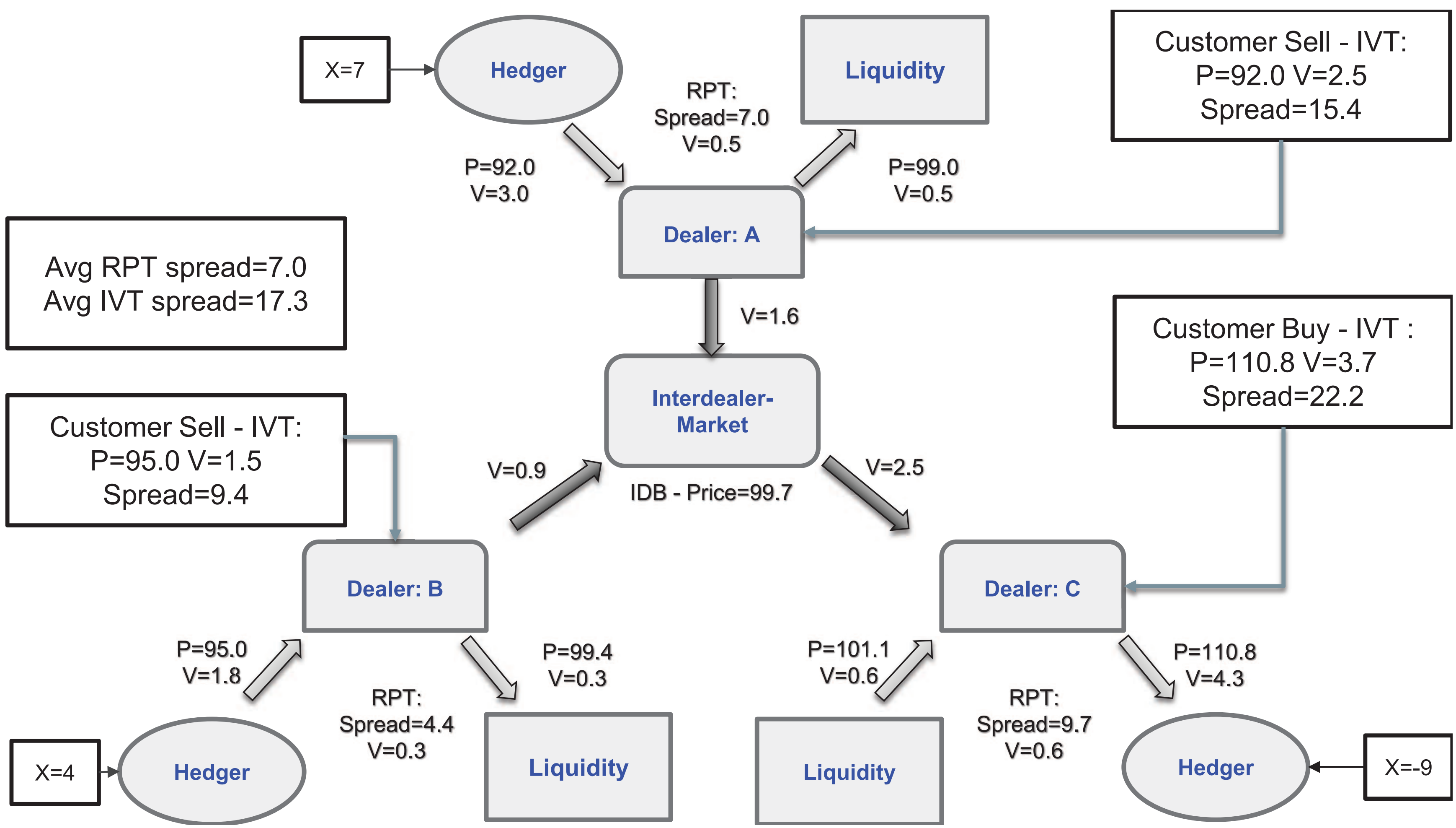
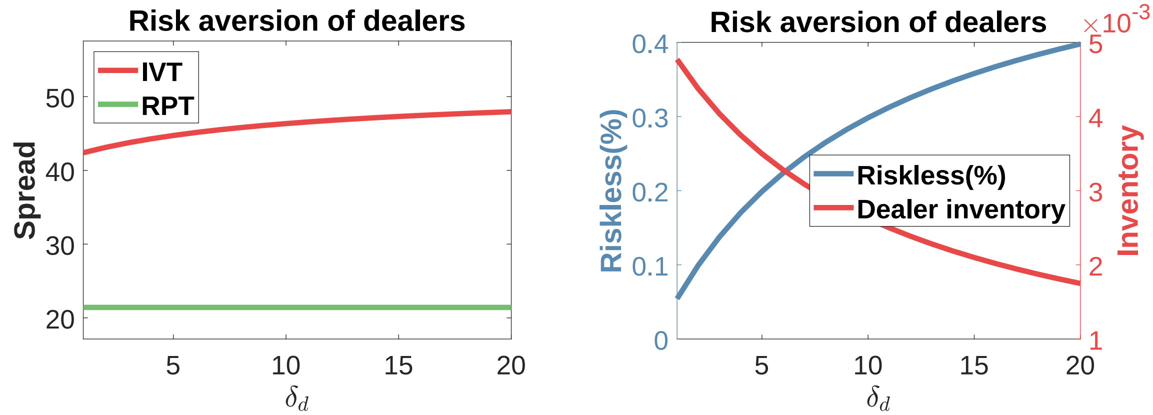


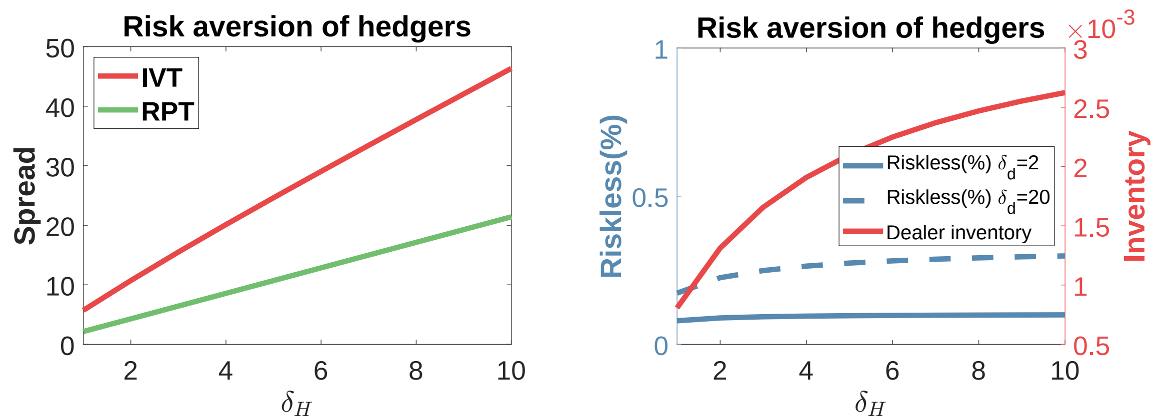
Figure 8: **Comparative statics**

These figures report the comparative statics of equilibrium spreads for inventory transactions, spreads for riskless principal transactions, fraction of riskless principal trading volume, and average dealer inventory level. Results are simulated by liquidity shocks $\{X_k\}_{k=1}^{K}$ that are randomly and independently drawn 100,000 times from identical normal distributions $N(0, 5^2)$. In each trail, I compute the corresponding quantities as described in Internet Appendix B. Reported are the average of each quantity over the 100,000 draws.

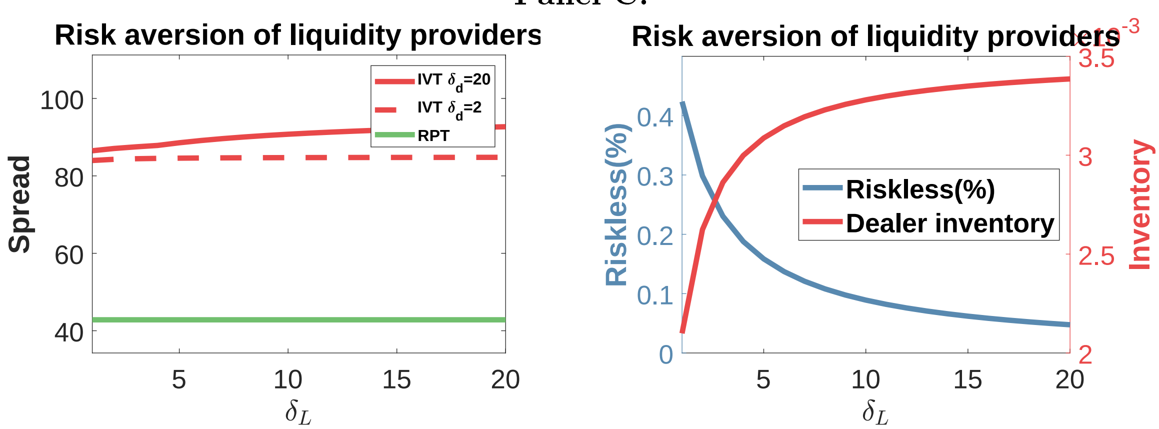
Panel A:



Panel B:



Panel C:



I Internet Appendix

A Solve the equilibrium

The problem is equivalent to:

$$\max_{P_k^H, P_k^L, m_k} \quad N_H\Theta_{H,k}P_k^H + N_L\Theta_{L,k}P_k^L - m_k\left(\frac{\nu}{\gamma} - \frac{\eta}{\gamma}X_{-k} + \frac{1}{(K-1)\gamma}m_k\right)$$
$$+\left(-N_H\Theta_{H,k} - N_L\Theta_{L,k} + m_k\right)\bar{V} - \frac{1}{2}\delta_d\sigma_v^2\left(-N_H\Theta_{H,k} - N_L\Theta_{L,k} + m_k\right)^2. \tag{A-1}$$

The optimal demand for the customers H and L are:

$$\Theta_{H,k} = \frac{P_k^{R,H} - P_k^H}{\delta_H\sigma_v^2} \quad \text{and} \tag{A-2}$$
$$\Theta_{L,k} = \frac{P^{R,L} - P_k^L}{\delta_L\sigma_v^2}. \tag{A-3}$$

F.O.C. wrt P_k^H is

$$N_H\Theta_{H,k} - N_H\frac{P_k^H}{\delta_H\sigma_v^2} + \frac{N_H\bar{V}}{\delta_H\sigma_v^2} - \frac{\delta_d}{\delta_H}N_H\left(-N_H\Theta_{H,k} - N_L\Theta_{L,k} + m_k\right) = 0. \tag{A-4}$$

It reduces to

$$(2\delta_H + \delta_d N_H)\Theta_{H,k} + \delta_d\left(N_L\Theta_{L,k} - m_k\right) = -\frac{\delta_H\sigma_{lv}X_k}{\sigma_v^2}, \tag{A-5}$$

F.O.C. wrt P_k^L is

$$N_L\Theta_{L,k} - N_L\frac{P_k^L}{\delta_L\sigma_v^2} + \frac{N_L\bar{V}}{\delta_L\sigma_v^2} - \frac{\delta_d}{\delta_L}N_L\left(-N_H\Theta_{H,k} - N_L\Theta_{L,k} + m_k\right) = 0. \tag{A-6}$$

It reduces to

$$(2\delta_L + \delta_d N_L)\Theta_{L,k} + \delta_d\left(N_H\Theta_{H,k} - m_k\right) = 0. \tag{A-7}$$

F.O.C. wrt m_k is

$$-\left(\frac{\nu}{\gamma} - \frac{\eta}{\gamma}X_{-k} + \frac{1}{(K-1)\gamma}m_k\right) - \frac{1}{(K-1)\gamma}m_k + \bar{V} - \delta_d\sigma_v^2\left(-N_H\Theta_{H,k} - N_L\Theta_{L,k} + m_k\right) = 0 \tag{A-8}$$

It reduces to:

$$P^{R,L} - P^D - \frac{1}{(K-1)\gamma}m_k + \delta_d\sigma_v^2\left(N_H\Theta_{H,k} + N_L\Theta_{L,k}\right) - \delta_d\sigma_v^2 m_k = 0. \tag{A-9}$$

The solution to the system of three FOCs is

$$\begin{aligned}
\Theta_{H,k} &= -\frac{2\delta_d\delta_L\gamma\sigma_v^2(K-1)\left(P^D(m_k)-P_k^{R,H}\right)+(2\delta_H\delta_L+\delta_d\delta_H N_L)\sigma_{lv}X_k}{2\sigma_v^2\left(\delta_d\delta_L N_H+\delta_d\delta_H N_L+2\delta_H\delta_L\left(1+\delta_d\gamma(K-1)\sigma_v^2\right)\right)} \\
\Theta_{L,k} &= \frac{\delta_d\delta_H\left(-2\gamma\sigma_v^2(K-1)\left(P^D(m_k)-P^{R,L}\right)+N_H\sigma_{lv}X_k\right)}{2\sigma_v^2\left(\delta_d\delta_L N_H+\delta_d\delta_H N_L+2\delta_H\delta_L\left(1+\delta_d\gamma(K-1)\sigma_v^2\right)\right)} \\
m_k &= \frac{\gamma(K-1)\left(\left(P^{R,L}-P^D(m_k)\right)(2\delta_H\delta_L+\delta_d\delta_L N_H+\delta_d\delta_H N_L)-\delta_d\delta_H\delta_L N_H\sigma_{lv}X_k\right)}{\delta_d\delta_L N_H+\delta_d\delta_H N_L+2\delta_H\delta_L\left(1+\delta_d\gamma(K-1)\sigma_v^2\right)}. \quad \text{(A-10)}
\end{aligned}$$

Next, I solve for ν, γ and η by matching parameters from equation (8) and equation (A-10). Rearrange equation (A-10):

$$\begin{aligned}
m_k = {} & \frac{\gamma(K-1)(2\delta_H\delta_L+\delta_d\delta_L N_H+\delta_d\delta_H N_L)P^{R,L}}{\delta_d\delta_L N_H+\delta_d\delta_H N_L+2\delta_H\delta_L\left(1+\delta_d\gamma(K-1)\sigma_v^2\right)} \\
& -\frac{\gamma(K-1)(2\delta_H\delta_L+\delta_d\delta_L N_H+\delta_d\delta_H N_L)}{\delta_d\delta_L N_H+\delta_d\delta_H N_L+2\delta_H\delta_L\left(1+\delta_d\gamma(K-1)\sigma_v^2\right)}P^D(m_k) \\
& -\frac{\gamma(K-1)\delta_d\delta_H\delta_L N_H\sigma_{lv}}{\delta_d\delta_L N_H+\delta_d\delta_H N_L+2\delta_H\delta_L\left(1+\delta_d\gamma(K-1)\sigma_v^2\right)}X_k.
\end{aligned}$$

Match the coefficients with the conjectured demand curve in equation (8) and get the following system:

$$\nu = \frac{\gamma(K-1)P_U^R(2\delta_c+\delta(N_I+N_U))}{\delta(N_U+N_I)+2\delta_c+2\delta_c\delta\gamma(K-1)\sigma_v^2} \tag{A-11}$$

$$\gamma = \frac{\gamma(K-1)(2\delta_c+\delta(N_I+N_U))}{\delta(N_U+N_I)+2\delta_c+2\delta_c\delta\gamma(K-1)\sigma_v^2} \tag{A-12}$$

$$\eta = \frac{\gamma(K-1)\delta\delta_c N_I\sigma_{lv}}{\delta(N_U+N_I)+2\delta_c+2\delta_c\delta\gamma(K-1)\sigma_v^2}. \tag{A-13}$$

The solution is:

$$\gamma = \frac{(K-2)(2\delta_H\delta_L+\delta_d\delta_L N_H+\delta_d\delta_H N_L)}{2\delta_d\delta_L\delta_H(K-1)\sigma_v^2} \tag{A-14}$$

$$\nu = \frac{(K-2)(2\delta_H\delta_L+\delta_d\delta_L N_H+\delta_d\delta_H N_L)}{2\delta_d\delta_H(K-1)\sigma_v^2}P^{R,L} \tag{A-15}$$

$$\eta = \frac{(K-2)}{2(K-1)\sigma_v^2}N_H\sigma_{lv}. \tag{A-16}$$

The optimal m_k^* is

$$m_k^* = \gamma\left(P^{R,L}-P^D\right)-\frac{(K-2)}{2(K-1)\sigma_v^2}N_H\sigma_{lv}X_k. \tag{A-17}$$

The market clearing condition in equation (9) implies the interdealer price is

$$\sum_{k=1}^{K}\gamma\left(P^{R,L}-P^{D}\right)-\frac{(K-2)N_H\sigma_{lv}X_k}{2(K-1)\sigma_v^2}=0$$

and

$$P^{R,L}-P^{D}=\frac{N_H\sigma_{lv}\bar{X}}{\left(\frac{2}{\delta_d}+\frac{N_H}{\delta_H}+\frac{N_L}{\delta_L}\right)}, \tag{A-18}$$

where $\bar{X}$ is defined as $\frac{1}{K}\sum_{k=1}^{K}X_k$. And thus we have

$$m_k=\frac{(K-2)N_H\sigma_{lv}}{2(K-1)\sigma_v^2}\left(\bar{X}-X_k\right). \tag{A-19}$$

The optimal trading quantities and prices are:

$$\Theta_{L,k} = \frac{K-2}{2K}\frac{\delta_d\delta_H}{(\delta_d\delta_L N_H+\delta_d\delta_H N_L+2\delta_H\delta_L)}\frac{\sigma_{lv}N_H}{\sigma_v^2}\bar{X}_{-k}+\frac{\delta_d\delta_H}{K(\delta_d\delta_L N_H+\delta_d\delta_H N_L+2\delta_H\delta_L)}\frac{\sigma_{lv}N_H}{\sigma_v^2}X_k \tag{A-20}$$

$$\Theta_{H,k} = \frac{K-2}{2K}\frac{\delta_d\delta_L}{(\delta_d\delta_L N_H+\delta_d\delta_H N_L+2\delta_H\delta_L)}\frac{\sigma_{lv}N_H}{\sigma_v^2}\bar{X}_{-k}+\frac{\delta_d\delta_L}{K(\delta_d\delta_L N_H+\delta_d\delta_H N_L+2\delta_H\delta_L)}\frac{\sigma_{lv}N_H}{\sigma_v^2}X_k-\frac{\sigma_{lv}}{2\sigma_v^2}X_k \tag{A-21}$$

$$P_k^L = \bar{V}-\frac{K-2}{2K}\frac{1}{\left(\frac{2}{\delta_d}+\frac{N_H}{\delta_H}+\frac{N_L}{\delta_L}\right)}\sigma_{lv}N_H\bar{X}_{-k}-\frac{1}{K\left(\frac{2}{\delta_d}+\frac{N_H}{\delta_H}+\frac{N_L}{\delta_L}\right)}\sigma_{lv}N_H X_k \tag{A-22}$$

$$P_k^H = \bar{V}-\frac{K-2}{2K}\frac{1}{\left(\frac{2}{\delta_d}+\frac{N_H}{\delta_H}+\frac{N_L}{\delta_L}\right)}\sigma_{lv}N_H\bar{X}_{-k}-\frac{1}{K\left(\frac{2}{\delta_d}+\frac{N_H}{\delta_H}+\frac{N_L}{\delta_L}\right)}\sigma_{lv}N_H X_k-\frac{\sigma_{lv}\delta_H}{2}X_k \tag{A-23}$$

$$P^D = \bar{V}-\frac{1}{\left(\frac{2}{\delta_d}+\frac{N_H}{\delta_H}+\frac{N_L}{\delta_L}\right)}N_H\sigma_{lv}\bar{X}. \tag{A-24}$$

The ultimate inventory level is

$$-N_U\Theta_{U,k}-N_I\Theta_{I,k}+m_k=\frac{\delta_H\delta_L}{\sigma_v^2(\delta_d\delta_L N_H+\delta_d\delta_H N_L+2\delta_H\delta_L)}\left(N_H\sigma_{lv}\bar{X}\right). \tag{A-25}$$

Denote the quantity $\mathscr{D}^{-1}=\left(\frac{2}{\delta_d}+\frac{N_H}{\delta_H}+\frac{N_L}{\delta_L}\right)$, $\mathscr{D}^{-1}$ captures the total risk bearing capacity in the economy. The optimal traded quantities and prices reduce to

$$P_k^L = \bar{V}-\frac{1}{2}\mathscr{D}\sigma_{lv}N_H\left(\frac{K-2}{K}\bar{X}_{-k}+\frac{2}{K}X_k\right) \tag{A-26}$$

$$P_k^H = \bar{V}-\frac{1}{2}\mathscr{D}\sigma_{lv}N_H\left(\frac{K-2}{K}\bar{X}_{-k}+\frac{2}{K}X_k\right)-\frac{\sigma_{lv}\delta_H}{2}X_k \tag{A-27}$$

$$P^D = \bar{V}-\mathscr{D}\sigma_{lv}N_H\bar{X} \tag{A-28}$$

$$\Theta_{L,k} = \frac{1}{2}\frac{\mathscr{D}}{\delta_L}\frac{\sigma_{lv}N_H}{\sigma_v^2}\left(\frac{K-2}{K}\bar{X}_{-k}+\frac{2}{K}X_k\right) \tag{A-29}$$

$$\Theta_{H,k} = \frac{1}{2}\frac{\mathscr{D}}{\delta_H}\frac{\sigma_{lv}N_H}{\sigma_v^2}\left(\frac{K-2}{K}\bar{X}_{-k}+\frac{2}{K}X_k\right)-\frac{\sigma_{lv}}{2\sigma_v^2}X_k \tag{A-30}$$

$$-N_U\Theta_{U,k}-N_I\Theta_{I,k}+m_k = \frac{\mathscr{D}}{\delta_d}\frac{\sigma_{lv}N_H}{\sigma_v^2}\left(\frac{K-2}{K}\bar{X}_{-k}+\frac{2}{K}X_k\right). \tag{A-31}$$

B Numerical computation of spreads and volumes

First, transaction prices and volumes are computed based on equations (14) to (20). Equation 20 directly yields the average inventory level.

First, compute the RPT volume as described in equation (21) in each local market, denoted as

$$\Theta_k^{CDC} = \min(N_H|\Theta_{H,k}|, N_L|\Theta_{L,k}|)1_{\Theta_{H,k}\times\Theta_{L,k}<0}. \tag{A-32}$$

It follows that the ratio of customer-dealer-customer riskless principal transaction volume over total customer-dealer volume is given by:

$$\frac{\sum_{k=1}^{K}\Theta_k^{CDC}}{\frac{1}{2}\sum_{k=1}^{K}\left(N_H|\Theta_{H,k}|+N_L|\Theta_{L,k}|\right)} \tag{A-33}$$

The weighted average RPT spread is the difference between:

$$P_{Buy}^{CDC} = \frac{1}{\sum_{k=1}^{K}1_{\Theta_k^{CDC}>0}}\sum_{k=1}^{K}1_{\Theta_k^{CDC}>0}\left(1_{\Theta_{H,k}>0}P_k^H + 1_{\Theta_{L,k}>0}P_k^L\right) \tag{A-34}$$

and

$$P_{Sell}^{CDC} = \frac{1}{\sum_{k=1}^{K}1_{\Theta_k^{CDC}>0}}\sum_{k=1}^{K}1_{\Theta_k^{CDC}>0}\left(1_{\Theta_{H,k}<0}P_k^H + 1_{\Theta_{L,k}<0}P_k^L\right). \tag{A-35}$$

Then, compute the spread for inventory transactions, define the trading volume for inventory transaction as

$$\Theta_{H,k}^{IVT} = \min(N_H|\Theta_{H,k}| - \Theta_k^{CDC}, 0) \tag{A-36}$$

$$\Theta_{L,k}^{IVT} = \min(N_L|\Theta_{L,k}| - \Theta_k^{CDC}, 0) \tag{A-37}$$

The volume weighted average IVT spread is the difference between:

$$P_{Buy}^{IVT} = \frac{\sum_{k=1}^{K}\left(1_{\Theta_{H,k}^{IVT}>0}1_{\Theta_{H,k}>0}P_k^H + 1_{\Theta_{L,k}^{IVT}>0}1_{\Theta_{L,k}>0}P_k^L\right)}{\sum_{k=1}^{K}\left(1_{\Theta_{H,k}^{IVT}>0}1_{N_H\Theta_{H,k}>0} + 1_{\Theta_{L,k}^{IVT}>0}1_{\Theta_{L,k}>0}\right)} \tag{A-38}$$

and

$$P_{Sell}^{IVT} = \frac{\sum_{k=1}^{K}\left(1_{\Theta_{H,k}^{IVT}>0}1_{\Theta_{H,k}<0}P_k^H + 1_{\Theta_{L,k}^{IVT}>0}1_{\Theta_{L,k}<0}P_k^L\right)}{\sum_{k=1}^{K}\left(1_{\Theta_{H,k}^{IVT}>0}1_{N_H\Theta_{H,k}<0} + 1_{\Theta_{L,k}^{IVT}>0}1_{\Theta_{L,k}<0}\right)}. \tag{A-39}$$

In extreme cases that realizations of shocks are similar for all markets, all liquidity provider only provides liquidity to local hedgers. All the customer buy transactions in this realization are RPT. For instance, suppose each market receives the exact same size of positive shock, there will be no interdealer transactions and every dealer buys from hedgers and sell a fraction to local liquidity providers. A consequence is that P_{Buy}^{IVT} is not well defined. Without loss of generality, P_{Buy}^{IVT} is assumed be to P_{Buy}^{RPT} in those situations. This assumption is conservative because $P_{Buy}^{IVT} \geq P_{Buy}^{RPT}$. In addition, it follows the intuition that marginal increments of inventory buys would be traded at least at the current RPT transaction customer buy price.

Risk aversions of market makers and customer liquidity providers may slightly impact the spread for riskless principal transactions if hedgers and customer liquidity providers transact in the same direction with the market maker in a given local market, i.e. $sign(\Theta_{I,k}) = sign(\Theta_{U,k})$. As shown in Panel A of FigureA-1, it occurs when the absolute level of local shocks are too small, relative to the aggregate global shock. In those scenarios, there is no riskless principal transaction in this particular market. It is not a desirable feature since hedgers are effectively the same as customer liquidity providers because their main role is to provide liquidity to the global market, whereas the risk aversions of them are different. Panel B of FigureA-1 illustrate the simulated realized distribution of iid shocks of X_k drawn from $N(0,5)$. Comparative statics in Figure 8 excludes those realizations when at least one local dealer trades with hedgers and liquidity providers in the same direction. Results including those unsatisfying trails are reported in Figure A-2, which verifies that the impact is minimal. Panel C of FigureA-1 shows that those unsatisfying trails can be perfectly avoid if the data generating process for shocks are restricted at some distance away from zero. For example, shocks are uniformly drawn from $[-2,-1] \cup [1,2]$.

C The 3^{rd} restriction in SVAR

The optimal trading quantities $\Theta_{L,k}(\delta_L, \delta_H, \delta_d)$ and $\Theta_{H,k}(\delta_L, \delta_H, \delta_d)$:

$$\begin{aligned}
\Theta_{L,k} &= \frac{1}{2}\frac{\mathscr{D}}{\delta_L}\frac{\sigma_{lv}N_H}{\sigma_v^2}\left(\frac{K-2}{K}\bar{X}_{-k} + \frac{2}{K}X_k\right) \\
\Theta_{H,k} &= \frac{1}{2}\frac{\mathscr{D}}{\delta_H}\frac{\sigma_{lv}N_H}{\sigma_v^2}\left(\frac{K-2}{K}\bar{X}_{-k} + \frac{2}{K}X_k\right) - \frac{\sigma_{lv}}{2\sigma_v^2}X_k
\end{aligned}$$

are homogeneous functions of degree zero, where $\mathscr{D}^{-1} = \left(\frac{2}{\delta_d} + \frac{N_H}{\delta_H} + \frac{N_L}{\delta_L}\right)$. If hedgers, dealers and customer liquidity providers all become twice as risk averse as they were, volumes remains the same.

Formally, consider a function $f(g_H, g_L)$, where $g_H(\delta_L, \delta_H, \delta_d) = \frac{\mathscr{D}(\delta_L, \delta_H, \delta_d)}{\delta_H}$ and $g_L(\delta_L, \delta_H, \delta_d) = \frac{\mathscr{D}(\delta_L, \delta_H, \delta_d)}{\delta_L}$. We can rewrite:

$$\begin{aligned}
g_H = g_H' &= N_L + exp(\log(\delta_L) + \log(N_H) - \log(\delta_H)) + 2exp(\log(\delta_L) - \log(\delta_d)) \\
g_L = g_L' &= N_H + exp(\log(\delta_H) + \log(N_L) - \log(\delta_L)) + 2exp(\log(\delta_H) - \log(\delta_d)).
\end{aligned}$$

Apply the chain rule:

$$\begin{aligned}
\frac{\partial f}{\partial \log(\delta_L)} &= f_1\frac{\partial g'}{\partial \log(\delta_L)}+f_2\frac{\partial h'}{\partial \log(\delta_L)} \\
&= f_1 exp\left(\log(\delta_L)+\log(N_H)-\log(\delta_H)\right)+ \\
&\quad 2f_1 exp\left(\log(\delta_L)-\log(\delta_d)\right)-f_2 exp\left(\log(\delta_H)+\log(N_L)-\log(\delta_L)\right) \\
\frac{\partial f}{\partial \log(\delta_H)} &= f_1\frac{\partial g'}{\partial \log(\delta_H)}+f_2\frac{\partial h'}{\partial \log(\delta_H)} \\
&= -f_1 exp\left(\log(\delta_L)+\log(N_H)-\log(\delta_H)\right)+ \\
&\quad f_2 exp\left(\log(\delta_L)+\log(N_H)-\log(\delta_H)\right)+2f_2 exp\left(\log(\delta_H)-\log(\delta_d)\right) \\
\frac{\partial f}{\partial \log(\delta_d)} &= f_1\frac{\partial g'}{\partial \log(\delta_d)}+f_2\frac{\partial h'}{\partial \log(\delta_d)} \\
&= -2f_1 exp\left(\log(\delta_L)-\log(\delta_d)\right)-2f_2 exp\left(\log(\delta_H)-\log(\delta_d)\right).
\end{aligned}$$

Hence,

$$\frac{\partial f}{\partial \log(\delta_L)}+\frac{\partial f}{\partial \log(\delta_H)}+\frac{\partial f}{\partial \log(\delta_d)}=0$$

So is % RPT, $\mathbb{E}\left(\sum_{k=1}^{K}\min(N_I|\Theta_{I,k}|,N_U|\Theta_{U,k}|)1_{\Theta_{I,k}\times\Theta_{U,k}<0}\right)$:

$$\frac{\partial \%RPT}{\partial \log(\delta_L)}+\frac{\partial \%RPT}{\partial \log(\delta_H)}+\frac{\partial \%RPT}{\partial \log(\delta_d)}=0.$$

D What if shocks are correlated?

I show that my SVAR method is still valid when the orthogonality condition does not hold. Let

$$\begin{bmatrix} \epsilon_t^H \\ \epsilon_t^L \\ \epsilon_t^d \end{bmatrix} = \begin{bmatrix} \upsilon_t^H \\ \rho_2\upsilon_t^H+\rho_3\upsilon_t^d+\upsilon_t^L \\ \rho_1\upsilon_t^H+\upsilon_t^d \end{bmatrix}, \tag{A-40}$$

such that $\boldsymbol{\upsilon_t}=\begin{bmatrix} \upsilon_t^H \\ \upsilon_t^L \\ \upsilon_t^d \end{bmatrix}$ are orthogonal shocks, and ρ_1, ρ_2, and ρ_3 govern the covariance among shocks to market participants ($\boldsymbol{\epsilon_t}$).

υ_t^d is the shocks to dealers that are orthogonal to the shocks to the hedgers, whereas υ_t^L is the shocks to customer liquidity providers that are orthogonal to the other two types of shocks. Thus, the SVAR in equation (1) can be written as

$$\mathbf{y_t}=\mathbf{A_0}+\sum_i \mathbf{A_i}\mathbf{y_{t-i}}+\begin{bmatrix} b_1 & 0 & 0 \\ b_{2,1} & b_2 & b_{2,3} \\ b_{3,1} & b_{3,2} & b_3 \end{bmatrix}\begin{bmatrix} \upsilon_t^H \\ \rho_2\upsilon_t^H+\rho_3\upsilon_t^d+\upsilon_t^L \\ \rho_1\upsilon_t^H+\upsilon_t^d \end{bmatrix}. \tag{A-41}$$

We can rewrite the SVAR:

$$\mathbf{y_t} = \mathbf{A_0} + \sum_i \mathbf{A_i y_{t-i}} + \begin{bmatrix} b_1 & 0 & 0 \\ b_{2,1}+b_2\rho_2+b_{2,3}\rho_1 & b_2 & b_2\rho_3+b_{2,3} \\ b_{3,1}+b_{3,2}\rho_2+b_3\rho_1 & b_{3,2} & b_{3,2}\rho_3+b_3 \end{bmatrix} \underbrace{\begin{bmatrix} v_t^H \\ v_t^L \\ v_t^d \end{bmatrix}}_{\boldsymbol{v}_\mathbf{t}}. \tag{A-42}$$

Denote $\frac{b_{3,1}+b_{3,2}\rho_2+b_3\rho_1}{b_{3,1}} = \Xi_H$ and $\frac{b_{3,2}\rho_3+b_3}{b_3} = \Xi_d$, the system reads as

$$\mathbf{y_t} = \mathbf{A_0} + \sum_i \mathbf{A_i y_{t-i}} + \underbrace{\begin{bmatrix} \Xi_H^{-1} b_1 & 0 & 0 \\ \Xi_H^{-1}\left(b_{2,1}+b_2\rho_2+b_{2,3}\rho_1\right) & b_2 & \Xi_d^{-1}\left(b_2\rho_3+b_{2,3}\right) \\ b_{3,1} & b_{3,2} & b_3 \end{bmatrix}}_{\mathbf{B}_\Xi} \begin{bmatrix} \Xi_H v_t^H \\ v_t^L \\ \Xi_d v_t^d \end{bmatrix}. \tag{A-43}$$

Applying the same restrictions, as stated in equation (3), I can recover $\left[\Xi_H v_t^H,\ v_t^L,\ \Xi_d v_t^d\right]^T$, which are the desired series $\boldsymbol{v}_\mathbf{t}$, up to the scale factors Ξ_H and Ξ_d. The scale factors are harmless as long as they are positive. The positivity can be verified by (i) the movements of $\Xi_H v_t^H$ and $\Xi_d v_t^d$ over economic cycles and (ii) the signs in the estimates of the coefficients in $\mathbf{B}_\Xi$.

E Identify riskless principal transactions

The identification method for riskless principal transactions follows a Last In, First Out (LIFO) strategy for each dealer-Cusip-date sub-dataset of transactions records, following Choi and Huh (2019). Offsetting transactions are defined as two subsequent transactions where the dealer buys in one transaction and sell in another one within 15 minutes. Note that it is not necessary that the dealer buys in the earlier transaction and sells in the later one. It is also not necessary that the amounts are matched in the two transactions.

The implementation of the LIFO strategy is a recursive procedure described below. For every dealer-Cusip-date sub-dataset, first sorted by execution time. Denote this sub-dataset as $\mathbb{C}$, the collection of all transactions conducted by a dealer on a specific Cusip during a day. Denote $\mathbb{C}^{RPT}$ as the collection of riskless principal transactions. Denote $\mathbb{C}^{IVT}$ as the collection of inventory transactions. $\mathbb{C}^{RPT}$ and $\mathbb{C}^{IVT}$ are empty sets when initialized. The following steps are iterated until no new transactions are identified as riskless principal transaction.

1. Denote a dummy $RPT = 0$. Let n start from 1. Let N be the total number of transactions in $\mathbb{C}$. Focus on the n-th transaction. Break the loop as soon as $RPT = 1$ or $n = N$
2. Check if the dealer trades the same direction in the next transaction $n+1$:
   if yes, $n = n+1$; return to step 1;
3. Check if time difference between the n-th trade and the $n+1$-th trade is more than 15 minutes:
   if yes, $n = n+1$; return to step 1;
4. Since both steps 2 and 3 are satisfied, the n-th and $n+1$-th transactions are identified (partially) as riskless principal transactions. The volume of riskless principal transactions is the minimum of the trading volume of n-th and $n+1$-th transactions.
5. If the volumes of n-th and $n+1$-th transactions are the same, move both transactions from $\mathbb{C}$ to $\mathbb{C}^{RPT}$;
   If the volume of n-th transaction is greater than that of the $n+1$-th transaction, move the $n+1$-th

from $\mathbb{C}$ to $\mathbb{C}^{RPT}$, move the n-th from $\mathbb{C}$ to $\mathbb{C}^{RPT}$ but only with the riskless principal amount in step 4, and modify the volume of remaining part of the n-th in $\mathbb{C}$ as the difference between its original amount and riskless principal amount.
if the volume of n-th transaction is smaller than that of the $n+1$-th transaction, do the opposite.

6. Let $RPT = 1$.

If the procedure (1) to (6) breaks because $RPT = 1$, applied this procedure (1) to (6) on the resulted $\mathbb{C}$. If the procedure (1) to (6) breaks because $n = N$, move all the remaining transactions to $\mathbb{C}^{IVT}$.

Considering the type of counterparties, each transaction can be classified as riskless principal transaction to customers, riskless principal transaction to dealers, and inventory transaction. If a transaction is attributed to multiple types, the ultimate classification is type of the highest volume.

This algorithm will capture possible riskless principal transactions where there are multiple transactions in buy and sell legs. For example, considering the following example trading pattern $\mathbb{C}$:

	$\mathbb{C}$		
ID	Buy/Sell	amt	time
1	S	120	9:31
2	B	100	9:32
3	B	200	10:25
4	S	100	10:30
5	S	120	10:35
6	B	20	10:35
7	S	200	14:25

$\mathbb{C}$ is applied on the described algorithm. First, transactions 1 and 2 are identified as (partial) riskless principal transactions.

	$\mathbb{C}$				$\mathbb{C}^{RPT}$			
ID	Buy/Sell	amt	time	ID	Buy/Sell	amt	time	counter ID
1	S	20	9:31	1	S	100	9:31	2
				2	B	100	9:32	1
3	B	200	10:25					
4	S	100	10:30					
5	S	120	10:35					
6	B	20	10:35					
7	S	200	14:25					

In the 2^{nd} iteration, transactions 3 and 4 are identified as (partial) riskless principal transactions.

$\mathbb{C}$				$\mathbb{C}^{RPT}$				
ID	Buy/Sell	amt	time	ID	Buy/Sell	amt	time	counter ID
1	S	20	9:31	1	S	100	9:31	2
				2	B	100	9:32	1
3	B	100	10:25	3	B	100	10:25	4
				4	S	100	10:30	3
5	S	120	10:35					
6	B	20	10:35					
7	S	200	14:25					

In the 3^{nd} iteration, transactions 3 and 5 are identified as (partial) riskless principal transactions.

$\mathbb{C}$				$\mathbb{C}^{RPT}$				
ID	Buy/Sell	amt	time	ID	Buy/Sell	amt	time	counter ID
1	S	20	9:31	1	S	100	9:31	2
				2	B	100	9:32	1
				3	B	100	10:25	4
				4	S	100	10:30	3
				3	B	100	10:25	5
5	S	20	10:35	5	S	100	10:35	3
6	B	20	10:35					
7	S	200	14:25					

In the 4^{nd} iteration, transactions 5 and 6 are identified as (partial) riskless principal transactions.

$\mathbb{C}$				$\mathbb{C}^{RPT}$				
ID	Buy/Sell	amt	time	ID	Buy/Sell	amt	time	counter ID
1	S	20	9:31	1	S	100	9:31	2
				2	B	100	9:32	1
				3	B	100	10:25	4
				4	S	100	10:30	3
				3	B	100	10:25	5
				5	S	100	10:35	3
				5	S	20	10:35	6
				6	B	20	10:35	5
7	S	200	14:25					

In the last iteration, $\mathbb{C}$ contains $N = 2$ records and the loop breaks because $n = N$. So all the remaining transactions are moved to $\mathbb{C}^{IVT}$:

$\mathbb{C}^{IVT}$				$\mathbb{C}^{RPT}$				
ID	Buy/Sell	amt	time	ID	Buy/Sell	amt	time	counter ID
1	S	20	9:31	1	S	100	9:31	2
				2	B	100	9:32	1
				3	B	100	10:25	4
				4	S	100	10:30	3
				3	B	100	10:25	5
				5	S	100	10:35	3
				5	S	20	10:35	6
				6	B	20	10:35	5
7	S	200	14:25					

Transaction $\mathbf{1}$ is considered as riskless principal transaction because 83% of the volume is offset within 15 minutes. Transactions $\mathbf{3}$ to $\mathbf{6}$ are also riskless principal transactions. Despite that they all have different trading volume, the aggregated buy and sell volume matches and they all occur within 15 minutes.

F TVIX

Consider the price of a volatility contract payoff in the 30-year Treasury bond market:

$$TVIX_t^2 \quad = R_{f,t+1}^{-1}\mathbb{E}_t^Q\left(\log\left\{\frac{F_{t+1}}{F_t}\right\}^2\right), \tag{A-44}$$

where F_t is the price of a future contact at month t which expires in month $t+1$ and the underlying is a 30-year Treasury bond.

Define $G(F_{t+1}) = \log\left\{\frac{F_{t+1}}{F_t}\right\}^2$ as the payoff of the squared contract. Note $G(F_{t+1})$ is a twice-continuously differentiable function. Following the spanning engine in Bakshi and Madan (2000) and Bakshi, Kapadia, and Madan (2003), the payoff $G(F_{t+1})$ can be spanned by a continuum of out of the money (OTM) call options and put options. That is,

$$G(F_{t+1}) \quad = \quad G\left(\bar{F}\right) + \left(F_{t+1} - \bar{F}\right)G_{F_{t+1}}\left(\bar{F}\right) + \int_{\bar{F}}^{\infty} G_{F_{t+1}F_{t+1}}(K)(F_{t+1} - K)^+ \, dK \tag{A-45}$$

$$+ \int_0^{\bar{F}} G_{F_{t+1}F_{t+1}}(K)(K - F_{t+1})^+ \, dK, \tag{A-46}$$

where $\bar{F}$ represents a possible outcome of F_{t+1}, and $G_{F_{t+1}}\left(\bar{F}\right)$ is the first-order derivative for the payoff $G(F_{t+1})$ with respect to F_{t+1} evaluated at $\bar{F}$. Similarly, $G_{F_{t+1}F_{t+1}}(K)$ stands for the second-order derivative for $G(F_{t+1})$ with respect to F_{t+1} evaluated at a strike price K. $(F_{t+1} - K)^+$ and $(K - F_{t+1})^+$ are payoffs for call options and put options, where $(x)^+ = \max(0, x)$.

Thus, the price of the volatility contract payoff can be evaluated at $\bar{F} = F_t$ and be expressed as:

$$
\begin{aligned}
TVIX_t^2 &= R_{f,t+1}^{-1}\mathbb{E}_t^Q\left(\log\left\{\frac{F_{t+1}}{F_t}\right\}^2\right) && \text{(A-47)}\\
&= R_{f,t+1}^{-1}\mathbb{E}_t^Q\left(\int_{F_t}^{\infty} G_{F_{t+1}F_{t+1}}(K)(F_{t+1}-K)^+\,dK\right) && \text{(A-48)}\\
&\quad +R_{f,t+1}^{-1}\mathbb{E}_t^Q\left(\int_{0}^{F_t} G_{F_{t+1}F_{t+1}}(K)(K-F_{t+1})^+\,dK\right) && \text{(A-49)}\\
&= \int_{F_t}^{\infty} 2\frac{1-\log\frac{K}{F_t}}{K^2}\mathbb{E}_t^Q\left\{R_{f,t+1}^{-1}(F_{t+1}-K)^+\right\}dK && \text{(A-50)}\\
&\quad +\int_{0}^{F_t} 2\frac{1-\log\frac{K}{F_t}}{K^2}\mathbb{E}_t^Q\left\{R_{f,t+1}^{-1}(K-F_{t+1})^+\right\}dK && \text{(A-51)}\\
&= 2\int_{F_t}^{\infty}\frac{1}{K^2}\left(1-\log\frac{K}{F_t}\right)C_t(K)dK+2\int_{0}^{F_t}\frac{1}{K^2}\left(1-\log\frac{K}{F_t}\right)P_t(K)dK, && \text{(A-52)}
\end{aligned}
$$

where $C_t(K)$ ($P_t(K)$) represent a call (put) option with the strike price K.

Options obtained from the CME group. over monthly expiration cycles on 30-year U.S. Treasury futures are employed to compute TVIX. The number of options used in computing the TVIX in each expiration cycle is sizable. The median is 40 options and the minimum is 15 options.

G Bootstrap used to compute p-values

To derive robust statistical inferences from time series of a limited size, I perform the following bootstrap approach. Considering a regression $y_t = \beta X_{1,t} + \gamma X_{2,t} + u_t$, where $X_{1,t}$ and $X_{2,t}$ are two sets of dummy variables. For $t = 1,\dots,T$, the interest is the null hypothesis that $\gamma = 0$. The following steps are implemented to compute the bootstrapped P-values:

1. Run OLS regression to compute $\hat{\beta}$ and $\hat{\gamma}$ and derive the residuals $\hat{u}_t$s. Label $\hat{u}_t$s into groups of periods (per-crisis, crisis, regulation periods, etc.).
2. For each trail, randomly draw u_s^b within each sub-period with replacement. For example, the period of Lehman Brothers is defined as 09/2008 - 12/2008. The set contains four months of $\hat{u}_t$s in this period. I randomly draw four observations from this set with replacement to construct the bootstrapped sample.
3. The resulted bootstrapped dataset contains the exact same number of data points as the original dataset in each sub-periods. Reconstruct y_s^b under the null hypothesis such that $y_s^b = \beta X_{1,s}^b + u_s^b$.
4. Run the regression $y_s^b = \beta X_{1,s}^b + \gamma X_{2,t}^b + \epsilon_s^b$ and obtain the OLS t-stats for $\hat{\gamma}$, denoted as t_γ^b.
5. Run steps (2) to (4) $10,000$ times and obtain the bootstrapped distribution of $\left\{t_\gamma^b\right\}_{b=1}^{100,000}$.
6. Compare the original t-stats t_γ with the bootstrapped distribution. Count the number of instances that $|t_\gamma| > |t_\gamma|^b$. The associated P-value is this total counts divided by the total number of bootstrapped, i.e., $100,000$.

The sub-period bootstrap is to ensure that the bootstrap sample has the same (small) size of observations when each dummy is one. For example, there are only four observations during the period of Lehman

Brothers bankruptcy and the bootstrapped sample always have four observations when the Lehman Brothers dummy is one. Due to the small size, the procedure will generate a bootstrapped heavier-tail distribution of t_γ under the null for the dummy Lehman Brothers.

Table A-1: **Correlation between the structural shocks and the VIX**
This table presents the relationship between the structural shocks and the CBOE VIX index for investment-grade bonds and high-yield bonds, respectively. Computed are the correlation coefficients between the VIX and cumulative shocks to hedgers ($\sum_{t-l+1}^{t} \hat{\epsilon}^H_{s-1\to s}$), to liquidity providers ($\sum_{t-l+1}^{t} \hat{\epsilon}^L_{s-1\to s}$), or to dealers $\sum_{t-l+1}^{t} \hat{\epsilon}^D_{s-1\to s}$, over a backward rolling window of $l = 1$, 3, 6, and 12 months. Estimated structural shocks are obtained from the system $\mathbf{y_t} = \mathbf{A_0} + \sum_i \mathbf{A_i y_{t-i}} + \mathbf{B}\boldsymbol{\epsilon}_\mathbf{t}$. Sample period is from 2006 to 2015.

Panel A: Investment-grade

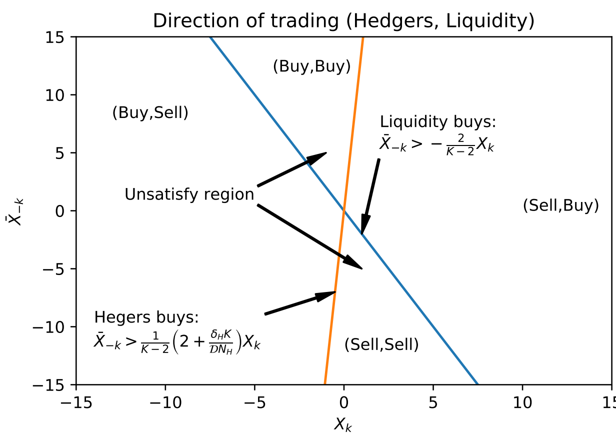
	$l=1$	$l=3$	$l=6$	$l=12$
$\sum_{t-l+1}^{t} \hat{\epsilon}^H_{s-1\to s}$	0.185	0.433	0.472	0.569
$\sum_{t-l+1}^{t} \hat{\epsilon}^L_{s-1\to s}$	0.025	0.074	0.020	-0.274
$\sum_{t-l+1}^{t} \hat{\epsilon}^D_{s-1\to s}$	0.182	0.411	0.469	0.303

Panel B: High-yield

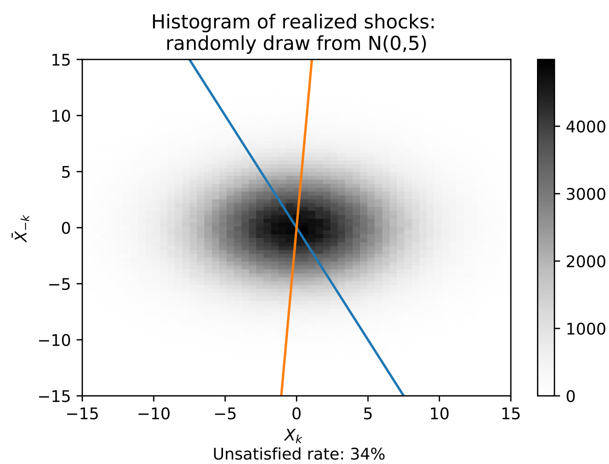
	$l=1$	$l=3$	$l=6$	$l=12$
$\sum_{t-l+1}^{t} \hat{\epsilon}^H_{s-1\to s}$	0.239	0.433	0.528	0.617
$\sum_{t-l+1}^{t} \hat{\epsilon}^L_{s-1\to s}$	-0.006	-0.017	0.190	-0.012
$\sum_{t-l+1}^{t} \hat{\epsilon}^D_{s-1\to s}$	0.235	0.375	0.489	0.231

Figure A-1: **Do hedgers and liquidity providers buy or sell?**
These figures describe the direction of trading for customers. x-axis represents the realization of local shock X_k whereas y-axis represents the average of shocks to other markets $\bar{X}_{-k}$. Hedgers buy if the local shock is small or negative, i.e. above the orange line. Liquidity providers buy if the local shock is large, i.e. above the blue line. Panel A presents the four regions indicating the four type of distinct trading decisions for pairs of local hedgers and liquidity providers. Panel B presents the realization of shocks uniformly drawn from $[-2,-1]\cup[1,2]$, while Panel C presents the realization of shocks from $N(0,5)$. Unsatisfied rate is the fraction of draws where at least one local dealer trades with hedgers and liquidity providers in the same direction.

Panel A:



Panel B:



Panel C:

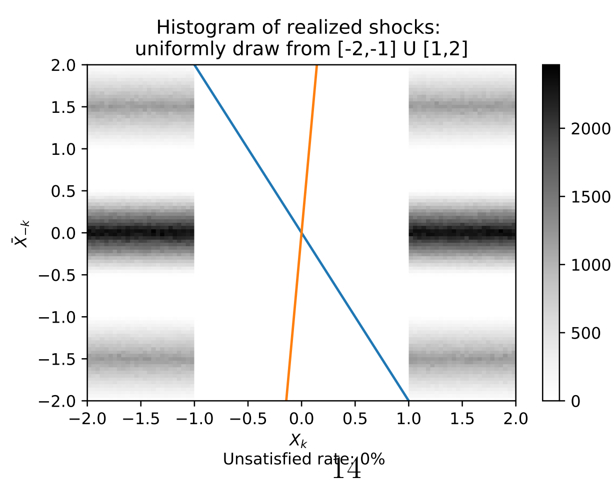
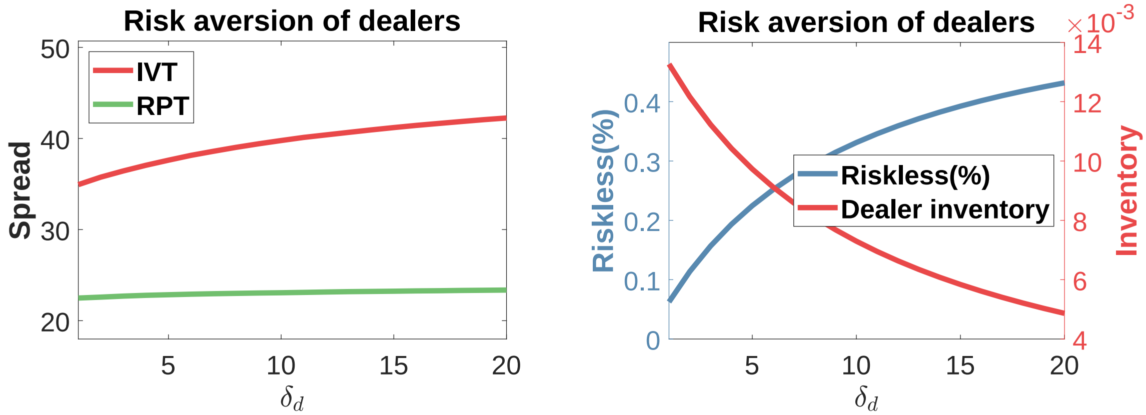
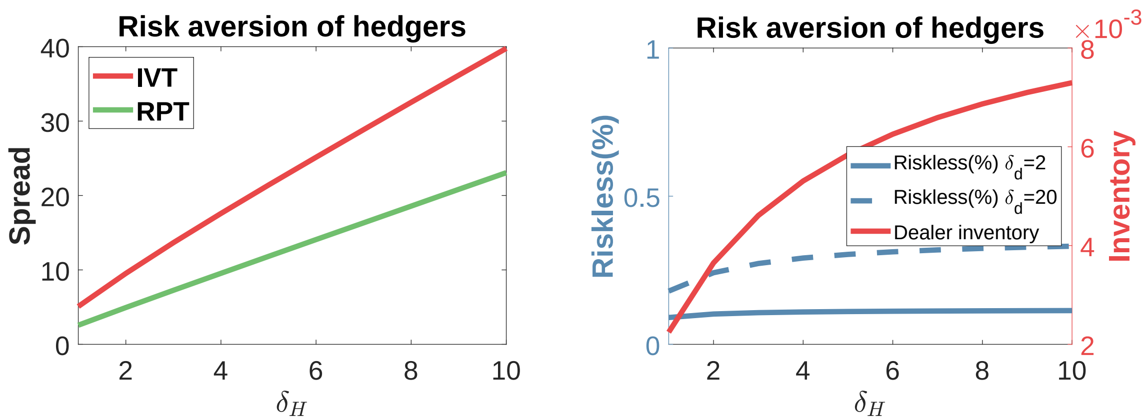


Figure A-2: **Comparative statics: with trivial liquidity shocks to hedgers**
These figures report the comparative statics of equilibrium spreads for inventory transactions, spreads for riskless principal transactions, fraction of riskless principal trading volume, and average dealer inventory level. Results are simulated by liquidity shocks $\{X_k\}_{k=1}^{K}$ that are randomly and independently drawn 100,000 times from identical normal distributions $N(0,5^2)$. In each trail, I compute the corresponding quantities as described in the Internet Appendix B. Reported are the average of each quantity over the 100,000 draws.

Panel A:



Panel B:



Panel C:

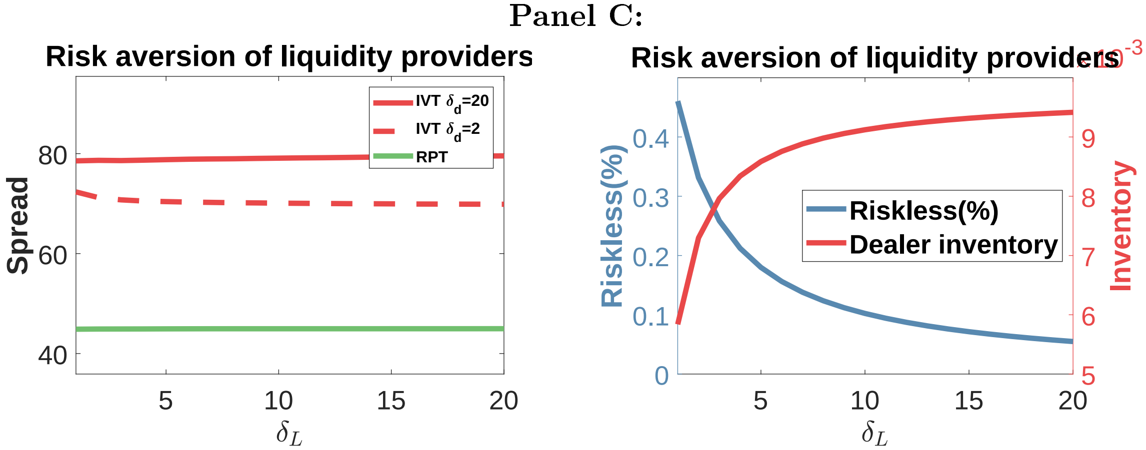


Figure A-3: **Trading characteristics of dealers in corporate bond market.**
These 3D plots depict the characteristics for all dealers trading corporate bonds based on a rolling 12-month data ending on the stated date. Each dot in the plot represents a dealer. Z-axis is the total trading (the sum of buy and sell) volume between this dealer and its clients, and y-axis is the total trading volume between this dealer and other dealers. X-axis approximates the proportion of riskless principal transactions conducted by this dealer, i.e. the volume of paired trades over the total volume. For each dealer i and bond c on a given day t, consider the total volume that dealer i buys $V_{c,t}^{B,i}$ and sells $V_{c,t}^{S,i}$, and the paired volume is the smaller one of $(V_{c,t}^{B,i}, V_{c,t}^{S,i})$. Then, the paired volumes are summed over all trading days and all traded bonds, and finally I normalize this quantity by the average of buy and sell volume, i.e. $\frac{2\sum_{c,t}\min(V_{c,t}^{B,i}, V_{c,t}^{S,i})}{\sum_{c,t}(V_{c,t}^{B,i}+V_{c,t}^{S,i}))}$.

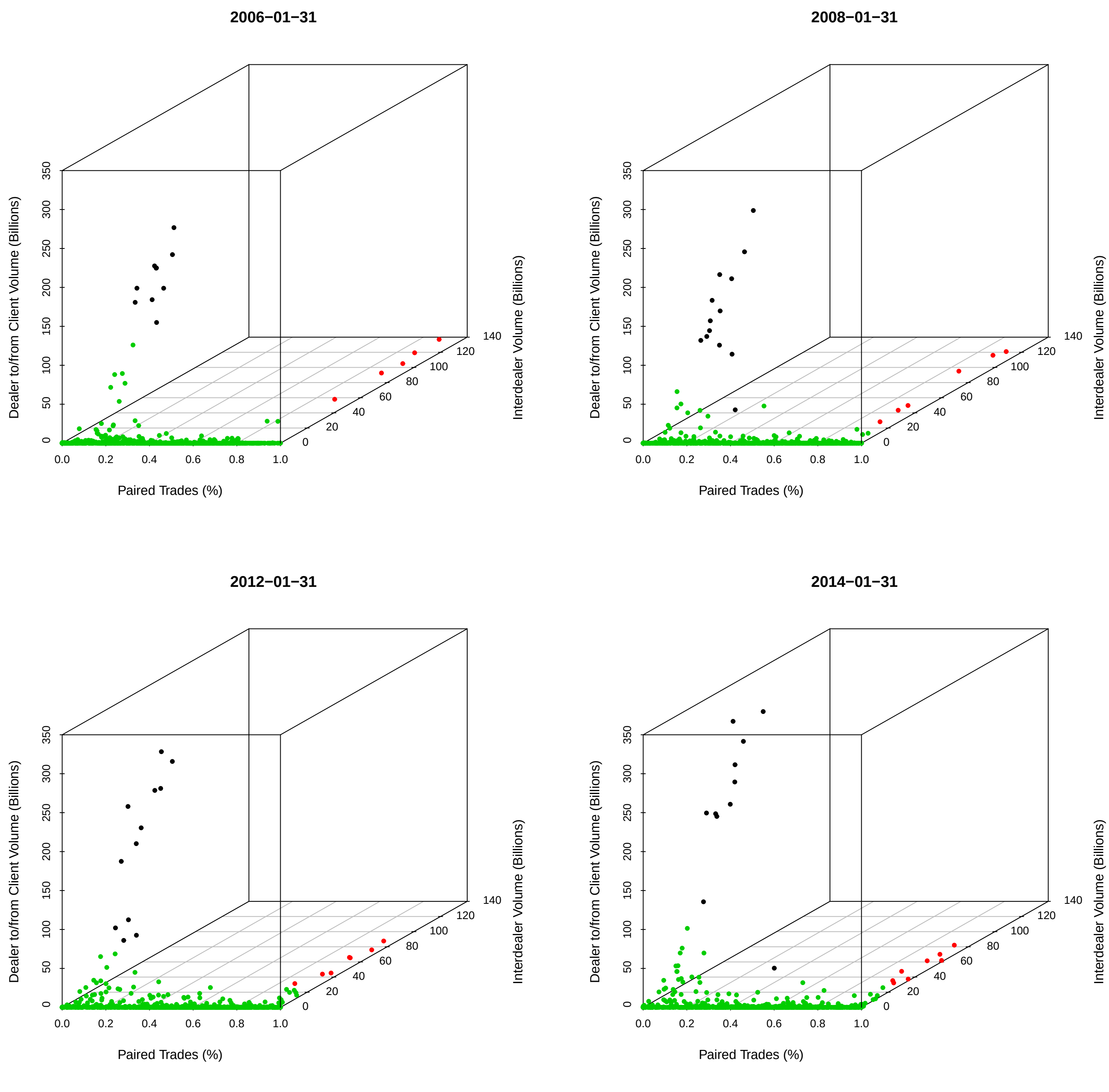


Figure A-4: Impulse response functions based on the agnostic method for high-yield bond markets
These figures present the impulse response functions of the SVAR model in equation (1) for investment-grade bond markets, using the agnostic method. The total number of lags selected is one. For each of the shocks to be recovered, I separately apply two inequality restrictions, up to a horizon of three periods, on candidate impulse response functions. To recover the shocks to hedgers, I impose the restrictions that an increase in ϵ_t^H increases $\mathbf{log}(\mathbf{Spread}_t^{\mathrm{RPT}})$ (i.e., $b_1 \geq 0$) and $\mathbf{log}(\mathbf{Spread}_t^{\mathrm{IVT}})$ (i.e., $b_{2,1} \geq 0$). To obtain the shocks to dealers, I apply the restrictions that an increase in ϵ_t^d increases $\boldsymbol{\%}\mathbf{RPT}_t$ (i.e., $b_3 \geq 0$) and $\mathbf{log}(\mathbf{Spread}_t^{\mathrm{IVT}})$ (i.e., $b_{2,3} \geq 0$). Finally, to derive the shocks to customer liquidity providers, I use the restrictions that an increase in ϵ_t^d decreases $\boldsymbol{\%}\mathbf{RPT}_t$ (i.e., $b_2 \leq 0$) and increases $\mathbf{log}(\mathbf{Spread}_t^{\mathrm{IVT}})$ (i.e., $b_{3,2} \geq 0$). Plotted are the median (in red) and 5-th and 95-th percentiles (in blue) of all feasible impulse response functions that satisfy the inequality constrains.

Panel A: Hedgers | Panel B: Customer liquidity providers | Panel C: Dealers

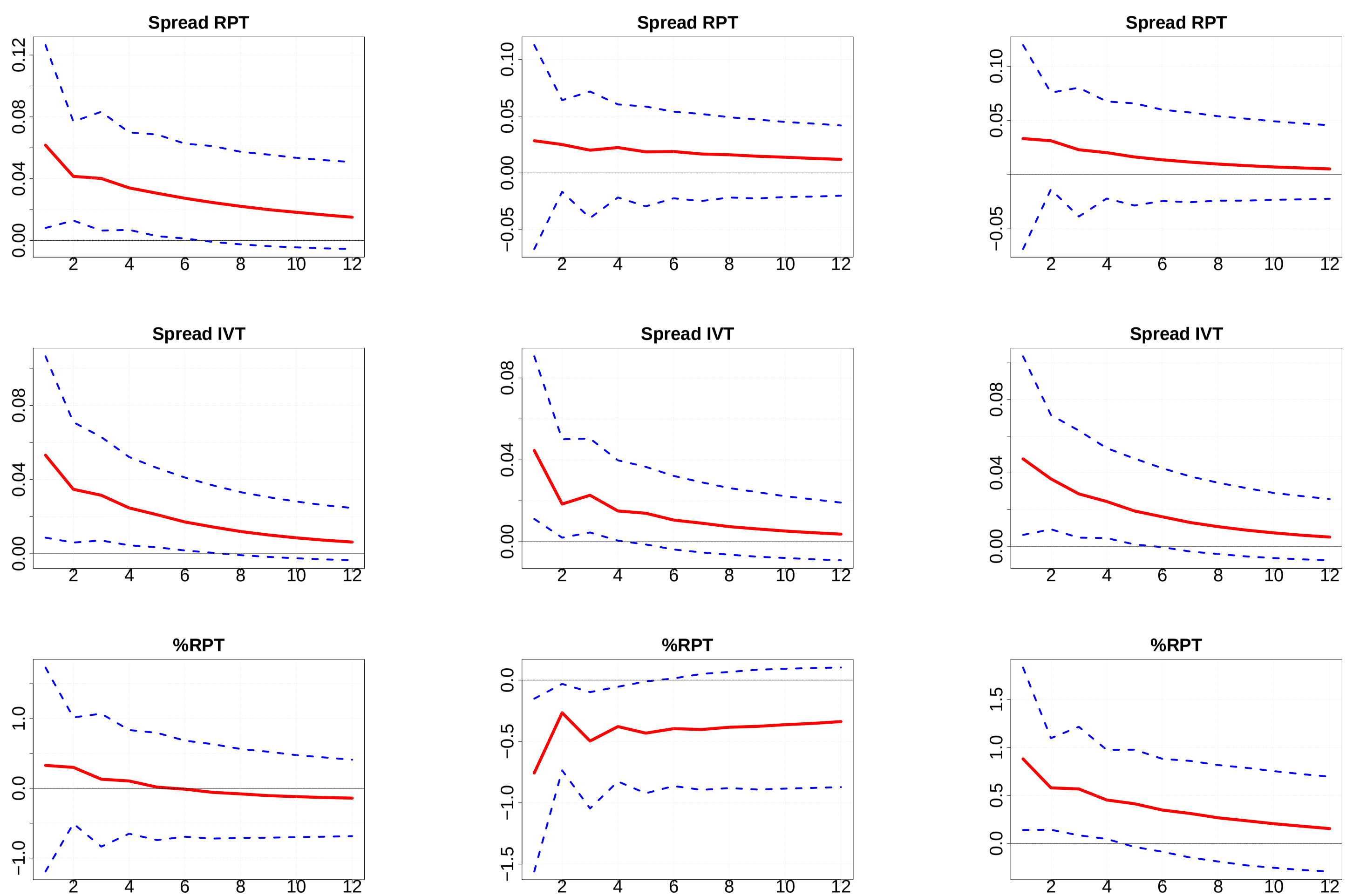


Figure A-5: Histograms of the initial impulse responses

These figures plots the posterior distribution of the initial impulse responses for high-yield bond markets, using the agnostic method. The total number of lags selected is two. For each of the shocks to be recovered, I separately apply two inequality restrictions, up to a horizon of three periods, on candidate impulse response functions. To recover the shocks to hedgers, I impose the restrictions that an increase in ϵ_t^H increases $\log(\mathbf{Spread}_t^{\mathrm{RPT}})$ (i.e., $b_1 \geq 0$) and $\log(\mathbf{Spread}_t^{\mathrm{IVT}})$ (i.e., $b_{2,1} \geq 0$). To obtain the shocks to dealers, I apply the restrictions that an increase in ϵ_t^d increases $\%\mathbf{RPT}_t$ (i.e., $b_3 \geq 0$) and $\log(\mathbf{Spread}_t^{\mathrm{IVT}})$ (i.e., $b_{2,3} \geq 0$). Finally, to derive the shocks to customer liquidity providers, I use the restrictions that an increase in ϵ_t^d decreases $\%\mathbf{RPT}_t$ (i.e., $b_2 \leq 0$) and increases $\log(\mathbf{Spread}_t^{\mathrm{IVT}})$ (i.e., $b_{3,2} \geq 0$). Red lines in the plots indicate the 2.5th, 16th, 50th, 84th, and 97.5th percentiles.

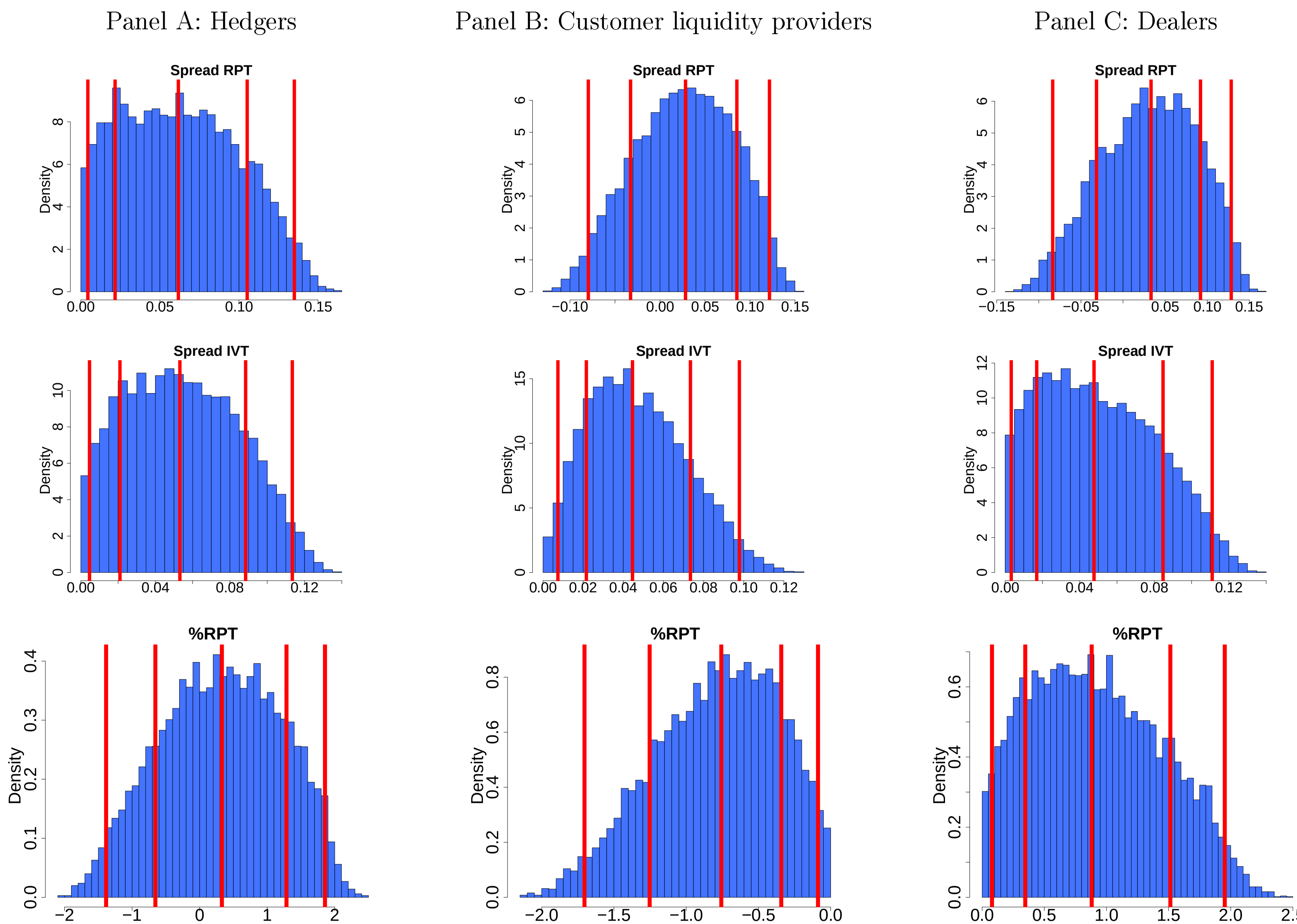


Figure A-6: **Structural shocks from the agnostic method for high-yield markets**
These plots compare the obtained structural shocks based on the full identification method versus the agnostic method. Panel A presents the scatter plots where each spot represents a pair of the shocks based on the two methods in the same month. Also reported are the correlation coefficients of the shocks generated by the two methods. Panel B exhibits the time series of 12-month rolling sum of the structural shocks. Colored and solid lines are based on the sign restrictions, while gray and dashed lines are based on the equality restrictions.