Bond Misallocation and Liquidity Risk*

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Abstract

Which corporate bond's yield is more exposed to search frictions? Is the exposure correlated with dealers' intermediation? We propose a measure of bond's misallocation among dealers and show its correlation with bond's liquidity risk which is attributed to search frictions. This measure is defined as the cross-sectional covariance of dealers' private valuations for a bond and their corresponding inventory positions. Using a transaction-level dataset on U.S. corporate bonds, we verify: a higher misallocation is associated with a higher magnitude of liquidity risk. A search-match model with dealers' endogeneous search efforts offers an explanation on this correlation.

Keywords: corporate bond market, bond misallocation, liquidity risk, search frictions
JEL Classifications: G10, G12, G20

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1 Introduction

U.S. corporate bonds trade in decentralized over-the-counter (OTC) markets, in which dealers provide liquidity to customer investors. Empirical studies starting from Collin-Dufresn, Goldstein, and Martin (2001) document that there is a common non-default component in the variations of all corporate bonds' yield spreads over time. This component can not be captured by bond fundamentals, firm-level fundamentals or macroeconomic variables. Later studies show that this common component is closely related to a market-level liquidity factor. Motivated by the theoretical rationalization on that OTC market frictions drive the liquidity-related part of transaction price in decentralized markets, Friewald and Nagler (2018) empirically show that OTC market frictions, namely systemic inventory, search and bargaining frictions, jointly explain a large proportion of the common component. However, to my best knowledge, there have not been papers talking about whether those market frictions drive different bonds' yield spreads by different magnitudes, and which market microstructural factors can explain this heterogeneity.

In this paper, we construct a measure of "bond's misallocation among dealers", and we find that this measure is closely correlated with bonds' heterogeneous yield spread loadings on the OTC search friction. The measure of a bond's misallocation is a moment of the joint distribution of dealers' two idiosyncratic states: private valuation for holding the bond and inventory position in the bond. Specifically, we define this measure as the covariance of those two states in the cross-section of dealers. At a lower and/or negative level of the cross-sectional covariance, there are more dealers of low private valuations holding the bond in their inventories, compared with a counterfactual frictionless market. In this case, the bond positions are more misallocated among the dealers, because in a frictionless market all the positions are held by dealers of relatively high private valuations. Correspondingly, a higher and positive level of the cross-sectional covariance implies a lower level of the bond's misallocation. The correlation between bond's misallocation and yield spread loading on the OTC search friction is motivated by the fact that in U.S. corporate bond markets, transactions happen bilaterally and the reallocation of bond positions rely on dealers' market-making and search efforts, which are costly and need to be compensated by transaction price. The OTC search friction determines how costly it is to invest in searching and make the market, and bond's misallocation determines how strong are dealers' incentives to make the market *at a given level of search friction*. In particular, a higher level of bond's misallocation leads to a higher portion of average transaction price compensating dealers for investment in searching and market-making, therefore the bond's price/yield is more sensitive to change in search friction over time.

Firstly, we use the TRACE data for the U.S. corporate bond market to test whether bonds have significantly heterogeneous yield spread loadings on the OTC search friction. Since the search friction is a market-level liquidity factor, in this paper, we also call yield spread loading as "bond's liquidity risk attributed to search frictions". This factor loading measures how much a bond's yield spread changes in response to one unit change in the OTC search friction. We use the length of intermediation chain as a measure of the OTC search friction. By theoretical rationalization in Hugonnier, Lester, and Weill (2018), the expected length of intermediation chain decreases with the level of search friction. Then we follow the literature to estimate bonds' heterogeneous liquidity risk attributed to search frictions in a reduced-form multi-factor model. Our estimation results are consistent with Friewald and Nagler (2018), and we further show that there is a high variation in the magnitude of liquidity risk across different bonds. In the cross-section of bonds, the standard deviation of the liquidity risk is more than three times of the mean level.

Secondly, we estimate the series of dealers' two idiosyncratic states, namely dealers' private valuations for holding each bond and their inventory positions in each bond, following the approaches in Liu (2020) and Hansch, Naik, and Viswanathan (1998). With the estimated series, we further construct a panel data which contains yearly series of empirical estimates on each bond's misallocation and liquidity risk. We verify that: at the bond level, a higher magnitude of misallocation among the dealers is associated with a higher magnitude of liquidity risk. This finding gives a preliminary market microstructural evidence which supports that: in a decentralized financial market, the distribution of market maker's idiosyncratic states correlates with the way by which the market-level friction drives the asset price over time.

Finally, we give a simple numerical explanation on the verified correlation between bond's misallocation and liquidity risk, by solving a search-and-match model with dealers' endogeneous search efforts. The numerical solutions show that in a stationary equilibrium with a higher level of bond misallocation, the higher gains from searching motivate more dealers to invest in a higher search intensity *at a given level of search friction*, to trade with each other and adjust their holding positions. As a result, the average search intensity across dealers in the cross-section is also high. With a qudratic-form search cost, the higher average search intensity also implies a higher average of marginal search costs across dealers, which is compensated by the bond's average transaction price. Therefore, the average search intensity across dealers is proxy for the *derivative* of the bond's price with respect to market-level search friction over time, and the empirical counterpart of this derivative is the bond's liquidity risk which is attributed to the OTC search friction. We also use the transaction level data to verify this channel. Specifically, we show that: [1] a dealer, whose bond position is more mis-aligned with her private valuation, is more likely to choose a higher search intensity and have a higher trading frequency; and [2] a bond, which is more misallocated among dealers, is more likely associated with a higher average search intensity across dealers in the market.

Related literature

This paper firstly contributes to the empirical literature initiated by Collin-Dufresn, Goldstein, and Martin (2001) that uncovers fundamental factors to explain U.S. corporate bonds' yield spread variations over time. In this literature, Collin-Dufresn, Goldstein, and Martin (2001) establish that there is an unexplained single common factor in corporate bonds' yield spreads after controlling for commonly used explanatory variables; Longstaff, Mithal, and Neis (2005) measure the size of the default and non-default components in corporate yield spreads, and show that the non-default component is related to bond-specific as well as macroeconomic measures of liquidity. Later papers add in other liquidity factors to improve the explanation, see Bao, Pan, and Wang (2011), De Jong and Driessen (2012), Bongaerts, De Jong, and Driessen (2017), Crotty (2013), Friewald and Nagler (2016), and He, Khorrami, and Song (2019), among others. Specifically, Friewald and Nagler (2018) attribute the unexplained part of the non-default component to over-the-counter (OTC) market frictions. In this paper, we specifically focus on bond's yield spread loading on the OTC search friction. Using similar measures, we further show that there is a high variation in the magnitude of this yield spread loading across different bonds. And we further construct a measure of bond's misallocation, and correlates it with the magnitude of the yield spread loading.

The model in this paper also belongs a 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. Our model studies a 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). Our model is most related to Hugonnier, Lester, and Weill (2018) in the setting of dealers' heterogeneous private valuation types and the incorporation of both the dealer and customer sectors in the model setup. The main difference 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 a homogeneous search intensity. Based on our model, we construct the covariance of private valuations and bond inventory positions in the cross-section of dealers as a measure of the bond's misallocation. Papers in this literature which also consider endogenous and/or heterogeneous search intensity include Shen, Wei, and Yan (2018), Neklyudov (2012), Üslü (2019), and Farboodi, Jarosch, and Shimer (2017), and etc.

This paper connects the empirical literature on explaining corporate bond's yield spread variations and the theoretical literature on studying the effects of OTC market structure on asset's price and liquidity. Most papers in the theoretical literature focus mainly on how searching and trading activities determine the transaction price and volume *between each two trading counterparties*. This paper instead focuses on giving a more structual explanation on bond-level yield spread patterns, rather than only bilateral-based terms of trade. Also, this paper considers the dealer-level market-making and searching behavior as a channel that connects the change in the OTC search friction and the bond-level yield spread variations. The empirical verification also motivates future theoretical research.

The rest of the paper is organized as follows: Section 2 describes the data we use. Section 3 describes and estimates bond's liquidity risk which is attributed to market-level search frictions. Section 4 proposes a measure of bond's misallocation and shows its correlation with bond's liquidity risk. Section 5 applies the numerical solution of a search-and-match model to provide an explanation on the correlation between bond's misallocation and liquidity risk. Section 6 tests the economics channel which is related to dealers' endogeneous search efforts, at both the dealer level and the market level. Section 7 concludes.

2 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 construct intermediation chains, and also construct the measure of bond misallocation within the dealer sector. [1] We filtered the data following the procedure in Dick-Nielsen (2014), and we recover the trading counterparties in locked-in and give-up trades[2].We merge

[1]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 of FINRA include broker-dealer firms, crowd-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.

[2]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).

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 dealerwise and bondwise variables[3].

Following the 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] To estimate bonds' factor loadings on OTC search frictions, we further drop the inactively traded bonds, defined as those which are traded in fewer than 25 months throught the whole sample period; [3] Finally, we exclude the "on-the-run" transactions which happened within three months since bonds' offering dates, to only consider secondary market transactions.

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.[4] Bonds on average have time to maturity as 7.6 years. There are 57,623,804 transactions with total par amount as \$27.8 trillion. The average trade size is \$482.41 thousand with standard deviation as \$4.47 thousand.

[3]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.

[4]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-.

3 Liquidity risk attributed to search frictions

In this paper, we specifically focus on bonds' liquidity risk attributed to over-the-counter (OTC) search frictions (henceforth "liquidity risk" for short). Friewald and Nagler (2018) show that changes in OTC market frictions can explain a large portion of variations in bond yield spreads, by fitting a multi-factor model using the same data set. The OTC market frictions they consider include search frictions, inventory frictions, and bargaining frictions, etc. Specifically, we follow the similar procedure to use the weighted average length of intermediation chain as a measure of OTC search frictions[5], and we regard the factor loading of bond yield spread[6] on the average chain length as the bond's liquidity risk attributed to OTC search frictions. We will show that the magnitude of this liquidity risk varies across different groups of bonds.

3.1 Length of intermediation chain

Intermediation chains were firstly constructed in Li and Schürhoff (2014) and Hollifield, Neklyudov, and Spatt (2017) to track how municipal bonds and securitization instruments are reallocated from a customer-seller to a customer-buyer through a series of dealers in the interdealer market. The length of an intermediation chain is defined as the number of dealers, through which the assets passed during the reallocation process. By Hugonnier, Lester, and Weill (2018), the expected length of intermediation chain decreases with the level of search frictions in the interdealer market. Specifically, in a more frictional interdealer market, it

[5]The weighted average length of intermediation chains is equal to the average number of dealers being involved in the intermediation process. Details about this measure are discussed in Appendix B.2.

[6]Yield spread is defined as the difference between corporate bond yield and the treasury yield whose term equals the corporate bond duration. Similar as in Crotty (2013), Friewald and Nagler (2018), etc, we calculate treasury yields of different terms through linearly interpolating between points on the treasury curve.

is more difficult for dealers to meet and trade with each other, so that there will be fewer dealers being involved in each reallocation of the asset between customers, then the average length of intermediation chain will be shorter.[7]

We calculate the average length of intermediation chain across all bonds for each month, using volumes of reallocation as weights. Figure 1 shows that the average chain length is relatively higher before the 2008 great financial crisis (GFS) when search frictions are relatively low in corporate bond markets. Then it decreases by as large as 6% during the crisis period when secondary market liquidity nearly dried up. Although the average chain length recovers slightly in the post-crisis period.[8], after Dodd-Frank act was signed into law in July, 2010, it further decreases by nearly 8% till the third quarter of 2015. This is consistent with the effects of Dodd-Frank act on restricting both dealers' proprietary tradings and dealers' liquidity provision to customers.

To verify that the average chain length is negatively correlated with the level of search frictions, we also plot the proportion of pre-arranged transactions in each month. This ratio tends to be higher when market is more frictional so that dealers are less willing to commit their capital to liquidity provision, but more willing to pre-arrange trades between buyers and sellers. In Figure 1, the ratio of pre-arranged trades is negatively correlated with the average length of intermediation chain.

[7]As market-level search frictions increase, although intermediation chains will on average be shorter, it does not necessarily mean the reallocations of assets between customers take shorter time.

[8]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).

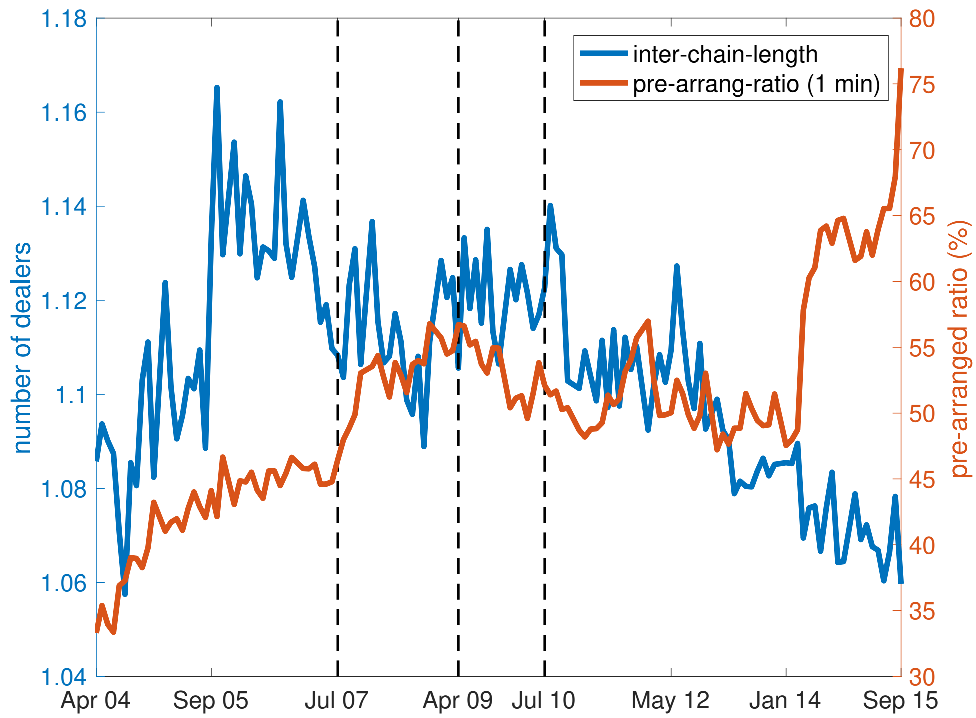

Figure 1: The value-weighted average length of intermediation chain (Apr 2004 - Sep 2015)

3.2 Bond liquidity risk

We estimate bonds' heterogeneous yield spread loadings on OTC search frictions using monthly panel data, and we use this factor loading as a measure of bond's liquidity risk attributed to search frictions. We calculate yield spread as the gap between bond's yield and the same-maturity treasury yield. Then we regress the change in yield spread on multiple regressors, including the regressors about the changes in other OTC market frictions in Friewald and Nagler (2018), regressors about the changes in market fundamental factors (e.g. equity pricing factors, market volatility, etc) in Fama and French (1993), Carhart (1997), Crotty (2013), and bond fundamentals. The yield spread loading on OTC search frictions is the estimate of bondwise coefficient on the regressor "average length of intermediation chain across all bonds". This coefficient measures how sensitively the non-default component of credit spread responds to the change in OTC search frictions. The model is as follows:

$$\triangle(YieldSpread)_{j,t} = \beta^j_{SysSearch}\triangle SystemChainLength_t + \beta^j_{SysNetConcen}\triangle SysNetConcen_t \tag{1}$$

$$+\beta^j_{MKT}R_{MKT,t} + \beta^j_{SMB}R_{SMB,t} + \beta^j_{HML}R_{HML,t} + \beta^j_{UMD}R_{UMD,t}$$

$$+\boldsymbol{\gamma}^j_1\triangle I_t + \boldsymbol{\gamma}^j_2\triangle B_t + \boldsymbol{\gamma}^j_3\triangle X^{(j)}_t + \epsilon_{j,t}$$

where $\triangle SystemChainLength_t$ is the change in the average length of intermediation chain, which is a proxy for shocks to OTC search frictions. Therefore, $\beta^j_{SysSearch}$ is the defined bond j's liquidity risk, and our main focus is to discuss how market structural factors (specifically, bond's misallocation among dealers) determine the magnitude of $\beta^j_{SysSearch}$. In Appendix B.4, we show that the factor loading $\beta^j_{SysSearch}$ is significantly priced in bonds' yield spreads.

The multi-factor model includes other controls as follows: [1] change in interdealer network concentration $\triangle SysNetConcen_t$, the network concentration is the summation of all dealers' average degree centralities[9] in month t; [2] returns on factor-portfolios $R_{MKT,t}$, $R_{SMB,t}$, $R_{HML,t}$ and $R_{UMD,t}$, namely market portfolio (S&P 500 portfolio), small-minus-big(SMB) portfolio, high-minus-low(HML) portfolio and up-minus-down(UMD) momentum-factor portfolio; [3] change in OTC inventory-related frictions
$\triangle I_t = (\triangle inv_{t-1}; \triangle amtout_t; \triangle prearrange_t)$, in which $\triangle inv_{t-1}$ is the one-month-lagged change

[9] Degree centrality is another measure of vertices' centralities in a network. Unlike eigenvector centrality, degree centrality only takes into account all direct links directed from or to each vertice. For a network with n vertices, the theoretical maximum value of the summation of all vertices' degree centralities is $n(n-1)$. Therefore, summation of all dealers' degree centralities in the interdealer network is a better measure of the concentration of the network. The closer the summation is to $n(n-1)$, where n is the number of dealers, the less concentrated the interdealer network is.

in all dealers' inventories in all bonds, $\triangle amtout_t$ is the change in all bonds' amount outstanding, $\triangle prearrange_t$ is the change in pre-arranged ratio of all transactions; [4] change in OTC bargaining frictions $\triangle B_t = (\triangle blocktrade_t; \triangle HHIdealer_t)$, in which $\triangle blocktrade_t$ is the change in the proportion of block trades, and $\triangle HHIdealer_t$ is the change in the average value of all bonds' HHI indices[10]; [4] all the other bondwise and market-aggregate controls $\triangle X_t = (\triangle(YieldSpread)_{j,t-1}, \triangle RF_t; (\triangle RF_t)^2; \triangle SLOPE_t; \triangle turnover_t^j; Rating_t^j; TTM_t^j)$ in Collin-Dufresn, Goldstein, and Martin (2001) and Friewald and Nagler (2018), in which $\triangle(YieldSpread)_{j,t-1}$ is the lagged term of change in yield spread, $\triangle RF_t$ is the change in 10-year treasury rate, $(\triangle RF_t)^2$ is the square value to capture potential non-linear effect, $\triangle SLOPE_t$ is the change in the slope of yield curve, $\triangle turnover_t^j$ is the change in bond j's current-month turnover rate, $Rating_t^j$ is bond j's credit rating in month t and TTM_t^j is bond j's time to maturity in month t.

The mean value of $\beta^j_{SysSearch}$ across all bonds is significantly negative, as shown in Table 1. This indicates that, when intermediation chains are longer (in other words, OTC search frictions decrease), bond's yield spread will decrease. The signs of other reported average coefficients in Table 1 are consistent with those in Friewald and Nagler (2018). The full regression results are in 6 in Appendix B.1.

However, the average magnitude of $\beta^j_{SysSearch}$ is significantly heterogeneous among different groups of bonds. We divide the whole sample of bonds into different groups based on bonds' credit rating and time to maturity. Table 2 shows that the factor loading $\beta^j_{SysSearch}$ has higher absolute values for high-yield bonds and/or bonds with a longer time to matu-

[10] Block trades are defined as trades with trading volume being larger than $\$1,000,000$. Each bond's HHI index is calculated by using all dealers' market shares in that bond. Both variables are proxy for systemic bargaining frictions in the U.S. corporate bond market: the higher the ratio of block trades is, the more bargaining power the corporate bond customers (investors) have, and the higher the average value of all bonds' HHI indices is, the more concentrated are bonds' transactions to a subset of dealers, therefore, the lower bargaining power of the customers (investors) have

Table 1: Bond-level liquidity risk

$\triangle(YieldSpread)_{j,t}$ (%)	(1)	(2)	(3)
$\triangle SystemChainLength_t$	-2.32***	-1.67***	-1.55***
	(-32.80)	(-21.38)	(-21.38)
$\triangle SysNetConcen_t$ (thousand)	-9.83e-03***	-4.77e-03***	-4.43e-03***
	(-48.16)	(-22.30)	(-20.10)
$\triangle inv_{t-1}$ ($trillion)	7.55***	5.55***	5.74***
	(24.07)	(16.39)	(17.51)
$\triangle prearrange_t$ (%)	0.26***	1.28***	1.08***
	(3.43)	(15.87)	(13.43)
$\triangle blocktrade_t$ (%)	-66.67***	-29.29***	-28.65***
	(-50.94)	(-22.37)	(-22.15)
$\triangle amtout_t$ ($trillion)	-0.32***	-0.47***	-0.38***
	(-6.17)	(-8.12)	(-6.54)
$\triangle HHIdealer_t$ (thousand)	-1.04***	-0.67***	-0.67***
	(-46.70)	(-28.99)	(-30.82)
$Mean\ Adj\ R^2$	0.18	0.35	0.37
$\#ofBonds$	11176	11176	9595
$\#ofObs$	515514	515514	479146
market aggregates and FFC 4 factors	NO	YES	YES
bond liquidity and fundamentals	NO	NO	YES

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. In Panel A, we exclude bonds with total number of observations smaller or equal to 19 for model (1)-(2) and smaller or equal to 25 for model (4). The reported estimated coefficients are average values taken across all bonds. The corresponding t-statistics are calculated by dividing each reported (average) coefficient value by the standard deviation of the estimates and scaling by the square root of the number of bonds.

rity. The higher the absolute value of $\beta^j_{SysSearch}$ is, the more sensitively the bond j's yield spread responds to shocks to OTC search frictions. Our next focus is to construct a new market microstructural variable, bond's misallocation among dealers, and use it to explain why different bonds have different magnitudes of liquidity risk attributed to OTC search frictions.

Table 2: Group-level liquidity risk

$\triangle(YieldSpread)_{j,t}$ (%)	(1)	(2)	(3)
$\triangle SystemChainLength_t$	-0.38***	-0.32***	-0.15*
	(-8.99)	(-6.29)	(-1.92)
$\triangle SystemChainLength_t \times \mathbb{1}\,(HY\_bonds)$		-0.19*	
		(-2.34)	
$\triangle SystemChainLength_t \times \mathbb{1}\,(TTM\_2nd)$			-0.57***
			(-5.20)
$\triangle SystemChainLength_t \times \mathbb{1}\,(TTM\_3rd)$			-0.43***
			(-3.98)
$Adj\ R^2$	0.1307	0.1307	0.1308
$\#ofBonds$	11703	11703	11703
$\#ofObs$	523586	523586	523586
market aggregates and FFC 4 factors	YES	YES	YES
bond liquidity and fundamentals	YES	YES	YES
OTC inventory and bargaining friction	YES	YES	YES

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. In Panel A, we exclude bonds with total number of observations smaller or equal to 19 for model (1)-(2) and smaller or equal to 25 for model (4). The reported estimated coefficients are average values taken across all bonds. The corresponding t-statistics are calculated by dividing each reported (average) coefficient value by the standard deviation of the estimates and scaling by the square root of the number of bonds. In Panel B: TTM_1st: 13 days∼3 years, TTM_2nd: 3∼6 years, TTM_3rd: $>$ 6 years.

4 Correlation between bond misallocation and liquidity risk

In this section, we construct a measure of bond's misallocation among dealers, and show that this measure is closely correlated with the magnitude of bond's liquidity risk. The main takeaway is: a bond which is more misallocated among the dealers has its yield spread being more exposed to shocks to OTC search frictions, because the dealers are more willing to reallocate the bond between themselves and a larger portion of the bond price will compensate the dealers for paying the search costs.

4.1 Bond misallocation among dealers

For each bond, we define its misallocation among dealers as the cross-sectional covariance of dealers' idiosyncratic private valuations[11] for holding the bond and their actual inventory positions in the bond. In the dealer sector, if there are more (less) low(high)-private-valuation dealers holding the bond, the level of this covariance will be lower, then we regard the bond as being more misallocated among the dealers.

Theoretical counterpart of bond misallocation The measure of bond misallocation is based on a structural search model with endogeneous search efforts. In this section, we give an overview on the model environment and a simple numerical example to show that a higher (lower) level of the cross-sectional covariance of dealers' private valuations and bond inventories implies a lower (higher) magnitude of bond misallocation among dealers.

The model environment is: there are two sectors of agents in the market, a continuum of customers with physical measure normalized to 1 and a continuum of dealers with physical measure as $m \leq 1$. Dealers and customers search and trade a single bond with fixed supply s. Each participant's bond position a is assumed to be either zero or one.[12] Each participant has a private valuation for the bond: customers' private valuation takes two possible values, either low or high, denoted by $y \in \{y_\ell, y_h\}$ with $y_\ell < y_h$, and follows a discrete distribution

[11]In the spirit of Duffie, Gârleanu, and Pedersen (2005), dealers' idiosyncratic private valuations can be understood as their idiosyncratic preferences in holding the bond, which can be determined by their idiosyncratic liquidity needs, financing costs, and hedging needs, etc. Within each bond, dealers can be ranked by their private valuation types. For example, a dealer who has a higher liquidity need or financing cost than other dealers will manifest a lower private valuation for holding the bond than others.

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

$P(y' = y_c) = \pi_c$, $c = \ell, h$; dealers' private valuations $\delta \in [\delta_\ell, \delta_h]$ lie in between customers' low type and high type, and follow a continuous distribution $f_D(\delta)$. The two types of customers cannot directly trade with each other, so the bond needs to be intermediated through the dealer sector. One position of the bond can be sold from a low-type customer to a dealer, and transacted between several dealers, and then finally sold to a high-type customer. Each customer periodically receives an idiosyncratic shock with Poisson intensity α, which makes her valuation switch between the high type and low type. This shock generates the fundamental trading needs in the market. Dealers do not receive such valuation shock, so their relative valuations remain fixed over time. Dealers endogeneously choose their search efforts $\lambda(a, \delta)$ based on their idiosyncratic states (a, δ), and pay a search cost $c \times \lambda^2(a, \delta)$ at each time, where $c > 0$ is a proxy for the market-level OTC search frictions.

The model generates a stationary equilibrium which includes a density function $\phi_1(\delta)$. The value of $\phi_1(\delta)$ on each $\delta \in [\delta_l, \delta_h]$ is the probability that a dealer with private valuation δ holds one position of the bond, i.e. this dealer is a dealer-owner in stationary equilibrium. Correspondingly, the probability that this dealer with private valuation δ is a dealer-nonowner is denoted as $\phi_0(\delta) = f_D(\delta) - \phi_1(\delta)$. As a result, the shape of the density function $\phi_1(\delta)$ determines how the bond is allocated among dealers, and it uniquely maps to the level of the cross-sectional covariance $Cov(\delta, a)$ of dealers' private valuations and bond positions. The covariance has the following form:

$$Cov(\delta, a) = \sum_{a \in \{0,1\}} \int_{\delta_\ell}^{\delta_h} (a - \overline{a}_d)(\delta - \overline{\delta}_d) \frac{\phi_a(\delta)}{m} d\delta = \int_{\delta_\ell}^{\delta_h} (\delta - \overline{\delta}_d) \frac{\phi_1(\delta)}{m} d\delta \tag{2}$$

where $\overline{\delta}_d$ is the average value of dealer's private valuation and has an expression as $\sum_{a \in \{0,1\}} \int_{\delta_\ell}^{\delta_h} \delta \phi_a(\delta) d\delta = \int_{\delta_\ell}^{\delta_h} \delta f_D(\delta) d\delta$. Based on the final expression $\int_{\delta_\ell}^{\delta_h} (\delta - \overline{\delta}_d) \frac{\phi_1(\delta)}{m} d\delta$ in

(2), we can regard the cross-sectional covariance $Cov(\delta, a)$ as a weighted average of $(\delta - \overline{\delta}_d)$, with the values of the density function $\phi_1(\delta)$ as weights.

The value of $Cov(\delta, a)$ is negatively correlated with the level of the bond's misallocation among dealers. For example, if there is a larger proportion of the bond positions being held by low-private-valuation dealers, in the term $\int_{\delta_\ell}^{\delta_h}(\delta - \overline{\delta}_d)\frac{\phi_1(\delta)}{m}d\delta$ larger weights will be imposed on lower δ, which leads to a lower value of $Cov(\delta, a)$.

A numerical example of this model is shown in Figure 2. The area below the density function $\phi_1(\delta)$ is equal to the total amount of bond positions being held by dealers. Suppose in Walrasian (frictionless) market, the minimum private valuation among all the dealer-owners is the middle level $\frac{\delta_l+\delta_h}{2}$, then we call the dealer of this level of private valuation as the "marginal investor". Since in Walrasian market all of the bond positions are held by dealers and customers with private valuations higher than this middle level, we assume there is *no* bond misallocation among dealers in the frictionless case. Then in any over-the-counter (OTC) market with search frictions, we regard any bond positions which are held by dealers with private valuations lower than this middle level $\frac{\delta_l+\delta_h}{2}$ as being misallocated. In the right graph of Figure 2, there are two OTC markets with the same level of search frictions but different levels of bond misallocations.[13] Market-1 has a relatively lower amount of bond positions being misallocated than market-2. The difference in the amount of misallocated positions between the two markets is the pink area in the figure. Correspondingly, the cross-sectional covariance $Cov(\delta, a)$ is higher in market-1 than in market-2.

Data estimate on bond misallocation We estimate the monthly series of dealers' idiosyncratic private valuations using realized transaction prices. Detailed explanations on the

[13]We apply the parameter α (the Poisson intensity at which customers receive idiosyncratic shock) to control the level of bond misallocation in OTC markets. The reason is discussed in more details in Section 5.

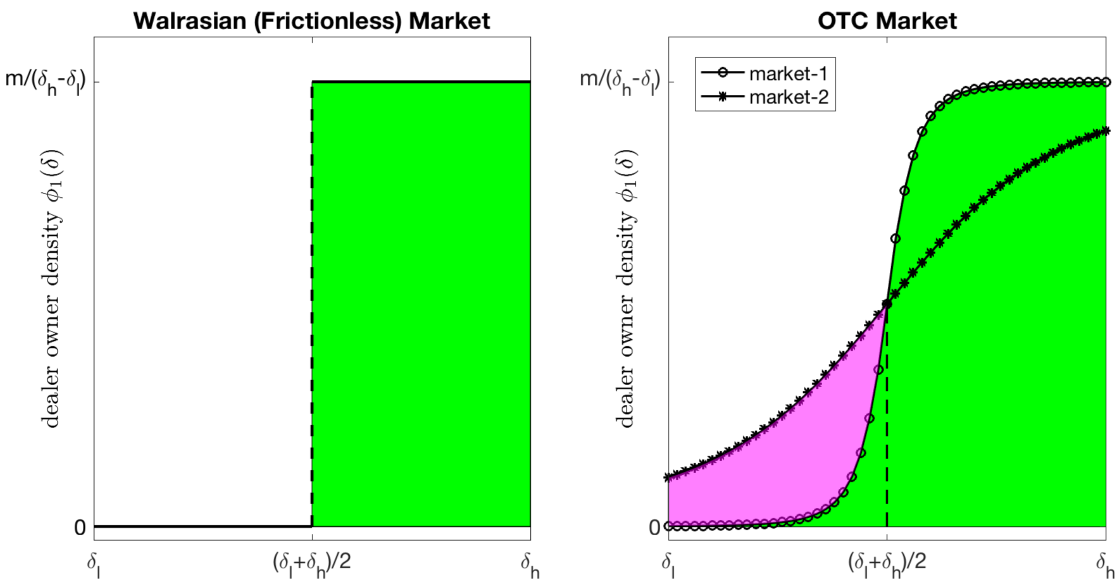

Figure 2: Numerical example of dealer owner density function and bond misallocation (**Walrasian market**: $Cov(\delta, a) = 0.130$. **market-1**: $Cov(\delta, a) = 0.103$, $c = 0.07$, $\alpha = 10^{-4}$. **market-2**: $Cov(\delta, a) = 0.092$, $c = 0.07$, $\alpha = 1$. **Other parameters and functions**: $s = m = \frac{1}{2}$, $f_D(\delta) \equiv 1$, $\forall \delta \in [\delta_\ell, \delta_h]$)

estimator is in Appendix A. For each bond-month pair, each dealer's private valuation is the simple average of the dealer's maximum buying price and minimum selling price for that bond-month pair. The estimator of a dealer's private valuation type δ is as follows[14]:

$$\hat{\delta}_{i,t}^{j} = \frac{max\{Buy^{j}_{i,n^{j,B}_{i,t}}\} + min\{Sell^{j}_{i,n^{j,S}_{i,t}}\}}{2} \tag{3}$$

[14]In finite samples, on the buy side of each dealer, the maximum buying 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 buying 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.

where $\{Buy^j_{i,n^{j,B}_{i,t}}\}$ ($\{Sell^j_{i,n^{j,S}_{i,t}}\}$) 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 correspondinng number of total buying (selling) transactions (including both dealer-customer and interdealer transactions) in month t.

We follow the procedure in Hansch, Naik, and Viswanathan (1998) to estimate the monthly series of dealers' inventory positions. We use $Q^j_{i,t}$ to denote the (unobservable) dealer i's inventory position in bond j and month t, s.t. $0 \leq t \leq T$, where T is the last month of our sample. We use $q^j_{i,t}$ to denote the corresponding observable signed net trading volume, which is positive (negative) when the dealer i increases (shrinks) her inventory position of bond j in month t. With unobservable initial inventory $Q^j_{i,0}$, $Q^j_{i,t}$ satisfies:

$$Q^j_{i,t} = Q^j_{i,0} + \sum_{s=1}^{t} q^j_{i,s} \tag{4}$$

Then we construct the standardized inventory for each dealer i, bond j and month t:

$$I^j_{i,t} = \frac{Q^j_{i,t} - \bar{Q}^j_i}{\sigma^j_i} \tag{5}$$

where $\bar{Q}^j_{i,t} = \frac{\sum_{s=0}^{T} Q^j_{i,s}}{T+1}$ and $\sigma^j_i = \sqrt{\frac{\sum_{s=0}^{T}(Q^j_{i,s} - \bar{Q}^j_{i,t})^2}{T}}$ are the sample mean and standard deviation of the monthly series.[15]

The standardized inventory $I^j_{i,t}$ essentially measures by how much the current inventory $Q^j_{i,t}$ deviates from the unobserved target level $\bar{Q}^j_{i,t}$, and the deviation is scaled by the volatility of the series within each pair of dealer i and bond j. By similar derivation in Hansch, Naik, and Viswanathan (1998), this standardization [1] excludes the effect of unobserved

[15]For a robustness check, we also follow Friewald and Nagler (2016) to calculate $\bar{Q}^j_{i,t}$ and $\sigma^j_{i,t}$ only using series of signed trading volumes within the fixed rolling time window $[t, t-R]$. We obtain similar results for our quantitative analysis.

initial inventory position $Q^j_{i,0}$ after issuance[16], and writes standardized inventory as a linear combination of a series of signed net trading volumes $\{q^j_{i,s}\}$; and [2] controls for differences in risk aversion to guarantee the comparability of inventories across dealers (see Friewald and Nagler (2016)).

With the estimated monthly series $\{\hat{\delta}^j_{i,t}\}$ and $\{I^j_{i,t}\}$, we calculate the cross-sectional covariance for each year by the following two steps: firstly, for each pair of dealer i and bond j in year y, we separately calculate the dealer's yearly weighted average of private valuation $\hat{\delta}^j_{i,y}$ and yearly weighted average of inventory position $I^j_{i,y}$, using the dealer's monthly trading volumes in year y as weights; secondly, for bond j and year y, we pool all dealers' yearly private valuations $\{\hat{\delta}^j_{i,y}\}_{i\in D_y}$ and inventory positions $\{I^j_{i,y}\}_{i\in D_y}$ together, and calculate the cross-sectional covariance as follows:

$$\widehat{Cov}(\hat{\delta}^j_{i,y}, I^j_{i,y}) = \frac{1}{N^y_d}\sum_{i\in D_y}\left(\hat{\delta}^j_{i,y} - \overline{\hat{\delta}}^j_y\right) * \left(I^j_{i,y} - \overline{I}^j_y\right) \tag{6}$$

where D_y is the collection of all the dealers who completed at least one transaction in bond j on both the buy and sell sides of the market in year y, and N^y_d is the number of dealers in group D_y; $\overline{\hat{\delta}}^j_y$ and $\overline{I}^j_y$ are the simple cross-dealer means of private valuation and inventory position in year y.

[16]We calculate the series of standardized inventory $\{I^j_{i,t}\}$ before dropping bond transactions during a 3-month on-the-run period following issuance.

4.2 Correlation between bond misallocation and bond liquidity risk

In this section, we show that bonds with a lower level of cross-sectional covariance of dealers' private valuation and inventory position (i.e. a higher magnitude of misallocation) will have its yield spread more exposed to shocks to OTC search frictions (i.e. a higher magnitude of liquidity risk). This finding gives a preliminary market microstructural evidence which shows that: the distribution of market maker's states correlates with the magnitude of corporate bond's liquidity risk.

To verify this correlation, we construct a yearly panel data on corporate bonds' factor loadings on OTC search frictions $\beta^j_{SysSearch,y}$ and within-bond average cross-sectional covariance $\overline{\widehat{Cov}}_y(\hat{\delta}^j_{i,ey}, I^j_{i,ey})$. Specifically, $\beta^j_{SysSearch,y}$ is estimated for bond j which has transactions completed in year y, using bond j's all transactions within the time window $[1, y]$. Correspondingly, $\overline{\widehat{Cov}}_y(\hat{\delta}^j_{i,ey}, I^j_{i,ey})$ is constructed as a weighted average of bond j's yearly cross-sectional covariance throughout all years $ey \in [1, y]$. Therefore, to construct each point $(\beta^j_{SysSearch,y}, \overline{\widehat{Cov}}_y(\hat{\delta}^j_{i,ey}, I^j_{i,ey}))$ in the yearly panel data, we make use of all the cumulative information until year y on bond transactions, market microstructure, bond fundamentals, and market aggregates, etc.

We estimate the following reduced-form model to verify the correlation between bond's misallocation $\overline{\widehat{Cov}}_y(\hat{\delta}^j_{i,ey}, I^j_{i,ey})$ and liquidity risk $\beta^j_{SysSearch,y}$:

$$\beta^j_{SysSearch,y} = \alpha_0 + \alpha_1 * \overline{\widehat{Cov}}_y(\hat{\delta}^j_{i,ey}, I^j_{i,ey}) + \boldsymbol{\alpha}_2 F^j_y + \eta_y + \epsilon^j_y \tag{7}$$

where the vector F^j_y includes the weighted averages of bond fundamentals, proportions of interdealer and dealer-customer transactions, liquidity measures, etc, and the year fixed effect

η_y controls the time window of cumulative information used to construct the data points.

The regression results in Table 3 indicate that, at the bond level, a higher magnitude of misallocation among the dealers (a lower level of $\widehat{Cov}_y(\hat{\delta}^j_{i,ey}, I^j_{i,ey})$) is associated with a higher magnitude of liquidity risk (a higher absolute magnitude of $\beta^j_{SysSearch,y}$).

Table 3: Correlation of bond misallocation and liquidity risk

$\beta^j_{SysSearch,y}$ (< 0)	(1)	(2)	(3)	(4)
$\widehat{Cov}_y(\hat{\delta}^j_{i,ey}, I^j_{i,ey})$ $(1,000 \times \%)$	0.25***	0.25***	0.25***	0.22***
	(6.00)	(6.00)	(5.99)	(5.14)
$turnover^j_y$ (%)		0.06	0.09	0.06
		(0.78)	(1.07)	(0.50)
$Num\_DD^j_y$ (thousand)			-0.64***	-0.47**
			(-4.23)	(-3.07)
$Num\_DC^j_y$ (thousand)			0.26**	0.20*
			(2.92)	(2.11)
$Amtout^j_y$ ($trillion)				-17.81
				(-0.24)
TTM^j_y (thousand days)				0.06***
				(5.47)
$Rating^j_y$				0.06***
				(4.56)
$Adj\ R^2$	0.02	0.02	0.03	0.03
F statistics	52.11	47.82	43.12	38.26
# of Bonds	4754	4754	4754	4754
# of Obs	22359	22359	22359	22359
Year FE	YES	YES	YES	YES

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All the following variables are weighted averages within the time window $[1, y]$: $turnover^j_y$ is turnover rate which is the ratio of total trading volume to total outstanding amount; $Num\_DD^j_y$ and $Num\_DC^j_y$ are numbers of interdealer- and dealer-customer transactions; bond fundamentals include outstanding amount $Amtout^j_y$, time to maturity TTM^j_y, and credit rating $Rating^j_y$.

Finally, in Table 9 of Appendix B.4, we show that the bond-level liquidity risk attributed to OTC search frictions is on average compensated by 8 bps yield spread across all bonds. We extend the yearly panel data by adding the cumulative weighted average yield spread for each observation point in the data. Therefore, the amount of yield spread compensating each unit of liquidity risk is also at a weighted aveage level on a cumulative basis. It varies across different bonds with a maximum value as high as 66 bps. In the cross-section of bonds, one standard deviation increase in liquidity risk is associated with about 18 bps increase in yield spread.

5 Numerical explanation by search-and-match model

In this section, we apply the numerical solutions of the model in Section 4.1 with different sets of parameters to give an explanation for the correlation between bond's misallocation and liquidity risk. The numerical solutions imply that dealers' endogeneous and state-dependent search intensity works as an important channel.

The mechnism is: in equilibrium where the covariance of dealers' private valuation and inventory position is at a low level, there are more dealers holding bond positions that are less aligned with their private valuation types. Specifically, there is a larger proportion of dealers who hold higher(lower)-than-average inventory positions but have lower(higher)-than-average private valuation types. This motivates more dealers in the market to spend a higher level of search effort to buy or sell to adjust their holding positions. We denote the average level of search effort in the dealer sector as $\frac{\Lambda}{m}$, where $\frac{\Lambda}{m} = \int_{\delta_\ell}^{\delta_h} \lambda(1,\delta)\frac{\phi_1(\delta)}{m}d\delta + \int_{\delta_\ell}^{\delta_h} \lambda(0,\delta)\frac{\phi_0(\delta)}{m}d\delta$, and Λ is the aggregate of all dealers' search intensities. With a qudratic-form search cost $c \times \left(\frac{\Lambda}{m}\right)^2$, the average level of marginal search cost across dealers can be approximated by $2c \times \frac{\Lambda}{m}$. Since this average marginal cost will be compensated by bond's average price (yield), those bonds with a higher average search effort across dealers $\frac{\Lambda}{m}$ will have their average transaction price (yield) more exposed to shocks to OTC search frictions c.[17]

In Figure 3, we draw the numerical solutions of the stationary equilibria in six markets with different levels of bond misallocation $Cov(\delta, a)$.[18] We focus on how bond's liquidity risk attributed to OTC search friction c varies across different markets *at each level of* c. In this figure, bond's average transaction price $\overline{P}$ is defined as the weighted average price across all transactions, and bond's price sensitivity to OTC search frictions is then defined as the corresponding derivative $\frac{\partial \overline{P}}{\partial c}$. This derivative has negative values since a higher level of search friction implies a lower level of average transaction price to compensate dealers and customers with a higher yield. Since bond's price fully determines its yield spread under a fixed risk-free rate, $\frac{\partial \overline{P}}{\partial c}$ can also be regarded as a theoretical counterpart of the bond liquidity risk $\beta_{SysSearch}$ as estimated in data. In graph-F of Figure 3, we further construct the derivative of bond's yield with respect to search frictions c, which approximates the *negative/absolute level* of the factor loading $\beta_{SysSearch}$.[19]

The numerical solutions verify that a bond with a higher magnitude of misallocation

[17]There also exists a second-order effect of change in search friction c on the aggregate search intensity Λ, but the magnitude of this effect is dominated by the first-order effect when equilibrium aggregate search intensity is at a high level.

[18]Specifically, we vary the Poisson intensity α at which customers' private valuation types switch between low and high values, to generate the varying level of bond misallocation $Cov(\delta, a)$ across the markets. Intuitively, for a bond with a higher α, customers receive i.i.d. shocks on their private valuation types at a higher intensity which drives customers to more frequently search to trade with randomly selected dealers. This increases the likelihood that a low-type dealer-nonowner or a high-type dealer-owner meets and trades with customers, because there always exists a positive trading surplus between a high-type customer-nonowner (low-type customer-owner) and any dealer-owners (dealer-nonowners). Therefore there will be a larger proportion of dealers holding inventory positions which are not well-aligned with their private valuation types and the value of $Cov(\delta, a)$ will be lower.

[19]Bond's yield is approximated by the formula $ApproxYTM = \frac{C + \frac{F-P}{n}}{\frac{F+P}{2}}$ where we choose time to maturity $n = 5$, face value $F = 100$, and coupon rate $C = 0$.

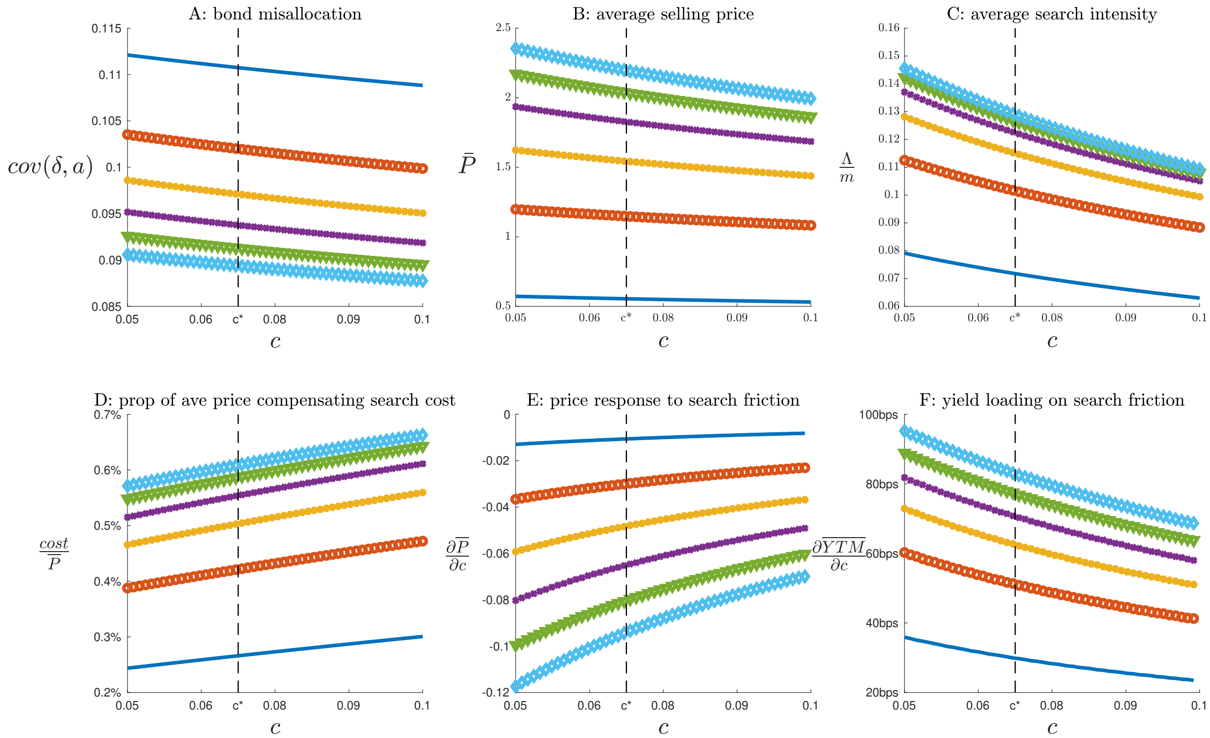

Figure 3: Aggregate trading incentive and bond price sensitivity to search friction ($s = \pi_h = 0.5$, $y_\ell = 0.5$, $y_h = 1.7$, $\delta_\ell = 0.6$, $\delta_h = 1.6$, $\rho = m = \theta = 0.5$, $r = 0.05$, $c \in [0.05, 0.1]$ and $\alpha \in [0.25, 0.75]$)

has a higher (absolute) magnitude of liquidity risk *at every level of search friction*. For example, we fix the search cost coefficient at c^*: when we move from the market with the lowest magnitude of bond misallocation (the top curve in graph-A with $\alpha = 0.25$) to the market with the highest magnitude of bond misallocation (the bottom curve in graph-A with $\alpha = 0.75$), the *absolute magnitude* of bond's liquidity risk attributed OTC search frictions $\frac{\partial \overline{YTM}}{\partial c}$ will increase across markets. The market-level average search intensity also increases across markets, which raises up the proportion of average price compensating search cost by graph-D.

6 Testing the endogeneous-search channel

In this section, we testify the economics channel which is related to dealers' endogeneous search efforts, at both the dealer level and the market level. Firstly, we estimate dealers' search intensities for each bond based on the search-and-match model in Section 4.1. The details about the estimation[20] are in Section C.2. Secondly, at the dealer level, we show that a dealer will choose a higher search intensity for a bond, if the dealer's inventory position is mis-aligned with her private valuation. Finally, at the market level, we show that a bond, whose misallocation measure is at a higher level, tends to have a higher average search intensity across all the dealers who trade this bond. For testing at both the dealer level and the market level, we estimate and use monthly series of search intensities, private valuations, inventory positions, and bond misallocations, etc. The purpose of using the monthly series is to show the dynamic process of dealers' adjustment in their search intensities works as a microfoundation for the correlation between bond's misallocation and liquidity risk over time. We define each market as a combination of bond j and month t.

Dealer-level search efforts At the dealer level, we estimate the model with the following specification, to show that dealers with inventory positions more mis-aligned with their

[20] We only estimate the search intensities up to a *same* constant for all dealers, since we are more interested in the *trend* of search intensity across dealers within the same cross section, and the *trend* of average search intensity when we move across markets with different bond misallocations. Also in this paper, since our focus is the documented correlation between bond's misallocation and liquidity risk, for the model part, we do not provide the details about: formally defining and proving the existance of stationary equilibrium, estimation of other model parameters except for dealers' search intensities, etc. Such details can be referred in Liu (2020).

private valuations are likely to choose higher search intensities:

$$\widehat{\overline{\lambda}}_{i,t}^{j} = \beta_0 + \beta_1 \times \widehat{\overline{\lambda}}_{i,t-1}^{j} + \beta_2 \times I_{i,t}^{j} + \beta_3 \times \hat{\delta}_{i,t}^{j} + \beta_4 \times \left(I_{i,t}^{j} - \overline{I}_{t}^{j}\right) \times \left(\hat{\delta}_{i,t}^{j} - \overline{\hat{\delta}}_{t}^{j}\right)$$
$$+ \Gamma_1 X_t^j + \Gamma_2 Y_{i,t} + \gamma_3 SystemOTCfriction_t + \tau_i + \phi_j + \eta_y + \epsilon_{i,t}^j \qquad (8)$$

where $\{I_{i,t}^j\}_{i=1}^{N_t^j}$ and $\{\hat{\delta}_{i,t}^j\}_{i=1}^{N_t^j}$ are series of estimated inventory positions and private valuations in the cross-section of dealers in market (j,t) with the number of dealers as N_t^j. $\overline{I}_t^j$ is the market average inventory position across dealers, and $\overline{\hat{\delta}}_t^j$ is the market average private valuation across dealers; the bondwise controls include bond j's credit rating, the HHI (Herfindahl index) calculated by using market shares of all dealers in bond j, and bond j's previous-three-month average turnover; the dealerwise controls include dealer i's monthly eigenvector centrality, the HHI calculated by using dealer i's trading positions in different bonds, and the HHI calculated by using dealer i's proportions of buy and sell trades. The last two HHI indices measure dealer i's specialization in specific bonds and in specific trading directions. $SystemOTCfriction_t$ includes two variables, namely the cross-bond average length of intermediation chains and the pre-arranged ratio of trades on all bonds. It is a proxy for the market-level search frictions. The model also includes dealer fixed effect τ_i, bond fixed effect ϕ_j and year effect η_y.

The coefficient we focus on is β_4. A negative value of β_4 implies that a dealer with a higher(lower)-than-average inventory position and a lower(higher)-than-average private valuation is likely to choose a higher search intensity. We regard such a dealer as the one with a mis-aligned inventory position, and the value of the term $\left(I_{i,t}^{j} - \overline{I}_{t}^{j}\right) \times \left(\hat{\delta}_{i,t}^{j} - \overline{\hat{\delta}}_{t}^{j}\right)$ is negative for such a dealer. The regression results in Table 4 verifies our conjesture. We also use one-sided search intensities and total number of transactions[21] as dependent variables for robustness check. The full regression results are in Table 10.

Table 4: Dealer-level endogeneous search efforts

Dependent Variable	$\widehat{\lambda}_{i,t}^{j}$	$\widehat{\lambda}_{i,t}^{S,j}$	$\widehat{\lambda}_{i,t}^{B,j}$	$\widehat{Trade}_{i,t}^{j}$
$I_{i,t}^{j}$ (\$1,000)	-0.1132*	-1.361***	1.2487***	0.0983***
	(-1.66)	(-29.37)	(28.28)	(14.55)
$\hat{\delta}_{i,t}^{j}$ (%)	0.3337***	0.7202***	-0.3847***	0.0034
	(16.42)	(51.07)	(-29.11)	(1.53)
$\left(I_{i,t}^{j} - \overline{I}_{t}^{j}\right)$	-0.1607***	-0.1008***	-0.0601***	-0.0038**
$* \left(\hat{\delta}_{i,t}^{j} - \overline{\hat{\delta}}_{t}^{j}\right)$	(-9.40)	(-8.56)	(-5.25)	(-2.04)
# of obs	6,241,692	6,241,692	6,241,692	6,241,692
Adj R^2	0.1671	0.1356	0.1635	0.4383
One period lag	YES	YES	YES	YES
F-value	669.93	594.05	628.35	3906.06
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. $\widehat{\lambda}_{i,t}^{B,j}$ and $\widehat{\lambda}_{i,t}^{S,j}$ are the estimated dealer i's monthly buy and sell search intensities in bond j in month t. $\widehat{Trade}_{i,t}^{j}$ is dealer i's total number of transactions in bond j in month t, and it is positively correlated with search intensity.

Market-level search efforts At the market level, we show that dealers in a market with a higher magnitude of bond misallocation (or a lower cross-sectional covariance) on average invest in a higher search intensity, thus spending a higher search cost. The market-level model has the following specification:

$$\overline{\widehat{\lambda}}_{t}^{j} = \beta_0 + \beta_1 \overline{\widehat{\lambda}}_{t-1}^{j} + \beta_2 \times \widehat{Cov}(\hat{\delta}_{i,t}^{j}, I_{i,t}^{j})_{t}^{j} + \Gamma_1 X_{t}^{j} + \Gamma_2 \overline{Y}_{t}^{j} + \phi_j + \eta_y + \epsilon_{t}^{j} \tag{9}$$

[21]For the number of realized transactions, we separately use buying-transactions, selling-transactions, and the summation of the above two as dependent variable. A dealer choosing a higher search intensity is likely to implement a higher number of transactions. The full regression results are available upon request.

where $\overline{\overline{\lambda}}_t^j$ is the average search intensity across all dealers trading bond j in month t; independent variables X_t^j and $\overline{Y}_t^j$ are similarly defined as model (8) except that the dealerwise control $\overline{Y}_t^j$ is calculated at the market level as the average value across dealers; bond and year fixed effects are also controlled. In Table 5, we show that in those markets with a higher $\widehat{Cov}(\hat{\delta}_{i,t}^j, I_{i,t}^j)_t^j$ (or a lower bond misallocation), the cross-dealer average search intensity is lower, either for $\overline{\overline{\lambda}}_t^j$ which combines the buy side and the sell side of the market or separately for each side. The full regression results are in Table 11.

Table 5: Bond misallocation and average search intensity across dealers

$Dep_{i,q}^j$	$\overline{\overline{\lambda}}_t^j$	$\overline{\overline{\lambda}}_{S,t}^j$	$\overline{\overline{\lambda}}_{B,t}^j$	$\overline{\overline{\lambda}}_t^j$	$\overline{\overline{\lambda}}_{S,t}^j$	$\overline{\overline{\lambda}}_{B,t}^j$
$\widehat{Cov}(\hat{\delta}_{i,t}^j, I_{i,t}^j)_t^j$ $(1,000 \times \%)$	-0.69*	-0.73**	-0.04	-1.05***	-0.34	-0.80***
	(-1.67)	(-2.33)	(-0.15)	(-2.91)	(-1.22)	(-3.20)
L_1				0.78***	0.77***	0.79***
				(349.13)	(253.39)	(147.50)
# of obs	507,736	507,367	507,001	405,573	405,213	404,890
$Adj\ R^2$	0.25	0.21	0.24	0.71	0.69	0.72
One period lag	NO	NO	NO	YES	YES	YES
Bond×Year FE	YES	YES	YES	YES	YES	YES

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered in dealer#bond#year. L_1 is one-period lagged value for dependent variables. $\overline{\overline{\lambda}}_{S,t}^j$ is the average sell-side search intensity across dealers. $\overline{\overline{\lambda}}_{B,t}^j$ is the average buy-side search intensity across dealers.

7 Conclusion

In this paper, we propose a measure of corporate bond's misallocation among dealers, and document that this measure is closely correlated with corporate bond's liquidity risk attributed to OTC search frictions. This measure of bond's misallocation is based on a structural search-and-match model with dealers' endogeneous search efforts, and it is defined as the cross-sectional covariance of dealers' private valuations for holding the bond and their actual inventory positions in the bond. Using the TRACE data for the U.S. corporate bond market, we construct a panel data which contains yearly series of empirical estimates on bond's misallocation and liquidity risk, and we verify that: at the bond level, a higher magnitude of misallocation among the dealers (or a lower level of the cross-sectional covariance of dealers' private valuations and inventory positions) is associated with a higher magnitude of liquidity risk. This finding gives a preliminary market microstructural evidence which supports that: the distribution of market maker's states correlates with the magnitude of corporate bond's liquidity risk. The numerical solutions of the search-and-match model gives a preliminary explanation on how the bond's misallocation affects bond's liquidity risk attributed to OTC search frictions, through driving dealers' investment in search efforts. The endogeneous-search channel can also be empirically verified by using the TRACE data.

Appendices

A Estimate of dealers' private valuation

In the search-and-match model, we denote dealer-owners' value function as $V_1(\delta)$ and dealer-nonowners' value function as $V_0(\delta)$, for $\delta \in [\delta_l, \delta_h]$. Then we define dealers' reservation value function for the bond is $\triangle V(\delta) = V_1(\delta) - V_0(\delta)$, for $\delta \in [\delta_l, \delta_h]$, which measures how much compensation each dealer requires for giving up holding one position of the bond. In the bilateral search environment, when two dealers (suppose one holds one position of the bond and the other does not hold any position) with different private valuations meet, trading only happens when the dealer-owner's private valuation is lower than that of the dealer-nonowner. The realized transaction price is determined by a symmetric Nash bargaining process. Specifically, for a dealer with a type $\delta \in [\delta_\ell, \delta_h]$, her transaction price with another dealer with a type $\delta' \in [\delta_\ell, \delta_h]$ is:

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

where whether $P(\delta, \delta')$ is a selling or buying price depends on whether the dealer δ "holds the bond and search on her sell side" or "does not hold the bond and search on her buy side".

For transactions happening on the sell side of the dealer δ, since $\triangle V(\delta') > \triangle V(\delta)$(or the transaction would not happen), if it is possible for dealer δ to meet a continuum of other dealers, the lowest selling price is exactly equal to $\triangle V(\delta)$. Vice versa, on the buy side of the dealer δ, since $\triangle V(\delta') < \triangle V(\delta)$, the highest buying price is exactly equal to $\triangle V(\delta)$. Again based on monotonicity of $\triangle V(\delta)$, in data, we construct the following consistent estimator[22] as a proxy for dealers' private

[22] In finite samples, on the buy side of each dealer, the maximum buying 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 buying 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

valuation type δ:

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

where $\{Buy^j_{i,n^{j,B}_{i,t}}\}$ ($\{Sell^j_{i,n^{j,S}_{i,t}}\}$) is the collection of all buying (selling) prices by dealer i for bond j within month t and $n^{j,B}_{i,t}$ ($n^{j,S}_{i,t}$) is the correspondinng number of total buying (selling) transactions (including both dealer-customer and interdealer transactions) within month t. [23]

B Bond liquidity risk attributed to search frictions

B.1 Factors driving yield spread change

The full regression results are in Table 6.

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.

[23]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.

Table 6: Bond yield loadings on multiple factors

$\triangle(YieldSpread)_{j,t}$ (%)	(1)	(2)	(3)
$\triangle SystemChainLength_t$	-2.32***	-1.67***	-1.55***
	(-32.80)	(-21.38)	(-21.38)
$\triangle SysNetConcen_t$ (thousand)	-9.83e-03***	-4.77e-03***	-4.43e-03***
	(-48.16)	(-22.30)	(-20.10)
$\triangle inv_{t-1}$ (\$trillion)	7.55***	5.55***	5.74***
	(24.07)	(16.39)	(17.51)
$\triangle prearrange_t$ (%)	0.26***	1.28***	1.08***
	(3.43)	(15.87)	(13.43)
$\triangle blocktrade_t$ (%)	-66.67***	-29.29***	-28.65***
	(-50.94)	(-22.37)	(-22.15)
$\triangle amtout_t$ (\$trillion)	-0.32***	-0.47***	-0.38***
	(-6.17)	(-8.12)	(-6.54)
$\triangle HHIdealer_t$ (thousand)	-1.04***	-0.67***	-0.67***
	(-46.70)	(-28.99)	(-30.82)
$\triangle RF_t$		-2.72***	-2.68***
		(-41.53)	(-22.15)
$(\triangle RF_t)^2$		-8.61***	-1.13***
		(-9.66)	(-14.96)
$R_{MKT,t}$		6.35***	6.31***
		(60.26)	(61.05)
$\triangle SLOPE_t$		0.24***	0.27***
		(19.93)	(22.67)
$R_{SMB,t}$		0.53***	0.44***
		(5.53)	(4.70)
$R_{HML,t}$		0.22**	0.08
		(2.05)	(0.75)
$R_{UMD,t}$		-2.58***	-2.60***
		(-34.07)	(-34.74)
$\triangle turnover_t^j$			-1.45e-03 ***
			(-3.10)
$Rating_t^j$			6.41e-03 ***
			(3.41)
TTM_t^j			1.20e-05 *
			(1.96)
$Mean\ Adj\ R^2$	0.18	0.35	0.37
$\#ofBonds$	11176	11176	9595
$\#ofObs$	515514	515514	479146

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Reported estimated coefficients are average values taken across all bonds. Similar to Friewald and Nagler (2018), the t-statistics are calculated by dividing each reported (average) coefficient value by the standard deviation of the estimates and scaling by the square root of the number of bonds.

B.2 Intermediation chain

The matching algorithm to construct intermediation chains is an extension of the algorithms in Hollifield, Neklyudov, and Spatt (2017) and Li and Schürhoff (2014). Similarly, the intermediation chains start from customer-sell-to-dealer trades and end at dealer-sell-to-customer trades. We also use the first-in-first-out(FIFO) matching algorithm to look for the next trades for each incomplete chain. The main difference is, we only allow the split matching in the first round of the loop. After the first round, we track a fixed par amount of a bond until finding the final customer buyer.

Each intermediation chain starts from a trade that a customer C_s sells some amount of a bond to a dealer D_1. We then look for the next trade completed by dealer D_1 selling to a customer or another dealer within a calendar time window from -1 day to +30 days around the initial C_s-sells-to-D_1 trade. The initial trade is then followed by a trade that the dealer D_1 sells the same amount (of the same bond) either to a customer C_e or to another dealer D_2. In the first case of selling-to-C_e, the current intermediation chain ends and it is recorded as a CDC chain, that is, there is one dealer on the chain; In the second case of selling-to-D_1, the current intermediation chain is not ended and is temporarily recorded as an incomplete chain CDD. We continue looking for trades completed by dealer D_2 selling to a customer or another dealer within the same calendar time window. This process will continue until finding a dealer-sell-to-customer trade of the same bond in same par amount.

We only consider "split matching" in the first round of loop in the sense that, given the initial C_s-sell-to-D_1 trade, we look for a trade with D_1 as the seller of the same bond and with the shortest time gap to the initial trade. Suppose the initial trade has par amount Q_1 and the next closest trade is "dealer D_1 sells Q_2 of the same bond to a dealer D_2". Then if $Q_1 > Q_2$, that is, the initial trade has larger par amount than the second trade, we split Q_1 into two pieces Q_2 and $Q_1 - Q_2$, and we record a new incomplete chain CDD with par amount Q_2 and put the remaining par amount $Q_1 - Q_2$ (sold by C_s to D_1) back to the pile of initial customer-to-dealer trades to be used to initiate

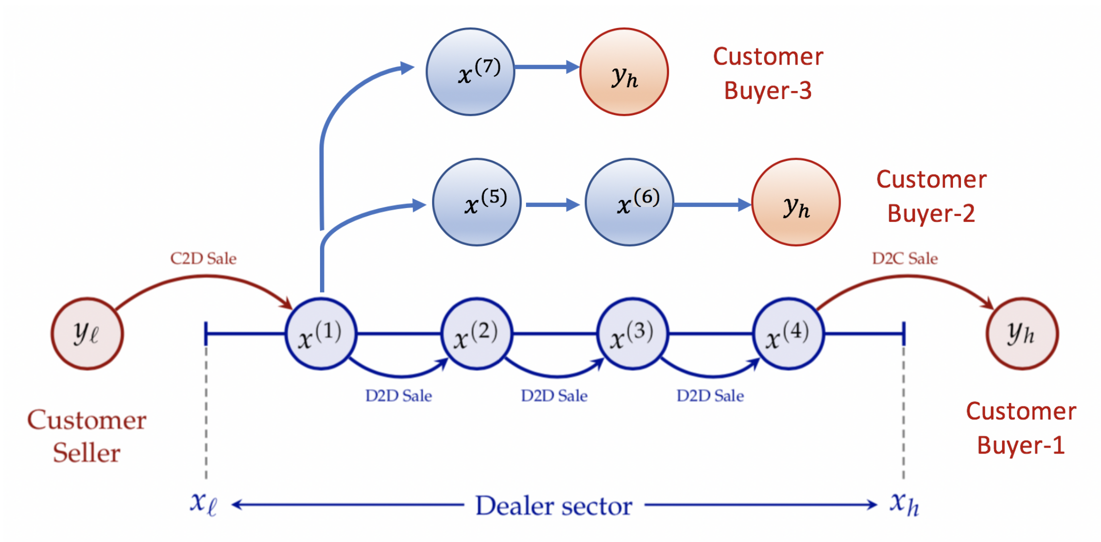

Figure 4: Split matching in constructing intermediation chains

new intermediation chains; If $Q_1 < Q_2$, similarly, we split Q_2 into two pieces Q_1 and $Q_2 - Q_1$, and we record a new incomplete chain CDD with par amount Q_1 and put the remaining par amount $Q_2 - Q_1$ (sold by D_1 to D_2) back to the pile of candidate interdealer trades that will be used to generate more intermediation chains. After the first round of the loop, for all incomplete chains CDD, we restrict that all matched trades on the same intermediation chain after the first round need to have exacty the same par amounts. Same as Li and Schürhoff (2014), we allow for up to 7 dealers on an intermediation chain. Figure 4 shows the "split matching" in the first round.

The matching algorithm matches a total of 6.7 million of complete intermediation chains. Table 7 reports the average trading information of intermediation chains of each length. The average trading size is generally lower for longer chains, which implies that it is more difficult for a larger amount of bond to be reallocated from the initial customer seller to the final customer buyer through too many dealers, since dealers may tend to split the large amount into smaller pieces when they trade with each other in the interdealer market. The total markup increases with the chain length, because dealers on average buy at lower prices and sell at higher prices to gain the intermediation profit. The total time gap also increases with the chain length, which is consistent with our expectation that in an interdealer market with the level of search frictions fixed, it takes a longer time for dealers to implement more trades with each other to form longer chains.

Table 7: Chain Length and Trade Information (Jan 2005 - Sep 2015)

	Num (thousands)	Vol($1,000)	Markup(%)	Total time(mins)	Pre-arranged(%)
CDC	3982.47	1092.33	0.999	10591.89	21.26
C(2)DC	1180.52	181.57	1.317	15192.10	2.37
C(3)DC	1028.50	155.09	2.102	16253.38	1.73
C(4)DC	351.85	55.57	2.334	19404.53	0.52
C(5)DC	104.86	112.42	2.112	25066.72	0.07
C(6)DC	32.57	64.68	2.374	34231.25	0.03
C(7)DC	12.69	125.46	2.272	40545.61	0.03

Note: C(i)DC means there are i dealers on the chain; Vol($1,000) is the average trading volume per chain calculated for each length throughout the whole sample period; Markup(%) is the average total markup per chain calculated for each length throughout the whole sample period. For each chain, the total markup is calculated by using the last dealer-sell-to-customer price on the chain minus the initial customer-sell-to-dealer price, then dividing the difference by the initial customer-sell-to-dealer price; Total time(mins) is the average total time gap per chain calculated for each length throughout the whole sample period. For each chain, the total time gap (in minutes) is the length of time between the time point at which the last dealer-sell-to-customer trade happens and the time point at which the initial customer-sell-to-dealer trade happens; We record an intermediation chain as being pre-arranged if its total time is shorter than 1 minute.

Table 8 reports the average bond information of intermediation chains for each length, which implies that dealers' search dynamics are heterogeneous across different bonds. This also motivates the extension of my preliminary model to consider the case of multiple assets.

Table 8: Chain Length and Bond Information (Jan 2005 - Sep 2015)

	Investment-grade(%)	Amount out($million)	Maturity(years)	TTM/TTO
CDC	68.21	881.92	10.85	22.54
C(2)DC	81.53	1169.34	10.54	4.89
C(3)DC	71.81	961.74	10.84	5.58
C(4)DC	68.99	964.9	11.30	3.46
C(5)DC	61.42	1042.67	11.24	4.72
C(6)DC	54.63	1370.50	11.27	4.04
C(7)DC	50.42	1490.65	11.20	5.26

Note: The higher the value of "Credit rating" is, the lower the credit rating of the bonds under an S&P rating scheme; Investment-grade(%) is the proportion of bonds that are investment grade ones with S&P credit ratings as BBB- or higher; Amount out($million) is the bonds' amount outstandings; Maturity(years) is the bonds' whole maturities; TTM/TTO is a calculated ratio of time to maturity versus time to offering, which is used to measure whether a bond is relatively young or not.

B.3 Heterogeneous bond-level liquidity risk

Figure 5 shows that for individual bonds, although the mean and median of $\beta^j_{SysSearch}$ are both negative, there exist quite a portion of bonds with positive $\beta^j_{SysSearch}$. Moreover, within the bonds of negative $\beta^j_{SysSearch}$, the absolute level of $\beta^j_{SysSearch}$ is heterogeneous across individual bonds. The more negative $\beta^j_{SysSearch}$ is, the more sensitively that bond j's yield responds to innovation in OTC search frictions. In Section B.4, we verify that the factor loading $\beta^j_{SysSearch}$ is significantly priced in corporate bond yield spread, in the sense that bonds with more negative $\beta^j_{SysSearch}$ will on average exhibit a higher level of yield spread.

B.4 Bond liquidity risk and level of yield spread

In this section, we test whether corporate bond's liquidity risk is priced in cumulative weighted average yield spread. Again, we estimate a reduced-form panel data model using the yearly panel data. We extend the data by adding a cumulative weighted average yield spread $YieldSpread_{j,y}$ for each point in the data. The model is:

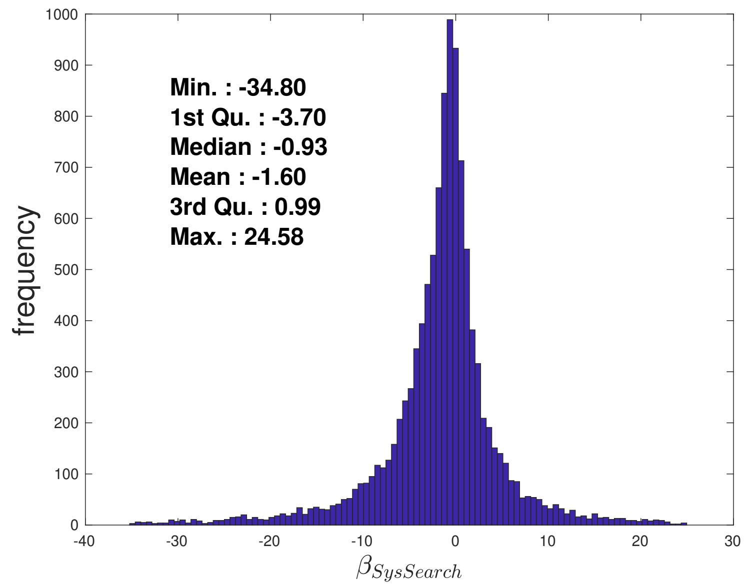

Figure 5: Distribution of yield loading on systemic search friction (bond-level yield spread loadings for 11176 bonds)

$$
\begin{aligned}
YieldSpread_{j,y} = {} & \lambda_{SysSearch} * \beta^j_{SysSearch,y} + \lambda_{SysNetConcen} * \beta^j_{SysNetConcen,y} \\
& + \lambda_{prearrange} * \gamma^j_{1,prearrange,y} + \lambda_{inv} * \gamma^j_{1,inv,y} \\
& + \lambda_{blocktrade} * \gamma^j_{2,blocktrade,y} + \lambda_{HHIdealer} * \gamma^j_{2,HHIdealer,y} + \overline{BF}^j_y + \eta_y + \epsilon^j_y
\end{aligned} \tag{12}
$$

where $\overline{BF}^j$ is a collection of bond-specific factors that are also important determinants of bond's yield spread, including bonds' liquidities measured by Amihud[24], trade concentration (among dealers), credit rating, bond-specific search frictions[25] and number of trades in segmented markets

[24] $Amihud^j_y$ is a liquidity measure proposed by Amihud (2002), which is calculated as the average absolute value of daily return divided by daily par dollar volume. Specifically, $Amihud^j_t = \frac{1}{d_{j,t}} \sum_{\tau=1}^{d_{j,t}} \frac{|r_{j,\tau}|}{Volume_{j,\tau}}$, where $d_{j,t}$ is the number of days with observed returns in month t for bond j, $r_{j,\tau}$ is the return for bond j on day τ, and $Volume_{j,t}$ is the par dollar volume traded on day τ.

[25] Bond-specific search frictions refer to the average time interval between consecutive trades on each intermediation chain, excluding the head and tail trades. The reason we exclude the head and tail segments

(interdealer market and dealer-customer market). All the points in the data are calculated by the time window $[1, y]$.

Table 9 shows that, nearly all of bond's exposures to OTC market frictions are consistently compensated by bond's yield spread. Specifically, since the estimated bond's liquidity risk $\beta^{j}_{SysSearch,y}$ is on average negative, the estimation results establish that a higher magnitude of liquidity risk (more negative $\beta^{j}_{SysSearch,y}$) implies a higher yield spread level. The regression results are robust when adding a collection of bond-specific factors or using truncated sample in which the max and min values of $\beta^{j}_{SysSearch,y}$ are both within three standard deviations from the mean level.

of intermediation chains is that these trades are more likely to be pre-arranged or more likely imply directed search of investors instead of the random search we focus on.

Table 9: Level of yield spread and factor loadings on systemic OTC market frictions

$YieldSpread_{j,y}$ (%)	(1)	(2)	(3)	(4)
$\beta^j_{SysSearch,y}$	-0.02***	-0.01***	-0.08***	-0.05***
	(-12.92)	(-10.81)	(-18.83)	(-13.53)
$\beta^j_{SysNetConcen,y}$	0.40	0.10	1.23*	2.08***
	(1.55)	(0.52)	(2.21)	(4.74)
$\gamma^j_{1,prearrange,y}$	226.8***	114.7***	738.8***	385.1***
	(23.56)	(15.76)	(41.13)	(26.82)
$\gamma^j_{1,inv,y}$	4.78e-03***	2.36e-03***	12.48e-03***	6.82e-03***
	(24.04)	(15.72)	(34.08)	(23.43)
$\gamma^j_{2,blocktrade,y}$	-24.73***	-10.81***	-58.19***	-28.91***
	(-40.18)	(-22.98)	(-54.17)	(-33.15)
$\gamma^j_{2,HHIdealer,y}$	-0.03***	-0.02***	-0.13***	-0.08***
	(-9.44)	(-8.91)	(-22.81)	(-19.16)
$Amihud^j_y$		212.4***		399.2***
		(6.35)		(7.44)
$Rating^j_y$		0.47***		0.37***
		(173.79)		(130.01)
$HHIdealer^j_y$ (1,000)		-0.10***		-0.11***
		(-12.16)		(-14.23)
$ChainTimeGap^j_y$ (mins)		9.91e-05***		9.50e-05***
		(15.81)		(15.57)
$Num\_DD^j_y$ (1,000)		0.42***		0.42***
		(10.61)		(11.30)
$Num\_DC^j_y$ (1,000)		-0.24***		-0.17***
		(-11.15)		(-7.93)
$Adj\ R^2$	0.08	0.48	0.20	0.51
Year FE	YES	YES	YES	YES
# of Obs	41332	41332	28932	28932
# of Bonds	11176	11176	8803	8803

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Regression (1) and (2) use all the bonds (obs). Regression (3) and (4) use the truncated sample which is obtained by dropping the bonds with $\beta^j_{SysSearch}$ ranked within the top and bottom 15% of the whole range of all the bonds, to eliminate the possible effect from extreme values. The reason we choose 15% as the cutoff is, by doing this, in the truncated sample, the max and min values are both within three standard deviations away from the mean.

C Search-and-match model with dealers' endogeneous search efforts

C.1 Moment conditions to identify dealers' search intensities

Before introducing the model generated moment conditions, we briefly discuss the matching technology in the model. 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 $m(\lambda, \rho) = \lambda \times \left(\frac{1}{1+m} + \frac{\rho}{m\Lambda}\right)$.

Due to the assumption that asset position $a \in \{0, 1\}$, each market participant switches between the buy side and the sell side of the market. 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. In Section 4.1, we defined the density function for dealer owners $\phi_1(\delta)$ and the density function for dealer-nonowners $\phi_0(\delta)$. There are also four groups of customers: high- and low-type owners and nonowners. We denote the corresponding physical measures by μ_{h1}, μ_{h0}, $\mu_{\ell 1}$, $\mu_{\ell 0}$. For simplicity, we change the notation of dealer-owner's optimal search intensity on the sell side as $\lambda(1, \delta) = \lambda_1^*(\delta)$, and for dealer-nonowner's optimal search intensity on the buy side as $\lambda(0, \delta) = \lambda_0^*(\delta)$.

We identify dealers' idiosyncratic search intensities separately on the buy- and sell-side of the market using the following transaction-related moments,[26] where variables with a hat are obtained

[26] We calculate the moments for each bond-and-month combination.

directly from the data:

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

$$\widehat{Trade}_S(\delta) = \phi_1(\delta)\lambda_1^*(\delta)\left[\underbrace{\left(\frac{1}{1+m}+\frac{\rho}{m\Lambda}\right)\mu_{h0}}_{\text{trading with customers}} + \underbrace{\frac{2m}{1+m}\int_\delta^{\delta_h}\frac{\lambda_0^*(\delta')}{\Lambda}\phi_0(\delta')d\delta'}_{\text{trading with higher-type dealer-nonowners}}\right] \tag{13}$$

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

$$\widehat{Trade}_B(\delta) = \phi_0(\delta)\lambda_0^*(\delta)\left[\underbrace{\left(\frac{1}{1+m}+\frac{\rho}{m\Lambda}\right)\mu_{\ell 1}}_{\text{trading with customers}} + \underbrace{\frac{2m}{1+m}\int_{\delta_\ell}^{\delta}\frac{\lambda_1^*(\delta')}{\Lambda}\phi_1(\delta')d\delta'}_{\text{trading with lower-type dealer-owners}}\right] \tag{14}$$

3. for each selling 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:

$$\widehat{Pr}\left[SellToDealers|Sell\right](\delta) = \frac{\frac{2m}{1+m}\int_\delta^{\delta_h}\frac{\lambda_0^*(\delta')}{\Lambda}\phi_0(\delta')d\delta'}{\left(\frac{1}{1+m}+\frac{\rho}{m\Lambda}\right)\mu_{h0} + \frac{2m}{1+m}\int_\delta^{\delta_h}\frac{\lambda_0^*(\delta')}{\Lambda}\phi_0(\delta')d\delta'} \tag{15}$$

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:

$$\widehat{Pr}\left[BuyFromDealers|Buy\right](\delta) = \frac{\frac{2m}{1+m}\int_{\delta_\ell}^{\delta}\frac{\lambda_1^*(\delta')}{\Lambda}\phi_1(\delta')d\delta'}{\left(\frac{1}{1+m}+\frac{\rho}{m\Lambda}\right)\mu_{\ell 1} + \frac{2m}{1+m}\int_{\delta_\ell}^{\delta}\frac{\lambda_1^*(\delta')}{\Lambda}\phi_1(\delta')d\delta'} \tag{16}$$

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.

Next we separately identify the average sell-side search intensity function $\phi_1(\delta)\lambda_1^*(\delta)$ and the average buy-side search intensity function $\phi_0(\delta)\lambda_0^*(\delta)$, both up to a same constant. The summation of those two one-sided intensities is our target search intensity to finally identify. For notational simplicity, we define the following functions based on data moments $\widehat{Trade}$ and $\widehat{Pr}$ for each dealer with type $\delta \in [\delta_\ell, \delta_h]$:

$$\widehat{f}_1(\delta) = \Big(1 - \widehat{Pr}\left[SellToDealers|Sell\right](\delta)\Big) \times \widehat{Trade}_S(\delta) \tag{17}$$

$$\widehat{f}_2(\delta) = \Big(1 - \widehat{Pr}\left[BuyFromDealers|Buy\right](\delta)\Big) \times \widehat{Trade}_B(\delta) \tag{18}$$

$$\widehat{f}_3(\delta) = \widehat{Pr}\left[SellToDealers|Sell\right](\delta) \times \widehat{Trade}_S(\delta) \tag{19}$$

$$\widehat{f}_4(\delta) = \widehat{Pr}\left[BuyFromDealers|Buy\right](\delta) \times \widehat{Trade}_B(\delta) \tag{20}$$

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.

By derivations[27] based on (13)-(20), we obtain the two one-sided search intensites, $\hat{\lambda}_S(\delta)$ and $\hat{\lambda}_B(\delta)$, and the target search intensity $\hat{\lambda}(\delta)$ as follows:

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

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

$$\hat{\lambda}(\delta) = \hat{\lambda}_S(\delta) + \hat{\lambda}_B(\delta) \tag{23}$$

where $\hat{\lambda}_S(\delta)$ ($\hat{\lambda}_B(\delta)$) is the identified sell-side (buy-side) search intensity of dealer with private valuation δ (up to a constant $\frac{2m}{1+m}$), and $\hat{\lambda}(\delta)$ is the identified search intensity we use to test the endogeneous-search channel connecting bond's misallocation and liquidity risk in Section 6.

[27] The detailed derivations are available upon request.

C.2 Estimation of search intensities

In our transaction level data, for each dealer with an estimated private valuation $\hat{\delta}$, we can directly observe the dealer's number of sell-to-customer, buy-from-customer, sell-to-dealer and buy-from-dealer transactions, which are used to estimate $\widehat{f}_1(\hat{\delta})$-$\widehat{f}_4(\hat{\delta})$ in (17)-(20).

In the data, we define each market as a combination of bond j and month t. Within each market (j,t), we estimate the unknown functions $\widehat{f}^j_{i,t}(\hat{\delta})$, $i = 1, 2, 3, 4$. The B-spline nonparametric estimator of the unknown functions have the following forms:

$$\widehat{f}^j_{i,t}(\hat{\delta}) = \sum_{k=1}^{5} \beta^j_{k,i} B^j_k(\hat{\delta}) \tag{24}$$

where $B^j_k(\hat{\delta}), k = 1, 2, 3, 4, 5$, are B-spline basis functions of all dealers' estimated types $\hat{\delta}$ in market (j,t), for a natural cubic spline with the degree of freedom equals 5 (4 intercept knots).

With the estimated $\widehat{f}^j_{1,t}(\hat{\delta})$-$\widehat{f}^j_{4,t}(\hat{\delta})$, we further construct the estimated search intensity function $\hat{\lambda}_t(\hat{\delta})$ for market (j,t), by (21)-(23).

Note on Table 10 $\widehat{\lambda}^{B,j}_{i,t}$ and $\widehat{\lambda}^{S,j}_{i,t}$ are the estimated dealer i's monthly buy and sell search intensities in bond j in month t. $\widehat{Trade}^j_{i,t}$ is dealer i's total number of transactions in bond j in month t, and it is positively correlated with search intensity. $EV_{i,t}$ is dealer i's eigenvector centrality in month t. $Rating_{j,t}$ is credit rating of bond j in month t, note that the higher the value, the lower the credit rating is. $Pre3Mturnover_{j,t}$ is bond j's previous-three-month turnover rate, which is used as a measure of bond former liqudity.

Table 10: Dealer-level endogeneous search efforts

Dependent Variable	$\widehat{\overline{\lambda}}_{i,t}^{j}$	$\widehat{\overline{\lambda}}_{i,t}^{S,j}$	$\widehat{\overline{\lambda}}_{i,t}^{B,j}$	$\widehat{Trade}_{i,t}^{j}$
$I_{i,t}^{j}$ (\$1,000)	-0.1132*	-1.361***	1.2487***	0.0983***
	(-1.66)	(-29.37)	(28.28)	(14.55)
$\hat{\delta}_{i,t}^{j}$ (%)	0.3337***	0.7202***	-0.3847***	0.0034
	(16.42)	(51.07)	(-29.11)	(1.53)
$\left(I_{i,t}^{j} - \overline{I}_{t}^{j}\right)$	-0.1607***	-0.1008***	-0.0601***	-0.0038**
$* \left(\hat{\delta}_{i,t}^{j} - \overline{\hat{\delta}}_{t}^{j}\right)$	(-9.40)	(-8.56)	(-5.25)	(-2.04)
$SystemChainLength_t$	12.8568***	6.61 ***	5.2986**	4.6378***
	(4.10)	(3.14)	(2.55)	(11.61)
$PreArrangeRatio_t$	-0.0703***	-0.1045 ***	-0.0007	0.0017
	(-7.15)	(-15.25)	(5.70)	(1.60)
$HHI_{i,t}^{bond}$ (thousands)	-0.6734***	0.1765*	-0.8487***	0.0288*
	(-4.80)	(1.86)	(-9.56)	(1.83)
$HHI_{i,t}^{type}$ (thousands)	-1.2314***	-1.9072***	0.6768***	-0.0279***
	(-10.17)	(-24.88)	(7.90)	(-3.01)
$HHI_{t}^{j,concen}$ (thousand)	-2.5997***	-1.1731***	-1.4224***	-0.3626***
	(-84.95)	(-54.11)	(-74.77)	(-73.79)
$EV_{i,t}$	14.0510***	3.8637***	10.1595***	1.5062***
	(22.25)	(9.10)	(25.45)	(23.76)
$Rating_{j,t}$	0.4699***	0.2884***	0.1811***	-0.0099***
	(16.62)	(14.67)	(10.24)	(-5.22)
$Pre3Mturnover_{j,t}$ (%)	0.0314***	0.0041*	0.0272**	0.0004
	(2.71)	(1.66)	(2.45)	(1.11)
$Coupon^{j}$ (%)	2.8156	20.0289***	-17.0748**	-0.0730
	(0.28)	(4.49)	(-2.09)	(-0.14)
# of obs	6,241,692	6,241,692	6,241,692	6,241,692
Adj R^2	0.1671	0.1356	0.1635	0.4383
One period lag	YES	YES	YES	YES
F-value	669.93	594.05	628.35	3906.06
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 11: Bond misallocation and average search intensity across dealers

$Dep_{i,q}^{j}$	$\overline{\widetilde{\lambda}}_{t}^{j}$	$\overline{\widetilde{\lambda}}_{S,t}^{j}$	$\overline{\widetilde{\lambda}}_{B,t}^{j}$	$\overline{\widetilde{\lambda}}_{t}^{j}$	$\overline{\widetilde{\lambda}}_{S,t}^{j}$	$\overline{\widetilde{\lambda}}_{B,t}^{j}$
$\widehat{Cov}(\hat{\delta}_{i,t}^{j}, I_{i,t}^{j})_{t}^{j}$ $(1,000 \times \%)$	-0.69*	-0.73**	-0.04	-1.05***	-0.34	-0.80***
	(-1.67)	(-2.33)	(-0.15)	(-2.91)	(-1.22)	(-3.20)
L_1				0.78***	0.77***	0.79***
				(349.13)	(253.39)	(147.50)
$EV_{i,t}$	1.72***	1.32***	0.01	1.43***	1.09***	-0.12
	(4.37)	(4.45)	(0.03)	(4.47)	(4.47)	(-0.57)
$HHI_{i,t}^{bond}$ (thousands)	1.89***	0.88***	1.18***	0.21*	0.16*	0.16**
	(12.52)	(7.69)	(10.95)	(1.85)	(1.85)	(2.13)
$HHI_{i,t}^{type}$ (thousands)	0.56***	0.18**	0.59***	0.20**	0.26***	0.12**
	(4.89)	(2.08)	(7.06)	(2.39)	(4.05)	(2.19)
$Coupon^{j}$ (%)	-8.85*	1.71	-11.07**	1.76	-1.05	3.48
	(-1.71)	(0.87)	(-1.99)	(0.30)	(-0.60)	(0.51)
$Rating_{j,t}$	0.02**	0.01	0.01**	0.01	0.007	0.004
	(2.52)	(1.41)	(1.99)	(1.64)	(1.29)	(0.94)
$HHI_{t}^{j,concen}$ (thousand)	-0.35***	-0.18***	-0.18***	-0.19***	-0.13***	-0.06***
	(-20.44)	(-13.63)	(-15.13)	(-15.28)	(-14.11)	(-7.67)
$Pre3Mturnover_{j,t}$ (%)	-0.003	-4.5e-04	-0.003***	-0.002	-0.001	-0.001**
	(-1.64)	(-0.24)	(-4.17)	(-0.78)	(-0.39)	(-2.41)
# of obs	507,736	507,367	507,001	405,573	405,213	404,890
$Adj\ R^2$	0.25	0.21	0.24	0.71	0.69	0.72
One period lag	NO	NO	NO	YES	YES	YES
Bond×Year FE	YES	YES	YES	YES	YES	YES

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered in dealer#bond#year. L_1 is one-period lagged value for dependent variables. $\overline{\widetilde{\lambda}}_{S,t}^{j}$ is the average sell-side search intensity across dealers. $\overline{\widetilde{\lambda}}_{B,t}^{j}$ is the average buy-side search intensity across dealers.

References

Gara Afonso. Liquidity and congestion. *Journal of Financial Intermediation*, 20(3):324–360, 2011. 6

Gara Afonso and Ricardo Lagos. Trade dynamics in the market for federal funds. *Econometrica*, 83(1):263–313, 2015. 6

Yakov Amihud. Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, 5(1):31–56, 2002. 39

Yu An. Competing with inventory in dealership markets. *Available at SSRN 3284836*, 2019. 8

Andrew G Atkeson, Andrea L Eisfeldt, and Pierre-Olivier Weill. Entry and exit in otc derivatives markets. *Econometrica*, 83(6):2231–2292, 2015. 6

Jack Bao, Jun Pan, and Jiang Wang. The illiquidity of corporate bonds. *The Journal of Finance*, 66(3):911–946, 2011. 5, 8

Hendrik Bessembinder, Stacey Jacobsen, William Maxwell, and Kumar Venkataraman. Capital commitment and illiquidity in corporate bonds. Working paper, 2016. 10

Dion Bongaerts, Frank De Jong, and Joost Driessen. An asset pricing approach to liquidity effects in corporate bond markets. *The Review of Financial Studies*, 30(4):1229–1269, 2017. 5

Mark M Carhart. On persistence in mutual fund performance. *The Journal of finance*, 52(1):57–82, 1997. 11

Pierre Collin-Dufresn, Robert S Goldstein, and J Spencer Martin. The determinants of credit spread changes. *The Journal of Finance*, 56(6):2177–2207, 2001. 2, 5, 13

Kevin Crotty. Corporate yield spread and systemic liquidity. Working paper, 2013. 5, 8, 9, 11

Frank De Jong and Joost Driessen. Liquidity risk premia in corporate bond markets. *The Quarterly Journal of Finance*, 2(02):1250006, 2012. 5

Jens Dick-Nielsen. How to clean enhanced trace data. 2014. 7

Darrell Duffie, Nicolae Gârleanu, and Lasse Heje Pedersen. Over-the-counter markets. *Econometrica*, 73(6):1815–1847, 2005. 5, 16

Darrell Duffie, Nicolae Gârleanu, and Lasse Heje Pedersen. Valuation in over-the-counter markets. *The Review of Financial Studies*, 20(6):1865–1900, 2007. 6

Eugene F Fama and Kenneth R French. Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, 33(1):3–56, 1993. 11

Maryam Farboodi, Gregor Jarosch, and Robert Shimer. The emergence of market structure. Technical report, National Bureau of Economic Research, 2017. 6

Nils Friewald and Florian Nagler. Dealer inventory and the cross-section of corporate bond returns. 2016. 5, 8, 20, 21

Nils Friewald and Florian Nagler. Over-the-counter market frictions and yield spread changes. *Journal of Finance, Forthcoming*, 2018. 2, 3, 5, 8, 9, 11, 13, 34

Alessandro Gavazza. Leasing and secondary markets: Theory and evidence from commercial aircraft. *Journal of Political Economy*, 119(2):325–377, 2011. 6

Oliver Hansch, Narayan Y Naik, and S Viswanathan. Do inventories matter in dealership markets? evidence from the london stock exchange. *The Journal of Finance*, 53(5):1623–1656, 1998. 4, 20

Zhiguo He, Paymon Khorrami, and Zhaogang Song. Commonality in credit spread changes: Dealer inventory and intermediary distress. Technical report, National Bureau of Economic Research, 2019. 5

Burton Hollifield, Artem Neklyudov, and Chester Spatt. Bid-ask spreads, trading networks, and the pricing of securitizations. *The Review of Financial Studies*, 30(9):3048–3085, 2017. 9, 35

Julien Hugonnier, Benjamin Lester, and Pierre-Olivier Weill. Frictional intermediation in over-the-counter markets. Technical report, National Bureau of Economic Research, 2018. 3, 6, 9

Dan Li and Norman Schürhoff. Dealer networks. 2014. 9, 35, 36

Shuo Liu. Dealer's search intensity in u.s. corporate bond market. *Working paper, UCLA*, 2020. 4, 27

Francis A Longstaff, Sanjay Mithal, and Eric Neis. Corporate yield spreads: Default risk or liquidity? new evidence from the credit default swap market. *The Journal of Finance*, 60(5): 2213–2253, 2005. 5

Dale T Mortensen. Property rights and efficiency in mating, racing, and related games. *The American Economic Review*, 72(5):968–979, 1982. 42

Artem Neklyudov. Bid-ask spreads and the over-the-counter interdealer markets: Core and peripheral dealers. Technical report, Working Paper HEC Lausanne, 2012. 6

Rémy Praz. Equilibrium asset pricing with both liquid and illiquid markets. *Available at SSRN 2464421*, 2014. 6

Ji Shen, Bin Wei, and Hongjun Yan. Financial intermediation chains in an otc market. 2018. 6

Robert Shimer and Lones Smith. Matching, search, and heterogeneity. *Advances in Macroeconomics*, 1(1), 2001. 42

Alberto Trejos and Randall Wright. Search-based models of money and finance: An integrated approach. *Journal of Economic Theory*, 164:10–31, 2016. 6

Semih Üslü. Pricing and liquidity in decentralized asset markets. *Available at SSRN 2841919*, 2019. 6, 42

Dimitri Vayanos and Tan Wang. Search and endogenous concentration of liquidity in asset markets. *Journal of Economic Theory*, 136(1):66–104, 2007. 6

Dimitri Vayanos and Pierre-Olivier Weill. A search-based theory of the on-the-run phenomenon. *The Journal of Finance*, 63(3):1361–1398, 2008. 6

Pierre-Olivier Weill. Liquidity premia in dynamic bargaining markets. *Journal of Economic Theory*, 140(1):66–96, 2008. 6