Venue Participation and Transaction Cost: Evidence from All-to-All China Government Bonds Market*

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Abstract

This paper examines bond trading activity and transaction cost differences between the bilateral Over-the-Counter (OTC) and the centralized Central Limit Order Book (CLOB) venues in the China government bonds market, structured as all-to-all. Using a novel trade-level dataset, we estimate that CLOB reduces transaction costs by 0.66 bp compared to OTC, highlighting the efficiency of centralized trading mechanism. Furthermore, we document venue selection: CLOB disproportionately facilitates core traders, standardized orders, and newly issued bond. Despite CLOB's cost advantages, the continued use of OTC is justified by its unique benefits in mitigating information leakage, designating counterparties, and facilitating position rebalancing.

Keywords: over-the-counter, limit order book, transaction cost, all-to-all trading, China Government Bonds Market

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1 Introduction

For the sake of efficiency, redesigning trading mechanisms and reorganizing market structures for important debt securities (e.g., sovereign bonds) has attracted substantial attention in recent years, particularly in light of the global financial turmoil during the COVID-19 crisis. Ongoing debates focus on key issues such as the desirability of centralizing the traditional over-the-counter structure, the feasibility of integrating different markets and segmented trading systems, and the incentive compatibility of these practical innovation, among other considerations (Allen and Wittwer (2023), Duffie (2023), Chaboud et al. (2025)).

To address these debates, we ask a leading question: What is the impact of market microstructure on asset liquidity? Answering this question is valuable both for academic inquiry into financial market imperfections (e.g., transaction cost disparities), and for policymakers working to strengthen trading infrastructure and to enhance trading compliance across a broad range of fixed-income markets. This paper explores the question empirically.

A rigorous comparison of liquidity across different trading mechanisms (referred to as *venues* hereafter) requires two key conditions within the market setting. First, multiple venues coexist. Second, traders must have free access to these venues and must be unconstrained in choosing between them. However, the unavailability of data from such an ideal environment is a common empirical challenge in the literature. For example, markets such as the ones for U.S. corporate bonds only operate over-the-counter (OTC). Even in the U.S. Treasury market where centralized venue (e.g., order book) exists alongside OTC, access is typically restricted to a limited group of participants (dealers and principal trading firms).

We address this empirical challenge by introducing a novel dataset from the China Interbank Bond Market (CIBM). In the CIBM, first, a bilateral OTC venue and a centralized Central Limit Order Book (CLOB) venue coexist, and second, most traders in the CIBM can freely access both venues without restrictions. This unique market setting is enabled through a unified electronic trading platform provided by China's central bank. This unified platform, built with both OTC and CLOB venues, is provided as a public service, and therefore it is compulsory for all traders and offered for free. Using this dataset, we can observe venue choice at the trade level. We then focus on the trading and liquidity of China's central government bonds and policy bank bonds, both of which are regarded as risk-free instruments by participants in the local financial market (Clayton et al. (2025)).

The high granularity of this dataset allows us to effectively control for confounding factors affecting asset liquidity, including traders, terms-of-trade, and bond-specific characteristics. To achieve this, we apply three empirical strategies: namely sample refinement, finer fixed effects, and constructing a paired-trade sample. The paired-trade sample is a group of twin trades that are identical in all observable characteristics except for the venue of execution. Leveraging these three empirical strategies within the previously mentioned unique market setting, we isolate the venue-specific impact on asset liquidity and then draw causal inferences. These empirical strategies allow us to answer the leading question rigorously.

Our main result shows that the novel CLOB venue reduces the transaction cost[1] (our primary metric for liquidity) by 0.664 basis points (bp). Given that the annual total trading volume executed on the CLOB venue is about 28 trillion RMB (4 trillion USD), our estimates suggest an annual cost saving of around 930 million RMB (133 million USD)[2]. This considerable dollar value underscores the economic importance of introducing a centralized trading mechanism like the central limit order book for risk-free debt securities. Centralized trading is cost-effective in allocating assets across investors in the secondary market, leading to an improvement in liquidity compared to the OTC venue.

To achieve our main result, we examine cross-venue trading activities, which also provide two key insights into how market microstructure influences asset liquidity. First, the all-to-all market structure changes the landscape of liquidity provision. Specifically, we observe that customers (i.e., non-dealer financial institutions) are able to supply liquidity just as dealers traditionally do, such as by quoting bids and asks on the CLOB.[3] As a result, we adapt the transaction cost measure to better fit this all-to-all structure. Second, even with a centralized venue, the bilateral OTC venue persists in supplying liquidity. Specifically, we find that OTC still dominates total trading volume, as traders continue to favor it for their trades. Thus, we implement the aforementioned empirical strategies to address the bias from

[1]To be precise, we use the Choi-Huh measure (Choi et al. (2024)) but carefully tailor it to the all-to-all structure of the China Interbank Bond Market (CIBM), as discussed below.

[2]To calculate this, we divide the 0.664 basis points by two, as the spread measure is based on the round-trip cost, which includes a buy trade and a sell trade. This gives a payment saving of 332 RMB per 10 million RMB trade. By scaling this up to the total annual trading volume, we arrive at the aggregate cost saving. While the spread measure used here is not a perfect proxy for the actual cash transfer, we use it for the sake of simplicity. Conversely, our alternative matching approach with the paired-trades sample offers a more accurate representation, as detailed in Section 5.2.3.

[3]For example, 16.4% of CLOB total trading volume is executed at prices that are quoted by customers.

venue selection. We now elaborate on these two insights in greater detail.

First, the all-to-all market structure fundamentally alters the landscape of liquidity provision by decoupling the roles of traders in liquidity (demand or supply) from their formal status. Introduced by Duffie (2023) at the Jackson Hole Economic Symposium, *all-to-all* is a novel market structure in which any investor can directly trade with any other investor without intermediation, as illustrated in Figure 1. As a result, in this market structure, traders can freely choose to either demand or supply liquidity. This contrasts sharply with traditional dealer-intermediated markets, where dealers are the exclusive liquidity providers and each customer must approach a dealer, request a quote, and then execute a trade. Since liquidity provision is now an endogenous activity, we must identify it accurately. We base our identification on the buy-sell balance principle. That is, we assume that liquidity providers engage in relatively balanced trading on both sides (buy and sell) for the same bond within a short time window, while in contrast, liquidity consumers show one-sided behavior (either buying or selling). We implement this identifying principle at the bond-day level by assigning each trader into either a demand or a supply group.[4] With this re-assigned classification based on traders' *de facto* roles in liquidity demand and supply, we then apply the widely-used Choi-Huh transaction cost measure (Choi et al. (2024)). Our main measure, the *Spread*, is therefore closely tied to consumer surplus, which captures the average markup (or markdown) paid by liquidity consumers when buying from (or selling to) liquidity suppliers.

[Figure 1 about here.]

Second, sustained venue selection leads to the continued dominance of the bilateral over-the-counter (OTC) venue, as evidenced by its larger share of total trading volume. We highlight three key selection patterns across venues, stemming from traders, terms-of-trade, and bond characteristics respectively. (1) The CLOB venue is populated with core traders, while peripheral traders mostly opt for the OTC venue. (2) The CLOB venue is more focused on standardized transactions, such as those with standardized sizes and settlement terms, whereas customized transactions are almost exclusively carried out on the OTC venue. (3) Recently issued bonds are more heavily traded on the CLOB venue, while deeply off-the-run

[4]That is, in our analysis, we define such short time window as one day to examine each trader's buy-sell balance. Though simple, this assignment approach for identifying demand and supply aligns well with different practical operations in the real business world. We discuss this assignment in details in Section 5.1.

bonds tend to be traded on the OTC venue. Given these facts, to arrive at our main result, our aforementioned empirical strategies are specifically designed to account for these venue-selection patterns in order to ensure a causal inference. For instance, the sample-refinement step is applied to ensure the overlapping and balanced covariate distributions across venues.

Taking all these findings together, we conclude this paper with an explanation of the cross-venue cost disparity from an (unconstrained) equilibrium perspective. As traders in our sample are unconstrained in choosing between the two venues, what we observe is the optimal venue choice for each trader.[5] Therefore, to reconcile the observed equilibrium, we must account for implicitly unmeasured, venue-specific benefits that are unique to the OTC venue. We characterize three benefits of the OTC venue: mitigating information leakage, enabling counterparty designation with customized terms, and facilitating bond position re-balancing. These benefits arise from the inherent flexibility of OTC, in contrast to the rigid trading rules of CLOB. Therefore, at equilibrium, traders also derive utility from these unique beneficial characteristics of OTC, despite its higher transaction costs. We refer to this explanation as *inelastic demand*, where traders seeking these specific OTC benefits exhibit less elastic demand for the OTC venue.

The paper is organized as follows. In Section 2, we closely inspect the CLOB and OTC venues on the unified electronic trading platform, and accordingly detail how the all-to-all structure operates. Section 3 introduces our novel granular dataset. Section 4 documents the selection patterns between the two venues. Importantly, in Section 5, we demonstrate the adaption of transaction cost measure in Section 5.1, and detail the three empirical strategies along with the regression results in Section 5.2. Finally, Section 6 reconciles the seemingly contradictory findings of sustained OTC venue participation (from Section 4) and the CLOB cost-saving effect (from Section 5.2), by exploring the OTC venue-specific benefits.

Related literature

This paper primarily contributes to the literature that examines market structure and trading mechanisms in relation to trading activity, asset liquidity, and economic welfare.[6]

[5] Alternative explanations, such as constrained balance sheets, could also account for the cost disparity but are beyond the scope of this paper. Instead, we focus on explaining this disparity through venue-specific characteristics.

[6] See Bessembinder et al. (2020), a survey on fixed-income market microstructure and trading outcomes.

First, our paper is closely related to recent empirical studies that focus on the impact of electronic protocols on the bond market (e.g., Hendershott and Madhavan (2015), O'Hara and Zhou (2021), Allen and Wittwer (2023)). Unlike these studies, which primarily examine the Request-for-Quote (RFQ) protocol as an upgrade from traditional voice-message trading, our paper goes a step further by introducing the limit order book as the next-stage advancement in trading mechanisms, which breaks the traditional dealership structure.

To the best of our knowledge, this is the first paper to thoroughly present a Central Limit Order Book (CLOB) for trading bonds that is a unified system accessible to all traders across the entire market. In contrast, while order books exist in the U.S. Treasury and European government bonds markets (e.g., Bund), they are neither unified across the entire market, nor accessible to all market participants.[7] While the literature generally agrees on the higher efficiency of centralized trading, actual examples specific to bond markets are rare. Our study addresses this gap by providing comprehensive empirical evidence that supports the cost-saving effects of CLOB in the bond market.

Second, since our dataset combines the co-existence of OTC and centralized venues with traders' free choice between them, our results contribute to the theoretical literature on endogenous venue participation and its implications for optimal market structure design through welfare analysis (e.g., Glode and Opp (2020), Dugast et al. (2022), Lee and Wang (2025)). We provide empirical evidence that assesses the relevance of these models, particularly focusing on the stylized equilibrium selection patterns between venues, influenced by trader, trade terms, and bond characteristics. Additionally, we micro-found these conceptualized market structures, namely decentralized (i.e., OTC), centralized, and hybrid forms, by closely examining the practical operation of the trading mechanisms within each structure. Furthermore, given our granular dataset, we employ the language of a demand system for venues, which examines how traders' trading motives interact with the venue characteris-

[7]Specifically, in the U.S. Treasury market, order books are not unified across the entire market since multiple inter-dealer brokers offer their own separate books (e.g., BrokerTec versus TradeWeb). The order books are not accessible to all market participants either, with access often restricted to dealers and principal trading firms. Similarly, in the German government bond (Bund) market, several competing order books are offered by different brokers (e.g., BrokerTec EGB versus MTS), with access often limited to dealers and other authorized financial institutions (e.g., bank and bank-affiliated investment firms), barring non-bank institutions (e.g., hedge funds) from accessing (De Roure et al. (2019)).

tics.[8] Our findings provide insights that can inform future theoretical work in this area, particularly in optimizing market-structure design for a market with heterogeneous traders.

Additionally, we draw on key ideas on the emergence of new liquidity providers, outlined by Hendershott et al. (2021), Ma et al. (2022), Coen and Coen (2022), Comerton-Forde et al. (2025). We apply, tailor, and confirm these ideas in our all-to-all setting, which strictly adheres to the definition of all-to-all proposed by Duffie (2023). In doing so, we provide a real-world example for relevant policy discussions, such as the U.S. Treasury market reform proposals aimed at enhancing liquidity through the establishment of all-to-all trading, in response to constrained dealer intermediation during crises (Duffie (2023), Cochran et al. (2024), Chaboud et al. (2025)). The findings in this paper serve as a foundation for considering the potential impacts of microstructure reforms on trading activity and asset liquidity.[9]

Finally, our paper adds to the expanding literature on China bond markets (closely related to Amstad and He (2019), Holden et al. (2021), Clayton et al. (2025) etc.). Building on these broad discussions, we introduce an important novel dataset and provide detailed institutional pipelines that are closely aligned with up-to-date insights from real-world business.

2 Institutional background

2.1 Overview of the China Interbank Bond Market (CIBM)

The China Interbank Bond Market (CIBM) is the dominant secondary market for trading various types of debt securities in China. By the end of 2023, the CIBM accounted for approximately 80% of the total debt security trading volume in China, with the remaining 20% occurring in exchange markets.[10] The CIBM encompasses a broad spectrum of debt instru-

[8]For example, informed traders who aim to profit from their information advantage tend to prefer the OTC venue for executing trades, because the OTC venue prevents information leakage. Therefore, it makes their demand for the OTC venue less sensitive to transaction costs. This idea applies to other trading motives discussed in Section 6.

[9]Existing literature may often misunderstand or mis-specify the functionality of dealer-intermediated OTC markets, which may appear less liquid and less resilient, particularly during times of crisis. However, liquidity issues in these markets may stem from factors like balance sheet constraints on dealers, rather than from inherent weaknesses in the OTC venue or its decentralized trading mechanisms.

[10]In China, debt securities can also trade on exchange markets, primarily on the Shanghai Stock Exchange and the Shenzhen Stock Exchange. These exchange-traded bond markets primarily cater to retail investors, unlike the CIBM which is exclusively accessible to institutional investors.

ments, primarily central government bonds, local government bonds, policy bank bonds, and corporate bonds. Additionally, the market also features a significant presence of negotiable certificates of deposit (NCD), medium-term notes (MTN), commercial papers (CP), and asset-backed securities (ABS) among other debt instruments, reflecting the diverse financing needs of issuers and investors.

Market participants The China Interbank Bond Market (CIBM) operates as a wholesale market exclusively accessible to registered institutional investors. Its participants include banks, securities firms, asset management firms (such as mutual funds and hedge funds), insurance companies, pension funds and so forth. While the majority of these institutions are domestic, foreign investors can also participate in the CIBM through programs like CIBM Direct and Bond Connect (see Clayton et al. (2025)). Within the CIBM, institution investors hold different statuses — either dealers or customers. Specifically, those that meet certain qualifications can apply for dealer status, which is typically granted to large institutions with substantial capital and trading volume. The remaining institutional investors are automatically classified as customers.[11]

Regulator and organizer The primary regulator of the China Interbank Bond Market (CIBM) is the People's Bank of China (PBoC), the country's central bank. This regulatory framework reflects the crucial role of the bond market in facilitating open market operations and transmitting policy interest rates. Beyond its role as a regulator, the PBoC also functions as an organizer of the CIBM, which is an institutional feature that distinguishes China's bond market from those of many other economies, including the U.S. A key component of this organizational structure is the China Foreign Exchange Trade System (CFETS), a division of the PBoC, which provides the trading infrastructure for all market participants in the CIBM:

[11] We provide the regulatory rights and obligations to frame the cost-benefit analysis that determines the endogenous choice on dealership for those qualified institutions. Dealers are required to provide market-wide price quotes for at least a minimum number of bonds, but receive certain advantages such as priority access to government bond issuance in the primary market and reduced settlement fees in the secondary market. For regulatory details, see PBoC and China central government official websites http://www.pbc.gov.cn/jinrongshichangsi/147160/147247/147269/index.html and https://www.gov.cn/gzdt/2007-01/11/content_493346.htm.

CFETS independently develops and maintains a unified electronic trading platform.[12]

Unified electronic trading platform The unified electronic trading platform provided by CFETS is free and mandatory for all market participants to execute all trades for all financial instruments traded in the China Interbank Bond Market (CIBM). Indeed, the platform is a public service provided by the central bank. As stated in *The Handbook of China Interbank Bond Market (2023)*, "CFETS is the only bond trading platform approved by the PBoC in the China Interbank Bond Market. CFETS adheres to the core principle of using multiple technical approaches and various trading mechanisms to fulfill demands from multi-tiered markets."[13] As cited, this unified electronic trading platform offers multiple trading practices, which can be categorized into the Central Limit Order Book (CLOB) and the over-the-counter (OTC) venues. Moreover, this unified electronic trading system facilitates the CIBM to operate as an all-to-all structure. These will be discussed in greater detail in Sections 2.2 and 2.3.[14]

Government bonds In the local financial market, it is a longstanding convention to consider both China Government Bonds (CGBs) and Policy Bank Bonds (PBBs) as *risk-free* assets (Amstad and He (2019), Clayton et al. (2025)). In this paper, we collectively refer to CGBs and PBBs as "government bonds". CGBs are issued by the Ministry of Finance of the country. Similar to the sovereign debts in other countries, CGBs play a crucial role in China's economic system, serving as a benchmark for pricing all asset classes and a primary tool for

[12]Notably, approximately 200 IT professionals employed at CFETS are dedicated to maintaining and enhancing the platform's functionality, ensuring the system's stability and efficiency. A rough estimate of the total wage bill to these IT professionals is around 60 million RMB per year (8.5 million USD). Combined with the estimated annual cost saving of around 930 million RMB (133 million USD, generated solely by the CLOB function, without accounting for other functions on the platform), this suggests a substantial social welfare improvement from providing this unified electronic trading platform.

[13]For foreign investors, CFETS is also integrated with global trading platforms such as Bloomberg, TradeWeb, and MarketAxess via APIs. For *The Handbook of China Interbank Bond Market (2023)*, see CFETS official website https://iftp.chinamoney.com.cn/english/svcnrl/20231110/2750976.html.

[14]Here, we provide detailed historical background of this platform. This platform was first launched by CFETS in 2009 and has undergone several significant upgrades over the years. Key enhancements include the introduction of an Application Programming Interface (API) connection in 2012, the implementation of a Delivery-versus-Payment (DVP) mechanism in 2013, the launch of order books in 2016 (including the CLOB venue presented in this paper, but also for other transactions such as the repo and swap trades), the establishment of a unified Identity Verification System in 2019, and the launch of portfolio trading in 2023.

monetary and fiscal policy.[15] Distinctively, PBBs are issued by the country's policy banks.[16] Policy bank, an entity directly affiliated with the central government, finances strategic economic projects on behalf of the central government (such as landmark infrastructure in transportation and energy sectors). Given their nature, PBBs are widely perceived as being guaranteed by the central government similar to CGBs, because both instruments are effectively guaranteed by the central government's fiscal capacity.

2.2 Trading venues: CLOB versus OTC

We classify the trading practices built on the unified electronic trading platform into two categories: the Central Limit Order Book (CLOB) venue and the Over-the-Counter (OTC) venue. The key practical differences between them lie in the trading mechanisms for counterparty matching and price setting. Specifically, the CLOB venue operates through a centralized mechanism, where the order book automatically matches buy and sell orders based on a price-time priority rule, and once a match is found, the trade is automatically executed instantly. This sharply contrasts with the traditional mechanism of the OTC venue, where trading occurs in a bilateral way by one party making a take-it-or-leave-it offer to another.

As a result of these trading mechanisms, the CLOB venue has a unique market-wide clearing price whereas the OTC venue exhibits price dispersion, at any given moment. Figure 2 illustrates this distinction in equilibrium price by plotting all transaction prices of a representative bond over a single day across both venues. The uniqueness of equilibrium price in the CLOB venue at each point in time is an evidence for its full-degree centralization, as commonly assumed in the literature.[17]

[Figure 2 about here.]

We now proceed to describe how traders trade bonds in each venue in practice, with the focus on the counterparty matching and price-setting process. For a more intuitive

[15] By the end of 2023, the total outstanding amount of China Government Bonds (CGBs) reached 30.03 trillion RMB, equivalent to 23% of China's nominal GDP. During the sample period, the yield on 1-year China Government Bonds averaged 2.22 percentage points, exhibiting a gradual downward trend.

[16] In China, there are three policy banks in total: the China Development Bank, the Export-Import Bank of China, and the Agricultural Development Bank of China. Each of them issues its own bonds.

[17] For example, see the conclusion of Allen and Wittwer (2023) for a relevant discussion on CLOB's full-degree centralization.

understanding on the functionality and layout of each venue, we supplement our discussion with screenshots of the CFETS electronic trading platform's interface as seen by traders. These visuals, presented in Internet Appendix Figures A1 to A4, demonstrate how traders interact with the system, submit orders, and monitor market activity in real-time.

2.2.1 Central Limit Order Book (CLOB) venue

The Central Limit Order Book is an innovative practice for bond trading.[18] The CLOB venue closely resembles the order book mechanism used in stock exchanges. Both dealers and customers can place anonymous limit orders onto the order book with tick size to be 0.01 bp.[19] The CLOB is both pre-trade and post-trade transparent in that all traders can view the currently available best bids and asks for all bonds before placing orders, as well as the trading details (including bond code, price, and volume but not trader identities) immediately after each transaction occurred on CLOB.

The order book clears orders through a two-step process: counterparty matching and price setting. First, counterparty matching follows a price-time priority rule. That is, when the highest bid price meets or exceeds the lowest ask price, the order book automatically pairs the lowest ask with the highest bid to maximize trade gains. If multiple orders share the same best price, the one submitted first takes priority. Second, conditional on a successful match in the first step, the execution price is set by the quote placed earlier. For instance, if a buy order quoted at 102 is submitted at 9:00 a.m. and is later matched with a sell order quoted at 98 placed at 10:00 a.m., the execution price would be 102, since the bid quote was posted first.[20] The trade is executed instantly, with the transaction volume determined by the smaller of the two order sizes. If applicable, the unmatched portion will remain on the order book, ready for the next match. At the end of the day, unmatched orders are automatically withdrawn.

[18] The Central Limit Order Book is also widely known in the local market as "X-bond".

[19] The regulatory insight is that, this tick size is already small enough and almost never binding. Therefore, our transaction cost measures do not need to account for or adapt to the tick size. Again, this highlights the fact that the result in this paper should be viewed as an unconstrained equilibrium.

[20] In this example, although the sell order is a limit order, it functions as a market order by immediately consuming the available bid on the order book.

2.2.2 Over-the-Counter (OTC) venue

Within the OTC venue, CFETS offers two trading practices: Request-for-Quote (RFQ) and Request-with-Quote (RWQ). Both can be understood as a take-it-or-leave-it offer in a bilateral setting, allowing traders to designate counterparties and negotiate customized prices and other terms-of-trades.[21] Request-for-Quote and Request-with-Quote are mutually exclusive and collectively exhaustive for executing all trades in the OTC venue in the China Interbank Bond Market (CIBM). The details of each practice are outlined below.

Request-for-Quote A trader initiates a Request-for-Quote (RFQ) by sending a buy or sell request to one or multiple dealers simultaneously. Each receiving dealer can view key details, including the bond code, trade direction (buy/sell), requested volume, requesting trader's name, settlement date, and expiration time of the request. The dealer then has the option to respond with a quote or decline the request. The dealer's response functions as a take-it-or-leave-it offer. The requesting trader then compares the quotes received, and decides to accept one or decline all of them.

Request-with-Quote A trader initiates a Request-with-Quote (RWQ) by sending either a buy request with a bid price or a sell request with an ask price to a single trader. The key distinction from RFQ is that the requesting trader must include a price quote in the request. This effectively reverses the quoting dynamic, as the requesting trader now extends a take-it-or-leave-it offer to the recipient. The recipient can view the same trade details as in an RFQ but additionally with the quoted price provided by the sender. The recipient then has the option to either accept the offer or decline it.

Brokerage We recognize that traders may hire brokers (match-makers) to find counterparts and negotiate prices on their behalf, paying a commission fee.[22] This is common in the broad OTC literature where the sequential search history and bilateral negotiation process

[21] Both customers and dealers can initiate Request-for-Quote (RFQ) and Request-with-Quote (RWQ).

[22] In the CIBM, the brokerage business must be licensed. There are six brokerages operating in total. Since brokerage business is not free entry and results in only a few brokers, the CIBM is still very integrated. For the compliance of brokerages, see Xinhua News and China NFRA, http://www.news.cn/fortune/20250328/9d01502e5ab246b9837dac0b67a936e6/c.html.

behind a trade are possible but unobservable to econometricians.[23] In this case, Request-for-Quote and Request-with-Quote primarily serve as execution portals for pre-negotiated trades in which both parties have already agreed on all terms. This reasoning extends to other trading practices, such as one-on-one voice call or online text messaging. Regardless of these (unobserved) pre-trade processes in the real world, traders must ultimately use one of the two OTC practices to finalize their pre-negotiated trades. From this perspective, our measured OTC transaction costs in Section 5 represent a lower bound without taking the additional brokerage commission fee into account due to data unavailability.[24]

2.3 All-to-all market structure

This unified electronic trading platform establishes the China Interbank Bond Market (CIBM) as all-to-all. That is, any trader can directly trade with any other trader (Duffie (2023)), as opposed to the traditional dealer-intermediated market where the customer must go to a dealer, ask for a quote, and trade. This all-to-all system forms an institutional basis for a highly integrated market with minimal segmentation. Also, the advanced electronic technology embedded in this trading system mitigates the common frictions or wedges associated with bond trading, such as search friction, information friction and intermediation capacity constraint, which are widely discussed in the literature but largely absent in the CIBM.

The highly integrated, low-friction all-to-all market structure of the CIBM sets it apart from other major bond markets, such as the U.S., which continues to operate based on the dealership network, with segmented alternative trading systems and the continued prevalence of voice-based search methods (see Hendershott and Madhavan (2015), Duffie et al. (2023), Duffie (2023), and the SIFMA report on global fixed-income markets). Therefore, this paper contributes by presenting a real-world example of an all-to-all bond market, a concept that is widely discussed yet remains largely counterfactual in other major bond markets.

From a micro-finance perspective, this innovative all-to-all market structure fundamen-

[23] An exception is Kargar et al. (2023). The authors directly observe the sequential search process, including unsuccessful trade attempts before a successful trade occurs.

[24] For reference only, for each transaction on government bonds, the brokerage commission fee is usually about 0.1—0.3 bp of the order size, with a fee cap per transaction. For details, see the Reuters article https://www.reuters.com/article/world/china/-idUSL4S0ZW1ER/. Notably, traders only use OTC to finalize pre-negotiated trades. This is because, the CLOB venue is central-clearing and order-anonymity: it is impossible to deliver an order to a designated counterparty through CLOB.

tally changes the liquidity landscape. Unlike dealer-intermediated markets, traders in this setting can freely trade and therefore freely choose to act as liquidity demanders or suppliers, regardless of their formal classification as customers or dealers. This creates a more competitive liquidity environment, where traders have equal access to, and compete for, both liquidity supply and liquidity demand. We now turn to characterizing the liquidity landscape in the all-to-all market by examining how customers can take on dealer-like roles when supplying liquidity (Section 2.3.1). Accordingly, we revisit the transaction cost measure to account for the endogenous nature of liquidity demand and supply, by directly identifying each trader's role in liquidity (Section 2.3.2).

2.3.1 Customer liquidity provision

In the all-to-all China Interbank Bond Market (CIBM), customers can supply liquidity just as dealers traditionally do. The rise of these new liquidity providers has been widely discussed in industry (see BIS 2016) but remains underexplored in academic studies due to data unavailability. Our unique dataset makes it possible to uncover customer liquidity provision with detailed statistics as outlined below. Notably, though the literature does document instances of customer liquidity provision in markets such as the U.S. corporate bonds (e.g., Choi et al. (2024)), such customer liquidity provision typically involves dealer intermediation and thus follows an indirect trading path.[25] This is different from the customer liquidity provision in an all-to-all manner.

In contrast, customer-trades can take place directly without dealer intermediation in all-to-all markets. That is, customers can provide liquidity directly to any other trader. For example, in the CIBM, direct customer-to-customer trades account for 10% of the total trading volume, with 8.6% executed via Request-with-Quote on the OTC venue and 1.4% on the CLOB venue, while these numbers are nearly zero in the U.S. Furthermore, 16.4% of the total trading volume on CLOB is executed at the prices quoted by customers.[26]

Given the possibility of direct customer-trades, customers actively contribute to the market liquidity of the CIBM by trading in significant volumes, as well as engaging in both buying and selling in a balanced manner. Figure 3 shows that approximately 20% of customers have

[25] That is, a trade-chain where both the final buyer and seller are customers, and a dealer lies between intermediating the trade, i.e., customer-to-dealer(s)-to-customer.

[26] However, this information is unavailable for the OTC venue, as price originators cannot be identified from the realized transaction data.

total trading volumes exceeding the least active dealer, with some even surpassing the majority of dealers. Figure 4 highlights that about 30% of customers have buy volume ratios[27] in the range of $[0.4, 0.6]$, indicating well-balanced buying and selling activity. Taken together, Figure 3 and Figure 4 suggest that a non-negligible group of customers in the CIBM effectively "make the market", a role typically held only by dealers in other bond markets.

[Figure 3 about here.]

[Figure 4 about here.]

These customers' liquidity provision challenges the traditional monopoly of dealers in supplying liquidity. As a result, dealers are no longer able to charge significantly higher markups than customers in equilibrium. As shown in Figure 5, in the CIBM, dealers consistently earn markups that are about 1 basis point lower than those earned by customers. Indeed, the lower dealer markup underscores a potential profit redistribution under the innovative all-to-all structure. This also highlights why traditional liquidity providers, such as dealers, may resist the adoption of similar all-to-all trading protocols in other major dealer-intermediated bond markets, including the U.S. Treasury market (Chaboud et al. (2025)).

[Figure 5 about here.]

2.3.2 Transaction cost measure redux

The fact that liquidity supply and demand decouple from traders formal status presents an empirical challenge in measurement for this paper. To be specific, those widely-used transaction cost measures are typically designed for the U.S. bond markets, which are structured as dealer-intermediated. In those dealer-intermediated markets, transaction costs are straightforwardly measured as the markup charged by dealers when acting as intermediaries between customers (Kargar et al. (2021), Choi et al. (2024)). However, this approach is not directly applicable to an all-to-all market. This is because, all traders now can trade directly with each other without the necessity of dealer intermediation, and from data, as previously

[27] The buy volume ratio is the proportion of a trader's total trading volume over sample period that comes from the trades where the trader is the buyer. Therefore, maintaining a buy volume ratio close to 0.5 is evidence of balanced buying and selling activity.

emphasized, customers can supply liquidity by continuously buying and selling in large scale as if they were, in effect, dealers themselves.

To address this empirical challenge, we identify the actual role of each trader as a liquidity demander or supplier at the bond-day level, before we adopt those transaction measures in the literature. We base our identification on the buy-sell balance principle evidenced by Figure 4.[28] With this re-assigned classification, transaction costs now reflect the costs incurred by liquidity-demanding traders (liquidity consumers) when trading with liquidity-supplying traders (liquidity providers) in exchange for liquidity services. Therefore, we link transaction costs to welfare, specifically to the liquidity consumers' surplus.

This approach to identifying liquidity demand and supply is novel in the literature. Moreover, revisiting the measurement of transaction costs (and, more broadly, liquidity) is increasingly relevant in light of the rapid rise of fintech, which has significantly reshaped the landscape of liquidity. For example, in the U.S. Treasury market, principal trading firms have emerged as key liquidity providers, marking a clear departure from the traditional dealer-based model (BIS 2016). As such, empirical studies on liquidity should consider tailoring those measures to reflect the de facto roles of traders in liquidity provision and liquidity demand.[29] The granular dataset introduced in this paper enables us to implement this approach. We now proceed to describe the data.

3 Data

Our dataset includes all government bond transactions that took place in the China Interbank Bond Market (CIBM) from July 1, 2019 to June 30, 2023. Using government bond data has two advantages: (1) its high-frequency nature allows us to explore cross-sectional variation at a finer granularity, that is, within-bond-hour variation, and (2) its risk-free nature eliminates confounding factors related to credit risk. This transaction-level dataset is provided by the

[28]The empirical result of this identification (e.g., the proportion of traders acting as liquidity demanders and liquidity suppliers) will be discussed in greater details in Section 5.1.

[29]In fact, our view on the de facto roles in liquidity is largely consistent with the recent action by the U.S. Securities and Exchange Commission (SEC), which expanded the definition of "dealer" to include certain PTFs and other firms. Specifically, starting from April 2024, the SEC "requires all firms that regularly make markets, or otherwise perform important liquidity-providing roles, to register as dealers or government securities dealers." For details, see SEC Exchange Act Rules 3a5-4 and 3a44-2 https://www.sec.gov/newsroom/press-releases/2024-14.

China Foreign Exchange Trade System (CFETS). As CFETS operates its own electronic trading platform, the data are user-recorded rather than self-reported, ensuring high accuracy and granularity.

For each transaction, we observe two unique variables that are crucial for this paper: the venue (OTC or CLOB), and the anonymous IDs of both the buyer and the seller at the account level.[30] These unique variables allow us to study venue participation and transaction costs through a reduced-form analysis with credible identification. The dataset also provides comprehensive information on terms of trades and characteristics of traders, including transaction price, volume, bond code, execution time, settlement speed, trader's formal status (dealer or customer), trader's business type,[31] and the trader-affiliated institution's anonymous ID. The dataset also includes bond-specific information such as issue date, issuance amount and maturity.

For clarity, we refer to each account in the dataset as a *trader* rather than aggregating to the institution level. Importantly, this allows us to capture the differences in liquidity roles across accounts within the same institution. For example, within the same institution, one account may focus on long-term value investing (buy-and-hold) and thus act as a liquidity demander, while another account at the same institution may engage in short-term arbitrage trading (buy-and-resell) and thus act as a liquidity supplier.[32] This approach enables us to exploit the highest level of granularity available in the dataset.

After the necessary data filtering,[33] our dataset consists of 11,350,020 transactions with a total trading volume of 560 trillion RMB, approximately 125% of China's nominal GDP

[30]That is, we observe anonymous IDs for dealers as well as customers. This contrasts with other data sources, such as the Trade Reporting and Compliance Engine (TRACE) for the U.S., where typically only dealer anonymous IDs are disclosed.

[31]For example, commercial banks, securities firms, mutual funds, hedge funds, pension funds, insurance companies, and foreign investment banks, among other business types.

[32]In practice, an account within an institution typically represents a team focusing on a specific business line or investment strategy, and therefore operates independently from other teams. As such, differences in liquidity roles across accounts within the same institution are both plausible and relevant. In our data, each institution can own multiple active accounts, ranging from one to over a dozen.

[33]On the issue of recording errors, we suspect that some transaction prices are actually yields instead of clean prices (about 100 observations). We delete them from the dataset. For the outside-option venue, we exclude the trades executed on Electronic Streaming Price (ESP), a trading practice built on the platform but belonging to neither OTC nor CLOB. Therefore we exclude these observations (about 0.3% of total number of trades and total trading volume). We treat ESP as an outside option because the bid-ask-spread on ESP is significantly worse than the rest of the market. This also aligns with the industry insight. For details, see Appendix B.

during the same period. Among these transactions, 7,909,681 (69.7%) are from the OTC venue and 3,440,339 (30.3%) are from the CLOB venue. The dataset includes 579 China Government Bonds (CGBs) and 700 Policy Bank Bonds (PBBs). CGBs account for 186 trillion RMB (33.2%) and PBBs account for 374 trillion RMB (66.8%). On average, each bond is traded 2,218 times per year, though the density distribution of counts per bond is highly right-skewed. A total of 29,433 accounts from 5,066 institutions trade government bonds (CGBs and PBBs) in the CIBM during sample period. Among them, 92 accounts are formally registered as dealers,[34] and the remaining accounts are classified as customers.

The summary statistics reflect the all-to-all market structure as well. The trader network is relatively dense. Each trader trades with an average of 41 counterparts, and the median number is 9. In terms of trading volume by par value, 30% occur between dealers, 28% consist of customers selling to dealers, 32% consist of dealers selling to customers, and the remaining 10% occur directly between customers.

4 Selection patterns between OTC and CLOB venues

In this section, we document venue selection patterns on traders, terms-of-trades and bonds: that is, how the distributions of these observable characteristics differ across the two venues. In brief, the CLOB venue disproportionately facilitates core traders, orders with standardized sizes and settlement speeds, and newly issued bond trades, whereas the periphery traders, the more customized transactions, and the off-the-run bond trades are selected into the OTC venue. We also discuss potential reasons of these selection patterns. Given the salience of venue selection, it is crucial to carefully design our empirical strategy to account for selection bias when analyzing transaction cost differences across venues, as outlined in the next section.

To begin, we present the (unconstrained equilibrium) market share in Table 1 and Figure 6. Cross-sectionally, the CLOB venue accounts for a significantly smaller market share

[34]The list of dealers consists of the largest domestic financial institutions and international entities. For the latest list of dealers, see Bond Market Makers on the CFETS official website, https://www.chinamoney.org.cn/english/mdtmmbrmm/. The number of dealers on the webpage may differ from our dataset due to dealership entries and exits over time.

compared to the OTC venue, as shown in Table 1.[35] Government bonds exhibit a more balanced distribution across venues, while (riskier) corporate bonds are more concentrated on the OTC venue. Over time, the CLOB market share displays a pro-cyclical pattern, as illustrated in Figure 6. That is, trading activities tend to shift from CLOB to OTC during market distress. Specifically, CLOB market share declines sharply when market liquidity deteriorates, such as during the COVID-19 outbreak in early 2020 and during a local bond market turmoil from late 2022 to early 2023.[36]

[Table 1 about here.]

[Figure 6 about here.]

These market shares are driven by three salient venue selection patterns. Now we describe each of them in detail. First, core traders (i.e., high-volume traders) participate in both the CLOB and OTC venues, whereas periphery traders (i.e., low-volume traders) engage with the core traders exclusively through the OTC venue. To illustrate, out of 29,433 accounts in our sample, only 752 (2.5%) have ever participated in the CLOB venue, but surprisingly, as shown in Table 2, these traders collectively account for 99% of the total trading volume.[37] In other words, the CLOB venue is primarily used by the core traders, while the periphery traders rarely supply or demand liquidity on the CLOB venue. This venue selection of market participants resembles the microstructure of the U.S. Treasury market, where limit order books (e.g., BrokerTec) are primarily for trades between core traders (i.e., dealers and principal trading firms). However, the underlying mechanisms differ. In the U.S., limit order books are typically restricted by design to those core traders only. In contrast, in the

[35]Note, however, that for the OTC venue, longer intermediation chains can inflate the reported trading volume. This occurs because a single transaction between the final buyer and seller may involve multiple intermediaries, each generating a separate trade recorded in the dataset. In contrast, this issue does not arise in the CLOB venue, where trades are centrally cleared and executed anonymously, precluding such intermediation. As a result, Table 1 may overstate the volume share of the OTC venue.

[36]For bond market liquidity in Figure 6, we proxy it by the total trading volume of market-level government bonds in the CIBM. For instance, a significant decline in total trading volume occurred during early 2020 due to the COVID-19 outbreak, and during late 2022 and early 2023 due to local bond market turmoil. This turmoil in the local bond market from late 2022 to early 2023 was triggered by a wave of redemption in wealth management products (WMPs), a key funding source for the Chinese bond market, which effectively lead to a liquidity crunch. For details on this funding outflow shock, see the Financial Times article: https://www.ft.com/content/28cd9759-a97c-4b21-b903-667bcc44714c.

[37]On the other hand, in our sample, 29,430 traders (more than 99%) have ever participated in OTC.

CIBM, participation in the CLOB is open to all,[38] but in practice, many traders opt out by self-selection, preferring the OTC venue exclusively.

[Table 2 about here.]

Second, the majority of transactions on the CLOB venue are orders with standardized terms in size and settlement, whereas the ones with customized terms are mainly executed on the OTC venue. To illustrate, as shown in Figure 7, orders with less standardized sizes, such as very small orders (below 10 million RMB) and very large orders (above 100 million RMB), are disproportionately executed through the OTC venue.[39] As shown in Figure 8, trades with non-standard settlement speeds (non T+1 basis) are almost exclusively processed through the OTC venue. These patterns align with the historical emergence of venues. Over-the-counter is typically preferred when transaction terms require case-by-case negotiation between counterparties, whereas centralized exchanges (e.g., stock markets) are suited for trading standardized assets with no need for further negotiation. As a result, cross-venue selection on terms-of-trade in other major bond markets also exhibits a similar pattern: in the U.S. Treasury market, trade size increment is standardized on limit order books but customizable for OTC style protocols (Chaboud et al. (2025)).

[Figure 7 about here.]

[Figure 8 about here.]

Third, newly issued bonds are more intensively traded on the CLOB venue and then shift to the OTC venue over the bond's lifecycle. To illustrate, we examine CLOB volume

[38] Although there is no explicit regulatory restriction on CLOB entry, we suspect that in practice, some accounts in the CIBM are unable to freely choose between venues because of other regulatory policies (exogenous to our setting). For example, accounts with certain business types are only permitted to trade with dealers, which effectively forces them to trade on OTC (mostly by RFQ) and prevents them from accessing CLOB, given that the central-clearing on CLOB rules out the possibility of counterparty designation. For regulatory details, see the Shanghai Securities Journal (SSJ) article https://paper.cnstock.com/html/2023-06/06/content_1777069.htm. Due to data limitations, we are unable to identify these restricted accounts in our dataset. Our rough calculation suggests that they collectively account for 10% of total trading volume. To mitigate any potential bias from the implicit CLOB entry barriers, we exclude these restricted accounts in regression by data refinement introduced in Section 5.2.1.

[39] However, within transactions that involve standardized sizes, for instance, those between 10 million and 50 million RMB, trades are relatively evenly distributed across the two venues once they are normalized by the total number of observations within each venue.

proportion by bond age. As shown in Figure 9, the proportion of trading volume executed on the CLOB venue peaks between 90 and 180 days after the bond issuance, and then drops as the bond ages and eventually tends to stabilize once the bond is deeply off-the-run. This bond lifecycle pattern also shares similarity with the U.S. Treasury market, where limit order books have a major presence for on-the-run and near on-the-run Treasury notes and bonds (Chaboud et al. (2025)). In addition, the CLOB venue facilitates trades in "active" bonds, such as those with large issuance amounts, whereas "inactive" bonds are primarily traded on the OTC venue.[40]

[Figure 9 about here.]

5 Effect of venue on transaction costs

In this section, we examine the impact of venue-specific trading mechanisms on transaction costs by comparing the centralized CLOB and bilateral OTC venues in the all-to-all China Interbank Bond Market (CIBM). Our primary measure of transaction costs is the Choi-Huh spread (Choi et al. (2024)) and we adapt it for all-to-all in Section 5.1. Specifically, we first classify traders as either liquidity suppliers or liquidity demanders based on the buy-sell balance principle. We then compute the spread paid by liquidity demanders to liquidity suppliers, reflecting the cost of accessing liquidity services in each venue.

Next, in Section 5.2, we estimate the transaction costs difference between the two venues using three empirical strategies. We begin by refining our sample to address potential confounding factors stemming from the selection patterns discussed (Section 5.2.1). We then formally estimate the cross-venue cost difference at the bond-hour level with granular fixed effects (Section 5.2.2). Finally, we introduce a matching approach to construct a paired-trades sample, allowing us to assess the impact of trading on the CLOB venue on transaction costs (Section 5.2.3). This approach is analogous to estimating the average treatment effect (ATE). Overall, our findings indicate that the CLOB venue is consistently less costly than the OTC venue for transactions with similar characteristics, such as bond identity, counterparty identity, settlement speed, order size, and execution timing. This cost-saving effect of

[40]Here we provide the relevant statistics: 70% of the bonds in our sample were traded on both venues at some point. The remaining 30%, which were only traded on the OTC venue, account for just 1% of total trading volume. That is, the OTC-only bonds are inactive bonds.

the CLOB venue holds across multiple model specifications, measurement approaches, and considerations of heterogeneity (Section 5.2.4).

5.1 Measure of transaction cost

We construct the *Spread* measure as follows:

$$Spread_{j,b,t} = 2 \times Q_{j,b,t} \times \frac{traded\ price_{j,b,t} - reference\ price_{b,t}}{reference\ price_{b,t}} \times 10000 \tag{1}$$

This measure captures the deviation of the price of transaction j for bond b at execution hour[41] t, from its corresponding reference price. For $reference\ price_{b,t}$, we use the bond-hour-level mid-quote[42] from the order book, as it serves as the closest proxy for a frictionless benchmark price (see Glode and Opp (2020), Allen and Wittwer (2023)).

To align with the all-to-all market structure, we set $Q_{j,b,t}$=1 when a liquidity-demander buys from a liquidity-supplier, and $Q_{j,b,t}$= -1 when a liquidity-demander sells to a liquidity-supplier.[43] Accordingly, we calculate the *Spread* paid by liquidity demanders, as they generally buy at higher prices (markup) and sell at lower prices (markdown) when trading with liquidity suppliers, incurring transaction costs. Consequently, the *Spread* measure carries an implication for liquidity-consumer surplus, a key variable of interest when comparing different venues and assessing their design.

Based on the principle of buy-sell balance, we define liquidity demanders and suppliers as follows: for each bond on each day, a trader is assigned as a liquidity demander if and only if he exclusively buys or exclusively sells that bond throughout that day. That is, liquidity demanders do not engage in both buying and selling for the same bond on the same day, and

[41] In our data, execution times are recorded with a precision of up to 0.000001 seconds. Like Allen and Wittwer (2023), who also examine transaction data for highly liquid bonds (e.g., Canadian Government Bonds), we round execution times to hourly intervals. Specifically, a timestamp such as 2023-01-01 16:27:26.355000 is categorized under 2023-01-01 16:00:00.000000, grouping all trades executed between 2023-01-01 16:00:00.000000 and 2023-01-01 16:59:59.999999.

[42] The mid-quote is defined as $mid\text{-}quote_{b,t} \equiv 0.5 \times (ask_{b,t} + bid_{b,t})$, where $ask_{b,t}$ and $bid_{b,t}$ are volume-weighted averages of all available bids and asks in the order book within the bond-hour in which trades were executed. Approximately 8% of CLOB trades lack information on whether the transaction price corresponds to a bid or an ask. These observations are excluded from the mid-quote calculation.

[43] Notably, prior studies using Choi-Huh measure (e.g., Kargar et al. (2021), Choi et al. (2024)) always set Q=1 (-1) when a customer buys from (sells to) a dealer. We alter the expression on Q from the traders' formal status (dealers or customers) to their de facto liquidity role (liquidity-suppliers or liquidity-demanders).

conversely, traders who both buy and sell the same bond within the same day are assigned as liquidity suppliers.[44] Though it is simple, this assignment approach for identifying demand and supply aligns well with different practical operations in the real business world. Traders who effectively provide liquidity are those engaging in business such as quoting on both the buy and sell sides (e.g., the most traditional market-making activity), intermediating trades between final buyers and sellers (e.g., the prevailing pre-arranged agency trading), and arbitraging price differences (e.g., the modern high-frequency quantitative trading), etc.

Applying this assignment, we find that 29,241 traders (99% of the total) have ever acted as liquidity demanders at some point. In contrast, only 3,360 traders (11% of the total), including all registered dealers, have ever functioned as liquidity suppliers. We provide an economic rationale for these statistics. On the one hand, over a long period, most of incumbent traders in the market should experience some form of shock that necessitates rebalancing their bond holdings, or there should be some new traders entering the market to establish their initial asset positions. In both cases, those traders are more likely to exclusively buy or sell bonds within a single day, reinforcing our observation that nearly all traders have ever demanded liquidity at some point during the sample period. On the other hand, existing studies have well documented that market-making activities are often concentrated among a small group of traders (e.g., Hollifield et al. (2017), Li and Schürhoff (2019) for the U.S., and Coen and Coen (2022) for the U.K. etc). Our finding that only a small proportion of traders in the CIBM ever act as liquidity suppliers is consistent with the stylized fact documented in the literature.[45]

To validate our modified *Spread* measure, we additionally compute the price impact measure, *Amihud* (Amihud (2002)), defined as:

$$Amihud_{j,b,t} = \frac{\left| \frac{P_{j,b,t} - P_{j-1,b,t}}{P_{j-1,b,t}} \right|}{Q_{j,b,t}}, \tag{2}$$

[44]Thus, we allow trader switches in their liquidity roles across different sub-markets, which is defined as bonds $\otimes$ days. We do so intentionally. For example, given the portfolio composition (and therefore the role in liquidity), money market funds might be liquidity suppliers for short-term government bonds but demanders for long-term ones, and vice versa for insurance companies and pension funds, given their liability duration.

[45]Notably, in the CIBM structured as all-to-all, all traders can be viewed as the candidates of liquidity providers, while in those papers studying dealer-intermediated markets, only dealers are candidates. Therefore, our statistics align with those papers documenting that only a fraction of liquidity provider candidates result in substantial trades and thereby substantial liquidity services (such as the substantial liquidity services provided by the core dealers in the U.S. markets, a fact often summarized as a core-periphery network).

where j and $j-1$ denote two consecutive trades of the same bond within the same day, and $j = \{1, 2, ...J_{b,t}\}$ where $J_{b,t}$ is the total number of trades observed in the dataset for bond b in day t, and j denotes the j^{th} trade in chronological order. $P_{j,b,t}$ is the observed transaction price, and $Q_{j,b,t}$ represents the trading volume (in million RMB). By construction, the *Amihud* measure captures price impact, reflecting the sensitivity of price to order flow. There is an inverse relationship between liquidity and these measures, with higher liquidity corresponding to lower values of both measures.

The strong positive correlation between the daily aggregated series of *Spread* and *Amihud* cross-validates our measures, as shown in Figure 10. Additionally, the time-series patterns of both measures track market-wide price variance, which is a commonly used proxy for aggregate risk and thus exhibits a positive correlation with our measures (see Figure A5 in the internet appendix).[46]

[Figure 10 about here.]

Importantly, both *Spread* and *Amihud* measures indicate that transaction costs are significantly lower on the CLOB venue compared to the OTC venue, as illustrated in Figures 11 and 12. These figures present the venue-specific daily average transaction costs across the full sample period, using each measure separately, and reveal a persistent cost-saving effect of the CLOB venue. Next, we turn to a more rigorous empirical analysis to formally estimate the magnitude of the CLOB cost-saving effect.

[Figure 11 about here.]

[Figure 12 about here.]

5.2 Cost difference between venues

To rigorously quantify the cost-saving effect of the CLOB venue, we need to ensure that the allocation of trades across the two venues is as random as possible, as depicted in

[46] Beyond assessing how well the measures capture market-wide trends, here we offer relevant information to better understand the *Spread* measure magnitude. Specifically, we compare the level of *Spread* measure to the daily price range, which is defined as the maximum price minus the minimum price for a given bond within a given day. This is because, conceptually, the price range is the most expensive (realized) round-trip, while the *Spread* measure is the average (realized) costs of round-trip. In the data, the average daily price range is approximately 13 basis points.

Figure 13. However, the selection patterns documented in Section 4 suggest that trader characteristics, trade-specific attributes, and bond characteristics may serve as confounding factors that threaten identification. These confounders could be alternative explanations for the observed transaction cost differences through competing hypotheses.[47]

[Figure 13 about here.]

To mitigate these identification concerns, we employ three empirical strategies. We refine the dataset, incorporate granular fixed effects in the estimation model, and more rigorously, employ a matching approach to construct a sample of paired trades. Together, these strategies ensure that trades executed on different venues are as comparable as possible in terms of observable characteristics such as trader, bond, execution time, order size and settlement speed. We now proceed to elaborate on these strategies and present the estimation results.

5.2.1 Sample refinement

The goal of the refinement is to achieve overlapping and balanced distributions of the covariates between the OTC (control) and CLOB (treatment) venues, following the suggestion by Imbens (2015) for estimating treatment effect in general. After the refinement, the final dataset consists of 7,381,306 observations, with a total trading volume of 376 trillion RMB. This represents 65% of the original sample's observations and 67% of its total trading volume. Among these observations, 3,440,277 (47%) trades are executed on the CLOB venue, and 3,941,029 (53%) trades are executed on the OTC venue. Notably, compared to the original sample, the final dataset exhibits substantially improved balanced distribution across venues, successfully fulfilling the intended goal of the refinement.

In detail, our sample refinement proceeds in two steps. First, to address confounding from trader characteristics, we retain only those trades in which the buyer has executed

[47] We present three competing hypotheses corresponding to different sources of confounding. (1) Trader characteristics: Suppose peripheral traders incur higher transaction costs due to their limited access to advanced search technologies and pricing expertise. Since peripheral traders predominantly use the OTC venue, the observed cost difference (i.e. OTC venue is more costly than CLOB venue) may reflect trader heterogeneity rather than the venue itself. (2) Order size: Suppose larger trades tend to have higher transaction costs. Since larger trades are more frequently executed on the OTC venue, the higher OTC costs may stem from trade size rather than from the venue itself. (3) Bond age: Suppose that older bonds are less liquid and thus associated with higher transaction costs. Since older bonds are disproportionately traded on the OTC venue, this could generate higher transaction cost in the OTC venue as well.

trades as a buyer on both OTC and CLOB at least once during the sample period, and the seller has executed trades as a seller on both venues at least once. This trader-refinement ensures that the remaining traders have exercised free choice between the two venues, and therefore that they are certainly capable of freely choosing venues without any implicit venue entry barriers. The business types of the retained traders are primarily commercial banks, securities firms and asset management companies, including all traders formally registered as dealers. This is consistent with Table 2, which highlights that the refined dataset comprises core market participants.

Second, to address confounding from bond attributes, for a given bond in a given hour, we retain all observations associated with that bond-hour combination only if that bond is traded on both the OTC and CLOB venues within that hour. In other words, we exclude any bond-hour group where all observations occur exclusively on either CLOB or OTC. This bond-hour level data refinement prepares for exploiting the within bond-hour variation across venues, by introducing a bond-hour fixed effect into the estimation model. We now proceed to describe the estimation model.

5.2.2 Estimation model and result

Using the refined dataset, we estimate the following equation:

$$TransactionCost_{j,(b,t)} = \alpha + \beta \times \mathbf{1}\{CLOB\}_j + \mu_j + \mu_{(b,t)} + \epsilon_{j,(b,t)} \tag{3}$$

where j indexes individual trades, b represents the bond, and t denotes the execution hour. The notation (b,t) emphasizes that our estimation exploits variation within the *bond-hour* (i.e., within each group indexed by (b,t)), meaning that we compare transaction costs between CLOB and OTC trades occurring for the same bond within the same hour. Indicator function $\mathbf{1}\{CLOB\}_j$ equals 1 if the trade j is executed on CLOB and 0 otherwise. The measure $TransactionCost$ corresponds to either *Spread* or *Amihud* measure as defined in Equations 1 and 2. The trade-level fixed effect μ_j controls for key trade characteristics,

including trade size category, settlement speed, and buyer and seller anonymous IDs.[48]

Importantly, leveraging the bond-hour fixed effect term $\mu_{(b,t)}$, we mitigate omitted variable bias more effectively than a conventional two-way fixed effects model, which typically assumes $\mu_{(b,t)} = \mu_b + \mu_t + x_{b,t}$. This single but powerful term $\mu_{(b,t)}$ absorbs potential confounders such as bond age, time-to-maturity, outstanding amount, and any other time-varying bond characteristics, as well as bond-specific responses to time effects such as macroeconomic shocks. For robustness, we also estimate the equation specified with bond μ_b and time μ_t fixed effects in addition to $\mu_{(b,t)}$, and we find that the results remain unchanged.[49]

The regression results presented in Table 3 indicate that the CLOB venue enables lower transaction costs than the OTC venue. Specifically, using the *Spread* measure, the average transaction cost per trade on CLOB is 0.664 basis points lower than on OTC (column (2)). Similarly, using the *Amihud* measure, for each million RMB par value traded, the price impact is 0.271 basis points lower on CLOB than on OTC (column (4)). The CLOB transaction cost improvement likely stems from its greater information transparency, faster order matching and execution, and increased competition by expanding the number of bidders for each bond. These findings support the notion that a centralized trading mechanism allocates assets at lower costs across the investors in the secondary market, and therefore highlight the efficiency of the centralized trading venue.

[Table 3 about here.]

[48]For size category, we categorize trade size into four groups based on the distribution shown in Figure 7: small $(0, 10M)$, medium $[10M, 50M)$, large $[50M, 100M)$, and extra-large $[100M, \max]$ where M denotes million RMB. One caveat of our empirical strategy is that we categorize the order size, which should be a continuous variable rather than a categorical variable. This choice is necessary to avoid rank-deficiency in the estimand. While the empirical literature sometimes adopts a similar approach by using the size category instead of the actual size (e.g., Kargar et al. (2021)), we acknowledge this limitation and address it in the subsequent heterogeneous analysis. Specifically, there we run a series of regressions, each on a subset of observations with identical order size, and therefore we effectively eliminate any variation in order size and naturally shutdown the size-effect channel. The results remain consistent. For settlement speed, we classify settlement speed into groups of T+0, T+1, T+2, T+3, and so on.

[49]It suggests that the sources of variation typically addressed by a two-way fixed effects model have already been absorbed by the single term $\mu_{(b,t)}$. This is natural because $\mu_{(b,t)}$ essentially relaxes the (linear) functional form imposed by the two-way fixed effects model. This relaxation also in effect addresses the omitted variable concern that is typical in a two-way fixed effects model if $x_{b,t}$ contains unobservable factors.

5.2.3 A matching approach: paired-trades sample

To further validate the cost-saving benefits of CLOB, we adopt an alternative matching approach that constructs a sample of paired trades. This sample contains pairs of twin trades that are identical in all observable characteristics except for the venue of execution. Specifically, we match trades based on trader identity, trade terms, bond code and execution time within each pair, thereby effectively controlling for confounding factors. This paired-trade method closely resembles average treatment effect (ATE), where executing a trade on the CLOB venue is regarded as the treatment and executing the similar trade on OTC venue serves as the control. By selecting highly similar trade pairs, this approach facilitates a quasi-experimental comparison of transaction costs across the two venues.

We construct the paired-trades set G from the (unrefined) original sample as follows. Each pair consists of two trades, one trade executed on CLOB and the other on OTC. Within each pair, the two trades are executed by the same trader (referred to as the "starting trader") in the same direction (starting trader buys or sells) for the same bond with identical size and settlement speed, within a short time interval. To ensure robustness, we use various time intervals: 1 minute, 5 minutes, 15 minutes, 30 minutes, 1 hour, 2 hours, half a day, and 1 day. If multiple trades meet these criteria, we retain the two trades (one from CLOB and one from OTC) with the closest execution times. We further classify the paired trades into buy-side pairs (i.e., the starting trader buys in both trades of the pair) and sell-side pairs (i.e., the starting trader sells in both trades of the pair).

Using the paired-trades sample G, we estimate the following equation:

$$Q_g \times \tilde{P}_{v,g} = \alpha + \tilde{\beta} \times \mathbf{1}\{CLOB\}_v + \mu_g + \epsilon_{v,g} \tag{4}$$

where g represents each pair $g \in G$, v represents the venue $v \in \{\text{OTC}, \text{CLOB}\}$, and $1\{CLOB\}_v$ is an indicator variable equal to 1 if the trade is executed on CLOB and 0 otherwise. The term μ_g captures pair-specific fixed effects, including bond code, execution time, trade volume, settlement speed, and buyer (or seller) identity.

The dependent variable $Q_g \times \tilde{P}_{v,g}$ in Equation 4 is defined as:

$$Q_g \times \tilde{P}_{v,g} \equiv Q_g \times \frac{P_{v,g} - P_{\text{OTC},g}}{P_{\text{OTC},g}} \times 10000 \quad \text{for } \forall\ g \in G,\ v \in \{OTC, CLOB\} \tag{5}$$

where $P_{v,g}$ is the observed transaction price on venue v for pair g. The OTC price within each pair is used as the benchmark for normalization (i.e., $\tilde{P}_{OTC,g} = 0$ for all g). This normalization ensures that $\tilde{P}_{CLOB,g}$ represents the price deviation of the CLOB trade relative to its OTC counterpart within each pair, measured in basis points. This provides a direct measure of price improvement when trading on the CLOB venue.

To ensure consistency in interpretation, we define Q_g in Equation 5 as:

$$Q_g = \begin{cases} 1, & \text{if the pair } g \text{ is a buy-side pair,} \\ -1, & \text{if the pair } g \text{ is a sell-side pair.} \end{cases} \tag{6}$$

This transformation standardizes the interpretation of the dependent variable in Equation 4: a lower value of $Q_g \times \tilde{P}_{v,g}$ is always preferred by the starting traders, regardless of whether they are buying or selling. Specifically, a lower value of $Q_g \times \tilde{P}_{v,g}$ indicates that CLOB prices are lower than OTC prices for buy-side pairs thus benefiting the buyers, and higher than OTC prices for sell-side pairs thus benefiting the sellers. Accordingly, in Equation 4, $\tilde{\beta} < 0$ implies that CLOB provides better prices for the starting traders compared to OTC.[50]

The regression results in Table 4 confirm that CLOB offers better prices than OTC. Notably, the estimated coefficient $\tilde{\beta}$ in Equation 4 is comparable in magnitude to the earlier estimate of β in Equation 3, reinforcing the robustness of our findings. For instance, using the 1-hour time interval version of the paired-trades sample, multiplying the estimated $\tilde{\beta}$ by two,[51] we find that CLOB improves prices by $2 \times 0.187 = 0.374$ basis points, which is comparable to the 0.664 basis points found in column (2) of Table 3.

[Table 4 about here.]

This matching approach offers two advantages. First, it mitigates the bias that arises from measurement errors. Unlike the *Spread* measure, which requires additional assumptions for a valid construction (such as identifying liquidity demanders and suppliers or choosing an appropriate reference price), the price variable alone suffices for analysis. Second, as a consequence, this approach provides a direct and intuitive interpretation of cost savings. Based

[50] The starting trader also serves as an alternative way to conceptualize the trader who demands liquidity.

[51] This is because the *Spread* measure in Equation 1 reflects a round-trip transaction cost. It is a convention in the literature to multiply by two and we follow this convention. In contrast, Equation 5 is intentionally designed to capture only a half round-trip cost, as we approach the data from the starting trader's angle.

on the 1-hour version of the paired-trades sample, a trader executing a 10-million RMB bond trade on the CLOB venue saves approximately 187 RMB compared to executing the same trade on the OTC venue. In summary, the paired-trades analysis offers additional empirical support for the efficiency gains of centralized trading. It reinforces our earlier finding that the CLOB venue, with its centralized mechanism, significantly reduces transaction costs.

5.2.4 Heterogeneity analysis and other robustness checks

We further investigate how the cost-saving effect of the CLOB venue varies across different order sizes, building on prior research that highlights the heterogeneity of transaction costs by order size (e.g. Pinter et al. (2024)). To begin, we observe that in the CIBM, CLOB order sizes cluster at whole tens of millions, which is similar to the findings by Chaboud et al. (2025) in the U.S. Treasury market. For example, in our (unrefined) original sample, trades with volumes of 10, 20, and 30 million RMB account for 30%, 27%, and 17% of total CLOB transactions respectively.[52]

To account for this size heterogeneity, we conduct a series of regressions specified in Equation 3, each restricted to transactions with a specific order size of 10, 20, 30, 40, 50, 60, 70, 80, 90, or 100 million RMB, and with settlement speed of T+1. This design ensures that within each regression sample, variations in order size and settlement speed are completely eliminated. As a consequence, any estimated differences in transaction costs cannot be attributed to the terms-of-trade (order size and settlement speed), but rather to the venue.[53]

The regression results reveal that the cost-saving effect of CLOB is more pronounced for smaller orders. This is indicated by the larger absolute values of estimated β, graphically presented in Figure 14 and Figure 15. In addition, given that the majority of CLOB transactions are concentrated at 10, 20, and 30 million RMB (together comprising 74% of total CLOB trades), this finding also suggests that some traders may strategically split large orders into smaller transactions to maximize the cost-saving potential. Full regression results are available in Tables A1 and A2 in the internet appendix.

[52] In detail, in our (unrefined) original sample, trades with volumes of 10, 20, 30, 40, 50, 60, 70, 80, 90, and 100 million RMB account for 30%, 27%, 17%, 4%, 13%, 1%, 1%, 1%, 1%, and 2% of the total number of CLOB transactions, respectively. In fact, only a very small fraction of trades on the CLOB venue occur at sizes that do not follow increments of 10 million (accounting for less than 3%).

[53] Here, in all regressions, we use the previously refined sample described in Section 5.2.1, and include fixed effects for buyer, seller, and bond-hour. That is, the empirical strategy is the same as before.

[Figure 14 about here.]

[Figure 15 about here.]

Beyond this heterogeneity analysis, we additionally conduct two groups of robustness checks. First, to cross-validate our findings, we construct alternative liquidity measures inspired by prior literature, such as the buy-sell gap,[54] interquartile range, and transaction cost (Choi-Huh spread) based on the conventional classification of dealers and customers. The regression results using these alternative liquidity measures are presented in Table A3. Second, to assess the external validity of our findings, we expand our refined dataset by relaxing the bond-hour refinement criteria to the bond-day level instead. The regression results using this extended sample are presented in Table A4. To summarize, all robustness checks consistently support our main finding: the CLOB venue reduces transaction costs compared to the OTC convention.

6 Explaining venue participation and cost disparity

The empirical results in Section 5 confirm that transaction costs on CLOB venue are lower than they are in the OTC venue. This naturally raises an important question: if trading on CLOB is indeed more cost-effective, why at equilibrium do we still observe a substantial volume of trades executed through OTC at a higher cost, as documented in Section 4? More fundamentally, how can we reconcile these persistent price differences across venues, which seemingly present arbitrage opportunities at equilibrium? While several explanations could account for this equilibrium observation, such as balance sheet constraints that hinder full arbitrage, we focus on the characteristics of the trading venues, which is the central theme of this paper.

We rationalize this persistence of OTC trades despite their higher transaction costs by uncovering the unique benefits that the OTC venue offers. Specifically, our transaction cost measures do not capture the implicit costs (or disutility) associated with the CLOB venue, or equivalently, the implicit benefits of the OTC venue that provide utility to traders. To explore

[54] When we construct the buy-sell gap measure, we also use a slightly different classification of de facto liquidity demanders and suppliers (still evidenced by Figure 3 and Figure 4), as a robustness check to the identification of trader's de facto role in liquidity.

this rationale, Section 6.1 examines two key distinctions between OTC and CLOB trading: information leakage and counterparty designation, arising from venue intrinsic characteristics and practical operation. These distinctions highlight the complementarity of the two venues and help explain the inelastic demand for the OTC venue, especially for trades with certain trading motives. To further illustrate this rationale, in Section 6.2, we empirically identify one specific trading motive, portfolio re-balancing, and analyze how this trading motive influences venue choice.

6.1 Inelastic demand: OTC unique benefits

First, the OTC venue mitigates potential trading costs associated with information leakage, as extensively discussed in the literature (see Baldauf and Mollner (2024) for a review). In practice, on the OTC venue, all transaction details, such as price, quantity, bond code, and the identity of the counterpart, remain confidential between the two trading parties. In contrast, the CLOB venue is fully transparent, with trade-related information disseminated to all traders in real time.[55] This information transparency could be particularly costly for informed traders[56] executing large orders. Specifically, if an informed trader expects bond prices to rise and attempts to accumulate a significant position by CLOB, this activity may attract attention from other market participants who could engage in front-running, and thus induce adverse price movement eroding the informed trader's expected capital gains. Such concerns over the leakage of valuable trading information make OTC a preferable venue, despite its higher explicit costs.

Second, the OTC venue allows counterparty designation. In practice, in both Request-for-Quote (RFQ) and Request-with-Quote (RWQ) practices of the OTC venue, the initiating trader can selectively send requests to specific counterparties, enabling customized trade execution. In contrast, the central-clearing process of the CLOB, governed by a price-time priority rule, effectively rules out this possibility. Counterparty designation is particularly relevant for government bonds, which often serve as risk-free instruments in more complex transactions. For example, a government bond trade could be embedded within a broader

[55]For example, best bid and best ask prices with associated trade volumes are available as pre-trade information, and all trade-related details except for trader identities are disclosed immediately post-trade.

[56]We use the term "informed trade" in a neutral sense, referring to traders with superior knowledge of future prices with reduced uncertainty rather than necessarily possessing non-public information. This advantage may stem from superior forecasting ability, for instance.

transaction package, such as a portfolio trade or a repurchase agreement, where prices are prearranged along with other bundled assets. In such cases, the ability to deliver a predetermined trade to a specific counterparty makes the OTC venue indispensable, even if the CLOB offers lower transaction costs.

Given these distinctions, OTC and CLOB are unlikely to be perfect substitutes. Instead, by viewing venues as *differentiated products*, the cross-price elasticity of demand between the two venues is likely low. That is, the lowering cost of CLOB has little impact on the volume of trades executed on OTC. We refer to this rationale as *inelastic demand*. The demand for the OTC venue is particularly inelastic for trades that are information-sensitive or counterparty-predetermined. Notably, the venue practices discussed in this section are not unique to the CIBM, but instead reflect broader features common across many fixed-income markets. This is because they stem from intrinsic characteristics of the venues themselves, such as the central-clearing mechanism inherent in centralized trading, and the bilateral nature of over-the-counter arrangements. As a result, the venue analysis presented here may offer broader insights into cost disparities observed in other fixed-income markets as well.

6.2 An investigation: re-balancing motive

Beyond the above qualitative explanation focusing on the interaction between venue characteristics and trading motives,[57] we additionally conduct a quantitative analysis to further illustrate the idea of OTC unique benefits. Specifically, we explore how trader's re-balancing motive influences their trading volume allocation between the OTC and CLOB venues at the intensive margin. The results suggest that the OTC venue is more advantageous in facilitating traders' bond holding position re-balancing, which may also help rationalize the sustained use of the OTC venue despite its higher cost.

To begin our analysis, we identify *portfolio re-balancing* (see Koijen et al. (2021)) as the trading motive under investigation. Due to data limitations,[58] we approximate traders' re-

[57] We only do qualitative analysis partially due to the difficulty of identifying those trades with special motives in the data. That is, we lack a credible approach to construct transaction-level variables capturing such trade characteristics, which are unobservable to econometrician but potentially salient to market participants, and important when determine the equilibrium venue choice. For instance, how can one empirically identify informed trades, or trades that are price-predetermined with a designated counterparty, by measures other than transaction cost? We leave these questions for future research.

[58] Unlike prior studies that utilize holding data to directly measure portfolio re-balancing, we lack access to traders' holding information.

balancing motives by constructing a standardized inventory measure following Hansch et al. (1998). Specifically, for each trader i and bond b, we track their inventory level Q over time as follows:

$$Q_{(i,b),t} = Q_{(i,b),0} + \sum_{s=1}^{t} q_{(i,b),s} \tag{7}$$

where $Q_{(i,b),0}$ represents the initial inventory level, and $q_{(i,b),t}$ is the net volume traded on day t, calculated as the total buy volume minus the total sell volume. Even when there are no trades on day t, we maintain a continuous time series of inventory level such that $Q_{(i,b),t} = Q_{(i,b),t-1}$. From this sequence on inventory level, we derive the *standardized inventory* measure I as follows:

$$I_{(i,b),t} = \frac{Q_{(i,b),t} - \bar{Q}_{(i,b)}}{\sigma_{(i,b)}} \quad for\ \forall\ t \in \{1, 2, 3, .., T\} \tag{8}$$

where $\bar{Q}_{(i,b)} = \frac{1}{T+1}\sum_{t=0}^{T} Q_{(i,b),t}$ and $\sigma_{(i,b)} = \left(\frac{1}{T}\sum_{t=0}^{T}(Q_{(i,b),t} - \bar{Q}_{(i,b)})^2\right)^{\frac{1}{2}}$ are the sample mean and standard deviation of the inventory level sequence $\{Q_{(i,b),t}\}_{t=0}^{T}$. Notably, this transformation ensures that the measure is independent of the initial inventory level, allowing us to set (unobserved) $Q_{(i,b),0} = 0$ for computational convenience.

The interpretation of standardized inventory is straightforward: a trader with a stronger re-balancing motive will exhibit a larger absolute value of I, reflecting greater deviation from their (unobserved) typical holding level.[59] A positive I indicates an excess holding, while a negative I suggests a shortfall relative to the trader's normal position. We report the distribution of standardized inventory in Figure A6 in the Internet Appendix.

Using this standardized inventory measure, we estimate the following regression model:

$$OTCprop_{(i,b),t} = \alpha + \gamma \times \left|I_{(i,b),t-1}\right| + \eta \times X_{(i,b),t} + \epsilon_{(i,b),t} \tag{9}$$

where $OTCprop_{(i,b),t}$ represents the percentage of trader i's trading volume in bond b conducted via OTC on day t. The main explanatory variable, $|I_{(i,b),t-1}|$, captures the absolute deviation from the trader's typical inventory level at the beginning of the current day, serving as a proxy for start-of-day re-balancing motive. In $X_{(i,b),t}$, we control for

[59] We regard the sample mean $\bar{Q}_{(i,b)}$ as proxy for the unobserved long-term target inventory level for trader i for bond b.

$|\Delta I_{(i,b),t}| \equiv |I_{(i,b),t} - I_{(i,b),t-1}|$, the daily change in standardized inventory, which measures re-balancing intensity, along with other fixed effects.[60]

The estimation results show $\hat{\gamma} > 0$, as presented in Table 5. It suggests that when a trader's inventory level deviates significantly from their typical level, they exhibit a stronger re-balancing motive, leading to a higher proportion of OTC trading. Moreover, $\hat{\eta}$ is also positive. It implies that traders who intensively re-balance (i.e., exhibit larger daily changes in inventory) tend to shift even more of their trading activity to OTC.

[Table 5 about here.]

Overall, these findings in Table 5 reinforce the notion that OTC remains an essential venue for traders with strong re-balancing needs, despite its higher transaction costs. The inherent flexibility of OTC, as opposed to the rigid trading rule of CLOB, enables traders to execute immediate large-volume transactions that may not be feasible on CLOB. This result is consistent with the order-size distribution in Figure 7, showing that larger trades, which are typically associated with greater liquidity needs (such as stronger re-balancing motives), are disproportionately executed through the OTC venue.

To conclude, in Section 6, we explain the venue cost disparity along with the venue participation. In order to rationalize the sustained trading in OTC despite its higher cost, we highlight several unique benefits that contribute to inelastic demand for OTC trading. These benefits include mitigating information leakage, enabling counterparty designation, and facilitating position re-balancing, among other advantages. This analysis contributes to the broader literature that seeks to explain the seemingly counterintuitive persistence of over-the-counter market structures across a wide array of asset classes globally, even in environments where cost-effective, exchange-style trading platforms are available, such as in the China Interbank Bond Market (CIBM).[61]

[60] Notice that Equation 9 is not dynamic but rather a static view of the data. Thus, the standard fixed effects estimators for panel data remain valid. To ensure robustness, we include as many fixed effects as possible. Overall, the regression results remain largely unchanged across different fixed-effects specifications.

[61] For such discussion in the literature, see Biais and Green (2019), Collin-Dufresne et al. (2020) and Chapter 7 of Foucault et al. (2023) for literature review.

7 Conclusion

Leveraging a novel granular dataset, this paper examines the differences of trading activity and transaction cost between the bilateral over-the-counter (OTC) and centralized central limit order book (CLOB) venues. Our findings are threefold. First, trading activities are selected into venues. The CLOB venue primarily facilitates core traders, transactions with standardized sizes and settlement speeds, and bonds with shorter ages. Second, after controlling for these confounders, the CLOB venue is more cost-effective than the OTC venue. We attribute the cost-saving effect of CLOB to its advantageous centralized trading mechanism. Third, despite OTC higher transaction costs, OTC's unique abilities to mitigate information leakage, designate counterparty and facilitate position re-balancing, play important roles in maintaining its dominant market share and influencing traders' venue participation choices.

As financial market reform gains increasing attention in recent years, driven by the rapid rise of fin-tech and recent episodes of liquidity stress, this paper sheds light on the role of novel market microstructure in improving asset liquidity. Indeed, in the China Interbank Bond Market (CIBM), a unified electronic trading platform is offered in a novel all-to-all manner, and among all the trading practices built on the platform, the novel centralized limit order book achieves faster bond trades at lower costs. Future research could further investigate the empirical effects of venues on bond market equilibrium outcomes, such as trade allocation, price formation and arbitraging activity, as well as extend traditional over-the-counter theories by incorporating venues to better microfound these equilibrium outcomes.

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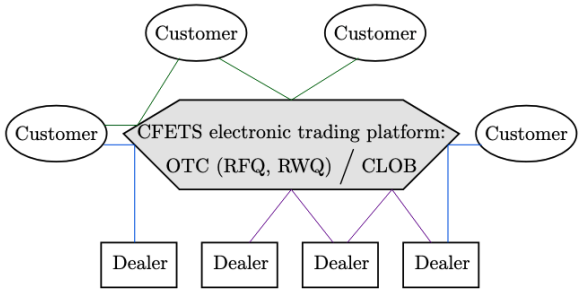
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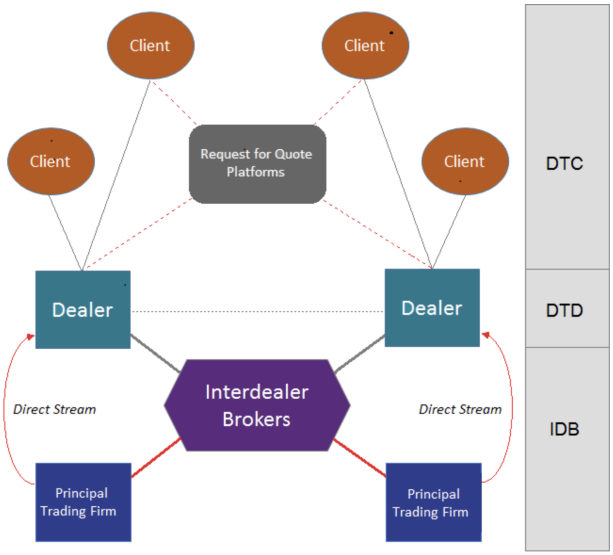
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Figures



Panel A: All-to-all China Interbank Bond Market (CIBM)



Panel B: Dealer-intermediated U.S. Treasury Market (Source: FEDS Notes 2018)

Figure 1: Market Structure: China Interbank Bond Market versus U.S. Treasury Market

Note: in this figure, we contrast the all-to-all China Interbank Bond Market (Panel A) to the dealer-intermediated U.S. Treasury market (Panel B). This figure demonstrates two important distinctions between the two markets. First, customers (a.k.a., clients) can trade directly with each other in all-to-all market, while they can only trade with dealers (even if through RFQ) in dealer-intermediated market. Second, all-to-all market is more integrated, in contrast to dealer-intermediated market, which is divided into a dealer-to-customer segment (DTC, where dealers intermediate customer trades) and an inter-dealer segment (DTD and IDB, where interdealer brokers intermediate dealer trades). An institutional basis of all-to-all is that all traders can equally access to an unified electronic platform consolidated with all trading mechanisms.

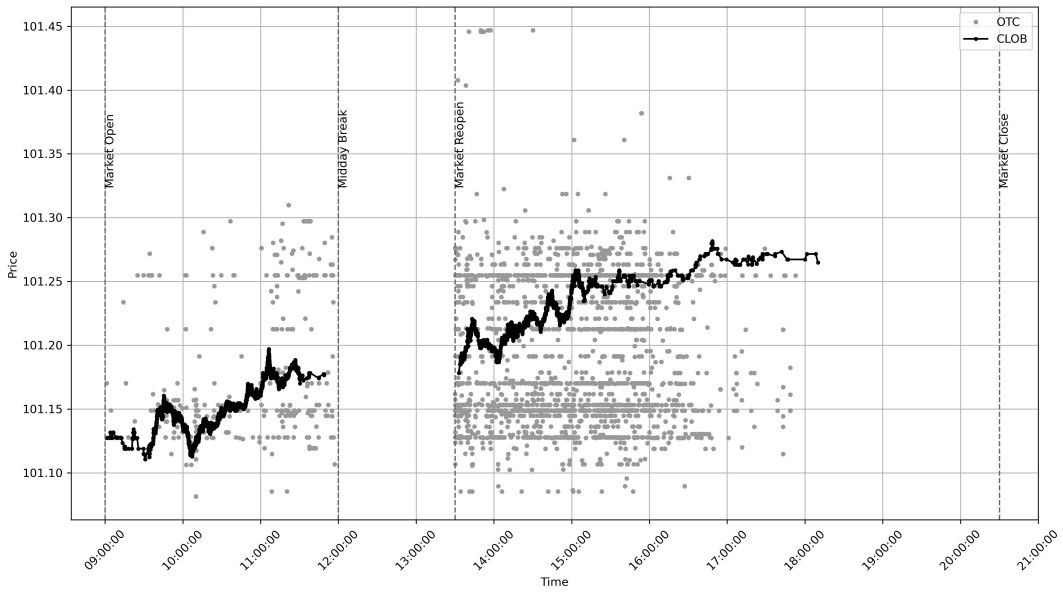


Figure 2: Intraday Transaction Prices, CLOB versus OTC

Note: in this figure, we plot all transaction prices of a representative bond over a single trading day, separated by the trading venues—either CLOB (dash-dot line) or OTC (dot), where each dot represents a transaction. At any given moment, the price on the CLOB venue is unique, while the prices on the OTC venue are dispersed. This figure highlights the full-degree centralization on CLOB, ensured by its centralized trading mechanism.

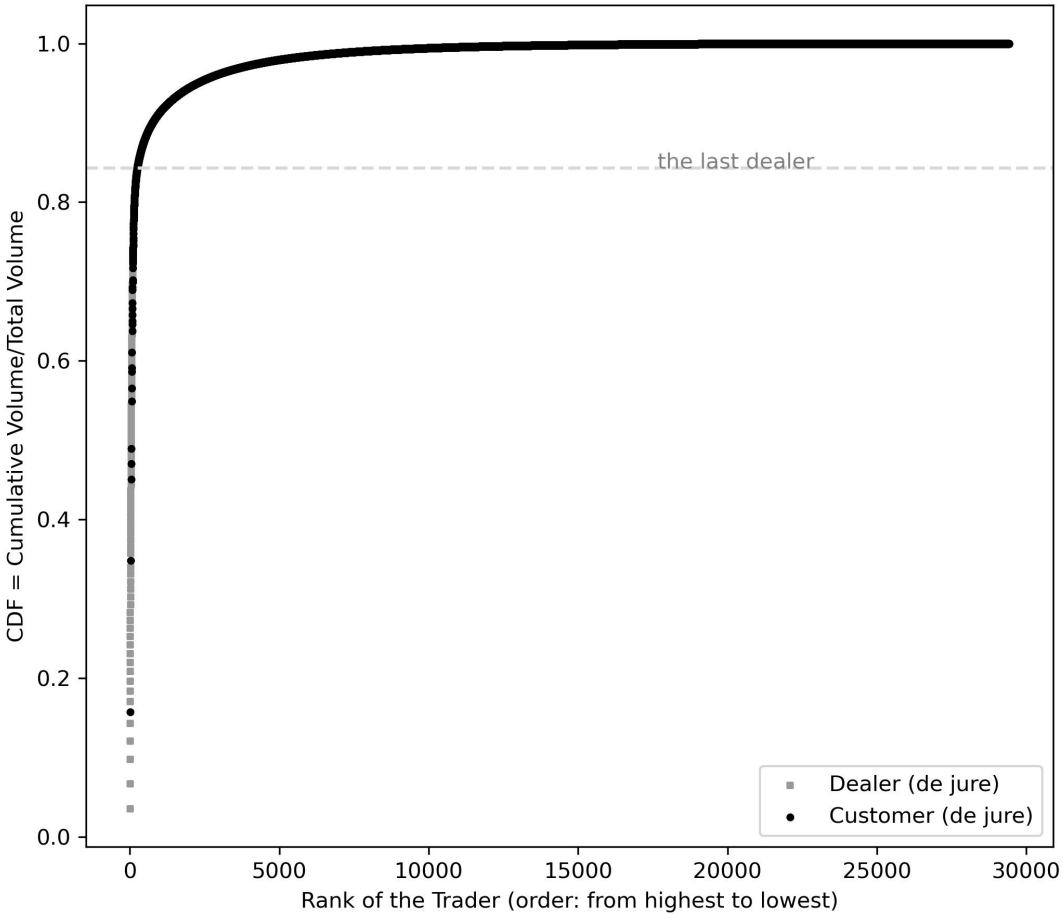


Figure 3: Distribution of trading volume by trader type: dealers versus customers

Note: in this figure, we plot the cumulative distribution of trading volume across individual traders. Each dot represents a trader, with customers shown in black and dealers in gray. This figure shows that some customers trade in significant volumes, comparable to dealers. It suggests that non-dealer financial institutions also play a meaningful role in providing market liquidity and making the market. To plot the cumulative distribution, we first rank traders by their total trading volume over the sample period. Cumulative volume is then calculated by summing the volumes from the highest-ranked trader to each subsequent trader. The highest-ranked trader (i.e., the leftmost point on the x-axis) corresponds to the trader with the highest total trading volume across all government bonds. To account for potential entry and exit of dealers over time, we classify a trader as a dealer if he was registered as such at any point during the sample period.

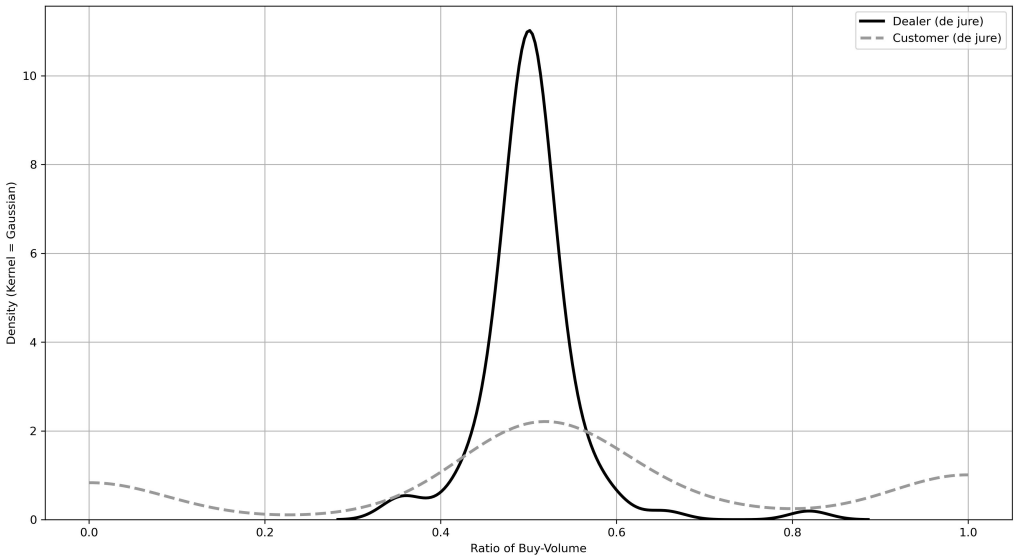


Figure 4: Distribution of buy volume ratio by trader type: dealers versus customers

Note: in this figure, we plot the density function of buy volume ratio. The buy volume ratio is calculated at the trader level, and the density is estimated separately for dealers (black solid line) and customers (gray dashed line). The figure reveals that some customers display well-balanced buying and selling activity, similar to dealers. It suggests that non-dealer financial institutions also play a meaningful role in providing market liquidity and making the market. The buy-volume ratio for each trader is defined as the total volume of their buy trades divided by their total trading volume (i.e., the sum of buy and sell volumes) over the sample period. To account for potential entry and exit of dealers over time, we classify a trader as a dealer if he was registered as such at any point during the sample period. We use a Gaussian kernel to estimate the density.

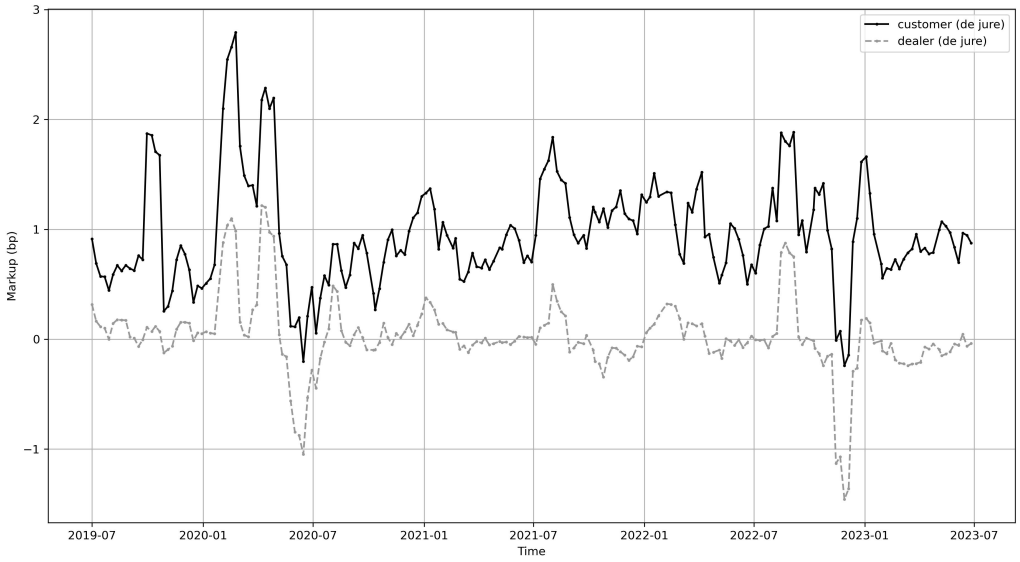


Figure 5: Time series of weekly markup per trader: dealers versus customers

Note: in this figure, we plot the time series of weekly markups earned by dealers (gray dashed line) and customers (black line). This figure shows that dealers earn lower markups than customers, by approximately 1 bp. It highlights customers competing to provide liquidity and a potential profit redistribution from dealers to customers. To plot the time series of markups, we first calculate $buy\ price_{i,b,t}$, the volume-weighted average transaction price for each trader i, each bond b and each week t, average across the trades where the trader i is the buyer. Next, for each trade j, we define $markup_{j,i,b,t} \equiv \left(\frac{transaction\ price_{j,i,b,t}}{buy\ price_{i,b,t}} - 1\right) \times 10000$, where trader i is the corresponding seller of trade j. In other words, markup reflects the return on asset. We then aggregate the trade-level markups to week-level by taking volume-weighted average. Note that by construction, trades where the seller did not purchase the same bond within the same week (i.e., missing *buy price*) are excluded when plotting this figure, together accounting for 14% of the total observations.

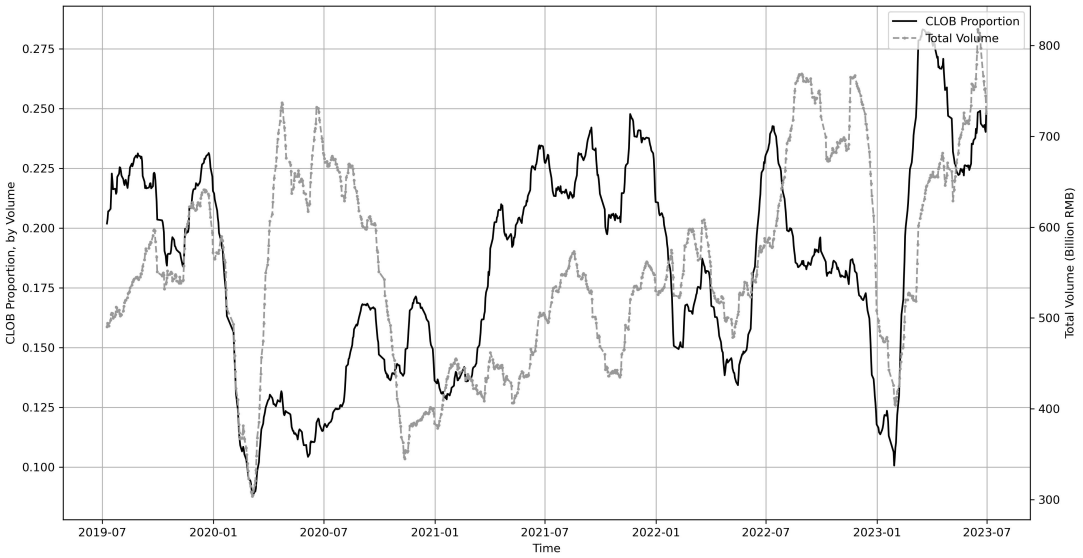


Figure 6: Time series of CLOB market share

Note: in this figure, we plot the time series of the daily CLOB market share (black line) and compare it to the time series of the daily total trading volume of all government bonds in the CIBM (gray dashed line). Over time, the trades executed on the CLOB venue account for approximately 10% to 30% of total trading volume, and exhibits a pro-cyclical pattern. When market liquidity experiences a crisis (i.e., total volume declines), traders tend to shift from CLOB to OTC, resulting in a lower CLOB market share, such as the COVID-19 shock in early 2020 and a local bond market turmoil from late 2022 to early 2023 (see Footnote 36 for details). To plot this figure, we apply a 90-day moving average to smooth both time series.

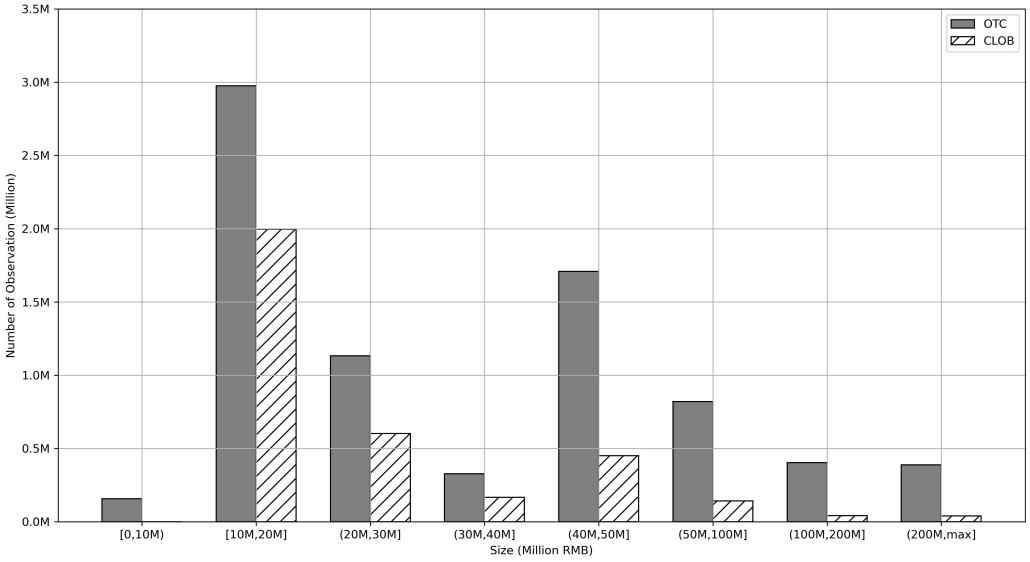


Figure 7: Size distribution: CLOB versus OTC

Note: in this figure, we plot the frequency distribution of order size, separated by venues—either CLOB (hatched) or OTC (solid gray). The x-axis represents the intervals of order size, and the y-axis denotes the number of observations within each interval (M denotes million). It shows that the orders with less standardized sizes, such as very small orders (below 10M RMB) and very large orders (above 100M RMB), are disproportionately executed through the OTC venue. In contrast, the CLOB venue is concentrated with standardized orders, for example, those sized between 10M RMB and 50M RMB.

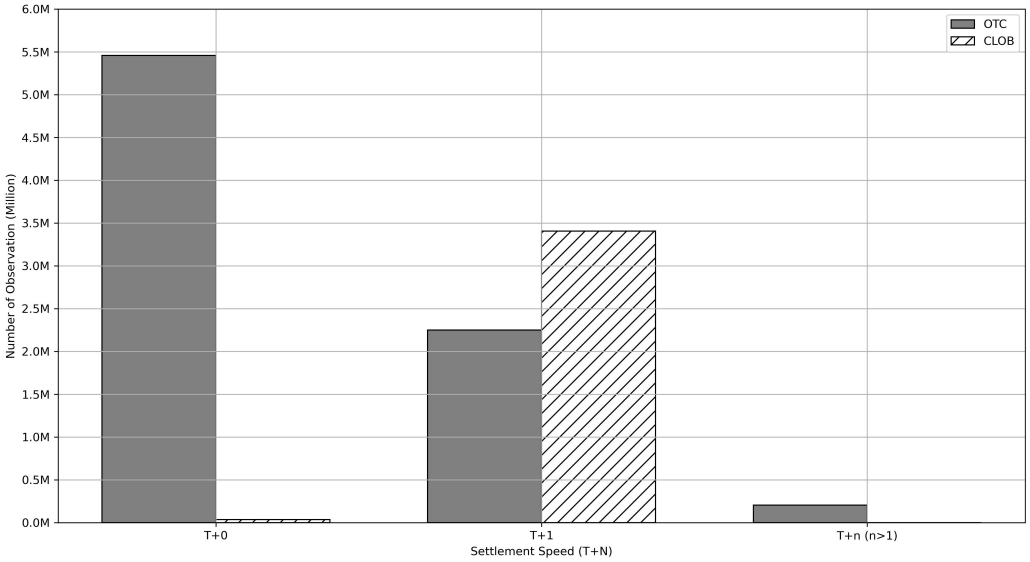


Figure 8: Settlement distribution: CLOB versus OTC

Note: in this figure, we plot the frequency distribution of order settlement speed, separated by venues—either CLOB (hatched) or OTC (solid gray). The x-axis represents categories of settlement, and the y-axis denotes the number of observations within each category. It shows that the orders with less standardized settlement speed, such as quick settlement (T+0) and slow settlement (equal to or greater than T+2), are almost exclusively executed through the OTC venue. In contrast, the CLOB venue is concentrated with standardized orders, i.e., those settled at T+1. By definition, T+0 refers to same-day settlement, while T+1 indicates settlement one day after execution, and so on.

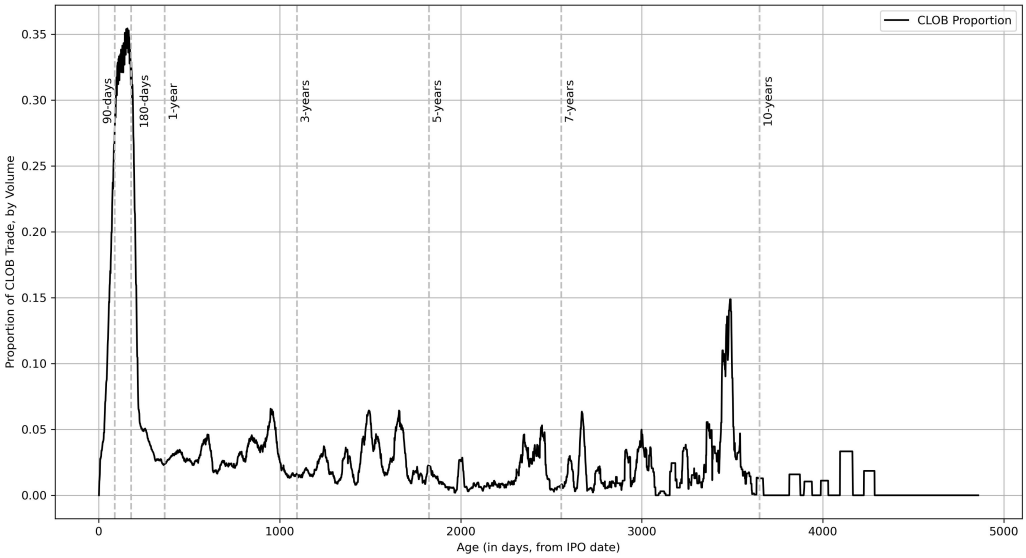


Figure 9: Evolution of CLOB trading share over bond lifecycle

Note: in this figure, we plot the average bond-level proportion of trading volume executed on the CLOB venue, grouped by bond age. This CLOB proportion peaks between 90 and 180 days after bond issuance, i.e., approximately 35% of the trading volume occurring on CLOB, and then drops as the bond ages. To plot this figure, we proceed in two steps. First, for each bond-day observations, we calculate the bond's daily CLOB volume proportion (defined as the bond's CLOB trading volume divided by its total trading volume on that day), and the bond's age (defined as the number of days since its offering date). Second, we aggregate these bond-day-specific CLOB proportions by bond age, by taking the arithmetic mean across all bond-days with the same age.

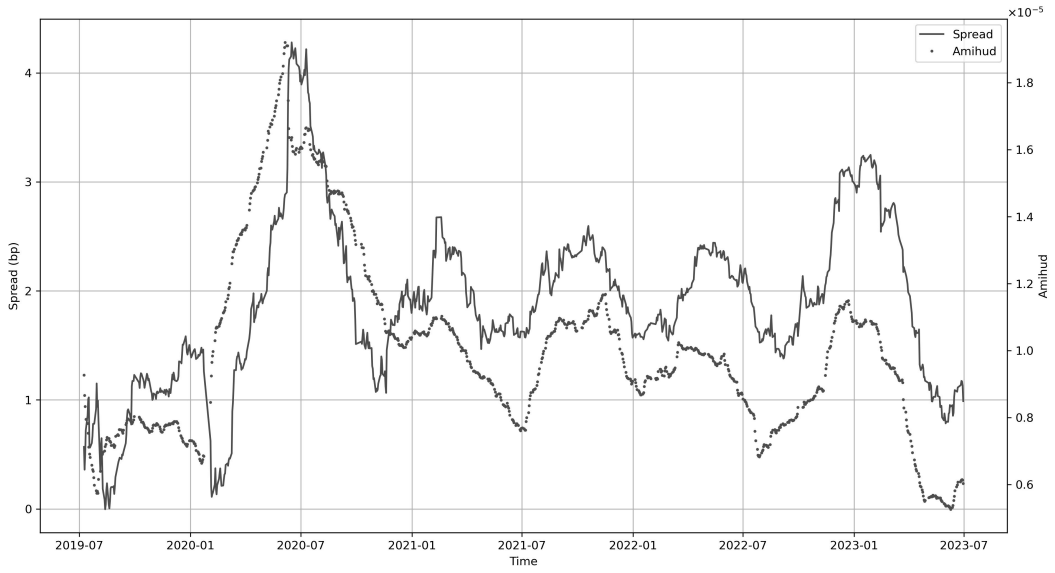


Figure 10: Time series of transaction cost measures: *Spread* and *Amihud*

Note: in this figure, we plot the time series of daily average transaction costs, using the *Spread* (left y-axis) and *Amihud* (right y-axis) measures, defined as Equation 1 and 2 respectively. The strong positive correlation between the two measures cross-validates their credibility. Transaction cost deteriorates significantly in early 2020 due to the COVID-19, and between late 2022 and early 2023 due to a local bond market turmoil (see Footnote 36 for details). To plot this figure, daily averages are calculated as volume-weighted means across all trades for which the measures are available. We apply a 90-day moving average to smooth both time series.

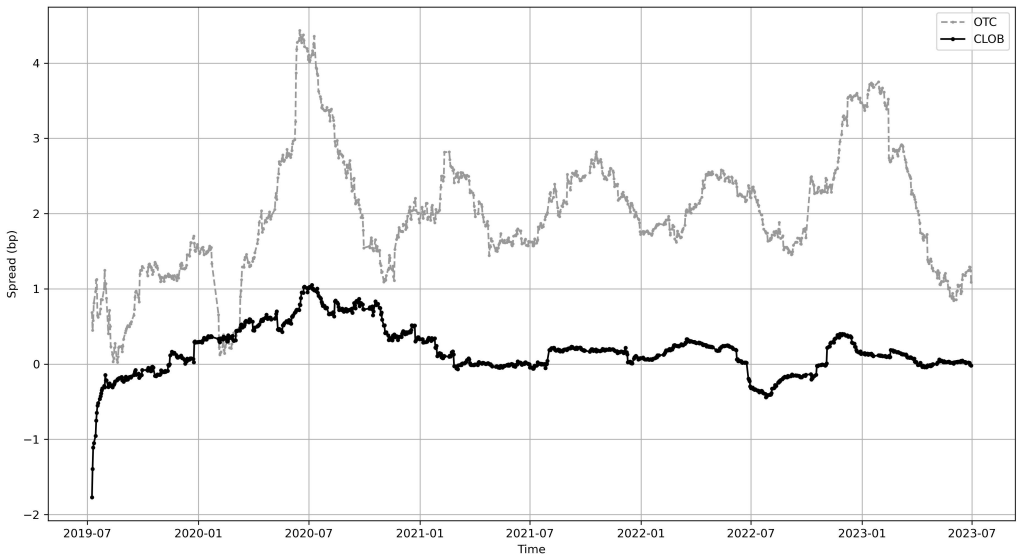


Figure 11: Time series of *Spread* measure: CLOB versus OTC

Note: in this figure, we plot the time series of daily average *Spread* defined as Equation 1, separately averaged across trades on the CLOB (black) and OTC (gray) venues. Measured by *Spread*, the transaction cost of the CLOB venue is significantly lower than the OTC venue. To plot this figure, daily averages are computed as volume-weighted means of all trade-level *Spread* measures within each venue-day. We apply a 90-day moving average to smooth both time series.

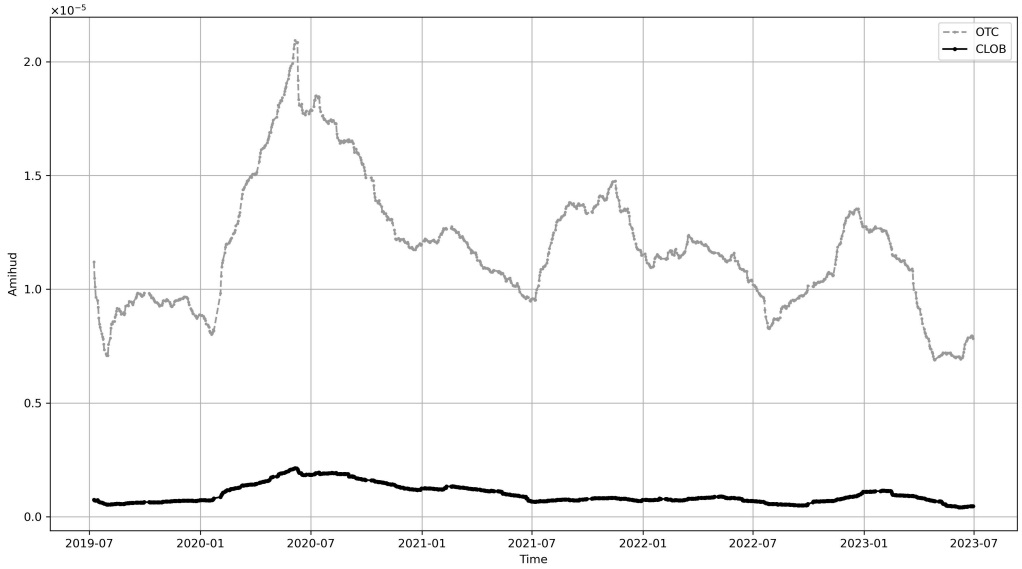


Figure 12: Time series of *Amihud* measure: CLOB versus OTC

Note: in this figure, we plot the time series of daily average *Amihud* defined as Equation 2, separately averaged across trades on the CLOB (black) and OTC (gray) venues. Measured by *Amihud*, the price impact of the CLOB venue is significantly lower than the OTC venue. To plot this figure, daily averages are computed as volume-weighted means of all trade-level *Amihud* measures within each venue-day. We apply a 90-day moving average to smooth both time series.

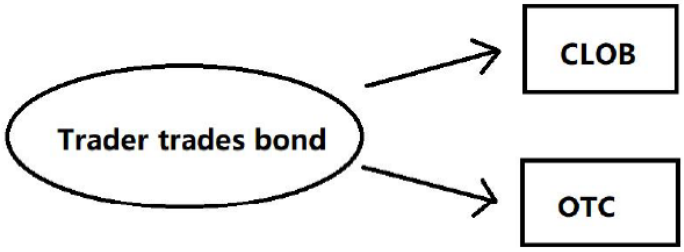


Figure 13: A conceptual framework: trades sorting into venues

Note: in this figure, we present a conceptual framework that guides the empirical analysis in Section 5.2. Specifically, when a trader seeks to execute a bond trade, either buying or selling, they can choose between the OTC and CLOB venues. Identifying the causal effect of trading venue on transaction costs requires that the assignment of trades to venues is random. While this condition is not strictly met, we approximate it as closely as possible using three empirical strategies: refining the dataset, incorporating granular fixed effects, and employing a matching approach. Together, these strategies help address potential confounding factors related to trader identity, trade terms, and bond characteristics.

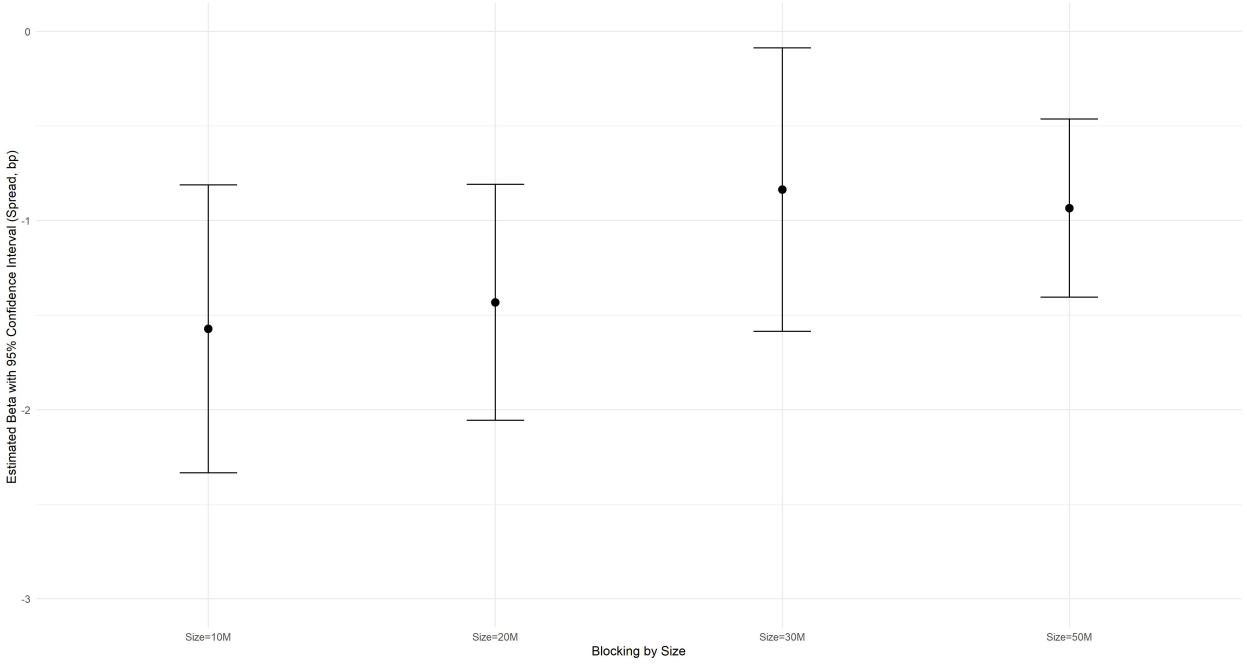


Figure 14: Heterogeneous CLOB cost-saving by order size, *Spread*

Note: in this figure, we plot the heterogeneous cost-saving effect of CLOB by order size, using *Spread* measure as dependent variable to estimate Equation 3: $TransactionCost_{j,(b,t)} = \alpha + \beta \times \mathbf{1}\{CLOB\}_j + \mu_j + \mu_{(b,t)} + \epsilon_{j,(b,t)}$. The y-axis is the value of estimated β (point estimates along with the 95% confidence intervals). When estimating, we use a subsample where the order size is equal to the corresponding x-axis category. The cost-saving effect of CLOB is more pronounced for smaller orders, as shown by the larger absolute values of the estimated β (i.e., lower values on the y-axis). To plot this figure, we include only the estimation results that are statistically significant. Full regression results are available in Table A1.

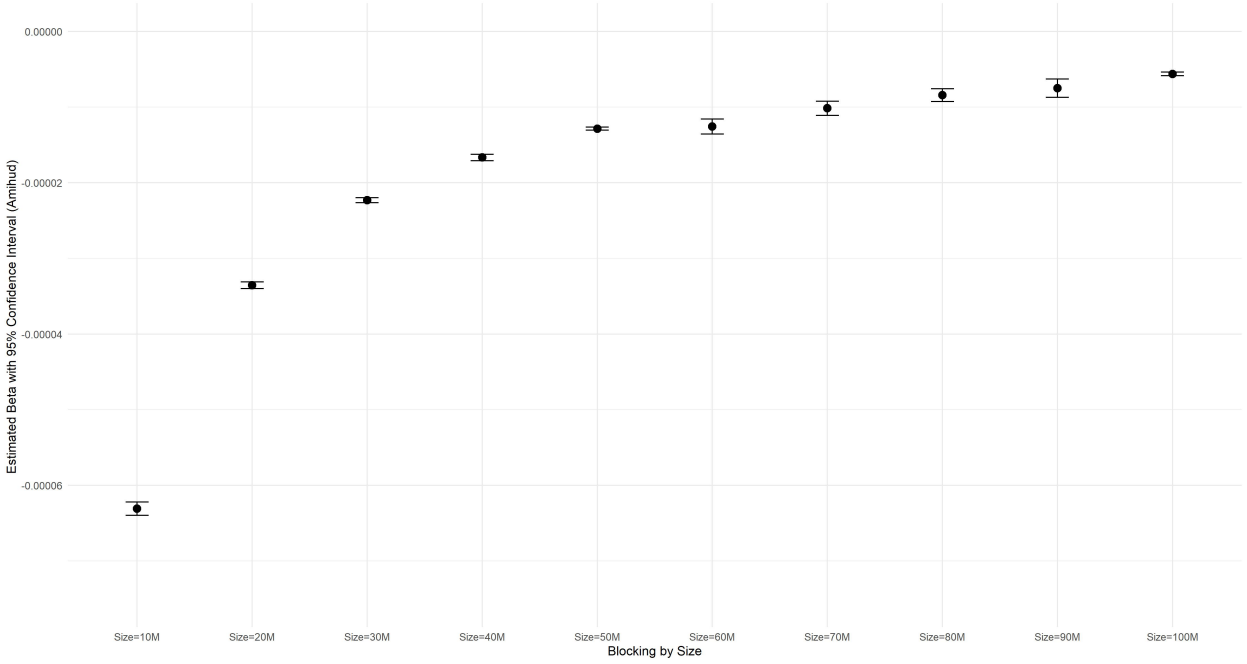


Figure 15: Heterogeneous CLOB cost-saving by order size, *Amihud*

Note: in this figure, we plot the heterogeneous cost-saving effect of CLOB by order size, using *Amihud* measure as dependent variable to estimate Equation 3: $TransactionCost_{j,(b,t)} = \alpha + \beta \times \mathbf{1}\{CLOB\}_j + \mu_j + \mu_{(b,t)} + \epsilon_{j,(b,t)}$. The y-axis is the value of estimated β (point estimates along with the 95% confidence intervals). When estimating, we use a subsample where the order size is equal to the corresponding x-axis category. The cost-saving effect of CLOB is more pronounced for smaller orders, as shown by the larger absolute values of the estimated β (i.e., lower values on the y-axis). To plot this figure, we include only the estimation results that are statistically significant. Full regression results are available in Table A2.

Tables

Table 1: Market share of venues

Market Share	Government Bonds	Corporate Bonds
CLOB	20%	1.8%
OTC	80%	98.2%

Note: in this table, we report the market share of each trading venue, expressed as a percentage of the total trading volume of government bonds and corporate bonds respectively. Thus, by construction, each column sums to 100%. This table suggests that the CLOB venue market share is significantly lower than the OTC venue, though the government bonds exhibit a more balanced distribution across the two venues, compared to corporate bonds.

Table 2: Volume share by traders' CLOB participation status

Seller / Buyer	Traders ever in CLOB	Traders never in CLOB
Traders ever in CLOB	68%	14%
Traders never in CLOB	17%	1%

Note: in this table, we report the percentage of total trading volume by trading counterparties' CLOB participation status, using all government bond trades from the entire sample period. The results indicate that CLOB participants are typically core traders (i.e., with large-scale trading volumes). To construct this table, we firstly classify all traders into two categories: those who have participated in CLOB at least once during the sample period (i.e., either bought or sold in CLOB) and those who have not. Each trader is assigned to one and only one of the two categories. We then compute the share of total trading volume transacted between each buyer-seller combination. For instance, 17% of the total trading volume involves a buyer who has never participated in the CLOB and a seller who has.

Table 3: Main results: CLOB cost-saving

	Spread (bp)		Amihud	
	(1)	(2)	(3)	(4)
1{CLOB}	-1.187***	-0.664***	-0.0000273***	-0.0000271***
	(0.133)	(0.155)	(1.69e-07)	(1.64e-07)
Size category FE	Yes	Yes	Yes	Yes
Settlement speed FE	Yes	Yes	Yes	Yes
Buyer and Seller FEs	No	Yes	No	Yes
Bond-hour FE	Yes	Yes	Yes	Yes
Observations	211,842	211,842	5,454,848	5,454,848
R^2	0.150	0.175	0.329	0.338
Adjusted R^2	0.061	0.083	0.319	0.328

Note: in this table, we present the estimation results of Equation 3: $TransactionCost_{j,(b,t)} = \alpha + \beta \times \mathbf{1}\{CLOB\}_j + \mu_j + \mu_{(b,t)} + \epsilon_{j,(b,t)}$, where dependent variable $TransactionCost$ corresponds to either *Spread* or *Amihud* measure calculated as Equation 1 and 2 respectively. The indicator variable $\mathbf{1}\{CLOB\}_j$ equals 1 if trade j is executed on the CLOB venue. We include four trade-level fixed effects μ_j: size category, settlement speed, buyer and seller (account anonymous ID), as well as a bond-hour fixed effect $\mu_{(b,t)}$. We use column (2) to interpret the benchmark result: the average transaction cost on CLOB is 0.664 basis points lower than on OTC. Therefore, CLOB is cost-saving. When estimating, we truncate each transaction cost measure at the 1st and 99th percentiles, and cluster standard errors at the bond-hour level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 4: Paired-trades: CLOB price improvement

	CLOB price deviation from OTC: $Q_g \times \tilde{P}_{v,g}$ (bp)							
	1min	5min	15min	30min	1hour	2hour	halfday	day
1{CLOB}	-0.233***	-0.222***	-0.186***	-0.191***	-0.187***	-0.183***	-0.184***	-0.182***
	(0.090)	(0.052)	(0.039)	(0.033)	(0.029)	(0.027)	(0.027)	(0.024)
Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,132	45,566	78,424	100,768	120,452	134,162	135,876	157,462
R^2	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
Adjusted R^2	0.0004	0.0004	0.0003	0.0003	0.0003	0.0003	0.0003	0.0004

Note: in this table, we present the estimation results of Equation 4: $Q_g \times \tilde{P}_{v,g} = \alpha + \tilde{\beta} \times \mathbf{1}\{CLOB\}_v + \mu_g + \epsilon_{v,g}$, where the dependent variable $Q_g \times \tilde{P}_{v,g}$ is calculated as Equation 5 and 6, capturing the CLOB price deviation from its OTC counterpart within each pair. The indicator variable $\mathbf{1}\{CLOB\}_v$ equals 1 if the trade is executed on CLOB. We include pair fixed effect μ_g. Each column corresponds to the time interval used for constructing the paired-trades from the (unrefined) original sample. By construction, the number of pairs in each column equals half the number of observations, since each pair consists of two trades with identical terms, except one on CLOB and the other on OTC. We use column 1hour for interpretation: on average, prices on the CLOB venue are improved by 0.187 basis points relative to those on the OTC venue. When estimating, we truncate the dependent variable $Q_g \times \tilde{P}_{v,g}$ at the 1st and 99th percentiles, and cluster standard errors at the pair level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 5: OTC unique benefit: re-balancing holding position

	OTCprop (pp)		
	(1)	(2)	(3)
$\lvert I_{(i,b),t-1}\rvert$	0.531***	0.441***	0.204***
	(0.078)	(0.061)	(0.062)
$\lvert \Delta I_{(i,b),t}\rvert$			1.419***
			(0.086)
Bond FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Trader FE	Yes	Yes	Yes
Bond-day FE	No	Yes	Yes
Trader-day FE	No	Yes	Yes
Trader-bond FE	No	Yes	Yes
Observations	277,772	277,772	277,772
R^2	0.275	0.788	0.788
Adjusted R^2	0.269	0.515	0.516

Note: in this table, we present the estimation results of Equation 9: $OTCprop_{(i,b),t} = \alpha + \gamma \times \left|I_{(i,b),t-1}\right| + \eta \times X_{(i,b),t} + \epsilon_{(i,b),t}$. The dependent variable $OTCprop_{(i,b),t}$ represents the share of trader i's trading volume in bond b executed on the OTC venue on day t, $OTCprop_{(i,b),t} \in [0\%, 100\%]$ with units in percentage points (pp). The independent variable is the absolute value of the standardized inventory $I_{(i,b),t-1}$ constructed as Equation 8, which captures the strength of the re-balancing motive at the beginning of day t. We include covariate $|\Delta I_{(i,b),t}| \equiv |I_{(i,b),t} - I_{(i,b),t-1}|$, the daily change in standardized inventory, which measures the realized re-balancing intensity. We also include as many fixed effects as possible for robustness. We use column (3) for interpretation: on average, when a trader's inventory deviates from his typical level $\bar{Q}_{(i,b)}$ by 1 standard deviation $\sigma_{(i,b)}$, his OTC trading share increases by 0.2 pp. This result suggests OTC-specific benefit in facilitating bond holding position re-balancing. When estimating, we exclude those traders whose $OTCprop \equiv 0$ over the sample period (see Footnote 38 for details), and use only those trader-bond-day combinations where trader i trades bond b on day t (i.e., buy volume$_{(i,b),t}$+ sell volume$_{(i,b),t} > 0$). We truncate the dependent variable at the 1st and 99th percentiles, and cluster standard errors at the trader-bond level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Internet Appendix

A Screenshots of the electronic trading platform

To better understand venues characteristics and practical operations, we provide the screenshots of each trading practice built on the CFETS electronic trading platform. These screenshots illustrate the differences in choice set and information set of traders between the OTC and CLOB venues.

Specifically, to illustrate the choice set, we present the screenshots of the forms that the initiating trader is required to complete when sending a request via Request-for-Quote (Figure A1) and Request-with-Quote (Figure A2) practices on the OTC venue, as well as the form of limit order placed on CLOB (Figure A3). The key differences between OTC and CLOB are whether the initiating trader must select counterparty and quote price, emphasizing their distinctive trading mechanisms as described in Section 2. To illustrate the information set, we present the screenshot of the order book visible to all traders in real-time (Figure A4), showing CLOB information transparency both pre-trade and post-trade.

[Figure A1 about here.]

[Figure A2 about here.]

[Figure A3 about here.]

[Figure A4 about here.]

B Additional details about the data

In this paper, we use the China Government Bonds (CGBs) and Policy Bank Bonds (PBBs) transaction-level data in the China Interbank Bond Market (CIBM) between July 1st 2019 and June 30th 2023.[1] We collectively refer to CGBs and PBBs as government bonds in this paper, since they are guaranteed by the central government's fiscal capacity and thus considered as risk-free instruments by local investors.[2]

Hypothetically, the dataset provided by CFETS should not require any cleaning, compared to other self-reported dataset such as U.S. TRACE. This is because all transactions in the CIBM are, in fact, the platform's user records. Thus it rules out the possibility of cancellations[3] or corrections due to mis-reporting, which commonly occurs in TRACE. However, we still suspect the presence of error on price. Specifically, we observe approximately 100 trades, with transaction prices falling within the range of [1, 4]. They are likely to represent yield-to-maturity rather than clean price. Therefore, to ensure the credibility of our analysis, we truncate the dataset by removing observations with prices below the 0.0001st percentile and above the 99.9999th percentile. This approach effectively removes all yield-like observations along with some other outliers, which, while not necessarily erroneous, could oth-

[1] For real-time bond prices in the China Interbank Bond Market (CIBM), refer to CFETS official website: https://www.chinamoney.org.cn/english/mdtqapcbt/.

[2] In fact, in the local financial market, CGBs and PBBs are collectively so-called *Rate*-bonds. It is a widely recognized local classification and terminology, which reflects their yields close connection to policy *rates* rather than credit fundamentals. They contrast with the bonds issued by local governments, financial institutions (such as stated-owned commercial banks), and non-financial corporations (both stated-owned enterprises and private firms), all of which carry credit risk. To illustrate, for instance, in practice, when regulators assess banks' capital requirements, government bonds (both CGBs and PBBs) receive a zero risk-weight (Amstad and He (2019)).

[3] In the CIBM, failing to settle a trade after execution on the platform is considered as a default. That is, trader cannot "cancel" a trade that has been already executed on the platform.

erwise distort our liquidity measure and estimation result to extreme values.

In addition, there exists an outside option venue in the CIBM known as Electronic Streaming Price (ESP), and we exclude all transactions on ESP. The ESP venue is an outside option both statistically and economically. Statistically, execution on the ESP venue are very rare, accounting for 0.3% of the total number of observations and 0.3% of the total trading volume. Economically, the transaction cost (bid-ask spread) on the ESP venue is significantly worse than the rest of the market, including both OTC and CLOB. Therefore, we refer to ESP as the outside option since it stands as an upper bound of the ask price and a lower bound of the bid price, and thus traders rarely use this venue to execute bond trades.[4]

C Robustness checks

C.1 Comprehensive results for heterogeneity analysis

In this subsection, we present the regression results associated with Figure 14 and Figure 15 in Table A1 and Table A2 respectively.

[Table A1 about here.]

[Table A2 about here.]

[4]Here we describe the practical operation of Electronic Streaming Price (ESP). On the ESP venue, only dealers can place non-anonymous bid and ask quotes with a volume cap, and these quotes are disseminated and executable to all traders in real-time (i.e., resembling CLOB price-setting rule). All traders can then select the favored one to trade, on a first-come, first-served basis (i.e., resembling OTC counterpart-matching rule). Therefore, given these trading mechanisms, the ESP venue is neither OTC nor CLOB but instead a mixture of both, and thus falls beyond the scope of this paper. In practice, in the CIBM, ESP is likely to be an advertisement. That is, the quotes on ESP should be characterized as indicative quotes, and it is possible to get a better quote if a trader negotiates with the quoting dealer bilaterally on OTC venue. Those who are still willing to trade at this worst price can be interpreted as being in urgent need of liquidity, or driven by other regulatory considerations. All in all, the rarity of observations on ESP makes its effect negligible.

C.2 Other measurements on liquidity

In this subsection, to cross-validate the cost saving effect of CLOB, we construct alternative liquidity measures drawing from the literature: $BuySellGap$, IQR, and $Spread^{dejure}$. In specific, $BuySellGap$ and $Spread^{dejure}$ can be regarded as alternative measures for transaction cost, and IQR is a measure for liquidity in general. We now describe the construction of these alternative measures, and present the regression results using these alternative measures.

First, following the principle that liquidity suppliers should continuously buy and sell to make the market, a natural way to proxy the bid-ask spread convention is to measure the price gap between liquidity suppliers' buy and sell orders. This price gap represents the markup charged by liquidity suppliers, or equivalently, the cost incurred for a conceptual round-trip intermediated by liquidity suppliers. Thus, we define:

$$BuySellGap_{b,t,v} = \frac{vwavg(\text{LS sell})_{b,t,v} - vwavg(\text{LS buy})_{b,t,v}}{\frac{1}{2} \times (vwavg(\text{LS sell})_{b,t,v} + vwavg(\text{LS buy})_{b,t,v})} \times 10000 \tag{A1}$$

where b denotes the bond, t denotes the execution day, and v denotes the venue, i.e., $v \in \{OTC, CLOB\}$. LS stands for liquidity suppliers, and $vwavg$ represents the volume-weighted average of the corresponding prices. This $BuySellGap$ measure aligns with the measurements in the literature, such as Hong and Warga (2000), Chakravarty and Sarkar (2003), Choi et al. (2024).

To further strengthen the robustness, we explore a different way to classify liquidity suppliers and liquidity demanders, justified by Figure 3 and Figure 4. Unlike the $Spread$ measure in Section 5.1, when constructing $BuySellGap$, we do not allow a trader to switch its liquidity role across different bonds and

days. That is, a trader is either a liquidity supplier or a liquidity demander for all bond trades throughout the entire sample period. Specifically, for a given trader, we classify the trader as liquidity supplier (LS) if and only if: (1) the trader's total trading volume (buy volume plus sell volume) is greater than or equal to that of the smallest dealer, and (2) the trader's buy volume ratio (buy volume divided by total trading volume) falls within the range of $[0.4, 0.6]$. Consequently, in the data, we identify 210 liquidity suppliers (LS),[5] and the remaining traders are classified as liquidity demanders.

Second, we construct the IQR measure following the literature (e.g., Pu (2009), Han and Zhou (2016)) to capture the second moment of the price distribution at the bond-day level. That is, capturing volatility, which is commonly viewed as a proxy for aggregate risk (Duffie et al. (2023)). Specifically, we compute:

$$IQR_{b,t,v} = \frac{P^{75th}_{b,t,v} - P^{25th}_{b,t,v}}{P^{50th}_{b,t,v}} \times 10000 \tag{A2}$$

where $P^{25th}_{b,t,v}$, $P^{50th}_{b,t,v}$, and $P^{75th}_{b,t,v}$ represent the 25th, 50th, and 75th percentiles of the price distribution for bond b on day t in venue v.

Third, although in this paper we emphasize the importance of identifying de facto liquidity demanders and suppliers given the all-to-all market structure, for robustness, we still use the conventional de jure classification of customers and dealers to construct the Choi-Huh measure (Choi et al.

[5]Specifically, among these liquidity suppliers, 87 are dealers and 123 are customers.

(2024)). Specifically, we construct:

$$Spread^{dejure}_{j,b,t,v} = 2 \times Q_{j,b,t,v} \times \frac{traded\ price_{j,b,t,v} - reference\ price_{b,t}}{reference\ price_{b,t}} \times 10000 \tag{A3}$$

where b denotes the bond, t represents the execution day, v denotes the venue, and j indexes each trade. We set $Q_{j,b,t,v}$ to 1 (-1) when a customer buys from (sells to) a dealer. To further strengthen the robustness, we use $reference\ price$ different from Section 5.1: here we use the volume-weighted average price of all trades of a given bond within a given day, in regardless of the venue for execution.[6] We aggregate this trade-level measure to the bond-day-venue level $Spread^{dejure}_{b,t,v}$ by taking the volume-weighted average among all trades where the measures are available.

Notably, by construction, these three measures, $BuySellGap$, IQR, and $Spread^{dejure}$, are at bond-day-venue level. As emphasized in Section 4 and Section 5.2, confoundings from trader characteristics, terms of trade, and bond attributes are threats to identification. To address, we pre-refine the original dataset before we construct these three measures.[7] For pre-refining, we retain the observations where (1) the buyer has purchased in both OTC and CLOB, and the seller has sold in both OTC and CLOB during the sample period, (2) the order size falls within the range of [10M, 50M],[8] and (3) the bond is traded on both OTC and CLOB venues within that day.

Using these three liquidity measures constructed from the pre-refined dataset,

[6] The *Spread* measure is comparable across venues only if the reference price is identical for both venues.

[7] Thus, each of these three measures is a function (i.e., an aggregator) of covariates that are similarly distributed across the two venues. Thus, it ensures that no endogenous sorting is embedded in the construction of the measure.

[8] As shown in Figure 7, this size category is the most frequently observed one in CLOB, and exhibits the most balanced distribution across the two venues.

we estimate the equation as follows:

$$illiquidity_{(b,t),v} = \alpha + \beta_{robust} \times \mathbf{1}\{CLOB\}_v + \mu_{(b,t)} + \epsilon_{(b,t),v} \tag{A4}$$

where b denotes the bond, t denotes the day, and v denotes the venue, i.e., $v \in \{OTC, CLOB\}$. $illiquidity$ is one of the three liquidity measures: $BuySellGap$, IQR, $Spread^{dejure}$. The indicator function $\mathbf{1}\{CLOB\}_v$ equals 1 if the venue v is CLOB. Our hypothesis is $\beta_{robust} < 0$, indicating that CLOB improves liquidity (reduces illiquidity).[9] The fixed effect $\mu_{(b,t)}$ represents bond-day effect.[10]

The regression results using alternative liquidity measures are presented in Table A3. All estimated β_{robust} are negative, with magnitudes similar to those in Table 3. Therefore, our conclusion regarding the cost-saving effect of the CLOB venue remains robust.

[Table A3 about here.]

C.3 Sample refinement at bond-day level

In this subsection, we relax the second step of sample refinement outlined in Section 5.2.1, in order to test the external validity of the CLOB cost-saving effect. For Table 3, we require that, at the bond-hour level, trades must be observed in both OTC and CLOB venues. Here we relax this requirement to the bond-day level. That is, an observation is included for regression as long as that bond is traded on both OTC and CLOB within that day (instead of

[9] Notably, for these three liquidity measures, higher values indicate lower liquidity (higher illiquidity).

[10] We control for the size effect by selecting trades with order sizes between 10M and 50M in pre-refinement, and control for the trader effect by ensuring buyers and sellers have bought and sold in both OTC and CLOB during sample period in pre-refinement.

hour).[11] This relaxation increases the number of observations, and therefore tests the external validity of the results.

The estimation equation and the transaction cost measures are identical to Equation 3. The regression results are presented in Table A4. As shown in Table A4, estimated β remains negative, with the magnitude largely consistent with those in Table 3, and the number of observations now extends. Therefore, the conclusion that the CLOB venue is cost-saving remains robust even when external validity is taken into account.

[Table A4 about here.]

[11] Specifically, we conduct bond-day refining after refining the dataset to balanced buyer and seller in both venues, which is identical to the first step of sample refinement described in Section 5.2.1.

Figures



Figure A1: Request-for-Quote (RFQ)

Note: in this figure, we present the screenshot of the form that a requesting trader is required to fill out when submitting a request through Request-for-Quote (RFQ) practice. The original Chinese text has been annotated with English translations. For confidentiality reasons, the traders' names have been blurred out in the screenshot. Note that the quote is provided by the receiving trader when replying this request (the screenshot of the reply is unavailable due to confidentiality).



Figure A2: Request-with-Quote (RWQ)

Note: in this figure, we present the screenshot of the form that a requesting trader is required to fill out when submitting a request through Request-with-Quote (RWQ) practice. The original Chinese text has been annotated with English translations. Compared to the RFQ practice, RWQ reverses the quoting dynamic, as the requesting trader now extends the quote to the recipient. In this screenshot, the untranslated fields contain market-wide bond information (e.g., time to maturity, valuation, and credit rating), which are automatically populated when the requesting trader inputs the Bond Code.

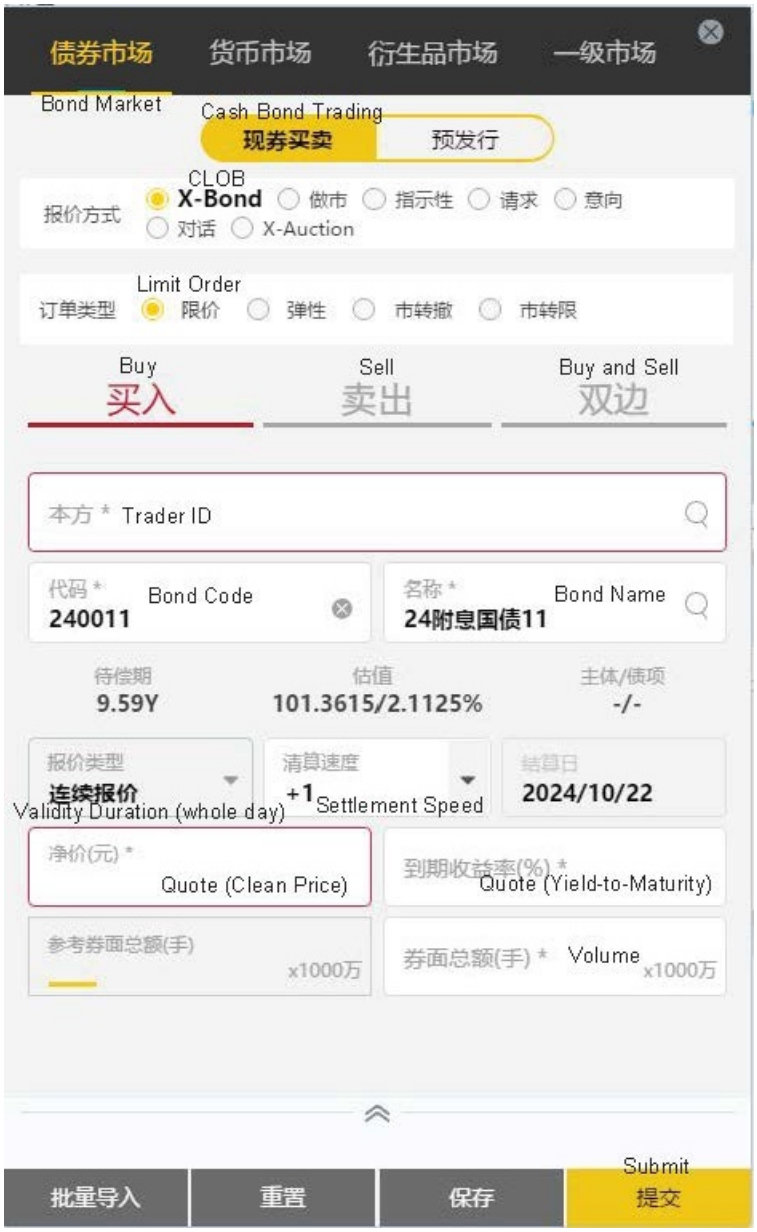


Figure A3: Central Limit Order Book (CLOB)

Note: in this figure, we present the screenshot of the form that a trader is required to fill out when submitting a limit order through Central Limit Order Book (CLOB) practice. The original Chinese text has been annotated with English translations. Compared to the OTC practices (RFQ and RWQ), the orders on CLOB is central-clearing based on the price-time priority rule, as the trader cannot select the receiving counterparties. In this screenshot, the untranslated fields contain market-wide bond information (e.g., time to maturity, valuation, and credit rating), which are automatically populated when the trader inputs the Bond Code.



Figure A4: Order Book

Note: in this figure, we present the screenshot of the order book of the CLOB venue. The original Chinese text has been annotated with English translations. The screenshot consists of two sections, both of which are visible to all traders. They together suggest both pre-trade and post-trade information transparency on CLOB, compared to the OTC venue. First, the top section displays information on currently available orders (i.e., unmatched orders), such as the best bid and ask prices. Second, the bottom-left section provides information on realized transactions, including the latest transaction price and other terms-of-trade. In this screenshot, the bottom-right section will display the trader's own order after submitting the limit order form as illustrated in Figure A3. Due to limited space, some terms-of-trade for realized transaction (e.g., volume) are not fully displayed in the bottom-left section of this screenshot, but also visible to all traders.

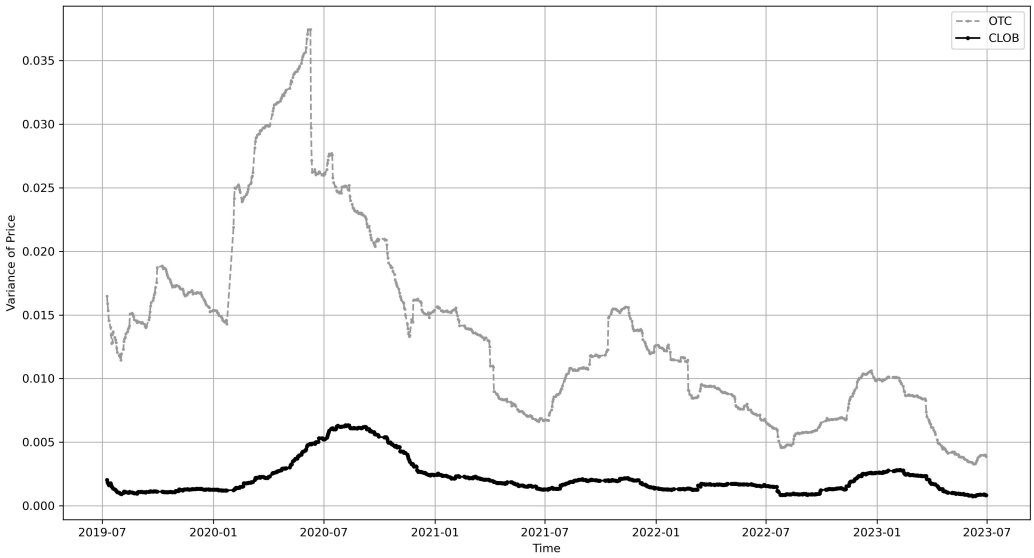
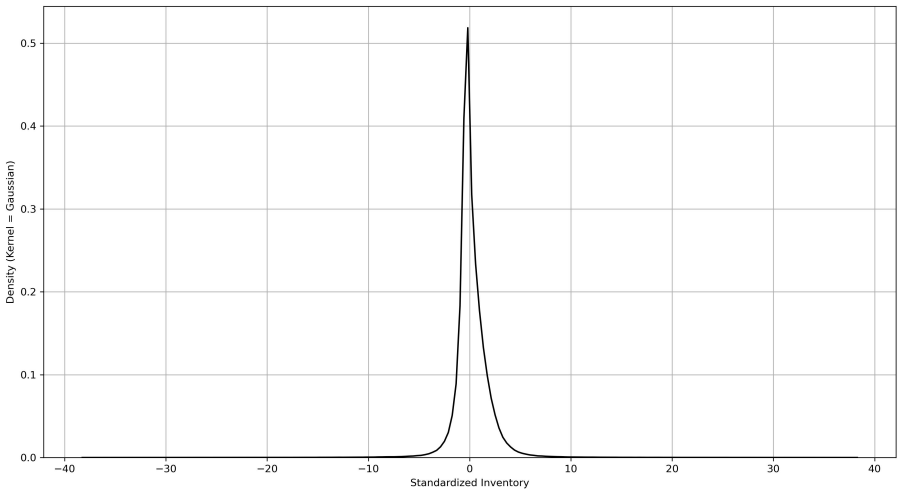
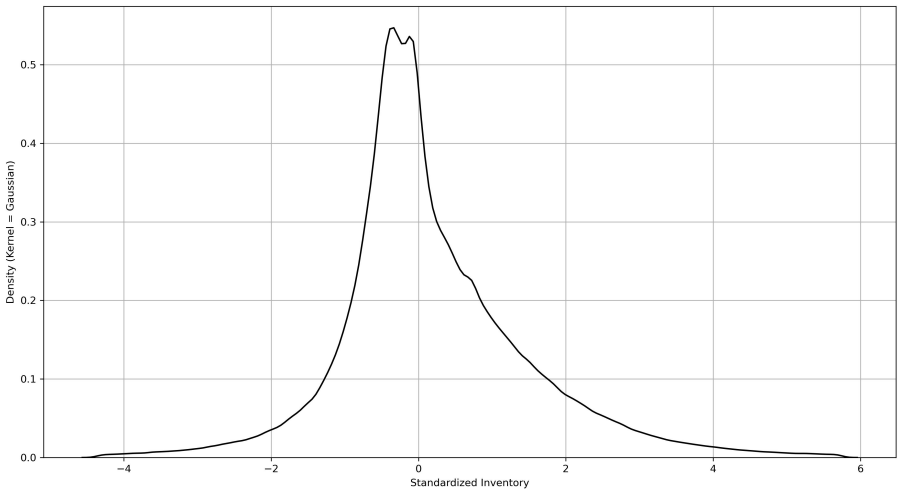


Figure A5: Time-series of price variance: CLOB versus OTC

Note: in this figure, we plot the time series of daily average bond price variance, separately averaged across trades on the CLOB (black) and OTC (gray) venues. The price variance on the CLOB venue is significantly lower than on the OTC venue. The time series also track with the *Spread* and *Amihud* measures as shown in Figure 10. Therefore, this figure cross-validates our measures on transaction cost. To plot this figure, we first compute the price variance of each bond for each venue on each day. We then truncate the price variances at the 1st and 99th percentiles. We then aggregate the bond-venue-day level price variances to the venue-day level, by taking the arithmetic mean among all bonds' price variances within each day and venue. We apply a 90-day moving average to smooth both time series.



Panel A: All observations



Panel B: Truncating at the 1st and 99th percentiles

Figure A6: Distribution of the standardized inventory I

Note: in Panel A, we plot the density of the standardized inventory I by pooling all trader-bonds' daily measures together. The distribution exhibits a long-tail, with the maximum absolute standardized inventory $|I|$ reaching approximately 40. Therefore, in Panel B, we truncate the standardized inventory I at the 1st and 99th percentiles for a closer inspection on the distribution. The standardized inventory I is defined in Equation 8. To plot this figure, we use the Gaussian kernel to estimate the density.

Tables

Table A1: Heterogeneous cost-saving effect of CLOB by order size, Spread measure

	Spread (bp)									
	10M	20M	30M	40M	50M	60M	70M	80M	90M	100M
1{CLOB}	-1.573^{***}	-1.433^{***}	-0.836^{**}	1.867	-0.934^{***}	-4.000	-1.295	0.895	3.101	-2.053^{*}
	(0.388)	(0.318)	(0.383)	(1.340)	(0.240)	(0.000)	(0.000)	(1.391)	(5.185)	(0.967)
Buyer and Seller FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond-hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,140	10,057	5,854	589	11,740	28	22	26	8	639
R^2	0.527	0.446	0.535	0.980	0.445	1.000	1.000	1.000	0.383	0.944
Adjusted R^2	0.180	0.088	0.096	1.175	0.137	1.000	1.000	1.000	-3.322	-2.987

Note: in this table, we present the estimation results of Equation 3: $TransactionCost_{j,(b,t)} = \alpha + \beta \times \mathbf{1}\{CLOB\}_j + \mu_j + \mu_{(b,t)} + \epsilon_{j,(b,t)}$, and each column presents estimates using a subsample where the order size equals to the corresponding volume, and the settlement speed is T+1. The dependent variable is *Spread* defined in Equation 1, and the indicator variable $\mathbf{1}\{CLOB\}_j$ equals 1 if trade j is executed on the CLOB venue. We include two trade-level fixed effects μ_j: buyer and seller (account anonymous ID), as well as a bond-hour fixed effect $\mu_{(b,t)}$. Figure 14 plots estimated β for 10M (Million RMB), 20M, 30M, and 50M groups, and its 95% confidence interval. It reveals that the cost-saving effect of CLOB is more pronounced for smaller orders. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A2: Heterogeneous cost-saving effect of CLOB by order size, Amihud measure

	Amihud									
	10M	20M	30M	40M	50M	60M	70M	80M	90M	100M
1{CLOB}	−6.310e-05***	−3.355e-05***	−2.231e-05***	−1.664e-05***	−1.284e-05***	−1.255e-05***	−1.015e-05***	−8.415e-06***	−7.480e-06***	−5.596e-06***
	(4.49e-07)	(2.23e-07)	(1.65e-07)	(2.16e-07)	(9.65e-08)	(5.02e-07)	(4.79e-07)	(4.30e-07)	(6.15e-07)	(1.20e-07)
Buyer and Seller FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond-hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	603,071	630,254	378,342	61,710	371,914	4,939	3,309	2,904	1,035	26,351
R^2	0.528	0.513	0.508	0.539	0.459	0.640	0.660	0.666	0.780	0.503
Adjusted R^2	0.513	0.494	0.480	0.476	0.417	0.426	0.415	0.405	0.395	0.369

Note: in this table, we present the estimation results of Equation 3: $TransactionCost_{j,(b,t)} = \alpha + \beta \times \mathbf{1}\{CLOB\}_j + \mu_j + \mu_{(b,t)} + \epsilon_{j,(b,t)}$, and each column presents estimates using a subsample where the order size equals to the corresponding volume, and the settlement speed is T+1. The dependent variable is *Amihud* defined in Equation 2, and the indicator variable $\mathbf{1}\{CLOB\}_j$ equals 1 if trade j is executed on the CLOB venue. We include two trade-level fixed effects μ_j: buyer and seller (account anonymous ID), as well as a bond-hour fixed effect $\mu_{(b,t)}$. Figure 15 plots estimated β for all size groups, and its 95% confidence interval. It reveals that the cost-saving effect of CLOB is more pronounced for smaller orders. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A3: Robustness check: alternative liquidity measures

	BuySellGap (bp)	IQR (bp)	Spread^{dejure} (bp)
1{CLOB}	-0.987***	-3.634***	-0.164***
	(0.178)	(0.032)	(0.053)
Bond-day FE	Yes	Yes	Yes
Observations	3,208	60,940	34,656
R^2	0.511	0.720	0.506
Adjusted R^2	0.022	0.441	0.011

Note: in this table, we present the estimation results of Equation A4: $illiquidity_{(b,t),v} = \alpha + \beta_{robust} \times \mathbf{1}\{CLOB\}_v + \mu_{(b,t)} + \epsilon_{(b,t),v}$, where the dependent variable *illiquidity* corresponds to one of the three alternative liquidity measures: $BuySellGap$, IQR, and $Spread^{dejure}$, calculated as Equation A1, A2 and A3 respectively. The indicator function $\mathbf{1}\{CLOB\}_v$ equals 1 if the venue v is CLOB. We include bond-hour fixed effect $\mu_{(b,t)}$. All estimated β_{robust} are negative, with magnitudes similar to those in Table 3. Therefore, our conclusion regarding CLOB cost-saving remains robust. When estimating, we truncate each liquidity measure at the 1st and 99th percentiles, and cluster standard errors at the bond-day level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A4: Robustness check: sample refinement at bond-day level

	Spread (bp)		Amihud	
	(1)	(2)	(3)	(4)
1{CLOB}	-1.222***	-0.754***	-0.0000271***	-0.0000268***
	(0.130)	(0.157)	(3.28e-07)	(3.10e-07)
Size category FE	Yes	Yes	Yes	Yes
Settlement speed FE	Yes	Yes	Yes	Yes
Buyer and Seller FEs	No	Yes	No	Yes
Bond-hour FE	Yes	Yes	Yes	Yes
Observations	277,124	277,124	6,065,177	6,065,177
R^2	0.075	0.099	0.299	0.309
Adjusted R^2	0.045	0.066	0.295	0.306

Note: in this table, we present the estimation results of Equation 3: $TransactionCost_{j,(b,t)} = \alpha + \beta \times \mathbf{1}\{CLOB\}_j + \mu_j + \mu_{(b,t)} + \epsilon_{j,(b,t)}$, where b denotes bond, t denotes hour and j denotes trade. We retain the observation in regressions if that bond is traded on both OTC and CLOB venues within that day (for estimation, we still introduce bond-hour fixed effect). By relaxing the sample refinement process to the bond-day level instead, compared to Table 3, this table includes a greater number of observations, and therefore we test the external validity of our result. In this table, the estimated β remains negative, with the magnitude largely consistent with those in Table 3. Therefore, the conclusion that the CLOB venue is cost-saving remains robust even when external validity is taken into account. When estimating, we truncate each transaction cost measure at the 1st and 99th percentiles, and cluster standard errors at the bond-hour level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.