Dealers' Search Intensity in U.S. Corporate Bond Markets*

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July 5, 2020

Abstract

Are dealers' search efforts endogeneous in decentralized markets? How do dealers' search efforts affect market efficiency? We propose a model with dealers choosing idiosyncratic search intensities, and estimate the model using transaction data on U.S. corporate bonds. We find that: [1] with dealers ranked by their private valuations for a bond, the middle-type dealer chooses the highest search intensity, and she reallocates bond positions from lower-type dealers to higher-type dealers; [2] the estimated model predicts that the search costs and bond misallocation in current OTC markets generate 13.7% welfare loss relative to a counterfactual frictionless market.

Keywords: corporate bond market, endogeneous search intensity, market inefficiency, search model estimation

*For helpful comments and discussions at various stages of this paper, I thank Pierre-Olivier Weill, Lee E. Ohanian, Bernard Herskovic, Saki Bigio, Zhipeng Liao, Andrew Atkeson, Francois Geerolf, Christopher J. Waller, David Andolfatto, B. Ravikumar, Serdar Birinci, YiLi Chien, Bill Dupor, Sungki Hong, Julian Kozlowski, Fernando M. Martin, Paulina Restrepo-Echavarria, Juan M. Sanchez, Yongseok Shin, Yi Wen, Yu An, and participants at the UCLA Macroeconomics proseminar and Federal Reserve Bank St. Louis dissertation intern workshop. All errors are mine.

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1 Introduction

In the U.S. corporate bonds markets, dealers manage bond inventories to provide liquidity to customers. Inventory management is facilitated by a decentralized over-the-counter (OTC) interdealer market subject to search frictions: dealers need to locate other dealer-counterparties with whom to trade. To overcome search frictions, dealers need to decide how much time and how many resource to spend in building connections with other dealers or to hire how many traders to staff their trading desks. Empirical papers on trading structures of decentralized financial markets show that dealers exhibit persistently heterogeneous trading frequencies[1]. Does this market structure emerge from dealers' heterogeneous search efforts? How does dealers' choice of search efforts affect market efficiency? Examing these questions will help provide a framework to study how search frictions affect the welfare of market participants through affecting dealers' trading activities and asset liquidity.

In this paper, we propose and estimate a search-based model for the U.S. corporate bond market, extending Hugonnier, Lester, and Weill (2018). There are two aspects of contribution: on the theory side, the innovation is to consider dealers' endogeneous and state-dependent choice of search intensity based on dealers' idiosyncratic states (holding position and private valuation[2] for each bond). Dealers' endogeneous search intensity drives heterogeneous frequency of trade and ultimately determines the total welfare of the market; on the empirical side, we offer a structural estimation of dealers' search intensities and model parameters by using the academic version of TRACE data. This dataset includes the information on the identities of the dealer-counterpartie(s) in each transaction. Using the estimated search intensities, we validate the theoretical predictions on dealers' heterogeneous roles in the intermediation process. Using the estimated search model, we further quantify the over-the-counter inefficiencies in terms of welfare per capita and bond misallocation in U.S corporate bond markets.

[1] The recent empirical studies on OTC markets commonly use a conceptual framework inherited from the analysis of static networks to document a "core-periphery" trading structure within the interdealer market. Such market structure is documented by Di Maggio, Kerman, and Song (2017) for the U.S. corporate bond market, Li and Schürhoff (2014) for the U.S. treasury bond market, Hollifield, Neklyudov, and Spatt (2017) for the U.S. securitizations market, and Bech and Atalay (2010) for the fed funds market.

[2] In the spirit of Duffie, Gârleanu, and Pedersen (2005), market participants have idiosyncratic private valuation type (preference) for the target asset which is modelled as a "consol". By holding the asset, market participants obtain flow utility, the level of which equals the level of their valuation for the asset.

This model has the following features that distinguish it from the other search-based models which also focus on explaining dealers' heterogeneous frequency of trade:

First, dealers' heterogeneous search intensities can be identified from transaction-level data. The identification depends on the "separation" of the dealer sector from the customer sector, and also depends on the assumed matching technology in the model: [1] the separation of the dealer sector from the customer sector allows us to identify the relative level of search intensities across the dealers on the *same* side[3] of the market. If moving across dealers on the same side, all the dealers have the same probability of meeting and trading with a customer. This implies that, on the same side of the market, the number of dealer's completed transactions with customers is proportional to their idiosyncratic search intensities. This allows us to identify the relative trend of searching activity across the dealers on the same side. Intuitively, dealers who trade more actively with customers are more likely to be the ones who spend more search efforts; [2] the matching technology further allows us to identify each dealer's search intensities on the two sides of the market *up to a same constant*, which makes it possible for us to test model predictions[4]. For each dealer, the difference between the number of buy-from-customer transactions and the number of sell-to-customer transactions is generated by two components: difference between buying- and selling- search intensities and difference in the probability of trading with customers between the buy and the sell sides. If we can identify any one of the two differences for each dealer, we can then identify the other. The second difference is further monotonic with the difference between the whole dealer sector's aggregate buying- and aggregate selling- search intensities, because in equilibrium the dealer sector buy and sell equal amounts of the bond with customers, and maintain a balanced inventory position. Our matching technology assumes for each dealer, the probability of contacting (being contacted by) a trading counterparty is proportional to the counterparty's (the dealer's) search intensity[5]. This allows us to use the realized

[3]By "the same side", we mean either the buy side of the market where dealer-nonowners search to buy the bond from potential trading counterparties, or the sell side of the market where dealer-owners search to sell the bond.

[4]In the search-and-match model, this "same constant" is trivally equal to one. One of the model predictions focuses on the trend of the summation of search intensities over the two sides of the market, when we move across dealers of different private valuation types. To verify the prediction, we need to identify each dealer's buying- and selling- search intensities up to a same constant, and then sum up the two for each dealer.

[5]This matching technology is discussed and used by Mortensen (1982), Shimer and Smith (2001), and Üslü (2019)

transactions of two specific dealers, dealers with the maximum and the minimum private valuations, to identify the ratio of the dealer-sector's aggregate buying-search intensity over its aggregate selling-search intensity (i.e., the second difference above), because those two dealers have positive trading surplus with all the other dealers on their opposite sides in the market. By identifying the second difference above, we finally identify the difference in each dealer's buying and selling intensity, or in other words, we identify the two intensities up to a same constant.

Second, the model gives predictions on whether dealers' search efforts are endogeneous or not, through characterizing the shape of the distribution of search intensity among dealers, and connecting it with dealers' heterogeneous roles in the intermediation of bonds. My model generates the following two predictions that can both be empirically verified: [**1**] dealers' total search intensity is a hump-shaped function of dealers' private valuation. Within each cross section, dealers of intermediate private valuations choose higher total search intensities and dealers of extreme (either low or high) private valuations choose relatively lower total search intensities. Moreover, the lower total search intensities of the low(high)-type dealers are mainly driven by lower selling(buying) intensities. This prediction implies that the intermediate-type dealers behave as the intermediary and they trade actively on both sides of the market to intermediate the bond from low-type dealers to high-type ones. Empirically verifying this prediction gives us the evidence that dealers' search efforts in OTC financial markets are more likely to be endogeneous other than exogeneous; and [**2**]: dealers play heterogeneous roles in the intermediation process by specializating in transactions of different directions. Low-type dealers spend more resources searching on the buy side and specialize in buying the bond from customers and selling to other dealers; high-type dealers spend more resources searching on the sell side and specialize in selling the bond to customers and buying from other dealers. Intermediate-type dealers on average invest in equal amounts of buying and selling intensities, and contribute most to intermediating the bond from low-type dealers and/or customers to high-type ones.

Finally, state-dependent search intensity allows the model to be used as a framework to study how search frictions affect the total welfare of market participants, through driving dealers' trading activities. The estimates of model parameters indicate nontrivial market inefficiencies compared with frictionless markets, in terms of welfare per capita and bond misallocation.[6] In this paper, we define each market as a combination of bond j and quarter q, and conduct counterfactual analysis similar as Gavazza (2016) for each $Market(j, q)$. The main findings include: **[1]** search frictions and bond misallocation together generate on average 13.7% welfare loss across all markets, compared with corresponding frictionless markets. For each market, we calculate the total welfare as the difference between the total utility flow and the total search costs spent by all the dealers. For each counterfactual frictionless market, the total welfare is trivally equal to the total utility flow in the case of no bond misallocation; **[2]** for each bond, there are on average 1.68% of total positions being mis-allocated, in the sense of being held by customers and/or dealers with private valuations lower than the marginal investor in a frictionless market; and **[3]** The levels of these two dimensions of inefficiencies exhibit high variations across bonds and over time.

Related literature

The model with state-dependent search intensity contributes to the theoretical literature initiated by Duffie, Gârleanu, and Pedersen (2005) that uses a search-and-match model to study asset price and liquidity in over-the-counter markets. My model studies fully decentralized market structure by setting a random search environment, which is similar to one strand of the literature developed by Duffie, Gârleanu, and Pedersen (2007), Vayanos and Wang (2007), Vayanos and Weill (2008), Weill (2008), Afonso (2011), Gavazza (2011), Praz (2014), Trejos and Wright (2016), Afonso and Lagos (2015), Atkeson, Eisfeldt, and Weill (2015). Another strand of literature focuses on *semi-decentralized* market structure in which dealers trade in a frictionless centralized interdealer market which allows them to immediately offload inventories through trading with other dealers, as in Weill (2007), Lagos and Rocheteau (2009), Feldhütter (2011), Lester, Rocheteau, and Weill (2015), and Pagnotta and Philippon (2018).

My model is most related to Hugonnier, Lester, and Weill (2018) in the setting of dealers' heterogeneous valuation types and the incorporation of both dealer and customer sectors. The main difference in my model is that we consider dealers' explicit choice of state-dependent search intensity based on their idiosyncratic states. In Hugonnier, Lester, and Weill (2018), dealers are endowed with homogeneous search intensities.

[6] Bond misallocation means the proportion of amount of bond that is being held by agents (either dealers or customers) with valuation types lower than that of the marginal agent.

My model is different from Shen, Wei, and Yan (2018) who is the first to consider the search intensity decision. They discuss the endogenous entry and exit of investors into an over-the-counter market based on investors' idiosyncratic trading needs and a common search cost, which focuses more on the extensive margin of choosing whether to search or not. Once entering the market, investors will adopt the same level of search intensity. We instead consider dealers' intensive margin of choosing how fast to search within the market, based on dealers' idiosyncratic trading needs and bond positions. The empirical identification of dealers' heterogeneous search intensities shows that the intensive margin of choosing the search speed is significant within the dealer sector.

There is a contemporaneous strand of literature that also considers heterogeneous search intensity under a random search environment: Neklyudov (2012) considers exogeneously heterogeneous search intensity among dealers and two discrete valuation types; Üslü (2019) introduces *ex-ante* heterogeneity in meeting rates into a fully decentralized market model with unrestricted asset holdings; Farboodi, Jarosch, and Shimer (2017b) consider *ex-ante* choice of (distribution of) search intensity at the initial time, after which each agent maintains a fixed level of search intensity even though their private valuations may change, but my model allows dealers to change their search intensities as long as their state variables change.[7]

Moreover, my model relates to papers with alternative, other than search intensity, mechnisms of endogeneous intermediation, including Farboodi (2014) on bank heterogeneous risk exposure, Neklyudov and Sambalaibat (2015) on dealers' serving clients with different liquidity needs, Wang (2016) on the trade-off between trade competition and inventory efficiency, Farboodi, Jarosch, and Menzio (2017a) on dealers' heterogeneous bargaining power, and Bethune, Sultanum, and Trachter (2018) on private information and heterogeneous screening ability, among others.

This paper fills the gap in empirical analysis on heterogeneous search intensity/frequency of trade in the search-based literature. Among existing papers, heterogeneity in dealers' frequency of trade is mostly motivated by the documented core-periphery structure based on the network approach, as in Li and Schürhoff (2014) for the U.S. treasury bond market,

[7]There exist other related papers that consider other mechnisms, other than heterogeneous search intensity, to generate heterogeneous frequency of trade among market participants. For example, in Farboodi, Jarosch, and Menzio (2017a), dealers' frequency of trade is driven by heterogeneous bargaining power instead of their search intensity.

Di Maggio, Kerman, and Song (2017) for the U.S. corporate bond market, Hollifield, Neklyudov, and Spatt (2017) for the U.S. securitizations market, and Bech and Atalay (2010) for the fed funds market. By using transaction-level data on corporate bonds, this paper quantifies this interdealer core-periphery structure by a search-based approach. From the search-and-match perspective, the core dealers are the ones choosing higher total search intensity over both sides of the market and the periphery ones choose relatively lower total search intensity.

Finally, my paper empirically identifies dealers' search intensity in an over-the-counter financial market, based on which dealers' search cost and financial asset misallocation are quantified. In terms of estimation, my paper is most related to Gavazza (2016), who estimates a search-and-bargaining model of a decentralized market by using transaction data on business aircraft, and quantifies the effects of trading frictions on asset price, allocation and social welfare. Hendershott, Li, Livdan, and Schürhoff (2017) also do structural estimation for a one-to-many search-and-match model with endogeneous network size and transaction prices, and quantify the effects of client-dealer relations on execution quality in the OTC market for corporate bonds. Other papers that structually estimate search models focus mostly on labor markets, including Eckstein and Wolpin (1990), and Eckstein and Van den Berg (2007), among others.

2 Model

2.1 Environment

Market participants and preferences Market participants include a continuum of customers with physical measure normalized to 1 and a continuum of dealers with physical measure $m \leq 1$. Dealers and customers trade a long-lived indivisible bond in fixed supply $s < 1 + m$, and each participant's holding position a is assumed to be either zero or one.[8] Market participants are all risk neutral and discount future utility flow at rate r. By holding one unit of bond, each participant obtains a utility flow per unit time, which is equal to her

[8]This $\{0, 1\}$ assumption for bond holding and the indivisibility of bonds determine that the trading volume in each transaction equals one.

idiosyncratic private valuation type.[9]

Customers' private valuation type takes two possible values, either low or high, denoted by $y \in \{y_\ell, y_h\}$ with $y_\ell < y_h$. Each customer draws a new private valuation with intensity α. Private valuation processes are independent across customers and independent of everything else. Customers' new private valuation y' follows a discrete distribution with $P(y' = y_c) = \pi_c$, $c = \ell, h$. In a stationary equilibrium, π_c is equal to the physical measure of customers with type c.

Dealers' private valuation type $\delta \in [\delta_\ell, \delta_h]$ follows an arbitrary continuous distribution with pdf $f(\delta)$. As in Hugonnier, Lester, and Weill (2018), we assume dealers' private valuations are stable over time.[10]

Search, matching, and trade All market participants randomly search and trade in the market. Each dealer chooses her idiosyncratic optimal search intensity $\lambda_a^*(\delta)$ as a function of her current asset position $a \in \{0, 1\}$ and private valuation type $\delta \in [\delta_\ell, \delta_h]$. The flow cost of choosing $\lambda_a^*(\delta)$ is given by $c \times \lambda_a^*(\delta)^2$ with $c > 0$. The value of c captures the market level of search friction. Customers have constant search intensity $\rho > 0$. We assume each dealer searches to meet and trade with both customers and other dealers, while customers can only search to meet and trade with dealers. Since the two types of customers cannot directly trade with each other, all of the bond positions which are reallocated between customers need to be intermediated through the dealer sector.

We adopt the matching technology discussed by Mortensen (1982), Shimer and Smith (2001), and Üslü (2019). The intensity with which a dealer with search intensity λ contacts or is contacted by another dealer with search intensity λ' equals $m(\lambda, \lambda') = 2 \times \frac{m}{1+m} \times \lambda \frac{\lambda'}{\Lambda}$, where $\frac{m}{1+m}$ is the probability of meeting a dealer given that a meeting happens and Λ is the aggregate level of all dealers' search intensities. Therefore the intensity of meeting a specific trading counterparty is not only proportional to the counterparty's corresponding physical measure but also proportional to the counterparty's search intensity. Similarly, the intensity with which a dealer with search intensity λ contacts or is contacted by a customer equals

[9]The private valuation can be determined by dealers' idiosyncratic liquidity needs, financing costs, and hedging needs, etc. Within each cross section, dealers can be ranked by their private valuation types.

[10]In the data, dealers' trading behavior (measured by dealers' total trading volume, fractions of trading volumes in different directions, and dealers' centralities in the interdealer trading network, etc) is much more stable than customers'.

$m(\lambda, \rho) = \lambda \times \left(\frac{1}{1+m} + \frac{\rho}{m\Lambda}\right)$.

Once two participants meet, trade only happens when there exist positive gains from trade, and the transaction price is determined by a Nash bargaining process. We assume all dealers have the equal bargaining power (i.e. $\frac{1}{2}$) when they trade with each other in the interdealer market. Dealers' bargaining power over customers is equal to θ s.t. $0 < \theta < 1$.

2.2 Model solutions and stationary equilibrium

Within each group of dealers of the same private valuation type δ, there exist dealer-owners and dealer-nonowners based on their idiosyncratic holding position a. We denote the density of dealer-owners of type δ by $\phi_1(\delta)$ and that of dealer-nonowners of the same type by $\phi_0(\delta)$. Dealer-owners each hold one unit of bond and search to sell the bond to other dealers or customers. Once a sale is completed, they become dealer-nonowners and search to buy the bond. There are four groups of customers: high- and low-type owners and nonowners. We denote the corresponding physical measures by μ_{h1}, μ_{h0}, $\mu_{\ell 1}$, $\mu_{\ell 0}$.

A dealer or customer's willingness to pay for the bond is determined by her reservation value, which is equal to the difference between the value of holding the bond and the value of not-holding the bond. Let $V_a(\delta)$ denote the value of a dealer with type δ and bond position a, then her reservation value is $\triangle V(\delta) = V_1(\delta) - V_0(\delta)$. Similarly, the value and reservation value of a customer with type y and bond position a are denoted by $W_a(y)$ and $\triangle W(y) = W_1(y) - W_0(y)$.

2.2.1 Dealers' reservation value

As is standard, $V_a(\delta)$, with $a \in \{0, 1\}$ and $\delta \in [\delta_\ell, \delta_h]$, satisfies the HJB equation:

$$\begin{aligned} rV_a(\delta) = \max_{\lambda} \quad & \Bigg\{ -c\lambda^2 + a\delta + \sum_{c \in \{\ell, h\}} \lambda \left(\frac{1}{1+m} + \frac{\rho}{m\Lambda} \right) \mu_{c,1-a} \theta \left((2a-1)(\triangle W(y_c) - \triangle V(\delta)) \right)^+ \\ & + \int_{\delta_\ell}^{\delta_h} 2\lambda \frac{m}{1+m} \frac{\lambda^*_{1-a}(\delta')}{\Lambda} \phi_{1-a}(\delta') \frac{\left((2a-1)(\triangle V(\delta') - \triangle V(\delta)) \right)^+}{2} d\delta' \Bigg\} \end{aligned} \tag{1}$$

where $x^+ = \max\{0, x\}$, $\lambda^*_0(\delta)$ is the optimal search intensity of a dealer-nonowner with type δ, $\lambda^*_1(\delta)$ is the optimal search intensity of a dealer-owner with type δ, and Λ is the aggregate level of all dealers' search intensities $\Lambda = \int_{\delta_\ell}^{\delta_h} \lambda_0^*(\delta)\phi_0(\delta)d\delta + \int_{\delta_\ell}^{\delta_h} \lambda_1^*(\delta)\phi_1(\delta)d\delta$.

According to (1), by choosing search intensity λ, a dealer of type δ who holds $a = 1$ unit of bond pays flow cost $c\lambda^2$ and enjoys the utility flow δ until one of following two events occur: first, with intensity $2\lambda\frac{m}{1+m}$ the dealer-owner contacts or is contacted by a dealer-nonowner of higher private valuation type and obtains half of the trade surplus; second, with intensity $\lambda\left(\frac{1}{1+m} + \frac{\rho}{m\Lambda}\right)$ the dealer-owner contacts or is contacted by a customer-nonowner with type y_h and receives θ share of the trade surplus. Similar interpretations work for dealer-nonowners with holding position $a = 0$ and not enjoying any utility flow.

Given the distributions, reservation values, and all dealers' optimal search intensities, by FOCs of the HJB equation (1), the optimal search intensity functions $\lambda_1^*(\delta)$ and $\lambda_0^*(\delta)$ satisfy the following conditions:

$$\begin{aligned} 2c\lambda_1^*(\delta) = &\left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\mu_{h0}\theta(\triangle W(y_h) - \triangle V(\delta)) \\ &+ \frac{m}{1+m}\int_{\delta}^{\delta_h} \frac{\lambda_0^*(\delta')\phi_0(\delta')}{\Lambda}(\triangle V(\delta') - \triangle V(\delta))d\delta' \end{aligned} \tag{2}$$

$$\begin{aligned} 2c\lambda_0^*(\delta) = &\left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\mu_{\ell 1}\theta(\triangle V(\delta) - \triangle W(y_\ell)) \\ &+ \frac{m}{1+m}\int_{\delta_\ell}^{\delta} \frac{\lambda_1^*(\delta')\phi_1(\delta')}{\Lambda}(\triangle V(\delta) - \triangle V(\delta'))d\delta' \end{aligned} \tag{3}$$

$\forall \delta \in [\delta_\ell, \delta_h]$. Then the HJB equation of the reservation value function $\triangle V(\delta)$ is:

$$\begin{aligned} r\triangle V(\delta) = &- c\lambda_1^{*2}(\delta) + c\lambda_0^{*2}(\delta) + \delta + 2\lambda_1^*(\delta)\frac{m}{1+m}\int_{\delta}^{\delta_h} \frac{\lambda_0^*(\delta')}{\Lambda}\phi_0(\delta')\frac{\triangle V(\delta') - \triangle V(\delta)}{2}d\delta' \\ &+ \lambda_1^*(\delta)\left(\frac{1}{1+m} + \frac{\rho}{m\Lambda}\right)\mu_{h0}\theta(\triangle W(y_h) - \triangle V(\delta)) \\ &- 2\lambda_0^*(\delta)\frac{m}{1+m}\int_{\delta_\ell}^{\delta} \frac{\lambda_1^*(\delta')}{\Lambda}\phi_1(\delta')\frac{\triangle V(\delta) - \triangle V(\delta')}{2}d\delta' \\ &- \lambda_0^*(\delta)\left(\frac{1}{1+m} + \frac{\rho}{m\Lambda}\right)\mu_{\ell 1}\theta(\triangle V(\delta) - \triangle W(y_\ell)) \end{aligned} \tag{4}$$

The equations (2)-(4) presume the monotonicity of reservation value function $\triangle V(\delta)$ and that dealers always want to buy from low-type customers and sell to high-type customers.[11]

2.2.2 Customers' reservation value

The reservation value of a customer with private valuation type $y \in \{y_\ell, y_h\}$ satisfies the following HJB equation by similar steps:

$$
\begin{aligned}
r\triangle W(y) =& y + \sum_{j\in\{\ell,h\}} \alpha\pi_j \left(\triangle W(y_j) - \triangle W(y)\right)^+ \\
&+ \left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)(1-\theta)\int_{\delta_\ell}^{\delta_h} \lambda_0^*(\delta)\phi_0(\delta)(\triangle V(\delta) - \triangle W(y))^+ d\delta \\
&- \left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)(1-\theta)\int_{\delta_\ell}^{\delta_h} \lambda_1^*(\delta)\phi_1(\delta)(\triangle W(y) - \triangle V(\delta))^+ d\delta
\end{aligned}
\tag{5}
$$

The difference between a customer's and a dealer's reservation value is: with intensity α, a customer switches her private valuation type. Again, equation (5) presumes that dealers always want to buy from low-type customers and sell to high-type customers.

2.2.3 Distribution of dealers and customers

The densities of dealer-owner $\phi_1(\delta)$ satisfy the following inflow-outflow equations in equilibrium:

$$
\begin{aligned}
&\frac{2m}{1+m}\phi_1(\delta)\lambda_1^*(\delta)\int_{\delta}^{\delta_h} \frac{\lambda_0^*(\delta')}{\Lambda}\phi_0(\delta')d\delta' + \left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\phi_1(\delta)\lambda_1^*(\delta)\mu_{h0} \\
=& \frac{2m}{1+m}\phi_0(\delta)\lambda_0^*(\delta)\int_{\delta_\ell}^{\delta} \frac{\lambda_1^*(\delta')}{\Lambda}\phi_1(\delta')d\delta' + \left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\phi_0(\delta)\lambda_0^*(\delta)\mu_{\ell 1}
\end{aligned}
\tag{6}
$$

$\forall \delta \in [\delta_\ell, \delta_h]$. In (6), the left-hand side is the outflow due to trading with higher-type dealer-nonowners and high-type customer-nonowners. The right-hand side is the inflow due to trading with lower-type dealer-owners and low-type customer-owners. Given the condition $\phi_1(\delta) + \phi_0(\delta) = f(\delta)$, $\forall \delta \in [\delta_\ell, \delta_h]$, the inflow-outflow equation of $\phi_0(\delta)$ is redundant.

The measures of high-type customer-nonowner μ_{h0} and low-type customer-owner $\mu_{\ell 1}$

[11] The presumption of monotonicity of $\triangle V(\delta)$ is a guess and will be verified in the proof of Proposition 1. The presumptions that dealers always want to buy from (sell to) low-type (high-type) customers require a parametric restriction, as in Hugonnier, Lester, and Weill (2018). We will verify numerically that these restrictions hold in the numerical examples.

satisfy the following inflow-outflow equations:

$$\alpha\mu_{\ell 0}\pi_h = \mu_{h0}\left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\int_{\delta_\ell}^{\delta_h} \lambda_1^*(\delta)\phi_1(\delta)d\delta + \alpha\mu_{h0}\pi_\ell \tag{7}$$

$$\alpha\mu_{h1}\pi_\ell = \mu_{\ell 1}\left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\int_{\delta_\ell}^{\delta_h} \lambda_0^*(\delta)\phi_0(\delta)d\delta + \alpha\mu_{\ell 1}\pi_h \tag{8}$$

In both (7) and (8), the left-hand side represents the inflow due to type switching and the right-hand side represents the outflow due to both type switching and trading with dealers. Given the physical measures of high-type customer π_h and low-type customer π_ℓ, the inflow-outflow equations of μ_{h1} and $\mu_{\ell 0}$ are also redundant.

Then we define stationary equilibrium as follows:

Definition 2.1: *A stationary equilibrium contains $\triangle V(\delta)$, $\phi_0(\delta)$, $\phi_1(\delta)$, $\lambda_0^*(\delta)$, $\lambda_1^*(\delta)$ and $\triangle W(y_\ell)$, $\triangle W(y_h)$, $\mu_{\ell 0}$, $\mu_{\ell 1}$, μ_{h0}, μ_{h1}, such that*

1. *Given distributions $\phi_0(\delta)$, $\phi_1(\delta)$, $\mu_{\ell 0}$, $\mu_{\ell 1}$, μ_{h0}, μ_{h1}, and $f(\delta), \delta \in [\delta_\ell, \delta_h]$:*
   - *$\triangle V(\delta), \lambda_0^*(\delta), \lambda_1^*(\delta)$ solve dealers' HJB equation (4) and first-order conditions for search intensities (2)-(3);*
   - *$\triangle W(y_\ell)$, $\triangle W(y_h)$ solve customers' HJB equation (5).*
2. *Given $\lambda_0^*(\delta)$, $\lambda_1^*(\delta)$, ρ, the endogeneous distributions $\phi_0(\delta)$, $\phi_1(\delta)$, $\mu_{\ell 0}$, $\mu_{\ell 1}$, μ_{h0}, μ_{h1} satisfy:*
   - *$\phi_0(\delta) + \phi_1(\delta) = f(\delta), \forall \delta \in [\delta_\ell, \delta_h]$ where $\int_{\delta_\ell}^{\delta_h} f(\delta)d\delta = m$;*
   - *$\mu_{\ell 1} + \mu_{\ell 0} = \pi_\ell$, $\mu_{h1} + \mu_{h0} = \pi_h$ where $\pi_\ell + \pi_h = 1$;*
   - *the inflow-outflow equations (6)-(8).*
3. *Market clears:*
   - $\int_{\delta_\ell}^{\delta_h} \phi_1(\delta)d\delta + \mu_{\ell 1} + \mu_{h1} = s$

As for the existence of such a stationary equilibrium, we consider a continuous and compact mapping based on a system of equations. This system of equations includes dealers' and customers' HJB equations, the first-order conditions for search intensities, the evolution equation of the dealer-owner density function $\phi_1(\delta)$, the evolution equation of the high-type customer-nonowner density μ_{h0}, and the evolution equation of the low-type customer-owner density $\mu_{\ell 1}$.[12] A proof of existence will not be included in this paper, and a similar proof based on Schauder's fixed-point theorem can be referred in Liu (2018).[13]

2.3 Model Predictions

Compared with models with either constant or exogeneously heterogeneous search intensity, this model allows us to characterize how search intensity varies as a function of private valuation type and also how it varies between owners and nonowners, since search intensity is now dealer's state-dependent choice. The distribution of search intensity also determines the distribution of trading volume across dealers, which further implies the different roles played by dealers in the intermediation process.

2.3.1 Dealers' heterogeneous search intensities

We define the total search intensity of a dealer with type $\delta \in [\delta_\ell, \delta_h]$ as follows:

$$\bar{\lambda}(\delta) = \phi_1(\delta) \times \lambda_1^*(\delta) + \phi_0(\delta) \times \lambda_0^*(\delta) \tag{9}$$

where $\phi_1(\delta) \times \lambda_1^*(\delta)$ is interpreated as the selling intensity of a dealer with type δ, and $\phi_0(\delta) \times \lambda_0^*(\delta)$ is the corresponding buying intensity. Total search intensity is empirically relevant since it can be regarded as a measure of a dealer's total search efforts over both the buy and sell sides of the market at each time point. Alternatively, it can be interpreted as a dealer's instantaneous search effort with many traders. We can imagine a dealer is a continuum coalition of traders with identical types but idiosyncratic trading histories. The size of the coalition of type-δ traders is equal to $f(\delta)$, where a fraction $\phi_1(\delta)$ of the traders each hold one unit of the bond and a fraction $\phi_0(\delta)$ of the traders do not hold the bond.

[12] All the evolution equations are based on the inflow-outflow equations that at each time the net change in the density of a specific group of agents is obtained by subtracting the outflow from the inflow of that group.

[13] In the numerical algorithm, we obtain the other equilibrium components ϕ_0, μ_{h1}, and $\mu_{\ell 0}$ by equilibrium conditions $\phi_0(\delta) + \phi_1(\delta) = f(\delta)$, $\mu_{\ell 1} + \mu_{\ell 0} = \pi_\ell$, and $\mu_{h1} + \mu_{h0} = \pi_h$. The market clear condition is used for checking whether the model solution converges to a fixed point.

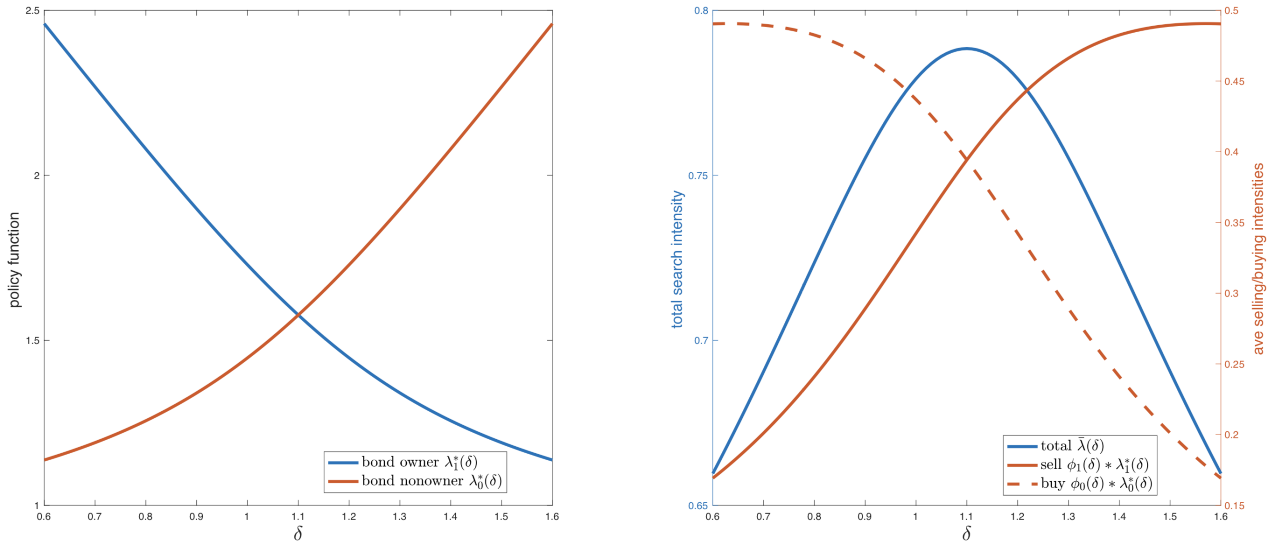

Figure 1: Policy functions and total search intensity

($s = \pi_h = 0.5$, $y_\ell = 0.5$, $y_h = 1.7$, $\delta_\ell = 0.6$, $\delta_h = 1.6$, $\alpha = \rho = m = \theta = 0.5$, $c = r = 0.05$)

As for the distribution of dealer's total search intensity $\bar{\lambda}(\delta)$, we have the following proposition:

Proposition 1: *In any stationary equilibrium with $\triangle W(y_\ell) < \triangle V(\delta) < \triangle W(y_h)$, $\forall \delta \in [\delta_\ell, \delta_h]$:*

1. *$\lambda_1^*(\delta)$ is strictly decreasing in δ, $\lambda_0^*(\delta)$ is strictly increasing in δ;*

2. *If the distribution of private valuation $f(\delta)$ is a uniform distribution on $[\delta_\ell, \delta_h]$, there exists a symmetric equilibrium s.t. $\phi_1(\delta) = \phi_0(\delta_\ell + \delta_h - \delta)$ and $\lambda_1^*(\delta) = \lambda_0^*(\delta_\ell + \delta_h - \delta)$, $\forall \delta \in [\delta_\ell, \delta_h]$. In this symmetric equilibrium, $\exists c^* > 0$ s.t. for any $c < c^*$, $\bar{\lambda}(\delta)$ is hump-shaped and attains its maximum at the middle type $\frac{\delta_\ell + \delta_h}{2}$.*

All proofs are in the Appendix A.1. The condition $c < c^*$ implies that the hump-shaped property applies for a not very high level of search friction. When $c > c^*$, this property may fail. Specifically, for a large enough c, the function of $\bar{\lambda}(\delta)$ may switch to be u-shaped.

With the holding position a fixed, dealer's search intensity is a monotonic function of private valuation type. Specifically, on the buy side ($a = 0$), the higher a dealer-nonowner's private valuation is, the more incentivized she is to choose a high-level search intensity to acquire the bond from the market participants on the sell side, because she values the bond more than most other dealers on the buy side. Similarly on the sell side ($a = 1$), the lower a dealer-owner's private valuation is, more incentivized she is to choose a high-level search intensity to offload the bond to the market participants on the buy side.

Dealer's total search intensity is hump-shaped with private valuation $\delta \in [\delta_\ell, \delta_h]$. Dealers with extreme valuations (either very high or very low) choose lower total search intensities than the middle-type dealer. This is driven by a composition effect given that the market-level search friction is at a low enough level. To understand this finding, consider a dealer with a very high private valuation type. As analyzed above, when this dealer is on the buy side, she is able to search and buy very quickly under a low enough search friction. Once she acquires the bond, she switches to the sell side and also switches to a low-level search intensity, since there are very few potential buyers with private valuations higher than hers and thus the gains from searching to sell is very low. In stationary equilibrium, although this high-valuation dealer buys very quickly, she spends less time on the buy side (i.e. lower density $\phi_0(\delta)$) and spends more time on the sell side (i.e. higher density $\phi_1(\delta)$). Regarding the densities $\phi_0(\delta)$ and $\phi_1(\delta)$ as weights, her total search intensity is at a low level due to a higher weight on the low-level search intensity on the sell side. Similar result works for a low-type dealer, she sells very quickly and is more likely to be on the buy side, also with a low search intensity, which makes her total search intensity at a low level. By contrast, the middle-type dealer imposes equal weights on the buy and the sell sides of the market, with relatively high search intensity on both sides. So considering the overall search effort, she searches more actively than other dealers.

Another way to understand the hump-shaped property of total search intensity $\bar{\lambda}(\delta)$ is that it depends on the equilibrium condition that the netinflow of bond position is equal to zero for each type of dealer. For example, within the dealers with private valuation types in the lower half, as type moves from the lowest level δ_ℓ to the middle level $\bar{\delta} = \frac{\delta_\ell + \delta_h}{2}$, for per unit increase, the decrease in a dealer-owner's probability of trading with another dealer $|\frac{d}{d\delta}\left(\int_{\delta}^{\delta_h} \frac{\lambda_0^*(\delta')}{\Lambda}\phi_0(\delta')d\delta'\right)| = \frac{\lambda_0^*(\delta)\phi_0(\delta)}{\Lambda}$ is always larger than the increase in that of a dealer-nonowner $|\frac{d}{d\delta}\left(\int_{\delta_\ell}^{\delta} \frac{\lambda_1^*(\delta')}{\Lambda}\phi_1(\delta')d\delta'\right)| = \frac{\lambda_1^*(\delta)\phi_1(\delta)}{\Lambda}$, because the buying intensity is always above the selling intensity in the neighbourhood of each $\delta \in [\delta_\ell, \bar{\delta}]$. This drives the amount by which the selling intensity $\lambda_1^*(\delta)\phi_1(\delta)$ curve increases to be larger than that by which the buying intensity $\lambda_0^*(\delta)\phi_0(\delta)$ curve decreases, to maintain that the total number of selling transactions equals that of buying transactions. This further determines that $\bar{\lambda}(\delta)$ increases with δ in the lower half. Similiar explanations apply for the decreasing of $\bar{\lambda}(\delta)$ in the higher half.

2.3.2 Dealers' heterogeneous roles in the intermediation process

In this section, we analyze the implications of endogeneous and state-dependent search intensity on dealers' heterogeneous roles in the intermediation process. Dealer's heterogeneous roles can be characterized by both the absolute levels and the proportions of trading volumes in different directions. Specifically, for each dealer of private valuation type δ, we calculate the dealer's four types of trading volumes: sell-to-customer $V_{S2C}(\delta)$, buy-from-customer $V_{BfC}(\delta)$, sell-to-dealer $V_{S2D}(\delta)$, and buy-from-dealer $V_{BfD}(\delta)$. Figure 2 compares the levels of these four types of transactions among dealers. Figure 3 shows how the proportions of trading volumes in different directions (within each dealer's *total* trading volume) change with private valuation types. Both examples are under the symmetry restrictions.

Dealers with different ranges of private valuation types play heterogeneous roles in the reallocation of bonds between high-type and low-type customers. The model assumption on random search-and-match can be verified if in the data we can obtain similar transaction patterns as follows: [1] lower-type dealers spend more time on the buy side than other dealers and contribute most to buying the bond from (low-type) customer-owners and selling to higher-type dealer-nonowners. Therefore, low-type dealers are net buyers in the dealer-customer market and net sellers in the interdealer market; [2] intermediate-type dealers invest in equal levels of buying and selling intensities and contribute most to intermediating the bond from lower-type participants to higher-type ones, in both the interdealer and dealer-customer markets. In the interdealer market, the intermediate-type dealers behave as the dealer of dealers and tend to lie in the middle of intermediation chains defined in Hugonnier, Lester, and Weill (2018); Meanwhile in the dealer-customer market, these dealers also directly buy and sell to customers at equal amounts[14]; [3] higher-type dealers, which are closer to the high-type customer buyers, spend more time on the sell side and contribute most to selling the bond to (high-type) customers and buying from lower-type dealer-owners. Therefore,

[14]Interpreting by intermediation chains, the intermediate-type dealers also contribute most to constructing chains with only one dealer (themselves) to connect customer sellers and buyers.

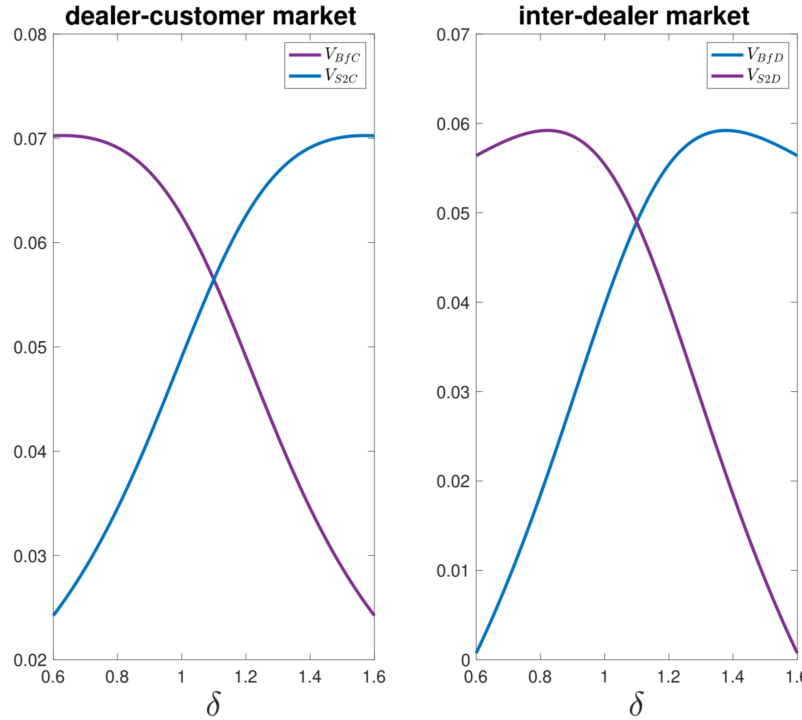

Figure 2: Model implied levels of different transaction types
($s = \pi_h = 0.5$, $y_\ell = 0.5$, $y_h = 1.7$, $\delta_\ell = 0.6$, $\delta_h = 1.6$, $\alpha = \rho = m = \theta = 0.5$, $c = r = 0.05$)

they are net sellers in the dealer-customer market and net buyers in the interdealer market.

3 Identification

Testing the model's predictions creates two key challenges: the first is to identify dealers' private valuations, the second is to measure dealers' search intensities. In this section, by using bond transaction-level data with dealer identities, we construct a measure of dealers' private valuation based on the Nash bargaining process and separately identify dealers' buying- and selling intensities using a group of transaction-related moments.

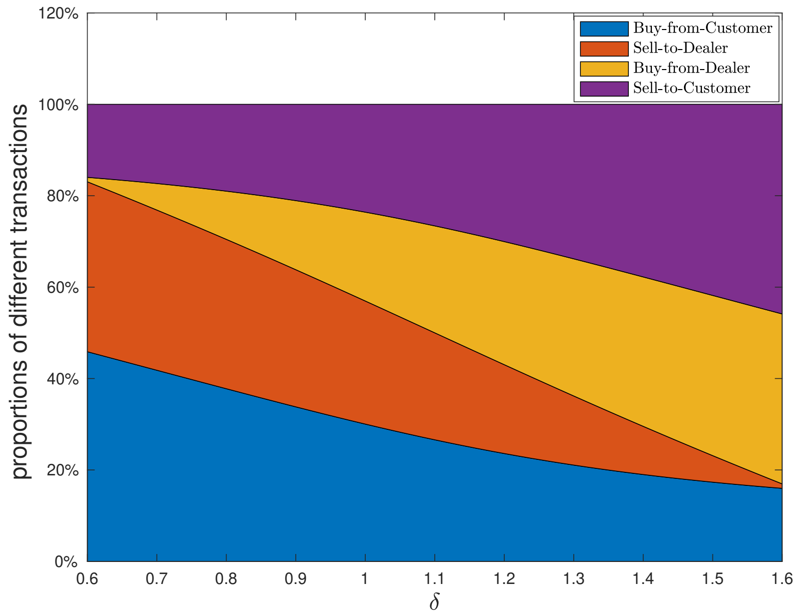

Figure 3: Model implied proportions of different transaction types

($s = \pi_h = 0.5$, $y_\ell = 0.5$, $y_h = 1.7$, $\delta_\ell = 0.6$, $\delta_h = 1.6$, $\alpha = \rho = m = \theta = 0.5$, $c = r = 0.05$)

3.1 Data description

We use the Academic Corporate Bond TRACE Data set provided by the Financial Industry Regulatory Authority (FINRA). This data set contains dealers' reports to the Trade Reporting and Compliance Engine (TRACE) which disclose information on all transactions in corporate bonds. One advantage of the data is we can observe identities of the dealers in all transactions. This allows us to track how the bonds are transacted between the dealers, so that we can characterize how actively each dealer trades with the other dealers and/or the outside bond investors.[15]

We filtered the data following the procedure in Dick-Nielsen (2014), and we recover

[15]In the analysis, we define all registered members of FINRA as dealers and all non-registered outside trading counterparties as customers. The main registered firm members of FINRA include broker-dealer firms, funding portals, and capital acquisition brokers, etc, which are all dealer-like firms. The ID numbers assigned by FINRA to registered members are all virtual IDs. In the data, non-registered trading counterparties are assigned with the ID of "C" by FINRA.

the trading counterparties in locked-in and give-up trades[16].We merge the cleaned data with the Mergent Fixed Income Securities Database (FISD) and Wharton Research Data Services (WRDS) Bonds Return Database to obtain bond fundamental characteristics and credit ratings. We construct a monthly panel containing both dealer-wise and bond-wise variables[17].

Following the academic literature using the same data set, we further filtered the data by excluding some "unusual bonds" and some specific types of transactions: [1] We exclude bonds with optional characteristics, such as variable coupon, convertiable, exchangable, and puttable, etc, and we also exclude asset-backed securities and private placed instruments; [2] We exclude the "on-the-run" transactions which happened within two months since bonds' offering dates, to only consider secondary market transactions; [3] To be consistent with the model assumption that dealers take inventories of bond positions, we only consider the "normal" principal trades by excluding agency-like and riskless-principal transactions;[18] [4]

[16]By the user guide of FINRA, a "Give Up" trade report is reported by one FINRA member on behalf of another FINRA member who is the real one to buy or sell the bonds and thus has a reporting responsibility. For such reports, we call the FINRA members, who asked other members to submit reports for them, the true trading counterparties; Locked-in report is a trade report representing both sides of a transaction. FINRA members such as Alternative Trading Systems (ATSs), Electronic Communications Networks (ECNs), and clearing firms have the ability to match buy and sell orders, and therefore to report on behalf of multiple parties using a single trade report submitted to FINRA and indicate that the trade is locked-in. Similarly, we call the FINRA members who submit the buy or sell orders, instead of those clearing platforms, as the true trading counterparties. In the error filters, for these two types of trades, we use the IDs of the true trading counterparties as dealers' IDs and we adjust the reported prices accordingly to account for the agency fees charged by reporting firms and clearing platforms (ATSs, ECNs, and clearing firms).

[17]The raw data is high-frequency data that records the time of each transaction in seconds. In empirical literature using TRACE data to analyze U.S. corporate bond market liquidity, it is common practice to process the data to monthly frequency as corporate bonds are relatively illiquid compared with stock markets, see Bao, Pan, and Wang (2011), Crotty (2013), Friewald and Nagler (2016), and Friewald and Nagler (2018), etc. Specifically, An (2019) documents that dealers' average inventory duration in the U.S. corporate bond market is around three weeks by using the same data, which implies that the average frequency dealers adjust their inventories is around one month.

[18]Dealers conduct agency-like transactions by behaving as "match-makers" to pre-arrange transactions between buyers and sellers, and do not hold bonds in their inventories. Each pair of agency-like transactions have the same price and volume, and happen at exactly the same execution time. In the data set, agency-like transactions can be identified by the fields "Buyer/Seller Capacity". Riskless-principal transactions are also pre-arranged by dealers and have the same characteristics as agency-like ones (same price, volume and execution time, etc). The only difference is, in risk-less principal transactions, dealers temporarily take bond positions in their inventories but without taking any inventory risk. In the data set, we identify riskless-principal transactions through matching buy and sell transactions with the fields of "Buyer/Seller Capacity" as "Principal", but conducted by the same dealer and with the same volume, price and execution time.

Finally, to faciliate measuring each dealer's search intensity for each single bond, we further drop the inactively traded bonds, defined as those traded in fewer than 25 months throught the whole sample period.

The final sample ranges from Jan 2005 to Sep 2015, and contains 10760 bonds traded by 3050 dealers. The total outstanding amount of all bonds in our sample is $5.37 trillion. The average bond rating is BBB by the S&P rating categories. Among these bonds, around 84% are investment grade and the remaining ones are high-yield or non-rated.[19] The Panel A in Table 1 reports additional bond fundamentals.

The summary statistics in the Panel B of Table 1 suggests that we can possibly ignore the different values of transaction size since the standard deviation of trading volume is much lower than its average level. Then we can assume all transactions have the same size as the average level, and use the number of realized transactions to calculate the transaction-related moments to estimate the model.

3.2 Identifying dealer's private valuation

In the model with a continuum of dealers, for a dealer with type $\delta \in [\delta_\ell, \delta_h]$, her transaction price with another dealer with type $\delta' \in [\delta_\ell, \delta_h]$ is:

$$P(\delta, \delta') = \frac{\triangle V(\delta) + \triangle V(\delta')}{2} \tag{10}$$

When the dealer with type δ is on the sell side of the market, positive trading surplus requires $\triangle V(\delta') > \triangle V(\delta)$. Since the dealer can meet a continuum of potential buyers, her lowest selling price is exactly equal to $\triangle V(\delta)$. Similarly, when she is on the buy side, we have $\triangle V(\delta') < \triangle V(\delta)$ and her highest buying price is also equal to $\triangle V(\delta)$. Based on monotonicity of $\triangle V(\delta)$, in data, we construct the following consistent estimator[20] of each

[19] By the S&P rating categories, investment grade are S&P BBB or higher; and high-yield(junk) are below or equal to S&P BBB-.

[20] In finite samples, on the buy side of each dealer, the maximum purchasing price is a downward biased estimate for the dealer's marginal valuation; on the sell side, the minimum selling price is an upward biased estimate for the dealer's marginal valuation. Taking the average of the sample maximum purchasing price and the sample minimum selling price will make the bias cancel out. In small samples with dealers' unbalanced buy and sell trades, the levels of the upward bias and the downward bias may not be equal. Then to make the bias cancel out completely, the weights assigned on the two extreme prices can be adjusted according to the realized number of buy and sell trades.

Table 1: Descriptive Statistics on the Final Sample of TRACE Data (Jan 2005 - Sep 2015)

Panel A: bond fundamental characteristics (10760 bonds)

	Mean	Std. dev.	Q5	Q50	Q95
Offering amount ($million)	458.97	577.99	5.74	300.00	1500.00
Coupon(%)	5.72	1.88	2.50	5.65	9.00
Maturity (years)	11.29	7.61	3.28	9.99	30.03
Amount outstanding($million)	499.35	615.95	6.88	350.00	1750.00
Credit rating	8.53 (BBB)	3.94	3.00 (AA)	8.00 (BBB+)	16.00 (B-)
Age (years)	3.70	2.55	0.48	3.17	8.72
Month turnover (%)	6.92	11.42	0.39	3.57	23.76

Note: [1] For variables "Offering amount ($million)," "Coupon(%)," and "Maturity (years)," we calculate summary statistics based on bond-wise observations; for variables "Amount outstanding($million)," "Credit rating," "Age (years)," and "Month turnover (%)," we calculate summary statistics based on bond-month observations as these variables change over time; [2] Month turnover is calculated using bonds' monthly total trading volumes (par amounts) and dividing by bonds' average amount outstanding for that month.

Panel B: dealer trading activity (3050 dealers)

	All	Sale to customer	Buy from customer	Interdealer
Num of trades (million)	57.62	20.88	15.43	21.31
Total par value($trillion)	27.80	10.57	10.52	6.70
Average par value ($million)	0.48	0.51	0.68	0.31
Average vol (thousand)	482.41	506.25	681.86	314.59
Std. vol (thousand, all bonds)	4.47	5.47	4.46	3.22
Std. vol (thousand, within bond)	1.58	1.62	1.89	0.87

Note: [1] Total par value ($ trillion) is calculated by summing up the par values of all transactions. Average par ($million) is calculated through dividing "Total par value ($trillion)" by "Num trades." [2] Trading volume ("trade vol") is in unit of share of bonds. "Std. vol (thousand, all bonds)" is the standard deviation of all trading volumes (unit: share) by pooling all dealers transactions for all bonds in corresponding markets (customer-dealer or interdealer market). "Std. vol (thousand, within bonds)" is the average standard deviation of trading volumes within each bond. "Std. vol (thousand, within bonds)" measures whether volume per trade has a large dispersion among the cross section of dealers within each bond.

dealer's private valuation type:

$$\hat{\delta}^j_{i,t} = \frac{max\{Buy^j_{i,k}\}_{k=1}^{n^{j,B}_{i,t}} + min\{Sell^j_{i,k}\}_{k=1}^{n^{j,S}_{i,t}}}{2} \tag{11}$$

where $\{Buy^j_{i,k}\}_{k=1}^{n^{j,B}_{i,t}}$ ($\{Sell^j_{i,k}\}_{k=1}^{n^{j,S}_{i,t}}$) is the collection of all buying (selling) prices by dealer i for bond j in month t, and $n^{j,B}_{i,t}$ ($n^{j,S}_{i,t}$) is the size of the corresponding collection. [21]

3.3 Identifying dealer's search intensity

We identify dealers' idiosyncratic search intensities separately on the buy- and sell-side of the market using the following transaction-related moments,[22] where variables with a hat are obtained directly from the data:

1. expected number of selling transactions for each dealer of type $\delta \in [\delta_\ell, \delta_h]$:

$$\widehat{Trade}_S(\delta) = \phi_1(\delta)\lambda_1^*(\delta)\left[\underbrace{\left(\frac{1}{1+m} + \frac{\rho}{m\Lambda}\right)\mu_{h0}}_{\text{trading with customers}} + \underbrace{\frac{2m}{1+m}\int_\delta^{\delta_h}\frac{\lambda_0^*(\delta')}{\Lambda}\phi_0(\delta')d\delta'}_{\text{trading with higher-type dealer-nonowners}}\right] \tag{12}$$

2. expected number of buying transactions for each dealer of type $\delta \in [\delta_\ell, \delta_h]$:

$$\widehat{Trade}_B(\delta) = \phi_0(\delta)\lambda_0^*(\delta)\left[\underbrace{\left(\frac{1}{1+m} + \frac{\rho}{m\Lambda}\right)\mu_{\ell 1}}_{\text{trading with customers}} + \underbrace{\frac{2m}{1+m}\int_{\delta_\ell}^{\delta}\frac{\lambda_1^*(\delta')}{\Lambda}\phi_1(\delta')d\delta'}_{\text{trading with lower-type dealer-owners}}\right] \tag{13}$$

3. for each selling transaction made by a dealer of type $\delta \in [\delta_\ell, \delta_h]$, the probability that

[21] In quantitative analysis, we define each market by one bond j and one quarter q. Each dealer i's private valuation for bond j in quarter q is calculated as the weighted average of all monthly private valuations $\hat{\delta}^j_{i,t}$ in quarter q weighted by dealer i's monthly total trading volume in bond j.

[22] We calculate the moments at the bond and month/quarter level.

the dealer δ's trading counterparty is another dealer rather than a customer:

$$\widehat{Pr}\left[SellToDealers|Sell\right](\delta) = \frac{\frac{2m}{1+m}\int_{\delta}^{\delta_h} \frac{\lambda_0^*(\delta')}{\Lambda}\phi_0(\delta')d\delta'}{\left(\frac{1}{1+m} + \frac{\rho}{m\Lambda}\right)\mu_{h0} + \frac{2m}{1+m}\int_{\delta}^{\delta_h} \frac{\lambda_0^*(\delta')}{\Lambda}\phi_0(\delta')d\delta'} \tag{14}$$

4. for each buying transaction made by a dealer of type $\delta \in [\delta_\ell, \delta_h]$, the probability that the dealer δ's trading counterparty is another dealer rather than a customer:

$$\widehat{Pr}\left[BuyFromDealers|Buy\right](\delta) = \frac{\frac{2m}{1+m}\int_{\delta_\ell}^{\delta} \frac{\lambda_1^*(\delta')}{\Lambda}\phi_1(\delta')d\delta'}{\left(\frac{1}{1+m} + \frac{\rho}{m\Lambda}\right)\mu_{\ell 1} + \frac{2m}{1+m}\int_{\delta_\ell}^{\delta} \frac{\lambda_1^*(\delta')}{\Lambda}\phi_1(\delta')d\delta'} \tag{15}$$

where $\widehat{Trade}$ is the number of transactions and $\widehat{Pr}$ is the probability of having dealers other than customers as trading counterparties given that a trade happens.

We show how to identify the total-selling-intensity function $\phi_1(\delta)\lambda_1^*(\delta)$ and total-buying-intensity function $\phi_0(\delta)\lambda_0^*(\delta)$ both up to a constant. For notational simplicity, we define the following measures based on data moments $\widehat{Trade}$ and $\widehat{Pr}$ for each dealer with type $\delta \in [\delta_\ell, \delta_h]$:

$$\widehat{f}_1(\delta) = \left(1 - \widehat{Pr}\left[SellToDealers|Sell\right](\delta)\right) \times \widehat{Trade}_S(\delta) \tag{16}$$

$$\widehat{f}_2(\delta) = \left(1 - \widehat{Pr}\left[BuyFromDealers|Buy\right](\delta)\right) \times \widehat{Trade}_B(\delta) \tag{17}$$

$$\widehat{f}_3(\delta) = \widehat{Pr}\left[SellToDealers|Sell\right](\delta) \times \widehat{Trade}_S(\delta) \tag{18}$$

$$\widehat{f}_4(\delta) = \widehat{Pr}\left[BuyFromDealers|Buy\right](\delta) \times \widehat{Trade}_B(\delta) \tag{19}$$

where $\widehat{f}_1(\delta)$ is the number of sell-to-customer transactions for a dealer with type δ and $\widehat{f}_2(\delta)$ is the corresponding number of buy-from-customer transactions.

The following Proposition 2 gives the identification results of the selling- and buying intensities, up to a same constant number $\frac{2m}{1+m}$ which is only related to the measure of all dealers m. Proof of Proposition 2 is in Appendix A.2.

Proposition 2: *Assuming that the selling intensity of the minimum-type dealer-owner equals the buying intensity of the maximum-type dealer-nonowner:*

$$\phi_1(\delta_\ell)\lambda_1^*(\delta_\ell) = \phi_0(\delta_h)\lambda_0^*(\delta_h) \tag{20}$$

the following functions of private valuation type and the ratio of aggregate buying intensity versus aggregate selling intensity $\frac{\Lambda_0}{\Lambda_1}$ *are identified by:*

$$\frac{2m}{1+m}\phi_1(\delta)\lambda_1^*(\delta) = \frac{\widehat{f}_3(\delta_\ell) + \widehat{f}_4(\delta_h)}{\widehat{f}_1(\delta_\ell)} \times \widehat{f}_1(\delta) \tag{21}$$

$$\frac{2m}{1+m}\phi_0(\delta)\lambda_0^*(\delta) = \frac{\widehat{f}_3(\delta_\ell) + \widehat{f}_4(\delta_h)}{\widehat{f}_2(\delta_h)} \times \widehat{f}_2(\delta) \tag{22}$$

$$\frac{\Lambda_0}{\Lambda_1} = \frac{\widehat{f}_3(\delta_\ell)}{\widehat{f}_4(\delta_h)} \tag{23}$$

where $\widehat{f}_1(\delta) - \widehat{f}_4(\delta)$ *are defined by* (16)-(19).

The key to the identification results is: on both the buy- and sell sides of the market, dealer's number of transactions with customers can be decomposed into two parts: $[P1]$ "the search intensity (on buy/side)" multiplied by $[P2]$ "the conditional probability of trading with a customer other than a dealer given that a trade happens".

The identification of dealers' total buying- and selling intensities up to a *same* constant mainly include the following three steps: [1] we identify dealers' search intensities on each side of the market as their number of completed transactions with customers divided by the conditional probability of trading with customers other than dealers given that a trade happens. This step is based on the random search assumption. On each side, if we line up and move across dealers with idiosyncratic private valuation types, the $[P2]$ component above is a constant regardless of dealers' choices of search intensities on that side. Therefore, $\widehat{f}_1(\delta)$ ($\widehat{f}_2(\delta)$) is equal to $\phi_1(\delta)\lambda_1^*(\delta)$ ($\phi_0(\delta)\lambda_0^*(\delta)$) multiplied by the constant part $[P2]$ for each $\delta \in [\delta_\ell, \delta_h]$. However, the value of $[P2]$ is different between the sell side and the buy side. [2] To adjust for this difference to identify $\phi_1(\delta)\lambda_1^*(\delta)$ and $\phi_0(\delta)\lambda_0^*(\delta)$ up to a same constant[23], we follow the equilibrium result that the total volume of bonds that all dealers buy from customers is equal to the total volume that all dealers sell to customers. Based on this

[23]The reason we want to identify the buy-side and sell-side search intensities up to a same constant is, we want to look at the trend of dealer's total search intensity across different private valuation types. The trend of total search intensity can be obtained by summing up search intensities over the buy and sell sides for each dealer, which is only doable when buy-side and sell-side search intensities are identified up to the same constant.

result, the identification of the relative level of $[P2]$ between the buy and sell sides can be further transfered to the relative level of the aggregate of all dealers' search intensities between the buy and sell sides. [3] Finally, the latter relative level can be identified by using the interdealer transactions of two specific dealers: dealers with the minimum and maximum private valuation types, δ_ℓ and δ_h. The reason is: there always exists a positive trading surplus between the δ_ℓ-type dealer-owner (δ_h-type dealer-nonowner) and all other dealer-nonowners (owners), so that the total volume of interdealer transactions of the δ_ℓ-type dealer-owner (δ_h-type dealer-nonowner) is proportional to the aggregate of search intensiteis of all the (other) dealers on the buy (sell) side.

3.4 Identifying other parameters

Identifying $\{s, m\}$ and the markup of the dealer sector Before we introduce the second system of equations to identify parameters $\{\pi_h, \pi_\ell, \alpha, \rho, c, \theta\}$, we discuss the identification of two parameters: bond supply per capita s and the physical measure of the dealer sector m. And we also identify another moment, the average markup of the dealer sector, which will be used later to identify the remaining parameters.

The identification works as follows: [1] we identify the bond supply per capita s through dividing the total outstanding amount of each bond by its average trade size, then further dividing it by the number of customers N. For N, we use the value in Hugonnier, Lester, and Weill (2018) assuming half of the household population from the U.S. Census is directly or indirectly investing in financial market in general[24], but in that paper, they focus on municipal bond markets. To adjust for this, we further calculate the proportion of corporate bonds in households' portfolios of liquidity assets relative to that of municipal bonds throughout 2002 to 2015, using the factbook provided by the Securities Industry and Financial Markets Association (SIFMA). The adjusted number of customers per bond is $N \approx 35,896$. [2] To help identify the physical measure of the dealer sector m, we firstly identify the (average) fraction of bond positions that are held by the dealer sector, i.e., $\frac{m_1}{s}$, using the data on security broker-dealers' holding positions of corporate bonds from Flow of Funds. The average fraction throughout the sample period 2005-2015 is around 2.82%. Details of calculation are in Appendix B.2. [3] By the equilibrium condition $m = m_1 + m_0 = \int_{\delta_\ell}^{\delta_h} \phi_1(\delta) d\delta + \int_{\delta_\ell}^{\delta_h} \phi_0(\delta) d\delta$,

[24] This assumption in Hugonnier, Lester, and Weill (2018) is also motivated by data from the Survey of Consumer Finance (SCF) and Bricker (2017).

we can further identify m through identifying the ratio of $\frac{m_1}{m_0} = \frac{\int_{\delta_\ell}^{\delta_h} \phi_1(\delta)d\delta}{\int_{\delta_\ell}^{\delta_h} \phi_0(\delta)d\delta}$, with m_1 identified in the second step. We identify this ratio based on the intepretation of $\phi_1(\delta)$ ($\phi_0(\delta)$) as the proportion of unit period that dealer with private valuation δ stays on the sell (buy) side. Using the transaction times in the data which are round to seconds, we identify the total length of time that each dealer spends on the buy side, which is equal to $\phi_0(\delta)$ multiplied by a constant, and the total length of time that she spends on the sell side, which is equal to $\phi_1(\delta)$ multiplied by the same constant. Finally, we identify the ratio $\frac{m_1}{m_0}$ by the ratio of the sum of all dealers' time spent on the sell side divided by the sum of all dealers' time spent on the buy side. Details of this identification are in Appendix B.1.

The average markup of the dealer sector, $Markup_D$, is defined as follows:

$$\begin{aligned} Markup_D &= \frac{E(P_{DC})}{E(P_{CD})} - 1 \\ &= \frac{\int_{\delta_\ell}^{\delta_h} \frac{\lambda_1^*(\delta)\phi_1(\delta)}{\Lambda_1}[(1-\theta)\triangle V(\delta) + \theta\triangle W(y_h)]d\delta}{\int_{\delta_\ell}^{\delta_h} \frac{\lambda_0^*(\delta)\phi_0(\delta)}{\Lambda_0}[(1-\theta)\triangle V(\delta) + \theta\triangle W(y_\ell)]d\delta} - 1 \end{aligned} \tag{24}$$

where $E(P_{DC})$ is the average price of dealer-sell-to-customer transactions and $E(P_{CD})$ is the average price of dealer-buy-from-customer transactions. This condition will be included in the second system of equations to identify dealers' average bargaining power to customers θ.

Identifying $\{\pi_h, \pi_\ell, \alpha, \rho, c, \theta\}$ With identified search intensity functions $\{\lambda_1^*(\delta)\phi_1(\delta), \lambda_0^*(\delta)\phi_0(\delta)\}$, reservation values[25] $\{\triangle V(\delta), \triangle W(y_\ell), \triangle W(y_h)\}$, number of transactions in different directions $\{\widehat{f_1}(\delta), \widehat{f_2}(\delta), \widehat{f_3}(\delta), \widehat{f_4}(\delta)\}$, model equilibrium moments $\{m_1, m_0, Markup_D\}$, and parameters $\{s, m\}$, we use the following system of equations to identify the remaining model parameters $\{\pi_h, \pi_\ell, \alpha, \rho, c, \theta\}$:

$$\alpha\mu_{\ell 0}\pi_h = \alpha\mu_{h0}\pi_\ell + \mu_{h0}\left(\frac{1}{1+m} + \frac{\rho}{m\Lambda}\right)\int_{\delta_\ell}^{\delta_h} \lambda_1^*(\delta)\phi_1(\delta)d\delta \tag{25}$$

$$\pi_h = \mu_{h0} + \mu_{h1} \tag{26}$$

[25]In Section 3.2, the mid-point of each dealer's maximum buying and minimum selling prices is a direct measure of the dealer's reservation value and an indirect measure of the dealer's private valuation, because in equilibrium solutions dealers' reservation valuations are monotonic with their private valuation types.

$$\pi_\ell = \mu_{\ell 0} + \mu_{\ell 1} \tag{27}$$

$$\pi_h + \pi_\ell = 1 \tag{28}$$

$$s = \mu_{h1} + \mu_{\ell 1} + m_1 \tag{29}$$

$$\left(1 + \frac{(1+m)\rho}{m\Lambda}\right)\frac{\mu_{h0}}{m} = \frac{2\widehat{f}_1(\delta_\ell)}{\widehat{f}_3(\delta_\ell) + \widehat{f}_4(\delta_h)} \tag{30}$$

$$\left(1 + \frac{(1+m)\rho}{m\Lambda}\right)\frac{\mu_{\ell 1}}{m} = \frac{2\widehat{f}_2(\delta_h)}{\widehat{f}_3(\delta_\ell) + \widehat{f}_4(\delta_h)} \tag{31}$$

$$Markup_D = \frac{\int_{\delta_\ell}^{\delta_h} \frac{\lambda_1^*(\delta)\phi_1(\delta)}{\Lambda_1}[(1-\theta)\triangle V(\delta) + \theta\triangle W(y_h)]d\delta}{\int_{\delta_\ell}^{\delta_h} \frac{\lambda_0^*(\delta)\phi_0(\delta)}{\Lambda_0}[(1-\theta)\triangle V(\delta) + \theta\triangle W(y_\ell)]d\delta} - 1 \tag{32}$$

$$\begin{aligned} 2c\Lambda_1 = &\left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\mu_{h0}\theta(\triangle W(y_h)m_1 - \int_{\delta_\ell}^{\delta_h} \triangle V(\delta)\phi_1(\delta)d\delta) \\ &+ \frac{m}{1+m}\int_{\delta_\ell}^{\delta_h} \phi_1(\delta)\int_{\delta}^{\delta_h} \frac{\lambda_0^*(\delta')\phi_0(\delta')}{\Lambda}(\triangle V(\delta') - \triangle V(\delta))d\delta' d\delta \end{aligned} \tag{33}$$

$$\begin{aligned} 2c\Lambda_0 = &\left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\mu_{\ell 1}\theta(\int_{\delta_\ell}^{\delta_h} \triangle V(\delta)\phi_0(\delta)d\delta - \triangle W(y_\ell)m_0) \\ &+ \frac{m}{1+m}\int_{\delta_\ell}^{\delta_h} \phi_0(\delta)\int_{\delta_\ell}^{\delta} \frac{\lambda_1^*(\delta')\phi_1(\delta')}{\Lambda}(\triangle V(\delta) - \triangle V(\delta'))d\delta' d\delta \end{aligned} \tag{34}$$

where (25)-(29) are equilibrium conditions, (30)-(31) are obtained by Proposition 2 and the first system of equations for identifying search intensities, and (33)-(34) are obtained by the first order conditions on dealers' choice of search intensities (2)-(3).

The identification works generally as follows: in (30)-(31), given any value of ρ, we obtain the values of μ_{h0} and $\mu_{\ell 1}$ as a function of ρ. These two values can be plugged into (26)-(29) to obtain the values of $\{\pi_h, \pi_\ell, \mu_{h1}, \mu_{\ell 0}\}$. Then by (25), we further identify the value of α also as a function of ρ. The bargaining power θ can be identified by (32). Finally, the remaining parameters ρ and c can be identified through plugging all formerly obtained values (as functions of ρ) into (33)-(34).

4 Quantitative analysis

4.1 Estimation

The estimation contains two main steps. In the first step, we construct B-spline nonparametric estimators[26] of unknown functions $\widehat{f}_1(\delta)$-$\widehat{f}_4(\delta)$, which are used to identify dealers' buying- and selling- search intensities. Then we plug in the fitted functions back to the group of moment conditions (12)-(13) and follow the generalized method of moments (GMM) method to estimate the two following constant terms: $\left(1+\frac{(1+m)\rho}{m\Lambda}\right)\frac{\mu_{h0}}{m}$ and $\left(1+\frac{(1+m)\rho}{m\Lambda}\right)\frac{\mu_{\ell 1}}{m}$. These two constant terms will be included in constaints on parameters in next step. In the second step, we follow the two-step simulated method of moments (SMM)[27] approach to estimate the unknown parameters $\psi = \begin{bmatrix}\pi_h & \alpha & \rho & c & \theta\end{bmatrix}^T$. The moment vector includes seven moments, namely the average number of sell-to-customer transactions $E[\widehat{f}_1(\delta)]$, the average number of buy-from-customer transactions $E[\widehat{f}_2(\delta)]$, the average number of sell-to-dealer transactions $E[\widehat{f}_3(\delta)]$, the average number of buy-from-dealer transactions $E[\widehat{f}_4(\delta)]$, the average markup of the whole dealer sector $Markup_D$, the aggregate of all dealers' search intensities on the sell side Λ_1, and the aggregate of all dealers' search intensities on the buy side Λ_0. Our estimation is also subject to constraints on parameters which include (25)-(31) above.

By similar notations, the two-step estimator takes the form

$$\hat{\psi} = \underset{\psi\in\Psi}{argmin}\frac{(m(\psi)-m_s)'}{m_s}\Omega(\tilde{\psi})\frac{(m(\psi)-m_s)}{m_s}$$

where $m(\psi) = \left[\{m_i(\psi)\}_{i=1}^{7}\right]^T$ is the moment vector that computed from the stationary equi-

[26] Expressions of estimators are in Appendix B.3.

[27] Seminal papers developing simulated method of moments (SMM) include McFadden (1989), Duffie and Singleton (1990), and etc. Papers using SMM for estimation of search model includes Gavazza (2016).

librium solutions which are evaluated at the parameter vector ψ; $\quad m_s = \left[\{m_{i,s}\}_{i=1}^{7}\right]^T$ is the vector of sample moments; Ψ is the parameter space. We firstly use identity matrix as the weight matrix to calculate the preliminary consistent estimate $\tilde{\psi}$ of ψ, then we use the consistent estimate of the inverse of asymptotic variance-covariance matrix $\Omega(\tilde{\psi})$ as the weight matrix in the second step. We minimize the percentage deviation of model-implied moments from sample moments.

We construct Ψ as follows: [1] as for the candidate range of ρ, we target on the intensity with which a *single* customer meets dealer-buyers, $\left[\frac{1}{1+m} + \frac{\rho}{m\Lambda}\right] \frac{\int_{\delta_\ell}^{\delta_h} \phi_0(\delta)\lambda_0^*(\delta)d\delta}{N}$, which is similar as in Hugonnier, Lester, and Weill (2018). With identified aggregate of dealer-nonowners' search intensity $\int_{\delta_\ell}^{\delta_h} \phi_0(\delta)\lambda_0^*(\delta)d\delta$, aggregate of dealer-owners' search intensity $\int_{\delta_\ell}^{\delta_h} \phi_1(\delta)\lambda_1^*(\delta)d\delta$, and the (normalized) physical measure of all dealers m, the target intensity can determine the candidate range of ρ. The target intensity is derived from the average trading delay for customers to contact dealers through voice-based OTC trading in corporate bonds, which is calibrated by a combination of results of Pagnotta and Philippon (2018), Feldhütter (2012), and He and Milbradt (2014).[28] The parametric subspace for ρ is $P = [687, 16478]$; [2] we allow for a large enough range of dealers' bargaining power $\Theta = [0.01, 1]$; [3] we set the range of search cost coefficient as $C = [0.0006, 0.002]$, which is calculated by equalizing the total search cost of the whole dealer sector in each market, $c \times \Lambda^2$, with the gap between $E(P_{DC})$ and $E(P_{CD})$ in that market.[29] For example, the upper bound 0.002 is associated with an aggregate search intensity $\Lambda = 42.5$ in a market, which implies that within one quarter, the total search cost that all dealers spend is approximately 5% (500 bps) of the bond's par value. [4] the subspaces for the remaining parameters $(\pi_h, \alpha) \in \Pi_h \times A$ is determined by constraints (25)-(31). Then the parametric space $\Psi = P \times \Theta \times C \times \Pi_h \times A$.

[28]Similar as Hugonnier, Lester, and Weill (2018), we calibrate the average trading delay as five business days, so in each quarter, a single customer on average completes $\frac{1}{5/62.5} = 12.5$ trades with dealers. We obtain a candidate ρ for each market by solving $\left[\frac{1}{1+m} + \frac{\rho}{m\Lambda}\right] \frac{\int_{\delta_\ell}^{\delta_h} \phi_0(\delta)\lambda_0^*(\delta)d\delta}{N} = 12.5$, the whole set of values is $[687, 16478]$, which will be used as the parametric space P. The reason we have the calibrated total number of customers N on the denominator is, the intensity is for a *single* customer.

[29]In our model, the cost coefficient c and transaction prices are both expressed in percentage of bond's par value. By equalizing $c \times \Lambda^2$ with $E(P_{DC}) - E(P_{CD})$, we set an upper bound of c for each market, which makes the total search cost approximately comparable to the total gains from intermediation.

Estimates We define each market by one bond j and one quarter q, and denote it as $Market(j, q)$. The reason we define each market in this way is: dealers' private valuations are more likely to be stable within each quarter. This is consistent with the model setup. We further restrict that there are at least 25 cross sectional unites in each market, and each unit is a trading history of one dealer i in $Market(j, q)$ who trades on both sides of the market. This restriction further shrinks our sample [30] used for estimation to include 6301 bonds and 47634 markets. For each dealer i in $Market(j, q)$, we construct the dealer's volume-weighted private valuation for bond j using her monthly private valuations $\hat{\delta}^j_{i,t}$ within quarter q.

For each $Market(j, q)$, we estimate the dealers' search intensity functions and model parameters, based on the systems of equations in the previous section. Figure 4 shows the trends of quarterly volume-weighted average search intensities, separately for investment grade and speculative grade bonds. Search intensities are generally more volatile over time for lower-rated bonds, and manifest a decreasing trend after the great financial crisis for all the bonds. Moreover, the selling intensities are on average higher than the buying intensities, which is consistent with the estimation result that the measure of high-type customers π_h is much lower than that of low-type customers π_ℓ. Given that the whole dealer sector maintains balanced inventory positions over time, the much smaller group of high-type customers requires the whole dealer sector to search more actively on the sell side. Note that the levels of search intensities in Figure 4 are generally higher than the aggregate level search intensity Λ that shown in Table 3, as the latter is the integral of identified search intensities over the range of dealers' private valuations.

The estimated model parameters and corresponding model implied components (both on a quarterly basis) in Table 2 and Table 3 will be used for the welfare analysis in Section 4.3. Table 10 in Appendix B.4 compares the fitted model-implied moments with the empirical moments calculated from data.

[30] The reason we choose one quarter as the time period for each market is that for each market, we would like to have a relatively large size of cross section of observations, which allows us to obtain more accurate estimates. The median size of cross section (number of dealers) across all markets is 38 dealers for quarterly data, compared with 12 dealers for monthly data. For robustness check, we re-do all quantitative analysis for markets defined by monthly data, i.e., each market is defined as a bond j and month t, and the results are qualitatively same, except that there is quite a proportion of dealers only trading on one side (only buy or only sell) within one month, which could generate negative estimated search intensities for the direction with no transaction.

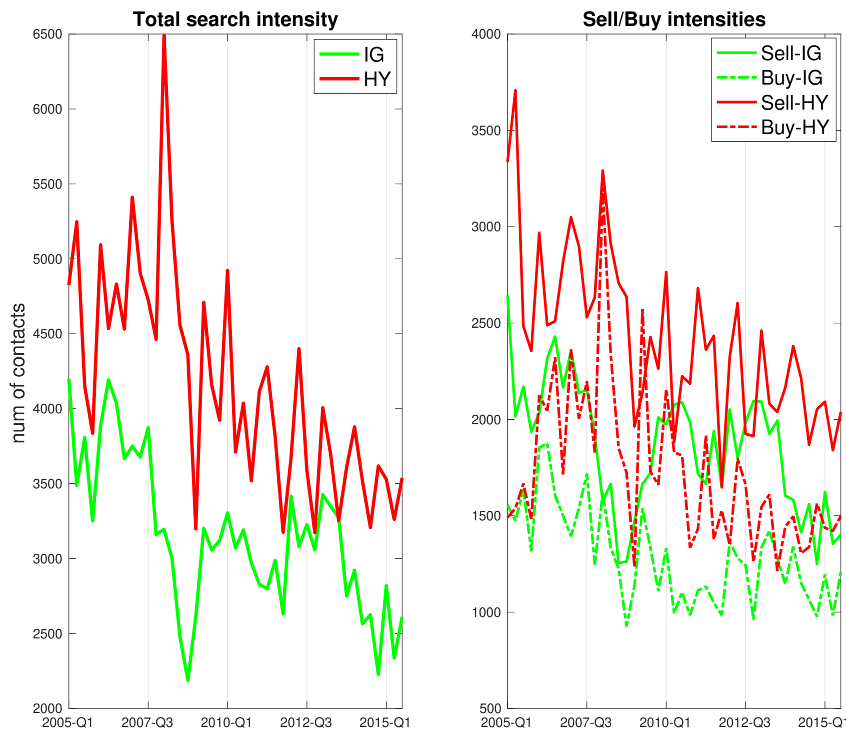

Figure 4: Average estimated search intensities across bond grades

(IG: Investment grade (S&P BBB- or above), HY: High-yield grade (below S&P BBB-), Total search intensity: weighted average of dealers' identified total search intensities, $\widehat{\phi_1(\delta)\lambda_1^*}(\delta) + \widehat{\phi_0(\delta)\lambda_0^*}(\delta)$, within IG and HY groups for each quarter, Sell/Buy intensities: weighted average of dealers' identified sell/buy search intensities, $\widehat{\phi_1(\delta)\lambda_1^*}(\delta)/\widehat{\phi_0(\delta)\lambda_0^*}(\delta)$, within IG and HY groups for each quarter.)

The estimates in Table 2 and Table 3 exhibit large variation across markets and are highly right-skewed. We have several takeaways from the estimates: [1] the estimate of the measure of high-type customer π_h has a very close distribution to that of bond supply per capita s. This indicates that the marginal investors in most frictionless markets have private valuation types close to that of the high-type customer y_h. This is shown in Figure 5 and also Table 9 in appendix. [2] the group of customers with a high private valuation is much smaller than that with a low private valuation. This further implies that to intermediate bonds between customers, the dealer sector is expected to invest in a higher selling intensity on aggregate. [3] by the estimates of μ_{h0} and $\mu_{\ell 1}$, there are very few bond positions being "mis-allocated" within the customer sector, in the sense that there are very few high-type customers not holding the bond or very few low-type customers holding the bond. However, this does not necessarily mean all bond positions are well-aligned with bond-holders' private valuations. We will show in section 4.3 that most bond misallocation happen within the dealer sector. [4] the estimate of dealer's bargaining power to customers θ is surprisingly low. This is driven by the low level of dealer-sector's markup in most markets. Across all markets in our sample, the average dealer-sector's markup is on average 46 bps, but the total potential markup using the identified customers' reservation values $\frac{\triangle W(y_h)}{\triangle W(y_\ell)} - 1$ is on average 907 bps. This implies in corporate bond markets, the broker-dealer sector has a very low bargaining power.

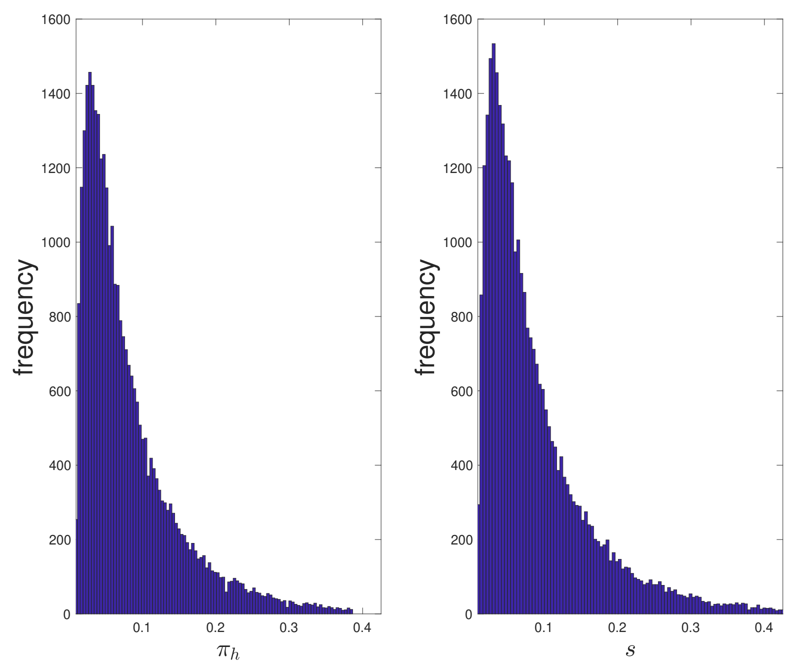

Figure 5: Summary of estimate of π_h and bond supply per capita s

Table 2: Estimated and Calibrated Parameters for 47634 markets (6301 bonds)

Parameter	Description	Mean	Median	Std. dev.
	Estimates			
ρ	customer search intensity (per quarter)	4860.8	3345.1	4277.99
α	customer intensity of switching type (per quarter)	4.25	1.18	9.21
m	measure of dealers	0.0065	0.0045	0.0062
π_h	measure of high-type customers	0.0888	0.0657	0.0698
π_ℓ	measure of low-type customers	0.9112	0.9344	0.0698
c	coefficient of search cost function $c \times \lambda^2$	0.0012	0.0012	0.0003
θ	dealers' bargaining power to customers	0.049	0.049	0.0047
	Calibration			
s	bond supply (per capita)	0.09	0.07	0.07
m_1/s	proportion of bond positions held by dealers	0.0282	N/A	N/A
m_1/m_0	measure of dealer-owners vs dealer-nonowners	0.84	0.79	0.35

Note: "Mean", "Median" and "Std.dev." are calculated across all markets, with each market defined by one bond and one quarter.

4.2 Dealers' search intensity and roles in intermediation

Distribution of search intensity among dealers We give examples of two markets to intuitively show how the identified search intensities are distributed among dealers, as in Figure 6. Market-1 has the maximum number of dealers among all markets, and Market-2 has the median number of dealers. In both the markets, the distributions of search intensities are "hump-shaped". This is consistent with the theoretical predictions of the model with endogeneous search efforts. Moreover, the distribution of search intensity deviates from that of dealers' private valuations. This implies that it is more likely that dealers choose heterogeneous search intensities, other than being endowed with homogeneous search inten-

Table 3: Model-implied endogeneous components for 47634 markets (6301 bonds)

Measures	Description	Mean	Median	Std. dev.
μ_{h0}	measure of high-type customer-nonowner	6.88e-07	2.72e-07	1.29e-06
μ_{h1}	measure of high-type customer-nonowner	0.0888	0.0657	0.0698
$\mu_{\ell 0}$	measure of low-type customer-owner	0.9112	0.9344	0.0698
$\mu_{\ell 1}$	measure of low-type customer-owner	8.92e-07	2.35e-07	2.10e-06
Λ_1	aggregate dealer-sector selling intensity	418.34	81.25	1119.47
Λ_0	aggregate dealer-sector buying intensity	287.15	44.23	834.90
Λ	aggregate dealer-sector total search intensity	705.49	180.44	1487.43
m_1	measure of all dealer-owners	0.0027	0.0019	0.0025
m_0	measure of all dealer-non-owners	0.0038	0.0025	0.0038

Note: "Mean", "Median" and "Std.dev." are calculated across all markets, with each market defined by one bond and one quarter.

sity, because if the latter case applies, we would expect that the distribution of dealers' total search intensity overlap with that of dealers' private valuation types.

Using estimation results of all the markets, we fit search intensities as a quadratic function of dealers' scaled private valuation $\hat{\delta}^j_{S,i,q}$, which is computed through dividing each quarterly private valuation $\hat{\delta}^j_{i,q}$ by the cross-dealer mean level $\hat{\bar{\delta}}^j_q$ of $Market(j,q)$ [31]. The quardratic fitting has the following specification:

$$\widehat{\overline{\lambda}}^j_{i,q} = \beta_0 + \beta_1 \times \hat{\delta}^j_{S,i,q} + \beta_2 \times (\hat{\delta}^j_{S,i,q})^2 + \Gamma_1 X^j_q + \Gamma_2 Y_{i,q} + \tau_i + \phi_j + \eta_y + \epsilon^j_{i,q} \tag{35}$$

where the vector X^j_q includes bond-related controls, such as credit rating, HHI (Herfindahl index) calculated by using market shares of all dealers to measure whether transactions

[31]The scaled private valuation is expressed in percentage of the cross-dealer mean level, thus being a measure of the distance of dealers' private valuation to the cross-dealer mean level. The reason we divide the raw private valuations by cross-dealer mean level is to control for unobserved factors that drive bonds to be traded at a discount or premium.

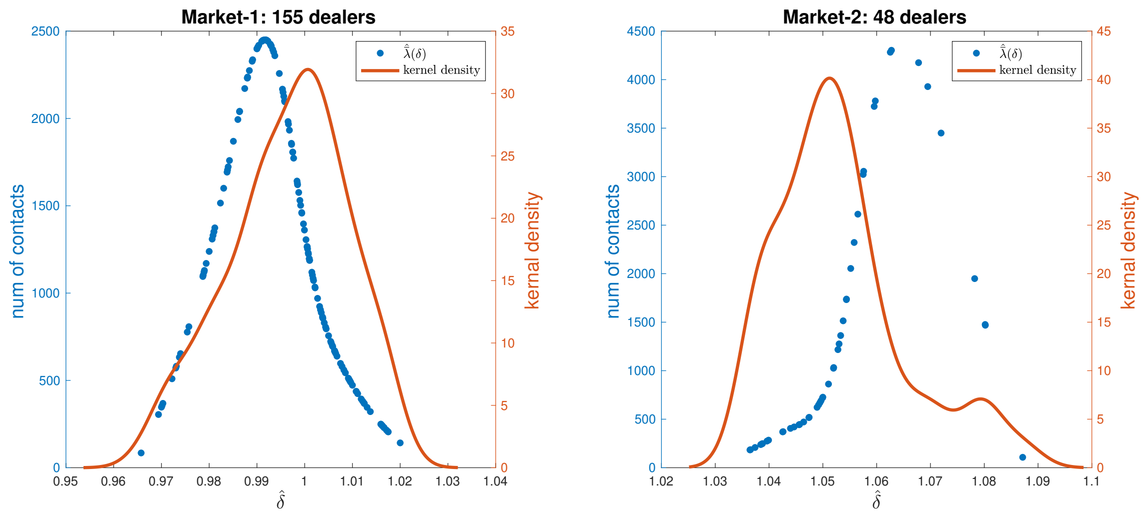

Figure 6: Examples of two markets

(Market-1: bond 013817AP6, 2010-Q3, BBB-, terms to maturity 8.6 years, 750k shares; Market-2: bond 803111AM5, 2010-Q3, BBB, terms to maturity 22.2 years, 500k shares.)

are concentrated to a specific group of dealers, previous-three-month turnover, outstanding amount, time to maturity and coupon rate; the vector $Y_{i,q}$ includes dealer-related controls, such as each dealer's quarterly eigenvector centrality[32] in the interdealer network, "HHI for bonds" calculated by using each dealer's trading shares in different bonds, and "HHI for trade types" calculated by using each dealer's trading shares in different trading directions (customer-to-dealer, dealer-to-customer or dealer-to-dealer). These two HHI indices are to measure whether a dealer specializes in a specific bond or specific direction; and fixed effects by dealer τ_i, bond ϕ_j and year η_y are also controlled. Besides the total search intensity $\widehat{\overline{\lambda}}_{i,q}^{j}$ over both sides of the market, we also include selling intensity $\widehat{\overline{\lambda}}_{i,q}^{S,j}$ and buying intensity $\widehat{\overline{\lambda}}_{i,q}^{B,j}$

[32] "Eigenvector centrality" is one measure of vertices' network centralities. By using all the interdealer transactions, we construct an interdealer network in which we regard each dealer as one "vertice" and each transaction record as a link connecting two vertices. The advantage of using eigenvector centrality is it incorporates not only direct but also indirect trading counterparties for each dealer and thus more accurately measures each dealer's importance in the network by assigning scores to them. The higher the value of eigenvector centrality, the more central and important the dealer is in the interdealer network. We calculate daily values of eigenvector centrality on a rolling basis. Specifically, for each day, we use all the previous-90-day transactions of each dealer to calculate her eigenvector centrality for the current day. Then we calculate the quarterly average by using daily values.

as dependent variables. In Table 4, we mainly report estimates of β_1 and β_2.

Table 4: Distribution of search intensity among dealers (quadratic form)

$Dep^j_{i,q}$	$\widehat{\overline{\lambda}}^{j}_{i,q}$	$\widehat{\overline{\lambda}}^{S,j}_{i,q}$	$\widehat{\overline{\lambda}}^{B,j}_{i,q}$
$\hat{\delta}^j_{S,i,q}$ (%)	1788.54***	968.84***	466.04***
	(36.92)	(35.77)	(28.12)
$(\hat{\delta}^j_{S,i,q})^2$	-8.93***	-4.54***	-2.57***
	(-36.89)	(-33.65)	(-30.97)
# of obs	1,500,047	1,499,186	1,500,090
Adj R^2	0.1547	0.1241	0.1689
Dealer×Bond×Year FE	YES	YES	YES

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered in dealer#bond#year.

Regression results of (35) verify that, within each $Market(j, q)$, total search intensity $\widehat{\overline{\lambda}}^{j}_{i,q}$ is hump-shaped over dealers' private valuations. Specifically, the composition effect in stationary equilibrium is consistently verified by the estimation results for $\widehat{\overline{\lambda}}^{S,j}_{i,q}$ and $\widehat{\overline{\lambda}}^{B,j}_{i,q}$. Figure 7 shows that the increasing total search intensity in the lower range of private valuation is driven by the faster increase in selling intensity $\widehat{\overline{\lambda}}^{S,j}_{i,q}$ than the decrease in buying intensity $\widehat{\overline{\lambda}}^{B,j}_{i,q}$; and the decreasing total search intensity in the higher range of private valuation is driven by the faster decrease in buying intensity $\widehat{\overline{\lambda}}^{B,j}_{i,q}$ than the increase in selling intensity $\widehat{\overline{\lambda}}^{S,j}_{i,q}$. The buying intensity $\widehat{\overline{\lambda}}^{B,j}_{i,q}$ (selling intensity $\widehat{\overline{\lambda}}^{S,j}_{i,q}$) is monotonically decreasing (increasing) within the sample range of dealers' private valuation, since its maximum point is on the left (right) side of the lower (upper) bound of the sample range. The full regression result is in the Internet Appendix. Additionally, for robustness check on the "hump-shaped" distribution of search intensity among dealers, we re-run the regression using monthly data and we also consider another specification with an alternative measure of the distance of each dealer's private valuation to the cross-dealer mean level. The robustness check results are also in the Internet Appendix.

Dealers' heterogeneous roles in the intermediation process We verify the model predictions on dealers' heterogeneous roles in the intermediation process by replacing the de-

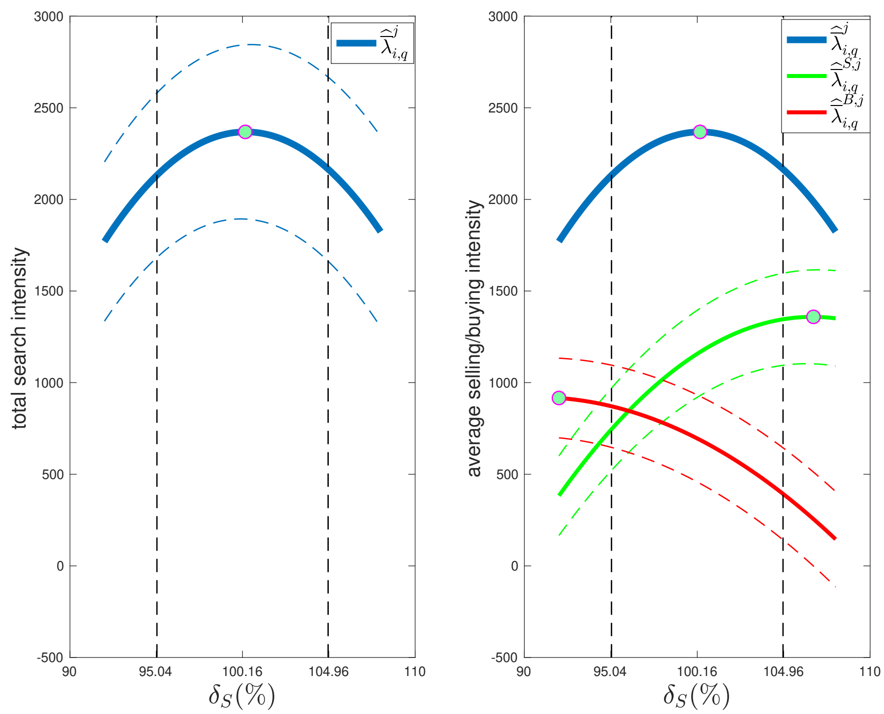

Figure 7: Distribution of search intensity among dealers (quadratic form)

pendent variables in (35) with the following empirical moments[33]: number of sell-to-customer transactions $V^j_{S2C,i,q}$, number of buy-from-customer transactions $V^j_{BfC,i,q}$, number of sell-to-dealer transactions $V^j_{S2D,i,q}$, and number of buy-from-dealer transactions $V^j_{BfD,i,q}$.

Regression results in Table 5 and Figure 8 verify that as private valuation type ranges from low to high, dealers switch from "buying from customers and selling to dealers" to "buying from dealers and selling to customers." Dealers with private valuations closer to the mean level, by composition effect, on aggregate trade more actively than other dealers in both the dealer-customer and interdealer markets. Moreover, those dealers trade at approximately equal amounts on the buy- and sell side of the market to intermediate bond positions from

[33]Here we mainly show the results for dependent variables as the *number* of transactions of different directions, which is consistent with the low standard deviation of trading volume in Panel B of Table 1, and also consistent with the measures of search intensities which are also identified using the number of transactions. In the Appendix, we show the results for dependent variables as the *volume* of transactions of different directions for the robustness check.

Table 5: Distribution of transactions of different directions

$Dep^j_{i,q}$	$V^j_{S2C,i,q}$	$V^j_{BfC,i,q}$	$V^j_{S2D,i,q}$	$V^j_{BfD,i,q}$
$\hat{\delta}^j_{S,i,q}$ (%)	2.29***	1.02***	2.08***	1.99***
	(28.56)	(21.68)	(21.76)	(28.09)
$(\hat{\delta}^j_{S,i,q})^2$	-0.0111***	-0.0054***	-0.0111***	-0.0094***
	(-27.41)	(-23.06)	(-23.37)	(-26.52)
# of obs	1,500,090	1,500,090	1,500,090	1,500,090
Adj R^2	0.1731	0.2178	0.2193	0.2249
Dealer×Bond×Year FE	YES	YES	YES	YES

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered in dealer#bond#year.

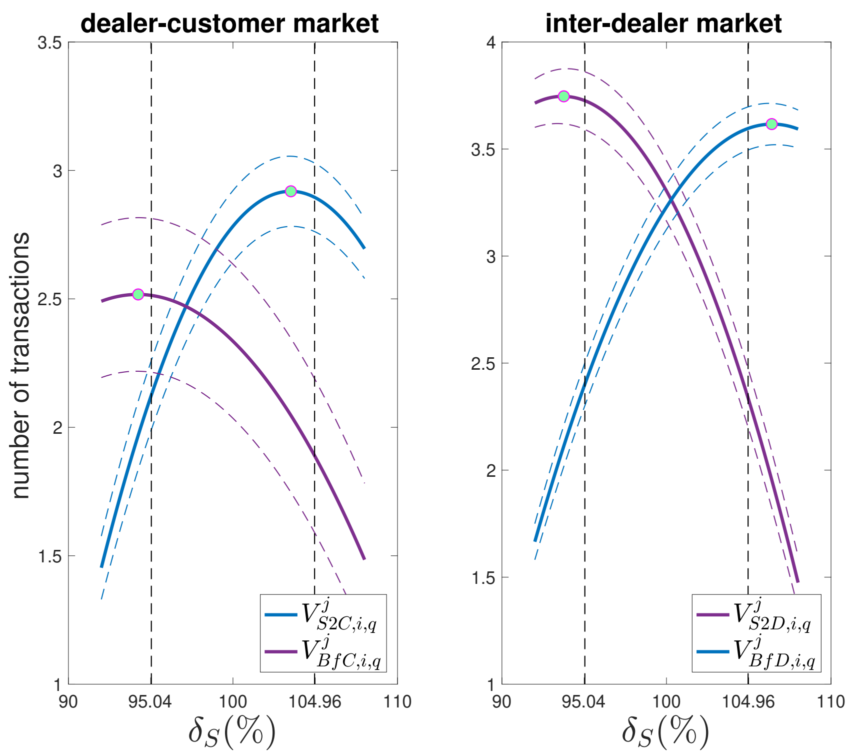

Figure 8: Distribution of transactions of different directions (quadratic form)

low-type customers/dealers to high-type ones. The full regression result is in the Internet Appendix.

We further characterize how dealers' trading specialization correlates with the signed distance[34] of dealers' private valuations to the mean level across all dealers. Figure 9 shows how dealers' shares of trading in different directions vary with the signed distance. We also characterize this relationship separately for each subperiod in Appendix D. Figure 9 indicates that: [1] at each level of private valuation, the aggregate share of selling transactions (either with customer or with other dealers as trading counterparties) is close to that of buying transactions; [2] as private valuation ranges from low to high, on the buy side, dealers switch from "buying *mainly* from customers" to "buying *mainly* from other dealers." On the sell side, dealers switch from "selling *mainly* to other dealers" to "selling *mainly* to customers"; [3] dealers in the lower range of private valuations take the main roles to buy from low-type customers and sell to higher-type dealers, and similarly, dealers in the higher range of private valuations take the main roles to buy from lower-type dealers and sell to high-type customers; [4] dealers with private valuations close to the mean level trade at equal frequencies and amounts in each of the four directions.

4.3 Market efficiency compared to a frictionless market

We conduct a counterfactual analysis to evaluate how search frictions affect bond prices and allocation of bond positions among market participants. Search frictions refers to frictions to contact/locate potential trading counterparties, which are generated by the decentralized market structures. The counterfactual scenarios would be Walrasian markets with the same estimated model parameters but with centralized exchanges to which both customers and dealers have frictionless access.

Walrasian price Consider a Walrasian market in which there is a central exchange where customers and dealers can buy or sell the target bond immediately at equilibrium price P. As is standard, we have $P = \frac{u^*}{r}$ where u^* is the private valuation (utility flow) of the marginal investor which is defined as the asset owner with the lowest private valuation type among

[34] The signed distance is defined as $\frac{\hat{\delta}^j_{i,q} - \hat{\bar{\delta}}^j_q}{|\hat{\delta}^j_{h,q} - \hat{\delta}^j_{l,q}|}$, i.e., the normalized distance without absolute value on the numerator. The signed distance measures not only how far each dealer's private valuation is to the corresponding cross-dealer mean level, but also indicates whether the value is below or above the mean level. The difference in the scaled private valuation is that it also controls for the dispersion of all dealers' private valuations for the same bond and same month.

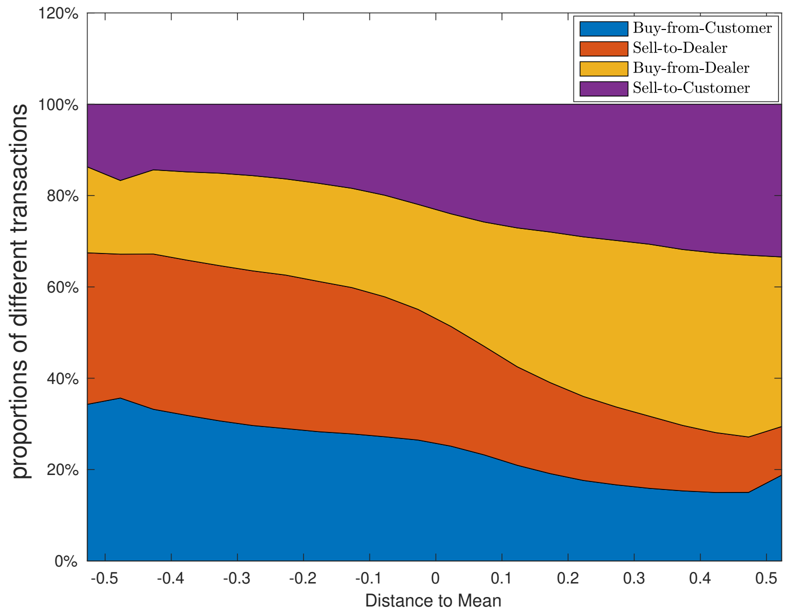

Figure 9: Dealer's private valuation and proportions of transactions in different directions (values are averages taken over all bonds and all quarters)

all market participants in a Walrasian market:

$$u^* = \begin{cases} y_h & \text{if } s <= \pi_h; \\ \{u \in [\delta_\ell, \delta_h] : \pi_h + \int_{u^*}^{\delta_h} f(\delta) d\delta = s\} & \text{if } \pi_h < s < \pi_h + m; \\ y_\ell & \text{if } s >= \pi_h + m. \end{cases}$$

In all of the markets in our filtered sample, we have $\pi_h < s < \pi_h + m$. This indicates that all of the markets have their marginal investors as a dealer.[35] Therefore, in the remaining section, we only consider the case of $\pi_h < s < \pi_h + m$, and we denote the marginal investor's private valuation type as δ^*. The derivation and estimation of Walrasian price P are in

[35] In the TRACE data for the U.S. corporate bond market, since we are not able (or allowed by FINRA) to uncover the true identities of registered members (or dealers), some of the registered members may behave more like a customer based on their trading behavior, for example, they may trade on one side of the market in most time, but under the regulation of FINRA (so they are identified as dealers in our sample). Since in our sample, we exclude the dealers that only trade on one side of the market, this may lead to an under-estimation of the measure of high-type customers π_h, and thus the proportion of markets with the marginal investor as high-type customers in corresponding frictionless markets.

Appendix C.

We report the Walrasian prices and volume-weighted average OTC prices (and all other measures of interest) in Table 6. The average Walrasian price is lower than the average OTC price in most markets. The possible reason is,[36] in most of those markets, total search costs on the sell side are higher than the buy side, which requires the average transaction price to be higher to compensate the dealers for intermediating the bond positions. On the other hand, since the private valuation of the marginal investor is lower than that of the high-type customers, for dealers with private valuations in between, there still exist positive gains from intermediation, which makes it possible to drive the average OTC price above the Walrasian price.

Bond misallocation In this paper, bond misallocation is defined as the proportion of bond positions being held by market participants with private valuation types lower than that of the marginal investor in a counterfactual frictionless market.

The ratio of bond misallocation $Rmis$ is formally defined as below:

$$Rmis = \begin{cases} \frac{s-\mu_{h1}}{s} \text{ or } \frac{\mu_{\ell 1}+m_1}{s} & \text{if } s \leq \pi_h; \\ \frac{\mu_{\ell 1}+\int_{\delta_\ell}^{\delta^*} \phi_1(\delta) d\delta}{s} & \text{if } s > \pi_h. \end{cases}$$

Within the markets in our sample (all with $s > \pi_h$), the bond misallocation ratio ranges from 0.61% to 3.97%. The mean across all markets is 1.68% with a standard deviation as 0.42%. This indicates there are on average 1.68% of bond positions being held by market participants with private valuations lower than the estimated marginal-investor's level. By the estimates in Table 2 and Table 3, we know the misallocation of bond positions mainly happen within the dealer sector, since there are very few customers with bond positions mis-aligned with their private valuation types.

Total utility flow Total flow utility is defined as the summation of all bond-owners' utility flows in stationary equilibrium:

$$Tot\_utility = \int_{\delta_\ell}^{\delta_h} \phi_1(\delta)\delta d\delta + \mu_{h1} y_h + \mu_{\ell 1} y_\ell \tag{36}$$

[36]This is indicated by formula of Walrasian price (91) in Appendix C.

Total utility flow measures the total benefits of all market participants by holding bond positions, and it positively contributes to the total welfare of each market. In Table 6, total utility flow is expressed in percentage of bond's par value and further scaled by the number of customers in each market.

Dealers' search costs For the whole dealer sector, the total search cost is calculated as follows:

$$Tot\_SearchCost = c \times \int_{\delta_\ell}^{\delta_h} \left(\lambda_1^{*2}(\delta)\phi_1(\delta) + \lambda_0^{*2}(\delta)\phi_0(\delta) \right) d\delta \tag{37}$$

In Table 6, the total search cost is also scaled by the number of customers in each market. In OTC markets, the gains from intermediation, which is caused by limited bond supply and higher level of bond misallocation, motivate dealers to spend on searching. Across all markets in our sample, the mean level of total search cost (per customer) is around 0.07% of bond's par value, with standard deviation as 0.30%.

Finally, we calculate the total welfare (per customer) as the difference between total utility flow and total search costs. Compared with Walrasian markets, OTC markets exhibit a comparable level of total utility flow but nontrivial total search costs. This on average reduces the welfare in OTC markets by about 13.7% relative to Walrasian markets.

5 Conclusion

In this paper, we propose a search-based model for the U.S. corporate bond market with dealers' endogeneous and state-dependent search intensity. The model generates the following implications that can be empirically verified: [1] endogeneous intermediation: dealers with intermediate private valuation type choose higher search intensities than others, and these dealers intermediate bond positions from low-type to high-type dealers. Low-type dealers mainly trade on the buy side to buy bonds from customer-sellers. High-type dealers mainly trade on the sell side to sell bonds to customer-buyers; [2] over-the-counter inefficiency: the estimated model indicates a nontrivial market inefficiency such that, taking the average across all markets in our sample, dealers' total search cost is 0.07% of bond's par value on a per customer basis, which generates 13.7% welfare loss relative to corresponding frictionless markets, and there is on average 1.68% of bond positions being misallocated.

Table 6: Comparison with corresponding frictionless markets for 47634 markets (6301 bonds)

Markets with $\pi_h < s < \pi_h + m$	OTC market (mean/std.dev)	Walrasian market (mean/std.dev)
Bond misallocation $\frac{\mu_{\ell 1}+\int_{\delta_\ell}^{\delta^*}\phi_1(\delta)d\delta}{s}$ (%)	1.68%	0
	(0.42%)	(N/A)
Tot flow utility (% of par value)	0.4873%	0.4875%
	(0.3922%)	(0.3923%)
Tot search costs (% of par value)	0.0694%	0
	(0.2959%)	(N/A)
Welfare (% of par value)	0.4192%	0.4875%
	(0.5283%)	(0.3923%)
average price (% of par value)	102.03%	95.04%
	(7.62%)	(16.43%)

Note: Mean/Std.dev are calculated across all markets in the sample. "Tot flow utility", "Tot search costs" and "Welfare" are all on a per customer basis.

Moreover, the level of market inefficiency exhibits large variation across different bonds and over time.

Appendices

A Proof of propositions

A.1 Proof of proposition 1

In this proof, we assume stationary equilibrium exists.[37]

[**1**] $\lambda_1^{*\prime}(\delta) < 0$ and $\lambda_0^{*\prime}(\delta) > 0$:

By (2)-(4), we obtain:

$$r\triangle V(\delta) = \delta + c\lambda_1^{*2}(\delta) - c\lambda_0^{*2}(\delta) \tag{38}$$

$$\lambda_1^{*\prime}(\delta) = (-\triangle V'(\delta))\frac{1}{2c}\left[\left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\mu_{h0}\theta + \frac{m}{1+m}\int_{\delta}^{\delta_h}\frac{\lambda_0^*(\delta')\phi_0(\delta')}{\Lambda}d\delta'\right] \tag{39}$$

$$\lambda_0^{*\prime}(\delta) = \triangle V'(\delta)\frac{1}{2c}\left[\left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\mu_{\ell 1}\theta + \frac{m}{1+m}\int_{\delta_\ell}^{\delta}\frac{\lambda_1^*(\delta')\phi_1(\delta')}{\Lambda}d\delta'\right] \tag{40}$$

(38)-(40) $\implies$

$$\begin{aligned} r\triangle V'(\delta) &= 1 + 2c \times \lambda_1^*(\delta)\lambda_1^{*\prime}(\delta) - 2c \times \lambda_0^*(\delta)\lambda_0^{*\prime}(\delta) \qquad (41) \\ &= 1 + (-\triangle V'(\delta))\left(\lambda_1^*(\delta)\left[\left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\mu_{h0}\theta + \frac{m}{1+m}\int_{\delta}^{\delta_h}\frac{\lambda_0^*(\delta')\phi_0(\delta')}{\Lambda}d\delta'\right]\right. \\ &\qquad \left. + \lambda_0^*(\delta)\left[\left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\mu_{\ell 1}\theta + \frac{m}{1+m}\int_{\delta_\ell}^{\delta}\frac{\lambda_1^*(\delta')\phi_1(\delta')}{\Lambda}d\delta'\right]\right) \end{aligned}$$

(41) $\implies$

$$\begin{aligned} &\triangle V'(\delta) \\ &= \frac{1}{r + \lambda_1^*(\delta)X_1(\delta) + \lambda_0^*(\delta)X_0(\delta)} \\ &> 0 \end{aligned} \tag{42}$$

[37] The proof of existance of stationary equilibrium is similar as in Liu (2018) and Hugonnier, Lester, and Weill (2018).

where

$$X_1(\delta) = \left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\mu_{h0}\theta + \frac{m}{1+m}\int_{\delta}^{\delta_h} \frac{\lambda_0^*(\delta')\phi_0(\delta')}{\Lambda}d\delta'$$
$$X_0(\delta) = \left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\mu_{\ell 1}\theta + \frac{m}{1+m}\int_{\delta_\ell}^{\delta} \frac{\lambda_1^*(\delta')\phi_1(\delta')}{\Lambda}d\delta'$$

(39)-(40) and (42) $\implies$

$$\lambda_1^{*\prime}(\delta) < 0 \text{ and } \lambda_0^{*\prime}(\delta) > 0$$

[2] If symmetric restrictions apply and the distribution $f(\delta)$ is uniform distribution, then $\exists c^* > 0$, s.t. for any $c < c^*$:

$$\bar{\lambda}'(\delta) > 0, \quad \forall\delta \in [\delta_\ell, \frac{\delta_\ell + \delta_h}{2}] \text{ and } \bar{\lambda}'(\delta) < 0, \quad \forall\delta \in [\frac{\delta_\ell + \delta_h}{2}, \delta_h]$$

Proof: When symmetric restrictions apply and $f(\delta) \equiv \overline{U}$, such that $\overline{U} = \frac{1}{\delta_h - \delta_\ell}$, search intensity policy functions and density functions trivally satisfy the following conditions:

$$\lambda_1^*(\frac{\delta_\ell + \delta_h}{2}) = \lambda_0^*(\frac{\delta_\ell + \delta_h}{2}) \tag{43}$$

$$\lambda_1^*(\delta) > \lambda_0^*(\delta) \text{ and } \phi_1(\delta) < \phi_0(\delta), \qquad \forall\delta \in [\delta_\ell, \frac{\delta_\ell + \delta_h}{2}) \tag{44}$$

$$\lambda_1^*(\delta) < \lambda_0^*(\delta) \text{ and } \phi_1(\delta) > \phi_0(\delta), \qquad \forall\delta \in (\frac{\delta_\ell + \delta_h}{2}, \delta_h] \tag{45}$$

$$\phi_1'(\delta) > 0 \text{ and } \phi_0'(\delta) < 0, \qquad \forall\delta \in [\delta_\ell, \delta_h] \tag{46}$$

$$\lambda_1^{*\prime}(\delta) = -\lambda_0^{*\prime}(\delta_h + \delta_\ell - \delta) \text{ and } \phi_1'(\delta) = -\phi_0'(\delta_h + \delta_\ell - \delta), \qquad \forall\delta \in [\delta_\ell, \delta_h] \tag{47}$$

$$\mu_{h0} = \mu_{\ell 1} \text{ and } \Lambda_0 = \Lambda_1 \tag{48}$$

where $\mu_{h0} = \mu_{\ell 1}$ is obtained by inflow-outflow equations (7)-(8) and also $\Lambda_0 = \Lambda_1$.

Then by definition,

$$\bar{\lambda}'(\delta) = \phi_1'(\delta)\lambda_1^*(\delta) + \phi_1(\delta)\lambda_1^{*\prime}(\delta) + \phi_0'(\delta)\lambda_0^*(\delta) + \phi_0(\delta)\lambda_0^{*\prime}(\delta) \tag{49}$$
$$= \underbrace{\phi_1'(\delta)(\lambda_1^*(\delta) - \lambda_0^*(\delta))}_{*}$$
$$+ \frac{1}{2c}\triangle V'(\delta)\left(\underbrace{(\phi_0(\delta)\mu_{\ell 1} - \phi_1(\delta)\mu_{h0})\left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\theta}_{**} + (\phi_0(\delta)a(\delta) - \phi_1(\delta)b(\delta))\frac{m}{1+m}\right)$$

where

$$a(\delta) = \int_{\delta_\ell}^{\delta} \frac{\lambda_1^*(\delta')\phi_1(\delta')}{\Lambda} d\delta' \tag{50}$$

$$b(\delta) = \int_{\delta}^{\delta_h} \frac{\lambda_0^*(\delta')\phi_0(\delta')}{\Lambda} d\delta' \tag{51}$$

By (43)-(48), both terms $*$ and $**$ in (49) are positive for $\forall \delta \in [\delta_\ell, \frac{\delta_\ell+\delta_h}{2})$. To characterize the sign of $\phi_0(\delta)a(\delta) - \phi_1(\delta)b(\delta)$ in the range of $[\delta_\ell, \frac{\delta_\ell+\delta_h}{2})$, we use the inflow-outflow equation (6) for $\phi_1(\delta)$:

$$\frac{2m}{1+m}\phi_1(\delta)\lambda_1^*(\delta)\int_{\delta}^{\delta_h} \frac{\lambda_0^*(\delta')}{\Lambda}\phi_0(\delta')d\delta' + \left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\phi_1(\delta)\lambda_1^*(\delta)\mu_{h0} \tag{52}$$
$$= \frac{2m}{1+m}\phi_0(\delta)\lambda_0^*(\delta)\int_{\delta_\ell}^{\delta} \frac{\lambda_1^*(\delta')}{\Lambda}\phi_1(\delta')d\delta' + \left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\phi_0(\delta)\lambda_0^*(\delta)\mu_{\ell 1}$$

$\Longrightarrow$

$$\frac{\phi_0(\delta)}{\phi_1(\delta)} = \frac{\lambda_1^*(\delta)}{\lambda_0^*(\delta)} \frac{\frac{2m}{1+m}\int_{\delta}^{\delta_h} \frac{\lambda_0^*(\delta')}{\Lambda}\phi_0(\delta')d\delta' + \left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\mu_{h0}}{\frac{2m}{1+m}\int_{\delta_\ell}^{\delta} \frac{\lambda_1^*(\delta')}{\Lambda}\phi_1(\delta')d\delta' + \left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\mu_{\ell 1}} \tag{53}$$
$$= \frac{\lambda_1^*(\delta)}{\lambda_0^*(\delta)} \frac{\frac{2m}{1+m}b(\delta) + \left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\mu_{h0}}{\frac{2m}{1+m}a(\delta) + \left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\mu_{\ell 1}}$$

By inflow-outflow equations of measures of high-type customer-non-owner and low-type customer-owner (7)-(8),

$$\mu_{h0} = \frac{\alpha\mu_{\ell 0}\pi_h}{\left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\Lambda_1 + \alpha\pi_\ell} \tag{54}$$

$$\mu_{\ell 1} = \frac{\alpha\mu_{h1}\pi_\ell}{\left(\frac{\rho}{m\Lambda} + \frac{1}{1+m}\right)\Lambda_0 + \alpha\pi_h} \tag{55}$$

Since $\mu_{\ell 0} < \pi_\ell \leq 1$, $\mu_{h1} < \pi_h \leq 1$, $\Lambda_0 = \Lambda_1 = \frac{\Lambda}{2}$, also $\Lambda_1 \to \infty$ and $\Lambda_0 \to \infty$ as $c \to 0$, we have:

$$\underset{c\to 0}{lim}\mu_{h0} = \underset{c\to 0}{lim}\mu_{\ell 1} = 0 \tag{56}$$

Then by (44) and (53)-(56), we have:

$$\begin{aligned}\underset{c\to 0}{lim}\frac{\phi_0(\delta)}{\phi_1(\delta)} &= \frac{\lambda_1^*(\delta)}{\lambda_0^*(\delta)}\frac{\frac{2m}{1+m}b(\delta)}{\frac{2m}{1+m}a(\delta)} \\ &> \frac{b(\delta)}{a(\delta)}, \qquad \forall\delta \in [\delta_\ell, \frac{\delta_\ell+\delta_h}{2})\end{aligned} \tag{57}$$

$\Longrightarrow$

$$\underset{c\to 0}{lim}\left(\phi_0(\delta)a(\delta) - \phi_1(\delta)b(\delta)\right) > 0, \qquad \forall\delta \in [\delta_\ell, \frac{\delta_\ell+\delta_h}{2}) \tag{58}$$

Then in (49), we have for $\forall\delta \in [\delta_\ell, \frac{\delta_\ell+\delta_h}{2})$:

$$\underset{c\to 0}{lim}\bar{\lambda}'(\delta) > \frac{1}{2c}\triangle V'(\delta)\frac{m}{1+m}\underset{c\to 0}{lim}\left(\phi_0(\delta)a(\delta) - \phi_1(\delta)b(\delta)\right) > 0 \tag{59}$$

by $\triangle V'(\delta) > 0$, and both terms $*$ and $**$ in (49) are positive for $\forall\delta \in [\delta_\ell, \frac{\delta_\ell+\delta_h}{2})$.
Finally, by symmetry conditions,

$$\bar{\lambda}'(\delta) = -\bar{\lambda}'(\delta_h + \delta_\ell - \delta) \qquad \forall\delta \in [\delta_\ell, \delta_h] \tag{60}$$

$\Longrightarrow \forall\delta \in (\frac{\delta_\ell+\delta_h}{2}, \delta_h]$:

$$\underset{c\to 0}{lim}\bar{\lambda}'(\delta) < 0 \tag{61}$$

$\square$

A.2 Proof of proposition 2

We use P to denote the *intensity* of trading at different directions *conditional* on the choice of selling/buying intensity for each individual dealer, and use Pr to denote the conditional probability that trading counterparty is a dealer or customer *conditional* on that transaction of specific direction happens. Notations with hat refer to identified data moments. Specifically, for each dealer with type $\delta \in [\delta_\ell, \delta_h]$, we denote:

$$P(S2D|\delta) = \frac{2m}{1+m} \int_{\delta}^{\delta_h} \frac{\lambda_0^*(\delta')}{\Lambda} \phi_0(\delta') d\delta' \tag{62}$$

$$P(BfD|\delta) = \frac{2m}{1+m} \int_{\delta_\ell}^{\delta} \frac{\lambda_1^*(\delta')}{\Lambda} \phi_1(\delta') d\delta' \tag{63}$$

$$P(S2C) = \left(\frac{1}{1+m} + \frac{\rho}{m\Lambda} \right) \mu_{h0} \tag{64}$$

$$P(BfC) = \left(\frac{1}{1+m} + \frac{\rho}{m\Lambda} \right) \mu_{\ell 1} \tag{65}$$

In (12)-(13), replace $P(S2D|\delta)$ and $P(BfD|\delta)$ by (14)-(15), the following two functions are identified:

$$\widehat{f}_1(\delta) = \left(1 - \widehat{Pr}\left[SellToDealers|Sell\right](\delta)\right) \times \widehat{Trade}_S(\delta) = \phi_1(\delta)\lambda_1^*(\delta) \times P(S2C) \tag{66}$$

$$\widehat{f}_2(\delta) = \left(1 - \widehat{Pr}\left[BuyFromDealers|Buy\right](\delta)\right) \times \widehat{Trade}_B(\delta) = \phi_0(\delta)\lambda_0^*(\delta) \times P(BfC) \tag{67}$$

In (12)-(13), replace $P(S2C)$ and $P(BfC)$ with $P(S2D|\delta)$ and $P(BfD|\delta)$ by (14)-(15), the following two functions are identified:

$$\widehat{f}_3(\delta) = \widehat{Pr}\left[SellToDealers|Sell\right](\delta) \times \widehat{Trade}_S(\delta) = \frac{2m}{1+m} \phi_1(\delta)\lambda_1^*(\delta) \int_{\delta}^{\delta_h} \frac{\lambda_0^*(\delta')}{\Lambda} \phi_0(\delta') d\delta' \tag{68}$$

$$\widehat{f}_4(\delta) = \widehat{Pr}\left[BuyFromDealers|Buy\right](\delta) \times \widehat{Trade}_B(\delta) = \frac{2m}{1+m} \phi_0(\delta)\lambda_0^*(\delta) \int_{\delta_\ell}^{\delta} \frac{\lambda_1^*(\delta')}{\Lambda} \phi_1(\delta') d\delta' \tag{69}$$

Plug in δ_ℓ in (68) and plug in δ_h in (69), obtain:

$$\widehat{f}_3(\delta_\ell) = \frac{2m}{1+m}\phi_1(\delta_\ell)\lambda_1^*(\delta_\ell)\frac{\Lambda_0}{\Lambda} \tag{70}$$

$$\widehat{f}_4(\delta_h) = \frac{2m}{1+m}\phi_0(\delta_h)\lambda_0^*(\delta_h)\frac{\Lambda_1}{\Lambda} \tag{71}$$

by assumption $\phi_1(\delta_\ell)\lambda_1^*(\delta_\ell) = \phi_0(\delta_h)\lambda_0^*(\delta_h)$, we obtain:

$$\frac{\widehat{f}_3(\delta_\ell)}{\widehat{f}_4(\delta_h)} = \frac{\Lambda_0}{\Lambda_1} \quad , \quad \frac{\frac{\widehat{f}_3(\delta_\ell)}{\widehat{f}_4(\delta_h)}}{1+\frac{\widehat{f}_3(\delta_\ell)}{\widehat{f}_4(\delta_h)}} = \frac{\Lambda_0}{\Lambda} \quad , \quad \frac{1}{1+\frac{\widehat{f}_3(\delta_\ell)}{\widehat{f}_4(\delta_h)}} = \frac{\Lambda_1}{\Lambda} \tag{72}$$

then plug (72) into (70)-(71), we obtain:

$$\widehat{f}_3(\delta_\ell) + \widehat{f}_4(\delta_h) = \frac{2m}{1+m}\phi_1(\delta_\ell)\lambda_1^*(\delta_\ell) = \frac{2m}{1+m}\phi_0(\delta_h)\lambda_0^*(\delta_h) \tag{73}$$

Plug in δ_ℓ in (66) and plug in δ_h in (67), obtain:

$$\widehat{f}_1(\delta_\ell) = \phi_1(\delta_\ell)\lambda_1^*(\delta_\ell) \times P(S2C) \tag{74}$$

$$\widehat{f}_2(\delta_h) = \phi_0(\delta_h)\lambda_0^*(\delta_h) \times P(BfC) \tag{75}$$

Since $\frac{2m}{1+m}$, $P(S2C)$ and $P(BfC)$ are all constants (within each market), by (73)-(75), we obtain:

$$\frac{\widehat{f}_1(\delta_\ell)}{\widehat{f}_3(\delta_\ell)+\widehat{f}_4(\delta_h)} = \frac{P(S2C)}{\frac{2m}{1+m}} \tag{76}$$

$$\frac{\widehat{f}_2(\delta_h)}{\widehat{f}_3(\delta_\ell)+\widehat{f}_4(\delta_h)} = \frac{P(BfC)}{\frac{2m}{1+m}} \tag{77}$$

The (76)-(77) allow us to replace trading intensities $P(S2C)$ and $P(BfC)$ in (66)-(67), obtain:

$$\widehat{f}_1(\delta) = \phi_1(\delta)\lambda_1^*(\delta) \times \frac{\widehat{f}_1(\delta_\ell)}{\widehat{f}_3(\delta_\ell)+\widehat{f}_4(\delta_h)} \times \frac{2m}{1+m} \tag{78}$$

$$\widehat{f}_2(\delta) = \phi_0(\delta)\lambda_0^*(\delta) \times \frac{\widehat{f}_2(\delta_h)}{\widehat{f}_3(\delta_\ell) + \widehat{f}_4(\delta_h)} \times \frac{2m}{1+m} \tag{79}$$

then $\frac{2m}{1+m}\phi_1(\delta)\lambda_1^*(\delta)$ and $\frac{2m}{1+m}\phi_0(\delta)\lambda_0^*(\delta)$ can be identified as:

$$\frac{2m}{1+m}\phi_1(\delta)\lambda_1^*(\delta) = \frac{\widehat{f}_3(\delta_\ell) + \widehat{f}_4(\delta_h)}{\widehat{f}_1(\delta_\ell)} \times \widehat{f}_1(\delta) \tag{80}$$

$$\frac{2m}{1+m}\phi_0(\delta)\lambda_0^*(\delta) = \frac{\widehat{f}_3(\delta_\ell) + \widehat{f}_4(\delta_h)}{\widehat{f}_2(\delta_h)} \times \widehat{f}_2(\delta) \tag{81}$$

and then $\frac{2m\Lambda_1}{1+m}$ and $\frac{2m\Lambda_0}{1+m}$ can also be identified by calculating the full integral over $[\delta_\ell, \delta_h]$. $\square$

B Identification and estimation

B.1 Identifying the ratio of $\frac{m_1}{m_0}$

For a dealer with private valuation as δ^*, if she is searching on the sell side with search intensity $\lambda_1^*(\delta^*)$, the average length of time before successfully selling the bond $\tau_S(\delta^*)$ is:

$$E[\tau_S(\delta^*)] = \frac{1}{\lambda_1^*(\delta^*)\left[\left(\frac{1}{1+m} + \frac{\rho}{m\Lambda}\right)\mu_{h0} + \frac{2m}{1+m}\int_{\delta}^{\delta_h} \frac{\lambda_0^*(\delta')}{\Lambda}\phi_0(\delta')d\delta'\right]} \tag{82}$$

If she is searching on the buy side with search intensity $\lambda_0^*(\delta^*)$, the average length of time before successfully buying the bond $\tau_B(\delta^*)$ is:

$$E[\tau_B(\delta^*)] = \frac{1}{\lambda_0^*(\delta^*)\left[\left(\frac{1}{1+m} + \frac{\rho}{m\Lambda}\right)\mu_{\ell 1} + \frac{2m}{1+m}\int_{\delta_\ell}^{\delta} \frac{\lambda_1^*(\delta')}{\Lambda}\phi_1(\delta')d\delta'\right]} \tag{83}$$

By moment conditions (12)-(13), we obtain the total length of time that dealer δ^* spends on the sell side $Total\_\tau_S$ is:

$$Total\_\tau_S(\delta^*) = E[\tau_S(\delta^*)] \times \widehat{Trade}_S(\delta^*) = \phi_1(\delta^*) \tag{84}$$

and the total length of time that dealer δ^* spends on the sell side $Total\_\tau_B$ is:

$$Total\_\tau_B(\delta^*) = E[\tau_B(\delta^*)] \times \widehat{Trade}_B(\delta^*) = \phi_0(\delta^*) \tag{85}$$

Then in the data, we identify the ratio of $\frac{m_1}{m_0}$ as follows:

$$\frac{m_1}{m_0} = \frac{\int_{\delta_\ell}^{\delta_h} \phi_1(\delta) d\delta}{\int_{\delta_\ell}^{\delta_h} \phi_0(\delta) d\delta} = \frac{\int_{\delta_\ell}^{\delta_h} Total\_\tau_S(\delta) d\delta}{\int_{\delta_\ell}^{\delta_h} Total\_\tau_B(\delta) d\delta} \tag{86}$$

As for how to identify $Total\_\tau_S(\delta)$ and $Total\_\tau_B(\delta)$, for each dealer, we calculate the total length of time that the dealer stays on the sell side and that on the buy side. The calculation is feasible because the execution time is round to seconds. Suppose a dealer with private valuation δ has an idiosyncratic trading history in the market which can be characterized by a series of trading time $\{\tau^1_{\delta,D_1}, \tau^2_{\delta,D_2}, ..., \tau^{N_\delta}_{\delta,D_{N_\delta}}\}$, $D_t \in \{S, B\}$, $1 \leq t \leq N_\delta$ and N_δ is the total number of realized transactions. For each transaction t starting from the second one, the length of time from the previous transaction to the current one is denoted as $T^t_{\delta,D_t} = \tau^t_{\delta,D_t} - \tau^{t-1}_{\delta,D_{t-1}}$, $2 \leq t \leq N_\delta$. Then we identify the total length of time on the sell side and that on the buy side as follows:

$$Total\_\tau_S(\delta) = \sum_{t=2}^{N_\delta} T^t_{\delta,D_t} \mathbb{1}(D_t = S) \tag{87}$$

$$Total\_\tau_B(\delta) = \sum_{t=2}^{N_\delta} T^t_{\delta,D_t} \mathbb{1}(D_t = B) \tag{88}$$

If we define each market as a bond j and a quarter q, i.e. $Market(j, q)$, by the calculation above, we ignore the length of time that from the start of each quarter to the first trading time τ^1_{δ,D_1} in each dealer's idiosyncratic trading history, and also the length of time starting from the last trading time $\tau^{N_\delta}_{\delta,D_{N_\delta}}$ to the end of the quarter. Table 7 shows the distribution of $Total\_\tau_S(\delta)$ and $Total\_\tau_B(\delta)$ among all dealers and across all markets, and the distribution of identified $\frac{m_1}{m_0}$ across all markets.

Table 7: Summary of estimate of π_h and bond supply per capita s

Variable	Mean	Std dev	Min	Q25	Q50	Q75	Max
$Total\_\tau_S(\delta)$ (hours)	438.76	546.34	0	0.23	180.32	756.48	2297.02
$Total\_\tau_B(\delta)$ (hours)	562.91	640.98	0	0.20	298.16	1019.04	2547.83
$\frac{m_1}{m_0}$	0.8512	0.3514	0.0561	0.6189	0.808	1.0255	5.01

B.2 Calibration of average fraction of positions held by broker-dealer sector

Table 8: Holding positions on corporate and foreign bonds ($billion) by different sectors

Year	Ratio of Broker-dealer (%)	Broker-dealer (asset+liability)	Total assets
2005	4.59	378.1	8236.1
2006	4.57	424.3	9275.2
2007	4.20	447.6	10653.5
2008	2.17	220.9	10167.1
2009	2.36	247.3	10477.4
2010	3.06	319.2	10441.2
2011	1.87	196.3	10502.5
2012	2.09	230.2	10995.8
2013	2.17	241.3	11134.7
2014	2.06	239.4	11600
2015	1.91	223.4	11722.2
Average	2.82	288	10473.3

Sources: Flow of Funds L.213, Federal Reserve Board.

Table 9: Summary of estimate of π_h and bond supply per capita s

Variable	Mean	Std dev	Min	Q25	Q50	Q75	Max
π_h	0.0888	0.0698	0.0135	0.0354	0.0657	0.1212	0.2642
s	0.0916	0.0723	0.0139	0.0365	0.0676	0.1248	0.2725

Note: π_h is the measure of high-type customers; s is the bond supply (per capita).

B.3 B-spline nonparametric estimator of unknown functions

The B-spline nonparametric estimator of unknown functions $\widehat{f}_i(\delta)$, $i = 1, 2, 3, 4.$ in (66)-(69) have the following forms:

$$\widehat{f}_i(\delta) = \sum_{k=1}^{5} \beta_{k,i}^{j} B_k^j(\delta) \tag{89}$$

where $B_k^j(\delta), k = 1, 2, 3, 4, 5$ are B-spline basis functions of dealers' type δ for bond j, for a natural cubic spline with degree of freedom equals 5 (4 intercept knots).

B.4 Model fits

For model fitting results, please refer to Table 10.

Table 10: Model Fit for 47634 markets (6301 bonds)

Theoretical Moment (1)	Empirical Value (2)	Fitted Value (3)
$\int_{\delta_\ell^j}^{\delta_h^j} \phi_1^j(\delta)\lambda_1^{j*}(\delta)\left(\frac{1}{1+m^j}+\frac{\rho^j}{m^j\Lambda^j}\right)\mu_{h0}^j d\delta$	2.246 (0.927)	2.758 (6.284)
$\int_{\delta_\ell^j}^{\delta_h^j} \phi_0^j(\delta)\lambda_0^{j*}(\delta)\left(\frac{1}{1+m^j}+\frac{\rho^j}{m^j\Lambda^j}\right)\mu_{\ell 1}^j d\delta$	2.971 (1.062)	1.748 (3.725)
$\int_{\delta_\ell^j}^{\delta_h^j} \phi_1^j(\delta)\lambda_1^{j*}(\delta)\frac{2m^j}{1+m^j}\int_{\delta}^{\delta_h^j}\frac{\lambda_0^{j*}(\delta')}{\Lambda^j}\phi_0^j(\delta')d\delta' d\delta \quad (*)$	3.572 (1.007)	2.534 (4.868)
$\int_{\delta_\ell^j}^{\delta_h^j} \phi_0^j(\delta)\lambda_0^{j*}(\delta)\frac{2m^j}{1+m^j}\int_{\delta_\ell^j}^{\delta}\frac{\lambda_1^{j*}(\delta')}{\Lambda^j}\phi_1^j(\delta')d\delta' d\delta \quad (**)$	3.471 (0.960)	2.534 (4.868)
$\frac{\int_{\delta_\ell^j}^{\delta_h^j}\frac{\lambda_1^{j*}(\delta)\phi_1^j(\delta)}{\Lambda_1^j}[(1-\theta^j)\triangle V^j(\delta)+\theta^j\triangle W^j(y_h^j)]d\delta}{\int_{\delta_\ell^j}^{\delta_h^j}\frac{\lambda_0^{j*}(\delta)\phi_0^j(\delta)}{\Lambda_0^j}[(1-\theta^j)\triangle V^j(\delta)+\theta^j\triangle W^j(y_\ell^j)]d\delta}-1$	0.0046 (0.0038)	0.0094 (0.0529)
$\Lambda_1^j=\int_{\delta_\ell^j}^{\delta_h^j}\phi_1^j(\delta)\lambda_1^{j*}(\delta)d\delta$	187.389 (234.12)	66.736 (95.794)
$\Lambda_0^j=\int_{\delta_\ell^j}^{\delta_h^j}\phi_0^j(\delta)\lambda_0^{j*}(\delta)d\delta$	324.870 (462.735)	125.852 (160.168)

Note: For both Empirical Value and Fitted Value, the mean level and standard deviation across all markets are reported. The mappings between the theoretical and empirical moments are in Internet Appendix. The simulated moment (*) of "average sell-to-dealer trades" is equal to that (**) of "average buy-from-dealer trades", because in our model we assume constant trade size, then each "dealer-sell-to-another-dealer" transaction is always associated with a "dealer-buy-from-another-dealer" transaction.

C Walrasian price

As in the earlier version of Hugonnier, Lester, and Weill (2018), the objectives of both customers and dealers are to choose an asset-holding process $a_t \in \{0, 1\}$, subject to their utility-type process, to maximize the following objective function:

$$
\begin{aligned}
E_{0,u}\left[\int_0^\infty u_t a_t e^{-rt}dt - \int_0^\infty P e^{-rt} da_t\right] &= E_{0,u}\left[\int_0^\infty u_t a_t e^{-rt}dt - P e^{-rt} a_t\Big|_0^\infty + \int_0^\infty P a_t e^{-rt}(-r)dt\right] \quad (90)\\
&= E_{0,u}\left[\int_0^\infty u_t a_t e^{-rt}dt + P a_0 + \int_0^\infty P a_t e^{-rt}(-r)dt\right]\\
&= P a_0 + E_{0,u}\left[\int_0^\infty a_t e^{-rt}(u_t - rP)dt\right]
\end{aligned}
$$

where u_t denotes customers' or dealers' utility-type process, $y_t \in \{y_\ell, y_h\}$ or $\delta_t \in [\delta_\ell, \delta_h]$, the expectation operator $E_{0,u}$ is conditional on initial time and initial utiltiy type u, a_0 is initial holding position, and $da_t \in \{1, -1\}$.

The optimal asset-holding process for both customers and dealers are:

$$
a_t = \begin{cases} 1 & \text{if } u_t > rP; \\ 1 \text{ or } 0 & \text{if } u_t = rP; \\ 0 & \text{if } u_t < rP. \end{cases}
$$

By market clear condition, there exists $\exists! u^* \in [\delta_\ell, \delta_h] \cup \{y_\ell, y_h\}$ s.t. $P = \frac{u^*}{r}$ and u^* has the expression:

$$
u^* = \begin{cases} y_h & \text{if } s <= \pi_h; \\ inf\{u \in [\delta_\ell, \delta_h] : \pi_h + m - \int_{\delta_\ell}^u f(\delta)d\delta \leq s\} & \text{if } \pi_h < s < \pi_h + m; \\ y_\ell & \text{if } s >= \pi_h + m. \end{cases}
$$

Based on estimation results, we calculate the corresponding Walrasian prices based on reservation values of the marginal investors in OTC markets which solve (2)-(5):

For $\pi_h < s < \pi_h + m$: $$P = \frac{\delta^*}{r} = \triangle V(\delta^*) - \frac{c\lambda_1^{*2}(\delta^*) - c\lambda_0^{*2}(\delta^*)}{r} \quad (91)$$

D Proportions of different types of transactions in subperiods

We look at the relationship between the distribution of transactions of different types with distance of dealers' private valuations to cross-dealer mean level within each subperiod. Similar as Bessembinder, Jacobsen, Maxwell, and Venkataraman (2016), we divide the whole sample period into five subperiods: Pre-crisis (Jan 2006-Jun 2007), Crisis (Jul 2007-Apr 2009), Post-crisis (May 2009-Jun 2010), Regulation (Jul 2010-Mar 2014), Volcker (post April 1, 2014).

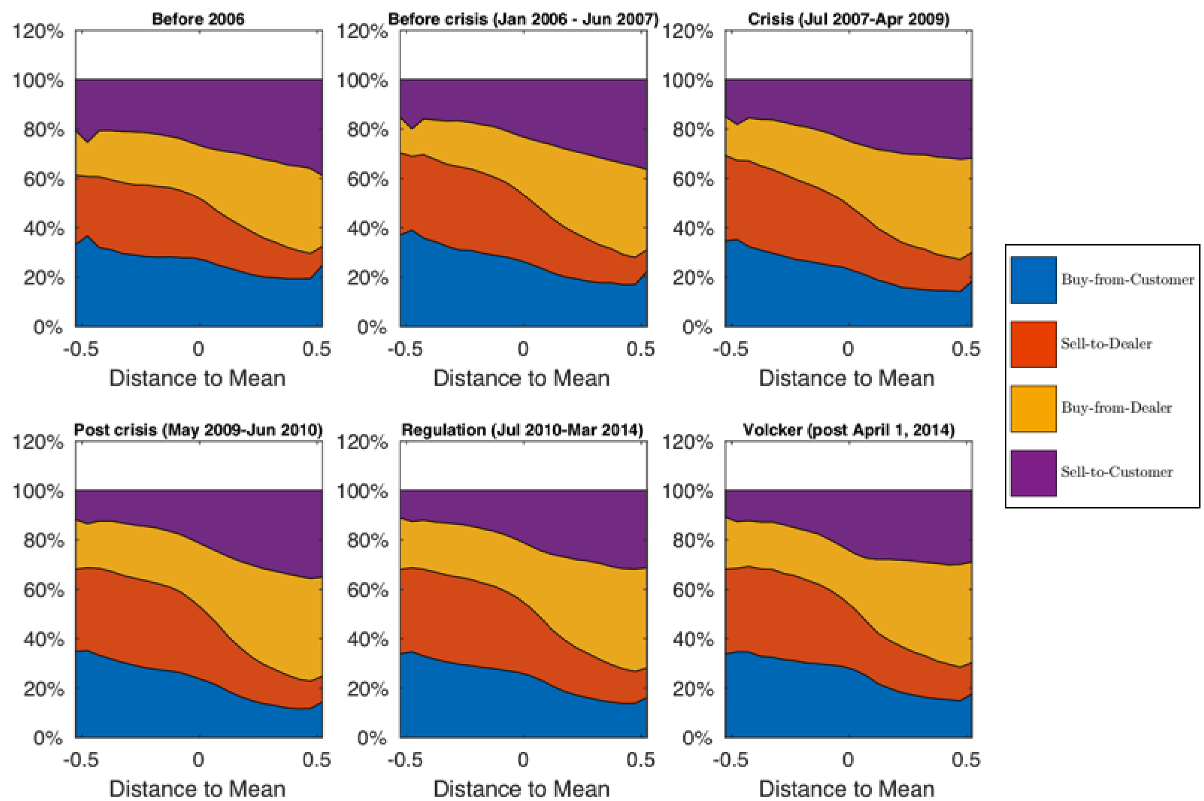

Figure 10: Dealer's private valuation and proportions of transactions in different directions (by subperiod)

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Internet Appendix

Robustness check: distribution of search intensity among dealers by monthly data

Specification of the same form with quarterly data

The quardratic fitting using monthly data has the following specification:

$$\widehat{\overline{\lambda}}^{j}_{i,t} = \beta_0 + \beta_1 \times \hat{\delta}^{j}_{S,i,t} + \beta_2 \times (\hat{\delta}^{j}_{S,i,t})^2 + \Gamma_1 X^{j}_{t} + \Gamma_2 Y_{i,t} + \tau_i + \phi_j + \eta_y + \epsilon^{j}_{i,t} \tag{1}$$

where the controls are similarly defined except for monthly basis. In Table 1, the results verify that total search intensity is still a hump-shaped function of dealers' (scaled) private valuation. In the lower range of private valuation, the upwards slope of total search intensity is driven by the increase in average selling intensity; and in the higher range, the downwards slope of total search intensity is driven by the decrease in average buying intensity.

Specification with alternative measure of distance to cross-dealer average private valuation

For each dealer i, we calculate $\frac{|\hat{\delta}^{j}_{i,t} - \hat{\overline{\delta}}^{j}_{t}|}{|\hat{\delta}^{j}_{h,t} - \hat{\delta}^{j}_{l,t}|}$ as the measure of distance of dealer i's private valuation type $\hat{\delta}^{j}_{i,t}$ to the cross-dealer mean level $\hat{\overline{\delta}}^{j}_{t}$ among the cross section of dealers within each bond j, which is further normalized by the difference between the maximum and minimum private valuations. To verify the model prediction about the shape of total search intensity

Table 1: Distribution of search intensity among dealers (quadratic form)

$Dep^j_{i,t}$	$\widehat{\overline{\lambda}}^j_{i,t}$	$\widehat{\overline{\lambda}}^{S,j}_{i,t}$	$\widehat{\overline{\lambda}}^{B,j}_{i,t}$
$\hat{\delta}^j_{S,i,t}$ (%)	8.2698***	5.4695***	3.3484***
	(6.30)	(8.97)	(3.58)
$(\hat{\delta}^j_{S,i,t})^2$	-0.0423***	-0.0172***	-0.0279***
	(-5.91)	(-6.33)	(-5.23)
$HHI^{bond}_{i,t}$ (thousands)	1.9031	3.0577***	-1.2108**
	(1.64)	(2.78)	(-2.46)
$HHI^{type}_{i,t}$ (thousands)	-6.9322***	-5.8018***	-0.6129
	(-4.27)	(-3.81)	(-0.83)
$HHI^{j,concen}_t$ (thousands)	-17.097***	-9.7139***	-7.6099***
	(-19.44)	(-12.42)	(-17.36)
$EV_{i,t}$	110.0916***	46.4680**	64.4953***
	(4.85)	(2.13)	(9.55)
$Rating^j_t$	2.0028***	3.1608***	-1.1348***
	(5.05)	(8.12)	(1.11)
$Pre3Mturnover^j_t$ (%)	0.2300***	0.1108***	0.1211***
	(6.31)	(5.89)	(5.6)
$amtout^j_t$ (million) (%)	-0.022***	0.0019	-0.0248***
	(-9.96)	(1.56)	(-13.81)
TTM^j_t (days)	1.1006***	0.9427***	0.2178*
	(3.57)	(3.25)	(1.84)
$Coupon^j$ (%)	-0.7678**	-2.9136	-10.8165
	(-2.28)	(-0.56)	(-1.54)
# of obs	11,606,655	11,434,333	11,406,360
$Adj\ R^2$	0.0593	0.0493	0.1241
Dealer×Bond×Year FE	YES	YES	YES

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered in dealer#bond#year.

among each cross section of dealers, we run the following regression:

$$\widehat{\overline{\lambda}}^j_{i,t} = \beta_0 + \beta_1 \times \frac{|\hat{\delta}^j_{i,t} - \hat{\overline{\delta}}^j_t|}{|\hat{\delta}^j_{h,t} - \hat{\delta}^j_{l,t}|} + \Gamma_1 X^j_t + \Gamma_2 Y_{i,t} + \tau_i + \phi_j + \eta_t + \epsilon^j_{i,t} \tag{2}$$

where all the other controls are same as (35) in the paper.

Regression results are in Table 2. where we also include $Trade^{j}_{i,t}$, $\widehat{\overline{\lambda}}^{S,j}_{i,t}$ and $\widehat{\overline{\lambda}}^{B,j}_{i,t}$ as dependent variables. The results indicate that average selling intensity always increases with private valuation on both sides of the cross-dealer mean level, and average buying intensity increases on the left side of the mean level and decreases on the right side. By composition effect, total search intensity increases on the left side of the mean level and decreases on the right side, which is mainly driven by decrease in buying intensity.

Table 2: Distribution of search intensity among dealers

$Dep_{i,t}^j$	$\widehat{\overline{\lambda}}_{i,t}^j$	$Trade_{i,t}^j$	$\widehat{\overline{\lambda}}_{i,t}^{S,j}$	$\widehat{\overline{\lambda}}_{i,t}^{B,j}$
$\frac{\lvert\hat{\delta}_{i,t}^j-\hat{\overline{\delta}}_t^j\rvert}{\lvert\delta_{h,t}^{\hat{j}}-\delta_{l,t}^{\hat{j}}\rvert}$	-136.2285***	-6.1430***	-85.3014***	-54.3122***
	(-24.77)	(-384.71)	(-13.58)	(-21.63)
$\frac{\lvert\hat{\delta}_{i,t}^j-\hat{\overline{\delta}}_t^j\rvert}{\lvert\delta_{h,t}^{\hat{j}}-\delta_{l,t}^{\hat{j}}\rvert} \times \mathbb{1}(\hat{\delta}_{i,t}^j > \hat{\overline{\delta}}_t^j)$			46.9200***	-40.2532***
			(7.27)	(-16.51)
$HHI_{i,t}^{bond}$ (thousand)	1.9887 *	2.82e-04	3.1318***	-1.1766***
	(1.71)	(0.05)	(2.86)	(-2.39)
$HHI_{i,t}^{type}$ (thousand)	-4.9329***	-0.0344***	-5.155***	0.2775
	(-3.04)	(-7.04)	(-3.39)	(0.37)
$HHI_t^{j,concen}$ (thousand)	-15.9301***	-0.446***	-9.1246***	-7.0549***
	(-18.12)	(-182.23)	(-11.68)	(-16.14)
$EV_{i,t}$	107.2886***	2.7191**	9.2142***	63.1459***
	(4.73)	(54.23)	(1.57)	(9.36)
$Rating_t^j$	1.5266***	0.0056***	2.2030***	-0.6837***
	(4.34)	(4.13)	(6.44)	(-6.45)
$Pre3Mturnover_t^j$ (%)	0.0022***	7.31e-05***	0.0010***	0.0013***
	(6.25)	(7.18)	(5.62)	(5.54)
$amtout_t^j$ (million)	-0.024***	-3.22e-04**	0.0028**	-0.0281***
	(-11.25)	(-2.52)	(2.40)	(-15.75)
TTM_t^j (days)	1.0714***	0.0067***	0.9386***	0.1920***
	(3.47)	(7.89)	(3.23)	(1.62)
$Coupon^j$ (%)	-0.6868**	-0.0459**	9.2142	-21.8105***
	(-2.19)	(-2.22)	(1.57)	(-3.08)
# of obs	11,606,655	11,606,655	11,434,333	11,406,360
$Adj\ R^2$	0.0593	0.1168	0.1241	0.1241
Dealer×Bond×Year FE	YES	YES	YES	YES

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered in dealer#bond#year.

Table 3: Mapping between Theoretical and Empirical Moments

Theoretical Moment (1)	Empirical Moment (2)
$\int_{\delta_\ell^j}^{\delta_h^j} \phi_1^j(\delta)\lambda_1^{j*}(\delta)\left(\frac{1}{1+m^j}+\frac{\rho^j}{m^j\Lambda^j}\right)\mu_{h0}^j d\delta$	$\hat{E}^j(Trade_{D2C}^j)$ (average selling-to-customer trades)
$\int_{\delta_\ell^j}^{\delta_h^j} \phi_0^j(\delta)\lambda_0^{j*}(\delta)\left(\frac{1}{1+m^j}+\frac{\rho^j}{m^j\Lambda^j}\right)\mu_{\ell 1}^j d\delta$	$\hat{E}^j(Trade_{C2D}^j)$ (average buying-from-customer trades)
$\int_{\delta_\ell^j}^{\delta_h^j} \phi_1^j(\delta)\lambda_1^{j*}(\delta)\frac{2m^j}{1+m^j}\int_{\delta}^{\delta_h^j}\frac{\lambda_0^{j*}(\delta')}{\Lambda^j}\phi_0^j(\delta')d\delta' d\delta$	$\hat{E}^j(Trade_{S2D}^j)$ (average selling-to-dealer trades)
$\int_{\delta_\ell^j}^{\delta_h^j} \phi_0^j(\delta)\lambda_0^{j*}(\delta)\frac{2m^j}{1+m^j}\int_{\delta_\ell^j}^{\delta}\frac{\lambda_1^{j*}(\delta')}{\Lambda^j}\phi_1^j(\delta')d\delta' d\delta$	$\hat{E}^j(Trade_{BfD}^j)$ (average buying-from-dealer trades)
$\dfrac{\int_{\delta_\ell^j}^{\delta_h^j}\frac{\lambda_1^{j*}(\delta)\phi_1^j(\delta)}{\Lambda_1^j}[(1-\theta^j)\triangle V^j(\delta)+\theta^j\triangle W^j(y_h^j)]d\delta}{\int_{\delta_\ell^j}^{\delta_h^j}\frac{\lambda_0^{j*}(\delta)\phi_0^j(\delta)}{\Lambda_0^j}[(1-\theta^j)\triangle V^j(\delta)+\theta^j\triangle W^j(y_\ell^j)]d\delta}-1$	$\hat{E}^j(Markup_D^j)$ (average dealer's markup)
$\Lambda_1^j=\int_{\delta_\ell^j}^{\delta_h^j}\phi_1^j(\delta)\lambda_1^{j*}(\delta)d\delta$	$\widehat{\Lambda_1}^j$ (aggregate selling intensity over all dealers)
$\Lambda_0^j=\int_{\delta_\ell^j}^{\delta_h^j}\phi_0^j(\delta)\lambda_0^{j*}(\delta)d\delta$	$\widehat{\Lambda_0}^j$ (aggregate buying intensity over all dealers)

Note: The $\hat{E}^j$ denotes sample mean, which is taken across all dealers within each bond j.

Table 4: Full reg results: distribution of search intensity among dealers (quadratic form)

$Dep^j_{i,q}$	$\widehat{\lambda}^j_{i,q}$	$\widehat{\lambda}^{S,j}_{i,q}$	$\widehat{\lambda}^{B,j}_{i,q}$
$\hat{\delta}^j_{S,i,q}$ (%)	1788.54***	968.84***	466.04***
	(36.92)	(35.77)	(28.12)
$(\hat{\delta}^j_{S,i,q})^2$	-8.93***	-4.54***	-2.57***
	(-36.89)	(-33.65)	(-30.97)
$EV_{i,q}$	11.71	24.66*	-21.32**
	(0.45)	(1.88)	(-2.44)
$HHI^{bond}_{i,q}$ (thousands)	-18.23**	-10.99***	-0.06
	(-2.48)	(-2.98)	(-0.02)
$HHI^{type}_{i,q}$ (thousands)	-3.77	5.85*	-12.98***
	(-0.60)	(1.87)	(-6.19)
$Coupon^j$ (%)	4296.98***	4015.50***	-106.40
	(4.65)	(14.12)	(-0.25)
$Rating^j_q$	13.30***	7.06***	-1.29***
	(9.72)	(10.52)	(-2.77)
$HHI^{j,concen}_q$ (thousands)	128.70***	50.53***	52.86***
	(31.18)	(25.14)	(38.06)
$turnover^j_{q-1}$ (%)	55.34***	22.42***	16.20***
	(107.92)	(89.65)	(94.12)
$AmtOut^j_q$ ($billion)	-1.11***	-0.25***	-0.43***
	(-10.72)	(-4.66)	(-13.27)
TTM^j_q (days)	0.78	0.26	1.17***
	(0.91)	(0.67)	(3.91)
# of obs	1,500,047	1,499,186	1,500,090
$Adj\ R^2$	0.1547	0.1241	0.1689
Dealer×Bond×Year FE	YES	YES	YES

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered in dealer#bond#year. $EV_{i,q}$ is dealer-i's eigenvector centuality in interdealer network in quarter q; $HHI^{bond}_{i,q}$ and $HHI^{type}_{i,q}$ are HHI index for dealer i in quarter q, which are calculated using dealer-i's shares of trading in different bonds and different directions. Those two indices measure whether a dealer specializes in trading specific bonds or in specific directions; $Coupon^j$, $Rating^j_q$, $AmtOut^j_q$, TTM^j_q are bond j's coupon rate, credit rating, outstanding amount and time to maturity in quarter q; $HHI^{j,concen}_q$ is an HHI index for bond j in quarter q, which is calculated using the bond's shares of trading completed by different dealers. This index measures whether a bond's trading is concentrated to a specific group of dealers; and $turnover^j_{q-1}$ is bond j's previous-quarter turnover rate.

Table 5: Full reg results: distribution of transactions of different directions

$Dep^j_{i,q}$	$V^j_{S2C,i,q}$	$V^j_{BfC,i,q}$	$V^j_{S2D,i,q}$	$V^j_{BfD,i,q}$
$\hat{\delta}^j_{S,i,q}$ (%)	2.29***	1.02***	2.08***	1.99***
	(28.56)	(21.68)	(21.76)	(28.09)
$(\hat{\delta}^j_{S,i,q})^2$	-0.0111***	-0.0054***	-0.0111***	-0.0094***
	(-27.41)	(-23.06)	(-23.37)	(-26.52)
$EV_{i,q}$	-2.36***	-0.94***	3.76***	5.89***
	(-25.06)	(-20.62)	(45.05)	(59.60)
$HHI^{bond}_{i,q}$ (thousands)	-0.08***	-0.06***	-0.20***	-0.25***
	(-7.91)	(-8.45)	(-24.52)	(-33.59)
$HHI^{type}_{i,q}$ (thousands)	-0.34***	-0.37***	0.26***	0.68***
	(-27.81)	(-46.50)	(21.83)	(60.15)
$Coupon^j$ (%)	-12.71**	0.29	-4.26*	-6.01***
	(-2.57)	(0.35)	(-1.86)	(-3.17)
$Rating^j_q$	0.01***	0.01***	0.02***	0.03***
	(3.20)	(5.89)	(9.77)	(11.70)
$HHI^{j,concen}_q$ (thousands)	-0.34***	-0.08***	-0.41***	-0.41***
	(-43.23)	(-13.84)	(-54.01)	(-60.21)
$turnover^j_{q-1}$ (%)	0.04***	-0.0043***	0.03***	0.03***
	(33.43)	(-6.27)	(27.23)	(36.32)
$AmtOut^j_q$ (\$tillion)	0.42**	0.58***	0.39***	0.48***
	(2.09)	(4.67)	(2.66)	(3.40)
TTM^j_q (days)	-0.0026	0.0099***	0.0047**	0.0063***
	(-1.27)	(8.42)	(2.58)	(4.00)
# of obs	1,500,090	1,500,090	1,500,090	1,500,090
Adj R^2	0.1731	0.2178	0.2193	0.2249
Dealer×Bond×Year FE	YES	YES	YES	YES

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered in dealer#bond#year. $EV_{i,q}$ is dealer-i's eigenvector centuality in interdealer network in quarter q; $HHI^{bond}_{i,q}$ and $HHI^{type}_{i,q}$ are HHI index for dealer i in quarter q, which are calculated using dealer-i's shares of trading in different bonds and different directions. Those two indices measure whether a dealer specializes in trading specific bonds or in specific directions; $Coupon^j$, $Rating^j_q$, $AmtOut^j_q$, TTM^j_q are bond j's coupon rate, credit rating, outstanding amount and time to maturity in quarter q; $HHI^{j,concen}_q$ is an HHI index for bond j in quarter q, which is calculated using the bond's shares of trading completed by different dealers. This index measures whether a bond's trading is concentrated to a specific group of dealers; and $turnover^j_{q-1}$ is bond j's previous-quarter turnover rate.