The More Illiquid, The More Expensive: the Reversed Liquidity Premium in Corporate Bonds

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Abstract

We show that illiquid bonds can become more expensive than liquid bonds with almost identical cash flows during market distress times. The economic mechanism behind the results is search frictions. When the search friction is high, marginal traders prefer to sell liquid bonds at lower prices than illiquid bonds because failure to find buyers can be costly. We empirically identify the reversed liquidity premium through within-issuer-date matching of bonds and the regression discontinuity design based on newly issued corporate bonds. In both the identification settings, we find that the yield differentials between illiquid and liquid bonds become negative during the market distress times. Using insurance company trades, we document transaction-level evidence for the reversed liquidity premium for same-issuer bonds on the same day that are traded by the same insurer.

JEL Classification: G10, G12, G20, D83

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1 Introduction

It is widely documented that corporate bonds carry illiquidity discounts. As they are traded in the over-the-counter (OTC) markets with search frictions, the standard search-based theories also predict that holding corporate bonds requires price compensations and these bonds tend to be cheaper than otherwise similar bonds.[1] While most existing empirical studies agree with such theoretical predictions, recent studies also document that liquid bonds can experience heavy net selling pressure during market distress times.[2] Can liquid bond prices be lower than illiquid bond prices? In this paper, we show that illiquid bonds can become more expensive than liquid bonds with almost identical cash flows when the market is more seller-driven.

Our results are puzzling and an apparent violation of the law of one price. We provide a simple stylized model to deliver the intuition, straightforward yet powerful explanation based on search frictions. Liquidity premium can reverse depending on market-wide sell pressure. When buyers are marginal investors, their valuation determines asset prices. They need to be compensated through an illiquidity discount (i.e., higher profit) for sacrificing immediacy in trading. Consequently, illiquid assets should generally be priced lower than liquid assets. When selling pressure is stronger, however, sellers become the marginal investors whose risk premium predominantly determines asset prices. Sellers also weigh the tradeoff between immediacy and trading profits, but the effect of their valuation on asset prices is opposite to that of buyers. Sellers, who experience greater disutility in holding assets due to holding costs, seek higher profits (i.e., higher sale prices) as compensation for sacrificing immediacy when trading illiquid securities. Likewise, they are willing to sacrifice profits to attain immediacy. Therefore, when sellers dominate the market, liquid assets can become even cheaper than illiquid assets because selling liquid assets at lower prices can provide sellers with a greater benefit of immediacy.

The main contribution of this paper is to identify the reversed effects of liquidity on prices and demonstrate the existence of negative liquidity spreads (i.e., a reversed liquidity premium) in distress times. Identifying the effects of liquidity on price is empirically challenging, however, because the liquidity is endogenous. Any unobservable changes in fundamental values can affect both asset price and liquidity. Also, flight to liquidity tends to be coupled with flight to quality since high quality assets tend to be more liquid. We use corporate bond data from the enhanced and academic Trade Reporting and Compliance Engine (TRACE) for the period from 2005 through 2021 and employ several identification strategies that leverage the unique features of the US corporate bond market.

First, we use same-issuer bonds to find bonds that have (almost) identical cash flows but differing liquidity. To this end, we match a bond to another bond that is issued by the same issuer and have same maturities and credit rating but different bond age, following the identification method in

[1] For the theoretical studies of search-based price discounts, see Duffie, Gârleanu, and Pedersen (2005), Duffie, Gârleanu, and Pedersen (2007), Vayanos and Wang (2007), Vayanos and Weill (2008), Weill (2008), Lagos and Rocheteau (2009), Lagos, Rocheteau, and Weill (2011), among many others

[2] See, e.g., Duffie (2020), Kargar et al. (2021), O'Hara and Zhou (2021a), and He et al. (2022); Ma et al. (2022)

Choi, Hoseinzade, Shin, and Tehranian (2020). This approach allows us to control for unobservable time-varying information shared by bonds issued by the same firm, thereby isolating the effects of liquidity. Through careful matching, we are able to demonstrate that liquidity spreads are time-varying and tend to become negative during market-wide events. For example, average yield spreads of these matched pairs between old illiquid and young liquid bonds fall to -0.3% (-0.2%) following the announcement of Lehman Brothers' bankruptcy (the COVID pandemic), suggesting that liquid bonds were in fact cheaper than illiquid bonds during the time of distress. Throughout our other empirical strategies, we keep this idea of exploiting the same-issuer bonds to control for the unobservable time-varying information related to the fundamental values.

Moreover, we provide our unique identification strategy using regression discontinuity design based on new bond issues with salient maturities. We first observe a prominent discontinuity in the relationship between liquidity and time to maturity at the 10-year and 30-year marks. Various liquidity-related variables, such as customer and interdealer trade turnovers, proportion of zero trading days, and bid-ask spreads, show a significant increase in average liquidity of sample bonds at the 10-year and 30-year time to maturity cutoffs. This is driven by that disproportionately large number of bonds being issued with specific salient maturities, such as 10 years and 30 years. This phenomenon of salient issuance maturity can be attributed to several factors. First, there may be heuristics or conventions followed by firms when issuing bonds. For example, they may choose to issue 30-year bonds as a standard practice for long-term financing, rather than selecting alternative maturities such as 29 years or 31 years. Similarly, the choice of 10-year maturity may be driven by its salience for intermediate-term bond issues. In addition, the preference of bond investors and their investment objectives and mandates can also play a role in shaping the issuance of bonds with specific maturities. For instance, intermediate bond funds often mandates to hold bonds with maturities between 5 and 10 years. Consequently, issuing a 10-year bond would attract a larger customer base and potentially lead to better pricing at the time of issuance compared to, for example, issuing an 11-year bond. These newly issued bonds tend to be highly liquid during a short period after the issuance, driving the discontinuity observed in the sample.

We leverage this discontinuity sourced by the salient new-issue maturity to identify the effects of liquidity on prices. Specifically, we employ the regression discontinuity design (RDD) around the time to maturity cutoffs of 10- and 30-years. The "treated" group consists of bonds newly issued with these salient maturities, while the "control" group includes existing older bonds with time to maturity at the issuance longer than the salient choices. We then estimate the local treatment effects on bond yield spreads while controlling for issuer-day fixed effects and bond IPO underpricing to account for any potential informational differences that may not vary smoothly at the cutoffs. Also, by the design, we control for any unobservable term-structure effects.

We find positive local treatment effects on yield during times of distress, consistent with the reversed liquidity premium and negative liquidity spread. In contrast, we find the negative treatment effects in general, indicating the well-known liquidity premium. For example, during the period with below-median VIX (TED and DEF), our results show that the liquid newly issued bonds have discontinuously lower yields at the cutoff by about 11 basis points (6 and 8 basis points). During the distress times, however, we find the opposite. The treatment effects are positive, by about 24 basis points (15 and 30 basis points) during the period with VIX (TED and DEF) above its 80th percentile. We also find positive treatment effects during the 2008 financial crisis and the 2020 COVID crisis, indicating the reversed liquidity premium.

Next, we construct measures of search friction, such as dealer network centrality, length of intermediation chain, and the ratio of interdealer trades by using transaction data including dealer identifier from the academic verison of TRACE. These measures are used in the previous literature on the OTC market search friction, including studies by Li and Schürhoff (2019), Friewald and Nagler (2019), Goldstein and Hotchkiss 2020, and O'Hara and Zhou (2021b), among others. We then examine the relationship between yield and search friction measures, while controlling for issuer-day fixed effects and bond characteristics. Our findings align with the predictions of our model. Specifically, lower search friction is associated with lower yields (thus higher prices) during normal times, but higher yields (thus lower prices) during distressed periods. We also find consistent results within the bond-day context across different dealers with varying levels of search friction, as measured by dealer centrality.

One question might still remain: do we know whether investors actually sell the liquid bond at a lower price, when they also hold the illiquid bond with the same fundamental value traded in the market at a higher price? We find that they do. To show it directly, we use transaction-level data of insurance companies obtained from the National Association of Insurance Commissioners (NAIC). We show that constrained insurance companies (the risk-based capital ratio higher than the median) who hold multiple downgraded bonds of a same issuer choose to sell more liquid bonds at lower prices following downgrades of bond credit rating. We do not find such results from placebo settings such as placebo event days of 3-year prior to the downgrades and a placebo group of unconstrained insurance companies.

Overall, the results support our hypothesis that in seller-dominated markets, investors tend to prioritize immediacy even by selling more liquid bonds at lower prices. It is important to note that even if an illiquid bond is traded at a higher price in the OTC market on the same day, it does not guarantee that an investor could sell the same bond at that price on that day due to the presence of search friction in OTC markets.

Note that we do not argue that our mechanism is the only economic force at work. There are other potential explanations. Boudoukh, Brooks, Richardson, and Xu (2019), for example, argue the liquidity spread narrows (but is still positive) because of price pressure arising from flight from low-quality sovereign bonds. Chaderina, Mürmann, and Scheuch (2022) document that liquid price declines are greater because of coordination failure among insurance companies by examining fire sales of P&C insurance company after the catastrophic hurricanes. Lou and Sadka (2011) show that liquid stock returns are lower during financial crisis because they are more sensitive to market wide returns. Ma, Xiao, and Zeng (2022) focus on the price pressures from the pecking order of mutual funds in selling their more high-quality liquid holdings during the COVID-19 crisis and find that price declines are greater for higher-quality liquid holdings such as Treasury and high-quality bonds. Our view is that these explanations including ours are not necessarily mutually exclusive. Certainly, a more realistic view is that all these forces can even have amplifying effects on the pricing impact of illiquidity. It is worth noting, however, that unique importance of our search friction channel is that it can amplify all the other channels working through the OTC markets.

We also want to emphasize that our study differs from these studies in the following important ways. First, we show how the liquidity spread can become *negative*: not only price declines are greater, but the price levels of liquid assets are lower than those of illiquid assets. We provide a stylized model to show how search frictions can explain this seemingly-counter-intuitive empirical findings. As our model shows, incorporating search friction is crucial in generating this effect. More importantly, our novel empirical strategies including the RDD based on salient new issue maturity identify the effects of liquidity on prices showing that illiquid bond prices can in fact be higher than liquid bond prices and that this effect is driven by the search friction channel in the distress periods. Also, we provide a set of granular customer transaction-level evidence by using insurance company trading with the reversed liquidity premium.

The existence of *negative* liquidity spreads carries significant implications for liquidity management. It suggests that the perceived *value* of liquid assets in OTC markets may be relatively lower when investors require liquidity the most. This implies that relative amounts of liquidity buffers, which is often based on average valuation during normal periods, might have been overestimated. Therefore, it highlights the importance of maintaining cash and cash-like buffers as reliable sources of liquidity during periods of market distress. Also, in trading venues with minimal search frictions like exchanges, we would not expect to observe such an inversion of prices between liquid and illiquid assets. Thus, they can be a complimentary source of liquidity buffers for investors holding OTC assets. In addition, our findings underscore the importance of considering the dynamic valuation of liquid assets. The dominance of sellers in the market has a direct impact on the price of liquidity in the search-based OTC markets. Therefore, when determining the adequate amount of liquid buffers in a portfolio, it is crucial to account for the *dynamic valuations* of liquid assets based on different scenarios of market conditions.

Our paper is related to the literature on search-based asset pricing. In their seminal work, Duffie, Gârleanu, and Pedersen (2005) show that liquidity premium arises due to search frictions using an OTC market setup with a single asset. Duffie, Gârleanu, and Pedersen (2005) further extend this framework with risk averse investors to study asset pricing implications in OTC markets. More closely-related works to our paper include search-based models with multiple assets such as Vayanos and Wang (2007) and Weill (2008), and Vayanos and Weill (2008). Vayanos and Wang (2007) and Weill (2008) show that buyers' market choice can create cross-sectional variations in prices due to endogenous liquidity difference. In these models, however, sellers do not have market choices. One common feature among the existing OTC market models with multiple markets is that sellers are never marginal investors who drive cross-sectional variations. As a result, liquid assets are generally more expensive whenever there are cross-sectional variations.[3] Our paper differs from this line of literature because we allow sellers become marginal investors instead of buyers in a simple model, which is the key mechanism which generate negative liquidity spread between liquid and illiquid assets. We empirically show that this is the case.

Our paper contributes to the literature on the pricing of liquidity (Amihud and Mendelson 1988, Acharya and Pedersen 2005), the liquidity premium of corporate bonds (Chen et al. 2007, Lin et al. 2011, De Jong and Driessen 2012, Acharya et al. 2013), and that of sovereign bonds (Cornell and Shapiro 1989, Amihud and Mendelson 1991, Longstaff et al. 2005, Pasquariello and Vega 2009, Favero et al. 2010, Goyenko et al. 2011, among many others) by documenting the seemingly counter-intuitive situation in relative prices of liquid securities during times of distress.

Our paper also contributes to the literature on price pressures in bond markets (Greenwood and Vayanos 2014, Ellul et al. 2011a, Feldhütter 2012, Manconi et al. 2012, D'Amico and King 2013, Goldstein et al. 2017, Boudoukh et al. 2019, Choi et al. 2020, Helwege and Wang 2019, Chernenko and Doan 2020). Especially, our paper builds on Feldhütter (2012) who examine bonds trading at different prices due to search frictions in OTC markets to identify liquidity crises. Also, our paper provides the mechanism and rationale behind recent findings of Boudoukh, Brooks, Richardson, and Xu (2019) that liquid government bonds become cheaper during times of distress as well as Ma, Xiao, and Zeng (2022) that high-quality liquid holdings of mutual funds such as Treasures and high-quality corporate bonds experience lower returns during the 2020 COVID crisis.

The rest of paper is organized as follows. In Section 2, we present our model. In Section 3, we describe our data and sample construction as well as key variables. In Section 4, we document the empirical strategies to identify the illiquiidty premium and present the results. Section 4.4 examines the insurance company transactions. In Section 5, we conclude.

2 An Illustration with a Simple Model

We first demonstrate the main economic mechanism using a simple stylized model. Consider two identical assets (asset 1 and asset 2) which pay one unit of consumption good in the next period. The discount rate is fixed to zero. Asset 1 is traded in market 1, and asset 2 is traded in market 2. Due to search frictions, an investor is able to trade if the investor is matched with a counterparty. An investor choosing market $i = 1, 2$ is matched successfully with probability f_i. We assume $f_1 > f_2$ so that that market 1 is more liquid than market 2.

Consider a risk-neutral buyer who can choose to trade in either of the two markets. With a successful match in market i, the buyer acquires asset i by paying price p_i. Otherwise, the buyer keeps the reservation utility of zero. The buyer's value of trading in market k is given by

$$V_i = Pr(\text{Success}) \times \text{Trading gains} + Pr(\text{Fail}) \times \text{Reservation value} = f_i(1 - p_i)$$

[3] Most of the existing papers with multiple assets also have generic symmetric equilibria where there is no cross-sectional variation.

If the buyer is indifferent between the two markets, the expected value of choosing each market should be the same:

$$f_1(1-p_1) = f_2(1-p_2)$$

Because the probability of a successful buying trade is higher for asset 1 (i.e., $f_1 > f_2$), the trading gain of the buyer should be smaller for the asset (i.e., $1-p_1 < 1-p_2$.) That is, the price of asset 1 should be higher than that of asset 2. The liquidity spread between asset 1 and 2 is positive because

$$p_1 - p_2 = \frac{f_1 - f_2}{f_1}(1-p_2) > 0$$

Therefore, when buyers are marginal investors, it has to be the case that liquid assets should be more expensive.

Now, we consider the case of a seller who can choose between the two markets. We assume that the seller has a lower valuation of the asset than the buyer; he has to pay a holding cost of δ if he does not sell it immediately. The seller's value of trading in market k is given by

$$V_i = f_i p_i + (1-f_i)(1-\delta) = f_i(p_i - 1 + \delta) + 1 - \delta$$

If the seller is indifferent between the two markets, the expected value of choosing each market should be the same:

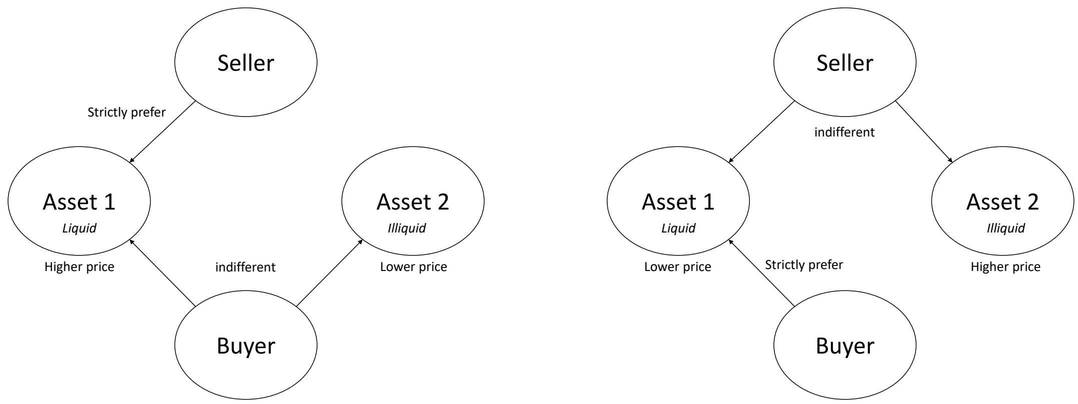
$$f_1(p_1 - 1 + \delta) = f_2(p_2 - 1 + \delta)$$

Because the probability of a successful selling trade is higher for asset 1 (i.e., $f_1 > f_2$), the trading gain of the seller should be smaller for the asset (i.e., $p_1 - 1 + \delta < p_2 - 1 + \delta$.) That is, the price of asset 1 should be lower than that of asset 2. The liquidity spread between asset 1 and 2 is negative because

$$p_1 - p_2 = \frac{f_2 - f_1}{f_1}(p_1 - 1 + \delta) < 0$$

Therefore, when sellers are marginal investors, it has to be the case that liquid assets should be cheaper.

Fixing liquidity as an exogenous input, this simple model illustrates the relation between liquidity and asset prices in two different cases by setting marginal investors differently. When there are sufficiently large number of buyers relative to that of sellers, buyers become marginal investors, in which case asset prices are set by the trade-off between liquidity and trading gains in terms of buyers' valuations. In this case, sellers strictly prefer trading in liquid market. On the other hand, when there are sufficiently large number of sellers relative to that of buyers, an opposite situation



(a) buyers are marginal investors

(b) sellers are marginal investors

Figure 1. Liquidity Premia under Different Marginal Investors

arises. This is illustrated in Figure 1.

3 Data

In this section, we describe the data and our sample, motivate and explain key variables related to search friction and market distress, and present descriptive statistics.

3.1 Corporate Bond Data and Sample Construction

Our data source for corporate bond pricing is the enhanced and academic Trade Reporting and Compliance Engine (TRACE) databases from the Financial Industry Regulatory Authority (FINRA). The academic version of TRACE has an advantage of having a masked identifier for dealers. The academic version becomes available with 36-month delays and our academic TRACE data ends at the end of 2017. We extend the sample period to December 2021 by using the enhanced TRACE. Thus, our sample period runs from February 7, 2005 through December 31, 2021.[4] We exclude retail-sized trades (i.e., trades with volumes below $100,000) following Bessembinder, Kahle, Maxwell, and Xu (2008) and also exclude observations with negative yields. We also obtain bond-specific information including ages, credit ratings, maturity, amounts outstanding, and other characteristics from the Mergent Fixed Income Securities Database (FISD). Our sample contains fixed-coupon bonds after excluding convertible and foreign currency bonds. Finally, our main sample contains 10,442,580 bond-day observation.

[4] The TRACE becomes comprehensive after February 7, 2005 as it begins the full dissemination of bond transactions for the entire universe of corporate bonds. To filter the reporting errors in TRACE, we follow the standard filtering procedures described in Dick-Nielsen (2009) and Dick-Nielsen (2014) for the enhanced TRACE and Choi et al. (2022) for the academic TRACE. We also employ price-sequence-based filters (reversal and median filters) as suggested in Dick-Nielsen (2014) and Edwards, Harris, and Piwowar (2007).

In addition, we supplement the main sample by constructing a subsample at a more granular level by using the insurance company data obtained from the National Association of Insurance Commissioners (NAIC). The use of NAIC insurance company data offers distinct advantages, as it allows us to access customer-level information. Specifically, this enables us to precisely identify specific bonds held by an insurance company (IC) on a given day and further discern the bonds they opt to sell, along with the corresponding dates and prices. The availability of such granular data is not readily accessible for other bond investors, rendering ICs as a unique and suitable subject for examining our underlying premises. We use the subsample in Section 4.4 and more details on the subsample construction are described in Appendix A.

3.2 Key Variables

This section explains two key variables related to the economic forces in our story that generate the reversed liquidity premium: search friction and seller-driven markets.

3.2.1 Proxies of Search Friction

To construct measures of search friction, we use the academic TRACE, which includes the identifier of dealer at the transaction level. Specifically, we employ three different proxies to capture the search friction.

Dealer network centrality. Previous studies have highlighted the significance of dealer networks in facilitating search processes in OTC markets (e.g., Di Maggio et al. 2017, Li and Schürhoff 2019, Friewald and Nagler 2019, and Goldstein and Hotchkiss 2020). Dealers with higher centrality are better connected and can more easily find counterparties, indicating lower search friction. Therefore, bonds more often traded by more central dealers are easier to locate and have lower search friction.

Thus, we calculate the eigenvector centrality of the dealer network to measure the connectivity of dealers. Specifically, each month, the dealer network is defined by dealers and connections between two dealers. The two dealers are connected if there are interdealer trades between them during that month and we assign weights to the connection based on numbers of trades. Using this dealer network, we calculate the eigenvector centrality for each dealer to define the dealer network centrality measure, *DlrCentrality*. We also define the bond-level centrality measure, *Centrality*, as an average of *DlrCentrality* weighted by the number of trades made by the dealer for that particular bond during the month.

Length of intermediation chain. More intermediation trades between two customer trades (i.e., a longer intermediation chain) indicates a greater reliance on intermediation to find a suitable counterparty, implying higher difficulty and a lengthier search process (e.g., Friewald and Nagler 2019). Also, Shen et al. (2021) show that a higher search intensity (lower search friction) is associated with shorter chains, because a customer is more likely to find alternative counterparties quickly instead of waiting for a dealer to arrange the intermediation.[5] Thus, the longer chain length is related to the higher search friction.

Thus, we use intermediation chain length as another measure of search friction by following Friewald and Nagler (2019). The intermeidation chains are defined as a chain of trades starting from a customer sale that moves the initial volumes to customers through dealers. The length of these chains are dfeind as the number of dealers involved in the transaction.

Ratio of interdealer trades. We also use the ratio of interdealer trades to all trades to measure the level of search friction, following O'Hara and Zhou (2021b). Holding customer trades constant, a higher interdealer trade ratio indicates a greater reliance on more interdealer trades to find counterparties, suggesting difficulty in finding counterparties and thus a higher degree of search friction.

3.2.2 Proxies of Market Distress

To capture the presence of greater seller mass in the market, we employ several widely used proxies such as the VIX (CBOE Volatility Index), TED spread (difference between 3-Month LIBOR and 3-Month Treasury Bill rates), and default spread (difference between Moody's seasoned Baa and Aaa corporate bond yields). We define the distress periods as periods in which it exceeds its 80th percentile within the sample.

These measures serve as general indicators of market conditions and are associated with increased selling pressure in the corporate bond market. Prior studies also document consistent evidence. For example, Goldstein et al. (2017) show that during high VIX and TED periods, underperforming bond mutual funds experience more severe outflows holding else constant, indicating increased selling activity in corporate bonds. Also, in times of greater uncertainty reflected by high VIX, investors are more likely to sell corporate bonds rather than spending cash-like assets to buffer liquidity needs (e.g., Jiang et al. 2021).

Additionally, we use specific episodes of market crises—the 2008 financial crisis and the COVID pandemic—to capture periods of heightened seller dominance.

3.3 Summary Statistics

Table 1 shows the summary statistics of full sample. Panel A shows the descriptive statistics for our main sample of bond-day observations with available daily yields. Our sample bonds on average have the yield spread of 2.34% and time to maturity of 9.07 years. $Centrality$ and $ChainLength$ have smaller number of observations since they require the academic TRACE data to be calculated. The average $Centrality$ is 0.58 where 0 and 1 is the sample minimum and maximum score for the dealer centrality. *daily bidask* also has lower number of observations since it requires both

[5] Difference aspects of search friction can affect the chain length differently. For example, Shen et al. (2021) also show that a lower search costs (i.e., costs associated with maintaining trading infrastructure) is related to longer chains. However, we focus on the search friction as the search intensity because the likelihood finding the counterparty is the main economic channel in our intuition.

customer sell and buy transactions on a day to be well-defined. In Panel B, we also present descriptive statistics for transaction-level observations from the academic TRACE to calculate the $DlrCentrality$. In Panel C, we show statistics for the bond-quarter panel which includes bond-quarter observations without any transactions as well. For example, the zero trading day (ztd) has a median of 1 which indicates that more than half of bond-quarter of our sample bonds during the sample period does not have any transaction. Definitions of all variables are detailed in Appendix B.

4 Reversed Liquidity Premium

Our key hypothesis is that illiquid securities can be traded at higher prices than liquid securities of the same cash flows during the seller-dominated markets due to the search friction. To identify the effects of liquidity on security prices, it is essential to account for any unobservable time-varying information that may be associated with the fundamental cash flows of bonds. For example, the liquidity can be positively correlated with credit quality and fundamental value, both of which positively affect the bond prices.

To address this challenge, we employ several distinct empirical strategies to isolate the effects of liquidity and validate the existence of reversed liquidity premium. For each strategy, we explain our motivation and empirical setup to identify the reversed liquidity premium and then present the results.

4.1 Matching Same-issuer Bonds with Different Level of Liquidity

Our first strategy is to examine the yields of corporate bonds that are issued by a same firm but with different level of liquidity, following the identification strategy of Choi, Hoseinzade, Shin, and Tehranian (2020). We first explain the methodology and present results.

4.1.1 Matching: Empirical Setup

We exploit the relationship between bond age and liquidity to capture the variation in liquidity across different bonds issued by the same firm.

Newly issued young bonds tend to have higher level of liquidity. Over time, as bonds mature, they generally become less liquid as a significant portion of the issued bonds are acquired by buy-and-hold investors, such as insurance companies, who are prominent participants in the bond market.[6] Additionally, starting immediately after issuance, bonds tend to experience active trading due to demand from investors who were unable to participate in the competitive primary markets.[7] Such demand for newly issued bonds becomes satiated as an increasing number of investors acquire

[6]Many papers document the bond age as a strong proxy for the liquidity. See, e.g., Sarig and Warga (1989), Alexander, Edwards, and Ferri (2000), Schultz (2001), Houweling, Mentink, and Vorst (2005), and Ericsson and Renault (2006), among many others.

[7]E.g., Nikolova et al. (2020)

the bonds, leading to decreasing liquidity over time. Figure 2 visually illustrate this relationship by using liquidity proxies, including customer-dealer and inter-dealer volumes, days of zero trading (ZTD), and bid-ask spreads, for bonds with different maturities throughout the lifespan of the bonds.

Given this relationship, we implement a matching strategy based on the age of the bonds to create pairs of bonds that exhibit contrasting levels of liquidity within the same issuer. Specifically, we define liquid bonds as those with an age of less than one year. We exclude bonds with an age of less than 30 days (since issuance) to account for the bond IPO underpricing.[8] We then match each liquid bond with an older bond (the illiquid bond) issued by the same firm. In our matching, we require that the difference in time-to-maturity is less than one year and that there is a minimum age difference of three years between the matched bonds. Additionally, the matched bonds should be of the same credit rating and seniority. We also exclude bonds with remaining time-to-maturity less than three years.[9] In situations where multiple potential matches are available, we prioritize the match based on several criteria in the following order: minimizing the difference in time-to-maturity, minimizing the difference in amount outstanding, and maximizing the difference in age. By following this approach, we aim to ensure that the matched bonds have nearly identical fundamental values yet notable difference in the liquidity.

We check the quality of matching in Table 2. The matched sample contains 241,426 bond-day with available transaction yields from both matched bonds of 1,994 unique matched pairs from 505 issuers between 2005 and 2021. By construction, they have very similar time-to-maturities but very different age. On average, young bonds in our sample have the average age of 0.19 years, while old bonds have the average age of 6.58 years when they first appeared on the matched sample. Meanwhile, average time-to-maturities for the young and matched old bonds are 6.71 and 6.70, respectively. Approximately 90% of the bonds in our sample are investment-grade (IG) bonds, showing that the sample is heavily skewed towards investment grade bonds. This is because the matching within IG firms are more successful than HY firms due to larger number of issues. Panel B of Table 2 shows summary statistics for daily Liquidity Spreads as well as differences in age and time to maturity. While the Liquidity Spread is on average positive, we can observe that negative spread is also presence. In Panel C, we examine mean differences between old and young bonds. Overall, they are well-matched. Young bonds have statistically significant (at the 10% level) longer maturities and smaller amount outstanding than old bonds on average, but the magnitude of mean difference is tiny. All liquidity-related variables indicate the young bonds are traded more actively with higher level of liquidity than matched old bonds.

Finally, we construct a measure for the liquidity premia, *Liquidity Spread*, as differences in

[8] E.g., Cai et al. (2007)

[9] The age effects on short-term bonds are typically marginal due to their shorter lifespan. As the remaining time-to-maturity of these bonds approaches zero, they tend to become more similar to cash-like instruments. Also, buy-and-hold investors, such as insurance companies, generally do not acquire young short-term bonds, as depicted in Figure A1. In addition, when comparing short-term bond prices, even smaller differences in time to maturity might be relatively more significant. Thus, we exclude the short-term bonds as our matching strategy is less reliable for them.

yield spreads between liquid bond and illiquid bond of a matched pair for each day. By construction, the negative *Liquidity Spread* means that price of liquid bond is lower (i.e. yield is higher) than its matched counterpart of illiquid bond. In this section, we visually inspect the reversed liquidity premium by using time series of *Liquidity Spread* during market distress periods.

4.1.2 Matching: Results

In Figure 3, we present the time series of the 20-day moving average of the liquidity spread from 2005 to 2021. It is visually evident that the *Liquidity Spread* turns negative during the 2008 financial crisis and the COVID pandemic. Specifically, following the collapse of Lehman Brothers in 2008 and the COVID pandemic in 2020, the average *Liquidity Spread* experiences a sharp decline, reaching levels over -0.3% (-0.2% during the COVID pandemic). Subsequently, the *Liquidity Spread* gradually reverts towards near-zero and eventually returns to positive levels. We also observe decreases in the liquidity spread coinciding with other market distress events and high-VIX periods, such as the European debt crisis between 2010 and 2012. The *Liquidity Spread* starts narrowed in 2013 and stayed near-zero level until the COVID shock.

Indeed, examining the time-series of the *Liquidity Spread* provides an intuitive understanding of the reversed liquidity premium during market distress. The periods of negative liquidity spreads, particularly during the 2008 financial crisis and the COVID pandemic, indicate a reversed relationship between price and liquidity. However, it is crucial to acknowledge that the matched sample we employ covers only a tiny fraction of the overall bond population by construction. This limited sample size is a result of the stringent matching criteria we have established, prioritizing accurate matching over sample size. Although relaxing the matching criteria could potentially yield a larger sample, it would come at the expense of compromised matching accuracy. We prioritize the smaller yet cleaner sample to pinpoint the reversed liquidity premium in this matching approach. We rely on other empirical strategies to examine the more general sample of bonds.

4.2 Regression Discontinuity Design

In this section, we show the existence of reversed liquidity premium using an identification strategy that employs a regression discontinuity design (RDD) based on the saliency in maturity profiles at issuance, similar to those in Bai et al. (2023) and Bretscher et al. (2023).

4.2.1 RDD: Empirical Setup

We begin by observing a noticeable discontinuity in the relationship between liquidity and time-to-maturity within the corporate bond universe. This discontinuity is also documented in Bai et al. (2023) and Bretscher et al. (2023). Figure 4 provides a non-parametric visualization of this relationship, through liquidity-related variables such as customer and interdealer trading turnover (trading volume divided by amount outstanding), the fraction of days without any trade (referred to as the zero trading day, *ztd*), and bid-ask spreads. Clear jumps are evident around the 10- and

30-year marks of time-to-maturity. The results illustrated in Figure 4 suggest that, in general, corporate bonds exhibit significantly higher levels of trading activity and liquidity around these specific maturity cutoffs of 10 and 30 years.

The observed discontinuity can be attributed to the salient maturity profiles of new bond issues.[10] The disproportionately large number of bonds issued with specific salient time-to-maturities contributes to this observed discontinuity. Specifically, 10-year bonds are the most commonly issued, followed by 30-year and 5-year bonds, as depicted in Figure 5. The substantial supply of new issues to the bond universe, coupled with distinctly high levels of liquidity of newly issued younger bonds discussed in Section 4.1.1, creates the discontinuity observed in the sample.[11]

It is worth noting that we do not observe a prominent spike around the 5-year cutoff. This can be attributed to a relative difference of 5-year bond issues compared to existing bonds. There is larger amount outstanding of older bonds around 5-year time to maturity as bonds with longer when-issued maturities are accumulated. Also, the significant issuance of 10-year bonds, combined with that a chunk of the issuance being distributed between 5 and 10 years when issued, contributes to reducing the relative age gap between newly issued 5-year bonds and existing older bonds with similar time-to-maturity.

Regression Discontinuity Design. To establish a discontinuity design, we focus on two cutoffs: 10 years and 30 years, which correspond to the salient time to maturity points of new issues. We define the "treated" group comprising bonds that are issued with a time to maturity of 10 years (for the 10-year cutoff) or 30 years (for the 30-year cutoff). We allow a margin of 2 months from these when-issued maturities to account for small variations in the maturities.[12] We also require time to maturity to be less than the cutoff to ensure the sharp design of discontinuity. As a next step, we define the "control" group as bonds issued with a time-to-maturity strictly greater than the cutoff after accounting for the margin (i.e., cutoff plus 2 months), and with a minimum age of 0.5 years. This ensures that any bonds in the control group are older than any bonds in the treated group at any given date at any point of the running variable (time to maturity). Thus, this establishes a clear distinction between the treated and control groups, that the treated groups have higher level of liquidity around the new issuance. We call this combined sample of "treated" and "control" bonds as the RDD sample. By the design, bonds in our RDD sample exhibit a discontinuous increase in the level of liquidity at the cutoff as the running variable (time to maturity) decreases.

Using the RDD sample, we examine the local treatment effects at the time-to-maturity cutoffs on bond yield spreads. We use two different ways of running our regression discontinuity design.

[10] This phenomenon is not present within the lifetime of an individual bond. For instance, Figure 2 illustrates that there is no discontinuity around the 10-year time-to-maturity mark for bonds issued with 20- and 30-year maturities.

[11] The discontinuity we observed in Figure 4 can be also resembled in institutional ownership such as mutual fund shares (e.g., Figure A2). Figure A1 shows that this is likely due to that they tend to acquire newly issued bonds with desirable maturity that matches their investment strategy and mandates, because the newly issued bonds are more liquid and easier to search. Consistently, we do not find any jump in institutional ownership holding the when-issued maturity constant in Figure A1.

[12] In other words, the when-issued maturities are within the range of (cutoff − 2 months, cutoff + 2 months).

First, we visually inspect the discontinuity in a non-parametric way by using binned scatter plots of Cattaneo et al. (2019) within a fixed bandwidth of 6 months around the cutoffs. Second, we estimate the local treatment effects from the sharp RDD. We let bandwidths to be selected in an optimal data-driven way by following Calonico et al. (2014a) and Calonico et al. (2015). To implement the sharp RDD, we exclude bonds from the control group if their time to maturity is shorter than the specified cutoffs.

To address any potential systematic differences in fundamental values between the treated and control groups at the cutoffs, such as fundamentally different firms issuing long-term bonds in control groups, we control for the issuer-day fixed effects using the full sample. Also, we control for the IPO underpricing by including a dummy variable that indicates the period of 30 days following the initial offering date.[13] This control variable helps to capture any effects related to the initial pricing of bonds in the IPO market.

During normal times, we expect to observe discontinuously lower yields (higher prices) for newly issued liquid bonds (treated group) compared to older bonds with lower liquidity (control group). However, during distress times and seller-dominated markets, our story predicts the opposite: discontinuously higher yields (lower prices) for newly issued liquid bonds.

4.2.2 RDD: Results

Figure 6 displays the relationship between yield spreads and time to maturity as the running variable, with cutoffs of 10 years (Panels A1, B1, and C1) and 30 years (Panels A2, B2, and C2) and a fixed bandwidth of 0.5 years. We examine the different impacts of the local treatment (liquid new issuance at the cutoffs) on yield spreads during normal (below median VIX, TED, or DEF) and stress (VIX, TED, or DEF above its 80th percentile) periods by plotting them separately. The solid line represents the relationship between the yield spread and the running variable for the newly issued "treated" bonds, while the dashed line represents the relationship for the older "control" bonds. The local treatment effects are quantified as the difference between the solid and dashed lines at the respective cutoffs indicated by vertical lines.

The results in Figure 6 confirms our main hypothesis. For example, in Panels A1, the local treatment effects at the 10-year cutoff are approximately -6 basis points during the normal period. However, during the high VIX period, the local treatment effects become positive, around +15 basis points. These effects are statistically significant as the bands around fitted lines represents the 95% confidence interval. This finding aligns with our prediction that the treated group, bonds with higher liquidity, tends to be discontinuously cheaper (more expensive) on average during distressed (normal) periods than bonds in the control group around the time-to-maturity cutoffs. We find qualitatively similar results for the 30-year cutoff (Panel A2). Results are also similar when we use TED and DEF instead of VIX in Panels B and C.

[13] For example, Cai et al. (2007) document a positive initial return on the first trading day within a week following the bond IPO. The returns are not significant after the second trading days.

In Table 3, we present the results of the RDD analysis with data-driven optimal bandwidth selection, as described in Section 4.2.1. The results consistently support our narrative across all specifications. In Column 1 of Panel A, we observe a negative and statistically significant local treatment effect (-1.8 basis points) around the cutoff of 10-year, confirming the existence of an average liquidity premium. This negative local treatment effects become more pronounced during periods of below-median VIX, with an estimated effect of around -11 basis points (see Column 2 of Panel A), indicating a stronger liquidity premium. During periods when the VIX is between its median and 80th percentile, the treatment effects remain negative but with a smaller magnitude (-5 basis points). However, when the VIX is high (above its 80th percentile), the sign of the local treatment effect flips. The estimated effect becomes positive (24.5 basis points) and statistically significant at the 1% level, supporting the presence of an reversed liquidity premium. The results are qualitatively similar when using a cutoff of 30 years (Colums 5 through 8). In Panels B and C, we replicate the analysis using TED and DEF instead of VIX as measures of market conditions. We find similar results, providing additional support for our hypothesis outlined in Section 4.2.1.

In Panel D of Table 3, we examine the sub-samples of the 2008 financial crisis and the 2020 COVID crisis separately. The 2008 financial crisis sub-period covers the period from July 2007 to March 2009. The COVID period in 2020 is divided into three sub-periods: *COVID1* (January 30 to March 14), *COVID2* (March 15 to March 22), and *COVID3* (March 23 to April 8).[14] Previous studies have shown that selling pressures from bond investors peaked between March 15 and March 22, and started to stabilize after March 23 (e.g., Ma et al. 2022). The results of Panel B show that, consistent with our hypothesis, the local treatment effects are reversed (i.e., becoming positive and consistent with the reversed liquidity premium) during market-wide crisis events. For example, Columns 1 and 5 show that the average treatment effects around the 10-year (30-year) time-to-maturity cutoff during the 2008 financial crisis period are approximately 31 basis points (10 basis points). Similarly, we find the positive and significant treatment effects around the 10-year time-to-maturity cutoff during the *COVID2* sub-period.

Overall, The results in Section 4.2 indicate a clear discontinuity in the relationship between bond yield and time to maturity around the salient cutoffs of 10 and 30 years. Importantly, we find the reversed treatment effects between normal and seller-dominated markets, confirming our hypothesis. Under the identifying assumption that any unobserved confounders, except the higher level of liquidity in the treated group of new issues, are smoothly varying around the time to maturity cutoffs, we identify the liquidity premium during the normal periods and the reversed liquidity premium during the seller-dominated periods.

[14]These periods align with major events during the early 2020, such as the declaration of a Public Health Emergency by WHO on January 30, the Fed rate cut to zero and announcement of QE on March 15, and the Fed's announcement of extensive new measures to support the economy including the Primary Market Corporate Credit Facility (PMCCF) and the Secondary Market Corporate Credit Facility (SMCCF) on March 23.

4.3 Search Frictions and Reversed Liquidity Premium

In the previous sections, we focus on identifying the reversed effects of liquidity on bond prices. In this section, we focus on the search friction channel. To do so, we take advantage of our granular data with dealer IDs by employing proxies of search friction discussed in Section 3.2.1.

We first discuss results within the same-issuer bonds. Then we present results comparing trades of a same bond by different dealers.

4.3.1 Comparing Same-issuer Bonds with Different Levels of Search Frictions

We examine the effects of search friction on yields of same-issuer bonds by running the following regression:

$$YS_{i,t} = \alpha + \beta_1 SF_{i,t} \cdot HighX_t + \beta_2 SF_{i,t} + ctrls_{i,t} + \mu_{v,t} + \varepsilon_{i,t} \tag{1}$$

where the dependent variable, YS, represents the daily yield spread of the bond. We include a dummy variable, $HighX_t$, which equals one when the VIX (or TED or DEF) is above its 80th percentile, and zero otherwise. The independent variable of interest, SF, captures different aspects of search friction. Specifically, we employ three measures: $Centrality$, $ChainLength$, and $InterDealerRatio$. The variable definitions are detailed in Section 3.2.1 and the Appendix B. We control for bond characteristics, denoted as $ctrls_{i,t}$, including the logged time-to-maturity, logged amount outstanding, and logged age of the bond. We also include issuer-times-day fixed effects to account for unobservable time-varying factors specific to each issuer.

Table 4 shows the estimated results of the regression specification (1). The results are consistent with our notion that bonds with higher search friction are priced lower during the seller-dominated markets and higher during normal periods. In Column (1) of Panel A, for example, the coefficient on $Centrality$ alone is negative (-0.260) and significant at the 1% level. This indicates that bonds with higher centrality (indicating lower search friction) are priced higher compared to bonds with lower centrality. Also, the coefficient on the interaction term $Centrality \cdot HighX$ is positive (0.505) and statistically significant at the 1% level. The sum of two coefficients ($\beta_1 + \beta_2$) are also positive and significant at the conventional level. This suggests that bonds with higher centrality are priced lower during the high-VIX period, indicating the reversed liquidity premium. The estimated coefficients imply that liquidity premium for bonds with average centrality is 15 basis points in normal periods and -14 basis points during the high-VIX period. Qualitatively similar results are obtained when using other measures of search friction, different proxies of seller-dominated markets, and during market-wide crisis episodes (in Panel B).

In Figure 7, we examine the effects of search friction measures on yields across quintiles of VIX, TED, and DEF. Specifically, we use the following specification:

$$YS_{i,t} = \alpha + \sum_{n=1}^{5} \beta_n SF_{i,t} \cdot \mathbb{1}(X\ quintile = n)_t + ctrls_{i,t} + \mu_{v,t} + \varepsilon_{i,t} \tag{2}$$

where we use a dummy variable for n-th quintile of VIX, TED, or DEF, $\mathbb{1}(X\ quintile = n)$ and the search friction measures, $SF_{i,t}$, including $Centrality$, $ChainLength$, and $InterDealerRatio$.

The findings in Figure 7 are consistent with the results presented in Table 4. We observe a reversed relationship between search friction measures and yields, which indicates the reversed liquidity premium, during periods of market distress characterized by high VIX, TED, and DEF. In addition, while they all shows the evidence of reversed liquidity premium, different search friction measures exhibit slightly different patterns across levels of VIX, TED, and DEF, reflecting the various channels through which search friction operates. For instance, the coefficient on $Centrality$ is only positive in the fifth quintile, but generally increases as the seller-market proxy (ex. VIX) rises. This is consistent with decreases in the liquidity premium as seller dominance is heightened. On the other hand, the coefficients on $ChainLength$ are mostly statistically insignificant, except during high levels of VIX, TED, and DEF, which are indicative of seller-dominated markets. These non-significant results during normal periods may be due to confounding effects in the $ChainLength$ measure. Shen et al. (2021) document that longer chain lengths are associated with higher search friction through the search intensity channel but it can also be related to lower search costs associated with dealers maintaining trading infrastructure (which can lead to a lower search friction). When sellers dominate the market, the search intensity channels may become prominent, driving the observed results. The coefficients on $InterDealerRatio$ generally exhibit a decreasing pattern with higher levels of seller-market proxies, which aligns with our hypothesis. It is also worth noting that not only the highest quintile but also the second highest quintile show signs consistent with the existence of an reversed liquidity premium.

In Figure 8, we replicate the analysis in Figure 7 after excluding the issuer-times-day fixed effects, thus without controlling for unobservable fundamental values. Notably, all patterns in Figure 8 are opposite to those observed in Figure 7. In all specifications, the sign of the coefficient indicates that bonds with lower search friction are associated with higher prices, consistent with the liquidity premium. In particular, the results indicate even stronger liquidity premium during periods of market distress characterized by high VIX, TED, and DEF. This result confirms our premise that controlling for both observable and unobservable time-varying fundamental values is crucial for identifying the effects of liquidity on the asset prices. Without controlling them, the relationship between search friction (liquidity) and price is endogenous to the quality, hence positive.

4.3.2 A Same Bond on a Same Day Traded by Different Dealers

We now examine a same bond traded on a same day but by different dealers. The different dealers have different level of search ability, proxied by their network centrality within the interdealer network. Using this setting, we can pin-down our key intuition that it is the different levels of search friction that drives the reversed effects on prices since we control for any unobservable time-varying factors at the bond level.

To further illustrate the setup, we can consider an example where these transactions of the bond had different waiting times although they executed on a same day. In other words, customer transactions via peripheral dealers, on average, would have experienced longer waiting times (thus higher search friction) compared to transactions on the same day but facilitated by central dealers. If sellers tend to sacrifice their profits during seller-dominated markets for immediacy, customer-sell transactions conducted through more central dealers within a bond-day would be associated with higher yields (lower prices) than transactions conducted by peripheral dealers. Also, we would not observe this for the transactions where customer buys from dealers nor for the normal periods.

To test this idea, we estimate the following regression model, seperately for customer sells and buys:

$$YS_{i,k,d,t} = \alpha + \beta_1 DlrCentrality_{d,t} \cdot HighX_t + \beta_2 DlrCentrality_{d,t} + \mu_{i,t} + \varepsilon_{i,k,d,t} \tag{3}$$

where the dependant variable is yield spread of transaction. The main independent variable is dealer-level centrality, $DlrCentrality$, which we calculate for each dealer by using interdealer network each month. $HighX$ is a dummy variable for the VIX (or TED or DEF) above its 80th percentile. We also include bond-times-day fixed effects ($\mu_{i,t}$). In addition, we control for the log of trade size as well as dealer fixed effects.

Table 5 shows results from estimating regression specification (3). The estimated coefficients on $DlrCentrality \cdot HighX_t$ is positive and significant at the conventional levels when we examine customer-sell transactions (see, Panel A). However, when we examine customer-buy transactions, we found coefficients on $DlrCentrality \cdot HighX_t$ that are marginal and statistically insignificant (see, Panel B). The results are similar when we examine the 2008 financial crisis. Overall, the results are consistent with our notion that sellers may prioritize immediacy over profits.

In sum, the results are consistent with our hypothesis that the liquidity measured by search friction has positive effects on prices during normal periods but negative effects on prices during seller-dominated markets proxied by high levels of VIX, TED, and DEF as well as during the market-wide crisis of the 2008 financial crisis and the 2020 COVID crisis.

4.4 Same-customer Trades and Reversed Liquidity Premium: Evidence from Insurance Company

Our results so far are consistent with the reversed liquidity premium story. However, we have not examined the customer side story. For example, can the results be driven by differences in customers' bargaining power rather than dealers search ability? Do investors sell more liquid bonds at lower prices even when they also hold illiquid bonds at the same time traded at higher prices?

In this section, we provide a direct evidence controling for the customer side by leveraging insurance company transaction data obtained from the National Association of Insurance Commissioners (NAIC). The use of NAIC insurance company data offers distinct advantages, as it allows us to access customer-level transaction data reported in the NAIC Schedule D filings. This enables us to precisely identify the specific bonds held by an insurance company (IC) on a given day and further discern the bonds they opt to sell, along with the corresponding dates and prices. The availability of such granular data is not readily accessible for other bond investors, rendering ICs as a unique and suitable subject for examining our underlying premises.

4.4.1 Same-customer Trades: Empirical Setup

To examine the seller-dominated situation where the reversed liquidity premium might arise, we use downgrades of bond credit rating as a testing ground. Additionally, we specifically concentrate on ICs that hold multiple bonds from the same issuer. This allows us to investigate the ICs' decision regarding which bonds they elect to sell based on the varying levels of liquidity, as well as the corresponding prices at which these transactions occur. The sample construction is detailed in Section 3.1 and Appendix A.

While in general a downgrade of an individual bond does not necessarily create market-wide selling pressures, it does, however, tend to create localized selling pressures on the specific bond. This can be attributed to the heightened default risks associated with the downgrade, as well as increased holding costs under limited regulatory balancesheet capacity or investor mandates. For example, insurance companies often respond to such downgrades by reducing their holdings of the affected bond, at least partly, primarily driven by the amplified regulatory costs incurred as a consequence (e.g., Ellul et al. 2011b).

Our aim is to compare bonds that are identical except for their search frictions. To achieve this, we narrow our focus to bonds issued by the same firm that were downgraded on the same day. We construct our sample by conditioning on the trading activities of ICs who hold multiple downgraded bonds from the same issuer. It is worth noting that our empirical design does not provide conclusive evidence on whether "ICs on average" exert fire-sale pressures for the downgraded bonds. This is because our sample is conditioned ex-post based on multiple same-issuer bonds and the trading by ICs.[15] Instead, our aim is to directly observe whether investors tend to sell bonds with lower

[15] For example, as a result, our sample can be skewed towards firms with a higher number of bonds and ICs with

search friction at lower prices than market prices of same-issuer bonds with higher search friction that they also possess.

We include all downgrades in order to ensure an adequate number of observations in our sample. Later, we examine downgrades to investment grade and high-yield rating, separately. In principle, the regulatory costs for ICs may remain unaffected if a bond downgrade does not alter the NAIC risk categories, which are based on rating groups. This is due to the NAIC assigning the same regulatory costs within a given NAIC risk category when calculating the regulatory measure of risk-based capital (RBC). However, even if this is the case, a downgrade can still heighten the regulatory concerns and expected regulatory costs from a more pessimistic outlook on the credit risks associated with the bond and potential subsequent downgrades. Consequently, ICs may indeed face regulatory pressures to sell at least a portion of the bonds, particularly when their regulatory capacity is more constrained. It is important to note that our sample construction is conditioned on IC trades, which means we are likely to selectively examine cases where there is greater regulatory pressure. Also, we specifically focus on a subset of constrained ICs (with below-median RBC ratio) that face greater regulatory pressures, motivated by Ellul et al. (2011b). [16] Subsequently, we examine the less constrained ICs as a placebo group for comparative purposes.

Thus, our identifying assumptions for the analyses of ICs are as follow. The downgraded bonds are traded in the locally seller-dominated markets. We focus on ICs who are constrained by the regulatory measure, hold multiple downgraded bonds of the same firm, and trade at least a portion of their downgraded holdings. We posit that these ICs have compelling reasons, such as regulatory pressures, to sell the bonds with a sense of urgency.

As a next step, we confirm our premises that constrained ICs are more likely to sell downgraded bonds with lower search friction to a greater extent than same-issuer downgraded bonds with higher search friction. To do so, we first calculate a rank of search friction among same-issuer downgraded bonds for each IC.[17] Specifically, we define $CtrRank$ as a ranking of $Centrality$ within a IC-issuer as of the downgrade month. For example, $CtrRank$ of 1 represents the most liquid bond (measured by $Centrality$) within the downgrade-issuer-IC group. We assign $CtrRank$ of 5 for the 5th ranks and below. If two bonds within issuer-IC have an exactly same centrality, we assign both to a lower rank.[18] Table A2 presents the frequency distribution of each $CtrRank$ value in the downgrade-bond-IC sample. The table indicates that we have a total of 7,254 downgrade-issuer-IC groups involving multiple bonds from the same issuer held by an IC that have been downgraded. Notably, approximately 40% of these cases involve the downgrading of at least three distinct bonds from the same issuer held by an IC.

We now examine whether ICs are more likely to sell more liquid bonds to a larger extent.

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more corporate bond holdings.

[16] Ellul et al. (2011b) shows that more constrained ICs with below-median risk-based capital ratio exerts significantly larger selling pressures by examining corporate bonds downgraded to high-yield bonds.

[17] We do this for each IC since the selling decision is made within an IC.

[18] For example, $CtrRank$ of three bonds is assigned as $\{1, 3, 3\}$ when the later two bonds have have the same centrality. This is why $CtrRank = 2$ has less observations than $CtrRank = 1$ when all IC-issuer pairs have at least two bonds by the construction.

In Figure 9, Panel A shows that more than 50% of bonds in the lowest search friction group ($CtrRank = 1$) are net sold by ICs after the downgrade during the sample window. The second lowest search friction group ($CtrRank = 2$) is also sold about 48% cases. On the other hand, a substantially smaller number of bonds with higher search friction has been sold. For example, only less than 20% of bonds in the least liquid group ($CtrRank = 5$) are sold. Panel B of Figure 9 shows that those bonds with lower search friction are also sold by larger amounts. For example, the holding size on average decreased by more than 40% (about 10%) for the bonds in the most (least) central group.

In Figure 10, we examine the daily average net trading volume for each $CtrRank$ group over a period of 180 days following the downgrade date. The results indicate that the most liquid bonds consistently experience larger selling pressures throughout the entire sample window, particularly in the immediate aftermath of the downgrade.

Overall, the results indicate that bonds with lower search friction are subject to greater and more immediate selling pressure compared to their less liquid counterparts. In the next section, we examine the price effects and liquidity premium among these bonds.

4.4.2 Same-customer Trades: Results

We first investigate whether ICs who sell bonds with lower search friction (hence more liquid) trade them at lower prices compared to the less liquid same-issuer bond holdings which are traded in the market on the same day.

Based on the results in the previous section, we define a group of liquid bonds as bonds with the highest two $Centrality$ values within IC-issuer-day (i.e., $CtrRank$ of 1 and 2). We define the variable $HighCtr$ as a dummy variable that equals one if $CtrRank \leq 2$ and zero otherwise. Similarly, we define the variable $LowCtr$ as a dummy variable that equals one if $CtrRank \geq 3$ and zero otherwise. With these variables, we then run the following regression:

$$\begin{aligned} YS_{i,t} =& \alpha + \beta_1 HighCtr_{j,i,t} \cdot ICsell_{j,i,t} + \beta_1 LowCtr_{j,i,t} \cdot ICsell_{j,i,t} \\ &+ \beta_3 HighCtr_{j,i,t} + ctrl_{i,t} + \mu_{v,t} + \varepsilon_{j,i,t} \end{aligned} \tag{4}$$

where $YS_{i,t}$ is the daily yield spread of bond. $ICsell_{j,i,t}$ is a dummy variable for bond i sold by IC j on day t. We also include $\log(ttm)$, $\log(age)$, and $\log(amtout)$ as control variables as well as downgrade-issuer-IC-day fixed effects. Consequently, there should be available yields for both $HighCtr$ and $LowCtr$ groups within the same issuer and same day to be included in the analyses.

Table 6 shows the estimated results from the regression model specified in equation (4). The results imply that constrained ICs tend to sell more liquid bonds at lower prices following downgrades, consistent with our story. In Column 1, the coefficient on $HighCtr$ is 0.28 and statistically significant at the 1% level. This suggests that the market yield of bonds with lower search friction sold by ICs was, on average, 0.28% higher than the market yield of their same-issuer bond holdings with higher search friction ($LowCtr$) traded on the same day. This indicates that ICs sold their more liquid ($HighCtr$) bond holdings at lower prices than their less liquid ($LowCtr$) holdings of same-issuer bonds. The results are even more pronounced for bonds that have been downgraded to high-yield status (Columns 3). This could be attributed to a higher prevalence of sellers for high-yield bonds and greater regulatory pressures that prompt ICs to place a higher value on immediacy. However, we do not find similar results for $LowCtr$ bonds sold by ICs. If any, the coefficients are negative, although it lacks statistical power, suggesting that bonds with higher search frictions were sold at higher prices (lower yields).

The daily market prices may not necessarily be the same as the prices at which ICs actually traded. Thus, in Columns 4 through 6, we refine our analysis by further pinning-down on the transaction prices at which ICs actually sold the bonds. We calculate the dependent variable, YS, using only customer-sell transactions. For each bond i sold by IC j on day t, we use the yield of that specific transaction to calculate the yield spread. However, if IC j did not sell bond i on day t, we use the average yield from customer-sell transactions. This approach enables us to directly compare the yield at which ICs sold their bonds with the market yields of their same-issuer bond holdings on a same day. We find qualitatively similar and quantitatively stronger results (Columns 4–6 of Table 6) confirming our premises that ICs sell bonds with lower search friction at lower prices.

In Figure 11, we illustrate the differences in average yield spreads among bonds categorized by their search friction levels, specifically bonds with the lowest ($CtrRank$ of 1) and second lowest ($CtrRank$ of 2) search friction, as well as the remaining bonds ($CtrRank$ over 3). We define $CtrRank(n)$ as dummy variables for each group (n =1, 2, and 3). We also distinguish between days with and without IC sells and $ICsell$ represents a dummy variable for days with IC sell. The benchmark average yield is based on bonds with high search friction ($CtrRank$ over 3) and no IC sells. The differences from the benchmark yield are estimated by running the following regression:

$$YS_{i,t} = \alpha + \sum_{n=1}^{3} \beta_n CtrRank(n)_{j,i,t} \cdot ICsell_{j,i,t} + \sum_{n=1}^{2} \gamma_n CtrRank(n)_{j,i,t} + \mu_{v,j,t} + \varepsilon_{i,t} \qquad (5)$$

where the difference of each group from the benchmark can be estimated from the coefficient estimates β_n and γ_n.

Consistent with previous findings, we observe higher yields for bonds with lower search friction in Figure 11. Additionally, the most liquid bonds (highest $Centrality$) are priced at the lowest levels (i.e., have highest yield spreads). Notably, when IC sells bonds with higher search friction, they do so at a lower yield. This aligns with our intuition that sacrificing immediacy requires a compensation. However, it is worth noting that this may occur less frequently and involve limited quantities (e.g., Figures 9 and 10).

For robustness, we conducted placebo tests by replicating Figure 11 using dates three years prior to the actual downgrade dates as placebo event dates. Figure 12 presents the replicated graphs. Interestingly, we did not find significant differences across the search friction rankings

($CtrRank$) or between days with and without IC sells in this placebo setting. This suggests that the observed differences in average yield spreads in the original analysis are specific to the actual downgrade events and not a result of random variation. This is consistent with our notion that both seller-dominated markets and search frictions are key drivers of the reversed liquidity premium.

4.4.3 Same-customer Trades: Results from ICs selling multiple same-issuer bonds

In Figure 13, we observe similar findings when we focus on a subset of ICs who sell multiple same-issuer bonds on the same day. This consistently supports our hypothesis that sellers are willing to forego profits in favor of enhanced liquidity, resulting in liquid and easily searchable bonds being sold lower than illiquid bonds with higher search friction. One possible explanation for this phenomenon is that it was challenging to sell the illiquid bonds in significant quantities due to their higher search friction. Moreover, the results may also be driven by the fact that the market price for liquid (easy-to-search) bonds was lower, driven by the sellers' valuation in the market.

We also use the placebo event dates to replicate Figure 13 for the robustness check. The replicated results in Figure 14 demonstrate that there are no significant differences in yields of bonds sold by ICs across different levels of search frictions ($CtrRank$) within the same IC-issuer on the same day. These findings align with our premises that the trade-off between immediacy and profits is the primary driver of the reversed liquidity premium.

4.4.4 Additional Evidence: Same bond, Different Customers

We further take advantage of the IC data where we know the customer identity. In particular, we explore the scenario where the same bonds are traded by different ICs on the same day. In this case, our assumption is that ICs with lower searching ability may have experienced greater difficulties in searching, such as longer waiting times for trades, compared to ICs who have higher searching ability. There can be many sources for different search ability by ICs, but we focus on their past trading relationship to more central dealers since we can measure it with our data. Thus, by observing the transactions of ICs with different search ability on the same day for the same bonds, we can examine the role of search friction in determining trading outcomes, after controlling for the unobservable fundamental value as well as observed IC-level characteristics such as size and the RBC ratio. Specifically, we run the following regression:

$$YS_{j,i,t} = \alpha + \beta_1 CentralIC_{j,i,t} + ctrl_{j,t} + \mu_{i,t} + \varepsilon_{j,i,t} \tag{6}$$

where $YS_{j,i,t}$ is the yield spread calculated from the sell transaction by IC j of bond i on day t. To define $CentralIC$, we first calculate the *IC-level centrality* as average $DlrCentrality$ of dealers involved in transactions with the IC during the past 180 days from the day of bond downgrade. We then define $CentralIC$ as a dummy variable that takes one if the *IC-level centrality* is above its 75th percentile and zero otherwise.

Table 7 shows the results from the regression specification (6). The results are consistent with our story. The coefficients on $CentralIC$ are positive and statistically significant at the conventional levels in all specifications. For example, Column 1 shows that the coefficient on $CentralIC$ is 0.47, implying that sell-transactions by ICs with higher search ability (i.e., traded with more central dealers) have on average 47 basis points higher yield spread within a same bond-day. The results are both qualitatively and quantitatively stronger for bonds downgraded to HY than IG.

In sum, by observing insurance company trades we find results consistent with the reversed liquidity premium that in the seller-dominated markets investors sell more liquid (easier-to-search) bonds at a lower price, instead of their less-liquid (difficult-to-search) same-issuer bond holdings that are traded in the market on the same day.

4.4.5 Alternative Explanation: Coordination Failure

We run robustness checks to examine whether a coordination failure of insurance company trading drives our results. Chaderina et al. (2022) documents that bonds most commonly held by ICs experience disproportionally more selling pressures from ICs due to a failure of coordination during fire-sale events from hurricane disasters, since more liquid bonds are commonly held and ICs are more likely to sell them. We test whether our results remain intact after controlling for the number of ICs holding the bonds.

In addition to the regression specification of equation (4), we include controls for the measures of commonality in IC holdings and their interaction with IC sell day, $ICsell$. We construct two commonality measures similarly following the approach of Chaderina et al. (2022): $Commonality$, defined as number of IC bond holders divided by total number of ICs in our sample; $HighComm$, defined as a dummy variable that equals to one if $Commonality$ greater than its sample 75th percentile and zero otherwise. By incorporating these variables, we aim to control for the influence of commonality in IC holdings on the relationship between search friction and yield spreads. However, it is important to note that these channels are not mutually exclusive. Given that our analysis focuses on a selective sample of ICs with multiple same-issuer downgraded bonds, our results cannot establish the presence or absence of the coordination channel.

Table 8 shows the results. The coefficient estimates for $HighCtr \cdot ICsell$ remain both qualitatively and quantitatively intact after controlling for the commonality, compared with those reported in Table 6. Overall, the results suggest that the coordination failure channel is unlikely to be the driving force behind our results in Section 4.4.2.

4.4.6 Placebo Results: Less Constrained Insurance Companies

We additionally conduct placebo tests using a group of less constrained ICs as a comparison. Our underlying assumption is that the more constrained ICs value immediacy more and therefore may trade more liquid bonds at lower prices. If this is the case, in contrast, we expect the less constrained ICs to be less motivated to sell more liquid bonds at lower prices, as they have greater flexibility in their trading decisions. Thus, we created a placebo sample consisting of less constrained ICs (RBC ratios above the median) and similarly analyze their transactions. Figure A3 confirms that the less constrained ICs exert smaller selling pressures consistent with Ellul et al. (2011b), and do not show the pattern of immediacy trading in more liquid bonds compared to Figure 10.

Table 9 presents the results of the placebo test. Coefficient estimates for $HighCtr \cdot ICsell$ are not statistically significant at the conventional level. Also, the economic magnitudes of the coefficients are smaller compared to those reported in Table 6. An exception is Column (2) where the coefficient is marginally significant. One possible explanation for this marginal significance is that certain ICs may still have the intention to sell downgraded bonds due to risk management or potential future regulatory concerns. Another explanation could be that other constrained ICs also sell bonds with lower search friction during similar time periods. However, overall, the results support our hypothesis that constrained ICs are more willing to sacrifice their profits in order to benefit from lower search friction.

4.4.7 Discussion: Why Not Selling the Less Liquid Bond?

Why investors do not sell their less liquid bond holding which is traded at a higher price on the same day? Our intuition claims that this can be explained by the search friction in OTC markets. Investors are less likely to find a counterparty to sell less liquid bonds in the seller-dominated markets. Although some investors in the market are able to sell the bonds on the day, it does not mean that the other investors can immediately sell the bond at the same price because of the search friction in the OTC markets and limited amounts of buyers. Thus, the constrained sellers such as the constrained ICs with multiple downgraded bonds are better off selling more liquid bonds even at a lower price for the immediacy. Whether the equilibrium market price of liquid bond becomes lower than the illiquid counterpart is thus a function of mass of sellers (constrained investors) in the market and the likelihood of matching (search friction). This is exactly the key intuition we are trying to capture. Overall, the evidence from insurance company transactions in Section 4.4 show the results consistent with our economic intuition.

5 Conclusion

In this paper, we provide evidence that prices of liquid assets with lower search friction in OTC markets can be lower than those of illiquid assets with similar fundamental characteristics but higher search friction. We propose a simple model to illustrate the equilibrium prices of liquidity, which can be reversed depending on whether the buyer's or seller's valuation determines the price. When buyers are marginal investors, liquid assets are generally more expensive than illiquid assets because buyers who hold the illiquid asset should be compensated with higher profits. On the other hand, when sellers are marginal investors, an opposite situation arises. Sellers who sell the illiquid asset should be compensated with higher trading gains through higher prices. This leads to the reversed liquidity premium. Such an equilibrium arises due to the feedback between liquidity and investor concentration.

We then provide empirical evidence that identifies the reversed liquidity premium through several distinct empirical strategies. First, we use the unique feature of corporate bond markets that there are multiple bonds issued by an issuer but with different levels of search friction. Moreover, we provide our unique identification strategy using the regression discontinuity design based on the salient maturity of new issuance. In addition, we exploit the rich transaction-level data with dealer identifier to construct measures of search friction and examine effects of search-based measures of liquidity on yields within issuer-day across different market conditions. Overall, we find that bonds with lower search friction (hence more liquid) become cheaper than the less liquid bonds after controlling for the fundamental values during the seller-dominated markets proxied by periods of high VIX, TED, and DEF measures as well as the market-wide crisis events during the 2008 financial crisis and the 2020 COVID crisis.

In addition, we explore a granular database of insurance company transactions to provide a more direct evidence of investors trading with the reversed liquidity premium. We use constrained insurance companies holding multiple downgraded bonds of the same issuer as a testing ground. We find that insurance companies tend to sell bonds with lower search friction at lower prices compared to their same-issuer bond holdings with higher search friction traded at higher prices in the market. This suggests that the search friction takes an important role in shaping the reversed liquidity premium.

Our findings challenge the notion that holding more liquid corporate bonds is an effective strategy to mitigate liquidity events. For example, investors chasing high-yields, such as high-yield mutual funds, tend to minimize cash-like holdings in their portfolio and hold liquid corporate bonds as a buffer mandated by the SEC liquidity management rule since holding cash is especially costly to them. We highlight the importance of diversifying holdings to include cash and cash-like securities that are traded in markets with smaller search frictions.

In addition, our results have important implications for liquidity regulations aimed at enhancing the financial stability. For example, the recent proposal by the SEC in November 2022 to enhance open-end fund liquidity frameworks aligns with our findings.[19] It recognizes the difference in liquidity between normal and stressed conditions. Our findings further emphasize that the "valuation" of liquid assets in search-based OTC markets can diminish when investors need them the most. This implies that the size of liquidity buffers may be overestimated during normal times. Therefore, effective liquidity management should not only consider the time-varying market liquidity but also the dynamic valuation of liquidity in OTC markets.

[19] In November 2022, the SEC proposed "enhancements to open-end fund liquidity framework" to emphasize the difference in the liquidity between normal and stressed conditions. E.g., https://www.sec.gov/news/press-release/2022-199

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Table 1. Descriptive Statistics

This table provides descriptive statistics. The sample period from February 7, 2005 through December 31, 2021. In Panel A, we present bond-day level variables. YS is the daily yield spread in percentage. The daily yield is calculated as a trade-volume-weighted yield to maturity for each day using non-retail sized transactions (greater than $100k in values). We then calculate the yield spread as the difference between the daily yield and a risk-free yield from the Treasury yield curve. Time-to-maturity (*ttm*) are remaining years to the maturity. *age* is defined as years passed after the issuance. We also report the dollar amount outstandings in millions of dollars (*amtout*). *Credit Rating* is the median credit rating among three ratings from the S&P, Moody's and Fitch in the numeric scale (AAA=21). *daily bidask* is the realized bid-ask spread calculated by customer buy and sell trades within bond-day. We also report descriptive statistics for search friction measures. $InterdealerRatio$ is a ratio of interdealer transaction among all transaction during the past 180 days. *Centrality* is the dealer network centrality calculated from monthly interdealer network, averaged at the bond-month level weighted by number of transactions. *Chain Length* is the average length of intermediation chains during the past 180 days. We follow Friewald and Nagler (2019) to calculate the chain length and assign 0 if there is no intermediation chain. We use the Academic TRACE to calculate *Centrality* and *Chain Length*, thus the sample period is limited to 2017 for these variables. In Panel B, we present transaction-level variables from the academic TRACE from February 7, 2005 through December 31, 2017. YS is based on the yield of each transaction. *DlrCentrality* is the dealer eigenvector centrality of interdealer network, calculated each month for each dealer. *log*(*trade size*) is log of trade volume in par value. In Panel C, we present variables calculated at the bond-quarter level. $CusVol$ and $IdVol$ are sum of customer volume and interdealer volume, respectively, scaled by amount outstanding for the bond during the quarter. *ztd* is the zero trading day, defined as a fraction of days without any trade during the quarter for the bond. *quarterly bidask* is defined as a median of *daily bidask* during the quarter for the bond. The variable definitions are detailed in Appendix B. We report the number of observations (N), mean, standard deviation (Std.), and 5%, 25%, 50% (median), 75%, and 95% quantiles.

	N	Mean	Std	P5	P25	P50	P75	P95
Panel A. Bond-day								
YS (%)	10,442,580	2.341	3.815	0.292	0.757	1.369	2.575	7.039
ttm (*year*)	10,442,580	9.07	9.066	0.846	3.242	5.971	9.528	28.46
age (*year*)	10,442,580	3.881	3.62	0.285	1.322	2.943	5.273	9.977
amtout ($\$MM$)	10,442,580	925.7	764.5	250	450	725	1140	2500
$Credit\ Rating$	10,424,399	13.07	3.63	6	12	13	16	18
daily bidask (*bps*)	3,560,421	34.96	58.6	-7.833	6.291	20.49	42.44	134.81
$InterdealerRatio$	10,425,859	0.138	0.08	0.04	0.079	0.12	0.181	0.292
$Centrality$	6,652,508	0.583	0.122	0.377	0.508	0.588	0.661	0.774
$ChainLength$	6,652,508	0.329	0.337	0	0	0.242	0.571	0.998
Panel B. Transaction-level (academic TRACE, up to 2017)								
YS (%)	13,005,484	3.333	5.406	0.377	0.972	1.886	3.796	10.127
$DealerCentrality$	13,005,484	0.591	0.278	0.094	0.373	0.621	0.837	0.99
$log(tradesize)$	13,005,484	13.45	1.41	11.51	12.21	13.28	14.51	15.89
Panel C. Bond-quarter								
$CusVol$	1,310,548	0.054	0.118	0	0	0	0.055	0.289
$IdVol$	1,310,548	0.016	0.045	0	0	0	0.009	0.089
ztd	1,310,548	0.851	0.265	0.19	0.817	1	1	1
quarterly bidask (*bps*)	405,838	33.26	43.7	0.445	10.27	22.05	38.13	110.93

Table 2. Descriptive Statistics of Matched Bonds and Matching Quality

This table provides descriptive statistics for 1,994 unique matched pairs of the young and the old bonds in our matched sample from February 2005 through December 2021. There are 241,426 bond-day-level observations in the matched sample (i.e., 120,713 daily matched pair). The matching process is described in Section 4.1.1. In Panel A, we report summary statistics of bond characteristics, such as *ttm*, *age*, *amtout*, and *Credit Rating* for young and old bonds separately. The *rating* is reported just once because bonds in a matched pair have exactly same rating. The reported variables in Panel A are calculated when the bond pairs are first appeared on our matched sample. We report mean, standard deviation (Std.), and 5%, 25%, 50% (median), 75%, and 95% quantiles. Panel B shows descriptive statistics for *Liquidity Spread* as well as differences in *age* and *ttm* between matched bonds. Panel C provides the mean differences between young and matched old bonds by using the bond-day sample. In addition to the bond characteristics, we include: daily customer trade volume scaled by amount outstanding, *daily CusVol*; daily interdealer trade value scaled by amount outstanding, *daily IdVol*; fraction of zero-trading days during the previous quarter, *ZTD*; and daily bid-ask spread, *daily bidask*. Definitions for all variables are detailed in the Appendix B. We report averages of each variable for the matched bonds and the mean differences. Also, the numbers in parentheses are the standard errors two-way clustered at the issuer and day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Bond characteristics as of the first matched date

	Mean	Std.	5%	25%	50%	75%	95%
age, young	0.193	0.198	0.085	0.090	0.099	0.178	0.717
age, old	6.580	4.723	3.417	4.400	5.094	5.925	19.828
ttm, young	6.705	4.396	3.830	4.906	4.942	6.919	19.775
ttm, old	6.696	4.434	3.833	4.668	5.303	6.407	19.671
amtout, young	878.1	753.8	27	400	686	1100	2500
amtout, old	906.0	841.4	110	350	600	1150	2750
rating	14.689	2.758	10	13	15	16	19

Panel B. Daily Matched Pair

	Mean	Std	P5	P25	P50	P75	P95
Liquidity Spread (%)	0.020	0.249	-0.330	-0.057	0.028	0.121	0.357
Difference in *age*	5.081	2.536	3.228	4.027	4.736	5.268	9.199
Difference in *ttm*	-0.030	0.522	-0.903	-0.419	-0.038	0.361	0.860

Panel C. Mean Differences in Bond-Day Sample

	Young	Old	Difference	*s.e.*
age	0.528	5.609	-5.081***	(0.094)
ttm	5.855	5.825	0.030*	(0.016)
amtout	1,241.4	1,340.4	-98.952*	(55.125)
daily CusVol (*bps*)	51.143	26.516	24.627***	(1.453)
daily IdVol (*bps*)	18.630	9.265	9.365***	(1.086)
ztd	0.154	0.325	-0.171***	(0.015)
daily bidask (*bps*)	25.754	34.756	-9.001***	(1.225)

Table 3. Regression Discontinuity: Local Treatment Effects of Search Friction on Yield Spread

The table presents regression discontinuity design results using different time-to-maturity thresholds (10- and 30-years). The dependent variable is the yield spread. The sub-sample of treated and control bonds is used for a sharp RDD, as explained in Figure 6. Panel A displays local treatment effects for the entire sample (Columns 1 and 5) and sub-samples based on VIX levels (Columns 2–4 and 6–8). Panels B and C uses TED and DEF instead of VIX, respectively. In Panel D, we use sub-samples for specific time periods, including 2008$Crisis$ (July 1, 2007 – March 31, 2009), $COVID1$ (January 30, 2020 - March 14, 2020), $COVID2$ (March 15, 2020 - March 23, 2020), and $COVID3$ (March 23, 2020 - April 8, 2020). The bandwidth is optimally chosen for each sample following Calonico et al. (2014a) and Calonico et al. (2015). In addition to conventional estimates, bias-corrected estimates with robust standard errors, following Calonico et al. (2014b) and Calonico et al. (2020), are reported. We control for the issuer-day fixed effects, log of amount outstanding, and a dummy variable for bond age less than 30 days, by using the full sample. Standard errors are clustered at the day level. The sample period spans from 2005 to 2021. N(left) and N(right) indicate the number of observations within the bandwidth on the left and right of the cutoff, respectively. Similarly, N(left_bc) and N(right_bc) are corresponding number of observations within the bias-corrected bandwidth. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Local treatment effects across Level of VIX

	Cutoff: ttm = 10				Cutoff: ttm = 30			
		VIX level				VIX level		
		$<50^{th}$	50^{th}–80^{th}	$> 80^{th}$		$<50^{th}$	50^{th}–80^{th}	$> 80^{th}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conventional	-0.013*	-0.100***	-0.039***	0.245***	-0.019***	-0.022***	-0.016***	0.123***
	(0.007)	(0.009)	(0.008)	(0.021)	(0.004)	(0.006)	(0.006)	(0.012)
Bias-corrected	-0.018***	-0.105***	-0.046***	0.235***	-0.018***	-0.024***	-0.018***	0.133***
	(0.007)	(0.009)	(0.008)	(0.021)	(0.004)	(0.006)	(0.006)	(0.012)
Robust	-0.018**	-0.105***	-0.046***	0.235***	-0.018***	-0.024***	-0.018***	0.133***
	(0.007)	(0.010)	(0.009)	(0.023)	(0.004)	(0.006)	(0.007)	(0.013)
Bandwidth	1.016	0.984	1.071	1.571	3.097	2.517	3.093	1.459
N(left)	440725	203504	143561	132973	550577	226981	175084	62161
N(right)	34522	16534	11780	8991	14811	6946	4811	1799
Bias-corr. Bandwidth	2.188	2.007	2.138	2.255	6.627	6.522	5.414	4.197
N(left_bc)	869231	396910	267456	170775	926422	457538	259294	133080
N(right_bc)	62157	28912	19721	11537	23687	10818	6750	2896

Panel B. Local treatment effects across Level of TED

	Cutoff: ttm = 10			Cutoff: ttm = 30		
		TED level			TED level	
	$<50^{th}$	50^{th}–80^{th}	$> 80^{th}$	$<50^{th}$	50^{th}–80^{th}	$> 80^{th}$
	(1)	(2)	(3)	(4)	(5)	(6)
Conventional	-0.059***	-0.051***	0.141***	-0.036***	-0.071***	0.054**
	(0.006)	(0.011)	(0.020)	(0.005)	(0.009)	(0.022)
Bias-corrected	-0.062***	-0.054***	0.148***	-0.036***	-0.068***	0.064***
	(0.006)	(0.011)	(0.020)	(0.005)	(0.009)	(0.022)
Robust	-0.062***	-0.054***	0.148***	-0.036***	-0.068***	0.064***
	(0.007)	(0.013)	(0.023)	(0.006)	(0.009)	(0.023)
Bandwidth	0.923	1.841	1.787	3.057	2.045	0.898
N(left)	240,766	199,100	98,974	337,568	98,664	28,217
N(right)	15,795	15,809	10,297	9,280	3,476	903
Bandwidth_bias	1.668	3.067	2.975	5.717	4.294	3.072
N(left_bc)	414,735	314,360	150,364	518,374	183,756	70,015
N(right_bc)	26,758	23,158	13,608	13,538	4,608	1,376

Panel C. Local treatment effects across Level of DEF

	Cutoff: ttm = 10			Cutoff: ttm = 30		
	DEF level			DEF level		
	$<50^{th}$	50^{th}–80^{th}	$> 80^{th}$	$<50^{th}$	50^{th}–80^{th}	$> 80^{th}$
	(1)	(2)	(3)	(4)	(5)	(6)
Conventional	-0.077***	-0.056***	0.284***	-0.041***	-0.044***	0.071***
	(0.008)	(0.009)	(0.023)	(0.005)	(0.010)	(0.020)
Bias-corrected	-0.082***	-0.056***	0.296***	-0.041***	-0.047***	0.082***
	(0.008)	(0.009)	(0.023)	(0.005)	(0.010)	(0.020)
Robust	-0.082***	-0.056***	0.296***	-0.041***	-0.047***	0.082***
	(0.009)	(0.010)	(0.025)	(0.006)	(0.010)	(0.020)
Bandwidth	0.817	1.241	1.436	2.394	2.355	0.707
N(left)	179,908	164,217	105,700	239,488	134,127	27,703
N(right)	16,856	10,423	7,157	8,661	3,561	922
Bias-corr. Bandwidth	1.837	1.832	3.004	4.235	5.046	2.651
N(left_bc)	394,452	225,966	190,162	368,505	238,948	82,923
N(right_bc)	32,087	14,837	11,300	11,272	5,134	1,496

Panel D. Local treatment effects: the 2008 crisis and COVID period

	Cutoff: ttm = 10				Cutoff: ttm = 30			
	$2008Crisis$	$Covid1$	$Covid2$	$Covid3$	$2008Crisis$	$Covid1$	$Covid2$	$Covid3$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conventional	0.286***	0.035	0.523*	-0.245**	0.093***	0.059***	-0.182*	-0.094*
	(0.030)	(0.036)	(0.284)	(0.106)	(0.019)	(0.022)	(0.105)	(0.050)
Bias-corrected	0.308***	0.051	0.629**	-0.195*	0.101***	0.064***	-0.180*	-0.075
	(0.030)	(0.036)	(0.284)	(0.106)	(0.019)	(0.022)	(0.105)	(0.050)
Robust	0.308***	0.051	0.629*	-0.195*	0.101***	0.064**	-0.180*	-0.075
	(0.033)	(0.037)	(0.323)	(0.115)	(0.020)	(0.026)	(0.104)	(0.054)
Bandwidth	1.300	1.302	3.760	2.816	1.855	5.743	6.665	2.580
N(left)	30,126	5,734	2,321	4,880	22,262	11,130	1,855	2,698
N(right)	4,452	333	141	345	273	488	82	113
Bias-corr. Bandwidth	2.921	3.333	6.699	5.315	3.961	5.935	13.44	4.667
N(left_bc)	56,982	12,892	4,137	9,392	30,301	11,533	2,618	4,047
N(right_bc)	5,682	1,016	474	979	349	489	141	139

Table 4. Effects of Search Friction on Yields

This table provides the regression results for the following model:

$$YS_{i,t} \quad = \quad \alpha + \beta_1 SF_{i,t} \cdot HighX_t + \beta_2 SF_{i,t} + ctrls_{i,t} + \mu_{v,t} + \varepsilon_{i,t}$$

where the dependent variable $YS_{i,t}$ is daily yields in percentage. $SF_{i,t}$ is a measure of search friction: *Centrality*, *ChainLength*, and *InterDealerRatio*. *Centrality* is the dealer eigenvector centrality in the interdealer network calculated each month. We first calculate the centrality for dealer-month and aggregate them at the bond-level by taking average weighted by number of transactions. *ChainLength* is average length of the intermediation chain during past 180 days, where we assign the length of 0 to non-changed transactions. *InterDealerRatio* is the ratio of interdealer transactions to all transactions during past 180 days. The definitions are detailed in Appendix B. The sample period runs from February 7, 2005 through December 31, 2017, except when we use *InterDealerRatio*. Then, the sample period extends to 2021. In Panel A, $HighX_t$ is a dummy variable that equals one if a seller-market proxy X (VIX, TED, or DEF) is higher than its sample 80th percentile and zero otherwise.In Panel B, we employ a set of distressed dummy variables, $\{2008Crisis, COVID\}$, indicating the following sub-periods of {July 2017–March 2009 and March 15–March 23, 2020}, respectively. The control variables, *ctrls*, include: logged time-to-maturity, $log(ttm)$; logged amount outstandings, $log(amtout)$; and logged bond age, $log(age)$. We also include issuer-times-day fixed effects ($\mu_{v,t}$). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are standard errors two-way clustered at the issuer and day levels.

Panel A. High VIX, TED, and DEF

High X:	VIX			TED			DEF		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Centrality \cdot HighX$	0.505***			0.498***			0.435***		
	(0.112)			(0.131)			(0.108)		
$Centrality$	-0.260***			-0.246***			-0.258***		
	(0.038)			(0.039)			(0.037)		
$ChainLength \cdot HighX$		-0.078**			-0.097*			-0.098***	
		(0.038)			(0.051)			(0.034)	
$ChainLength$		-0.013			-0.014			-0.007	
		(0.010)			(0.010)			(0.009)	
$InterDealerRatio \cdot HighX$			-1.282***			-2.203***			-2.200***
			(0.266)			(0.332)			(0.355)
$InterDealerRatio$			0.374***			0.430***			0.437***
			(0.075)			(0.076)			(0.076)
$log(ttm)$	0.282***	0.282***	0.303***	0.282***	0.282***	0.302***	0.282***	0.282***	0.302***
	(0.012)	(0.012)	(0.009)	(0.012)	(0.012)	(0.009)	(0.012)	(0.012)	(0.009)
$log(amtout)$	-0.032	-0.031	-0.030**	-0.031	-0.031	-0.029**	-0.032*	-0.031	-0.029**
	(0.019)	(0.019)	(0.013)	(0.019)	(0.019)	(0.013)	(0.019)	(0.019)	(0.013)
$log(age)$	0.071***	0.070***	0.054***	0.071***	0.070***	0.054***	0.071***	0.070***	0.053***
	(0.007)	(0.007)	(0.004)	(0.007)	(0.007)	(0.004)	(0.007)	(0.007)	(0.004)
$\beta_1 + \beta_2$	0.244**	-0.091**	-0.908***	0.252**	-0.111**	-1.773***	0.177*	-0.105***	-1.762***
Issuer·day f.e.	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	5,183,228	5,183,228	8,578,288	5,183,228	5,183,228	8,578,288	5,183,228	5,183,228	8,578,288
Adj. R^2	0.920	0.920	0.924	0.920	0.920	0.924	0.920	0.920	0.924

Panel B. The 2008 crisis and COVID

SF:	$Centrality$ (1)	$ChainLength$ (2)	$InterDealerRatio$ (3)
$SF \cdot 2008Crisis$	0.774***	-0.158**	-3.917***
	(0.186)	(0.073)	(0.725)
$SF \cdot COVID$			-5.900***
			(1.012)
SF	-0.245***	-0.014	0.338***
	(0.038)	(0.010)	(0.077)
$\beta_{1,2008} + \beta_2$	0.530***	-0.171**	-3.579***
$\beta_{1,covid} + \beta_2$			-5.562***
Control	Y	Y	Y
Issuer·day f.e.	Y	Y	Y
N	5,183,228	5,183,228	8,578,288
Adj. R^2	0.920	0.920	0.924

Table 5. Effects of Different Dealer Centrality on Yields within a Same Bond on a Same Day

This table presents the regression results for the model specified as follows:

$$YS_{i,k,d,t} \quad = \quad \alpha + \beta_1 DlrCentrality_{d,t} \cdot HighX_t + \beta_2 DlrCentrality_{d,t} + \mu_{i,t} + \varepsilon_{i,k,d,t}$$

where the dependent variable $YS_{i,k,d,t}$ represents the yield spread for each transaction k of bond i by dealer d on day t. $DlrCentrality_{d,t}$ is the eigenvector centrality calculated from interdealer network each month. $HighX_t$ is a dummy variable that equals one if the VIX (TED or DEF) is greater than its 80th percentile, and zero otherwise. In Columns 1–3 (Columns 4–6), we use customer-sell (customer-buy) transaction only. We include bond-times-day fixed effects ($\mu_{i,t}$). In Columns 3 and 6, we additionally include the dealer fixed effect. We also control for the log of transaction volume, $log(trade\ size)$. The sample period runs from February 7, 2005 through December 31, 2017. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are standard errors two-way clustered at the bond and day levels.

Panel A. Customer Sell

Distress:	VIX			TED			DEF		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$DlrCentrality \cdot HighX$	0.036***	0.033***	0.027**	0.058***	0.052***	0.032**	0.029**	0.027**	0.022**
	(0.012)	(0.012)	(0.011)	(0.018)	(0.018)	(0.016)	(0.012)	(0.011)	(0.011)
$DlrCentrality$	-0.024***	-0.024***	0.012*	-0.025***	-0.025***	0.012	-0.023***	-0.023***	0.013*
	(0.003)	(0.003)	(0.007)	(0.002)	(0.002)	(0.007)	(0.003)	(0.003)	(0.007)
$log(trade\ size)$		-0.020***	-0.011***		-0.020***	-0.011***		-0.020***	-0.011***
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
$\beta_1 + \beta_2$	0.012	0.008	0.039**	0.033*	0.027	0.043**	0.006	0.003	0.035**
Bond·day f.e.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Dealer f.e.	N	N	Y	N	N	Y	N	N	Y
N	3,156,435	3,156,435	3,156,186	3,156,435	3,156,435	3,156,186	3,156,435	3,156,435	3,156,186
Adj. R^2	0.995	0.995	0.995	0.995	0.995	0.995	0.995	0.995	0.995

Panel B. Customer Buy

Distress:	VIX			TED			DEF		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$DlrCentrality \cdot HighX$	0.001	0.005	0.000	-0.010	-0.003	-0.004	-0.003	-0.001	-0.007
	(0.008)	(0.008)	(0.010)	(0.011)	(0.011)	(0.013)	(0.008)	(0.007)	(0.008)
$DlrCentrality$	0.030***	0.029***	-0.000	0.031***	0.031***	0.000	0.031***	0.031***	0.001
	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.005)
$log(trade\ size)$		0.031***	0.016***		0.031***	0.016***		0.031***	0.016***
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
$\beta_1 + \beta_2$	0.031***	0.034***	0.000	0.021**	0.028***	-0.004	0.027***	0.029***	-0.006
Bond·day f.e.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Dealer f.e.	N	N	Y	N	N	Y	N	N	Y
N	4,345,602	4,345,602	4,345,414	4,345,602	4,345,602	4,345,414	4,345,602	4,345,602	4,345,414
Adj. R^2	0.996	0.996	0.997	0.996	0.996	0.997	0.996	0.996	0.997

Panel C. The 2008 crisis

	Customer Sell			Customer Buy		
	(1)	(2)	(3)	(4)	(5)	(6)
$DlrCentrality \cdot 2008Crisis$	0.081***	0.074***	0.057**	-0.017	-0.009	-0.013
	(0.026)	(0.025)	(0.026)	(0.018)	(0.017)	(0.022)
$DlrCentrality$	-0.023***	-0.024***	0.011	0.031***	0.031***	0.001
	(0.003)	(0.003)	(0.007)	(0.002)	(0.002)	(0.005)
$log(trade\ size)$		-0.020***	-0.011***		0.031***	0.016***
		(0.001)	(0.001)		(0.001)	(0.001)
$\beta_1 + \beta_2$	0.058**	0.050**	0.068**	0.014	0.022	-0.013
Bond·day f.e.	Y	Y	Y	Y	Y	Y
Dealer f.e.	N	N	Y	N	N	Y
N	3,156,435	3,156,435	3,156,186	4,345,602	4,345,602	4,345,414
Adj. R^2	0.995	0.995	0.995	0.996	0.996	0.997

Table 6. Do Insurance Companies Sell More Liquid Bonds at Lower Prices?

This table provides the regression results for the following model:

$$YS_{i,t} = \alpha + \beta_1 HighCtr_{j,i,t} \cdot ICsell_{j,i,t} + \beta_1 LowCtr_{j,i,t} \cdot ICsell_{j,i,t} + \beta_3 HighCtr_{j,i,t} + ctrl_{i,t} + \mu_{v,j,t} + \varepsilon_{j,i,t}$$

where the dependent variable is the yield spread. In Columns 1–3, we use the daily yield spread, $YS_{i,t}$. In Columns 4–6, we use yield spreads calculated from sell transactions only, where we use the yield of sell transaction of IC j for bond i on day t obtained from the NAIC if available; otherwise, we use the all sell transactions in the TRACE for bond i on day t. $HighCtr_{j,i,t}$ is a dummy variable that equals one if $CtrRank \leq 2$ and zero otherwise. $LowCtr_{j,i,t}$ is a dummy variable that equals one if $CtrRank \geq 3$ and zero otherwise. $CtrRank$ is the ranking of $Centrality$ within the same-issuer holdings of an IC in our sample, where 1 represents the highest centrality bond. $ICsell_{j,i,t}$ is a dummy variable that equals one if the bond i is sold by IC j on day t, and zero otherwise. In Columns 2-3 and 5-6, we also divide the sample into two groups: bonds downgraded to IG; and bonds downgraded to HY, respectively. All specification includes control variables of log(ttm), ttm, and log($amtout$) as well as downgrade-issuer-IC-day fixed effects ($\mu_{v,j,t}$). The numbers in parentheses are standard errors clustered at the issuer and day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	YS			YS (sell transaction)		
	All	IG	HY	All	IG	HY
	(1)	(2)	(3)	(4)	(5)	(6)
$HighCtr \cdot ICsell$	0.279***	0.179**	0.437***	0.451***	0.146*	0.870***
	(0.079)	(0.081)	(0.156)	(0.104)	(0.087)	(0.219)
$LowCtr \cdot ICsell$	-0.244	-0.225	-0.059	-0.271	-0.261	-0.033
	(0.159)	(0.156)	(0.216)	(0.173)	(0.173)	(0.218)
$HighCtr$	0.066	0.051	0.281	0.080	0.060	0.353*
	(0.047)	(0.047)	(0.177)	(0.061)	(0.066)	(0.204)
$log(ttm)$	-0.135	0.142	-1.130	-0.421	-0.005	-1.708*
	(0.227)	(0.107)	(0.721)	(0.331)	(0.162)	(0.898)
$log(amtout)$	0.296**	0.137***	0.799*	0.350*	0.118*	0.962*
	(0.141)	(0.047)	(0.408)	(0.204)	(0.063)	(0.500)
$log(age)$	0.194	0.116**	0.572	0.205	0.152**	0.562
	(0.140)	(0.054)	(0.534)	(0.189)	(0.075)	(0.635)
Down·Issuer·IC·Day f.e.	Y	Y	Y	Y	Y	Y
N	1,727,757	1,159,839	567,918	1,060,258	677,387	382,871
Adj R^2	0.907	0.889	0.886	0.887	0.860	0.872

Table 7. Do Insurance Companies with Different Search Friction Trade at Different Prices?

This table provides the regression results for the following model:

$$YS_{j,i,t} = \alpha + \beta_1 CentralIC_{j,i,t} + ctrl_{j,t} + \mu_{i,t} + \varepsilon_{j,i,t}$$

where the dependent variable is yield spread calculating using each IC sell transaction, $YS_{j,i,t}$. $CentralIC_{j,t}$ is a dummy variable that takes one if IC-level centrality is above its 75th percentile and zero otherwise. The IC-level centrality is an average of dealer centrality of transactions by IC j during the past 180 days from the downgrade day. We include downgrade-bond-day fixed effects ($\mu_{i,t}$). The control variable, $ctrl$, include the risk-based capital ratio and log of total assets of IC. The numbers in parentheses are standard errors clustered at the issuer and day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	All	IG	HY	All	IG	HY
	(1)	(2)	(3)	(4)	(5)	(6)
$CentralIC$	0.466**	0.158*	0.861**	0.455***	0.152*	0.842**
	(0.180)	(0.084)	(0.370)	(0.172)	(0.084)	(0.350)
$RBCratio$				-0.017	-0.017	-0.014
				(0.019)	(0.013)	(0.042)
$\log(ICsize)$				-0.025	-0.016***	-0.038
				(0.023)	(0.006)	(0.053)
Down·Bond·Day f.e.	Y	Y	Y	Y	Y	Y
N	2,653	1,337	1,316	2,653	1,337	1,316
Adj R^2	0.997	0.999	0.996	0.997	0.999	0.996

Table 8. Robustness Check: Coordination Failure as Alternative Explanation

This table reports results from replicating Table 6 after controlling for the commonality in IC holdings. We use two variables of commonality: number of distinct ICs who hold the bond as of a day before the downgrade scaled by number of ICs in our sample, *Commonality*; and a dummy variable for *Commonality* greater than its sample 75th percentile, *HighComm*. We also include interaction terms between the commonality variables and *ICsell*. All other specifications are the same as Table 6. The numbers in parentheses are standard errors clustered at the issuer and day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A.

	YS			YS (sell transaction)		
	All	IG	HY	All	IG	HY
	(1)	(2)	(3)	(4)	(5)	(6)
$HighCtr \cdot ICsell$	0.242**	0.124*	0.412**	0.528***	0.083	1.095***
	(0.096)	(0.066)	(0.202)	(0.144)	(0.120)	(0.278)
$LowCtr \cdot ICsell$	-0.288*	-0.287*	-0.076	-0.182	-0.332	0.269
	(0.152)	(0.167)	(0.243)	(0.261)	(0.209)	(0.343)
$HighCtr$	0.064	0.050	0.296*	0.079	0.059	0.368*
	(0.047)	(0.046)	(0.169)	(0.062)	(0.065)	(0.193)
$Commonality \cdot ICsell$	1.119	1.746	0.403	-2.431	1.981	-7.500
	(2.207)	(2.867)	(3.443)	(3.585)	(3.494)	(5.195)
$Commonality$	2.709	1.095	10.827	1.452	0.175	9.381
	(4.686)	(2.163)	(8.305)	(6.174)	(2.984)	(9.375)
Control	Y	Y	Y	Y	Y	Y
Down·Issuer·IC·Day f.e.	Y	Y	Y	Y	Y	Y
N	1,727,757	1,159,839	567,918	1,060,258	677,387	382,871
Adj R^2	0.907	0.889	0.886	0.887	0.860	0.873

Panel B.

	YS			YS (sell transaction)		
	All	IG	HY	All	IG	HY
	(1)	(2)	(3)	(4)	(5)	(6)
$HighCtr \cdot ICsell$	0.232***	0.185***	0.309*	0.474***	0.161**	0.915***
	(0.082)	(0.068)	(0.161)	(0.124)	(0.082)	(0.261)
$LowCtr \cdot ICsell$	-0.305**	-0.218	-0.214	-0.249	-0.242	0.032
	(0.152)	(0.135)	(0.259)	(0.197)	(0.151)	(0.299)
$HighCtr$	0.064	0.051	0.286	0.076	0.060	0.353*
	(0.048)	(0.047)	(0.180)	(0.062)	(0.065)	(0.205)
$HighComm\cdot ICsell$	0.129	-0.018	0.376	-0.075	-0.042	-0.168
	(0.210)	(0.189)	(0.426)	(0.197)	(0.193)	(0.392)
$HighComm$	0.237	-0.003	1.043**	0.256	-0.014	1.072**
	(0.159)	(0.108)	(0.434)	(0.196)	(0.148)	(0.465)
Control	Y	Y	Y	Y	Y	Y
Down·Issuer·IC·Day f.e.	Y	Y	Y	Y	Y	Y
N	1,727,757	1,159,839	567,918	1,060,258	677,387	382,871
Adj R^2	0.907	0.889	0.887	0.887	0.860	0.873

Table 9. Placebo Test using Less Constrained ICs

This table reports results from the replication of Tables 6 by using the sample of less constrained ICs (i.e., ICs with above-median RBC ratio). The numbers in parentheses are standard errors clustered at the issuer and day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	YS			YS (sell transaction)		
	All (1)	IG (2)	HY (3)	All (4)	IG (5)	HY (6)
$HighCtr \cdot ICsell$	0.121	0.191*	0.078	0.316	0.160	0.626
	(0.131)	(0.115)	(0.245)	(0.230)	(0.142)	(0.534)
$LowCtr \cdot ICsell$	-0.190	-0.199	-0.215	-0.312	-0.367	-0.218
	(0.153)	(0.176)	(0.210)	(0.204)	(0.257)	(0.271)
$HighCtr$	0.009	0.033	0.113	0.014	0.051	0.125
	(0.055)	(0.043)	(0.191)	(0.074)	(0.059)	(0.218)
Control	Y	Y	Y	Y	Y	Y
Down·Issuer·IC·Day f.e.	Y	Y	Y	Y	Y	Y
N	995,896	710,898	284,998	613,907	421,165	192,742
Adj. R^2	0.911	0.889	0.891	0.892	0.862	0.877

Figure 2. Relationship between Time-to-maturity and Trading Volume, Frequency, and Bid-ask Spread across Maturity at Issuance

This figure shows relationships between time-to-maturity (*ttm*) and the four liquidity-related variables in 4 for bonds with when-issued *ttm* of 3, 5, 7, 10, 20, and 30 separately. We use binned scatter plot of Cattaneo et al. (2019) to fit non-parametric way.

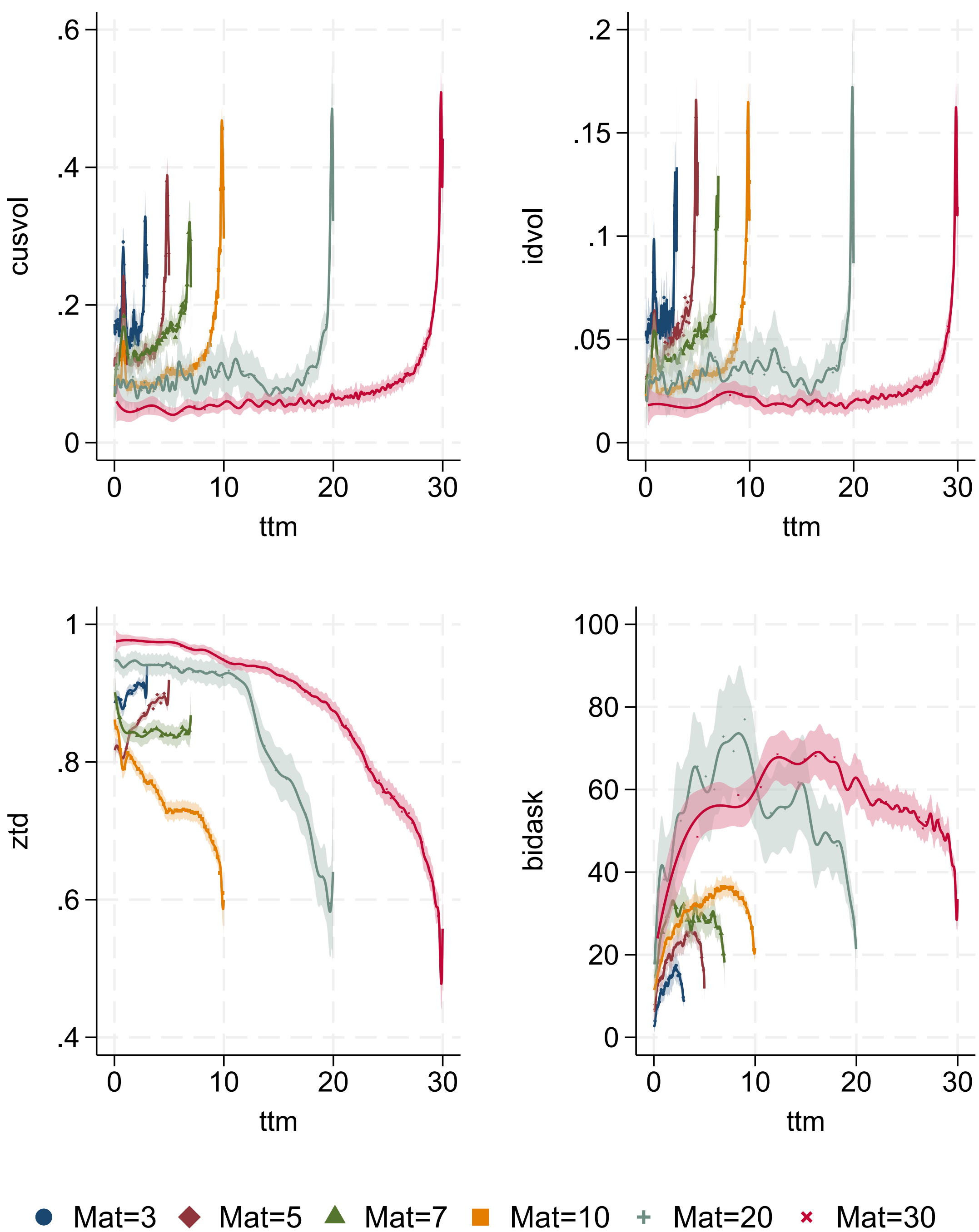


Figure 3. Time Series of Liquidity Spread

This figure depicts the time series of the liquidity spread. The *LiquiditySpread* is defined as illiquid bond yields minus matched liquid bond yields. The matching is detailed in Section 4.1.1. We calculate the spread each day if both yields from liquid and matched illiquid bonds are available for the same day. To remove effects of outliers, we winsorize the yields of liquid and illiquid bonds at the 1% level as well as the liquidty spreads at the 0.5% level. The sample period runs from February 7, 2005 through December 31, 2021. The black solid line represents the 20-days moving average of *LiquiditySpread*. We also add a scatter plot to visualize *LiquiditySpread* of each matched pair. The grey area plot in the bottom shows the VIX. Dashed vertical lines indicate the Lehman Brothers Bankruptcy (September 15, 2008), and the COVID pandemic (March 2020). The x-axis represents calendar dates and the y-axis represents *LiquiditySpread* in percentages.

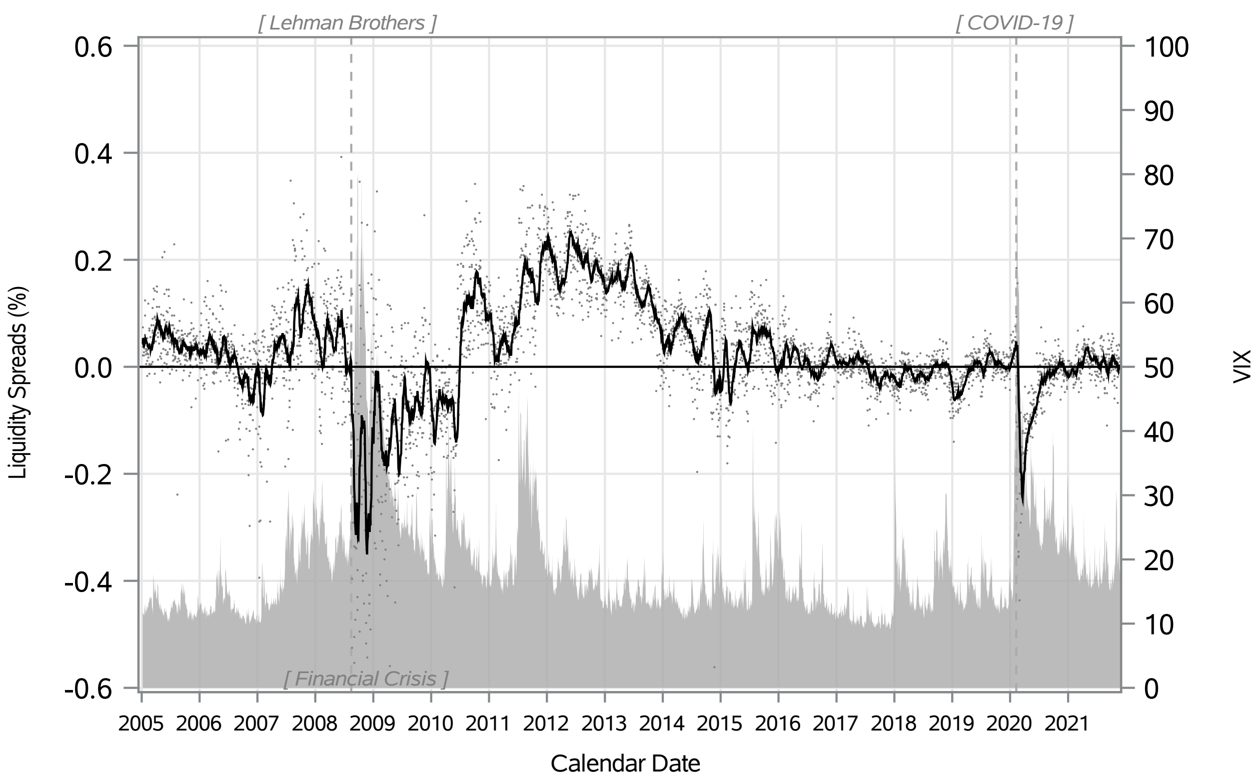


Figure 4. Relationship between Time-to-maturity and Trading Volume, Frequency, and Bid-ask Spread in Pooled Sample

This figure shows the relationship between time-to-maturity (ttm) and liquidity-related variables in a non-parametric way. Specifically, we use customer trading volume scaled by amount outstanding, $CusVol$; interdealer trading volume scaled by amount outstanding, $IdVol$; fraction of zero-trading days, ztd; and quarterly median bid-ask spreads, $bidask$. All variables are calculated quarterly. We use data-driven non-parametric binned scatter plot of Cattaneo et al. (2019).

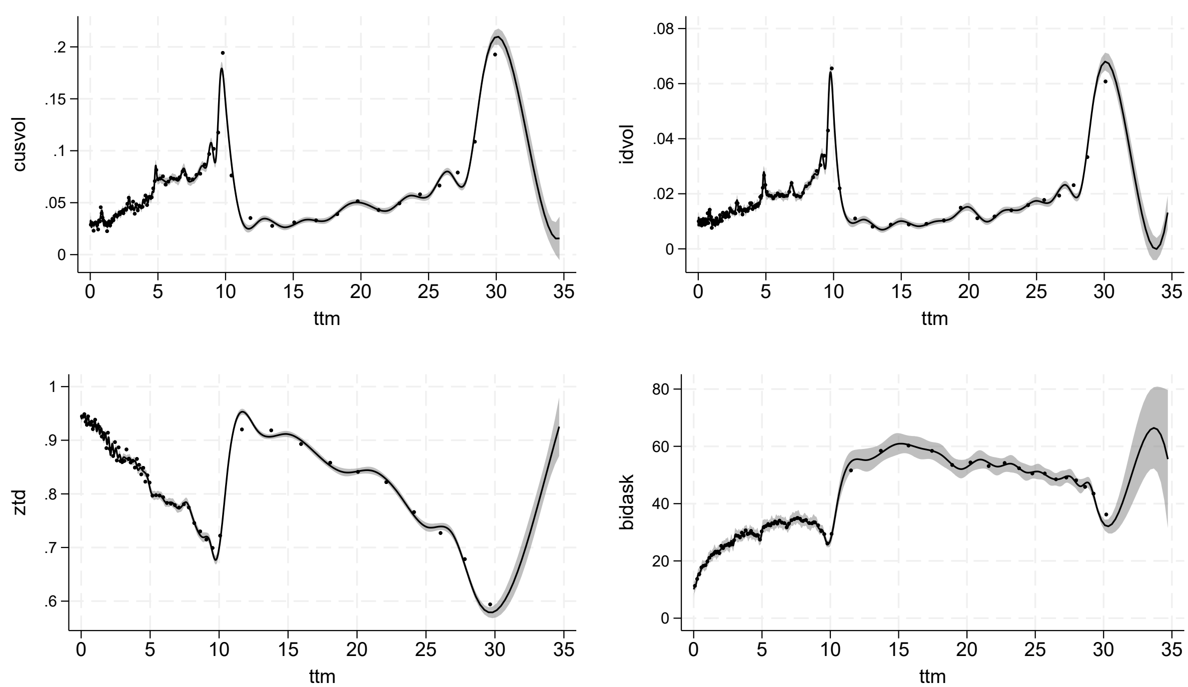


Figure 5. Histogram of Time-to-maturity at Issuance

This figure provides a histogram of times-to-maturity at the issuance of bonds. The x-axis represents time-to-maturity at the issuance in years. Each bin has a width of month.

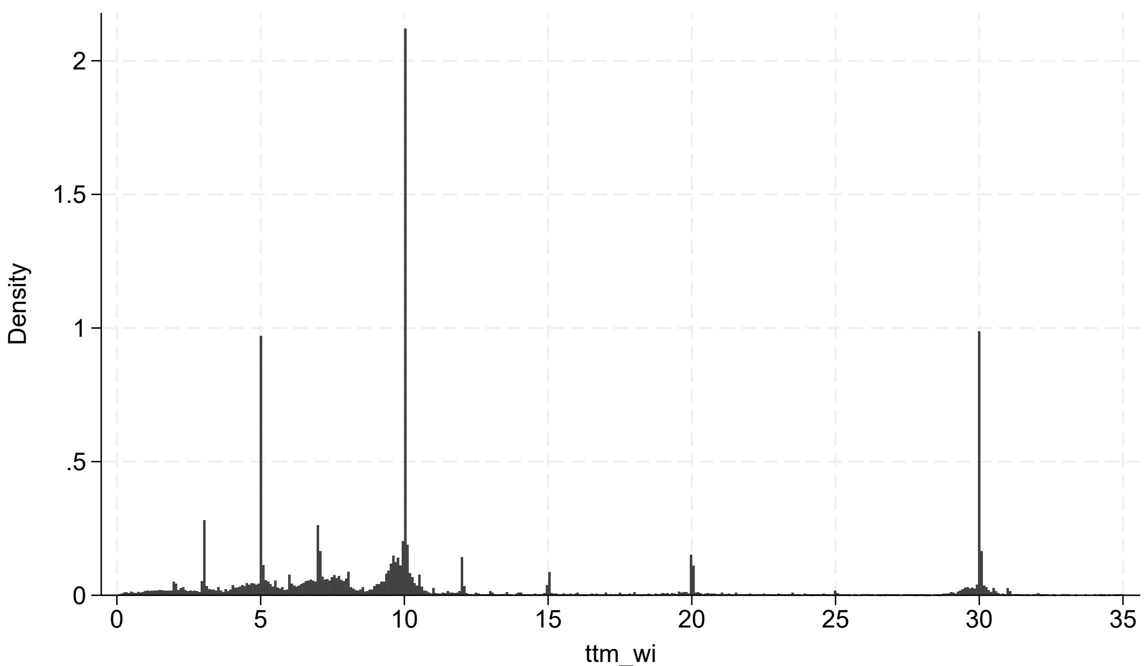
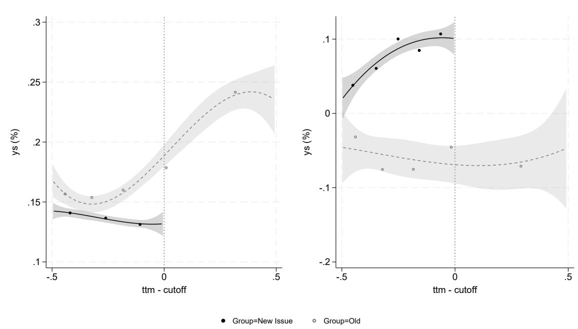


Figure 6. Regression Discontinuity Based on Newly Issued Bonds

This figure visualizes the regression discontinuity around *ttm* cutoffs of 10-years (Panels A1, B1, and C1) and 30-years (Panels A2, B2, and C2). We use the binscatter regression method of Cattaneo et al. (2019), which plots non-parametric relationships through data-driven binned scatter plots with cubic fitted lines. The dependent variable is the yield spread (YS). The x-axis represents the difference between *ttm* and the cutoff. The bandwidth is 0.5 years. The "new issue" group (black, solid line) includes bonds with when-issued *ttm* within a range of ± 2 months from the cutoffs. The "older" group (gray, dashed line) is defined as bonds with when-issued *ttm* >cutoff + 2 months and *age* > 0.5. This practically limits the minimum age of "older" group is at least 0.5 years older than the maximum age of "new issue" group around the cutoffs. In Panel A, we seperately plot period with VIX below its median and the distressed period of VIX above its 80th percentile. In Panels B and C, we use TED and DEF instead of VIX. The shaded area indicates the 95% confidence interval using standard errors clustered by date.

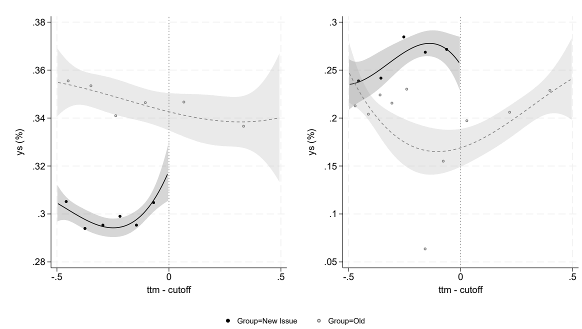
Panel A1. VIX, *Cutoff = 10*

High VIX



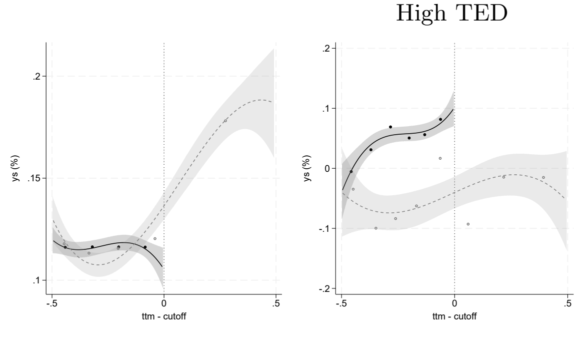
Panel A2. VIX, *Cutoff = 30*

High VIX



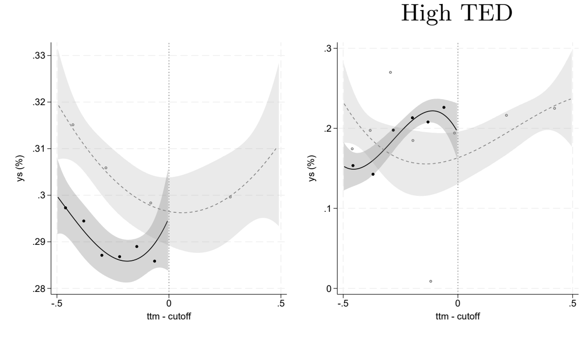
Panel B1. TED, *Cutoff = 10*

High TED



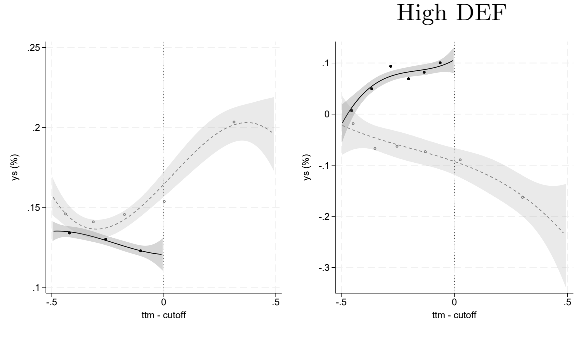
Panel B2. TED, *Cutoff = 30*

High TED



Panel C1. DEF, *Cutoff = 10*

High DEF



Panel C2. DEF, *Cutoff = 30*

High DEF

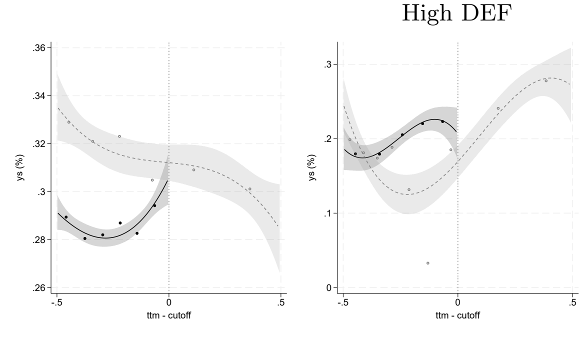


Figure 7. Effects of Search Friction on Yields across Quintiles of VIX, TED, and DEF

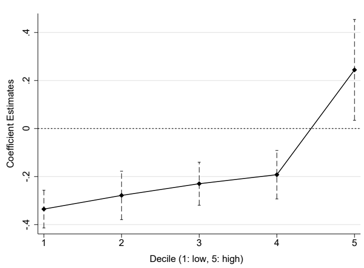
This figure plots the coefficient estimates from the following regressions:

$$YS_{i,t} \quad = \quad \alpha + \sum_{n=1}^{5} \beta_n SF_{i,t} \cdot \mathbb{1}(X \ quintile = n)_t + ctrls_{i,t} + \mu_{v,t} + \varepsilon_{i,t}$$

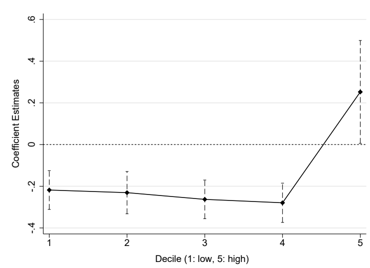
where $\mathbb{1}(X \ quintile = n)$ is a dummy variable that equals to one if VIX (or TED or DEF) belongs to its n-th quintile. Quintile 1 contains the lowest values. $SF_{i,t}$ is the search friction measure: *Centrality* (Panel A); *ChainLength* (Panel B); and *InterDealerRatio* (Panel C). We also include log(ttm), log($amtout$), log(age), as well as issuer-times-day fixed effects. We plot coefficient estimates for β_n for each specification. The vertical band represents the confidence interval at the 95% level using standard errors two-way clustered at the issuer and day levels.

Panel A. *Centrality*

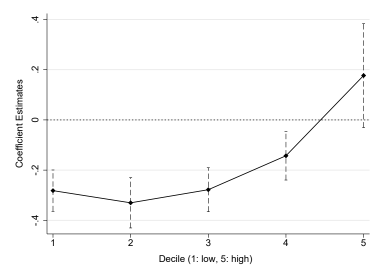
Panel A1. *VIX*



Panel A2. *TED*

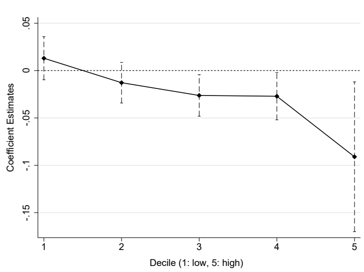


Panel A3. *DEF*

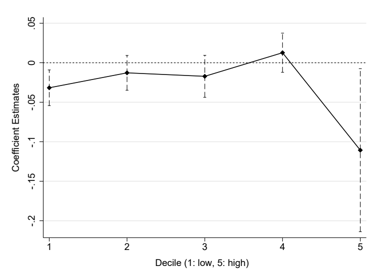


Panel B. *ChainLength*

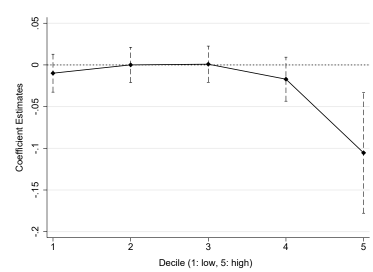
Panel B1. *VIX*



Panel B2. *TED*

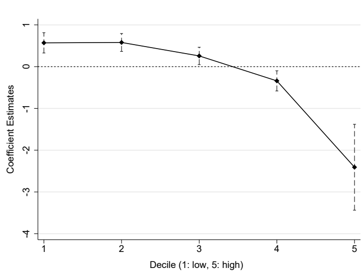


Panel B3. *DEF*

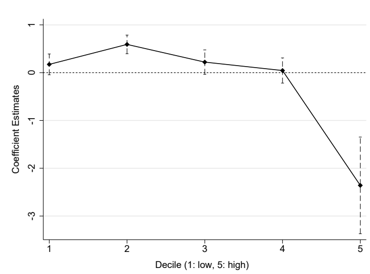


Panel C. *InterDealerRatio*

Panel C1. *VIX*



Panel C2. *TED*



Panel C3. *DEF*

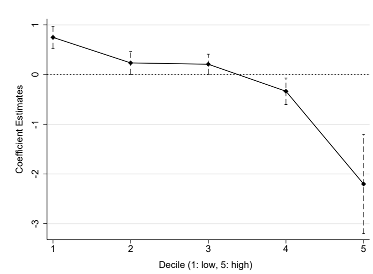
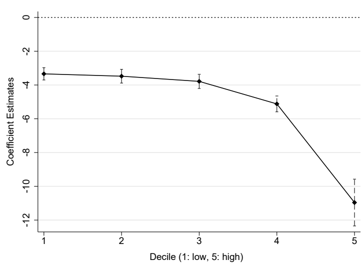


Figure 8. Without Controlling Fundamental Values: Effects of Search Friction on Yields across Quintiles of VIX, TED, and DEF

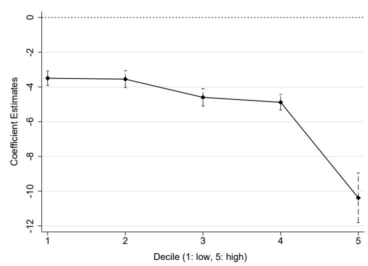
In this figure, we reproduce Figure 7 without controlling for the issuer-times-day fixed effects. Instead, we only include the day fixed effects.

Panel A. *Centrality*

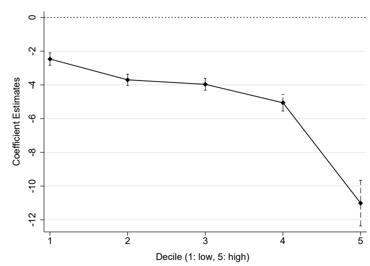
Panel A1. *VIX*



Panel A2. *TED*

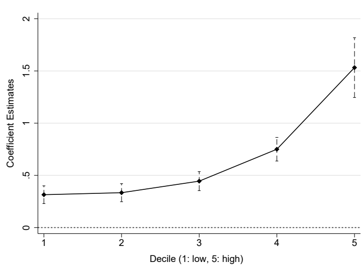


Panel A3. *DEF*

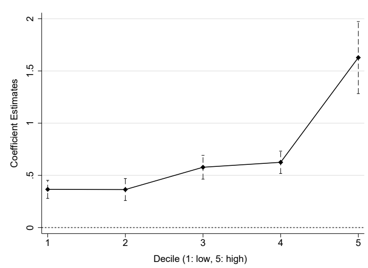


Panel B. *ChainLength*

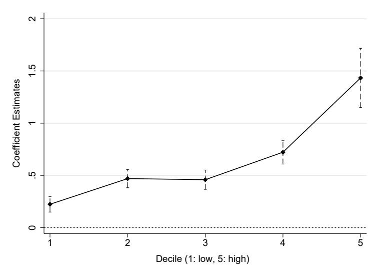
Panel B1. *VIX*



Panel B2. *TED*

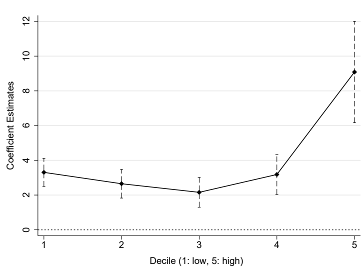


Panel B3. *DEF*

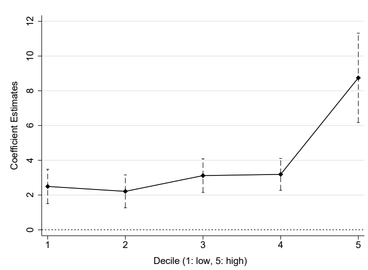


Panel C. *InterDealerRatio*

Panel C1. *VIX*



Panel C2. *TED*



Panel C3. *DEF*

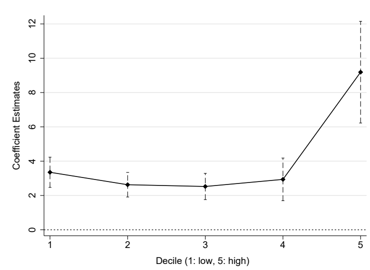


Figure 9. Average Selling Decision and Net Changes in Holding across Level of Liquidity

This figure shows the relationship between *CtrRank* and ICs' selling decision. The x-axis represents *CtrRank*. In Panel A, y-axis is 1(Sold), a dummy variable that equals to one if the IC net sells the bond during the sample window and zero otherwise. In Panel B, y-axis is d(Holding) which is the net change in holdings during the sample window calculated for each IC and bond. The dot represents an average of variables within each *CtrRank*. The vertical band shows the 95% confidence interval.

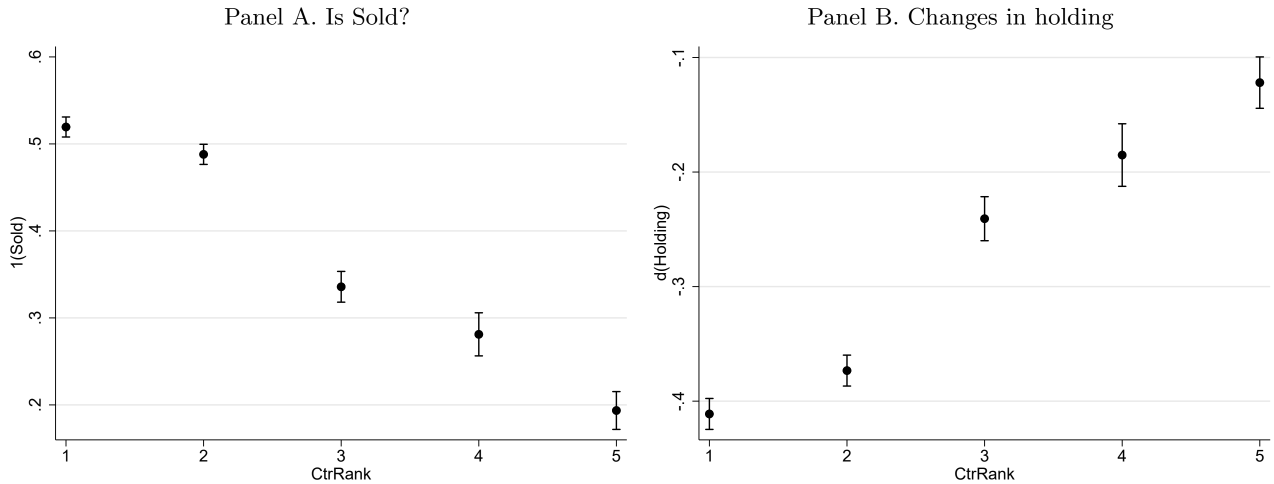


Figure 10. Net Trading of Insurance Company Following Downgrades

This figure displays the average dollar amounts (in par value) of net trades conducted by insurance companies in our sample after experiencing downgrades, plotted separately for each level of *CtrRank*. To visualize the trend, we have employed non-parametric local mean smoothing. The x-axis indicates the number of days following the downgrades.

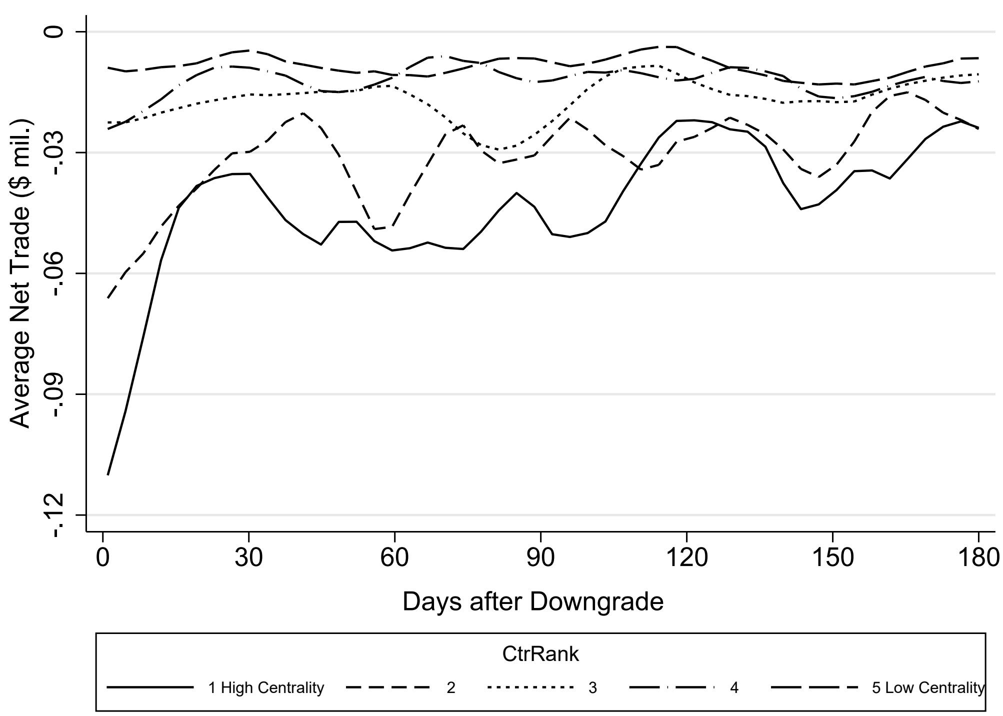


Figure 11. Do Insurance Companies Sell More Liquid Bonds at Lower Prices?

This figure shows the average yield spreads of sample bonds compared to a benchmark group of same-issuer bonds with lower centrality ($CtrRank >= 3$) on days without IC sales. The bond-day observations are divided into six groups based on centrality ranking ($CtrRank = 1, 2, and \geq 3$) and whether IC sells the bond on that day. To estimate the difference from the benchmark for each group, we perform a regression analysis using the following model:

$$YS_{i,t} \quad = \quad \alpha + \sum_{n=1}^{3} \beta_n CtrRank(n)_{j,i,t} \cdot ICsell_{j,i,t} + \sum_{n=1}^{2} \gamma_n CtrRank(n)_{j,i,t} + \mu_{v,j,t} + \varepsilon_{i,t}$$

where $CtrRank(n)$ represents a dummy variable that equals one if $CtrRank = n$ for $n = 1, 2$, and $CtrRank \geq n$ for $n = 3$; otherwise, it is zero. $ICsell_{j,i,t}$ is a dummy variable that equals one if IC j sold bond i on day t, and zero otherwise. We also include downgrade-issuer-IC-day fixed effects ($\mu_{v,j,t}$). The coefficients β_n and γ_n estimate the difference of each group from the benchmark. In Panel A, we use the yield spreads ($YS_{i,t}$) as the dependent variable. In Panel B, we use the yield spreads from sell transactions as Table 6. The vertical dashed line represents the 95% confidence interval for testing the difference from the benchmark average. We use standard errors two-way clustered at the issuer and day levels.

Panel A. Yield spreads

Panel B. Yield spreads (sell transaction)

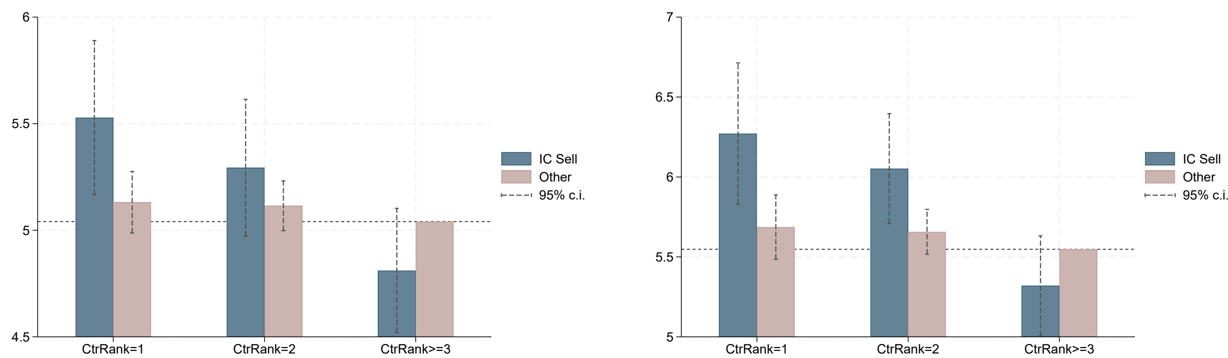


Figure 12. Placebo Events of Three Years Prior to Downgrades: Replicating Figure 11

This figure replicates Figure 11 using placebo dates that are three years prior to the actual downgrades. We use the downgraded bonds in the sample used in Section 4.4 and define placebo downgrade dates as three years before the actual downgrade dates. Since our TRACE sample starts from 2005, the sample is limited to bonds that have placebo events between 2005 and 2017.

Panel A. Yield spreads

Panel B. Yield spreads (sell transaction)

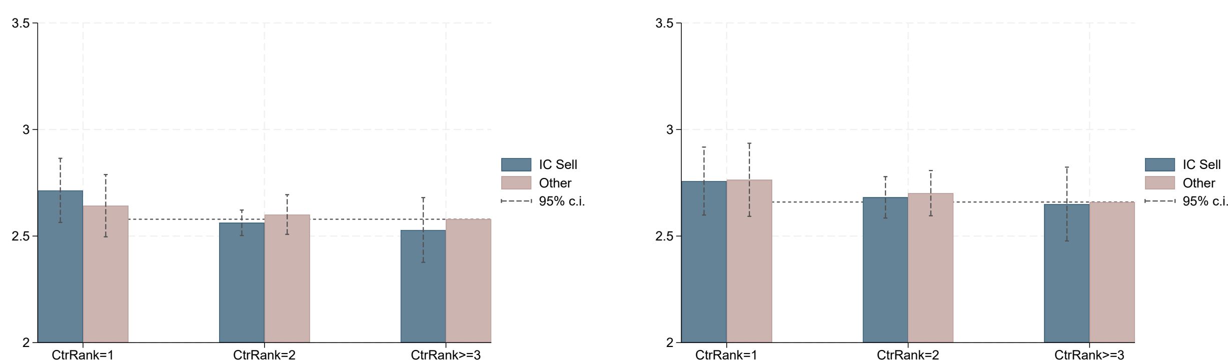


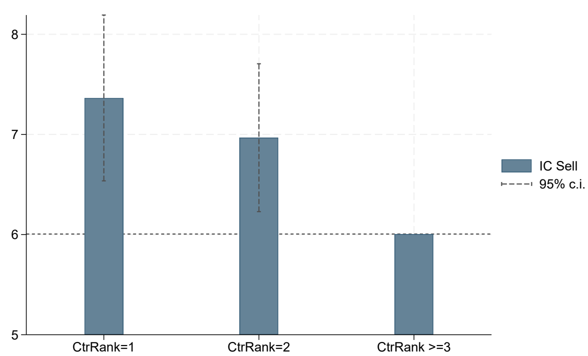
Figure 13. Do Insurance Companies Sell More Liquid Bonds at Lower Prices *on the Same Day?*

This figure shows the estimated average yield spreads of bonds sold by an IC on the same day across different centrality rankings ($CtrRank = 1, 2, and \geq 3$) within the same issuer, in comparison to a benchmark group of bonds with the lowest centrality ($CtrRank >= 3$). We only use bond-day observations with IC sales. We first plot the average yield of benchmark group. To determine the difference from the benchmark average for each group, we conduct the following regression:

$$YS_{i,t} \quad = \quad \alpha + \sum_{n=1}^{2} \beta_n CtrRank(n)_{j,i,t} + \mu_{v,j,t} + \varepsilon_{i,t}$$

where $CtrRank(n)$ represents a dummy variable that takes the value one if $CtrRank = n$ for $n = 1, 2$, and $CtrRank \geq n$ for $n = 3$; otherwise, it is zero. We also include the downgrade-issuer-IC-day fixed effects. The coefficients β_n estimate the difference of each group from the benchmark. This specification leaves us 1,709 IC-bond-day observations where an IC sold multiple same-issuer bonds on a same day. In Panel A, we use the yield spreads ($YS_{i,t}$) as the dependent variable. In Panel B, we use yield spreads from the sell transactions as described in Table 6. The vertical dashed line represents the 95% confidence interval for testing the difference from the benchmark. Standard errors are two-way clustered at the issuer and day levels.

Panel A. Yield spread



Panel B. Yield spread (sell transaction)

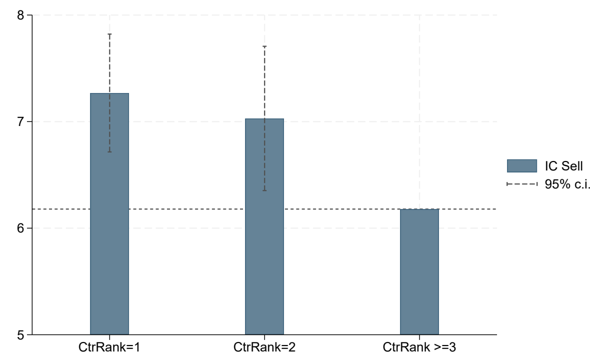
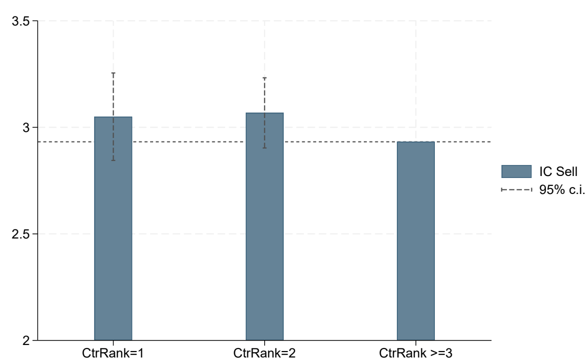


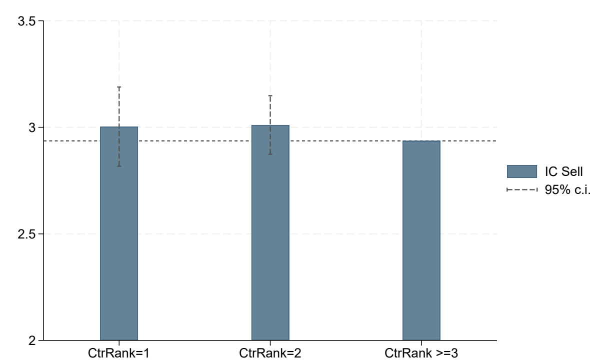
Figure 14. Placebo Events of Three Years Prior to Downgrades: Replicating Figure 13

This figure replicates Figure 13 using placebo dates that are three years prior to the actual downgrades. We use the downgraded bonds in the sample used in Section 4.4 and define placebo downgrade dates as three years before the actual downgrade dates. Since our TRACE sample starts from 2005, the sample is limited to bonds that have placebo events between 2005 and 2017.

Panel A. Yield spreads



Panel B. Yield spreads (sell transaction)



Appendix

A NAIC Subsample Construction

In this section, we provide a detailed explanation of how we build the subsample of insurance company (IC) trades sourced from the NAIC. We use the subsample in Section 4.4 where we examine downgraded bonds held by ICs.

We start from a sample of corporate bonds downgraded between 2007 and 2017Q2.[20] The downgrade is defined based on the median rating of Moody's, S&P, and Fitch ratings.[21] We do not use downgrades that have another downgrade during previous 90 days to focus on the first downgrade in case of multiple consecutive downgrades of a bond. This gives us 14,450 downgrade-bond observations. We keep the downgrades only if there are multiple same-issuer bonds downgraded on the same day having the same ratings before and after the downgrade. The sample shrinks to 11,213 downgrade-bond. We populate the downgraded bond sample into downgrade-bond-IC sample by merging the insurance company holding data from the NAIC. We impute the daily snapshot of IC holdings by using the annual holding and daily transaction data from the NAIC Schedule D. We only keep the downgrade-bond-IC that have multiple same-issuer downgraded bonds held by a same IC. After this step, the sample consists of 140,461 downgrade-bond-IC from 8,011 bond-downgrade observations. We remove downgrade-bond-IC if the IC has not traded the bond or any other same-issuer bonds during the sample window. Our sample window runs from downgrade date through 180 days after the downgrade date. Afterwards, we have 31,861 downgrade-bond-IC from 5,835 downgrade-bond observations. We also add *Centrality* calculated from the Academic TRACE data. We remove downgrade-bond-IC observations if *Centrality* is identical within downgrade-issuer-IC level. The sample consists of 31,720 downgrade-bond-IC observations populated from 5,758 downgrade-bonds.

As a next step, we merge daily transaction data from the downgrade date through 180 days after the downgrade to construct the sample of downgrade-bond-IC-day observations. If there is no transaction in a given bond-date, we still keep the observation in the sample by setting the IC trade volume to be zero and yield variables to be missing. Bonds are removed from the sample if their amount outstanding becomes zero, for example, by the maturity. Finally, we keep only ICs with below-median RBC ratio. The median RBC is calculated each year by using all ICs in the NAIC database. The RBC ratio is obtained from the NAIC data at the end of previous year. As a result, we have 3,256,753 daily observations (2,052,151 observations with available yield) from 19,703 downgrade-bond-IC and 5,076 downgrade-bond observations.

[20] The sample period is limited to our availability of the NAIC database and the Academic TRACE.

[21] If only two ratings are available, we use the lower one.

B Variable Definition

Yield and *YS*. The *Yield* is yield-to-maturity obtained from the TRACE database. We follow Bessembinder, Kahle, Maxwell, and Xu (2008) in defining the daily yield. Specifically, we calculate a daily yield of bond as the trading-volume-weighted average yield for each day, after excluding the negative yields and yields larger than 250%. *YS* is calculated by subtracting a maturity-matched risk-free yield obtained from the Treasury yield curve.

Liquidity Spread. We define the liquidity spread between matched bonds. The matching process is detailed in Section 4.1.1. For the liquid (young) bond and illiquid (old) bond within a matched pair, for each day, we calculate *Liquidity Spread* as following:

$$Liquidity\ Spread \equiv Yield_{\text{(illiquid)}} - Yield_{\text{(liquid)}} \tag{B1}$$

where both yields are available for the day.

daily bidask. We calculate a realized bid-ask spreads as Adrian, Fleming, Shachar, and Vogt (2017). Specifically, we calculate the following daily bid-ask spread for each bond i and day t:

$$bidask_{i,t} \equiv \frac{ask_{i,t} - bid_{i,t}}{(ask_{i,t} + bid_{i,t})/2} \tag{B2}$$

where $ask_{i,t}$ and $bid_{i,t}$ are the transaction-volume-weighted average prices of customer-buy and customer-sell transactions, respectively, for bond i during day t.

CusVol. The sum of customer trading volumes for a bond during a quarter divided by amount outstanding of the bond in par values. *daily CusVol* is calculated daily instead of quarterly.

IdVol. The sum of interdealer trading volumes for a bond during a quarter divided by amount outstanding of the bond in par values. *daily IdVol* is calculated daily instead of quarterly.

ztd. The number of trading days without any trade divdied by the number of all trading days, calculated for each bond and each quarter.

DlrCentrality and *Centrality*. We first calculate the centrality of dealers, *DlrCentrality*, by computing the eigenvector centrality of interdealer network similar to Li and Schürhoff (2019) and Friewald and Nagler (2019). Each month, two dealers (nodes of the network) are connected if there are interdealer trades between the two dealers during the month. We weight the connections by numbers of trades between the two dealers during the month. We aggregate *DlrCentrality* at the bond-level to calculate *Centrality* by taking an average of the dealer centrality weighted by numbers of trades by the dealer on the bond during the month.

ChainLength. We define the intermediation chain as linked round-trip trades by following Friewald and Nagler (2019) and identify the intermediation chains using their algorithm. Specifically, an intermediation chain is defined as a chain of trades which starts from customer sales and ends when the initial volumes are moved to customers through dealer trades. Following Friewald and Nagler (2019), we define the length of chain as number of unique dealer in an intermediation chain. Finally, *ChainLength* is an average length of chains duirng the past 180 days. We assign zero length if there is no intermediation chain.

InterDealerRatio. We define number of interdealer trades divided by number of all trades during the past 180 days as *InterDealerRatio*.

VIX. The CBOE Volatility Index.

TED. The 3-Month London Interbank Offered Rate (LIBOR) based on US dollars minus 3-Month Treasury Bill rates.

DEF. Moody's seasoned Baa corporate bond yields minus Moody's seasoned Aaa corporate bond yields.

C Other Tables and Figures

Table A1. Descriptive Statistics: Downgraded Bonds held by Insurance Company

This table provides descriptive statistics of sample of downgraded bonds held by insurance company. The sample construction is detailed in the Section 3.1.

	N	Mean	Std	P5	P25	P50	P75	P95
Credit Rating (before)	19,703	13.618	3.479	7	12	14	16	18
Credit Rating (after)	19,703	12.431	3.624	6	10	13	15	17
Rating Difference	19,703	1.187	0.558	1	1	1	1	2
YS	2,052,151	5.729	8.182	0.631	1.500	3.177	6.398	19.584
YS (sell transaction)	1,452,085	6.308	9.008	0.702	1.661	3.588	7.072	21.355
ttm	2,052,151	7.375	7.413	0.917	2.888	5.281	7.830	25.990
age	2,052,151	4.285	2.728	1.106	2.248	3.715	5.728	9.142
amtout	2,052,151	1458	1040	349	700	1157	2000	3500
Centrality	2,052,151	0.551	0.155	0.255	0.504	0.580	0.638	0.725

Table A2. Frequency Table across $CtrRank$

This table provides frequency of sample observations across $CtrRank$. We define $CtrRank$ as a ranking of the centrality ($Centrality$) within the same-issuer bond held by an IC. $CtrRank = 1$ represents the highest centrality bond.

CtrRank:	1	2	3	4	5
N:	7,254	7,162	2,746	1,270	1,271

Figure A1. Relationship between Time-to-maturity and Institutional Ownership across Maturity at Issuance

This figure shows relationships between time-to-maturity (*ttm*) and the four liquidity-related variables in 4 for bonds with when-issued *ttm* of 3, 5, 7, 10, 20, and 30 separately. We use binned scatter plot of Cattaneo et al. (2019) to fit non-parametric way.

Panel A. Mutual Fund Panel B. Insurance Company

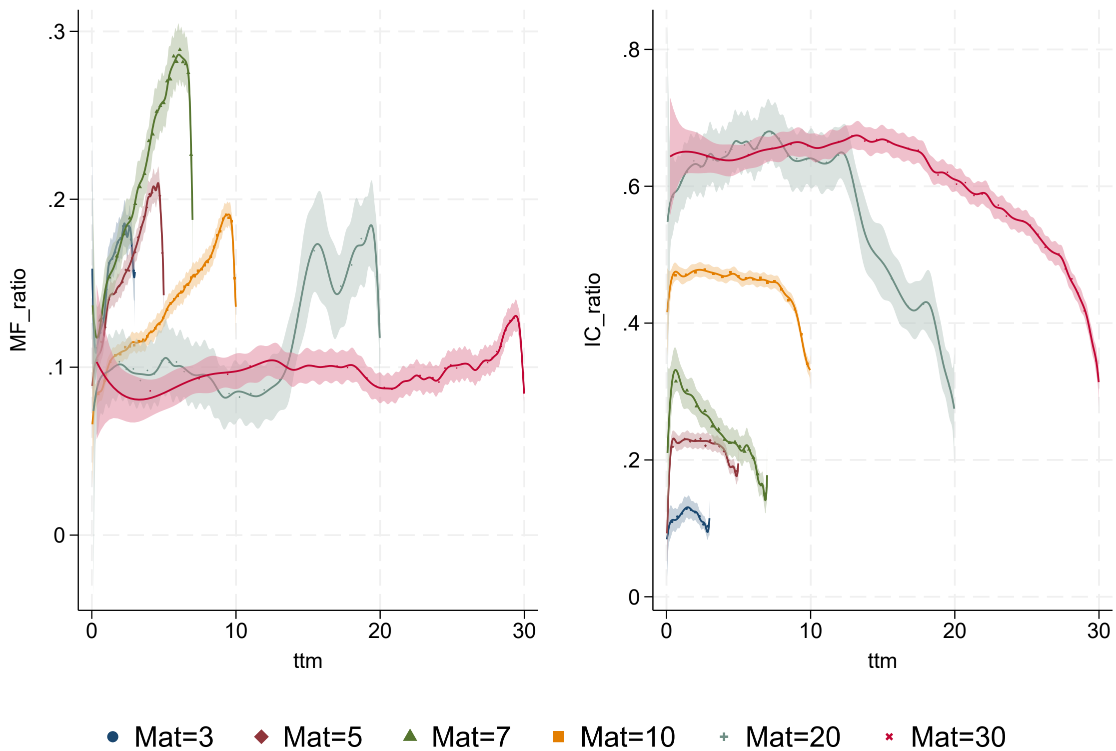


Figure A2. Relationship between Time-to-maturity and Institutional Ownership in Pooled Sample

This figure shows the relationship between time-to-maturity (*ttm*) and ownerships of mutual fund and insurance company in a non-parametric way. The ownership information is obtained from the eMAXX and calculated each quarter-end. We use data-driven non-parametric binned scatter plot of Cattaneo et al. (2019).

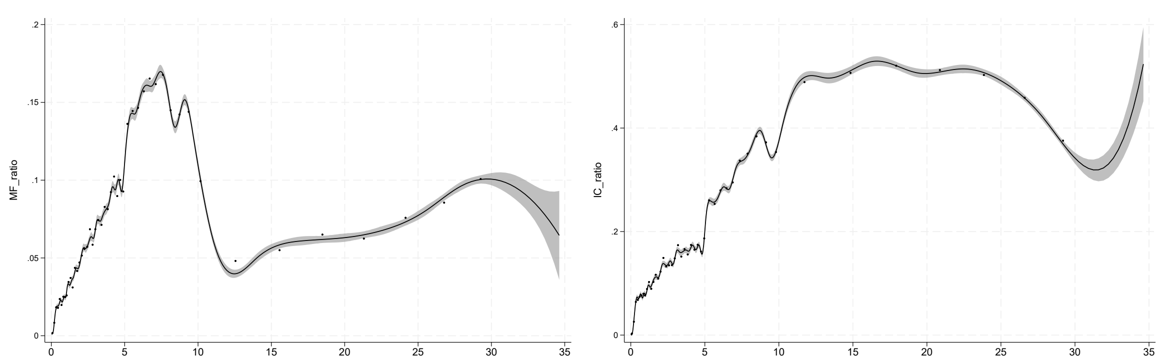


Figure A3. Net Trading of Less-constrained Insurance Company Following Downgrades

This figure displays the average dollar amounts (in par value) of net trades conducted by less-constrained insurance companies after experiencing downgrades, plotted separately for each level of *CtrRank*. To visualize the trend, we have employed non-parametric local mean smoothing. The x-axis indicates the number of days following the downgrades.