Centralizing Over-the-Counter Markets: Evidence from the China Interbank Bond Market

Songtao Wang* Shunwei Zhu†

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Abstract

A centralized trading mechanism, namely X-Bond, was introduced in the China Interbank Bond Market (CIBM) in September 2016. Using proprietary transaction-level data on central government bonds from the China Foreign Exchange Trade System (CFETS), we find that X-Bond trading has significantly lower price impact and execution cost than decentralized bilateral inquiry and RFQ trading. This finding holds true even after controlling for bond characteristics and addressing the endogeneity issue. Nonetheless, the market share of X-Bond is low, only at 20%−30%. To rationalize this phenomenon, we develop a theoretical model in which traders' choice of trading mechanism is jointly determined by the liquidity effect and the learning effect. The model shows that when traders' valuations are idiosyncratic component dominates and private signals about asset value are imprecise, most traders optimally prefer the decentralized OTC market even if the centralized market is more liquid. As information precision improves, however, the model predicts a shift toward the centralized market—consistent with the empirical evidence.

Keywords: Trading mechanisms, Liquidity, Learning effect, Information precision, Endogenous market structure.

JEL codes: D53, D83, G14

*Antai College of Economics and Management, Shanghai Jiao Tong University, Shanghai, China, 200030; e-mail: st.wangzh@gmail.com

†Antai College of Economics and Management, Shanghai Jiao Tong University, Shanghai, China, 200030; e-mail: zhushunwei@sjtu.edu.cn.

1 Introduction

Traditional over-the-counter (OTC) markets rely on human intermediaries and are characterized by bilateral search and bargaining (Duffie, Gârleanu, and Pedersen, 2005). For many asset classes, such as corporate and municipal bonds, mortgage-backed securities, foreign currencies, spot commodities, and non-standard derivatives, OTC markets are the prevailing trading platforms. In recent years, there has been a marked tendency towards the centralization of OTC markets.[1]

In the China Interbank Bond Market (CIBM), a novel trading mechanism known as X-Bond was introduced in September 2016, with the objective of enhancing market efficiency and liquidity. Unlike other decentralized mechanisms—including bilateral inquiry and request for quote (RFQ)—in the CIBM, X-Bond is a centralized mechanism. Through X-Bond, traders submit orders anonymously, which are then matched automatically under price-time priority and cleared at a single price. Unmatched orders stay in the central limit order book (CLOB) for other participants to click. In this study, focusing on the CIBM, we investigate the impact of centralizing OTC markets on liquidity as well as the choice of traders between decentralized and centralized mechanisms in OTC markets and the underlying rational for the choice.

The extant literature has not yet reached a consensus on whether decentralized or centralized trading mechanisms offer greater liquidity. In decentralized trading, personal interaction with clients allows voice brokers to gather additional market information ("market color") and potentially obtain better prices (Barclay, Hendershott, and Kotz, 2006; Man, Wang, and Wu, 2013).[2] By contrast, centralized trading facilitates faster order submission and execution and enables a greater role for computer-driven and

[1] Nagel (2016) documents a major transformation in fixed income markets beginning in the late 1990s, when electronic communication networks (ECNs) started to gain prominence in interdealer trading of liquid sovereign bonds. These ECNs are trading systems that electronically match buy and sell orders for securities and frequently operate using a central limit order book (CLOB) protocol. Reflecting the global scope of this development, many countries have introduced platforms that function as ECNs, such as MTS in Italy, EuroMTS in Europe, eSpeed and BrokerTec in the United States, BB Super Trade and Tri-Trade in Japan, Selic in Brazil, NDS-OM in India, KTS in Korea, and E-bond in Singapore.

[2] In equity markets, floor-based trading (Venkataraman, 2001) and trading through upstair brokers (Bessembinder and Venkataraman, 2004) are found to deliver lower execution costs than CLOB trading. In the corporate bond market, O'Hara and Zhou (2021b) show that all-to-all trading, while providing some liquidity in crisis periods, does so at prohibitively high costs. In the Chinese foreign exchange market, Holden et al. (2021) document a non-monotonic pattern as trading migrates from CLOB to OTC: initially, one-way relative effective spreads are lower on the CLOB than OTC, then they converge, and eventually OTC spreads become lower. Theoretical work also explains why OTC trading can sometimes be cheaper than exchange trading. Lee and Wang (2022) develop a model in which OTC spreads are lower than exchange spreads because OTC trading requires a trader to reveal her identity. Dealers can then offer discounts to counterparties that pose low adverse selection risk. By contrast, informed traders prefer to trade on the exchange, where they can better conceal their identity. Their presence raises adverse selection risk and widens exchange spreads.

automated trading strategies (Fleming, Mizrach, and Nguyen, 2018).[3] These offsetting forces make it an empirical question which trading mechanism dominates in terms of liquidity.

Using a sample of 546 central government bonds issued by the Ministry of Finance and policy banks, with maturities of 2, 3, 5, 7, and 10 years, we examine the impact of X-Bond on bond illiquidity. Our analysis relies on two frequently used measures of bond illiquidity: one is the Amihud's (2002) illiquidity measure, which captures the price impact of order flow, and the other is the Roll's (1984) effective bid-ask spread, a proxy for execution cost. The descriptive statistics indicate that X-Bond trading has significantly lower price impact and execution costs than bilateral inquiry and RFQ trading. This finding holds true within subsamples sorted by bond age, maturity, issue size, and return volatility. The results obtained from a panel regression, controlling for bond characteristics as well as time and bond fixed effects, are similar.

A key concern is endogenous venue choice: market participants may route inherently more liquid bonds to X-Bond, so the observed liquidity advantage may reflect selection rather than X-Bond's anonymous, automated order-matching design. We address this concern in two different ways. First, we compare illiquidity of the same bond executed through X-Bond versus bilateral inquiry and RFQ on the same day, so that bond fundamentals and market-wide conditions are held consistent; any remaining differences in the illiquidity more plausibly reflect venue-specific design. Second, we estimate a Heckman (1979) selection model to correct for non-random participation in X-Bond. Both approaches deliver the same conclusion: X-Bond trades have significantly lower price impact and execution costs even after accounting for the selection bias.

Liquidity is an important determinant of trading-venue choice (e.g. Bessembinder and Venkataraman, 2004; Biais and Green, 2019); the lower price impact and execution costs of X-Bond trading suggests that it should dominate bond trading in the CIBM. However, we find that, from September 2017 to June 2021,

[3]Biais and Green (2019) show that, before World War II, corporate and municipal bonds traded actively on the NYSE's limit-order book, with municipal bond trading costs in 1926-1927 roughly half those in today's OTC markets. They also find that small investors' corporate bond trading costs in the 1940s were as low as, or lower than, current levels. These patterns suggest that rising transaction costs are closely linked to the shift from exchange-based to OTC market structures. The Israeli bond market illustrates that an active CLOB-based trading structure is feasible. Abudy and Wohl (2018) document that corporate bonds traded on the Tel Aviv Stock Exchange incur lower trading costs than stocks traded on the same exchange. Complementing this evidence, Kutai, Nathan, and Wittwer (2025) find that Israeli Treasury bonds traded on the Tel Aviv Stock Exchange exhibit higher liquidity during crises, and that substantial customer-to-customer trading persists on the exchange throughout these periods.

only 28.10% of trades are executed through X-Bond, and the market share of the corresponding trading volume is even lower, at 20.53%. One potential explanation for the low market share of X-Bond may be the information asymmetry: in centralized, anonymous trading, informed traders may trade more aggressively while concealing their identities, discouraging less-informed traders from participating (e.g., Kyle, 1985; Lee and Wang, 2022). This channel is less compelling in the CIBM, where participation is limited to qualified institutional investors who are likely to be relatively sophisticated, reducing within-market information disparities. Moreover, if X-Bond disproportionately attracted informed traders, standard adverse-selection logic would predict higher price impact and wider effective spreads on X-Bond. Instead, we find the opposite: X-Bond trading exhibits lower price impact and lower execution costs than bilateral inquiry and RFQ trading. Another possible explanation is that human intermediaries in decentralized bilateral inquiry and RFQ markets add value by using relationship-based information to locate counterparties and uncover hidden liquidity, especially in less active markets. Consistent with this view, Barclay, Hendershott, and Kotz (2006) argue that search-based OTC mechanism gains market share when U.S. Treasury securities go off the run. If human intermediation were the main force behind X-Bond's limited adoption, we would expect X-Bond to be used more for on-the-run bonds than for off-the-run bonds. Instead, we find that X-Bond's market share is similarly low for on-the-run bonds—31.17% by number of trades and 20.92% by trading volume—suggesting that dealers' order-matching role is unlikely to fully account for X-Bond's persistently low market share.

We develop a simple model of endogenous venue choice to rationalize the empirical puzzle. In the model, we consider a two-period economy with a risky asset traded by a finite number of strategic, risk-averse traders with quadratic utility functions. There are two trading venues in the economy: a decentralized OTC market that is non-anonymous and search-based, and a centralized market that is anonymous and automated. Each trader's valuation has a common component shared across traders and an idiosyncratic component that varies across traders. Idiosyncratic value components are correlated among traders. At period 0, each trader chooses to enter a market; at the beginning of period 1, the markets are open, and he receives a private signal about his valuation of the risky asset. In the centralized market, the equilibrium price effectively averages traders' signals, so idiosyncratic components

are largely diversified away, which reduces individual price impact. In the OTC market, traders can target counterparties whose asset valuations are most negatively correlated with theirs, which improves their learning about the asset value. Liquidity and learning effects create a trade-off in traders' venue choice.[4]

Our model shows that equilibrium venue choice is jointly determined by the relative importance of common versus idiosyncratic components in traders' valuations and the precision of traders' private signals, because these primitives govern the trade-off between liquidity and learning. When the idiosyncratic component dominates, traders prefer the OTC venue: bilateral, non-anonymous trading allows counterparty selection and facilitates learning about asset value. This learning advantage is amplified when private signals are noisy. By contrast, when valuations are largely common or private signals are sufficiently precise, the marginal benefit of learning is small and liquidity considerations dominate, leading traders to prefer the centralized market. Applied to the CIBM, the model implies that X-Bond can remain low market share despite superior liquidity because its anonymous, automated design limits learning relative to decentralized mechanisms such as bilateral inquiry and RFQ.

Furthermore, our model predicts that the number of traders who favor the centralized market increases with the information precision. Intuitively, as the information precision improves, the learning effect weakens and liquidity plays a dominant role in determining traders' venue choice. Consequently, the increasing liquidity effect attracts more traders to the centralized market where the price impact is lower and liquidity is higher.

We test this prediction in the cross-section of individual bonds. Using proprietary proprietary data on bond quotes from CFETS, we construct a daily measure of information precision for sample bonds with at least three quotes on a given day. We first examine the determinants of this measure in panel regressions and find that information precision is higher for older bonds, lower for bonds with longer time to maturity, and lower for bonds with higher return volatility. Turning to the model's central implication, we sort bonds into portfolios by information precision and show that X-Bond market share increases monotonically across the portfolios. This pattern indicates a systematic shift toward OTC trading when information precision is low and toward centralized trading when it is high. The positive

[4]In the model, the choice of trading venue is tantamount to the choice of trading mechanism, given that only a single trading mechanism is available in each venue.

relation between information precision and X-Bond market share remains statistically and economically significant after controlling for an extensive set of bond characteristics and including time and bond fixed effects.

2 Literature review and our contributions

A large market microstructure literature studies trading-mechanism choice in OTC markets where multiple mechanisms coexist. Empirically, one strand focuses on investors' choice between bilateral trading (one-to-one) and RFQ trading (one-to-many). In the U.S. corporate bond market, Hendershott and Madhavan (2015) and O'Hara and Zhou (2021a) show that RFQ activity is concentrated in more active and liquid bonds, yet RFQ accounts for a relatively low market share—below 14% by trading volume. Similarly, Allen and Wittwer (2023) find that bilateral trading continues to dominate in the Canadian government bond market, with limited migration to RFQ.

A related strand examines mechanism choice when automated, centralized all-to-all trading systems become available. In the U.S. corporate bond market, Hendershott, Livdan, and Schürhoff (2025) show that all-to-all trading grows steadily after its introduction in 2012 but remains limited, reaching only about 12% of electronic platform trades by 2018; O'Hara and Zhou (2021b) document that all-to-all liquidity provision increases during crisis periods but remains small. In the U.S. Treasury market, Barclay, Hendershott, and Kotz (2006) find that trading shifts from fully automated systems to voice brokers when bonds go off the run and liquidity deteriorates. In the U.S. foreign exchange market, King, Osler, and Rime (2012) report that electronic CLOB trading largely displaces OTC trading for liquid currency pairs, whereas Holden et al. (2021) show that in China, when a decentralized OTC market is introduced alongside a centralized CLOB, trading migrates primarily to the OTC venue. In the index CDS market, Collin-Dufresne, Junge, and Trolle (2020) and Riggs et al. (2020) find that even with access to a CLOB that supports all-to-all trading, CLOB activity represents only a small fraction of total volume.

Our paper contributes to this empirical literature by studying investors' venue choice between centralized and decentralized trading mechanisms in the China Interbank Bond Market (CIBM). In U.S. and European bond markets, trading typically features a two-tier structure, with a customer-dealer segment

and an interdealer segment. As a result, prior work generally examines either customers' mechanism choice in the customer-dealer segment of corporate bond markets (e.g., Hendershott and Madhavan, 2015; O'Hara and Zhou, 2021a) or dealers' mechanism choice in the interdealer segment of government bond markets (e.g., Barclay, Hendershott, and Kotz, 2006; Man, Wang, and Wu, 2013). By contrast, the CIBM does not exhibit a comparable two-tier segmentation. This institutional feature allows us to analyze trading-venue choice for both customers and dealers within a single, integrated market rather than within one segment in isolation.

Our paper also contributes to the theoretical literature on trading-mechanism choice. Glebkin, Yueshen, and Shen (2023) develop a model of investors' choice between bilateral trading and RFQ trading to explain the sluggish adoption of RFQ in OTC markets. A related empirical regularity is that, conditional on using RFQ, investors typically solicit quotes from only a small number of dealers. Riggs et al. (2020), Wang (2023), and Baldauf and Mollner (2024) rationalize this behavior by modeling the optimal number of dealers to contact under RFQ from complementary perspectives. In contrast to this RFQ-focused work, our theory emphasizes venue choice between decentralized and centralized mechanisms through a liquidity-learning trade-off.

A second strand of theoretical research studies investors' choice between search-based OTC markets and automated trading systems, motivated by the widespread observation that trading often remains concentrated in search-based OTC venues even when automation is available. Bolton, Santos, and Scheinkman (2016) develop a theory in which informed dealers in OTC markets can use their informational advantage to cream-skim good assets, thereby explaining the simultaneous growth of the financial intermediation sector and dealer compensation. Glode and Opp (2020) endogenize traders' expertise to account for the continued prevalence of OTC markets and compare the efficiency of OTC and CLOB markets in this setting. Dugast, Uslu, and Will (2022) study endogenous mechanism choice by banks with heterogeneous trading capacities and show that low- and high-capacity banks optimally select OTC, whereas intermediate-capacity banks prefer centralized trading. Lee and Wang (2022) propose a model in which OTC trading is privately optimal for uninformed traders, while exchange trading is optimal for informed traders.

Unlike much of the existing theory, our model centers on a trade-off between liquidity and learning in trading-mechanism choice. When the idiosyncratic component dominates traders' valuations, they prefer the OTC venue: bilateral, non-anonymous trading enables counterparty selection and facilitates learning about asset value. This learning advantage is amplified when private signals are noisy. When valuations are largely common or private signals are sufficiently precise, however, the marginal benefit of learning is small and liquidity considerations dominate, leading traders to prefer the centralized market. Our focus on learning in OTC markets relates to theories in which OTC trading facilitates information diffusion (Duffie, Malamud, and Manso, 2014; Golosov, Lorenzoni, and Tsyvinski, 2014; Babus and Kondor, 2018).

3 China interbank bond market

The China Interbank Bond Market (CIBM) was formed in 1997 after the People's Bank of China (PBOC) mandated commercial banks to move their bond trading out of the stock exchanges and into an over-the-counter (OTC) market. After more than two decades of rapid growth, the CIBM is now the largest domestic bond market in China[5] and the second largest in the world, only trailing the U.S. bond market. As of June 2021, the CIBM had approximately RMB 70.79 trillion (i.e. US$ 10.96 trillion) in outstanding volume. As a wholesale market, the CIBM restricts participation to qualified institutional investors, including commercial banks, mutual funds, insurance companies, and securities firms. In 2010, overseas investors were permitted to trade in the CIBM. The number of institutional participants in the CIBM has reached 21,338 by June 2021.

A variety of bonds are traded in the CIBM, and based on issuing entities, they can be classified into four broad categories: (1) central government bonds that include Treasury bonds issued by the Ministry of Finance and policy bank bonds issued by China Development Bank, Export-Import Bank of China, and Agricultural Development Bank of China. Central government bonds represent the creditworthiness of China as a sovereign nation and are backed by the fiscal revenue collected by the central government of China and are therefore default-free; (2) municipal bonds issued by local governments in China. Municipal bonds were first issued in 2009 as a part of the four-trillion-yuan stimulus plan in the wake of 2007-2008

[5]In China, there are two largely segmented bond markets: one is the CIBM and the other is the exchange-based bond market that is part of Shanghai and Shenzhen Stock Exchanges.

global financial crisis; (3) financial bonds issued by largely state-owned financial institutions that often operate with implicit government guarantee; (4) enterprise bonds issued by non-financial firms as an alternative to bank loans.[6] The outstanding volume of central government bonds (municipal bonds; financial bonds; enterprise bonds) amounted to RMB 21.45 (11.36; 7.44; 11.49) trillion at the end of June 2021.

Trading mechanisms

In the CIBM, prior to October 2013, bonds were primarily traded through bilateral inquiry and market-making quotation. Bilateral inquiry is a trading mechanism in which traders search for counterparties and then engage in bilateral negotiations with them, and market-making quotation is an alternative mechanism in which dealers quote prices at which they will buy and sell securities and at the same time the volume in which they are willing to trade.

In October 2013, the CFETS introduced a third trading mechanism, namely request for quote (RFQ), in the CIBM. By allowing a trader to query multiple dealers simultaneously, RFQ provides considerable time savings relative to the alternative of a sequence of bilateral negotiations with the same group of dealers. From an economic perspective, RFQ is a sealed bid auction with an undisclosed reservation price. At the end of the auction, the trader reviews the dealer responses and selects the best quote. In the CIBM, dealers are obligated to response to RFQ, and the number of responses is an indicator to be used in the annual assessment of their market-making performance. RFQ provides traders a way to source liquidity, along with market-making quotation.

In September 2016, to further enhance liquidity in the CIBM, the CFETS launched X-Bond, which, unlike bilateral inquiry, market-making quotation, and RFQ, is a centralized trading mechanism. Through X-Bond, traders can anonymously submit their orders that are automatically matched based on the principle of price and time priority and cleared at a single price, and unmatched orders stay in the CLOB (Central Limit Order Book) for other participants to click.[7]

In the presence of parallel trading mechanisms, a natural question to ask is which mechanism pre-

[6] See Amstad and He (2019) for a more detailed discussion of bond categories in the CIBM.

[7] Although not yet open to all market participants, the X-Bond platform has been granted to the most active investors, by whom more than 90% of trades in the CIBM are conducted.

dominates. In this study, we aim to examine traders' mechanism choice in the CIBM and to uncover the underlying motivations that drive the choice.

CIBM vs. U.S. bond market

The CIBM has a very different microstructure compared to the U.S. bond market.

First, there is no clear market stratification in the CIBM, and the role of dealers is somewhat blurry. Specifically, in the CIBM, in addition to serving as liquidity providers, dealers can also trade bonds and demand liquidity as investors; investors can trade directly with each other without dealers involving. In the U.S. bond market, however, the primary role of dealers is to provide liquidity, and investors can only trade with dealers.

Second, in the U.S. bond market, there are dedicated interdealer platforms such as BrokerTec and eSpeed in which dealers can trade with each other and manage their inventory risk; in the CIBM, there do not exist such platforms.

Third, different types of bonds can be traded on a single platform in the CIBM, while a trading platform is only for a specific category of bonds in the U.S. bond market (e.g. GovPX, BrokerTec, and eSpeed for Treasury securities; MSRB and Municenter for municipal bonds, and MarketAxess for corporate bonds).

4 Data

In this study, the transaction-level data we use is obtained from the CFETS, which, as the operating agency of the CIBM, collects detailed information on each bond trade in the CIBM, including bond ID, bond type, trade execution date and time, trade price and quantity, the identities of traders, etc. For trades executed through market-making quotation and RFQ, the CFETS also identifies the underlying dealers. The sample covers the period September 2017 through June 2021.[8]

We restrict our analysis to central government bonds with maturities of 2, 3, 5, 7, and 10 years, which are among the most actively traded bonds and have the highest outstanding volume in the CIBM.[9]

[8] As noted in Section 3, X-Bond was first introduced in the CIBM in September 2016. To reduce the potential impact of noise trades in the initial adaptation period, our analysis excludes observations in the year subsequent to the introduction of X-Bond.

[9] For robustness, we perform the empirical analysis for Treasury bonds and policy bank bonds as well as bonds with maturities of 3, 5, and 10 years, respectively, and the results are presented in Appendix Tables B.1 and B.5.

Unreported results indicate that for bonds in the sample, market-making quotation trades account for only less than 1% of the total and are excluded from the following empirical analysis. For the remaining trades, we classify them into two groups: one consists of bilateral inquiry and RFQ trades, and the other consists of X-Bond trades. Based on search and bargaining, bilateral inquiry and RFQ trades are both of the OTC type and are thus classified into the same group; in contrast, X-Bond trades are analogous to trades in the exchange as they are anonymous and automatically executed.

4.1 Summary statistics

As shown in Table 1, our sample comprises a total of 546 bonds, including 153 10-year, 135 7-year, 133 5-year, 96 3-year, and 29 2-year bonds. Of these bonds, 151 are issued by the Ministry of Finance and the remainder by three policy banks. Panel A of Table 2 provides summary statistics of bond characteristics such as issue size, age, time to maturity, number of trades, trading volume, and trade size.[10] The results indicate that bonds in the sample have an average age of 1.99 years and an average time to maturity of 4.08 years, and their issue size is quite large, averaging RMB 124.75 billion. From September 2017 to June 2021, 95 bonds are traded with 5,480 transactions a day. On average, a single bond is traded 54 times a day, and the daily trading volume is RMB 3.33 billion. The average trade size is up to RMB 129.12 million. Furthermore, we find that the bottom 25% of bonds are traded less than seven times a day, while the top 25% of bonds are traded more than 26 times a day, suggesting that the trading activity varies considerably across the sample. The last row of Panel A shows that the volatility of daily bond returns exhibits a highly right-skewed distribution, implying that some bonds are very volatile. In Panels B and C, we report summary statistics for bonds traded through bilateral inquiry and RFQ and through X-Bond, respectively. The statistics reveal that, on average, bonds traded through X-Bond are younger and more volatile and have a longer time to maturity, with larger issue and trade sizes.

4.2 Measures of bond illiquidity

In the market microstructure literature, a number of measures have been proposed to gauge the illiquidity of bonds.[11] In the following, our analysis relies on two frequently used measures of bond

[10] The statistics presented in Table 2 are the time-series means of daily cross-sectional statistics.

[11] Refer to Schestag, Schuster, and Uhrig-Homburg (2016) for a comprehensive survey of bond illiquidity measures.

illiquidity. The first one is the intraday version of Amihud's (2002) measure, and it reflects the impact of order flow on price. Precisely, for bond j on day t, this measure is defined as

$$Amihud_t^j = \frac{1}{N_t^j - 1} \sum_{k=2}^{N_t^j} \frac{\left| \frac{P_{t,k}^j - P_{t,k-1}^j}{P_{t,k-1}^j} \right|}{VOL_{t,k}^j} \tag{1}$$

where N_t^j is the number of trades on day t, $P_{t,k}^j$ is the execution price of trade k on day t, and $VOL_{t,k}^j$ is the volume of trade k on day t (in ten millions of Chinese yuan). A bond is more illiquid if a given trading volume generates a greater move in its price, that is, *Amihud* has a larger value for more illiquid bonds. The second bond illiquidity measure used in our analysis is the Roll (1984) effective bid-ask spread, which is defined as

$$Roll_t^j = \begin{cases} 2 \cdot \sqrt{-cov\left(r_{t,k}^j, r_{t,k-1}^j\right)}, & if\ cov\left(r_{t,k}^j,\ r_{t,k-1}^j\right) < 0 \\ 0, & otherwise \end{cases} \tag{2}$$

where $r_{t,k}^j$ is the return of trade k on day t. By definition, *Roll* is a proxy for execution cost, and a larger value of *Roll* implies higher execution cost and thus higher illiquidity.

To compute $Amihud_t^j$ and $Roll_t^j$, we require bond j to have at least three observations of return and trading volume on day t. For ease of exposition, $Amihud_t^j$ and $Roll_t^j$ are computed throughout by multiplying Eqs. (1) and (2) by 10,000.

Hendershott and Madhavan (2015) estimate a cost of transacting for each bond trade as the trade sign times the logarithm of the ratio of trade price to a benchmark price (e.g. the transaction price of the last trade in the underlying bond in the interdealer market),[12] and using this cost as a measure of illiquidity, they find that electronic auctions improve liquidity and are preferred over traditional "voice" negotiations as a trading mechanism for more active, liquid corporate bonds. Recently, O'Hara and Zhou (2021a) use the same measure in a research exploring the electronic evolution of corporate bond dealers. As noted in Section 3, there exist no dedicated interdealer platforms in the CIBM; moreover, the CFETS does not provide information on trade signs for bilateral inquiry and X-Bond trades. For these reasons, the approach of Hendershott and Madhavan (2015) cannot be adopted to estimate execution costs in the CIBM.

[12] Refer to Eq. (4) in Hendershott and Madhavan (2015).

5 Empirical results

Using intraday transaction data obtained from the CFETS, we compute the daily *Amihud* and *Roll* for each sample bond. Panel A of Table 3 reports the average daily *Amihud* and *Roll* for bonds traded through bilateral inquiry and RFQ and through X-Bond over the sample period. It is evident from the results that the price impact of X-Bond trading is substantially lower than that of bilateral inquiry and RFQ trading (the average daily *Amihud* of 0.31 versus 1.83), and the same is true for the execution cost (the average daily *Roll* of 2.60 versus 8.88).

In Panel B, we report the results obtained from grouping bonds by their characteristics. On each sample day, bonds are sorted into quartiles based on age, time to maturity, trade size, or volatility, and within each quartile, we compute the average daily *Amihud* and *Roll* across all bonds in the quartile. The results on the average daily *Amihud* indicate that the price impact exhibits a monotonic pattern across the quartiles. Specifically, the price impact strictly increases with time to maturity and volatility and decreases with age and trade size, which holds true for bilateral inquiry and RFQ trading as well as X-Bond trading. Díaz and Escribano (2017) document a roughly similar negative (positive) relation between age (time to maturity) and the impact of trading on price for U.S. Treasury notes; Fleming (2003) argues that trade size is a measure of market depth, so larger trades are associated with lower price impact. The positive relation between volatility and the price impact consists with the finding of previous research (e.g. Stoll, 1978; Chordia, Roll, and Subrahmanyam, 2001; Brunnermeier and Pedersen, 2009; Goyenko, Subrahmanyam, and Ukhov, 2011) that illiquidity is positively related to volatility. More importantly, we find that the price impact remains significantly lower for X-Bond trading within each quartile although the difference in the price impact between bilateral inquiry and RFQ trading and X-Bond trading varies across the quartiles. Similarly, grouping bonds by their characteristics does not alter the finding that the execution cost of X-Bond trading is significantly lower. It is noteworthy that the execution cost varies monotonically across the quartiles for bilateral inquiry and RFQ trading, but this is not the case for X-Bond trading.

The upper graph in Figure 1 plots the time series from September 2017 to June 2021 of the average daily *Amihud* for bonds traded through bilateral inquiry and RFQ and through X-Bond. This graph

illustrates that the price impact fluctuates over time and increases prominently in times of economic and financial distress (e.g. when the COVID-19 pandemic broke out in late 2019 and early 2020). In particular, the price impact of X-Bond trading is consistently and significantly lower almost throughout the entire sample period. The bottom graph displays a similar result for the execution cost.

5.1 Panel regression results

Column (1) of Table 4 presents the results obtained by regressing the daily *Amihud* (the daily *Roll*) on the dummy variable *TM* that takes value one for bonds traded through X-Bond and zero for bonds traded through bilateral inquiry and RFQ. The coefficient β_{TM} on *TM* is -1.52 (-6.28) in the case of the daily *Amihud* (the daily *Roll*) being the dependent variable and is statistically significant at the 1% level, implying that X-Bond trading is associated with significantly lower price impact and execution cost compared to bilateral inquiry and RFQ trading.

In column (2), we control for bond characteristics, including issue size (log scale), coupon rate, age, time to maturity, average trade size (log scale), volatility, and the on-the-run status. The most recently issued bonds of a particular maturity are said to be on the run, and bonds that have been issued prior to the most recent issue and remain outstanding are off the run. Clearly, bond characteristics cannot explain the difference in the price impact or execution cost between bilateral inquiry and RFQ trading and X-Bond trading. In the case of the price impact, the coefficient β_{TM} changes from -1.52 to -1.71 with a t-statistic of -11.78 when controlling for bond characteristics; in the case of the execution cost, the coefficient β_{TM} also becomes more negative. The results concerning the effects of age, time to maturity, trade size, and volatility on the price impact are consistent with the findings in Panel B of Table 3: the price impact significantly decreases with age and trade size and increases with time to maturity and volatility. Age, time to maturity, and volatility have similar effects on the execution cost, while the effect of trade size on the execution cost is significantly positive and opposite to that on the price impact. The on-the-run dummy variable, which takes value one for on-the-run bonds and zero for off-the-run bonds, has an insignificant effect on the price impact and execution cost. In the U.S. Treasury market, on-the-run bonds have been demonstrated to be significantly more liquid than off-the-run bonds (see, e.g. Amihud and Mendelson, 1991; Kamara, 1994; Goldreich, Hanke and Nath, 2005; Pasquariello and

Vega, 2009); the results in Appendix Table B.4 show that the on-the-run phenomenon appears when we focus our analysis on Treasury bonds. As evidenced by the adjusted R^2, the set of bond characteristics can collectively explain a significant proportion of the variation in the illiquidity of bonds in the sample.

In column (3), we report the regression results with day and bond fixed effects. The bond fixed effect controls for unobserved characteristics omitted in the regression, which may influence bond illiquidity, and the day fixed effect controls for time trends. Again, the coefficient β_{TM} is highly negative: -1.67 (-8.05) with a t-statistic of -10.97 (-11.83) in the case of the daily Amihud (the daily Roll) being the dependent variable, implying that the difference in the price impact or execution cost between bilateral inquiry and RFQ trading and X-Bond trading is not driven by unobserved bond characteristics.

5.2 Endogeneity issue

The results presented above demonstrate that X-Bond trading has significantly lower price impact and execution cost compared to bilateral inquiry and RFQ trading, which suggests that X-Bond is a more liquid mechanism. However, participants in the CIBM may prefer to trade more liquid bonds through X-Bond; in other words, the lower price impact and execution cost of X-Bond trading may not be attributed to the rules of anonymous quoting and automatic order matching in X-Bond, but rather to selection bias. In the following, we are going to address the endogeneity issue.

5.2.1 Identical bonds

A number of bonds in the sample are traded not only through bilateral inquiry and RFQ, but also through X-Bond. Thus, a way of addressing the selection bias issue is to compare the illiquidity of bonds traded through bilateral inquiry and RFQ with the illiquidity of the same bonds traded through X-Bond on the same days. The same bonds have identical characteristics, and the consistency of market conditions can be guaranteed on the same days. If bonds are more liquid when being traded through X-Bond, it can be deduced that the higher liquidity of X-Bond is not the result of endogenous mechanism choice.

As an example, we consider two bonds: one is the Treasury bond *"19GuoZhai15"* and the other is the policy bank bond *"20GuoKai15"*. Issued by the Ministry of Finance of the People's Republic of China

on November 20, 2019, *"19GuoZhai15"* has an annual coupon rate of 3.13% and matures on November 21, 2029; *"20GuoKai15"* was issued by China Development Bank on October 15, 2020 with an annual coupon rate of 3.7% and a maturity period of ten years. The upper graphs in Figure 2 plot the time series of the daily *Amihud* and *Roll* for *"19GuoZhai15"* in March 2020. We observe from these graphs that the price impact and execution cost are both considerably lower (except on the sixth trading day) in the case of *"19GuoZhai15"* being traded through X-Bond. The bottom graphs demonstrate a similar result for *"20GuoKai15"* in June 2021. The findings depicted in Figure 2 provide very preliminary evidence that the higher liquidity of X-Bond is not driven by the endogenous choice of trading mechanism.

5.2.2 Heckman (1979) two-stage procedure

In this subsection, following Madhavan and Cheng (1997), Bessembinder and Venkataraman (2004), and Hendershott and Madhavan (2015), we formally address the selection bias issue using the two-stage procedure proposed by Heckman (1979). Specifically, in the first stage, we develop a probit model of endogenous mechanism choice; in the second stage, we estimate the price impact and execution cost of bilateral inquiry and RFQ trading and of X-Bond trading while simultaneously correcting for selection bias.

Stage I: Endogenous mechanism choice

Suppose that traders choose the mechanism (bilateral inquiry and RFQ or X-Bond) that offers them the lowest cost of trading. First, the realized trading cost for a given mechanism greatly depends on the illiquidity of the mechanism, which can be modeled as follows:

$$ILLIQ_1 = \beta_1' X + u_1 \tag{3}$$

$$ILLIQ_2 = \beta_2' X + u_2 \tag{4}$$

where $ILLIQ_1$ ($ILLIQ_2$) denotes the illiquidity, measured by price impact or execution cost, of bonds traded through bilateral inquiry and RFQ (X-Bond), X is a vector of variables (e.g. a constant and bond characteristics), and u_1 and u_2 are error terms. The coefficients β_1 and β_2 reflect that the effect of bond characteristics on $ILLIQ$ may differ between trading mechanisms.

In addition, there may also exist other factors that influence the cost of trading. Taken together,

the difference between the cost of bilateral inquiry and RFQ trading and that of X-Bond trading can be expressed as

$$\Delta Cost = \alpha' Y + (ILLIQ_1 - ILLIQ_2) \tag{5}$$

where Y denotes a vector of state variables that capture other cost differentials relevant to the choice of trading mechanism. Substituting the expressions for $ILLIQ_1$ and $ILLIQ_2$ in Eqs. (3) and (4) into Eq. (5) yields

$$\Delta Cost = \alpha' Y + (\beta_1' - \beta_2')X + u \tag{6}$$

where $u = u_1 - u_2$. For simplicity, we assume that u follows a normal distribution with mean zero and variance σ_u^2.

By defining $Z = (Y, X)$, we can re-write $\Delta Cost$ as:

$$\Delta Cost = \gamma' Z + u \tag{7}$$

If $\Delta Cost > 0$, i.e. the cost of bilateral inquiry and RFQ trading is higher, traders would choose to trade bonds through X-Bond; otherwise, bilateral inquiry and RFQ are preferred. Let *TM* denote the dummy variable for mechanism choice, which takes value one for bonds traded through X-Bond and zero for bonds traded through bilateral inquiry and RFQ. We have

$$TM = \begin{cases} 1 & \text{if } \Delta Cost > 0 \\ 0 & \text{if } \Delta Cost \leq 0 \end{cases} \tag{8}$$

Column (1) of Table 5 presents the probit regression results obtained by using *TM* as the dependent variable. Bond characteristics, such as issue size (log scale), coupon rate, age, time to maturity, average trade size (log scale), volatility, and the on-the-run status, are included as independent variables in the probit regression. Following Hendershott and Madhavan (2015) and Holden et al. (2021), we use the calendar time dummies *Monday* and *Friday* for the beginning and end of the week to capture inventory effects around the weekend and a dummy *End of Month* (which takes value one for the last trading day of the month and zero otherwise) to reflect month-end portfolio rebalancing activity that may lead

to different mechanism choice. All continuous independent variables are demeaned to calculate average trading costs in subsequent regressions.

Consistent with the findings in Table 2, the estimated coefficients indicate that larger, younger, and more volatile bonds, as well as bonds with a longer time to maturity, are more likely to be traded through X-Bond; larger trades are also more X-Bond facilitated. The positive coefficient on the on-the-run dummy variable implies that on-the-run bonds have a higher likelihood of being traded through X-Bond, compared to off-the-run bonds. On Monday and Friday and at the end of the month, traders make greater use of bilateral inquiry and RFQ, this may be due to higher volumes (e.g. inventory and portfolio rebalancing flows) on these days.

Stage II: *Cost estimates controlling for selection bias*

It can be deduced from the properties of the normal distribution that the expected values of $ILLIQ_1$ and $ILLIQ_2$ conditional on the choice of trading mechanism are

$$E[ILLIQ_1 \mid TM = 0] = \beta_1' X + \frac{cov(u_1, u)}{\sigma_u} IMR_1 \tag{9}$$

$$E[ILLIQ_2 \mid TM = 1] = \beta_2' X + \frac{cov(u_2, u)}{\sigma_u} IMR_2 \tag{10}$$

with

$$IMR_1 = \frac{-\varphi(\frac{\gamma' Z}{\sigma_u})}{1 - \Phi(\frac{\gamma' Z}{\sigma_u})} < 0 \quad \text{and} \quad IMR_2 = \frac{\varphi(\frac{\gamma' Z}{\sigma_u})}{\Phi(\frac{\gamma' Z}{\sigma_u})} > 0$$

where $\varphi(\cdot)$ denotes the standard normal density function and $\Phi(\cdot)$ denotes the cumulative standard normal distribution.[13] In the right-hand side of Eqs. (9) and (10), the terms IMR_1 and IMR_2 stand for inverse Mill's ratios that serve to correct for selection bias.

Based on Eqs. (9) and (10), IMR_1 and IMR_2 computed from the first-stage probit regression are utilized to estimate the expected price impact and execution cost of bilateral inquiry and RFQ trading and of X-Bond trading, controlling for endogenous mechanism choice, and the results are presented in columns (2)−(5) of Table 5. Columns (2) and (4) show that IMR_1 has a strongly significant positive coefficient, which, together with the negative IMR_1, indicates that the expected price impact and execution cost

[13] Refer to Heckman (1979) for the derivation of Eqs. (9) and (10).

of bilateral inquiry and RFQ trading are significantly reduced after correcting for selection bias. In contrast, the coefficient on IMR_2, as shown in columns (3) and (5), implies an increase in the expected price impact and execution cost of X-Bond trading after adjustment for selection bias, though the increase lacks statistical significance.

More importantly, the comparison of regression intercepts reveals that X-Bond trading exhibits significantly lower price impact and execution cost even after accounting for the endogeneity issue. For instance, the results show that the conditional expected execution cost is 3.36 basis points for X-Bond trading and 8.45 basis points for bilateral inquiry and RFQ trading; the difference between these estimates is narrower than the one in Table 3, but still substantial.

In summary, the results presented in Sections 5.2.1 and 5.2.2 suggest that the higher liquidity of X-Bond is not a consequence of the endogenous choice of trading mechanism, but rather results from the rules of anonymous quoting and automatic order matching in X-Bond, which have been designed with the objective of enhancing liquidity.

5.3 Market share of X-Bond

Figure 3 plots the daily time series of the market share of X-Bond over the sample period: the solid line corresponds to the case of number of trades, and the dashed line the case of trading volume. At the beginning of September 2017, i.e. one year after the introduction of X-Bond, 1.83% of trades were executed through X-Bond, with the corresponding trading volume accounting for 0.64% of the total. Thereafter, the market share of X-Bond increased steadily, reaching up to above 50% (in terms of number of trades) by the end of July 2019. However, this increasing trend was reversed after this point, and the market share of X-Bond declined to below 10% at the beginning of 2020. From February 2020 to June 2021, the market share of X-Bond was on an upward trajectory again. In Table 6, the row labeled "Total sample" shows that throughout the sample period, 28.10% of trades were executed through X-Bond, and the share of the corresponding trading volume is lower, only 20.53%; the last two rows show that X-Bond has a low market share, ranging from 20% to 32%, for both on-the-run and off-the-run bonds.

In view of the findings presented in Figure 3 and Table 6, a natural question that one may ask is: why do bilateral inquiry and RFQ, which are less liquid mechanisms compared to X-Bond, dominate

trading in central government bonds? A potential explanation for the low market share of X-Bond could be the information asymmetry among participants in the CIBM, which keeps uninformed traders away from X-Bond, a centralized mechanism in which informed traders can hide their identities. As noted in Section 3, the CIBM restricts participation exclusively to qualified institutional traders who are widely recognized as informed traders among whom the information asymmetry is much less pronounced. Biais and Greeen (2019) argue that the OTC market should predominate when institutional traders are more prevalent, because they can use their larger average trade size to bargain for a better price in a decentralized mechanism and have enough market power to get what they want. However, our findings indicate that the price impact and execution cost of bilateral inquiry and RFQ trading are significantly higher than those of X-Bond trading within each trade size quartile. Barclay, Hendershott, and Kotz (2006) examine the choice of trading mechanism by dealers in U.S. Treasury securities over the period January 2001 through November 2002, and they find that the market share of automated trading systems operated by electronic interdealer brokers (IDBs) falls from 81% to 12% when Treasury securities go off the run. These authors argue that human intermediaries' knowledge of the market and its participants can uncover hidden liquidity and facilitate quicker and more efficient matching of customer orders in less active markets, and as a result, the market share of voice-based systems will increase and the market share of automated trading systems will decrease when Treasury securities go off the run. The order-matching function of human intermediaries is unlikely to be a rationale behind the low market share of X-Bond, given that the market share of X-Bond for on-the-run bonds is almost as low as that for off-the-run bonds.

6 A simple theoretical model

In this section, following Rostek and Yoon (2018) and Yoon (2019), we develop a simple theoretical model to explain why participants in the CIBM prefer to trade central government bonds through bilateral inquiry and RFQ although X-Bond is a more liquid mechanism. In the model, we introduce the liquidity effect and the learning effect: the liquidity effect is defined as the benefit from improved liquidity, while the learning effect refers to the benefit from learning the value of the traded asset. Liquidity and learning effects differ between centralized and decentralized mechanisms, and traders' mechanism choice is jointly

determined by these two effects.

6.1 Setup

In the theoretical model, we consider a two-period economy that consists of a riskless asset (the numeraire whose price is normalized to one) and a risky asset traded by $I < \infty$ strategic traders who are risk averse with a quadratic utility function as follows

$$u_i\left(q_i, p\right) = \tilde{v}_i q_i - \frac{\mu}{2} q_i^2 - p q_i \tag{11}$$

where $\mu > 0$ is the risk aversion coefficient that is common for all traders, p is the market price of the risky asset, q_i is the quantity of the risky asset demanded by trader i, and $\tilde{v}_i$ is the trader i's individual valuation of the risky asset with $\tilde{v}_i \sim \mathrm{N}\big(\mu_v, \sigma_v^2\big)$.[14]

We decompose $\tilde{v}_i$ into two components

$$\tilde{v}_i = \omega_{i,v} v + \omega_{i,\delta} \delta_i \tag{12}$$

where v is the common value component attributed to the future asset return, δ_i is the idiosyncratic value component coming from the return on individual portfolio consisting of other assets that are correlated to the traded risky asset, and $\omega_{i,v}$ and $\omega_{i,\delta}$ are weights of trader i's valuation on the common and idiosyncratic value components, satisfying $\omega_{i,v}^2 + \omega_{i,\delta}^2 = 1$.

Assume that the common and idiosyncratic value components are independent and randomly drawn from normal distribution: $v \sim \mathrm{N}\big(\mu_v, \sigma_v^2\big)$ and $\delta_i \sim \mathrm{N}\big(0, \sigma_v^2\big)$, while traders' idiosyncratic value components are correlated. Let $\sum_\delta$ denote the matrix of correlations between traders' idiosyncratic value components, i.e.

$$\sum\nolimits_\delta = \left(corr(\delta_i, \delta_j)\right)_{i,j} = \begin{pmatrix} 1 & \rho_{12} & \cdots & \rho_{1I} \\ \rho_{21} & 1 & \cdots & \rho_{2I} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{I1} & \rho_{I2} & \cdots & 1 \end{pmatrix}$$

where the correlations ρ_{ij} are heterogeneous across pair of traders $(i; j)$. Without loss of generality, the

[14]The homogeneous mean and variance of asset valuations across traders imply that the ex-ante trading needs are the same for all traders.

sum of correlations in a row $\sum_{j\neq i}\rho_{ij}$ is normalized to zero for all i. This prevents the heterogeneity in ρ_{ij} from being an additional source of common value and thus allows a clear separation of information aggregation.

In the economy, there are two trading venues: one is the over-the-counter (OTC) market, which operates through a decentralized mechanism, and the other is the centralized market, i.e. the market with a centralized mechanism. In the OTC market, a trader who wants to buy or sell the risky asset needs to find a counterparty with whom he would like to trade. If two traders are matched, they trade and leave the market. The OTC market ends when all traders participate in exactly one bilateral trade or when only a single trader is left. By contrast, traders in the centralized market can anonymously submit their orders that are automatically matched and cleared at a single price. In the centralized market, there are L ($2 \leq L < \infty$) liquidity traders who are not given a choice to enter the OTC market, and each liquidity trader l values the risky asset by $\tilde{v}_l = \omega_{l,v}v + \omega_{l,\delta}\delta_l$ with an independent idiosyncratic value component: $\text{corr}(\delta_l, \delta_j) = 0$ for any $j \neq l \in I \cup L$. The presence of liquidity traders in the centralized market ensures that a trader in the OTC market can consider a non-cooperative deviation to the centralized market.

6.2 Traders' problem

Figure 4 describes the time line of the economy. At period 0, each trader i chooses to enter a market. At period 1, the markets are open, and trader i receives a private signal regarding his individual valuation of the risky asset, $s_i = \tilde{v}_i + \varepsilon_i$ with an independent noise $\varepsilon_i \sim \text{N}\big(0, \sigma^2_{i,\varepsilon}\big)$. The precision of information contained in the private signal s_i is defined as

$$\phi_i = \frac{\sigma_v^2}{\sigma^2_{i,\varepsilon}} \tag{13}$$

A lager value of ϕ_i indicates that s_i has a relative lower variance of noise and thus a higher information precision. For liquidity traders, the information precision is set to be the lowest, i.e. $\sigma^2_{l,\varepsilon} = \max_{i\in I}\sigma^2_{i,\varepsilon}$. The information precision, together with the structure of correlations between individual asset valuations, defines traders' types. In the model, we assume that traders' types and prior distributions of individual asset valuations and private signals are common knowledge.

In the case of entering the centralized market at period 0, based on the private signal s_i, trader i

strategically submits his demand schedule $q_i(\cdot)$ as a function of p that maximizes his expected utility

$$\max_{q_i(\cdot)} E\left[u_i\left(q_i, p\right)|s_i\right] = \max_{q_i(p);\ \forall p \in R} \left\{ E\left[\tilde{v}_i|s_i, p\right] q_i - \frac{\mu}{2} q_i^2 - p q_i \right\} \tag{14}$$

If trader i instead enters the OTC market at period 0, he first needs to find a counterparty by ranking other traders based on their types, which are publicly known by assumption, and then submits his optimal demand schedule $q_i(\cdot)$.

6.3 Equilibrium

To simplify the problem and facilitate theoretical analysis, we focus on symmetric traders.[15]

Definition 1. *Traders are symmetric, if*

- *the weights* $(\omega_{i,v};\ \omega_{i,\delta})$ *are the same for all* i*:* $\omega_{i,v} = \omega_v$ *and* $\omega_{i,\delta} = \omega_\delta$;
- *the profile of correlations* $\{\rho_{ij}\}_{j \neq i}$ *is the same for all* i;
- *the information precision* ϕ_i *is the same for all* i*:* $\phi_i = \phi$.[16]

In a market with N symmetric traders, the average correlation to the residual market and the minimum correlation are the same across all traders

$$\bar{\rho}_i = \frac{1}{N-1} \sum_{j \neq i} \rho_{ij} = \bar{\rho} \tag{15}$$

and

$$\rho_i^{min} = \min_{j \neq i} \rho_{ij} = \rho^{min} \tag{16}$$

By taking the derivative of conditional expected utility with respect to q_i and setting it to zero, we obtain the first-order optimality condition

$$\begin{aligned} E\left[\tilde{v}_i|s_i, p\right] - \mu q_i &= p + \frac{\partial p}{\partial q_i} q_i \\ &= p + \lambda q_i \end{aligned} \tag{17}$$

[15] Closed-form solutions are available under this assumption, but the qualitative results do not change with traders being asymmetric.

[16] It is worth emphasizing that traders can receive different private signals, although their information precision is symmetric.

where $\lambda = \frac{\partial p}{\partial q_i}$ is the price impact that reflects the change in price when trader i increases his demand by one unit. Note that the trading strategies of symmetric traders are symmetric, so the price impact is the same for all traders. Following Kyle (1985), we define λ as a measure of illiquidity: a larger value of λ implies higher price impact and lower liquidity.

Solving the equation (17) yields a solution to the optimal demand schedule, and the equilibrium price is determined by the market clearing condition that the net demand of all traders is equal to zero.

Proposition 1. *In a symmetric market, a linear Bayesian Nash equilibrium is characterized by the following conditions*

- *the optimal demand schedule $q_i(\cdot)$ of trader i is*

$$q_i = \frac{E\left[\tilde{v}_i | s_i, p\right] - p}{\mu + \lambda} = \frac{c_v E\left[\tilde{v}_i\right] + c_s s_i - (1 - c_p)\, p}{\mu + \lambda} \tag{18}$$

  where $E\left[\tilde{v}_i | s_i, p\right] = c_v E\left[\tilde{v}_i\right] + c_s s_i + c_p p$, with the coefficients $\{c_v, c_s, c_p\}$ being determined by the Projection Theorem.

- *the price impact λ satisfies the consistency condition*

$$\lambda = -\left(\sum_{j \neq i} \frac{\partial q_j}{\partial p}\right)^{-1} = \left(\sum_{j \neq i} \frac{1 - c_p}{\mu + \lambda}\right)^{-1} \geq 0 \tag{19}$$

- *the equilibrium market clearing price p is*

$$p = \left(\sum_{i} \frac{1 - c_p}{\mu + \lambda}\right)^{-1} \sum_{i} \frac{c_v E[\tilde{v}_i] + c_s s_i}{\mu + \lambda} \tag{20}$$

Proof: See Appendix A.1. □

Given the results in Proposition 1, it is shown in Appendix A.2 that the unconditional expected utility of trader i, denoted by $E[u_i]$, can be written as

$$E[u_i] = \frac{1}{2\mu} \underbrace{\frac{\mu\,(\mu + 2\lambda)}{(\mu + \lambda)^2}}_{\textit{liquidity effect}} \underbrace{var\left(E[\tilde{v}_i | s_i, p] - p\right)}_{\textit{learning effect}} \tag{21}$$

In the right-hand side of Eq. (21), the term $\frac{\mu(\mu+2\lambda)}{(\mu+\lambda)^2}$ captures the liquidity effect on utility, which decreases as λ increases, meaning that trader i can achieve higher expected utility when trading in a more liquid

market. As demonstrated in Eq. (20), the equilibrium price aggregates all traders' private information on the value of the risky asset. Trader i can learn the asset value from the information revealed by p, and the learning effect on utility is captured by $var\left(E[\tilde{v}_i|s_i,p]-p\right)$.

In the centralized market, given the existence of $L \geq 2$ liquidity traders, the market size is larger and consequently the price impact is lower. In the OTC market, traders can target counterparties whose asset valuations are most negatively correlated with theirs, which improves their learning about the asset value. Liquidity and learning effects create a trade-off in traders' market choice.

6.4 Endogenous market structure

Let $E[u_i^{cm}]$ denote the unconditional expected utility that trader i can achieve if he chooses to enter the centralized market at period 0, and $E[u_i^{otc}]$ corresponds to the case of entering the OTC market. If $E[u_i^{otc}] > E[u_i^{cm}]$, trader i chooses the OTC market; otherwise, the centralized market is preferred.

Theorem 1. *The condition for trader i to choose the OTC market at period 0 is*

$$E[u_i^{otc}] > E[u_i^{cm}] \tag{22}$$

Under the assumption of symmetric traders, the inequality above holds if and only if

(1) $\omega_\delta^2 > \frac{(N_{cm}+L-2)/(2(N_{cm}+L-1))}{\frac{1}{(N_{cm}+L-1)}\sum_{j\neq i}\rho_{ij}-\min_{j\neq i}\rho_{ij}}$

(2) $\phi < \hat{\phi}\left(N_{cm}+L, \overline{\rho}_{cm}, \tilde{\rho}_{otc}^{min}\right)$

where N_{cm} is the number of traders who choose the centralized market, $\overline{\rho}_{cm} = \frac{\sum_{j\neq i} corr(\tilde{v}_i,\tilde{v}_j)}{N_{cm}+L-1} = \omega_v^2 + \omega_\delta^2 \frac{\sum_{j\neq i}\rho_{ij}}{N_{cm}+L-1}$ is the average correlation in the centralized market, $\tilde{\rho}_{otc}^{min} = \min_{j\neq i} corr(\tilde{v}_i,\tilde{v}_j) = \omega_v^2 + \omega_\delta^2 \min_{j\neq i}\rho_{ij}$ is the minimum correlation in the OTC market, and $\hat{\phi} > 0$ is defined in Appendix A.3.

Proof: See Appendix A.3. □

Theorem 1 gives a sufficient and necessary condition under which traders choose the OTC market. Specifically, the inequality (1) in Theorem 1 suggests that traders would opt for the OTC market when their asset valuations are sufficiently heterogeneous by relying more on the idiosyncratic component, that is, ω_δ^2 is sufficiently large. Under this inequality condition, the learning effect dominates, driving

traders to choose the OTC market where the targeted bilateral trading improves their learning about the idiosyncratic component of the asset value. The dominance of the learning effect is reinforced by low information precision, as the inequality (2) implies. Therefore, the low information precision creates a joint condition with the sufficiently heterogeneous asset valuation for traders to choose the OTC market.

Proposition 2. *Suppose that the idiosyncratic component of individual asset valuations is sufficiently large, i.e.* $\omega_\delta^2 > \frac{(N_{cm}+L-2)/(2(N_{cm}+L-1))}{\frac{1}{(N_{cm}+L-1)}\sum_{j\neq i}\rho_{ij}-\min_{j\neq i}\rho_{ij}}$. *If* $\frac{\partial\hat{\phi}}{\partial N_{cm}} > 0$, *then there exists an equilibrium in which* N_{cm}^* *traders choose the centralized market, while the remaining* $I - N_{cm}^*$ *traders enter the OTC market.*

Proof: See Appendix A.4. □

Proposition 2 suggests that the centralized and OTC markets can coexist in equilibrium. As noted in Theorem 1, some traders opt for the OTC market as the trading venue when ω_δ^2 is sufficiently large. If $\frac{\partial\hat{\phi}}{\partial N_{cm}} > 0$, the incentive for a marginal trader to choose the centralized market decreases with the number of existing traders in the centralized market, implying that there should exist $N_{cm}^* \in (0, I)$ such that $\hat{\phi}(N_{cm}^* + L) < \phi < \hat{\phi}(N_{cm}^* + L + 1)$ and no trader has an incentive to deviate from his market choice.

Corollary 1. *When the centralized and OTC markets coexist, the number of traders who choose the centralized market in equilibrium, denoted by* N_{cm}^*, *increases with the precision of information in traders' private signals about their asset valuations, that is,* $\frac{\partial N_{cm}^*}{\partial\phi} > 0$.

Proof: See Appendix A.5. □

Intuitively, as the information precision improves, the learning effect becomes weaker and liquidity plays a more important role in determining traders' market choice. The increasing liquidity effect attracts more traders to the centralized market where the price impact is lower and liquidity is higher.

From Theorem 1 and Corollary 1, it can be readily inferred that under the condition of sufficiently heterogeneous asset valuations, a majority of traders would opt for the OTC market as the trading venue if the information precision is sufficiently low.

6.5 An illustrative example

In this subsection, we use a numerical example to illustrate the endogenous market structure and the effect of the information precision on the distribution of traders between the centralized and OTC markets.

Example. Suppose that there are only two types of traders in the economy—buyers and sellers—with equal group sizes. Each trader has his own valuation of the risky asset as follows

$$\tilde{v}_i = \begin{cases} \omega_v v + \omega_\delta \delta_i, & \textit{if } i \textit{ is a buyer} \\ \omega_v v - \omega_\delta \delta_i, & \textit{if } i \textit{ is a seller} \end{cases} \tag{23}$$

with $corr\left(\delta_i, \delta_j\right) = \rho \ \forall i, j$. In the case when $\frac{I - N_{cm}}{2}$ pairs of a buyer and a seller trade in the OTC market and N_{cm} traders are present in the centralized market, the average correlation of individual asset valuations in the centralized market is

$$\overline{\rho}_{cm} = \frac{1}{N_{cm} + L - 1} \sum_{j \neq i} corr\left(\tilde{v}_i, \tilde{v}_j\right) = \omega_v^2 - \frac{\omega_\delta^2 \rho}{N_{cm} + L - 1} \tag{24}$$

and the minimum correlation in the OTC market is

$$\tilde{\rho}_{otc}^{min} = \min_{j \neq i} corr\left(\tilde{v}_i, \tilde{v}_j\right) = \omega_v^2 - \omega_\delta^2 \rho \tag{25}$$

For a given set of parameter values: $\omega_\delta^2 = 0.9$, $\rho = 0.8$, $L = 4$, $I = 36$, and $\phi = 0.7782$, Figure 5 shows the market structure in equilibrium: six traders choose the centralized market (i.e. $N_{cm}^* = 6$) and the remaining 30 traders enter the OTC market. The underlying price impact is 0.140 in the centralized market and 0.694 in the OTC market. These simulation results agree closely with the empirical findings documented in Section 5 that despite lowering the price impact and improving liquidity, the centralized mechanism X-Bond does not dominate trading in central government bonds in the CIBM. Figure 6 shows the liquidity effect and the learning effect for each trading venue, and it indicates that, compared to the OTC market, the centralized market has a smaller learning effect although its liquidity effect is larger. The smaller learning effect helps to explain why only a minority of traders choose the more liquid centralized market. Figure 5 also shows that the number of traders who choose the centralized market increases

monotonically as the information precision improves (i.e. as ϕ increases), consistent with Corollary 1.

6.6 Empirical test of the model prediction

The above theoretical model shows that the centralized and OTC markets can coexist under certain conditions. In addition, the model also predicts that, under the coexistence of centralized and OTC markets, the number (or fraction) of traders opting for the centralized market increases with the precision of information contained in traders' private signals about their valuations of the traded asset. In what follows, we empirically test the model prediction in the cross-section of individual bonds based on a measure of daily information precision constructed using data on bond quotes.

6.6.1 Bond quotes

The data used in the empirical test of the model prediction is obtained from CFETS, which has started to collect data on bond quotes on the X-Bond platform (for simplicity, we refer to these quotes as X-Bond quotes) since July 2018. The sample covers the period from July 2018 to June 2021 and consists of 393 non-bank institutions (mainly securities firms and funds), 240 small- and medium-sized banks, and 20 large banks. As depicted in Figure 7, the number of traders quoting on the X-Bond platform exhibits an upward trend, increasing from below 150 in July 2018 to over 210 in June 2021. The upper graph in Figure 8 plots the monthly time series from July 2018 to June 2021 of the number of X-Bond quotes and of the number of X-Bond trades, and it indicates that the number of X-Bond quotes increases steadily over time and so does the number of X-Bond trades. Specifically, the number of X-Bond quotes has increased from 33,702 in July 2018 to 4,044,605 in June 2021, while the number of X-Bond trades has increased from 16,458 to 124,077 over the same time period. The bottom graph indicates that the ratio of the number of X-Bond trades to the number of X-Bond quotes has undergone a precipitous decline from 49% in July 2018 to 3% in June 2021. This decline suggests that since the introduction of X-Bond, traders have progressively adapted to its rules and carried out strategic trading through quotation, cancellation, and other operations.

The upper graph in Figure 9 presents the results for different types of traders. It is evident from this graph that non-bank institutions are highly active on the X-Bond platform, providing the largest number

of quotes. Despite their limited number, large banks provide the second highest number of quotes, which may reflect that they often make tentative quotations through listing and canceling orders on the X-Bond platform. Small and medium-sized banks are least active, and the number of their quotes is less than half of the number of quotes by large banks. Nonetheless, the number of trades by small and medium-sized banks is the largest among all types of traders. The bottom graph shows that the ratio of the number of X-Bond trades to the number of X-Bond quotes is 19.89% for small and medium-sized banks, way higher than 4.32% for non-banking institutions and 3.01% for large banks.

6.6.2 A measure of daily information precision

Recall that, in the theoretical model with symmetric traders, each trader i receives a private signal s_i on his own asset valuation $\tilde{v}_i$ at the beginning of trading period, which satisfies

$$s_i = \tilde{v}_i + \varepsilon_i \tag{26}$$

where $\tilde{v}_i \sim \mathrm{N}\big(\mu_v, \sigma_v^2\big)$ and ε_i is an independent noise with $\varepsilon_i \sim \mathrm{N}\big(0, \sigma_\varepsilon^2\big)$. The precision of information contained in the private signal s_i, denoted by ϕ_i, is defined as

$$\begin{aligned} \phi_i &= \frac{\sigma_v^2}{\sigma_\varepsilon^2} \\ &= \frac{\sigma_v^2 + \sigma_\varepsilon^2}{\sigma_\varepsilon^2} - 1 \end{aligned} \tag{27}$$

Under the assumption of symmetric traders, ϕ_i is the same for all i: $\phi_i = \phi$. A larger value of ϕ is associated with higher information precision.

Based on the definition in Eq. (27), we construct a measure of daily information precision for each sample bond using data on bond quotes. To this end, assume that traders quote prices based on their private signals. Specifically, let $Q^j_{i,t,k}$ denote the k-th quote of trader i for bond j on day t, and it satisfies

$$\begin{aligned} Q^j_{i,t,k} &= s^j_{i,t,k} \\ &= \tilde{v}^j_{i,t} + \varepsilon^j_{i,t,k} \end{aligned} \tag{28}$$

where $s^j_{i,t,k}$ is the private signal received by trader i before submitting the k-th quote, $\tilde{v}^j_{i,t}$ is the trader i's valuation of bond j on day t with $\tilde{v}^j_{i,t} \sim \mathrm{N}\Big(\mu^j_{v,t}, (\sigma^j_{v,t})^2\Big)$, and $\varepsilon^j_{i,t,k}$ is an independent noise with $\varepsilon^j_{i,t,k} \sim$

$\mathrm{N}\Big(0,(\sigma^j_{\varepsilon,t})^2\Big)$. An implicit assumption in Eq. (28) is that the trader i's valuation of bond j remains invariant on day t.

From Eq. (28), we have

$$var(Q^j_{i,t,k}) = (\sigma^j_{v,t})^2 + (\sigma^j_{\varepsilon,t})^2 \tag{29}$$

The variance of traders' quotes for bond j on day t can therefore be used as an estimate of $(\sigma^j_{v,t})^2 + (\sigma^j_{\varepsilon,t})^2$, i.e.

$$\begin{aligned} \widehat{(\sigma^j_{v,t})^2 + (\sigma^j_{\varepsilon,t})^2} &= \frac{1}{M^j_t - 1}\sum_{i=1}^{I^j_t}\sum_{k=1}^{M^j_{i,t}}\left(Q^j_{i,t,k} - \overline{Q}^j_t\right)^2 \\ \overline{Q}^j_t &= \frac{1}{M^j_t}\sum_{i=1}^{I^j_t}\sum_{k=1}^{M^j_{i,t}} Q^j_{i,t,k} \end{aligned} \tag{30}$$

where I^j_t is the number of traders who quote prices for bond j on day t, $M^j_{i,t}$ is the number of trader i's quotes for bond j on day t, and M^j_t is the number of all quotes for bond j on day t (i.e. $M^j_t = \sum_{i=1}^{I^j_t} M^j_{i,t}$).

By taking the average of both sides of Eq. (28) across the quotes of trader i, we obtain

$$\begin{aligned} \overline{Q}^j_{i,t} &= \frac{1}{M^j_{i,t}}\sum_{k=1}^{M^j_{i,t}} Q^j_{i,t,k} \\ &= \tilde{v}^j_{i,t} + \frac{1}{M^j_{i,t}}\sum_{k=1}^{M^j_{i,t}} \varepsilon^j_{i,t,k} \end{aligned} \tag{31}$$

The average noise converges to zero when $M^j_{i,t}$ is sufficiently large, so the average of trader i's quotes on day t, $\overline{Q}^j_{i,t}$, can be used to proxy for his valuation of bond j on day t. Replacing $\tilde{v}^j_{i,t}$ with $\overline{Q}^j_{i,t}$ in Eq. (28) and rearranging yields

$$\varepsilon^j_{i,t,k} = Q^j_{i,t,k} - \overline{Q}^j_{i,t} \tag{32}$$

Given $\varepsilon^j_{i,t,k}$ computed following Eq. (32), the variance of the noise term $(\sigma^j_{\varepsilon,t})^2$ can be estimated as

$$\begin{aligned} \widehat{(\sigma^j_{\varepsilon,t})^2} &= \frac{1}{M^j_t - 1}\sum_{i=1}^{I^j_t}\sum_{k=1}^{M^j_{i,t}}\left(\varepsilon^j_{i,t,k} - \overline{\varepsilon}^j_t\right)^2 \\ \overline{\varepsilon}^j_t &= \frac{1}{M^j_t}\sum_{i=1}^{I^j_t}\sum_{k=1}^{M^j_{i,t}} \varepsilon^j_{i,t,k} \end{aligned} \tag{33}$$

Finally, given the results in Eqs. (30) and (33), the estimated precision of information contained in

symmetric traders' private signals about their individual valuations of bond j on day t, denoted by $\widehat{\phi_t^j}$, is given by

$$\begin{aligned}\widehat{\phi_t^j} &= \frac{\widehat{(\sigma_{v,t}^j)^2 + (\sigma_{\varepsilon,t}^j)^2}}{\widehat{(\sigma_{\varepsilon,t}^j)^2}} - 1 \\ &= \frac{\sum_{i=1}^{I_t^j} \sum_{k=1}^{M_{i,t}^j} \left(Q_{i,t,k}^j - \overline{Q}_t^j\right)^2}{\sum_{i=1}^{I_t^j} \sum_{k=1}^{M_{i,t}^j} \left(\varepsilon_{i,t,k}^j - \overline{\varepsilon}_t^j\right)^2} - 1 \end{aligned} \tag{34}$$

To compute $\widehat{\phi_t^j}$ defined in Eq. (34), we require bond j to have at least three X-Bond quotes on day t. By definition, the information precision must be positive, so observations with negative $\widehat{\phi_t^j}$ will be excluded from the subsequent analysis. Furthermore, we winsorize $\widehat{\phi_t^j}$ at the 5% and 95% levels to mitigate the impact of outliers.

In the sample, there are totally 376 bonds (67 bonds per day on average) with available data on $\widehat{\phi_t^j}$. The row labeled "All bonds" in Table 7 provides summary statistics of $\widehat{\phi_t^j}$ for these bonds over the period from July 2018 to June 2021.[17] Clearly, the information precision varies considerably across individual bonds, with $\widehat{\phi_t^j}$ having a mean of 0.93 and a standard deviation of 2.03. The results in the last two rows show that the information precision is higher for Treasury bonds than for policy bank bonds (the average $\widehat{\phi_t^j}$ of 1.09 versus 0.83).

6.6.3 Cross-sectional determinants of information precision

In Table 8, we examine what factors determine the information precision in the cross-section of individual bonds. The univariate regression results presented in columns (1)−(6) indicate that bond characteristics, with the exception of coupon rate, significantly affect the information precision. Specifically, bond age has a significant positive impact on the information precision, that is, older bonds have higher information precision; in contrast, the information precision is significantly and negatively related to a bond's time to maturity. Intuitively, the pricing of older bonds (or bonds with shorter time to maturity) is less sensitive to fluctuations in risk factors such as interest rate; as a result, the information contained in the private signals on traders' valuations of these bonds should be more accurate. The significant negative coefficient on the on-the-run dummy variable implies that the information precision is lower

[17] The statistics presented in Table 7 are the time-series means of daily cross-sectional statistics.

for on-the-run bonds, an unsurprising result given that on-the-run bonds are younger than off-the-run bonds. As expected, the effect of bond volatility on the information precision is significantly negative. Column (7) shows that, in a multivariate regression, the impact of bond characteristics on the information precision remains constant, except that the impact of issue size is reduced to statistical insignificance.

6.6.4 Information precision and market share of X-Bond

Finally, we investigate the effect of the information precision on traders' mechanism choice. To this end, on each sample day, we sort bonds into quintiles based on the information precision estimated following Eq. (34): bonds with the lowest information precision are sorted quintile 1, and bonds with the highest information precision are sorted into quintile 5. For each quintile, we first compute the daily average information precision and market share of X-Bond across all bonds in that quintile and then the time-series means of daily cross-sectional averages, and the results are presented in Table 9. By construction, the average information precision increases monotonically from 0.01 for quintile 1 to 3.84 for quintile 5. In accordance with the prediction of the theoretical model, the market share of X-Bond is notably larger for the higher information precision quintile. Specifically, the average market share of X-Bond is 11.72% (13.93%) for quintile 1 and 22.55% (25.40%) for quintile 5 in the case of number of trades (trading volume), and the 5−1 difference is statistically significant at the 1% level.[18]

Column (1) of Table 10 presents the estimation results of a bond-day panel regression of the market share of X-Bond on the information precision. The statistically significant and positive coefficient on the information precision implies that the market share of X-Bond increases as the information precision improves. In column (2), we control for bond characteristics that may affect the market share of X-Bond, and the results show that the trading of smaller, closer-to-maturity, and higher volatile bonds is more executed through X-Bond. Of importance, the effect of the information precision on the market share of X-Bond is robust to controlling for bond characteristics. Finally, column (3) demonstrates that the results remain unchanged when the day and bond fixed effects are further taken into account.

[18]In Appendix Table B.8, bonds are sorted into different groups based on their types and characteristics, and the relation between the information precision and the market share of X-Bond remains significantly positive within each group.

7 Conclusions

In September 2016, the CFETS launched X-Bond, a centralized bond trading mechanism, with the aim of promoting liquidity in the over-the-counter market CIBM. Focusing on central government bonds, our analysis shows that X-Bond significantly reduces the price impact and execution cost of bond trading in comparison with decentralized OTC mechanisms such as bilateral inquiry and RFQ. This finding holds true even after controlling for bond characteristics and addressing the selection bias issue. Moreover, we find that X-Bond does not dominate in the trading of central government bonds in the CIBM although it is a more liquid mechanism, which is contrary to our expectations.

We develop a simple theoretical model to explain the low market share of X-Bond. In the model, we consider a two-period economy with a risky asset traded by a finite number of risk-averse strategic traders. In the economy, there are two trading mechanisms: one is the OTC market operating as a decentralized mechanism, and the other is the centralized market where there are more than two liquidity traders who are not given a choice to enter the OTC market. Each trader has his individual valuation of the risky asset, which is normally distributed and consists of independent common and idiosyncratic components. Idiosyncratic value components are correlated between traders. At period 0, each trader chooses to enter a market; at period 1, the markets are open, and he receives a private signal about his valuation of the risky asset. In the centralized market, given the existence of liquidity traders, the market size is larger and the price impact is lower; in the OTC market, traders can target counterparties whose asset valuations are most negatively correlated with theirs, which improves their learning about the asset value. In equilibrium, traders' market choice is jointly determined by the effects of liquidity and learning on their utilities. Our theoretical model shows that a majority of traders would choose the OTC market if traders' asset valuations are sufficiently heterogeneous and the precision of information contained in traders' private signals is low enough. Furthermore, the model also predicts that the number of traders who choose the centralized market increases with the information precision. Based on the measure of information precision constructed using data on bond quotes on the X-Bond platform, we find empirical evidence that supports the model prediction.

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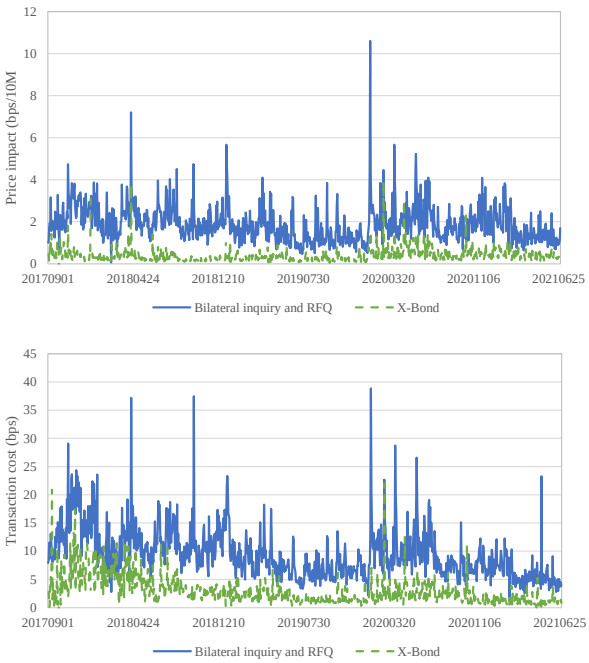


Figure 1. **Daily aggregate illiquidity**.
This figure plots the daily time series of the average price impact (the upper graph) and execution cost (the bottom graph) for bonds traded through bilateral inquiry and RFQ and through X-Bond. The sample period spans from September 2017 to June 2021.

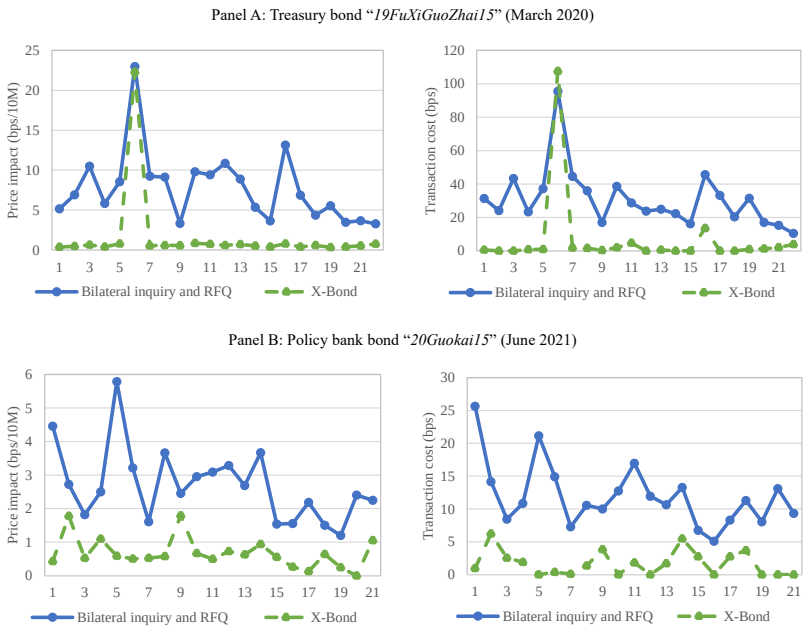


Figure 2. **Daily illiquidity of identical bonds**.
This figure plots the daily time series of the price impact and execution cost for the Treasury bond *"19GuoZhai15"* (Panel A) and the policy bank bond *"20GuoKai15"* (Panel B), which are traded through bilateral inquiry and RFQ and through X-Bond. The sample for *"19GuoZhai15"* covers March 2020, while the sample for *"20GuoKai15"* covers June 2021.

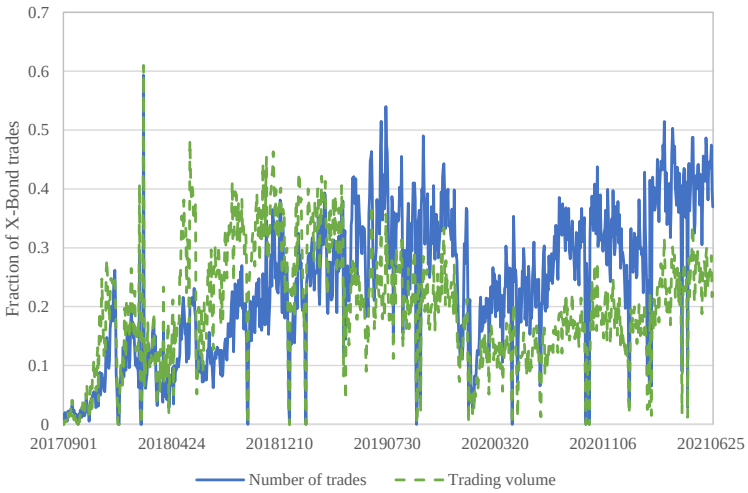


Figure 3. **Daily market share of X-Bond**.
This figure plots the daily time series of the market share of X-Bond, measured by the ratio of the number of trades executed through X-Bond to the total number of trades or the ratio of X-Bond trading volume to total bond trading volume. The sample period spans from September 2017 to June 2021.

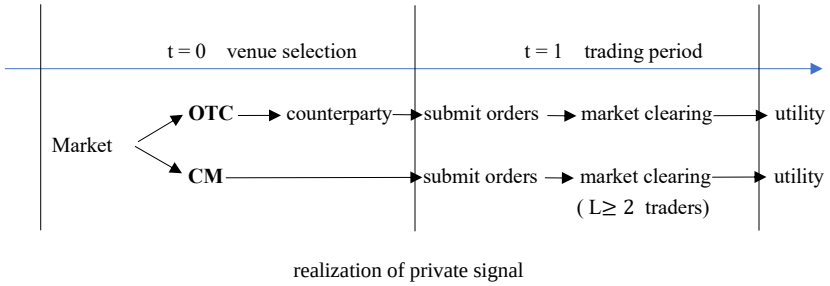


Figure 4. **Timeline of the economy**.
This figure describes the timeline of the economy. At period 0, each trader chooses to enter the over-the-counter (OTC) market or the centralized market (CM). At the beginning of period 1, the markets are open, and traders receive private signals about their individual valuations of the risky asset. Then, traders strategically submit demand schedules, trades are executed, and the markets clear. At the end of period 1, the market price of the risky asset is realized, and each trader's utility is evaluated at the realized asset price.

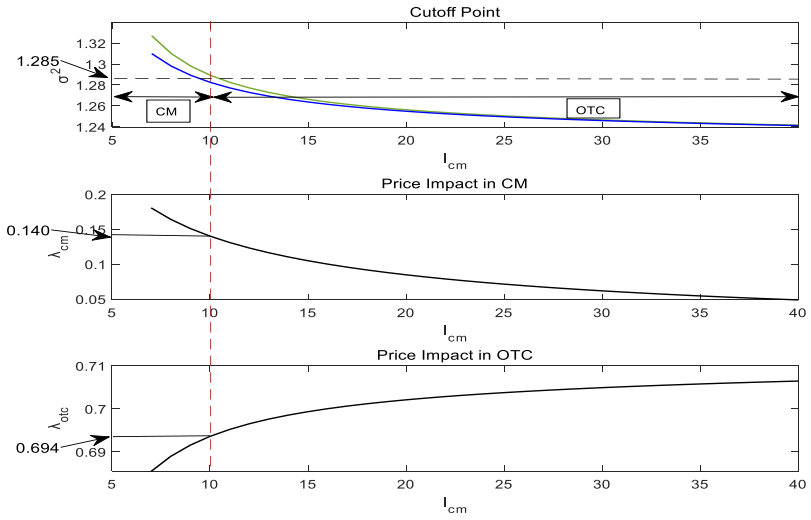


Figure 5. **Equilibrium market structure**.
This figure illustrates the equilibrium market structure obtained from the numerical simulation. The upper graph plots the cutoff noise variance σ^2—the inverse of the information precision ϕ—as a decreasing function of the number of traders I_{cm} $(= N_{cm} + L)$ in the centralized market (CM). When a marginal trader finds it optimal to switch from the over-the-counter (OTC) market to the CM, the next trader's incentive to follow is weaker, which underpins the existence of an interior equilibrium number of CM traders. The middle graph shows that the price impact in the CM, denoted by λ_{cm}, decreases with I_{cm}. The bottom graph shows that the price impact in the OTC, denoted by λ_{otc}, increases with I_{cm}. The vertical dashed line indicates, for the given information precision, the equilibrium number of traders in the CM and the corresponding price impact levels in both the OTC market and the CM. The numerical simulation is based on the following parameter values: $\omega_\delta^2 = 0.9$, $\rho = 0.8$, $L = 4$, $I = 36$, and $\phi = 0.7782$.

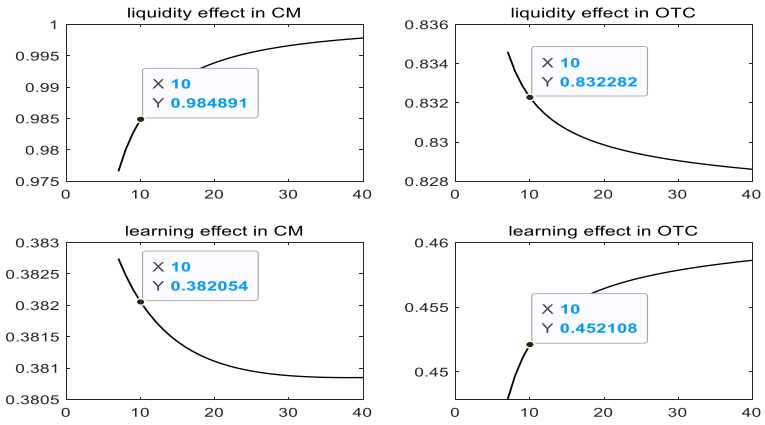


Figure 6. **Liquidity effect and learning effect**.
This figure illustrates the liquidity effect (the upper graphs) and the learning effect (the bottom graphs) in the over-the-counter (OTC) market and the centralized market (CM) as functions of the number of traders in the CM. In each graph, the solid black dot marks the equilibrium number of CM traders implied by the numerical simulation and the corresponding levels of the liquidity and learning effects in the OTC market and the CM. The numerical simulation is based on the following parameter values: $\omega_\delta^2 = 0.9$, $\rho = 0.8$, $L = 4$, $I = 36$, and $\phi = 0.7782$.

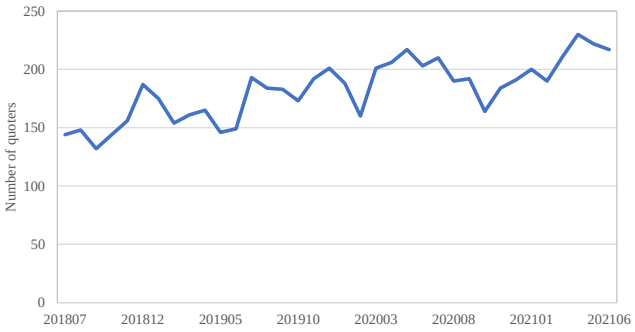


Figure 7. **Monthly number of quoting traders**.
This figure plots the monthly number of traders who quote on the X-Bond platform. The sample period spans from July 2018 to June 2021.

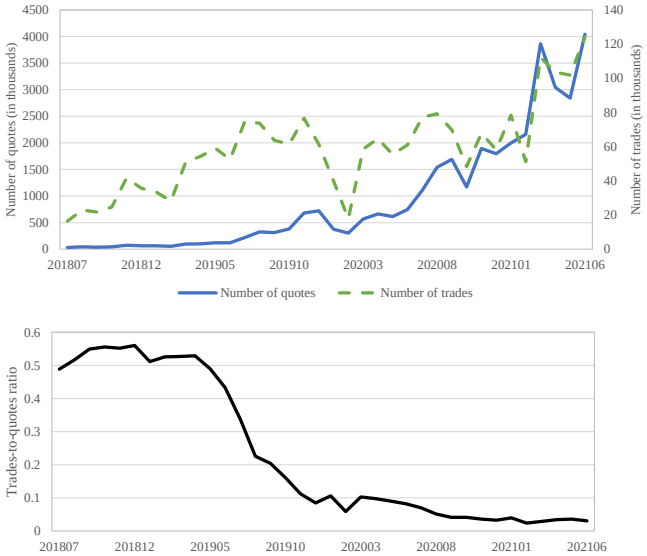


Figure 8. Monthly number of X-Bond quotes and trades.
This figure plots the monthly time series of the number of X-Bond quotes and trades (the upper graph) and the corresponding trade-to-quote ratio (the bottom graph). The sample period spans from July 2018 to June 2021.

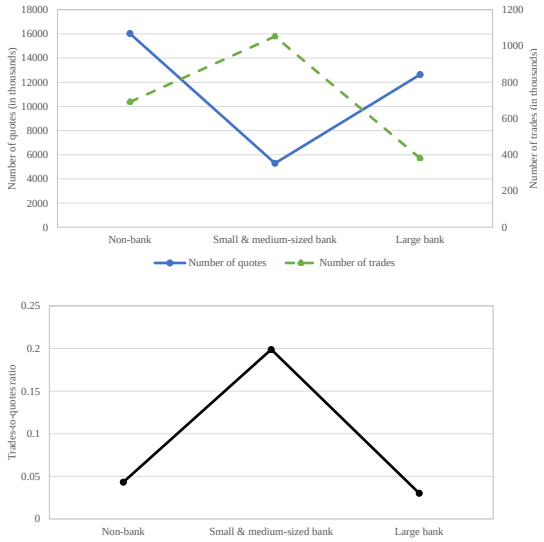


Figure 9. **Aggregate number of X-Bond quotes and trades**.
This figure plots the aggregate number of X-Bond quotes and trades (the upper graph) and the corresponding trade-to-quote ratio (the bottom graph) across different types of traders. The sample period spans from July 2018 to June 2021.

Table 1
Sample Bonds

This table reports the number of bonds included in the sample, classified by maturity. The sample period spans from September 2017 to June 2021.

	# of sample bonds	# of Treasury bonds	# of policy bank bonds
2 years	29	13	16
3 years	96	22	74
5 years	133	28	105
7 years	135	35	100
10 years	153	53	100

Table 2
Summary Statistics

This table reports summary statistics of bond characteristics and trades, which are calculated as the time-series means of daily cross-sectional statistics. Panel A presents the results for all bonds in the sample, Panel B for bonds traded through bilateral inquiry and RFQ, and Panel C for bonds traded through X-Bond. The sample period spans from September 2017 to June 2021.

	25%	50%	75%	Mean	Std
			Panel A: All bonds		
Issue size (RMB billion)	77.37	113.01	163.17	124.75	66.07
Age	0.69	1.51	2.81	1.99	1.75
Time to maturity	1.70	3.40	6.23	4.08	2.89
Number of trades	6.27	11.66	26.91	53.61	234.09
Trading volume (RMB billion)	0.72	1.50	3.14	3.33	7.81
Trade size (RMB million)	59.04	107.93	173.93	129.12	95.42
Volatility (bps)	0.00	0.04	0.36	1.78	8.66
	Panel B: Bonds traded through bilateral inquiry and RFQ				
Issue size (RMB billion)	79.09	115.44	166.14	126.91	66.53
Age	0.66	1.46	2.77	1.95	1.73
Time to maturity	1.75	3.53	6.40	4.17	2.91
Number of trades	6.18	11.22	25.93	41.71	128.45
Trading volume (RMB billion)	0.65	1.36	2.76	2.80	5.37
Trade size (RMB million)	53.91	94.78	159.84	120.91	96.11
Volatility (bps)	0.00	0.04	0.41	1.91	8.97
			Panel C: Bonds traded through X-Bond		
Issue size (RMB billion)	121.51	161.62	208.61	164.63	65.07
Age	0.44	0.84	1.50	1.14	1.04
Time to maturity	2.67	4.17	6.98	4.85	2.96
Number of trades	6.37	9.67	20.11	83.41	281.94
Trading volume (RMB billion)	0.76	1.21	2.00	3.03	6.95
Trade size (RMB million)	85.35	143.11	191.41	140.94	77.88
Volatility (bps)	0.83	2.08	6.37	7.88	18.10

Table 3
Aggregate Bond Illiquidity

This table reports the average daily price impact (*Amihud*) and execution cost (*Roll*) for bonds traded through bilateral inquiry and RFQ and through X-Bond. Panel A presents the results for the full sample. Panel B reports the results obtained from grouping bonds by their characteristics: on each sample day, bonds are sorted into quartiles based on a given characteristic, and within each quartile, we calculate the average daily *Amihud* and *Roll* across all bonds in that quartile. The sample period spans from September 2017 to June 2021.

	Amihud		*Roll*	
	Bilateral inquiry and RFQ	X-Bond	Bilateral inquiry and RFQ	X-Bond
Panel A: Full sample				
	1.83	0.31	8.88	2.60
Panel B: Grouping by bond characteristics				
Age				
Under 0.6 year	2.61	0.46	12.70	2.55
0.6−1.4 years	2.11	0.35	9.50	2.96
1.4−2.7 years	1.65	0.11	7.77	2.53
2.7+ years	1.15	0.08	6.45	1.99
Time to maturity				
Under 1.7 years	0.38	0.06	2.45	1.66
1.7−3.5 years	0.98	0.16	6.06	2.62
3.5−6.4 years	2.16	0.33	10.47	3.12
6.4+ years	3.92	0.61	17.08	2.76
Trade size				
Micro (<48M)	3.21	0.68	11.55	2.09
Odd (48−95M)	2.03	0.54	10.31	2.81
Round (95−192M)	1.24	0.23	7.95	2.55
Max (>192M)	0.56	0.10	4.63	2.89
Volatility				
Low	0.12	0.02	0.68	0.56
Medium	0.73	0.08	3.21	1.91
Large	2.01	0.23	9.11	3.47
High	4.99	0.64	25.21	3.33

Table 4
Panel Regressions

In this table, the first set of columns present the results of a panel regression of the daily price impact (*Amihud*) or execution cost (*Roll*) on the dummy variable *TM* that takes value one for bonds traded through X-Bond and zero for bonds traded through bilateral inquiry and RFQ. In the second set of columns, we control for issue size (log scale), coupon rate, age, time to maturity, trade size (log scale), volatility, and a dummy variable denoting on-the-run status. The day and bond fixed effects are further taken into account in the third set of columns. The t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from September 2017 to June 2021.

	(1)		(2)		(3)	
	Amihud	*Roll*	*Amihud*	*Roll*	*Amihud*	*Roll*
Intercept	1.83***	8.88***	6.06***	-3.32	10.60***	-2.24
	(16.85)	(20.23)	(4.37)	(-0.40)	(13.90)	(-0.72)
TM	-1.52***	-6.28***	-1.71***	-8.04***	-1.67***	-8.05***
	(-16.52)	(-13.94)	(-11.78)	(-12.14)	(-10.97)	(-11.83)
Log(Issue size)			0.10**	-0.19		
			(2.22)	(-0.62)		
Coupon rate			-0.72	38.53*		
			(-0.20)	(1.81)		
Age			-0.05***	-0.24**		
			(-3.47)	(-2.48)		
Time to maturity			0.27***	1.23***		
			(21.49)	(15.63)		
log(Trade size)			-0.43***	0.57***	-0.48***	0.59***
			(-11.16)	(3.01)	(-11.32)	(3.33)
Volatility			0.08***	0.42***	0.08***	0.41***
			(7.86)	(7.73)	(6.83)	(6.43)
On-the-run			-0.13	0.50	-0.28***	-0.05
			(-1.64)	(1.43)	(-3.62)	(-0.15)
Day FE	No	No	No	No	Yes	Yes
Bond FE	No	No	No	No	Yes	Yes
Adj. R^2	4.59%	3.77%	25.55%	19.92%	31.70%	28.33%
# of obs.	107,825	107,825	107,825	107,825	107,802	107,802

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 5
Heckman (1979) Two-Stage Selection Model

This table reports the results of Heckman (1979) two-stage regressions. The column labeled "Stage I" presents the estimation results of the probit model for the binary choice between bilateral inquiry and RFQ and X-Bond, where the dependent variable is a dummy variable that takes value one for bonds traded through X-Bond and zero for bonds traded through bilateral inquiry and RFQ. The column labeled "Stage II" presents the results on the determinants of the price impact (*Amihud*) or execution cost (*Roll*) for bonds traded through bilateral inquiry and RFQ and through X-Bond. Independent variables include issue size (log scale), coupon rate, age, time to maturity, trade size (log scale), volatility, a dummy variable indicating on-the-run status, and three calendar-time dummies (Monday, Friday, and End of month). IMR1 and IMR2 denote inverse Mill's ratios that serve to correct for selection bias. All continuous independent variables are demeaned. The t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from September 2017 to June 2021.

		Stage II			
		Amihud		*Roll*	
	Stage I	Bilateral inquiry and RFQ	X-Bond	Bilateral inquiry and RFQ	X-Bond
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.89***	1.77***	0.38***	8.45***	3.36***
	(-74.29)	(40.97)	(5.43)	(43.78)	(5.04)
Log(Issue size)	0.13***	0.14***	-0.00	0.33	-0.30
	(14.23)	(4.50)	(-0.16)	(1.47)	(-1.10)
Coupon rate	5.84***	-0.01	0.01	0.47***	-0.17
	(8.01)	(-0.46)	(0.88)	(3.23)	(-0.93)
Age	-0.17***	-0.22***	-0.08	-1.58***	-1.02*
	(-45.48)	(-3.93)	(-1.42)	(-6.70)	(-1.81)
Time to maturity	0.01***	0.92***	0.13***	4.15***	0.97***
	(5.51)	(22.39)	(6.55)	(17.15)	(3.48)
Log(Trade size)	0.47***	-0.24***	-0.08	1.87***	1.84*
	(70.23)	(-2.95)	(-0.77)	(4.55)	(1.87)
Volatility	0.02***	1.06***	0.04	5.82***	0.58
	(36.81)	(12.06)	(0.75)	(10.61)	(1.23)
On-the-run	0.13***	0.01	0.03	0.70***	0.15
	(10.65)	(0.39)	(1.53)	(4.63)	(1.02)
Monday	-0.03***				
	(-2.66)				
Friday	-0.03***				
	(-3.17)				
End of month	-0.10***				
	(-3.83)				
IMR1		2.09***		15.70***	
		(3.38)		(4.78)	
IMR2			0.35		3.48
			(1.08)		(1.22)
Adj. R^2	9.09%	31.26%	12.51%	26.77%	2.12%
# of obs	107,825	85,455	22,370	85,455	22,370

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 6
Market Share of X-Bond

This table reports the market share of X-Bond for the full sample as well as for two subsamples consisting of on-the-run and off-the-run bonds. The market share of X-Bond is measured by the ratio of the number of trades executed through X-Bond to the total number of trades or the ratio of X-Bond trading volume to total trading volume. The sample period spans from September 2017 to June 2021.

	Number of trades		Trading volume	
	Bilateral inquiry and RFQ	X-Bond	Bilateral inquiry and RFQ	X-Bond
Total sample	71.90%	28.10%	79.47%	20.53%
On-the-run bonds	68.83%	31.17%	79.08%	20.92%
Off-the-run bonds	74.18%	25.82%	79.66%	20.34%

Table 7
Summary Statistics of Information Precision

This table reports summary statistics, which are calculated as the time-series means of daily cross-sectional statistics, of the information precision for the full sample as well as for two subsamples consisting of Treasury bonds and policy bank bonds. The column labeled "# of bonds" shows the number of bonds with the information precision data, along with the average daily number of these bonds reported in parentheses. The sample period spans from July 2018 to June 2021.

	# of bonds	25%	50%	75%	Mean	Std
All bonds	376 (67)	0.03	0.14	0.63	0.93	2.03
Treasury bonds	129 (24)	0.07	0.22	1.07	1.09	2.03
Policy bank bonds	247 (43)	0.03	0.13	0.58	0.83	1.85

Table 8
Determinants of Information Precision

This table reports the results of panel regressions of the information precision measure on bond characteristics, including issue size (log scale), coupon rate, age, time to maturity, volatility, and a dummy variable denoting on-the-run status. The t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from July 2018 to June 2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	6.66***	0.90***	0.65***	1.30***	0.90***	0.98***	-0.57
	(3.31)	(3.25)	(10.48)	(11.78)	(16.03)	(15.42)	(-0.21)
Log(Issue size)	-0.23***						0.07
	(-2.86)						(0.62)
Coupon rate		-0.26					-0.32
		(-0.04)					(-0.05)
Age			0.15***				0.11***
			(5.68)				(3.52)
Time to maturity				-0.09***			-0.07***
				(-5.35)			(-3.30)
Volatility					-0.10***		-0.02*
					(-7.43)		(-1.91)
On-the-run						-0.41***	-0.15*
						(-5.56)	(-1.92)
Adj. R^2	0.33%	0.00%	1.03%	1.18%	0.52%	0.56%	1.91%
# of obs.	49,974	49,974	49,974	49,974	49,974	49,974	49,974

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 9
Information Precision and Market Share of X-Bond

This table reports the average market share of X-Bond, calculated based on the number of trades or trading volume, for bonds grouped by the information precision (denoted by ϕ). On each sample day, bonds are sorted into quintiles based on the information precision, and within each quintile, we first compute the cross-sectional averages of the information precision and the market share of X-Bond, and then take the time-series means of daily cross-sectional averages. The sample period spans from July 2018 to June 2021.

	ϕ	Number of trades (%)	Trading volume (%)
Low	0.01	11.72	13.93
2	0.04	15.55	17.83
3	0.15	16.13	18.51
4	0.51	19.16	21.76
High	3.84	22.55	25.40
High−Low	3.83***	10.83***	11.47***

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 10
Information Precision and Market Share of X-Bond: Panel Regression Results

In this table, the first set of columns present the results of a panel regression of the market share of X-Bond—calculated based on the number of trades or trading volume—on the bond-level information precision. In the second set of columns, we control for issue size (log scale), coupon rate, age, time to maturity, volatility, and a dummy variable denoting on-the-run status. The day and bond fixed effects are further taken into account in the third set of columns. The t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from July 2018 to June 2021.

	(1)		(2)		(3)	
	Number of Trades	Trading Volume	Number of Trades	Trading Volume	Number of Trades	Trading Volume
Intercept	0.15***	0.18***	2.42***	2.55***	0.17***	0.20***
	(16.74)	(15.88)	(6.26)	(5.66)	(50.89)	(56.77)
ϕ	0.01***	0.02***	0.01***	0.01***	0.01***	0.01***
	(8.04)	(8.39)	(7.52)	(7.85)	(7.72)	(7.85)
Log(Issue size)			-0.09***	-0.10***		
			(-6.45)	(-5.91)		
Coupon rate			4.43***	7.26***		
			(3.84)	(5.67)		
Age			0.00	-0.00		
			(0.68)	(-0.47)		
Time to maturity			-0.01***	-0.01***		
			(-3.98)	(-3.55)		
Volatility			0.02***	0.01***	0.00	-0.00
			(3.69)	(2.72)	(0.98)	(-0.64)
On-the-run			-0.01	-0.03*	-0.05***	-0.06***
			(-1.20)	(-1.86)	(-5.02)	(-5.20)
Day FE	No	No	No	No	Yes	Yes
Bond FE	No	No	No	No	Yes	Yes
Adj. R^2	2.14%	2.19%	14.23%	14.72%	48.17%	45.68%
# of obs.	49,974	49,974	49,974	49,974	49,974	49,974

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix

A Proofs

A.1 Proof of Proposition 1

As shown in Section 6.3, the optimal demand schedule q_i of trader i satisfies the following first-order condition

$$E\left[\tilde{v}_i|s_i,p\right]-\mu q_i=p+\lambda q_i \tag{A.1}$$

where $\lambda=\frac{\partial p}{\partial q_i}$ is the price impact. Solving Eq. (A.1) yields

$$q_i=\frac{E\left[\tilde{v}_i|s_i,p\right]-p}{\mu+\lambda} \tag{A.2}$$

It can be derived from the Projection Theorem that

$$E\left[\tilde{v}_i|s_i,p\right]=c_vE\left[\tilde{v}_i\right]+c_ss_i+c_pp \tag{A.3}$$

where the coefficients c_v, c_s, and c_p are defined as

$$\begin{aligned}c_v&=\frac{(1-\bar{\rho})\,\sigma^2}{(1+(I-1)\bar{\rho})(1-\bar{\rho}+\sigma^2)}\\ c_s&=\frac{1-\bar{\rho}}{1-\bar{\rho}+\sigma^2}\\ c_p&=\frac{I\bar{\rho}\sigma^2}{(1+(I-1)\bar{\rho})(1-\bar{\rho}+\sigma^2)}\end{aligned}$$

Substituting the result in Eq. (A.3) into Eq. (A.2) yields

$$q_i=\frac{c_vE\left[\tilde{v}_i\right]+c_ss_i-(1-c_p)p}{\mu+\lambda} \tag{A.4}$$

In the equilibrium, the market clearing condition $\sum_i q_i=0$ implies

$$\begin{aligned}&\sum_i\frac{c_vE\left[\tilde{v}_i\right]+c_ss_i-(1-c_p)p}{\mu+\lambda}=0\\ \Longrightarrow\ &p=\left(\sum_i\frac{1-c_p}{\mu+\lambda}\right)^{-1}\sum_i\frac{c_vE[\tilde{v}_i]+c_ss_i}{\mu+\lambda}\end{aligned} \tag{A.5}$$

and

$$
\begin{aligned}
q_i = -\sum_{j\neq i} q_j \quad &\Longrightarrow \quad \frac{\partial q_i}{\partial p} = -\sum_{j\neq i} \frac{\partial q_j}{\partial p} \\
&\Longrightarrow \quad \frac{\partial p}{\partial q_i} = -\left(\sum_{j\neq i} \frac{\partial q_j}{\partial p}\right)^{-1} \\
&\Longrightarrow \quad \lambda = -\left(\sum_{j\neq i} \frac{1-c_p}{\mu+\lambda}\right)^{-1} \\
&\Longrightarrow \quad \lambda = \frac{\mu}{(I-1)(1-c_p)-1}
\end{aligned} \tag{A.6}
$$

A.2 Liquidity effect and learning effect

Given the optimal demand schedule q_i in Eq. (A.2), the conditional expected utility $E[u_i|s_i,p]$ can be written as

$$
\begin{aligned}
E[u_i|s_i,p] &= E[\tilde{v}_i|s_i,p]\, q_i - \frac{\mu}{2} q_i^2 - p q_i \\
&= (E[\tilde{v}_i|s_i,p] - p)\, q_i - \frac{\mu}{2} q_i^2 \\
&= \frac{(E[\tilde{v}_i|s_i,p]-p)^2}{\mu+\lambda} - \frac{\mu}{2}\frac{(E[\tilde{v}_i|s_i,p]-p)^2}{(\mu+\lambda)^2} \\
&= \frac{\mu+2\lambda}{2(\mu+\lambda)^2}(E[\tilde{v}_i|s_i,p]-p)^2
\end{aligned} \tag{A.7}
$$

Applying the law of total expectation, we have

$$
\begin{aligned}
E[u_i] &= E[E[u_i|s_i,p]] \\
&= \frac{\mu+2\lambda}{2(\mu+\lambda)^2} E\left[(E[\tilde{v}_i|s_i,p]-p)^2\right]
\end{aligned} \tag{A.8}
$$

By definition, $var(E[\tilde{v}_i|s_i,p]-p) = E\left[(E[\tilde{v}_i|s_i,p]-p)^2\right] - (E[E[\tilde{v}_i|s_i,p]-p])^2$. Note that

$$
\begin{aligned}
E[\tilde{v}_i] &= E[\omega_v v + \omega_\delta \delta_i] \\
&= \omega_v \mu_v
\end{aligned} \tag{A.9}
$$

and

$$\begin{aligned} E[p] &= \left(\sum_i \frac{1-c_p}{\mu+\lambda}\right)^{-1} \sum_i \frac{c_v E[\tilde{v}_i] + c_s E[s_i]}{\mu+\lambda} \\ &= \left(\sum_i \frac{1-c_p}{\mu+\lambda}\right)^{-1} \sum_i \frac{c_v E[\tilde{v}_i] + c_s E[\tilde{v}_i + \varepsilon_i]}{\mu+\lambda} \\ &= \left(\sum_i \frac{1-c_p}{\mu+\lambda}\right)^{-1} \sum_i \frac{(c_v+c_s)\omega_v \mu_v}{\mu+\lambda} \\ &= \omega_v \mu_v \end{aligned} \tag{A.10}$$

The results in equations (A.9) and (A.10) imply

$$E[E[\tilde{v}_i|s_i,p] - p] = E[\tilde{v}_i] - E[p] = 0 \tag{A.11}$$

Thus, we have

$$\begin{aligned} var(E[\tilde{v}_i|s_i,p] - p) &= E\left[(E[\tilde{v}_i|s_i,p] - p)^2\right] - (E[E[\tilde{v}_i|s_i,p] - p])^2 \\ &= E\left[(E[\tilde{v}_i|s_i,p] - p)^2\right] \end{aligned} \tag{A.12}$$

and

$$\begin{aligned} E[u_i] &= \frac{\mu+2\lambda}{2(\mu+\lambda)^2} E\left[(E[\tilde{v}_i|s_i,p] - p)^2\right] \\ &= \frac{1}{2\mu} \underbrace{\frac{\mu(\mu+2\lambda)}{(\mu+\lambda)^2}}_{liquidity\ effect} \underbrace{var(E[\tilde{v}_i|s_i,p] - p)}_{learning\ effect} \end{aligned} \tag{A.13}$$

In the right-hand side of Eq. (A.13), the term $\frac{\mu(\mu+2\lambda)}{(\mu+\lambda)^2}$ is a function of λ and thus captures the liquidity effect on utility, while the term $var(E[\tilde{v}_i|s_i,p] - p)$ captures the learning effect on utility. Substituting $\lambda = \frac{\mu}{(I-1)(1-c_p)-1}$ into $\frac{\mu(\mu+2\lambda)}{(\mu+\lambda)^2}$ yields

$$\begin{aligned} \frac{\mu(\mu+2\lambda)}{(\mu+\lambda)^2} &= 1 - \frac{1}{[(I-1)(1-c_p)]^2} \\ &= 1 - \left(\frac{(1+(I-1)\bar{\rho})(1-\bar{\rho}+\sigma^2)}{(I-1)(1-\bar{\rho})(1+(I-1)\bar{\rho}+\sigma^2)}\right)^2 \end{aligned} \tag{A.14}$$

Using the result in Eq. (A.5), we have

$$\begin{aligned} E\left[\tilde{v}_i|s_i,p\right]-p &= c_v E\left[\tilde{v}_i\right]+c_s s_i-(1-c_p)p \\ &= c_v E\left[\tilde{v}_i\right]+c_s s_i-(1-c_p)\left(\sum_i \frac{1-c_p}{\mu+\lambda}\right)^{-1}\sum_i \frac{c_v E[\tilde{v}_i]+c_s s_i}{\mu+\lambda} \\ &= c_v\left(E\left[\tilde{v}_i\right]-\frac{\sum_i E\left[\tilde{v}_i\right]}{I}\right)+c_s\left(s_i-\frac{\sum_i s_i}{I}\right) \end{aligned} \tag{A.15}$$

and thus

$$\begin{aligned} var(E\left[\tilde{v}_i|s_i,p\right]-p) &= c_s^2 var\left(s_i-\frac{\sum_i s_i}{I}\right) \\ &= c_s^2\left(E\left[\left(s_i-\frac{\sum_i s_i}{I}\right)^2\right]-\left(E\left[s_i-\frac{\sum_i s_i}{I}\right]\right)^2\right) \\ &= c_s^2\left(E\left[s_i^2\right]-\frac{2E\left[s_i\left(\sum_i s_i\right)\right]}{I}+\frac{E\left[\left(\sum_i s_i\right)^2\right]}{I^2}\right) \\ &= c_s^2\left(E\left[s_i^2\right]-\frac{E\left[s_i\left(\sum_i s_i\right)\right]}{I}\right) \end{aligned} \tag{A.16}$$

Given that

$$\begin{aligned} E\left[s_i\left(\sum_i s_i\right)\right] &= E\left[s_i^2+\sum_{j\neq i} s_i s_j\right] \\ &= var(s_i)+\left(E[s_i]\right)^2+\sum_{j\neq i} E\left[s_i s_j\right] \\ &= \sigma_v^2+\sigma_\varepsilon^2+\omega_v^2\mu_v^2+\sum_{j\neq i} E\left[s_i s_j\right] \end{aligned} \tag{A.17}$$

where

$$\begin{aligned} \sum_{j\neq i} E\left[s_i s_j\right] &= \sum_{j\neq i}\left(E\left[s_i\right]E\left[s_j\right]+cov(s_i,s_j)\right) \\ &= \sum_{j\neq i}\left(\omega_v^2\mu_v^2+cov(\tilde{v}_i,\tilde{v}_j)\right) \\ &= (I-1)\omega_v^2\mu_v^2+\sigma_v^2\sum_{j\neq i} corr(\tilde{v}_i,\tilde{v}_j) \\ &= (I-1)\omega_v^2\mu_v^2+\sigma_v^2(I-1)\bar{\rho} \end{aligned} \tag{A.18}$$

the difference between $E\left[s_i^2\right]$ and $\frac{E\left[s_i\left(\sum_i s_i\right)\right]}{I}$ is equal to

$$\begin{aligned} E\left[s_i^2\right]-\frac{E\left[s_i\left(\sum_i s_i\right)\right]}{I} &= \sigma_v^2+\sigma_\varepsilon^2+\omega_v^2\mu_v^2-\frac{\sigma_v^2+\sigma_\varepsilon^2+\omega_v^2\mu_v^2+\sigma_v^2(I-1)\bar{\rho}+(I-1)\omega_v^2\mu_v^2}{I} \\ &= \frac{I-1}{I}\left(\sigma_v^2-\sigma_v^2\bar{\rho}+\sigma_\varepsilon^2\right) \end{aligned} \tag{A.19}$$

Finally, defining $\sigma^2 = \frac{\sigma_\varepsilon^2}{\sigma_v^2} = \frac{1}{\phi}$ and using the result in Eq. (A.19), we obtain

$$\begin{aligned} var(E\left[\tilde{v}_i|s_i,p\right]-p) &= c_s^2 E\left[\left(s_i - \frac{\sum_i s_i}{I}\right)^2\right] \\ &= \left(\frac{1-\bar{\rho}}{1-\bar{\rho}+\sigma^2}\right)^2 \frac{I-1}{I}\left(\sigma_v^2 - \sigma_v^2\bar{\rho} + \sigma_\varepsilon^2\right) \\ &= \left(\frac{1-\bar{\rho}}{1-\bar{\rho}+\sigma^2}\right)^2 \frac{I-1}{I}\left(1-\bar{\rho}+\sigma^2\right)\sigma_v^2 \\ &= \frac{I-1}{I}\frac{(1-\bar{\rho})^2}{1-\bar{\rho}+\sigma^2}\sigma_v^2 \end{aligned} \tag{A.20}$$

A.3 Proof of Theorem 1

Substituting the results in equations (A.14) and (A.20) into Eq. (A.13) yields

$$\begin{aligned} E\left[u_i\right] &= \frac{1}{2\mu}\frac{\mu(\mu+2\lambda)}{(\mu+\lambda)^2} var(E\left[\tilde{v}_i|s_i,p\right]-p) \\ &= \frac{1}{2\mu}\left\{1-\left(\frac{(1+(I-1)\bar{\rho})(1-\bar{\rho}+\sigma^2)}{(I-1)(1-\bar{\rho})(1+(I-1)\bar{\rho}+\sigma^2)}\right)^2\right\}\frac{I-1}{I}\frac{(1-\bar{\rho})^2}{1-\bar{\rho}+\sigma^2}\sigma_v^2 \\ &= \frac{\sigma_v^2}{2\mu}\frac{(I-1)^2(1-\bar{\rho})^2(1+(I-1)\bar{\rho}+\sigma^2)^2 - (1+(I-1)\bar{\rho})^2(1-\bar{\rho}+\sigma^2)^2}{I(I-1)(1-\bar{\rho}+\sigma^2)(1+(I-1)\bar{\rho}+\sigma^2)^2} \end{aligned} \tag{A.21}$$

Note that $I = N_{cm} + L$ & $\bar{\rho} = \bar{\rho}_{cm}$ for the centralized market and $I = 2$ & $\bar{\rho} = \tilde{\rho}_{otc}^{min}$ for the OTC market. Let $E\left[u_i^{cm}\right]$ denote the unconditional expected utility that trader i can achieve if he enters the centralized market at period 0, that is,

$$\begin{aligned} E\left[u_i^{cm}\right] = \frac{\sigma_v^2}{2\mu}\Bigg\{ &\frac{(N_{cm}+L-1)^2(1-\bar{\rho}_{cm})^2(1+(N_{cm}+L-1)\bar{\rho}_{cm}+\sigma^2)^2}{(N_{cm}+L)(N_{cm}+L-1)(1-\bar{\rho}_{cm}+\sigma^2)(1+(N_{cm}+L-1)\bar{\rho}_{cm}+\sigma^2)^2} - \\ &\frac{(1+(N_{cm}+L-1)\bar{\rho}_{cm})^2(1-\bar{\rho}_{cm}+\sigma^2)^2}{(N_{cm}+L)(N_{cm}+L-1)(1-\bar{\rho}_{cm}+\sigma^2)(1+(N_{cm}+L-1)\bar{\rho}_{cm}+\sigma^2)^2}\Bigg\} \end{aligned} \tag{A.22}$$

Instead, if trader i enters the OTC market at period 0, his unconditional expected utility $E\left[u_i^{otc}\right]$ is equal to

$$\begin{aligned} E\left[u_i^{otc}\right] &= \frac{\sigma_v^2}{2\mu}\frac{(1-\tilde{\rho}_{otc}^{min})^2(1+\tilde{\rho}_{otc}^{min}+\sigma^2)^2 - (1+\tilde{\rho}_{otc}^{min})^2(1-\tilde{\rho}_{otc}^{min}+\sigma^2)^2}{2(1-\tilde{\rho}_{otc}^{min}+\sigma^2)(1+\tilde{\rho}_{otc}^{min}+\sigma^2)^2} \\ &= \frac{\sigma_v^2}{2\mu}\frac{-2\tilde{\rho}_{otc}^{min}\sigma^2(1-(\tilde{\rho}_{otc}^{min})^2+\sigma^2)}{(1-\tilde{\rho}_{otc}^{min}+\sigma^2)(1+\tilde{\rho}_{otc}^{min}+\sigma^2)^2} \end{aligned} \tag{A.23}$$

Let $\mathcal{D}$ denote the difference between $E\left[u_i^{cm}\right]$ and $E\left[u_i^{otc}\right]$, that is,

$$\begin{aligned}\mathcal{D} &= E\left[u_i^{cm}\right] - E\left[u_i^{otc}\right] \\ &= \frac{\sigma_v^2}{2\mu}\frac{f(\sigma^2; N_{cm}, L, \bar{\rho}_{cm}, \tilde{\rho}_{otc}^{min})}{g(\sigma^2; N_{cm}, L, \bar{\rho}_{cm}, \tilde{\rho}_{otc}^{min})}\end{aligned} \tag{A.24}$$

where

$$\begin{aligned}&g(\sigma^2; N_{cm}, L, \bar{\rho}_{cm}, \tilde{\rho}_{otc}^{min}) \\ &= (N_{cm}+L-1)(1+(N_{cm}+L-1)\bar{\rho}_{cm}+\sigma^2)^2(1-\bar{\rho}_{cm}+\sigma^2)(1+\tilde{\rho}_{otc}^{min}+\sigma^2)^2(1-\tilde{\rho}_{otc}^{min}+\sigma^2)\end{aligned} \tag{A.25}$$

and

$$f(\sigma^2; N_{cm}, L, \bar{\rho}_{cm}, \tilde{\rho}_{otc}^{min}) = a_5\sigma^{10} + a_4\sigma^8 + a_3\sigma^6 + a_2\sigma^4 + a_1\sigma^2 + a_0 \tag{A.26}$$

with $a_5 = (N_{cm}+L-2) - 2(N_{cm}+L-1)(\bar{\rho}_{cm} - \tilde{\rho}_{otc}^{min})$ and $a_0 = (N_{cm}+L-2)[1+(N_{cm}+L-2)\bar{\rho}_{cm} - (N_{cm}+L-1)\bar{\rho}_{cm}^2]^2(1+\tilde{\rho}_{otc}^{min})^2(1-\tilde{\rho}_{otc}^{min})$.

Obviously, $g(\sigma^2; N_{cm}, L, \bar{\rho}_{cm}, \tilde{\rho}_{otc}^{min}) > 0$ and $a_0 > 0$. Regarding the coefficients a_5, a_4, a_3, a_2, and a_1 in Eq. (A.26), as shown in Yoon (2019), when $N_{cm} + L \geq 3$ and $\bar{\rho}_{cm} \geq 0 > \tilde{\rho}_{otc}^{min}$, if $a_n > 0$, then $a_{n-1} > 0$ for any $n = 2, \cdots, 5$. So, if $a_5 > 0$, a_4, a_3, a_2, a_1, and a_0 are all strictly positive, and then $f > 0$, meaning that all traders choose the centralized market.

Therefore, the necessary condition for the coexistence of the centralized market and OTC market is $a_5 < 0$. Under this condition, it can be shown that the coefficients a_5, a_4, a_3, a_2, a_1, and a_0 change the sign only once. For example, if $a_5 < 0$ and $a_4 < 0$, but $a_3 > 0$, a_2 and a_1 are both strictly positive. By definition, $a_0 > 0$. According to Descartes' rule of signs, a polynomial has an unique positive root if its coefficients change the sign only once. Consequently, if $a_5 < 0$, f only has a positive root. Assume that $\hat{\sigma}^2$ solves $f = 0$; in other words, trader i with the information precision $\hat{\phi} = \frac{1}{\hat{\sigma}^2}$ achieves the same expected utility regardless of whether he enters the centralized market or the OTC market. For $\sigma^2 = 0$, $f(0; \cdots) = a_0 > 0$, this implies that $f(\sigma^2; \cdots)$ decreases in σ^2. When $0 < \sigma^2 < \hat{\sigma^2}$, $f(\sigma^2; N_{cm}, L, \bar{\rho}_{cm}, \tilde{\rho}_{otc}^{min}) > 0$, so a trader i with the information precision $\phi = \frac{1}{\sigma^2} > \frac{1}{\hat{\sigma}^2} = \hat{\phi}$ chooses the centralized market. When $\sigma^2 > \hat{\sigma^2}$, $f(\sigma^2; N_{cm}, L, \bar{\rho}_{cm}, \tilde{\rho}_{otc}^{min}) < 0$, so a trader i with the information

precision $\phi = \frac{1}{\sigma^2} < \frac{1}{\hat{\sigma}^2} = \hat{\phi}$ chooses the OTC market.

In addition, $a_5 = (N_{cm} + L - 2) - 2(N_{cm} + L - 1)(\bar{\rho}_{cm} - \tilde{\rho}_{otc}^{min}) < 0$ can be simplified into

$$\frac{N_{cm} + L - 2}{2(N_{cm} + L - 1)} < \bar{\rho}_{cm} - \tilde{\rho}_{otc}^{min} \tag{A.27}$$

Substituting $\bar{\rho}_{cm} = \omega_v^2 + \omega_\delta^2 \frac{\sum_{j \neq i} \rho_{ij}}{N_{cm}+L-1}$ and $\tilde{\rho}_{otc}^{min} = \omega_v^2 + \omega_\delta^2 \min_{j \neq i} \rho_{ij}$ into the above equation yields

$$\frac{N_{cm} + L - 2}{2(N_{cm} + L - 1)} < \omega_\delta^2 \left(\frac{\sum_{j \neq i} \rho_{ij}}{N_{cm} + L - 1} - \min_{j \neq i} \rho_{ij} \right) \tag{A.28}$$

Thus, we have

$$\omega_\delta^2 > \frac{(N_{cm} + L - 2) \big/ (2(N_{cm} + L - 1))}{\left(\frac{1}{N_{cm}+L-1} \sum_{j \neq i} \rho_{ij} - \min_{j \neq i} \rho_{ij} \right)} \tag{A.29}$$

A.4 Proof of Proposition 2

As shown in Theorem 1, when $\omega_\delta^2 > \frac{(N_{cm}+L-2) \big/ (2(N_{cm}+L-1))}{\left(\frac{1}{N_{cm}+L-1} \sum_{j \neq i} \rho_{ij} - \min_{j \neq i} \rho_{ij} \right)}$, some traders prefer the OTC market to the centralized market. Let $N_{cm}^* \in (0, I)$ denote the number of traders who choose the centralized market, and it satisfies $\hat{\phi}(N_{cm}^* + L) < \phi < \hat{\phi}(N_{cm}^* + L + 1)$. If $\frac{\partial \hat{\phi}}{\partial N_{cm}} > 0$, then no trader has incentive to deviate in his market choice.

- If a marginal trader in the OTC market deviates to the centralized market, then $\phi < \hat{\phi}(N_{cm}^* + L + 1)$, so the trader has no incentive to deviate to the centralized market.
- If a marginal trader in the centralized market deviates to the OTC market, then $\phi > \hat{\phi}(N_{cm}^* + L - 1)$, so the trader has no incentive to deviate to the OTC market.

Therefore, the equilibrium in which N_{cm}^* traders choose the centralized market and the remaining $I - N_{cm}^*$ traders choose the OTC market is a stable one.

A.5 Proof of Corollary 1

We prove this corollary by contradiction. Recall that a condition for the centralized and OTC markets to coexist is that $\frac{\partial \hat{\phi}}{\partial N_{cm}} > 0$. Let N_{cm}^* (N_{cm}^{**}) denote the equilibrium number of traders who choose the centralized market when the precision of information contained in traders' private signals is ϕ_1 (ϕ_2), and

the stability of the equilibrium implies that N_{cm}^{*} and N_{cm}^{**} need to satisfy the following inequalities

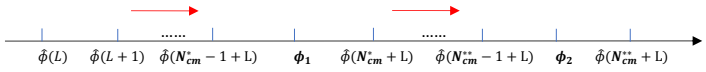
$$\hat{\phi}(N_{cm}^{*}+L) < \phi_1 < \hat{\phi}(N_{cm}^{*}+L+1) \tag{A.30}$$

$$\hat{\phi}(N_{cm}^{**}+L) < \phi_2 < \hat{\phi}(N_{cm}^{**}+L+1) \tag{A.31}$$

Assume that $\phi_2 > \phi_1$ and $N_{cm}^{**} < N_{cm}^{*}$. The condition of $\frac{\partial \hat{\phi}}{\partial N_{cm}} > 0$ implies that $\hat{\phi}(N_{cm}^{**}+L+1) \leq \hat{\phi}(N_{cm}^{*}+L)$, From Eq. (A.31), we have

$$\begin{aligned} & \phi_1 < \phi_2 < \hat{\phi}(N_{cm}^{**}+L+1) \\ \Longrightarrow \quad & \phi_1 < \phi_2 < \hat{\phi}(N_{cm}^{**}+L+1) \leq \hat{\phi}(N_{cm}^{*}+L) \\ \Longrightarrow \quad & \phi_1 < \hat{\phi}(N_{cm}^{*}+L) \end{aligned}$$

This contradicts the left inequality in Eq. (A.30). Therefore, if $\phi_2 > \phi_1$, $N_{cm}^{**} > N_{cm}^{*}$.



B Supplementary Figures and Tables

Table B.1a
Panel Regressions (Treasury Bonds)

This table reports the results of panel regressions of the *Amihud* and *Roll* illiquidity measures on the dummy variable *TM*, which equals one for bonds traded through X-Bond and zero for bonds traded through bilateral inquiry and RFQ. Control variables include Issue size (Log scale), Coupon rate, Age, Time to maturity, Trade size (Log scale), Volatility, and a dummy variable indicating On-the-run status. t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from September 2017 to June 2021.

	(1)		(2)		(3)	
	Amihud	*Roll*	*Amihud*	*Roll*	*Amihud*	*Roll*
Intercept	1.91***	6.88***	11.11**	57.70***	16.57***	12.89***
	(9.29)	(14.01)	(2.26)	(4.27)	(10.68)	(3.04)
TM	-1.63***	-4.24***	-1.65***	-4.91***	-1.48***	-4.85***
	(-9.28)	(-7.26)	(-7.51)	(-6.63)	(-6.73)	(-6.44)
Log(Issue size)			0.18	-1.78***		
			(0.95)	(-3.65)		
Coupon rate			20.92	-7.78		
			(1.46)	(-0.16)		
Age			-0.07**	-0.55***		
			(-2.38)	(-5.47)		
Time to maturity			0.19***	0.75***		
			(6.50)	(8.62)		
log(Trade size)			-0.82***	-0.41*	-0.79***	-0.34
			(-9.50)	(-1.77)	(-9.45)	(-1.46)
Volatility			0.25***	1.12***	0.22***	1.15***
			(5.27)	(6.26)	(3.59)	(5.62)
On-the-run			-0.85***	-0.67**	-0.86***	-1.28***
			(-5.69)	(-2.33)	(-6.77)	(-5.19)
Day FE	No	No	No	No	Yes	Yes
Bond FE	No	No	No	No	Yes	Yes
Adj. R^2	3.88%	3.62%	19.23%	22.47%	24.95%	28.99%
# of obs.	31,279	31,279	31,279	31,279	31,270	31,270

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.1b
Heckman (1979) Two-Stage Selection Model (Treasury Bonds)

This table reports the results of two-stage regressions. The column labeled "Stage I" presents probit models for the binary choice between bilateral inquiry and RFQ and X-Bond, where the dependent variable equals one if X-Bond is selected and zero otherwise. The column labeled "Stage II" reports the determinants of the *Amihud* and *Roll* illiquidity measures for trades executed via bilateral inquiry and RFQ and via X-Bond, controlling for endogenous selection. Independent variables include Issue size (Log scale), Coupon rate, Age, Time to maturity, Trade size (Log scale), Volatility, a dummy variable indicating On-the-run status, and three calendar-time dummies (Monday, Friday, and End of month). The Inverse Mills ratio terms included in the "Stage II" regressions are denoted IMR1 and IMR2. All continuous independent variables are demeaned. t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from September 2017 to June 2021.

		Stage II			
		Amihud		*Roll*	
	Stage I	Bilateral inquiry and RFQ	X-Bond	Bilateral inquiry and RFQ	X-Bond
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.74***	1.83***	0.29***	6.71***	2.84***
	(-35.15)	(20.45)	(6.36)	(34.73)	(6.46)
Log(Issue size)	0.11***	0.36***	-0.09**	-0.29	-1.20**
	(5.14)	(2.87)	(-2.38)	(-1.28)	(-2.11)
Coupon rate	26.37***	0.34**	-0.02	0.43	-0.01
	(11.34)	(2.25)	(-0.48)	(1.56)	(-0.02)
Age	-0.15***	-0.51*	-0.05	-1.66***	-1.05
	(-22.91)	(-1.80)	(-0.61)	(-2.84)	(-1.42)
Time to maturity	-0.04***	0.44***	0.09**	2.00***	0.71
	(-10.33)	(2.80)	(2.32)	(6.36)	(1.08)
Log(Trade size)	0.21***	-0.56***	-0.17**	-0.11	0.82
	(17.38)	(-2.96)	(-2.49)	(-0.26)	(1.42)
Volatility	0.06***	1.26***	0.14**	4.86***	0.60
	(17.10)	(5.76)	(2.29)	(7.72)	(1.10)
On-the-run	0.17***	-0.24**	-0.00	0.07	0.16
	(7.97)	(-2.36)	(-0.14)	(0.30)	(0.51)
Monday	-0.00				
	(-0.02)				
Friday	-0.02				
	(-1.06)				
End of month	-0.14***				
	(-3.24)				
IMR1		4.60*		10.03*	
		(1.86)		(1.76)	
IMR2			0.12		2.07
			(0.28)		(0.53)
Adj. R^2	4.40%	21.80%	18.56%	31.76%	5.68%
# of obs	31,279	23,580	7,699	23,580	7,699

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.2a
Panel Regressions (Policy Bank Bonds)

This table reports the results of panel regressions of the *Amihud* and *Roll* illiquidity measures on the dummy variable *TM*, which equals one for bonds traded through X-Bond and zero for bonds traded through bilateral inquiry and RFQ. Control variables include Issue size (Log scale), Coupon rate, Age, Time to maturity, Trade size (Log scale), Volatility, and a dummy variable indicating On-the-run status. t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from September 2017 to June 2021.

	(1)		(2)		(3)	
	Amihud	*Roll*	*Amihud*	*Roll*	*Amihud*	*Roll*
Intercept	1.82***	9.69***	4.77***	-25.94**	8.97***	-10.16**
	(14.17)	(17.42)	(2.68)	(-2.48)	(9.92)	(-2.47)
TM	-1.50***	-7.11***	-1.81***	-9.79***	-1.79***	-9.74***
	(-13.72)	(-12.76)	(-9.54)	(-11.14)	(-9.03)	(-10.87)
Log(Issue size)			0.06	0.17		
			(1.14)	(0.50)		
Coupon rate			0.98	-8.07		
			(0.26)	(-0.31)		
Age			-0.04***	-0.17		
			(-2.65)	(-1.56)		
Time to maturity			0.30***	1.49***		
			(21.09)	(15.40)		
log(Trade size)			-0.32***	1.39***	-0.39***	1.07***
			(-6.75)	(4.59)	(-7.73)	(4.57)
Volatility			0.06***	0.09***	0.05***	0.30***
			(8.57)	(5.57)	(6.54)	(6.10)
On-the-run			0.04	0.91*	-0.06	0.35
			(0.55)	(1.94)	(-0.74)	(0.85)
Day FE	No	No	No	No	Yes	Yes
Bond FE	No	No	No	No	Yes	Yes
Adj. R^2	4.69%	3.73%	28.45%	19.88%	35.22%	28.44%
# of obs.	76,546	76,546	76,546	76,546	76,528	76,528

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.2b
Heckman (1979) Two-Stage Selection Model (Policy Bank Bonds)

This table reports the results of two-stage regressions. The column labeled "Stage I" presents probit models for the binary choice between bilateral inquiry and RFQ and X-Bond, where the dependent variable equals one if X-Bond is selected and zero otherwise. The column labeled "Stage II" reports the determinants of the *Amihud* and *Roll* illiquidity measures for trades executed via bilateral inquiry and RFQ and via X-Bond, controlling for endogenous selection. Independent variables include Issue size (Log scale), Coupon rate, Age, Time to maturity, Trade size (Log scale), Volatility, a dummy variable indicating On-the-run status, and three calendar-time dummies (Monday, Friday, and End of month). The Inverse Mills ratio terms included in the "Stage II" regressions are denoted IMR1 and IMR2. All continuous independent variables are demeaned. t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from September 2017 to June 2021.

		Stage II			
		Amihud		*Roll*	
	Stage I	Bilateral inquiry and RFQ	X-Bond	Bilateral inquiry and RFQ	X-Bond
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.96***	1.74***	0.44***	9.31***	3.25***
	(-65.20)	(45.03)	(4.04)	(38.78)	(4.12)
Log(Issue size)	0.09***	0.07**	0.01	0.25	-0.17
	(8.28)	(2.02)	(0.52)	(1.04)	(-0.62)
Coupon rate	4.22*	0.02	0.02	0.07	-0.22
	(4.95)	(0.74)	(0.94)	(0.38)	(-1.39)
Age	-0.20***	-0.27***	-0.10	-1.05***	-0.77
	(-41.49)	(-5.45)	(-1.34)	(-3.97)	(-1.47)
Time to maturity	0.03***	1.06***	0.14**	5.12***	0.85***
	(12.11)	(22.08)	(4.04)	(14.56)	(3.13)
Log(Trade size)	0.58***	-0.05	-0.06	1.97***	1.48
	(69.03)	(-0.71)	(-0.40)	(4.26)	(1.47)
Volatility	0.02***	1.12***	0.02	5.57***	0.32
	(34.15)	(13.97)	(0.24)	(9.34)	(0.65)
On-the-run	0.04**	0.06*	0.03	0.58***	0.09
	(2.35)	(1.93)	(1.59)	(3.04)	(0.68)
Monday	-0.04***				
	(-3.28)				
Friday	-0.04***				
	(-3.00)				
End of month	-0.09***				
	(-2.86)				
IMR1		2.60***		11.27***	
		(5.00)		(3.23)	
IMR2			0.38		2.23
			(1.03)		(0.87)
Adj. R^2	12.03%	35.85%	11.72%	25.53%	1.08%
# of obs	76,546	61,875	14,671	61,875	14,671

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.3a
Panel Regressions (3-Year Bonds)

This table reports the results of panel regressions of the *Amihud* and *Roll* illiquidity measures on the dummy variable *TM*, which equals one for bonds traded through X-Bond and zero for bonds traded through bilateral inquiry and RFQ. Control variables include Issue size (Log scale), Coupon rate, Age, Time to maturity, Trade size (Log scale), Volatility, and a dummy variable indicating On-the-run status. t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from September 2017 to June 2021.

	(1)		(2)		(3)	
	Amihud	*Roll*	*Amihud*	*Roll*	*Amihud*	*Roll*
Intercept	0.63***	4.14***	5.30***	18.73***	4.72***	0.70
	(20.23)	(25.67)	(10.22)	(4.55)	(13.00)	(0.34)
TM	-0.48***	-1.78***	-0.50***	-2.65***	-0.48***	-2.65***
	(-18.44)	(-6.27)	(-13.29)	(-7.71)	(-13.52)	(-8.64)
Log(Issue size)			-0.01	-0.70***		
			(-0.63)	(-4.57)		
Coupon rate			-0.87	6.79		
			(-0.45)	(0.45)		
Age			-0.19***	-1.38***		
			(-13.77)	(-11.19)		
log(Trade size)			-0.23***	0.21*	-0.23***	0.15
			(-12.30)	(1.89)	(-11.45)	(1.33)
Volatility			0.89***	7.04***	0.83***	6.41***
			(15.09)	(17.66)	(15.48)	(16.22)
On-the-run			-0.08*	-0.64**	-0.08**	-0.53*
			(-1.86)	(-2.09)	(-2.02)	(-1.91)
Day FE	No	No	No	No	Yes	Yes
Bond FE	No	No	No	No	Yes	Yes
Adj. R^2	4.09%	1.25%	31.21%	33.13%	35.40%	36.66%
# of obs.	25,863	25,863	25,863	25,863	25,857	25,857

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.3b
Heckman (1979) Two-Stage Selection Model (3-Year Bonds)

This table reports the results of two-stage regressions. The column labeled "Stage I" presents probit models for the binary choice between bilateral inquiry and RFQ and X-Bond, where the dependent variable equals one if X-Bond is selected and zero otherwise. The column labeled "Stage II" reports the determinants of the *Amihud* and *Roll* illiquidity measures for trades executed via bilateral inquiry and RFQ and via X-Bond, controlling for endogenous selection. Independent variables include Issue size (Log scale), Coupon rate, Age, Time to maturity, Trade size (Log scale), Volatility, a dummy variable indicating On-the-run status, and three calendar-time dummies (Monday, Friday, and End of month). The Inverse Mills ratio terms included in the "Stage II" regressions are denoted IMR1 and IMR2. All continuous independent variables are demeaned. t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from September 2017 to June 2021.

		Stage II			
		Amihud		*Roll*	
	Stage I	Bilateral inquiry and RFQ	X-Bond	Bilateral inquiry and RFQ	X-Bond
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.84***	0.58***	0.11*	4.04***	3.25***
	(-34.75)	(33.06)	(1.77)	(48.24)	(3.26)
Log(Issue size)	-0.05***	0.00	-0.02	-0.29***	-0.72*
	(-2.87)	(0.27)	(-1.16)	(-3.73)	(-1.86)
Coupon rate	-2.25	-0.01	-0.00	0.02	-0.08
	(-1.56)	(-0.80)	(-0.43)	(0.26)	(-0.37)
Age	-0.35***	-0.32***	-0.01	-1.42***	-1.73*
	(-24.13)	(-12.56)	(-0.20)	(-10.49)	(-1.81)
Log(Trade size)	0.61***	0.02	-0.10	0.39***	1.78
	(39.55)	(0.76)	(-1.31)	(2.63)	(1.36)
Volatility	0.04**	0.56***	0.09***	4.33***	0.92***
	(2.48)	(18.30)	(5.28)	(22.19)	(5.64)
On-the-run	0.07**	-0.00	-0.01	-0.04	-0.37*
	(2.25)	(-0.25)	(-0.73)	(-0.34)	(-1.89)
Monday	-0.02				
	(-0.89)				
Friday	-0.04*				
	(-1.76)				
End of month	-0.07				
	(-1.41)				
IMR1		1.50***		3.41***	
		(7.28)		(2.80)	
IMR2			-0.18		4.07
			(-0.67)		(0.93)
Adj. R^2	9.27%	35.44%	15.77%	43.02%	8.16%
# of obs	25,863	20,198	5,665	20,198	5,665

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.4a
Panel Regressions (5-Year Bonds)

This table reports the results of panel regressions of the *Amihud* and *Roll* illiquidity measures on the dummy variable *TM*, which equals one for bonds traded through X-Bond and zero for bonds traded through bilateral inquiry and RFQ. Control variables include Issue size (Log scale), Coupon rate, Age, Time to maturity, Trade size (Log scale), Volatility, and a dummy variable indicating On-the-run status. t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from September 2017 to June 2021.

	(1)		(2)		(3)	
	Amihud	*Roll*	*Amihud*	*Roll*	*Amihud*	*Roll*
Intercept	1.33***	7.18***	5.47***	21.90	6.94***	-4.04
	(14.20)	(17.82)	(2.97)	(1.26)	(9.70)	(-1.03)
TM	-1.05***	-4.53***	-1.29***	-6.49***	-1.25***	-6.50***
	(-14.13)	(-9.54)	(-11.12)	(-9.94)	(-11.26)	(-10.52)
Log(Issue size)			0.05	-1.04*		
			(0.77)	(-1.79)		
Coupon rate			-3.61	14.60		
			(-1.02)	(0.54)		
Age			-0.28***	-1.59***		
			(-11.09)	(-7.01)		
log(Trade size)			-0.27***	0.72***	-0.31***	0.57***
			(-6.28)	(2.79)	(-7.84)	(2.61)
Volatility			0.46***	2.84***	0.41***	2.54***
			(12.59)	(9.47)	(10.78)	(9.02)
On-the-run			-0.21**	-0.59	-0.33***	-1.23***
			(-2.07)	(-1.23)	(-3.80)	(-3.12)
Day FE	No	No	No	No	Yes	Yes
Bond FE	No	No	No	No	Yes	Yes
Adj. R^2	5.52%	3.59%	30.92%	28.60%	36.22%	33.92%
# of obs.	25,535	28,535	28,535	28,535	28,524	28,524

Note: $^{*}p$ <0.1; $^{**}p$ <0.05; $^{***}p$ <0.01

Table B.4b
Heckman (1979) Two-Stage Selection Model (5-Year Bonds)

This table reports the results of two-stage regressions. The column labeled "Stage I" presents probit models for the binary choice between bilateral inquiry and RFQ and X-Bond, where the dependent variable equals one if X-Bond is selected and zero otherwise. The column labeled "Stage II" reports the determinants of the *Amihud* and *Roll* illiquidity measures for trades executed via bilateral inquiry and RFQ and via X-Bond, controlling for endogenous selection. Independent variables include Issue size (Log scale), Coupon rate, Age, Time to maturity, Trade size (Log scale), Volatility, a dummy variable indicating On-the-run status, and three calendar-time dummies (Monday, Friday, and End of month). The Inverse Mills ratio terms included in the "Stage II" regressions are denoted IMR1 and IMR2. All continuous independent variables are demeaned. t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from September 2017 to June 2021.

		Stage II			
		Amihud		*Roll*	
	Stage I	Bilateral inquiry and RFQ	X-Bond	Bilateral inquiry and RFQ	X-Bond
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.72***	1.27***	0.20***	7.04***	2.27***
	(-32.38)	(22.33)	(4.17)	(27.90)	(3.46)
Log(Issue size)	0.24***	0.14***	-0.07**	-0.40	-0.92*
	(12.05)	(2.77)	(-2.51)	(-1.13)	(-1.84)
Coupon rate	4.56***	-0.03	-0.02	0.24	-0.59***
	(3.29)	(-1.02)	(-0.97)	(1.41)	(-2.62)
Age	-0.19***	-0.61***	0.02	-2.79***	-0.51
	(-22.10)	(-9.26)	(0.33)	(-7.50)	(-0.85)
Log(Trade size)	0.49***	-0.08	-0.24***	0.63*	0.31
	(39.52)	(-0.94)	(-3.04)	(1.79)	(0.31)
Volatility	0.07***	1.07***	0.14***	6.36***	0.73**
	(13.10)	(17.16)	(5.12)	(12.78)	(2.36)
On-the-run	-0.02	-0.08**	0.01	-0.22	0.06
	(-0.80)	(-2.08)	(0.54)	(-1.22)	(0.32)
Monday	-0.04**				
	(-2.28)				
Friday	-0.05**				
	(-2.36)				
End of month	-0.12**				
	(-2.36)				
IMR1		1.76**		4.55	
		(2.59)		(1.43)	
IMR2			-0.39		-1.99
			(-1.59)		(-0.69)
Adj. R^2	8.64%	36.13%	19.99%	38.11%	5.26%
# of obs	28,535	21,663	6,872	21,663	6,872

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.5a
Panel Regressions (10-Year Bonds)

This table reports the results of panel regressions of the *Amihud* and *Roll* illiquidity measures on the dummy variable *TM*, which equals one for bonds traded through X-Bond and zero for bonds traded through bilateral inquiry and RFQ. Control variables include Issue size (Log scale), Coupon rate, Age, Time to maturity, Trade size (Log scale), Volatility, and a dummy variable indicating On-the-run status. t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from September 2017 to June 2021.

	(1)		(2)		(3)	
	Amihud	*Roll*	*Amihud*	*Roll*	*Amihud*	*Roll*
Intercept	3.51***	15.52***	22.05***	-2.77	19.94***	-2.24
	(20.45)	(23.72)	(5.11)	(-0.11)	(11.78)	(-0.41)
TM	-2.95***	-12.87***	-3.85***	-17.38***	-3.75***	-16.75***
	(-19.55)	(-18.80)	(-15.98)	(-17.43)	(-14.31)	(-15.30)
Log(Issue size)			-0.07	0.43		
			(-0.49)	(0.48)		
Coupon rate			-6.45	69.44		
			(-0.58)	(1.56)		
Age			-0.38***	-1.57***		
			(-9.95)	(-6.35)		
log(Trade size)			-0.87***	0.45	-0.91***	0.97***
			(-9.80)	(1.09)	(-9.53)	(3.06)
Volatility			0.04***	0.24***	0.03***	0.16***
			(9.95)	(10.22)	(7.63)	(7.37)
On-the-run			-0.40*	-0.71	-0.49**	-0.06
			(-1.83)	(-0.64)	(-2.22)	(-0.09)
Day FE	No	No	No	No	Yes	Yes
Bond FE	No	No	No	No	Yes	Yes
Adj. R^2	6.51%	6.93%	19.54%	17.08%	26.46%	26.99%
# of obs.	31,535	31,535	31,535	31,535	31,523	31,523

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.5b
Heckman (1979) Two-Stage Selection Model (10-Year Bonds)

This table reports the results of two-stage regressions. The column labeled "Stage I" presents probit models for the binary choice between bilateral inquiry and RFQ and X-Bond, where the dependent variable equals one if X-Bond is selected and zero otherwise. The column labeled "Stage II" reports the determinants of the *Amihud* and *Roll* illiquidity measures for trades executed via bilateral inquiry and RFQ and via X-Bond, controlling for endogenous selection. Independent variables include Issue size (Log scale), Coupon rate, Age, Time to maturity, Trade size (Log scale), Volatility, a dummy variable indicating On-the-run status, and three calendar-time dummies (Monday, Friday, and End of month). The Inverse Mills ratio terms included in the "Stage II" regressions are denoted IMR1 and IMR2. All continuous independent variables are demeaned. t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from September 2017 to June 2021.

		Stage II			
		Amihud		*Roll*	
	Stage I	Bilateral inquiry and RFQ	X-Bond	Bilateral inquiry and RFQ	X-Bond
	(1)	(2)	(3)	(4)	(5)
Intercept	-1.03***	3.19***	1.36***	13.77***	6.24***
	(-44.51)	(29.55)	(5.52)	(36.29)	(3.89)
Log(Issue size)	0.06***	-0.05	0.01	0.25	0.10
	(2.60)	(-0.54)	(0.18)	(0.42)	(0.34)
Coupon rate	-1.16	-0.17**	0.02	0.06	-0.07
	(-0.78)	(-2.10)	(0.90)	(0.19)	(-0.43)
Age	-0.18***	-2.23***	-0.90***	-10.90***	-4.09***
	(-26.29)	(-7.26)	(-3.81)	(-6.25)	(-2.72)
Log(Trade size)	0.29***	-0.16	0.37*	3.92***	3.53***
	(23.16)	(-0.95)	(1.84)	(3.88)	(2.74)
Volatility	0.01***	2.33***	0.48**	12.04***	2.52**
	(23.52)	(10.52)	(2.54)	(8.29)	(2.15)
On-the-run	0.23***	0.39***	0.24***	2.52***	1.18**
	(9.94)	(3.07)	(3.11)	(3.87)	(2.17)
Monday	-0.02				
	(-0.83)				
Friday	0.00				
	(0.06)				
End of month	-0.10**				
	(-2.08)				
IMR1		11.73***		62.74***	
		(5.14)		(4.50)	
IMR2			3.14***		14.21**
			(3.37)		(2.31)
Adj. R^2	10.28%	20.42%	7.91%	17.83%	0.73%
# of obs	31,535	25,641	5,894	25,641	5,894

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.6a
Panel Regressions (On-the-run Bonds)

This table reports the results of panel regressions of the *Amihud* and *Roll* illiquidity measures on the dummy variable *TM*, which equals one for bonds traded through X-Bond and zero for bonds traded through bilateral inquiry and RFQ. Control variables include Issue size (Log scale), Coupon rate, Age, Time to maturity, Trade size (Log scale), Volatility, and a dummy variable indicating On-the-run status. t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from September 2017 to June 2021.

	(1)		(2)		(3)	
	Amihud	*Roll*	*Amihud*	*Roll*	*Amihud*	*Roll*
Intercept	2.78***	13.59***	1.08	-46.41***	5.57***	-26.73***
	(15.38)	(17.91)	(0.34)	(-2.81)	(3.36)	(-3.27)
TM	-2.26***	-10.98***	-2.60***	-12.28***	-2.59***	-12.00***
	(-14.15)	(-14.94)	(-11.62)	(-12.90)	(-11.11)	(-11.91)
Log(Issue size)			0.15	0.52		
			(1.47)	(1.03)		
Coupon rate			19.11	149.31**		
			(1.54)	(2.35)		
Age			-0.02	-1.55*		
			(-0.14)	(-1.95)		
Time to maturity			0.28***	1.14***		
			(11.21)	(8.88)		
log(Trade size)			-0.24***	1.93***	-0.16*	2.20***
			(-3.29)	(5.15)	(-1.72)	(4.70)
Volatility			0.04***	0.19***	0.03***	0.17***
			(7.16)	(9.58)	(7.74)	(7.58)
Day FE	No	No	No	No	Yes	Yes
Bond FE	No	No	No	No	Yes	Yes
Adj. R^2	11.71%	12.60%	33.43%	29.18%	43.60%	40.09%
# of obs.	19,213	19,213	19,213	19,213	19,209	19,209

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.6b
Heckman (1979) Two-Stage Selection Model (On-the-run Bonds)

This table reports the results of two-stage regressions. The column labeled "Stage I" presents probit models for the binary choice between bilateral inquiry and RFQ and X-Bond, where the dependent variable equals one if X-Bond is selected and zero otherwise. The column labeled "Stage II" reports the determinants of the *Amihud* and *Roll* illiquidity measures for trades executed via bilateral inquiry and RFQ and via X-Bond, controlling for endogenous selection. Independent variables include Issue size (Log scale), Coupon rate, Age, Time to maturity, Trade size (Log scale), Volatility, a dummy variable indicating On-the-run status, and three calendar-time dummies (Monday, Friday, and End of month). The Inverse Mills ratio terms included in the "Stage II" regressions are denoted IMR1 and IMR2. All continuous independent variables are demeaned. t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from September 2017 to June 2021.

		Stage II			
		Amihud		*Roll*	
	Stage I	Bilateral inquiry and RFQ	X-Bond	Bilateral inquiry and RFQ	X-Bond
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.54***	2.66***	0.39****	12.99***	2.07***
	(-21.31)	(33.11)	(6.96)	(33.47)	(6.35)
Log(Issue size)	0.56***	0.81***	-0.45***	3.85***	-1.96**
	(24.13)	(3.82)	(-3.02)	(3.92)	(-2.44)
Coupon rate	7.38**	0.14	-0.06	1.39***	-0.19
	(4.00)	(1.59)	(-1.21)	(3.00)	(-0.84)
Age	0.38***	0.28***	-0.14***	0.99**	-0.90***
	(10.83)	(3.14)	(-2.65)	(2.19)	(-2.96)
Time to maturity	-0.04***	0.77***	0.29***	3.06***	1.27***
	(-8.03)	(7.18)	(4.57)	(5.77)	(4.21)
Log(Trade size)	0.03	-0.38***	-0.18***	0.92***	0.58***
	(1.60)	(-7.82)	(-5.92)	(3.83)	(2.94)
Volatility	0.01***	1.58***	-0.19**	7.87***	-0.71**
	(11.98)	(10.30)	(-2.56)	(10.89)	(-2.02)
Monday	-0.02				
	(-1.00)				
Friday	-0.05**				
	(-2.17)				
End of month	-0.11**				
	(-2.10)				
IMR1		5.37***		27.16***	
		(3.63)		(3.64)	
IMR2			-1.51**		-6.16*
			(-2.52)		(-1.83)
Adj. R^2	4.50%	40.16%	5.91%	33.29%	2.11%
# of obs	19,213	13,692	5,521	13,692	5,521

Note: $^{*}p$ <0.1; $^{**}p$ <0.05; $^{***}p$ <0.01

Table B.7a
Panel Regressions (Off-the-run Bonds)

This table reports the results of panel regressions of the *Amihud* and *Roll* illiquidity measures on the dummy variable *TM*, which equals one for bonds traded through X-Bond and zero for bonds traded through bilateral inquiry and RFQ. Control variables include Issue size (Log scale), Coupon rate, Age, Time to maturity, Trade size (Log scale), Volatility, and a dummy variable indicating On-the-run status. t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from September 2017 to June 2021.

	(1)		(2)		(3)	
	Amihud	*Roll*	*Amihud*	*Roll*	*Amihud*	*Roll*
Intercept	1.65***	7.99***	6.13***	0.70	11.57***	1.37
	(15.60)	(18.21)	(4.07)	(0.08)	(14.72)	(0.44)
TM	-1.41***	-5.39***	-1.42***	-6.74***	-1.36***	-6.83***
	(-15.35)	(-11.66)	(-11.01)	(-10.57)	(-10.08)	(-10.73)
Log(Issue size)			0.13**	-0.19		
			(2.56)	(-0.59)		
Coupon rate			-5.58	16.48		
			(-1.58)	(0.74)		
Age			-0.02	-0.08		
			(-1.32)	(-0.77)		
Time to maturity			0.26***	1.17***		
			(17.97)	(13.86)		
log(Trade size)			-0.48***	0.36*	-0.55***	0.33*
			(-12.31)	(1.94)	(-12.59)	(1.91)
Volatility			0.15***	0.91***	0.16***	0.91***
			(6.39)	(6.45)	(5.76)	(5.98)
Day FE	No	No	No	No	Yes	Yes
Bond FE	No	No	No	No	Yes	Yes
Adj. R^2	3.78%	2.70%	24.12%	18.95%	30.22%	27.16%
# of obs.	88,612	88,612	88,612	88,612	88,590	88,590

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.7b
Heckman (1979) Two-Stage Selection Model (Off-the-run Bonds)

This table reports the results of two-stage regressions. The column labeled "Stage I" presents probit models for the binary choice between bilateral inquiry and RFQ and X-Bond, where the dependent variable equals one if X-Bond is selected and zero otherwise. The column labeled "Stage II" reports the determinants of the *Amihud* and *Roll* illiquidity measures for trades executed via bilateral inquiry and RFQ and via X-Bond, controlling for endogenous selection. Independent variables include Issue size (Log scale), Coupon rate, Age, Time to maturity, Trade size (Log scale), Volatility, a dummy variable indicating On-the-run status, and three calendar-time dummies (Monday, Friday, and End of month). The Inverse Mills ratio terms included in the "Stage II" regressions are denoted IMR1 and IMR2. All continuous independent variables are demeaned. t-statistics, reported in parentheses, are based on robust standard errors with two-way clustering at the day and bond levels. The sample period spans from September 2017 to June 2021.

		Stage II			
		Amihud		*Roll*	
	Stage I	Bilateral inquiry and RFQ	X-Bond	Bilateral inquiry and RFQ	X-Bond
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.97***	1.62***	0.37***	7.55***	4.33***
	(-71.86)	(35.33)	(3.90)	(37.32)	(3.34)
Log(Issue size)	0.02**	0.11***	-0.01	-0.09	-0.46*
	(2.01)	(2.98)	(-0.46)	(-0.42)	(-1.77)
Coupon rate	6.59***	-0.05*	0.02	0.34**	-0.14
	(8.13)	(-1.85)	(1.19)	(2.31)	(-0.77)
Age	-0.19***	-0.09*	-0.11	-1.28***	-1.59*
	(-48.63)	(-1.70)	(-1.62)	(-6.33)	(-1.73)
Time to maturity	0.02***	0.82***	0.11***	3.80***	1.05***
	(7.84)	(18.94)	(6.11)	(15.80)	(2.58)
Log(Trade size)	0.57***	-0.37***	-0.02	1.89***	2.76*
	(75.11)	(-4.35)	(-0.14)	(4.70)	(1.74)
Volatility	0.05***	0.96***	0.10	5.87***	1.20
	(35.83)	(9.80)	(1.56)	(9.96)	(1.56)
Monday	-0.03***				
	(-2.58)				
Friday	-0.03**				
	(-2.38)				
End of month	-0.11***				
	(-3.46)				
IMR1		0.89*		13.69***	
		(1.69)		(4.96)	
IMR2			0.46		5.88
			(1.41)		(1.44)
Adj. R^2	11.69%	28.84%	14.11%	25.96%	2.34%
# of obs	88,612	71,763	16,849	71,763	16,849

Note: $^{*}p$ <0.1; $^{**}p$ <0.05; $^{***}p$ <0.01

Table B.8
Information precision and market share of X-Bond

This table reports the average market share of X-Bond, measured by the number of trades and by trading volume, for all bonds grouped by their information precision ϕ. On each sample day, bonds are sorted into quartiles based on information precision. Within each quartile, we first compute the cross-sectional averages of information precision and X-Bond's market share, and then take the time-series mean of these daily cross-sectional averages. The sample period spans from July 2018 to June 2021.

	ϕ	Number of trades (%)	Trading volume (%)
		Panel A.1: Treasury bonds	
Low	0.01	0.11	0.11
2	0.08	0.17	0.18
3	0.20	0.19	0.20
4	0.91	0.22	0.23
High	5.01	0.26	0.27
High−Low	5.00***	0.15***	0.16***
		Panel A.2: Policy bank bonds	
Low	0.01	0.13	0.16
2	0.04	0.15	0.17
3	0.13	0.15	0.18
4	0.47	0.18	0.21
High	2.89	0.21	0.25
High−Low	2.88***	0.08***	0.09***
		Panel B.1: On-the-run bonds	
Low	0.01	0.10	0.11
2	0.05	0.12	0.12
3	0.14	0.13	0.14
4	0.34	0.13	0.14
High	1.08	0.14	0.16
High−Low	1.07***	0.04***	0.05***
		Panel B.2: Off-the-run bonds	
Low	0.01	0.12	0.14
2	0.04	0.17	0.20
3	0.15	0.18	0.21
4	0.64	0.21	0.24
High	5.32	0.24	0.27
High−Low	5.31***	0.12***	0.13***
		Panel C.1: 3-year bonds	
Low	0.02	0.14	0.15
2	0.09	0.16	0.18
3	0.30	0.17	0.20
4	1.20	0.19	0.22
High	7.23	0.24	0.26
High−Low	7.21***	0.09***	0.11***
		Panel C.2: 5-year bonds	
Low	0.01	0.14	0.17
2	0.06	0.17	0.20
3	0.19	0.17	0.20
4	0.81	0.21	0.23
High	5.41	0.25	0.28
High−Low	5.40***	0.11***	0.11***
		Panel C.3: 10-year bonds	
Low	0.01	0.09	0.11
2	0.05	0.13	0.15
3	0.14	0.15	0.17
4	0.41	0.16	0.18
High	1.57	0.17	0.20
High−Low	1.56***	0.08***	0.09***

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$