Essays in Financial Economics: Securitizations Trading, Decentralized Interdealer Markets, and Strategic Information Acquisition with Overlaps

by

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To my parents, Vladimir and Iraida

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Abstract

This paper develops a model of an over-the-counter market where dealers differ in their trade execution efficiency to capture the core-peripheral nature of dealer networks documented in recent empirical studies. We investigate interdealer trading patterns and the relationship between dealers' trade execution efficiency and customer bid-ask spreads. In equilibrium, more efficient central dealers provide intermediation services to peripheral dealers. Customers can find better bargains when trading with peripheral dealers, even though peripheral dealers may charge wider bid-ask spreads on average. The extent of active shopping by customers can explain why the relationship between dealers' trade execution efficiency and customer bid-ask spreads varies across markets. The findings are consistent with both anecdotal and empirical evidence from municipal bond markets, markets for asset-backed securities and collateralized mortgage-backed obligations.

1 Introduction

Over-the-counter markets have, until quite recently, been opaque and difficult to study empirically. Recent regulatory initiatives in data collection have increased transparency of these markets for researchers and created opportunities to study intermediation patterns and dealer networks. In this paper, we develop a theoretical model of an over-the-counter market where dealers differ in their trade execution efficiency in order to capture the nature of dealer networks observed in the data. Our model provides implications for interdealer trading patterns and bid-ask spreads that are consistent with empirically documented facts for a wide variety of fixed-income instruments.

In the model, dealers' buy-and-hold asset valuations are exposed to random liquidity shocks. More interconnected dealers have higher trade execution efficiency and thus are less concerned about their liquidity state when bargaining with their counterparties. Conversely, peripheral dealers who have lower trade execution efficiency are more affected by liquidity shocks, and the variability of their reservation values is higher. This creates positive trading gains between central and peripheral dealers even when they are in the same liquidity state and have the same buy-and-hold asset valuation. Central dealers provide intermediation services to peripheral dealers in equilibrium and reduce inventory risk of the latter, which is consistent with the trading pattern documented in Li and Schürhoff [2012] for municipal bond markets.

Intermediation that occurs between central and peripheral dealers negatively affects the average terms of trade between peripheral dealers and customers. Even though a peripheral dealer in the low liquidity state is willing to make larger price concessions to a customer who buys the asset, in the steady-state customers are unlikely to find such better bargains—more interconnected dealers quickly intermediate these away from peripheral dealers. Thus, in the steady-state, customers are more likely to find a dealer in the same liquidity state as they are themselves and get mediocre terms of trade. Overall, this generates a negative relationship between average customer bid-ask spreads and dealers' trade execution efficiency in the baseline version of the model without active customer shopping, which is consistent with the empirical findings in Hollifield, Neklyudov, and Spatt [2012] in asset-backed securities and collateralized mortgage-backed obligations.

If customers are sufficiently more likely to trade with a dealer in the opposite liquidity state when trading gains are the largest, the relationship between average bid-ask spreads and dealers' trade execution efficiency becomes positive. Such a positive relationship is documented in Li and Schürhoff [2012] for municipal bond markets and can be interpreted as the evidence for a larger extent of shopping activity by customers of municipal bonds. Anecdotal evidence suggests that this can be the case—for example, strategies of some sophisticated customers on the municipal bond markets involve searching actively for dealers stuck with odd-lot distributions.

The motivation for this paper originates from empirical studies of the data collected recently for over-the-counter markets. The detailed transaction level data collected by Financial Industry Regulatory Authority (FINRA) in corporate bond markets and, more recently, in securitizations, and by the Municipal Securities Rulemaking Board (MSRB) in municipal bond market allows researchers to reconstruct and study trading networks comprising different counterparties using their dealer codes. Empirical studies of transaction level data document the core-peripheral structure of interdealer networks and significant heterogeneity of dealers in terms of volumes traded, interdealer market participation, and degree of interconnectedness with each other. A non-trivial relationship is empirically documented on dealers' interconnectedness and bid-ask spreads that customers face. Li and Schürhoff [2012] study MSRB municipal bond audit trail data and find that few central dealers charge up to 80% higher bid-ask spreads for medium-size transactions. Hollifield, Neklyudov, and Spatt [2012] study transaction-level data in asset-backed securities and non-agency collateralized mortgage obligations provided by FINRA and find that bid-ask spreads charged by central dealers tend to be lower, implying that the effect of interconnectedness on bid-ask spreads is ambiguous.

In the data, interdealer trades constitute a significant portion of daily trading activity in different instruments. Li and Schürhoff [2012] observe 16 million interdealer trades out of total 60 million transactions in 1.4 million municipal bonds between February 1998 and July 2011. Hollifield et al. [2012] observe a similar 10% to 20% proportion of trades between dealers among all transactions in ABS and non-agency CMO securities between May 2011 and February 2012. Both of these studies document significant heterogeneity in interconnectedness of different dealers and the resulting differences in the bid-ask spreads that customers face.

The empirical findings speak in favor of extending the existing theoretical models of over-the-counter markets that traditionally feature a centralized and homogenous interdealer market. First of all, on the centralized interdealer market modelled in the literature there is a common equilibrium interdealer price in each type of instrument, while in the data we observe a multitude of different interdealer prices. Secondly, when each dealer has access to the centralized interdealer market, the reservation price for the asset is the same across dealers, and it is difficult to rationalize varying quotes and bid-ask spreads customers face.[1]

[1] In this case only the customer's reservation value or dealer's bargaining power affects bargaining outcomes. Larger bid-ask spreads charged by a particular type of dealers would imply either higher bargaining

This paper contributes to a growing theoretical literature on search in over-the-counter markets. Duffie, Gârleanu, and Pedersen [2005, 2007] develop the seminal search-and-matching model of an over-the-counter market and derive bid-ask spread charged by marketmakers with access to a centralized interdealer market. Dunne, Hau, and Moore [2012] characterize dealers' intermediation role and inventory management between monopolistic customer market and competitive interdealer market. Atkeson, Eisfeldt, and Weill [2012] characterize single-period trading patterns in credit-default swaps contracts (CDS) between banks with heterogeneous exposures to the aggregate default risk and show that an interdealer market with close to common prices arises endogenously. Babus [2012] develops a model of endogenous formation of a central broker-dealer when agents are allowed to invest in trading relationships. In this paper, we take a different approach and introduce exogenously an interdealer market that allows for heterogeneity across dealers' search technologies and thus has the potential to explain the nature of dealer networks observed in the data. Our model is similar to Gofman [2011], in that dealers bargaining surplus affects bilateral prices along with private buy-and-hold values; however, in our model dealers are matched with their counterparties randomly according to a search-and-matching procedure, and the trading network arises as a realization of this random process. Unlike Zhu [2012], who studies pricing implications of a "ringing phone curse" when sellers contact buyers sequentially with possibility of a repeat contact, in our model the market is large enough so that reputation effects of repeat contacts do not occur.

The remainder of the paper is organized as follows. Section 2 describes the environment and introduces heterogeneity in dealers' trade execution efficiency. Section 3 studies the equilibrium implications for the bid-ask spreads charged by dealers. Section 4 presents numerical simulation of a symmetric trading equilibrium, analysis of dealer networks that emerge, customer shopping activity, and the robustness of the underlying bargaining procedure. Section 5 presents the discussion of reasons why dealers might be heterogenous in their trade execution efficiency. Section 6 concludes.

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power of these dealers or a type of market segmentation with most disadvantaged customers being served by these dealers. A question that then arises is why other dealers do not engage in competition for serving these disadvantaged customers.

2 The Environment

Over-the-counter markets for a majority of fixed-income instruments such as corporate bonds, municipal bonds, various types of securitized products—lack an institutional mechanism that would allow customers of these products to trade directly with each other. Instead, all transactions are intermediated by designated dealers who are registered with corresponding regulatory authorities. Trades are executed through bilateral meetings and negotiations between a customer and a dealer or between two dealers. In this section, we describe an exchange economy and introduce a random-matching technology for dealers who differ in their trade execution efficiency.

2.1 Customers and Dealers

There are two types of agents in the model: Customers and dealers, both risk-neutral and infinitely-lived. Every agent has measure zero in a continuum of agents. The set of dealers has measure $M_d \in (0,1)$, and the set of customers has measure $(1-M_d)$. Customers and dealers can hold and trade an asset in positive per capita supply $s \in (0,1)$, which is traded on an over-the-counter market with a search friction. All agents discount future cash flows at a constant rate $r > 0$.

At any point in time, customers and dealers differ in their marginal utilities of holding the asset and in terms of their trade execution efficiency in the over-the-counter market. For these two reasons, there are gains from trade.

Marginal utility of holding the asset $\theta_i(t)$ follows a two-state stochastic Markov process. Both customers and dealers can be either in "high" or "low" intrinsic liquidity state at any point in time. The liquidity state switches from low to high with intensity γ_{up} and from high to low with intensity γ_{dn}, independent across agents. A customer in the low liquidity state receives constant per unit utility flow $\theta_i(t) = \theta_{low}$, and a customer in the high liquidity state receives utility flow $\theta_i(t) = \theta_{high}$. A dealer in the low liquidity state receives $\theta_i(t) = \theta_l$, and a dealer in the high liquidity state receives $\theta_i(t) = \theta_h$. Throughout the paper we assume that $\theta_{high} > \theta_h \geq \theta_l > \theta_{low}$. Such stochastic variation in the utility flows generates gains from trade and is a traditional modeling tool used in the literature on over-the-counter markets (Duffie, Gârleanu, and Pedersen [2005, 2007]; Vayanos and Wang [2007]; Weill [2007]). Our setup allows for both customer-to-dealer and dealer-to-dealer transactions.

Asset holdings of agents are restricted to the $[0, 1]$ interval. Both short selling and holding more than one unit of the asset is not feasible for agents. In equilibrium, due to the risk-neutrality assumption and resulting linearity of the expected utility function, all agents hold either 0 or 1 unit of the asset. Thus, in the paper we refer to the two types of asset holdings: "Owners" hold one unit of the asset, and "non-owners" hold zero units. Together with the two liquidity states, both customers and dealers can be characterized by one of the following four types at any point in time: $\{ho, lo, hn, ln\}$—high owner, low owner, high non-owner, and low non-owner. This constitutes the complete set of possible types for customers, and we denote their measure in the overall population by $\mu^C_{ho}, \mu^C_{lo}, \mu^C_{hn}, \mu^C_{ln}$, respectively. The following identity holds for customers' masses:

$$\mu^C_{ho} + \mu^C_{lo} + \mu^C_{hn} + \mu^C_{ln} = (1 - M_d). \tag{1}$$

Customers in the model have the lowest level of trade execution efficiency, which is normalized to zero. Customers passively wait for dealers to find them on the market. Unlike customers, dealers differ in their trade execution efficiency $\lambda_i \in [0, +\infty)$, thus the number of different dealer types is infinite. More interconnected dealers are assumed to have higher trade execution efficiency and thus lower expected trade execution delays. In the following subsection 2.2, we describe how trade execution efficiency λ_i determines the likelihood of finding a counterparty. We assume that the distribution of λ_i in the population of dealers is characterized by strictly increasing and continuous cumulative density function $F(\lambda)$. Dealer i is born with trade execution efficiency $\lambda_i \in [0, +\infty)$, and it remains constant throughout his life. We let $\mu_{ho}(\lambda)$ be the measure of all high owner dealers with $\lambda_i \leq \lambda$ in the total population of agents, similarly we define functions $\mu_{lo}(\lambda)$,

$\mu_{hn}(\lambda)$, and $\mu_{ln}(\lambda)$. The following identities hold for dealers' masses:

$$\int_{\lambda=0}^{+\infty} d\mu_{ho}(\lambda) + \int_{\lambda=0}^{+\infty} d\mu_{lo}(\lambda) + \int_{\lambda=0}^{+\infty} d\mu_{hn}(\lambda) + \int_{\lambda=0}^{+\infty} d\mu_{ln}(\lambda) = M_d, \tag{2}$$

$$\int_{\lambda=0}^{+\infty} d\mu_{ho}(\lambda) + \int_{\lambda=0}^{+\infty} d\mu_{lo}(\lambda) = s - \left(\mu_{ho}^{C} + \mu_{lo}^{C}\right). \tag{3}$$

2.2 Random-Matching Technology

There is a search friction on the over-the-counter market. A pair of agents can execute a trade with each other only after they have been matched according to a specified random matching technology. This creates unintended transaction delays. Neither customers nor dealers are allowed to contact each other instantly; however, by construction transaction delays are less severe on the interdealer market. To model the search friction, we use the independent random matching technology described below.

At Poisson arrival times with intensity $\lambda_i \in [0, +\infty)$ each dealer contacts a customer or another dealer, chosen from the entire population randomly and uniformly. Contact times are pairwise independent. In this framework, λ_i represents "search efficiency" for each dealer: As dealer's trade execution efficiency increases, trade execution delays and dealer's exposure to the search friction diminishes.

Consider subset of customers that contains a fraction μ of the overall population. A dealer with trade execution efficiency λ_i contacts a customer from the given subset at an almost sure rate $\lambda_i\mu$. Note that this rate is the product of dealer's λ_i and the measure μ of the subset under consideration. The same line of argument cannot be directly applied to interdealer meetings. All dealers have different trade execution efficiency, and dealers with higher efficiency are more likely to find another dealer. The interdealer matching process is not uniform, and we cannot directly apply the Law of Large Numbers developed for the uniform random matching among a continuum of agents (Podczeck and Puzzello [2010], Ferland and Giroux [2008], Duffie and Sun [2007]). Fortunately, in our setting there exists an appropriate change of dealers' measure outlined below. Under the new dealers' measure the interdealer matching is back to being uniform, and standard results apply.

Consider two sets of dealers A and B, and let μ_A be the measure of set A and $F_A(\lambda)$ be the conditional cumulative density function of dealers in set A with $\lambda_i \leq \lambda$. Similarly, we define μ_B and $F_B(\lambda)$. For the set A define Radon-Nikodym derivative $f_A(\lambda_i) = \lambda_i / \int(\lambda) dF_A(\lambda)$ and for the set B define similarly $f_B(\lambda_i) = \lambda_i / \int(\lambda) dF_B(\lambda)$. We use f_A and f_B to rescale dealers in the two sets A and B, respectively. Dealers with higher trade execution efficiency are split in greater number of representatives for the matching purposes. Once rescaled, we assume there is independent uniform matching between representatives in sets A and B with the total meeting rate of $(\int(\lambda) dF_A(\lambda) + \int(\lambda) dF_B(\lambda))\mu_A \mu_B$. The exact Law of Large Numbers applies for meetings between dealers in A and B. It remains to verify that the described matching technology is consistent: The total meeting rate is additive for disjoint sets of dealers. We verify this claim in the following lemma:

Lemma 2.1. *Let A, B, and C be disjoint sets of dealers with measures μ_A, μ_B, and μ_C, respectively. Let $m(X, Y)$ be the total meeting rate between dealers in arbitrary sets X and Y. Under the described random matching technology the total meeting rate satisfies:*

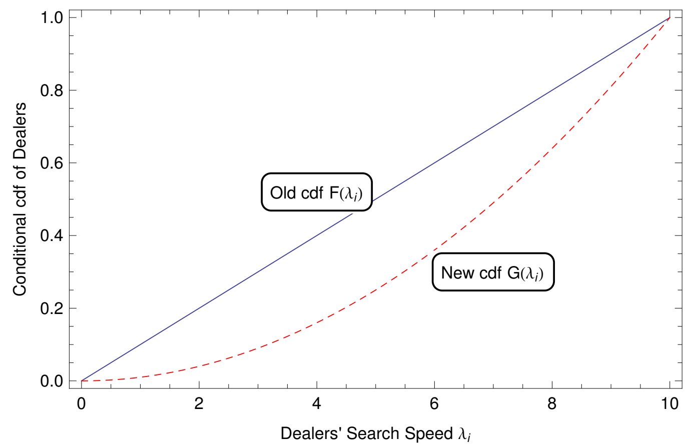
$$m(A, B \cup C) = m(A, B) + m(A, C). \tag{4}$$

Proof: See Appendix C.1.

To illustrate the change of measure described above, consider the following example. Let A be a set of dealers and let their trade execution efficiency λ_i be uniformly distributed on an interval from 0 to 10. In this case, the cumulative density function is $F_A(\lambda) = \lambda/10$, the mean execution efficiency level is $\int_0^{10} \lambda dF_A(\lambda) = 5$, and the Radon-Nikodym derivative is $f_A(\lambda_i) = \lambda_i/5$. The distribution of dealers under the new measure is $G_A(\lambda) = \lambda^2/100$. Figure 1 compares the original and the new distribution of dealers. Dealers with higher trade execution efficiency λ_i are overrepresented under the new measure, captured by convexity of $G_A(\lambda)$.

It follows, that the random matching technology can be applied to the entire population of dealers. Under this technology a dealer with trade execution efficiency λ_i contacts a dealer from set A with measure μ_A and conditional cumulative density function $F_A(\lambda)$ at

Figure 1: Example of a change of dealers' measure for matching technology.



the almost sure rate $(\lambda_i + \int(\lambda)dF_A(\lambda))\mu_A$. This expression corresponds to per capita limit of the total contact rate between sets A and B as the measure of set B goes to zero. The described random-matching technology is an example of a *linear search technology* used by Duffie, Gârleanu, and Pedersen [2005] and extended to heterogeneous search intensities setting. The idea originally was introduced by Diamond [1982] and Mortensen [1982]. Our random-matching technology closely relates to other literature that deals with heterogeneous search intensities in continuous time with continuum of agents in the population. Shimer and Smith [2001] develop a random-matching technology where each agent establishes a contact with a subset of agents according to his individual search intensity and then the potential partner is drawn randomly from the subset with likelihood proportional to partner's search intensity. It has been shown that the choice of particular random-matching technology affects agents' incentives for optimal search; however, in the context of our paper agents' search intensities are exogenous.

In the following section, we apply the described random matching technology to study customers' and dealers' equilibrium asset valuations and customer bid-ask spreads.

2.3 Trading Equilibrium

When an owner of the asset meets a non-owner, they bargain over the terms of trade. The asset changes hands when gains from trade are positive, otherwise trade does not happen.

In interdealer meetings, all dealers divide existing gains from trade according to the symmetric Nash bargaining solution. We assume the Nash bargaining power in interdealer meetings is equal to 0.5 for all dealers, and does not depend on dealers' trade execution efficiency λ_i. This assumption simplifies the exposition and establishes an important benchmark—the outcome of interdealer bargaining is being determined solely by dealers' outside options and not by relative differences in their market power. We discuss plausibility of this assumption and provide details on the underlying bargaining procedure in section 4.4.

In every transaction with a customer, all dealers have bargaining power $q \geq 0.5$. When there are positive trading gains in a customer-dealer meeting, the emerging transaction price is called "bid quote" when it is a buy from customer, and "ask quote" when it is a sell to customer. These quotes are used in the measurement of customer bid-ask spreads. Dealers may have higher bargaining power that customers in our model.

In our analysis, we focus on the steady-state dynamic trading equilibria. In these equilibria, agents' asset valuations and the distribution of agents' types in the overall population do not change over time. A *steady-state dynamic trading equilibrium* is characterized by a set of agents' state-contingent valuations and a distribution of masses that satisfy the two conditions below.

Definition 2.1. *A* steady state dynamic trading equilibrium *is characterized by state- and type-contingent asset valuations $\Delta \boldsymbol{V}_\sigma$ (customers' valuations ΔV_h^C and ΔV_l^C, and dealers' valuations as functions of their trade execution efficiency $\Delta V_h(\lambda_i)$ and $\Delta V_l(\lambda_i)$), and the distribution of agents' masses $\boldsymbol{\mu}$ (its components are listed in equations (2) and (3)), that satisfy the following consistency and optimality conditions:*

$$\textit{Optimality:} \qquad \Delta \boldsymbol{V}_\sigma(t) = E_t\{\max\left(V_\sigma(owner)\right) - \max\left(V_\sigma(non-owner)\right)|\boldsymbol{\mu}_t\}, \tag{5}$$

$$\textit{Consistency:} \qquad \frac{d\boldsymbol{\mu}_t}{dt}(\Delta \boldsymbol{V}_\sigma) = 0. \tag{6}$$

In the rest of this subsection, we describe components of the definition 2.1 presented above. Similar to Duffie, Gârleanu, and Pedersen [2005, 2007] we express each agent's value function in terms of the next stopping time τ_u at which agent's marginal utility changes, and the next stopping time τ_m at which the agent is matched with a counterparty. The optimality condition above implies that only trades with positive trading gains are executed. For example, the steady state value function for a dealer who holds one unit of the asset in high liquidity state, and has trade execution efficiency λ_i is:

$$\begin{aligned}
V_{ho}(\lambda_i) &= E_t\left(\int_t^{\min(\tau_u,\tau_m)} (\theta_h)e^{-r(u-t)}du + e^{-r(\tau_u-t)} \times A + e^{-r(\tau_m-t)} \times B\right), \qquad (7)\\
A &= V_{lo}(\lambda_i) \times \mathbb{1}_{\{\min(\tau_u,\tau_m)=\tau_u\}},\\
B &= E(\max(V_{hn}(\lambda_i) + \boldsymbol{P}, V_{ho}(\lambda_i))|\boldsymbol{\mu}_t) \times \mathbb{1}_{\{\min(\tau_u,\tau_m)=\tau_m\}}
\end{aligned}$$

In each bilateral meeting with positive trading gains, the asset is exchanged at the price set according to the Nash bargaining solution. We provide our discussion of the bargaining process in section 4.4. Note that we assume there is no asymmetric information about counterparties' types and thus all positive trading gains in this environment are realized in equilibrium. Let X and Y denote two opposite liquidity states. Equilibrium transaction prices have the following form:

$$\begin{aligned}
\text{Customer-Dealer:} \quad & P^{\text{ask/bid}}_{\text{XY}}(\lambda_i) = (1-q) \times \Delta V_X(\lambda_i) + q \times \Delta V^C_Y, \qquad (8)\\
\text{Interdealer:} \quad & P_{\text{XY}}(i,j) = 0.5 \times \Delta V_X(\lambda_i) + 0.5 \times \Delta V_Y(\lambda_j).
\end{aligned}$$

Finally, the evolution of agents' masses in the population is described by the following system of differential equations. The system for customers' masses is:

$$\begin{aligned}
\frac{d\mu^C_{\text{lo}}}{dt} &= -\gamma_{up} \times \mu^C_{\text{lo}} + \gamma_{dn} \times \mu^C_{\text{ho}} - \mu^C_{\text{lo}}\left(\int_0^{+\infty}(\lambda_j)\,d\mu_{\text{ln}}(\lambda_j) + \int_0^{+\infty}(\lambda_j)\,d\mu_{\text{hn}}(\lambda_j)\right),\\
\frac{d\mu^C_{\text{hn}}}{dt} &= -\gamma_{\text{dn}} \times \mu^C_{\text{hn}} + \gamma_{\text{up}} \times \mu^C_{\text{ln}} - \mu^C_{\text{hn}}\left(\int_0^{+\infty}(\lambda_j)\,d\mu_{\text{lo}}(\lambda_j) + \int_0^{+\infty}(\lambda_j)\,d\mu_{\text{ho}}(\lambda_j)\right),\\
\frac{d\mu^C_{\text{ln}}}{dt} &= -\gamma_{\text{up}} \times \mu^C_{\text{ln}} + \gamma_{\text{dn}} \times \mu^C_{\text{hn}} + \mu^C_{\text{lo}}\left(\int_0^{+\infty}(\lambda_j)\,d\mu_{\text{ln}}(\lambda_j) + \int_0^{+\infty}(\lambda_j)\,d\mu_{\text{hn}}(\lambda_j)\right),\\
\frac{d\mu^C_{\text{ho}}}{dt} &= -\gamma_{\text{dn}} \times \mu^C_{\text{ho}} + \gamma_{\text{up}} \times \mu^C_{\text{lo}} + \mu^C_{\text{hn}}\left(\int_0^{+\infty}(\lambda_j)\,d\mu_{\text{lo}}(\lambda_j) + \int_0^{+\infty}(\lambda_j)\,d\mu_{\text{ho}}(\lambda_j)\right). \qquad (9)
\end{aligned}$$

For any level of trade execution efficiency λ, the following system describes evolution of dealers' masses (the equation for dealers-owners is shown).

$$\begin{aligned}
\frac{d\mu_{\mathrm{Xo}}(\lambda)}{dt} &= \gamma_X \times \mu_{\mathrm{Yo}}(\lambda) - \gamma_Y \times \mu_{\mathrm{Xo}}(\lambda) + \int_0^{\lambda} \left(B_{\mathrm{Xn}}(\lambda_i) + A_{\mathrm{Xn}}(\lambda_i)\right) d\mu_{\mathrm{Xn}}(\lambda_i) - \int_0^{\lambda} \left(A_{\mathrm{Xo}}(\lambda_i) + B_{\mathrm{Xo}}(\lambda_i)\right) d\mu_{\mathrm{Xo}}(\lambda_i), \\
A_{\mathrm{Xo}}(\lambda_i) &= \int_0^{+\infty} \left(\mathbb{1}_{\{P_{\mathrm{Xl}}(i,j) > \Delta \mathrm{V}_l(\lambda_i)\}} \times (\lambda_i + \lambda_j)\right) d\mu_{\mathrm{ln}}(\lambda_j) + \int_0^{+\infty} \left(\mathbb{1}_{\{P_{\mathrm{Xh}}(i,j) > \Delta \mathrm{V}_l(\lambda_i)\}} \times (\lambda_i + \lambda_j)\right) d\mu_{\mathrm{hn}}(\lambda_j), \\
B_{\mathrm{Xo}}(\lambda_i) &= \mathbb{1}_{\left\{\Delta \mathrm{V}_h^C > P_{\mathrm{Xh}}^{\mathrm{ask}}(\lambda_i)\right\}} \times \lambda_i \times \mu_{\mathrm{hn}}^C.
\end{aligned} \tag{10}$$

We develop an algorithm to solve for the steady-state dynamic trading equilibrium. We conjecture, that dealers reservation prices for the asset $\Delta V_h(\lambda_i)$ and $\Delta V_l(\lambda_i)$ are monotonic functions of trade execution efficiency λ_i. Under this conjecture, we solve for equilibrium agents masses and asset valuations. We then verify that our conjecture holds for our solution. We provide details on the algorithm in the Appendix B. In the following section, we study emerging customer bid-ask spreads for dealers with different levels of trade execution efficiency.

3 Customer Bid-Ask Spreads

In environments with bilateral bargaining, heterogeneous agents have different outside options and consequently different reservation values for the asset. In order to understand how dealers' interconnectedness and levels of trade execution efficiency affects bid-ask spreads in equilibrium, we first study how dealers' reservation values are affected. A simplified environment below develops intuition behind the general theoretical results that follow.

3.1 Dealers' Reservation Values

Consider a simplified trading model with a search friction. We use it to develop economic intuition. There is a pool of customers comprised of buyers and sellers. At every instant of time $t \geq 0$, there is a continuum of buyers with common reservation values for an asset P^{buy} and a continuum of sellers with reservation values $P^{sell} < P^{buy}$, who cannot trade with each other. Dealer market consists of one single infinitesimal dealer who is risk-neutral, infinitely-lived, and discounts his cash flows at a rate $r > 0$. The dealer meets customers at a deterministic sequence of event times that are equally spaced in time: $t = \{\Delta, 2\Delta, 3\Delta, \ldots\}$. At every event time only one customer is met, either buyer or seller at the dealer's discretion. Asset holdings are restricted to $[0, 1]$, each unit of the asset provides constant cash flow of θ to the dealer such that $\theta/r \in (P^{sell}, P^{buy})$. Gains from trade are always positive and split according to the Nash bargaining solution in which dealer's bargaining power is $q \in [0, 1]$.

In the simplified environment, Δ is a proxy for dealers' trade execution efficiency. The larger Δ is, the longer it takes to trade with a counterparty. Dealers' intrinsic buy-and-hold valuation for the asset is θ/r. As Δ approaches infinity, dealer's reservation value for the asset approaches his buy-and-hold valuation. When Δ is finite, we write down the Bellman equations for the dealer' state-contingent value function (the states here are "owner" and "non-owner"):

$$V_{own} = \int_0^{\Delta} \theta e^{-rt} dt + (V_{non} + q \times P^{buy} + (1-q) \times (V_{own} - V_{non}))e^{-r\Delta}, \tag{11}$$

$$V_{non} = (V_{own} - q \times P^{sell} - (1-q) \times (V_{own} - V_{non}))e^{-r\Delta}. \tag{12}$$

The following lemma presents the equilibrium dealer's reservation value of the asset $(V_{own} - V_{non})$. It turns out, that in this environment the dealer's reservation value is a weighted average of dealer's buy-and-hold value and the average of customers' reservation prices, or market "midquote".

Lemma 3.1. *In the simplified environment, the equilibrium dealer's value of the asset is equal to the weighted average of dealer's buy-and-hold valuation and the average of customers' reservation prices:*

$$V_{own} - V_{non} = \left(\frac{P^{buy} + P^{sell}}{2}\right) \times \frac{2q}{e^{r\Delta} - 1 + 2q} + \left(\frac{\theta}{r}\right) \times \frac{e^{r\Delta} - 1}{e^{r\Delta} - 1 + 2q}. \tag{13}$$

Proof: See Appendix D.1.

The weight $2q/(e^{r\Delta} - 1 + 2q)$ on the customers' average reservation prices is monotonically increasing in both dealer's trade execution efficiency (inverse of Δ) and bargaining power q. Buy-and-hold valuation matters less for more efficient dealers. In the limit, as trade delays diminish $\Delta \to 0$ dealer's buy-and-hold valuation θ/r no longer matters for bargaining outcomes.

We establish a similar result when transaction delays are not symmetric for buying versus selling. This may be the case for dealers in low liquidity state that have higher likelihood of meeting buyers than sellers. In the following lemma, we assume the transaction delay for the dealer is longer when he sells to a customer-buyer ($k \times \Delta$, $k \in (1, +\infty)$) than when he buys from a customer-seller (Δ).

Lemma 3.2. *In the simplified environment, the equilibrium dealer's value of the asset is equal to the weighted average of dealer's buy-and-hold valuation and the weighted average of customers' reservation prices, so that when delays in dealing with customers-buyers are longer, the weight on customers-sellers reservation price is larger ($w_1 < 0.5$).*

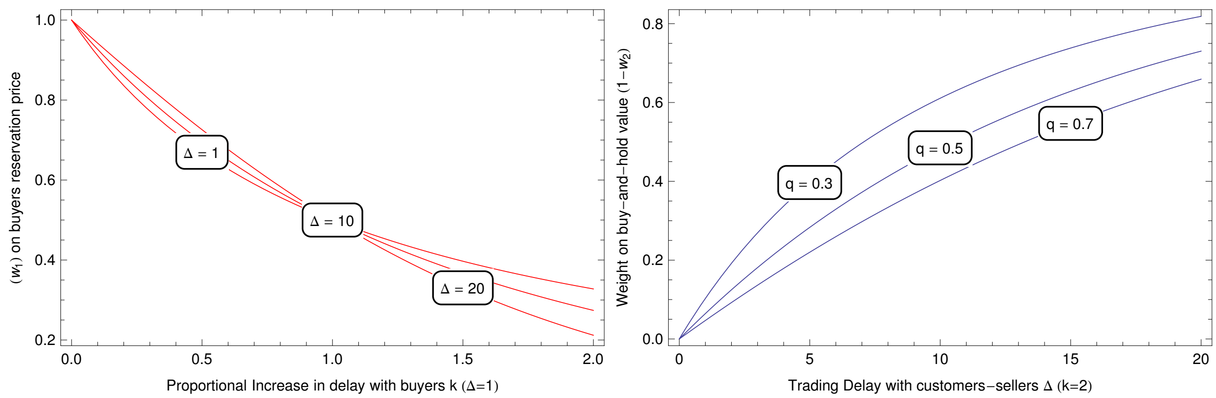
$$
\begin{aligned}
V_{own} - V_{non} &= \left(P^{buy} \times w_1 + P^{sell} \times (1 - w_1)\right) \times w_2 + \frac{\theta}{r} \times (1 - w_2)\,, \\
w_1 &= \frac{\left(e^{r\Delta} - 1\right)}{\left(e^{k \times r\Delta} + e^{r\Delta} - 2\right)}, \\
w_2 &= \frac{\left(e^{k \times r\Delta} + e^{r\Delta} - 2\right) q}{\left(e^{r\Delta} - 1\right)\left(e^{k \times r\Delta} - 1\right) + \left(e^{k \times r\Delta} + e^{r\Delta} - 2\right) q}.
\end{aligned}
\tag{14}
$$

Proof: See Appendix D.1.

Similarly to the symmetric case, the weight w_2 on the average reservation prices of customers is monotonically increasing in dealer's trade execution efficiency (inverse of Δ) and bargaining power q.

The simplified environment demonstrates that a dealer's reservation value for the asset lies in between his buy-and-hold value and an appropriately defined average market value. As dealer's trade execution efficiency increases, reservation value depends less on dealer's buy-and-hold value. This finding is intuitive, as a more efficient dealer has lower holding periods, for which the buy-and-hold utility flow matters. In a more general environment where dealers' buy-and-hold values are exposed to random liquidity shocks, we expect the quotes from more efficient dealers to be less affected by such variability. The market

Figure 2: Execution delays Δ and the dealer's value of the asset



Panel A: Effect of k on buyers' reservation price weight w_1

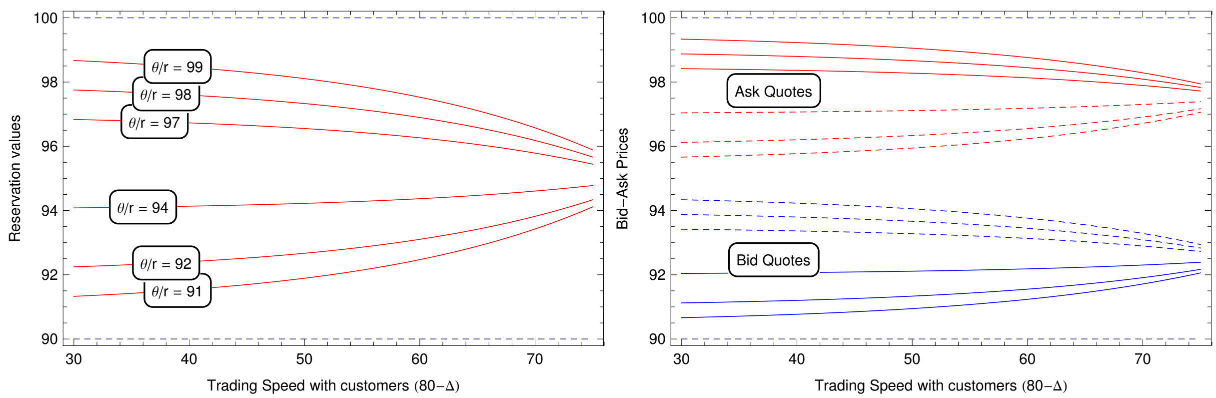
Panel B: Effect of Δ on dealer's buy-and-hold valuation weight $(1 - w_2)$

"mid-quote" is a more important determinant of bargaining positions for more efficient dealers. Thus, we expect variability of quotes posted by more efficient dealers to be smaller. Conversely, dealers with lower trade execution efficiency will be willing to provide a better deal to customers when they are in the opposite liquidity state.

We demonstrate the relationship between dealers' reservation values and customers bid-ask spreads graphically in Figure 3. The x-axis is the inverse of dealer's trade execution delay Δ—dealers with higher trade execution efficiency are on the right side along the x-axis. Panel B of Figure 3 demonstrates bid- and ask-quotes charged by the dealer. We observe lower variability of customer quotes for dealers with higher trade execution efficiency. This holds in the general model with multiple dealers and random matching. Higher variability of customer quotes offered by peripheral dealers is a testable prediction of our model.

The average bid-ask spread customers face when trading with different types of dealers depends on the cross-sectional distribution of dealers across liquidity states and asset ownership types. In Figure 3, the quotes shown on the dashed lines of Panel B correspond to dealers-sellers with relatively low buy-and-hold values (dashed ask quotes) and dealers-buyers with relatively high buy-and-hold values (dashed bid quotes). These quotes also correspond to relatively good deals for customers on each side of the market. In a similar

Figure 3: Relationship between dealers' reservation values and bid-ask spreads



Panel A: Dealers' reservation values for different buy-and-hold valuations

Panel B: Bid-ask spreads based on symmetric Nash bargaining solution

fashion, the quotes shown on the solid lines correspond to relatively bad deals for customers, because trading gains realized in such transactions are low. When owners and non-owners are uniformly distributed across different liquidity states in the cross-section, the dashed lines and dotted lines are equally likely to occur and the average bid-ask spread is the same for dealers with different trade execution efficiency and transaction delays Δ. However, the general model with search and matching that follows predicts that there are more owners in high liquidity state than owners in low liquidity state in the steady-state equilibrium, and thus on Figure 3 solid lines are more likely to occur. This implies a negative relationship between average customer bid-ask spread and dealers' trade execution efficiency. Less interconnected dealers are expected to offer wider spreads on average than more interconnected dealers, consistent with evidence in Hollifield, Neklyudov, and Spatt [2012] for ABS and CMO markets.

Now imagine that customers are actively shopping for good bargains provided by dealers in the opposite liquidity states, shown by dashed lines on Figure 3. This puts extra probability on smallest possible bid-ask spreads values and can eventually revert the relationship between average customer bid-ask spread and dealers' trade execution efficiency. The positive relationship observed documented by Li and Schürhoff [2012] for municipal bonds market is consistent with such customer shopping. We explore this extension of the general model in section 4.3.

3.2 General Model

A similar line of argument to the one developed above applies in the general environment. In any steady state dynamic trading equilibrium (definition 2.1) there exists a unique market "mid-quote" that serves as the limit for reservation values of dealers as trade execution efficiency increases. Dealers with higher trade execution efficiency are less affected by their buy-and-hold values when they bargain with customers. In our notation, this occurs when the gap in dealers' reservation values in two liquidity states $\Delta V_h(\lambda_i) - \Delta V_l(\lambda_i)$ is decreasing in dealer's trade execution efficiency λ_i.

In this subsection, we conjecture that a steady-state dynamic trading equilibrium exists. We are able to demonstrate existence and uniqueness of such equilibrium for symmetric markets in section 4. Let $\{\Delta \boldsymbol{V}_\sigma, \boldsymbol{\mu}\}$ be an equilibrium. Our first step is to identify the average market "mid-quote":

Definition 3.1. *For any steady state dynamic trading equilibrium* $\{\Delta \boldsymbol{V}_\sigma, \boldsymbol{\mu}\}$ *define the* average market mid-quote ΔV *as the limit of reservation price of a zero-measure dealer as that dealer's trade execution efficiency* λ_i *goes to infinity:*

$$\Delta V = \lim_{\lambda \to +\infty} (\Delta V(\lambda_i)). \tag{15}$$

Definition 3.1 states the average market mid-quote as the asset reservation price for a dealer not exposed to search friction. Such dealer does not have to exist for us to be able to compute the average market mid-quote. A single zero-measure dealer does not affect the steady state trading equilibrium $\{\Delta \boldsymbol{V}_\sigma, \boldsymbol{\mu}\}$ and can be added to the population without consequences.

Proposition 3.1. *Let* $\{\Delta \boldsymbol{V}_\sigma, \boldsymbol{\mu}\}$ *be a steady-state dynamic trading equilibrium. There exists* *a unique average market mid-quote ΔV, which is the fixed point of the following mapping:*

$$\begin{aligned}
\Delta V &= T_1(\Delta V), \qquad (16)\\
T_1(x) &= \Big(q \times (\max(\Delta V_h^C, x)\mu_{hn}^C + \max(\Delta V_l^C, x)\mu_{\ln}^C + \min(\Delta V_h^C, x)\mu_{ho}^C + \min(\Delta V_l^C, x)\mu_{lo}^C)\\
&\quad + \frac{1}{2} \times \Big(\int_0^{+\infty} \max(\Delta V_h(\lambda_j), x) d\mu_{hn}(\lambda_j) + \int_0^{+\infty} \max(\Delta V_l(\lambda_j), x) d\mu_{\ln}(\lambda_j)\\
&\quad + \int_0^{+\infty} \min(\Delta V_h(\lambda_j), x) d\mu_{ho}(\lambda_j) + \int_0^{+\infty} \min(\Delta V_l(\lambda_j), x) d\mu_{lo}(\lambda_j)\Big)\Big) \times\\
&\quad \times (q \times (1 - M_d) + 0.5 \times M_d)^{-1}.
\end{aligned}$$

Proof: See Appendix D.2.

The average market midquote can be thought of as the representative asset valuation on an over-the-counter market with heterogeneous participants. This is also a benchmark point above which any dealer with sufficiently high trade execution efficiency will be willing to sell, and below which the same dealer will be willing to buy.

In our analysis, we do not study asymmetric steady-state equilibria with some dealers having their reservation values on one side of the average market midquote in all possible liquidity states. In an asymmetric steady-state equilibrium, some dealers are always more likely to buy than sell, while others are always more likely to sell than buy. We concentrate on the subclass of market equilibria that are relatively symmetric, that is each dealer depending on its liquidity state can be on the either side of the midquote from time to time, and experience both buying and selling pressures. The definition of a relatively symmetric equilibrium follows:

Definition 3.2. *A steady state dynamic trading equilibrium $\{\Delta \boldsymbol{V}_\sigma, \boldsymbol{\mu}\}$ is* relatively symmetric *when the average market midquote ΔV is in between all agents' reservation values in the two opposite liquidity states:*

$$\Delta V_h(\lambda) > \Delta V > \Delta V_l(\lambda) \text{ , for } \forall \lambda \in [0, +\infty). \qquad (17)$$

Note that in Definition 3.2 perfect symmetry is not required, as the reservation values of dealers in the opposite liquidity states are not required to be *equidistant* from the average market midquote. However the case of perfect symmetry is interesting due to its tractability, and is presented in section 4.

Our key result is the following proposition. We are able to show that in any relatively symmetric steady-state equilibrium dealers with higher trade execution efficiency are less exposed to variability in their buy-and-hold values. This result allows us to demonstrate negative relationship between bid-ask spreads and dealers' trade execution efficiency.

Proposition 3.2. *Let $\{\Delta \boldsymbol{V}_\sigma, \boldsymbol{\mu}\}$ be a steady-state dynamic trading equilibrium that is relatively symmetric. Then $\Delta \boldsymbol{V}_\sigma$ satisfies the following property:*

$$\frac{d(\Delta V_h(\lambda) - \Delta V_l(\lambda))}{d\lambda} < 0. \tag{18}$$

Proof: See Appendix D.3.

This finding shows that the intuition developed in section 3 holds in the generalized setting with search and matching. The general model is used to compute the steady-state masses of different dealers in a cross-section and use these to compute average customer bid-ask spreads. We perform this analysis numerically in the following section.

4 Analysis of Symmetric Markets

In this section, we study a special type of steady-state dynamic trading equilibria that are symmetric. Such equilibria occur when the buy-and-hold values of dealers and customers are symmetric: $(\theta_{high}+\theta_{low})/2 = (\theta_h+\theta_l)/2$, the switching process between the two liquidity states for each agent is symmetric: $\gamma_{up} = \gamma_{dn} = \gamma$, and the asset initial supply is: $s = 1/2$.

Definition 4.1. *A steady-state dynamic trading equilibrium $\{\Delta \boldsymbol{V}_\sigma, \boldsymbol{\mu}\}$ is* symmetric *when* *the following conditions hold:*

$$
\begin{aligned}
\boldsymbol{\mu} \textit{ satisfies:} \qquad & \mu^C_{hn} = \mu^C_{lo} = \mu^C, \\
& \mu^C_{ho} = \mu^C_{ln} = (1 - M_d)/2 - \mu^C, \\
& \mu_{hn}(\lambda) = \mu_{lo}(\lambda) = \mu(\lambda),\ \forall \lambda \in [0, +\infty), \\
& \mu_{ho}(\lambda) = \mu_{ln}(\lambda) = (F(\lambda)/2 - \mu(\lambda)),\ \forall \lambda \in [0, +\infty).
\end{aligned}
$$

Any symmetric steady-state trading equilibrium is relatively symmetric as well, as it satisfies the property in Definition 3.2. The average market mid-quote for a symmetric market is $(\theta_{high} + \theta_{low})/2$ and any agent's valuation in the high liquidity state is above this value.

The following lemma allows us to solve for equilibrium masses of customers and dealers in a symmetric steady-state equilibrium.

Lemma 4.1. *In a* symmetric *steady-state dynamic trading equilibrium the function $\mu_{lo}(\lambda)$ (describing distribution of search speeds λ across dealers who hold the asset in low liquidity state) satisfies the following ODE:*

$$
\begin{aligned}
& \frac{M_d}{2}\left(\left(\gamma + x\mu^C - y(x) + 2xy'(x)\right)F'(x) + x(F(x) - 1)y''(x)\right) \qquad (19) \\
& = \left(2\gamma + 2x\mu^C - 2y(x) + 4xy'(x) + \int_x^{+\infty} \frac{1}{2} z M_d F'(x) dz\right) y''(x), \\
& \textit{where: } y(x) = \int_0^x \mu_{lo}(\lambda) d\lambda \\
& y(0) = 0, y'(0) = 0.
\end{aligned}
$$

Proof: See Appendix E.1.

We solve the model numerically. We let dealers' trade execution efficiency λ_i be uniformly distributed on an interval from 0 to 10. In this case, the conditional cumulative density function $F(\lambda) = \lambda/10$, and the mean execution efficiency level is $\int_0^{10} \lambda dF(\lambda) = 5$. Figure 7 demonstrates the solution for the following parameters of the model:

parameter	value	comment
$\gamma_{up} = \gamma_{dn}$	0.5	the same to ensure symmetry of equilibrium
M_d	1/2	half of the population are dealers
q	0.7	dealers have higher bargaining power than customers
θ_{high}	5.1	MU of customer in high state
θ_{low}	4.4	MU of customer in low state
θ_h	5	MU of dealer in high state
θ_l	4.5	MU of dealer in low state

4.1 Equilibrium Dealer Networks

In the dynamic trading equilibrium we find, dealers differ in the number of counterparties they meet over time. The numbers of transactions with customers and interdealer transactions differ as well. In equilibrium, there is an infinitely dense network of trading relationships, which is random at the level of individual agent, and deterministic in aggregate (by the appropriate law of large numbers, see Duffie and Sun [2007] for discussion). Despite the fact that the model features a continuum of dealers and customers, we are able to compute expected number of counterparties encountered over a given interval of time by a given agent, which would correspond to that agent's degree centrality. As all agents are infinitesimally small, no pair of agents will meet each other twice in the equilibrium almost surely, thus the number of trades and the number of counterparties are the same.

Consider a dealer with trade execution efficiency $\lambda_i \geq 0$. In the steady-state, the lifetime of this dealer follows a four-state continuous-time Markov chain with the generator matrix $\boldsymbol{Q}(\lambda_i)$:

$$\boldsymbol{Q}(\lambda_i) = \begin{array}{c} ho \\ lo \\ hn \\ ln \end{array} \begin{pmatrix} (-\gamma_{dn} - \boldsymbol{\lambda}_{sell}^{high}) & \gamma_{dn} & \boldsymbol{\lambda}_{sell}^{high} & 0 \\ \gamma_{up} & (-\gamma_{up} - \boldsymbol{\lambda}_{sell}^{low}) & 0 & \boldsymbol{\lambda}_{sell}^{low} \\ \boldsymbol{\lambda}_{buy}^{high} & 0 & (-\gamma_{dn} - \boldsymbol{\lambda}_{buy}^{high}) & \gamma_{dn} \\ 0 & \boldsymbol{\lambda}_{buy}^{low} & \gamma_{up} & (-\gamma_{up} - \boldsymbol{\lambda}_{buy}^{low}) \end{pmatrix}. \quad (20)$$

$$\begin{aligned}
\text{where: } \boldsymbol{\lambda}_{sell}^{high} &= \lambda_i \times \mu_{hn}^C + \int_{\lambda=0}^{\lambda_i} (\lambda_i + \lambda) d\mu_{hn}(\lambda) \\
\boldsymbol{\lambda}_{sell}^{low} &= \lambda_i \times \mu_{hn}^C + \int_{\lambda=0}^{\infty} (\lambda_i + \lambda) d\mu_{hn}(\lambda) + \int_{\lambda=\lambda_i}^{\infty} (\lambda_i + \lambda) d\mu_{ln}(\lambda) \\
\boldsymbol{\lambda}_{buy}^{high} &= \lambda_i \times \mu_{lo}^C + \int_{\lambda=0}^{\infty} (\lambda_i + \lambda) d\mu_{lo}(\lambda) + \int_{\lambda=\lambda_i}^{\infty} (\lambda_i + \lambda) d\mu_{ho}(\lambda) \\
\boldsymbol{\lambda}_{buy}^{low} &= \lambda_i \times \mu_{lo}^C + \int_{\lambda=0}^{\lambda_i} (\lambda_i + \lambda) d\mu_{lo}(\lambda).
\end{aligned}$$

The matrix of conditional probabilities $\boldsymbol{P}(t, \lambda_i)$ of a dealer residing in each given state at a given point in time can be obtained by solving the Kolmogorov equation $(\partial \boldsymbol{P}/\partial t)(t, \lambda_i) = \boldsymbol{Q}(\lambda_i) \times \boldsymbol{P}(t, \lambda_i)$. We then compute the expected number of transitions in this Markov chain over a given fixed period of time, using results on Markov chains from Guttorp [1995]. For example, the expected number of dealer's buys over time period $t \in (0, T)$ (both from customers and on interdealer market) is equal to:

$$E[N_{buy}] = \sum_{i=1}^{4} \left[Prob(X_0 = i) \times \int_0^T \left(\boldsymbol{\lambda}_{buy}^{high} P_{i \to hn}(t, \lambda_i) + \boldsymbol{\lambda}_{buy}^{low} P_{i \to ln}(t, \lambda_i) \right) dt \right]. \tag{21}$$

Note that we can compute the expected number of customer and interdealer trades separately as well, by using the relevant customer and interdealer portions of $\boldsymbol{\lambda}_{buy}^{high}$ and $\boldsymbol{\lambda}_{buy}^{low}$ in the formula above.[2] For the analysis below we assume that the initial state probabilities $Prob(X_0 = i)$ are consistent with the stationary distribution of this Markov chain. In this case unconditional probabilities of being in each state are constant in time and the above equation reduces to:

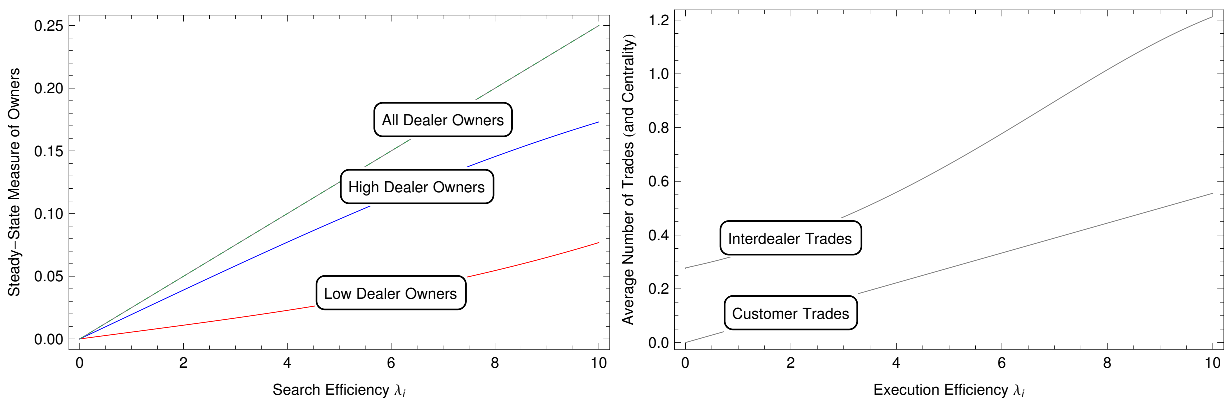
$$\begin{aligned}
E[N_{buy}] &= \int_0^T \left(\boldsymbol{\lambda}_{buy}^{high} P_{hn}(t, \lambda_i) + \boldsymbol{\lambda}_{buy}^{low} P_{ln}(t, \lambda_i) \right) dt, \\
\text{where: } P_{hn}(t, \lambda_i) &= \frac{\gamma_{up}(\gamma_{dn} \boldsymbol{\lambda}_{sell}^{low} + \boldsymbol{\lambda}_{sell}^{high}(\gamma_{up} + \boldsymbol{\lambda}_{buy}^{low} + \boldsymbol{\lambda}_{sell}^{low}))}{(\gamma_{dn} + \gamma_{up})(\gamma_{up}(\boldsymbol{\lambda}_{buy}^{high} + \boldsymbol{\lambda}_{sell}^{high}) + (\gamma_{dn} + \boldsymbol{\lambda}_{buy}^{high} + \boldsymbol{\lambda}_{sell}^{high})(\boldsymbol{\lambda}_{buy}^{low} + \boldsymbol{\lambda}_{sell}^{low}))}, \\
P_{ln}(t, \lambda_i) &= \frac{\gamma_{dn}(\gamma_{up} \boldsymbol{\lambda}_{sell}^{high} + \boldsymbol{\lambda}_{sell}^{low}(\gamma_{dn} + \boldsymbol{\lambda}_{buy}^{high} + \boldsymbol{\lambda}_{sell}^{high}))}{(\gamma_{dn} + \gamma_{up})(\gamma_{up}(\boldsymbol{\lambda}_{buy}^{high} + \boldsymbol{\lambda}_{sell}^{high}) + (\gamma_{dn} + \boldsymbol{\lambda}_{buy}^{high} + \boldsymbol{\lambda}_{sell}^{high})(\boldsymbol{\lambda}_{buy}^{low} + \boldsymbol{\lambda}_{sell}^{low}))}.
\end{aligned}$$

Here we study equilibrium trading frequencies and dealers' interconnectedness. The

[2] This is justified, since the future lifetime of a dealer does not depend on whether the asset was purchased on the interdealer market or from a customer. This allows to reduce the number of relevant states to 4.

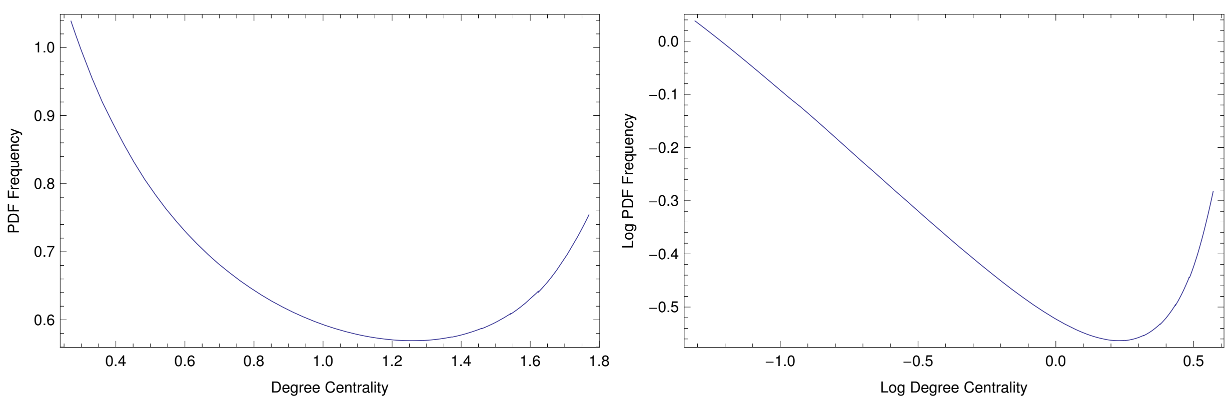
random matching between customers and dealers generates a network of trading relationships. In this section we characterize various properties of the realized network.

Figure 4: Dealers' Expected Centralities (and Volumes) in Symmetric Market



Panel A: Equilibrium dealers' masses ($s = 0.5$) Panel B: Dealers' Degree Centrality distribution

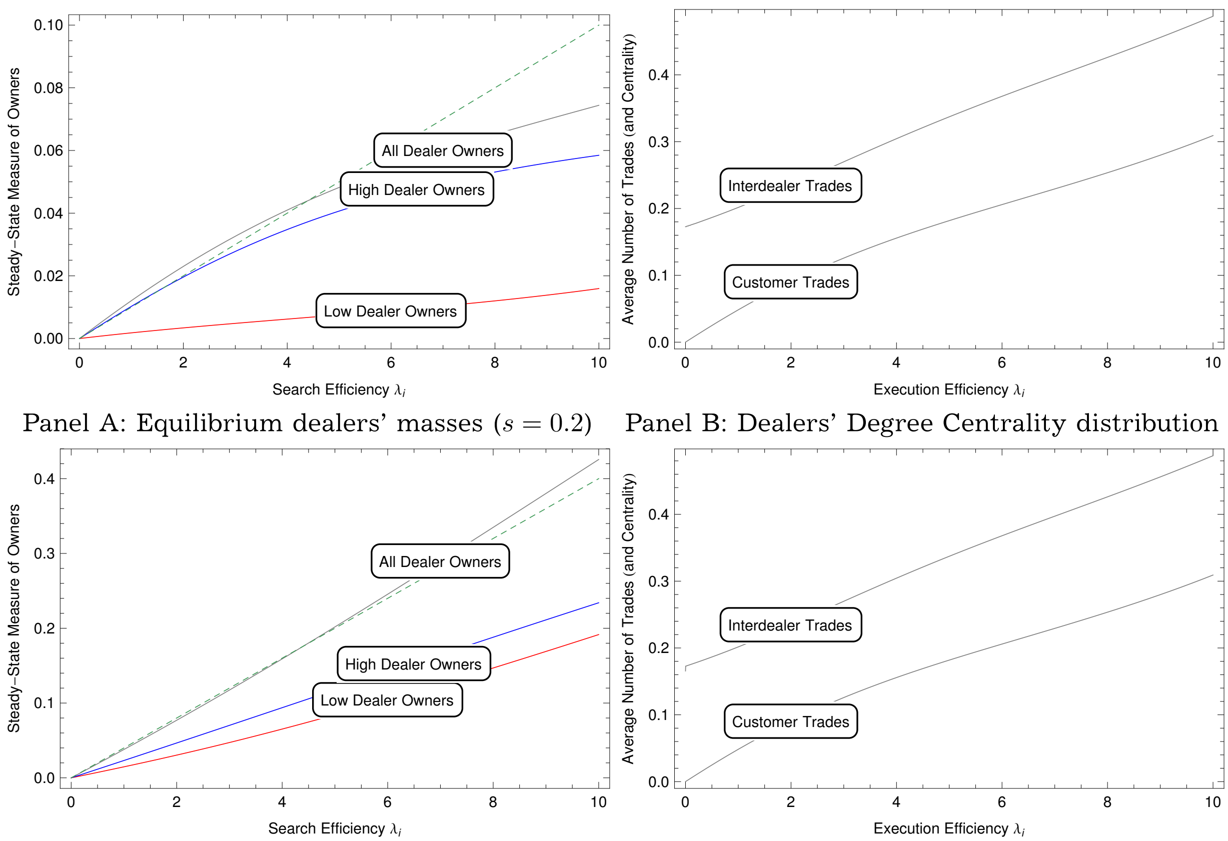
Figure 5: Degree Centrality Distribution in Symmetric Market



Panel A: The distribution of degree centralities for $s = 0.5$ Panel A: The distribution of degree centralities (in logs)

An empirical feature of many observed networks is a power law distribution of the number of links. Our model suggests that a uniform distribution of trade execution efficiency levels for dealers may generate a convex distribution of expected numbers of links (degree centrality) and trading volume across dealers. More efficient dealers endogenously receive larger volume of interdealer trades, shown on Figure 4. This convexity is explained by the endogenous intermediation role more efficient dealers obtain among the less efficient dealers. However such growth in degree centrality reduces once the efficiency reaches relatively high values on the market—the top dealers experience a reduction in the positive matching externality by always dealing with less efficient dealers. Thus, the distribution of degree centrality on the market is bi-modal (shown in Figure 5). It reflects an exponential decay for relatively lower values of λ (as in power law distributions), and fat right tails due to the matching externality effect.

Figure 6: Dealers' Expected Centralities (and Volumes) in Relatively Symmetric Market



Panel A: Equilibrium dealers' masses ($s = 0.2$) Panel B: Dealers' Degree Centrality distribution

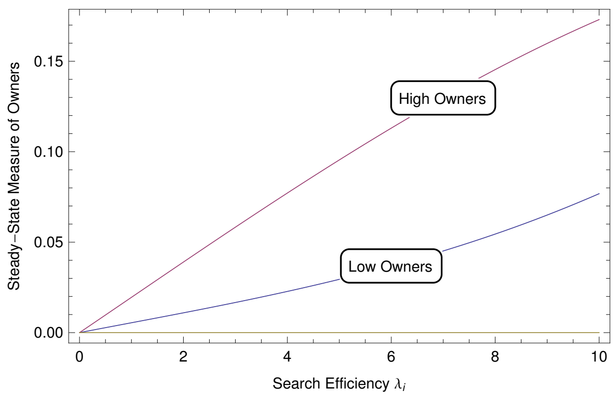
Panel C: Equilibrium dealers' masses ($s = 0.8$) Panel D: Dealers' Degree Centrality distribution

Large imbalances in the aggregate initial asset endowment may flatten out the convexity of the numbers of interdealer links, shown on Figure 6.

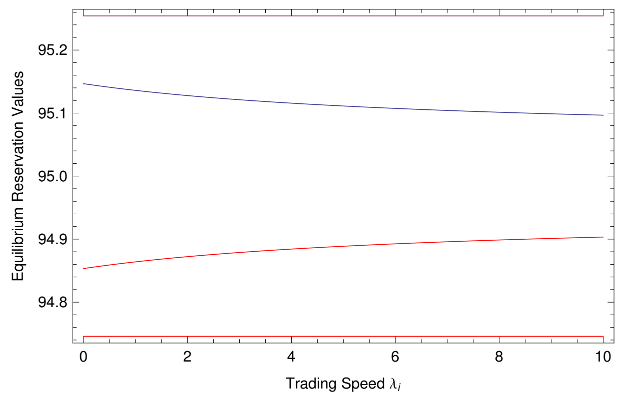
These results allow us to establish the mapping from the underlying search economy to the empirically observed network structure.

4.2 Customer Bid-Ask Spreads

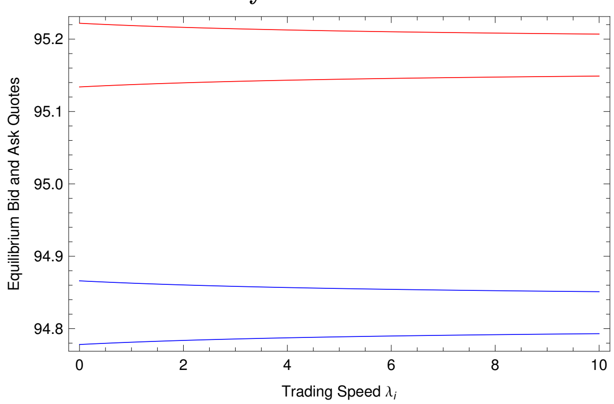
Figure 7: Numerical Solution for the symmetric steady-state trading equilibrium



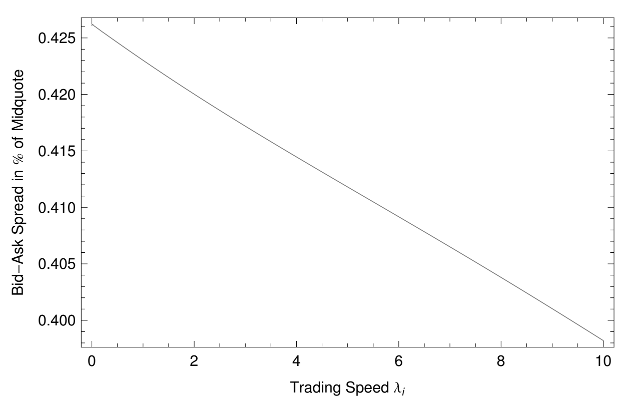
Panel A: Equilibrium cdf of dealers-owners, scaled by their total mass



Panel B: Customers' and dealers' equilibrium reservation values



Panel C: All possible Bid and Ask quotes in equilibrium



Panel D: Conditional Mean Bid-Ask Spreads in equilibrium

Based on the reservation values on Panel B of Figure 7 and the cross-sectional distribution of dealers, we compute conditional average bid-ask spreads customers face when meeting a dealer with a given level of trade execution efficiency λ_i. The resulting customer bid-ask spreads are presented on Panel D of Figure 7. We observe a negative relationship between bid-ask spreads and dealers' trade execution efficiency λ_i. It is possible to demonstrate that as the intensity of switching across liquidity states γ increases, the negative relationship between computed bid-ask spreads flattens in the limit.

The explanation for the negative relationship between dealers' trade execution efficiency and average bid-ask spreads observed is the following. In relatively symmetric steady-state equilibrium, less efficient dealers are more exposed to search friction and have more weight on their buy-and-hold valuations in their asset reservation values. Their buy-and-hold valuations are exposed to random liquidity shocks. More efficient dealers suffer less from these shocks, because their reservation values are closer to the constant average market midquote. Interdealer trading results in over-representation of high-owners and low-non-owners in the population, because owners in high liquidity state are less likely to sell than owners in low liquidity state. Dealers in the same liquidity state as customers cannot offer good bargains because trading gains are small. As dealer's trade execution efficiency diminishes, these trading gains become even lower. This is the reason, why we observe higher average bid-ask spreads for less interconnected dealers when they trade with customers.

4.3 Customers' Shopping Activity

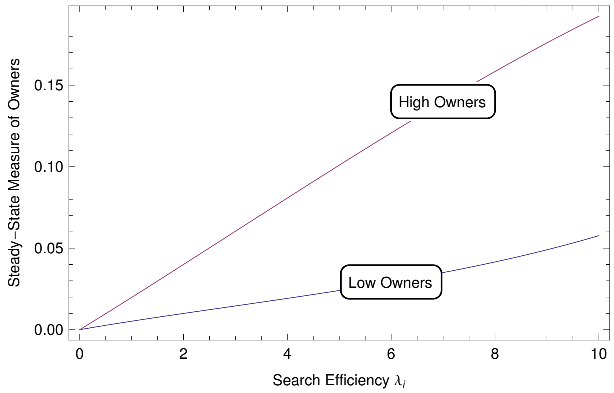
Active customer shopping for better quotes may have important consequences and reverse the negative relationship we observe in the general model. Below we define formally what active customer shopping stands for in our environment.

Definition 4.2. *A market is characterized by* active customer shopping *when a trade between a customer and a dealer is more likely to occur when the dealer and the customer are in the opposite liquidity states than when they are in the same liquidity state.*

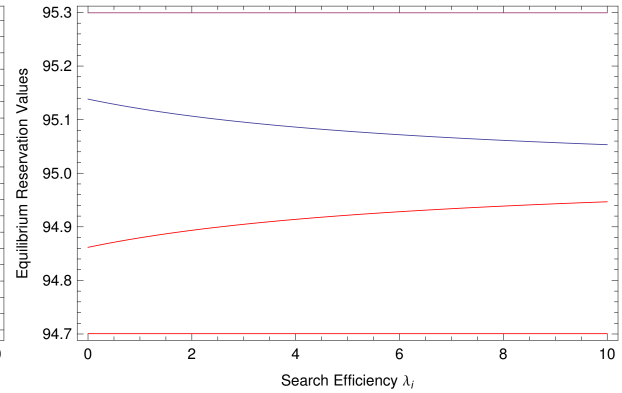
In the baseline model, any customer in a high liquidity state who does not have an asset can trade with both high-liquidity state dealers and low-liquidity state dealers. The high-liquidity state dealers are over-represented in the cross-section of dealers in the steady-state equilibrium and they have lower trading gains with customers.

Consider the following example. There are three dealers on a market and one customer. In this example, we assume the dealers have equal trade execution efficiency, to concentrate on the customer shopping. The customer does not have the asset and is in high liquidity state, so that the customer's buy-and-hold valuation is relatively high. The three dealers hold the asset, and their liquidity states as well as gains from trading with the customer are shown in the table:

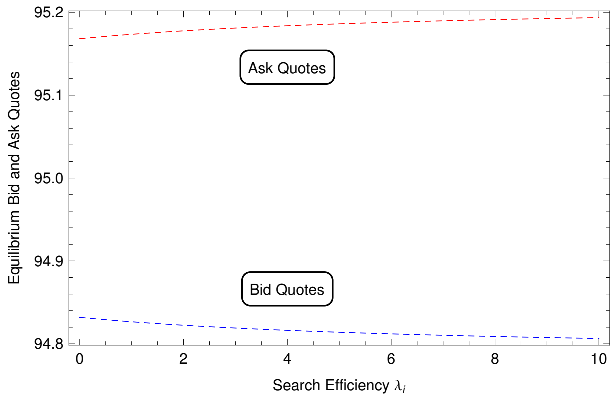
Figure 8: Numerical Solution for the symmetric equilibrium with shopping



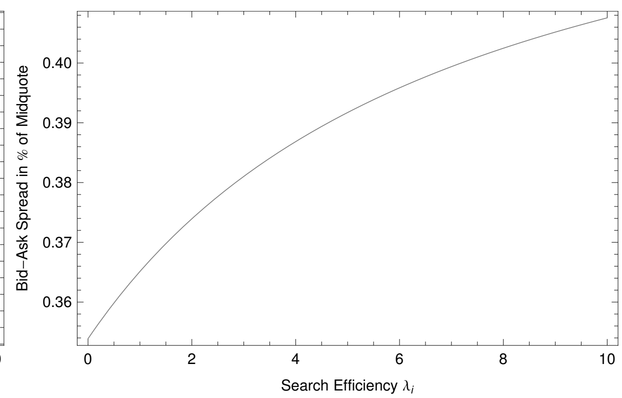
Panel A: Equilibrium cdf of dealers-owners, scaled by their total mass



Panel B: Customers' and dealers' equilibrium reservation values



Panel C: Bid and Ask quotes in equilibrium



Panel D: Conditional Mean Bid-Ask Spreads in equilibrium

	liquidity state	trading gains with the customer
dealer A	high	\$2 (lowest)
dealer B	high	\$3
dealer C	low	\$11 (highest)

All the three dealers have positive gains from trading with the customer. In the baseline model that would imply all the three transactions are equally likely. The probability p of a "Dealer C to customer" transaction occurring is $1/3$. Note that this dealer offers the highest gains from trading to the customer. Active customer shopping would occur when this probability is larger $p > 1/3$. In this section, we modify the random-matching technology of the baseline model and assume the extreme case scenario of such customer shopping—*no trade happens between a customer and a dealer in the same liquidity state*,

$p = 1$.

Active customer shopping may occur for various reasons. First, customers may apply an extra effort to locate low-liquidity owners among dealers and get better deals. Second, exogenous transaction costs may make transactions with small trading gains infeasible to carry out. For these reasons, active customer shopping is not necessarily associated with sophistication of customers, because sophisticated customers may be less sensitive to these exogenous transaction costs. Active customer shopping may not be observed on markets with relatively large overall magnitude of trading gains. When trading gains are large even for counterparties in the same liquidity state, all trades with positive gains will be executed as in the baseline version of the model.

In what follows, we assume that no trade happens between a customer and a dealer in the same liquidity state. We solve for the steady-state equilibrium of the modified model numerically using the same parameters values as in the previous subsection.

Panel D of Figure 8 demonstrates positive relationship between average bid-ask spreads and dealers' trade execution efficiency. The finding is consistent with empirical evidence in Li and Schürhoff [2012] on municipal bond markets.

4.4 The Bargaining Model

So far in our analysis we worked with Nash bargaining solution, where trading gains were split proportionally in all bilateral meetings (in all interdealer meetings the gains were split equally, while in customer-dealer meetings, dealers were getting fixed proportion q of the gains). Two questions we ask in this section are: 1) can these fixed proportions be justified using equilibrium outcomes of a dynamic bargaining model; and 2) how changes in the fixed proportions affect our results.

As it is known in the literature, in a bilateral bargaining game with simultaneous offers, any value of the fixed proportion q can be justified as a Nash equilibrium (discussed in Kreps [1990]). In the context of over-the-counter trading, Duffie et al. [2003] present a version of a dynamic bargaining game with alternating offers, where at each stage of the game one of the two agents is chosen randomly to make an ultimatum take-it-or-leave-it offer, and the continuous-time limit of such game is considered. In one version of the game, when agents are not allowed to search for other counterparties during bargaining process, the endogenous bargaining power arises as a function of model parameters and probabilities of making an ultimatum offer. The bargaining power is higher when the probability of making an offer is higher for each agent, or when agent's ability to meet other partners is lower (making the agent relatively more patient). In another version of the game, when agents are allowed to search for other counterparties during the bargaining process, the endogenous bargaining power of an agent is equal to the probability of making an ultimatum offer and does not depend on other model parameters. Intuitively, agent's ability to keep searching for counterparties during bargaining implies that there is no sacrifice being made when bargaining process is initiated. Higher ability of meeting other partners increases the likelihood of a breakdown in any given bargaining round.

We follow Duffie et al. [2003], and use the framework of Rubinstein and Wolinsky [1985] and others, to verify whether similar results can be obtained in a model with a continuum of different types of dealers, and what are the required assumptions. We show that under a set of reasonable assumptions, we are able to justify our Nash bargaining assumption in a dynamic bargaining game with alternating offers.

In our trading model, customers and dealers could be in one of the two liquidity states and can have different trade execution efficiency (note that trade execution efficiency of customers is normalized to zero). These agents' types determine a subset of potential counterparties with positive trading gains in the population for each agent. We take two arbitrary agents and assume they play a dynamic bargaining game when they are matched, in which they are allowed to exchange offers at discrete moments of time Δ_t. In each customer-dealer round, one agent is chosen randomly to make an ultimatum offer, so that the probability of a dealer making an ultimatum offer is $\hat{q}$. In each interdealer round, one of the dealers is chosen equally likely. From now on we will focus on customer-dealer meetings where customer is a buyer, and dealer has execution efficiency λ_i. Denote dealer's optimal offer by P_i and customer's optimal offer by P^C. Denote the expected transaction price by $\hat{P} = \hat{q}P_i + (1-\hat{q})P^C$. Similar analysis holds for customers-sellers, as well as for interdealer meetings with minor modifications.

Let A be a subset of dealers with measure μ_A, who have positive trading gains when matched with the given customer, and let λ_A be their average trade execution efficiency: $\lambda_A = \int_A \lambda dF_A(\lambda)$. Similarly, let B be a subset of other dealers and customers, who have positive trading gains with the given dealer, with average trade execution efficiency λ_B (here we assign zero trade execution efficiency for all customers in B). The rate, at which the customer finds a substitute for the dealer he is negotiating with is $\lambda_A\mu_A$, while a similar rate for the dealer is $(\lambda_i+\lambda_B)\mu_B$. Additionally, let γ_A be the rate at which the liquidity state of the customer switches ($\gamma_A = \gamma_{dn}$, as high-liquidity customers are the only buyers in the model), and let γ_B be the rate at which the dealer's liquidity state switches ($\gamma_B \in \{\gamma_{up}, \gamma_{dn}\}$, depending on the initial liquidity state of the dealer). Assume further that the bargaining process stops once any of the two agents is matched with another counterparty or when the liquidity state switches (we discuss plausibility of this in our setting below).

Under the assumption that both customer and dealer can search for other counterparties during the bargaining process, the optimal prices offered satisfy the following set of equations (here we use W to denote value function of an agent who has a counterparty to bargain with at the moment):

$$\begin{aligned}
P^C + V_n(\lambda_i) &= W_o(\lambda_i) = V_o(\lambda_i) + e^{-r\Delta_t}\left(e^{-(\gamma_A+\gamma_B+\lambda_A\mu_A+\lambda_B\mu_B)\Delta_t}\right)\left(\hat{P} - \Delta V(\lambda_i)\right), \quad (22)\\
V_o^C - P_i &= W_n^C = V_n^C + e^{-r\Delta_t}\left(e^{-(\gamma_A+\gamma_B+\lambda_A\mu_A+\lambda_B\mu_B)\Delta_t}\right)\left(\Delta V^C - \hat{P}\right),\\
&\lim_{\Delta_t\to\infty}(P^C) = \lim_{\Delta_t\to\infty}(P_i) = (1-q)\times\Delta V(\lambda_i) + q\times\Delta V^C,\\
&\text{where: } q = \hat{q}.
\end{aligned}$$

The result above suggests that as long as both agents are allowed to keep looking for counterparties while bargaining and the bargaining stops when such counterparty is encountered, the bargaining power does not depend on agents' search abilities (relative measures of A and B sets, and average trade execution efficiencies λ_A and λ_B). This is consistent with Duffie et al. [2003] and justifies the fixed proportion q for customer trades (and $1/2$ for interdealer trades) used in our trading model. Here we assumed that the bargaining process stops once any of the two agents finds a substitute counterparty or when the liquidity state switches. The latter can constitute an issue, when for example a customer-buyer is bargaining with a dealer in high liquidity state, while the dealer switches to low liquidity state in between rounds. Alternatively, a customer may find a counterparty with significantly lower trading gains, so that he would not want to drop out from bargaining. In Rubinstein and Wolinsky [1985] this is not a problem, because all matches generate the same amount of good to share.

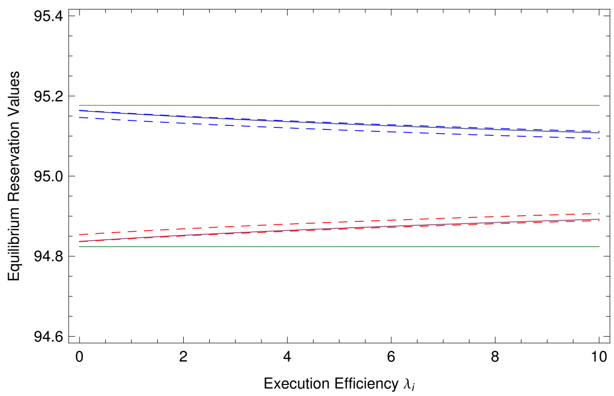
In our setting this is not the case. This observation suggests that in a match which is particularly favorable for one party, we may overestimate the bargaining power of this party by assuming the fixed proportion in the split of the pie. The results above require a credible commitment from such party to withdraw from bargaining process whenever other deal appears even with lower gains. Such situation occurs when customers bargain with dealers in the opposite liquidity state (the customer is unlikely to find a better deal and will be less likely to terminate bargaining).

The import of this discussion is that it is reasonable to modify the Nash bargaining assumption and instead think of q as a function of both the probability of making an offer in a bargaining round *and* the size of the trading gain relative to the market-wide average trading gain. In this case, customers who encounter a peripheral dealer in the same liquidity state will have slightly higher bargaining power than in our baseline model, and the negative relationship we find may be flattened. However, one should note, that such effect is of a second-order nature, and primaryly the bargaining power is still driven by the probability of making an ultimatum offer. The latter point implies that quantitatively this does not change the results too much, while it reduces tractability of the model.

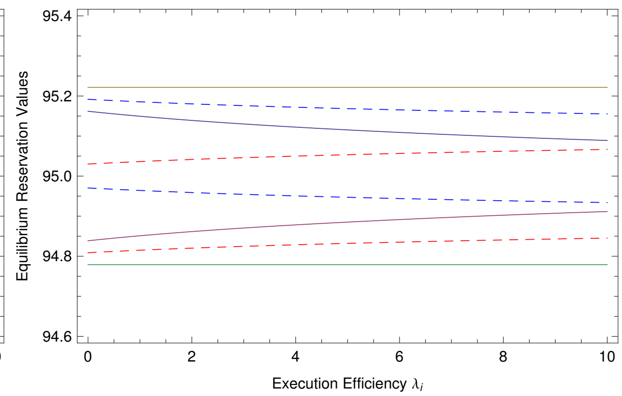
Moreover, the reverse logic applies to the case when agents are not allowed to look for other counterparties while bargaining. Here, both agents make a commitment to each other to continue bargaining and reject any other match. In this situation the party to which such commitment is most expensive (a more efficient party in finding good deals outside) has lower bargaining power, which is consistent with the finding in Duffie et al. [2003]. This suggests that the fixed proportions we use is somewhere in between the two models (with searching allowed and without) and makes them even more reasonable. Further, all these issues can be reconciled, when we let a more anxious party be more likely to make the ultimatum offer, effectively altering the probability of making an ultimatum offer so that in the end all gains are split in fixed proportions.

Finally we discuss comparative statics with respect to changes in the values of relative bargaining power of dealers and customers. The figure below shows agents' reservation values and associated bid-ask spreads for three different values of bargaining power $q \in \{0.05, 0.5, 0.95\}$, as well as the relationship between average bid-ask spreads and dealer's trade execution efficiency.

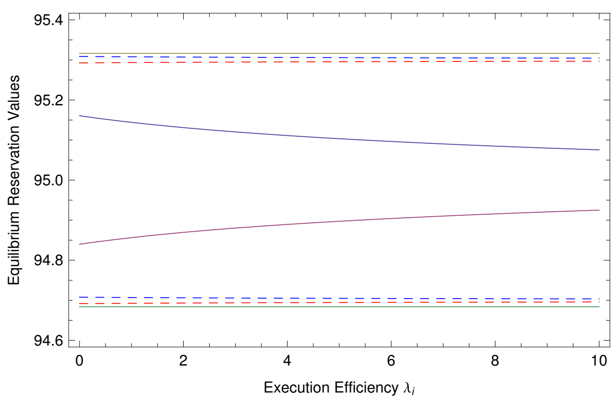
Figure 9: Equilibrium reservation values for different dealers' bargaining power values



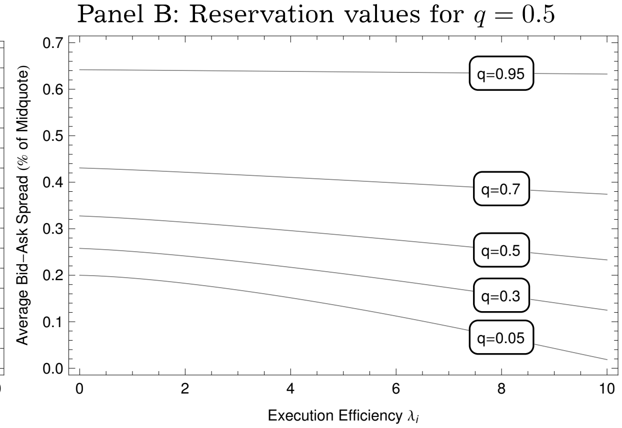
Panel A: Reservation values for $q = 0.05$



Panel B: Reservation values for $q = 0.5$



Panel C: Reservation values for $q = 0.95$



Panel D: Equilibrium Average Bid-Ask Spreads

It can be observed from Panel D of Figure 9 that the relationship between dealers' trade execution efficiency and average bid-ask spreads flattens out as q increases, while overall average spreads rise. Intuitively, when customers have little bargaining power with dealers, transaction prices are determined by customers' reservation values only, which do not depend on dealer's individual levels of trade execution efficiency. When dealers always make ultimatum offers to customers, the model predicts no relationship between average bid-ask spreads and dealers' trade execution efficiency. Presence of a negative relationship in the data suggests that customers may have significant bargaining power.

5 The Origins of $F(\lambda)$

In this section, we investigate the economics behind and possible origins of dealers' trade execution efficiency distribution $F(\lambda)$. In the model, dealers' trade execution efficiency corresponds to abilities of dealers to search for counterparties. The delay in trade execution is larger for dealers with lower λ_i, implying that it is more difficult and costly for these dealers to establish profitable matches on a decentralized market and realize gains from trading. When such dealers are hit with an adverse liquidity shock, it takes some time for them to rebalance their asset holdings. In the model, we assume dealers are born with a particular value of λ_i and this value remains unchanged throughout dealers' lifetime.

Technological "trading capital" can be one determinant of λ_i for each dealer. For example, in the over-the-counter equity space, there are several IT-infrastructure products that are designed to enhance the matching of counterparties, such as "OTC Link." These products often do not cover the securitizations trading, however it is reasonable to think that broker-dealers in securitizations rely on similar electronic communication systems (and potentially more sophisticated and fragmented systems). A broker-dealer with a wider access to these types of systems (or even owning and designing such a system) will have higher value of λ_i in the model. Then the distribution $F(\lambda)$ describes how the extent of such "trading capital" is distributed in the cross-section of dealers at a given point in time.[3]

In the model, a dealer with higher λ_i is more efficient at trading both with the pool of customers and with other dealers. Customer-relations capital, which includes the extent

[3] $F(\lambda)$ is assumed to be stable over time in the model.

of marketing activity, performance of the sales-efforts and sales-personnel, contributes to the speed of profitable customer trade execution. Hollifield, Neklyudov, and Spatt [2012] document that the extent of customer and interdealer activity of different dealers is highly correlated, with fairly few dealers having substantial differences in their customer and interdealer participation measures. Thus, a dealer with high λ_i is substantially invested in customer-relations capital as well. Finally, the legal support and the extent of in-house expertise contribute to the value of dealer's λ_i, especially for more advanced securitized products. These considerations suggest that λ_i in the model can be the result of a costly investment, and dealers with different λ_i differ in their equilibrium investment levels, captured by the cross-sectional distribution $F(\lambda)$.

5.1 Market shares of dealers

The link between costly "trading" capital and the trade execution efficiency distribution $F(\lambda)$ can be formalized as follows. The set of dealers in the population has measure M_d. Each dealer has obtained k_i amount of "trading capital", at cost $c_i(k_i)$. The heterogeneity of dealers comes from different cost functions for obtaining the same level of trading capital. Denote the measure of dealers with trading capital less than k by $H(k) = M_d \times Pr(k_i < k)$, and let $H^{-1}(F)$ be the inverse cumulative density function of trading capital. Denote the average level of trading capital across dealers by $\bar{k}$. Then the market share M_i of dealer $i \in [0, M_d]$ is:

$$M_i = \frac{1}{M_d} \times \frac{H^{-1}(i)}{\int_0^{M_d} H^{-1}(x)dx} = \frac{k_i}{\bar{k}}. \tag{23}$$

The trade execution efficiency of a dealer λ_i is proportional to the dealer's market share M_i, where $\bar{\lambda}$ is the average number of trades one dealer on a homogeneous market executes with a unit measure of customers with positive trading gains per unit of time (possibly a function of $\bar{k}$):

$$\lambda_i = \bar{\lambda}(\bar{k}) \times M_i. \tag{24}$$

This way $\bar{\lambda}$ can be thought of the average severity of search friction on the decentralized market. Note that there are two forces that determine dealers' λ_i: the crowding-out (or the arms-race), when investment of other dealers reduce the market share of a given dealer. This force is strongest, when $\bar{\lambda}$ is constant and does not depend on the average level of trading capital on the market. In this case only relative values of trading capital matter, while absolute levels do not. The other force is the overall market efficiency, which is strongest when $\bar{\lambda}$ is an increasing function of the average trading capital $\bar{k}$. In this case, each unit of trading capital contributes both to individual market share and the overall market efficiency.

Now we turn to the shapes of cost functions that may justify a particular $F(\lambda)$ distribution. In this sense, we think of dealers' trade execution efficiency levels as choice variables.

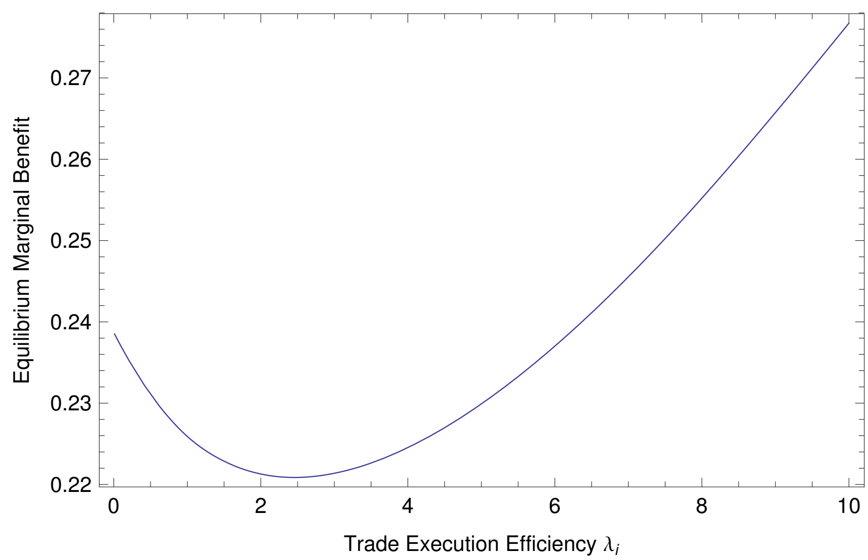
5.2 The costs of trade efficiency

In the trading model faster trade execution is a Pareto-improvement, as everybody benefits from it. For this reason, without an exogenous cost of faster trading, all parties would prefer to increase their trade execution efficiency λ_i to infinity. The exogenous cost can originate from the capital and human investment needed in order to increase one's efficiency (speed) of trading. We use our trading model to evaluate marginal benefits $MB(\lambda_i)$ of having a given level of efficiency on the market. The shape of the $MB(\lambda)$ curve can be used to deduce marginal costs of obtaining a given level of λ_i when dealers are able to choose optimally their levels of trade execution efficiency.

The argument is as follows. We take a given distribution $F(\lambda)$ and obtain the steady-state expected trading profits of dealers as a function of trade execution efficiency level λ. In our setting, there is a continuum of dealers, thus each single dealer's decision does not affect the overall market equilibrium. This is a simplifying feature of our analysis, and it allows us to obtain the individual marginal benefit curve $MB(\lambda)$ as the derivative of the cross-sectional expected trading profit function. We assume that each dealer in period $t = 0$ is assigned randomly one of the liquidity and asset-ownership types, according to the steady-state distribution of these for a particular level of trade execution efficiency λ_i. The model starts in its steady-state from the beginning of time. We use our results from section 4.1, where we characterize the steady-state probability distribution for the Markov chain that desribes each dealer's lifetime.

We use the same calibration as in Section 4 to illustrate our analysis and reveal economic principles that drive dealers' profitability on fragmented markets. The resulting marginal benefit curve is shown on Figure 10. The figure demonstrates that the marginal

Figure 10: Equilibrium marginal benefit of trade execution efficiency



benefit from trading on the market is increasing in the level of trade execution efficiency, except for the least efficient dealers. These dealers enjoy a positive matching externality and benefit indirectly from trading with more efficient dealers. They receive additional intermediation services from more efficient dealers. As their trade execution efficiency increases, the value of such externality drops, which is reflected in the downward-sloping portion of the marginal benefit curve. Dealers with different cost functions select their optimal efficiency levels along the curve. Generally, the marginal cost is smaller for less efficient dealers, which shows that being efficient is highly profitable on a decentralized interdealer market. The positive externality faced by less efficient dealers creates an additional barrier to entry to the top-league of dealers.

6 Conclusion

In this paper, we presented a model of a decentralized interdealer market where dealers differed in their trade execution efficiency. The model was designed to fit the core-peripheral structure of dealer networks documented in recent empirical studies of various fixed-income instruments. In equilibrium, more efficient dealers were intermediating order flow of peripheral dealers. The baseline model predicted a negative relationship between dealers' trade execution efficiency and customer average bid-ask spreads when customers were equally likely to trade irrespective of the size of positive trading gains. Our results demonstrate an interesting link between the extent of active customer shopping and the difference in average bid-ask spreads that customers face when they trade with central versus peripheral dealers.

In the context of over-the-counter markets, this paper links together traditional search-theory, in which intermediaries are typically homogeneous and the interdealer market is centralized, with network-theory, which allows for richer network structures that are typically non-stochastic and exogenously fixed. Here the network structure arises endogenously as a result of heterogeneity in dealers' search technologies. Dealers with ex ante higher trade execution efficiency emerge as more interconnected dealers in the steady-state trading equilibrium.

One particular application of these tools is the empirical analysis of transaction level data—the model allows us to evaluate the part of customer bid-ask spreads that is attributable to heterogeneity of dealers and their outside options. It is possible to estimate the distribution of dealers' trade execution efficiency separately for subcategories of different instruments and compare implications of the model. This is particularly relevant to highly segmented markets in securitized products and derivatives.

There are several directions for future research. Firstly, in the current paper we focus on the benchmark scenario under which dealers differ in trade execution efficiency, while bargaining power is the same across dealers. In reality, more efficient dealers may have greater market power in dealing with their counterparties. The analysis of exogenous differences in market power across dealers could strengthen our findings quantitatively.

Another important aspect of the current analysis is how the trading protocol is set up. Our analysis relies on random search-and-matching, where agents do not strategically choose other counterparties. The condition for a successful trade execution is positive training gains. An alternative way of setting up the trading process is a directed-search framework as in Burdett, Shi, and Wright [2001]. Under the directed-search methodology sellers post quotes and buyers strategically choose a seller to trade with. The directed-search methodology is not common in the literature on over-the-counter markets; however, it is important to evaluate robustness of our key findings to alternative specifications of the trading protocol.

Appendices

A Supplementary Notation

To simplify the exposition of the formulas in this appendix, we introduce and define the following variables and functions. We refer to this notation throughout the appendix as *supplementary*:

Agents' Masses in the Population

1. *The rate of meeting a dealer in set A with higher trade execution efficiency by a dealer with trade execution efficiency $\lambda_i = y$:*

$$\text{mfstD}(y, F_A(\cdot)) = \int_y^{\infty} (y+z) \times \mathrm{d}F_A(z). \tag{25}$$

2. *Similarly, the rate of meeting a dealer with lower trade execution efficiency:*

$$\text{mslwD}(y, F_A(\cdot)) = \int_0^{y} (y+z) \times \mathrm{d}F_A(z). \tag{26}$$

3. *The rate of meeting a dealer by a customer:*

$$\text{mDo} = \text{mfstD}(0, \mu_{ho}(\cdot)) + \text{mfstD}(0, \mu_{lo}(\cdot)), \textit{ for a non-owner customer;} \tag{27}$$
$$\text{mDn} = \text{mfstD}(0, \mu_{hn}(\cdot)) + \text{mfstD}(0, \mu_{ln}(\cdot)), \textit{ for an owner customer.} \tag{28}$$

4. *The difference between two rates: the total rate of meetings between low-owner dealers with trade execution efficiency lower than x and their conjectured counterparties, and the total rate of such meetings for low-non-owner dealers:*

$$\begin{aligned}\text{trdnetlow}(x) \;=\; & \int_0^x \Big(y \times \mu^C_{hn} + \text{mfstD}(y, \mu_{ln}(\cdot)) + \text{mfstD}(y, \mu_{hn}(\cdot)) + \text{mslwD}(y, \mu_{hn}(\cdot))\Big) \times \mathrm{d}\mu_{lo}(z) \\ & - \int_0^x \Big(y \times \mu^C_{lo} + \text{mslwD}(y, \mu_{lo}(\cdot))\Big) \times \mathrm{d}\mu_{ln}(z).\end{aligned} \tag{29}$$

5. *Similarly defined difference in rates for dealers in high-liquidity state:*

$$\begin{aligned}\text{trdnethigh}(x) \;=\; & -\int_0^x \Big(y \times \mu^C_{lo} + \text{mfstD}(y, \mu_{ho}(\cdot)) + \text{mfstD}(y, \mu_{lo}(\cdot)) + \text{mslwD}(y, \mu_{lo}(\cdot))\Big) \times \mathrm{d}\mu_{hn}(z) \\ & + \int_0^x \Big(y \times \mu^C_{hn} + \text{mslwD}(y, \mu_{hn}(\cdot))\Big) \times \mathrm{d}\mu_{ho}(z).\end{aligned} \tag{30}$$

Agents' Asset Valuations

6. *The customer trading mapping used to derive dealers' asset valuations:*

$$\begin{aligned}T^C(x) \;=\; & (1-M_d)^{-1} \times \Big(\max\left(\Delta \mathrm{V}^C_h, x\right) \mu^C_{\mathrm{hn}} + \max\left(\Delta \mathrm{V}^C_l, x\right) \mu^C_{\mathrm{ln}} \\ & + \min\left(\Delta \mathrm{V}^C_h, x\right) \mu^C_{\mathrm{ho}} + \min\left(\Delta \mathrm{V}^C_l, x\right) \mu^C_{\mathrm{lo}}\Big).\end{aligned} \tag{31}$$

7. *Dealers' measure in the population weighted by their trade execution efficiency levels:*

$$\begin{aligned} M_{\lambda d} &= \int_0^{+\infty} (\lambda_j)\, d\mu_{\text{hn}}(\lambda_j) + \int_0^{+\infty} (\lambda_j)\, d\mu_{\text{ln}}(\lambda_j) + \\ &+ \int_0^{+\infty} (\lambda_j)\, d\mu_{\text{ho}}(\lambda_j) + \int_0^{+\infty} (\lambda_j)\, d\mu_{\text{lo}}(\lambda_j)\,. \end{aligned} \tag{32}$$

8. *Two interdealer trading mappings (unweighted and weighted) used to derive dealers' asset valuations:*

$$\begin{aligned} T(x) &= (M_d)^{-1} \times \Bigg(\int_0^{+\infty} \max\left(\Delta \mathrm{V}_h(\lambda_j), x\right) \mathrm{d}\mu_{\text{hn}}(\lambda_j) + \int_0^{+\infty} \max\left(\Delta \mathrm{V}_l(\lambda_j), x\right) \mathrm{d}\mu_{\text{ln}}(\lambda_j) \\ &+ \int_0^{+\infty} \min\left(\Delta \mathrm{V}_h(\lambda_j), x\right) \mathrm{d}\mu_{\text{ho}}(\lambda_j) + \int_0^{+\infty} \min\left(\Delta \mathrm{V}_l(\lambda_j), x\right) \mathrm{d}\mu_{\text{lo}}(\lambda_j) \Bigg), \end{aligned} \tag{33}$$

$$\begin{aligned} T_\lambda(x) &= (M_{\lambda d})^{-1} \times \Bigg(\int_0^{+\infty} \lambda_j \max\left(\Delta \mathrm{V}_h(\lambda_j), x\right) \mathrm{d}\mu_{\text{hn}}(\lambda_j) + \int_0^{+\infty} \lambda_j \max\left(\Delta \mathrm{V}_l(\lambda_j), x\right) \mathrm{d}\mu_{\text{ln}}(\lambda_j) \\ &+ \int_0^{+\infty} \lambda_j \min\left(\Delta \mathrm{V}_h(\lambda_j), x\right) \mathrm{d}\mu_{\text{ho}}(\lambda_j) + \int_0^{+\infty} \lambda_j \min\left(\Delta \mathrm{V}_l(\lambda_j), x\right) \mathrm{d}\mu_{\text{lo}}(\lambda_j) \Bigg). \end{aligned} \tag{34}$$

In the following lemma, we prove that the mappings $T^C(x)$, $T(x)$, and $T_\lambda(x)$ are *contraction mappings*. We use this result in other proofs that follow.

Lemma A.1. *Let* $X = [(\theta_{low}/r), (\theta_{high}/r)]$ *and let* $\Delta V_h(\lambda), \Delta V_h(\lambda) : [0, +\infty) \to X$. *The mapping* $T(x) : X \to X$ *(standard Euclidean metric) satisfies the condition for being a contraction:* $\forall x, y \in X, \exists k : 0 < k < 1$ *and* $|T(x) - T(y)| \leq k \times |x - y|$. *Similarly, this result holds for mappings* $T^C(x)$ *and* $T_\lambda(x)$.

Proof. We present a proof of the claim for $T(x)$, the same line of argument applies to the two other mappings. For any continuous cdf function $F_A(\cdot)$ we have the following:

$$\int_0^{+\infty} \max\left(g(\lambda_j), x\right) \mathrm{d}F_A(\lambda_j) = x \times \int_0^{+\infty} \mathbb{1}_{\{g(\lambda_j) \leq x\}} \mathrm{d}F_A(\lambda_j) + \int_0^{+\infty} g(\lambda_j) \times \mathbb{1}_{\{g(\lambda_j) > x\}} \mathrm{d}F_A(\lambda_j)\,.$$

Take any $y < x \in \mathbb{R}$:

$$\begin{aligned} &\int_0^{+\infty} \left(\max\left(g(\lambda_j), x\right) - \max\left(g(\lambda_j), y\right)\right) \mathrm{d}F_A(\lambda_j) = \\ &= (x - y) \times \int_0^{+\infty} \mathbb{1}_{\{g(\lambda_j) \leq y\}} \mathrm{d}F_A(\lambda_j) + \int_0^{+\infty} (x - g(\lambda_j)) \times \mathbb{1}_{\{y < g(\lambda_j) \leq x\}} \mathrm{d}F_A(\lambda_j) = \\ &= (x - y) \times \int_0^{+\infty} \mathbb{1}_{\{g(\lambda_j) \leq x\}} \mathrm{d}F_A(\lambda_j) - \int_0^{+\infty} (g(\lambda_j) - y) \times \mathbb{1}_{\{y < g(\lambda_j) \leq x\}} \mathrm{d}F_A(\lambda_j)\,. \end{aligned}$$

Similarly, we establish:

$$\begin{aligned} &\int_0^{+\infty} \left(\min\left(g(\lambda_j), x\right) - \min\left(g(\lambda_j), y\right)\right) \mathrm{d}F_A(\lambda_j) = \\ &= (x - y) \times \int_0^{+\infty} \mathbb{1}_{\{g(\lambda_j) \geq x\}} \mathrm{d}F_A(\lambda_j) + \int_0^{+\infty} (g(\lambda_j) - y) \times \mathbb{1}_{\{x > g(\lambda_j) \geq y\}} \mathrm{d}F_A(\lambda_j) = \\ &= (x - y) \times \int_0^{+\infty} \mathbb{1}_{\{g(\lambda_j) \geq y\}} \mathrm{d}F_A(\lambda_j) - \int_0^{+\infty} (x - g(\lambda_j)) \times \mathbb{1}_{\{x > g(\lambda_j) \geq y\}} \mathrm{d}F_A(\lambda_j)\,. \end{aligned}$$

Use the facts established above to derive upper bound on $T(x)-T(y)$ (clearly $T(x)$ is non-decreasing in x, so $T(x)-T(y) \geq 0$ and we drop absolute value operators from the needed contraction condition):

$$\begin{aligned}
T(x)-T(y) &= (x-y)\times (M_d)^{-1}(\boldsymbol{A}) - (M_d)^{-1}(\boldsymbol{B}),\\
\text{where } \boldsymbol{A} &= \Big(\int_0^{+\infty} \mathbb{1}_{\{\Delta V_h(\lambda_j)\leq x\}} d\mu_{hn}(\lambda_j) + \int_0^{+\infty} \mathbb{1}_{\{\Delta V_l(\lambda_j)\leq x\}} d\mu_{ln}(\lambda_j) + \\
&\quad + \int_0^{+\infty} \mathbb{1}_{\{\Delta V_h(\lambda_j)\geq y\}} d\mu_{ho}(\lambda_j) + \int_0^{+\infty} \mathbb{1}_{\{\Delta V_l(\lambda_j)\geq y\}} d\mu_{lo}(\lambda_j)\Big), \text{ and}\\
\boldsymbol{B} &= \Big(\int_0^{+\infty} (\Delta V_h(\lambda_j)-y)\times \mathbb{1}_{\{y<\Delta V_h(\lambda_j)\leq x\}} d\mu_{hn}(\lambda_j) + \int_0^{+\infty} (\Delta V_l(\lambda_j)-y)\times \mathbb{1}_{\{y<\Delta V_l(\lambda_j)\leq x\}} d\mu_{ln}(\lambda_j) + \\
&\quad + \int_0^{+\infty} (x-\Delta V_h(\lambda_j))\times \mathbb{1}_{\{x>\Delta V_h(\lambda_j)\geq y\}} d\mu_{ho}(\lambda_j) + \int_0^{+\infty} (x-\Delta V_l(\lambda_j))\times \mathbb{1}_{\{x>\Delta V_l(\lambda_j)\geq y\}} d\mu_{lo}(\lambda_j)\Big).
\end{aligned}$$

We observe that $\boldsymbol{A}$ is the total measure of dealers, to which a dealer with reservation value x would have sold the asset and from which a dealer with reservation value y would have bought the asset. $\boldsymbol{B}$ is the mean trading gain for dealers with reservation values in between x and y when they buy from a dealer with reservation value x and sell to a dealer with reservation value y. As $\boldsymbol{A}$ increases, $\boldsymbol{B}$ increases by construction. The maximum possible value for $\boldsymbol{A}$ is M_d, and at this value $\boldsymbol{B} < 0$. Thus it is possible to define $k \in (0,1)$ such that:

$$T(x)-T(y) < (x-y)\times k.$$

One possible way to define k is as follows. Take any $\varepsilon \in (0,1)$. Over the set of any x and y such that the measure $\boldsymbol{A}$ is greater than $1-\varepsilon$ compute the minimum level $b(\varepsilon)$ of the conditional gains from trade $\boldsymbol{B}$, which is strictly positive (otherwise $\boldsymbol{A}$ must be zero, which results in a contradiction). Then a plausible value for k is:

$$k = \max\left(\varepsilon, 1-\frac{r\times b(\varepsilon)}{\theta_{high}-\theta_{low}}\right).$$

□

B Solving for Steady-State Equilibrium

We conjecture that in equilibrium dealers' reservation values $\Delta V_h(\lambda)$ and $\Delta V_l(\lambda)$ are monotonic functions of λ. We verify this conjecture once we obtain the solution for $\Delta V_h(\lambda)$ and $\Delta V_l(\lambda)$. Under this conjecture, the system of differential equations describing law of motion for agents' masses is (we use supplementary notation from appendix A).

$$\begin{aligned}
\frac{d\mu_{ln}(\lambda)}{dt} &= \gamma_{\text{dn}}\times\mu_{hn}(\lambda) - \gamma_{\text{up}}\times\mu_{ln}(\lambda) + \text{trdnetlow}(\lambda);\\
\frac{d\mu_{lo}(\lambda)}{dt} &= \gamma_{\text{dn}}\times\mu_{ho}(\lambda) - \gamma_{\text{up}}\times\mu_{lo}(\lambda) - \text{trdnetlow}(\lambda);\\
\frac{d\mu_{hn}(\lambda)}{dt} &= -\gamma_{\text{dn}}\times\mu_{hn}(\lambda) + \gamma_{\text{up}}\times\mu_{ln}(\lambda) + \text{trdnethigh}(\lambda);\\
\frac{d\mu_{ho}(\lambda)}{dt} &= -\gamma_{\text{dn}}\times\mu_{ho}(\lambda) + \gamma_{\text{up}}\times\mu_{lo}(\lambda) - \text{trdnethigh}(\lambda).
\end{aligned}$$

It follows that when $\Delta V_h(\lambda)$ and $\Delta V_l(\lambda)$ are monotonic functions of λ, Proposition 3.2 together with the relative symmetry condition from definition 3.2 implies that $\Delta V_h(\lambda)$ is decreasing in λ, while $\Delta V_l(\lambda)$ is increasing. In such an equilibrium, more efficient dealers in low liquidity state will be buying the asset from less efficient dealers in low liquidity state, while more efficient dealers in high liquidity state will be selling to less efficient dealers in high liquidity state. In our model, customers in high liquidity state never sell the asset, while customers in low liquidity never buy, and this is consistent with customers' equilibrium asset valuations. These trading patterns are imposed in the system of differential equations above.

Further, we note that the Markov-switching across liquidity types is independent of trading, thus in the steady state the proportion of agents in the high-liquidity state is always equal to $\gamma_{up}/(\gamma_{up}+\gamma_{dn})$. This allows us to solve for customers' masses in the population in terms of dealers' masses:

$$\mu_{lo}^C = \frac{\text{mDo}\,(1-M_d)\,\gamma_{\text{dn}}\gamma_{\text{up}}}{(\gamma_{\text{dn}}+\gamma_{\text{up}})\,(\text{mDn}\times\gamma_{\text{dn}}+\text{mDo}\,(\text{mDn}+\gamma_{\text{up}}))}, \qquad \mu_{ln}^C = \frac{\gamma_{\text{dn}}}{\gamma_{\text{up}}+\gamma_{\text{dn}}}\times(1-M_d)-\mu_{lo}^C;$$

$$\mu_{ho}^C = \frac{\text{mDo}\,(1-M_d)\,\gamma_{\text{up}}\,(\text{mDn}+\gamma_{\text{up}})}{(\gamma_{\text{dn}}+\gamma_{\text{up}})\,(\text{mDn}\times\gamma_{\text{dn}}+\text{mDo}\,(\text{mDn}+\gamma_{\text{up}}))}, \qquad \mu_{hn}^C = \frac{\gamma_{\text{up}}}{\gamma_{\text{up}}+\gamma_{\text{dn}}}\times(1-M_d)-\mu_{ho}^C.$$

We also have the following restrictions on dealers' masses:

$$\mu_{hn}(\lambda) = \frac{\gamma_{\text{up}}}{\gamma_{\text{up}}+\gamma_{\text{dn}}}\times F(\lambda)\times M_d-\mu_{ho}(\lambda), \quad \mu_{ln}(\lambda) = \frac{\gamma_{\text{dn}}}{\gamma_{\text{up}}+\gamma_{\text{dn}}}\times F(\lambda)\times M_d-\mu_{lo}(\lambda).$$

Dealers are born with a particular trade execution efficiency level λ. To simplify the exposition, we assume that liquidity state switching intensities are symmetric: $\gamma_{up}=\gamma_{dn}=\gamma$. In the steady state, the left-hand side of the system of differential equations above is zero, independent of λ. Thus we differentiate these equations with respect to λ and obtain:

$$\begin{aligned}
&\gamma\times\left(\mu_{lo}'(\lambda)-\mu_{ho}'(\lambda)\right)+\left(\lambda\times\mu_{hn}^C+\int_0^\lambda(\lambda+z)\mu_{hn}'(z)dz+\int_\lambda^\infty(\lambda+z)\left(\mu_{hn}'(z)+\mu_{ln}'(z)\right)dz\right)\mu_{lo}'(\lambda)-\\
&\quad-\left(\lambda\times\mu_{lo}^C+\int_0^\lambda(\lambda+z)\mu_{lo}'(z)dz\right)\mu_{ln}'(\lambda)=0,\\
&\gamma\times\left(\mu_{ho}'(\lambda)-\mu_{lo}'(\lambda)\right)-\left(\lambda\times\mu_{lo}^C+\int_0^\lambda(\lambda+z)\mu_{lo}'(z)dz+\int_\lambda^\infty(\lambda+z)\left(\mu_{ho}'(z)+\mu_{lo}'(z)\right)dz\right)\mu_{hn}'(\lambda)+\\
&\quad+\left(\lambda\times\mu_{hn}^C+\int_0^\lambda(\lambda+z)\mu_{hn}'(\lambda)dz\right)\mu_{ho}'(\lambda)=0.
\end{aligned}$$

We guess values of $A=\int_0^\infty\mu_{ho}(z)dz$ and $B=\int_0^\infty\mu_{lo}(z)dz$. Given our guesses for A and B, the above system simplifies to a two-dimensional system of second order ODEs in terms of $\int_0^\lambda\mu_{ho}(z)dz$, and $\int_0^\lambda\mu_{lo}(z)dz$. We solve the system numerically and obtain $\mu_{ho}(\lambda)$ and $\mu_{lo}(\lambda)$. We use this solution to update our guesses of A and B and iterate until convergence. The convergence occurs very quickly, we are working on a formal proof for this convergence. In the case of symmetric markets defined in 4.1, no iteration is needed, because the system of ODEs does not depend on A nor B, see Lemma 4.1.

Once we obtain agents' masses in a candidate equilibrium, it remains to solve for agents' asset valuations and verify our initial conjecture about monotonicity of dealers' valuations $\Delta V_h(\lambda)$ and $\Delta V_l(\lambda)$. The solution for agents masses does not depend on particular values of $\Delta V_h(\lambda)$ and $\Delta V_l(\lambda)$, because in the baseline model any trade is executed as long as trading gains are positive.

The Bellman equation for dealers' asset valuations implies (expression for $\Delta V_l(\lambda)$ is similar):

$$\begin{aligned}
\Delta\text{V}_h(\lambda) \quad = \quad & \boldsymbol{A}(\lambda)^{-1}\times\{\,r\times(\theta_{\text{h}}/r)+\gamma_{dn}\times\Delta\text{V}_l(\lambda)+\\
&+\lambda\times(q(1-M_d)T^C(\Delta\text{V}_h(\lambda))+0.5\times M_dT(\Delta\text{V}_h(\lambda)))+0.5M_{\lambda d}T_\lambda(\Delta\text{V}_h(\lambda))\,\}\\
&\text{where } \boldsymbol{A}(\lambda)=(r+\gamma_{dn}+\lambda\times(q\times(1-M_d)+0.5\times M_d)+0.5\times M_{\lambda d}).
\end{aligned}$$

We use Lemma A.1 that establishes contraction mapping property for $T^C(\cdot)$, $T(\cdot)$, and $T_\lambda(\cdot)$. Holding agents' masses fixed, we provide initial guess for $\Delta V_h(\lambda)$ and $\Delta V_l(\lambda)$ using agents' buy-and-hold valuations and no trading. We update our guesses using the system of two Bellman equations above. The convergence occurs very quickly, because the two Bellman equations are weighted averages of the three contraction mappings and a constant.

C Random-Matching Technology

C.1 Lemma 2.1

Let A, B, and C be disjoint sets of dealers with measures μ_A, μ_B, and μ_C, respectively. Let $m(X,Y)$ be the total meeting rate between dealers in arbitrary sets X and Y. Under the described random matching technology the total meeting rate satisfies $m(A, B \cup C) = m(A,B) + m(A,C)$.

Proof.

Recall that according to the described random matching technology:

$$m(A, B \cup C) = \left(\int (\lambda) dF_A(\lambda) + \int (\lambda) dF_{(B\cup C)}(\lambda) \right) \times \mu_A(\mu_B + \mu_C).$$

Use the fact that for two disjoint sets the conditional cumulative distribution of dealers satisfies:

$$F_{(B\cup C)}(\lambda) = \frac{F_B(\lambda) \times \mu_B + F_C(\lambda) \times \mu_C}{\mu_B + \mu_C}.$$

Combining these two facts and rearranging terms, we obtain the result:

$$\begin{aligned}
m(A, B \cup C) &= \left(\int (\lambda) dF_A(\lambda) + \frac{\int (\lambda) dF_B(\lambda) \times \mu_B + \int (\lambda) dF_C(\lambda) \times \mu_C}{\mu_B + \mu_C} \right) \times \mu_A(\mu_B + \mu_C) \\
&= \int (\lambda) dF_A(\lambda) \times \mu_A(\mu_B + \mu_C) + \int (\lambda) dF_B(\lambda) \times \mu_A \mu_B + \int (\lambda) dF_C(\lambda) \times \mu_A \mu_C \\
&= m(A,B) + m(A,C).
\end{aligned}$$

□

D Customer Bid-Ask Spreads

D.1 Lemma 3.1

In the simplified environment, the equilibrium dealer's value of the asset is equal to the weighted average of dealer's buy-and-hold valuation and the average of customers' reservation prices.

Proof.

Start with the Bellman equations for the dealer:

$$\begin{aligned}
V_{\text{own}} &= \int_0^{\Delta} (\theta) e^{-\text{rt}} dt + \left(V_{\text{non}} + q \times \text{P}^{\text{buy}} + (1-q) \times (V_{\text{own}} - V_{\text{non}}) \right) e^{-\text{r}\Delta} \\
&= \frac{\theta}{r} + \left(q \times \text{P}^{\text{buy}} + (1-q) \times (V_{\text{own}} - V_{\text{non}}) + V_{\text{non}} - \frac{\theta}{r} \right) e^{-\text{r}\Delta}, \\
V_{\text{non}} &= \left(V_{\text{own}} - q \times \text{P}^{\text{sell}} - (1-q) \times (V_{\text{own}} - V_{\text{non}}) \right) e^{-\text{r}\Delta}.
\end{aligned}$$

We can solve for dealer's value function V_{own} and V_{non} in terms of dealer's reservation value $(V_{own} - V_{non})$:

$$\begin{aligned}
V_{\text{own}} &= \frac{q \times r \times \left(\text{P}^{\text{buy}} - (V_{\text{own}} - V_{\text{non}}) \right) + \left(e^{\text{r}\Delta} - 1 \right) \theta}{\left(e^{\text{r}\Delta} - 1 \right) r}, \\
V_{\text{non}} &= \frac{q \left((V_{\text{own}} - V_{\text{non}}) - \text{P}^{\text{sell}} \right)}{e^{\text{r}\Delta} - 1}.
\end{aligned}$$

We take the difference of the above expressions and solve for $(V_{own} - V_{non})$:

$$(V_{\text{own}} - V_{\text{non}}) = \frac{\left(P^{\text{buy}} + P^{\text{sell}}\right)}{2} \times \frac{2q}{(e^{\text{r}\Delta} - 1 + 2q)} + \frac{\theta}{r} \times \frac{\left(e^{\text{r}\Delta} - 1\right)}{(e^{\text{r}\Delta} - 1 + 2q)}.$$

We now show the second part of the lemma that corresponds to unequal delays in trading with customers-buyers versus customers-sellers:

In the simplified environment, the equilibrium dealer's value of the asset is equal to the weighted average of dealer's buy-and-hold valuation and the weighted average average of customers' reservation prices, so that when delays in dealing with customers-buyers are longer, the weight on customers-sellers reservation price is larger.

When trading delays are more severe when selling to customers compared to buying from customers (the opposite case is symmetric), we modify the Bellman equations in the following way, with $k \in (1, +\infty)$:

$$\begin{aligned}
V_{\text{own}} &= \int_0^{\text{k}\Delta} (\theta) e^{-\text{rt}} dt + \left(V_{\text{non}} + q \times \text{P}^{\text{buy}} + (1-q) \times (V_{\text{own}} - V_{\text{non}})\right) e^{-k \times r\Delta} \\
&= \frac{\theta}{r} + \left(q \times \text{P}^{\text{buy}} + (1-q) \times (V_{\text{own}} - V_{\text{non}}) + V_{\text{non}} - \frac{\theta}{r}\right) e^{-k \times r\Delta}, \\
V_{\text{non}} &= \left(V_{\text{own}} - q \times \text{P}^{\text{sell}} - (1-q) \times (V_{\text{own}} - V_{\text{non}})\right) e^{-\text{r}\Delta}.
\end{aligned}$$

Similar steps as in Lemma 3.1 yield the following result:

$$\begin{aligned}
(V_{\text{own}} - V_{\text{non}}) &= \left(\text{P}^{\text{buy}} \times w_1 + \text{P}^{\text{sell}} \times (1 - w_1)\right) \times w_2 + \frac{\theta}{r} \times (1 - w_2), \\
& w_1 = \frac{\left(e^{r\Delta} - 1\right)}{\left(e^{k \times r\Delta} + e^{r\Delta} - 2\right)}, \\
& w_2 = \frac{\left(e^{k \times r\Delta} + e^{r\Delta} - 2\right) q}{\left(e^{r\Delta} - 1\right)\left(e^{k \times r\Delta} - 1\right) + \left(e^{k \times r\Delta} + e^{r\Delta} - 2\right) q}.
\end{aligned}$$

We observe that when delays in dealing with customers-buyers are longer ($k > 1$), the weight on customers-sellers reservation price is larger. □

D.2 Proposition 3.1

Proof.

Let $\{\Delta \boldsymbol{V}_{\sigma}, \boldsymbol{\mu}\}$ be a steady-state dynamic trading equilibrium. We write down the Bellman equations for a dealer's lifetime value function in terms of trade execution efficiency λ_i. As usual we use X and Y to refer to opposite liquidity states of the dealer (when $X = high$, $Y = low$, and vice versa).

For a dealer who owns a unit of the asset:

$$\begin{aligned}
r \times V_{\text{Xo}}(\lambda_i) &= \theta_{\text{iX}} + \gamma_Y \times \left(V_{\text{Yo}}(\lambda_i) - V_{\text{Xo}}(\lambda_i)\right) + \\
&+ \lambda_i \times \left(\text{Max}\left(\left(P^{\text{ask}}_{\text{Xh}}(\lambda_i) - \Delta\text{V}_l(\lambda_i)\right), 0\right) \mu^{C}_{\text{hn}} + \text{Max}\left(\left(P^{\text{ask}}_{\text{Xl}}(\lambda_i) - \Delta\text{V}_l(\lambda_i)\right) \mu^{C}_{\text{ln}}, 0\right)\right) + \\
&+ \int_0^{+\infty} \text{Max}\left(\left(P_{\text{Xh}}(i,j) - \Delta\text{V}_l(\lambda_i)\right), 0\right) \times (\lambda_i + \lambda_j)\, d\mu_{\text{hn}}(\lambda_j) + \\
&+ \int_0^{+\infty} \text{Max}\left(\left(P_{\text{Xl}}(i,j) - \Delta\text{V}_l(\lambda_i)\right), 0\right) \times (\lambda_i + \lambda_j)\, d\mu_{\text{ln}}(\lambda_j).
\end{aligned}$$

For a dealer who does not own the asset:

$$\begin{aligned} r \times V_{\mathrm{Xn}}(\lambda_i) &= \gamma_Y \times (V_{\mathrm{Yn}}(\lambda_i) - V_{\mathrm{Xn}}(\lambda_i)) + \\ &+\lambda_i \times \left(\mathrm{Max}\left(\left(\Delta \mathrm{V}_X(\lambda_i) - P^{\mathrm{bid}}_{\mathrm{Xh}}(\lambda_i)\right)\mu^C_{\mathrm{ho}}, 0\right) + \mathrm{Max}\left(\left(\Delta \mathrm{V}_X(\lambda_i) - P^{\mathrm{bid}}_{\mathrm{Xl}}(\lambda_i)\right)\mu^C_{\mathrm{lo}}, 0\right)\right) + \\ &+ \int_0^{+\infty} \mathrm{Max}\left(\left(\Delta \mathrm{V}_X(\lambda_i) - P_{\mathrm{Xh}}(i,j)\right), 0\right) \times (\lambda_i + \lambda_j)\, d\mu_{\mathrm{ho}}(\lambda_j) + \\ &+ \int_0^{+\infty} \mathrm{Max}\left(\left(\Delta \mathrm{V}_X(\lambda_i) - P_{\mathrm{Xl}}(i,j)\right), 0\right) \times (\lambda_i + \lambda_j)\, d\mu_{\mathrm{lo}}(\lambda_j)\,. \end{aligned}$$

Recall that the equilibrium prices satisfy:

$$\begin{aligned} \text{Customer-Dealer:} \quad & P^{\mathrm{ask/bid}}_{\mathrm{XY}}(\lambda_i) = (1-q) \times \Delta V_X(\lambda_i) + q \times \Delta V^C_Y\,, \\ \text{Interdealer:} \quad & P_{\mathrm{XY}}(i,j) = 0.5 \times \Delta V_X(\lambda_i) + 0.5 \times \Delta V_Y(\lambda_j). \end{aligned}$$

We take the difference of the two equations and obtain dealer's reservation value $\Delta V_X(\lambda_i)$:

$$\begin{aligned} \Delta \mathrm{V}_X(\lambda_i) &= \boldsymbol{A}(\lambda_i)^{-1} \times \{\ \theta_{\mathrm{iX}} + \gamma_Y \times \Delta \mathrm{V}_Y(\lambda_i) + \\ &+\lambda_i \times \left(q(1-M_d)T^C\left(\Delta \mathrm{V}_X(\lambda_i)\right) + 0.5 \times M_d T\left(\Delta \mathrm{V}_X(\lambda_i)\right)\right) + 0.5 M_{\lambda d} T_\lambda\left(\Delta \mathrm{V}_X(\lambda_i)\right)\ \} \\ &\text{where } \boldsymbol{A}(\lambda_i) = (r + \gamma_Y + \lambda_i \times (q \times (1-M_d) + 0.5 \times M_d) + 0.5 \times M_{\lambda d})\,. \end{aligned}$$

As $\lambda_i \to \infty$ the expression above gets arbitrarily close to:

$$\Delta \mathrm{V}_X(\lambda_i) = \frac{q \times (1-M_d) \times T^C\left(\Delta \mathrm{V}_X(\lambda_i)\right) + 0.5 \times M_d \times T\left(\Delta \mathrm{V}_X(\lambda_i)\right)}{q \times (1-M_d) + 0.5 \times M_d}.$$

Define the following mapping:

$$T_1(x) = \frac{q \times (1-M_d)}{q \times (1-M_d) + 0.5 \times M_d} \times T^C(x) + \frac{0.5 \times M_d}{q \times (1-M_d) + 0.5 \times M_d} \times T(x)\,.$$

$T_1(x)$ is a contraction mapping (as a linear combination of two contraction mappings using Lemma A.1). By definition, the average market mid-quote satisfies $\Delta V = T_1(\Delta V)$ and thus is a fixed point of $T_1(x)$. By contraction mapping theorem it exists and is unique.

□

D.3 Proposition 3.2

Proof.

Let $\{\Delta \boldsymbol{V}_\sigma, \boldsymbol{\mu}\}$ be a steady-state dynamic trading equilibrium that is *relatively symmetric*. It implies, that $\Delta V_h(\lambda) \geq \Delta V \geq \Delta V_l(\lambda)$ for any value of $\lambda \in [0, +\infty)$. We use the fact that $T_1(x)$ in the definition of the average market midquote is a contraction mapping (established in the proof of Proposition 3.1) and that ΔV is the fixed-point. The contraction property implies:

$$\text{when } x \geq \Delta V : \Delta V \leq T_1(x) \leq x.$$

Take $\lambda_1 > \lambda_2$ and show that:

$$\Delta V_h(\lambda_1) - \Delta V_l(\lambda_1) < \Delta V_h(\lambda_2) - \Delta V_l(\lambda_2).$$

Recall that the Bellman equation implies (expression for $\Delta V_l(\lambda)$ is similar):

$$\begin{aligned}\Delta \mathrm{V}_h(\lambda) &= \boldsymbol{A}(\lambda)^{-1} \times \{\, r \times (\theta_{\mathrm{h}}/r) + \gamma_{dn} \times \Delta \mathrm{V}_l(\lambda) + \\ &\quad +\lambda \times (q(1-M_d)T^C(\Delta \mathrm{V}_h(\lambda)) + 0.5 \times M_d T(\Delta \mathrm{V}_h(\lambda))) + 0.5 M_{\lambda d} T_\lambda(\Delta \mathrm{V}_h(\lambda)) \,\}, \\ &\quad \text{where } \boldsymbol{A}(\lambda) = (r + \gamma_{dn} + \lambda \times (q \times (1-M_d) + 0.5 \times M_d) + 0.5 \times M_{\lambda d}).\end{aligned}$$

The above expression for $\Delta V_h(\lambda)$ is a weighted average of dealer's buy-and-hold value in perpetual high-liquidity state (θ_h/r), dealer's reservation value in the opposite liquidity state $\Delta V_l(\lambda)$, and the two trading mappings:

$$\begin{aligned}\Delta V_h(\lambda) &= r\boldsymbol{A}(\lambda)^{-1} \times (\theta_h/r) + \gamma_{dn}\boldsymbol{A}(\lambda)^{-1} \times \Delta V_l(\lambda) + \\ &\quad +\lambda \times (q \times (1-M_d) + 0.5 \times M_d)\, \boldsymbol{A}(\lambda)^{-1} \times T_1(\Delta V_h(\lambda)) + \\ &\quad +0.5 \times M_{\lambda d}\boldsymbol{A}(\lambda)^{-1} \times T_\lambda(\Delta \mathrm{V}_h(\lambda)), \\ \text{where:} & \\ T_1(\Delta V_h(\lambda)) &= \frac{q \times (1-M_d)}{q \times (1-M_d) + 0.5 \times M_d} \times T^C(\Delta V_h(\lambda)) + \frac{0.5 \times M_d}{q \times (1-M_d) + 0.5 \times M_d} \times T(\Delta V_h(\lambda)).\end{aligned}$$

Using proposition above, we know that the fixed point of T_1 is the market mid-quote. Bellman equations for dealers' valuations imply the following for the difference between reservation values (similar expression holds for low liquidity state):

$$\begin{aligned}&(r + \gamma_{\mathrm{dn}}) \times (\Delta \mathrm{V}_h(\lambda_1) - \Delta \mathrm{V}_h(\lambda_2)) \\ &\leq \gamma_{\mathrm{dn}} \times (\Delta \mathrm{V}_l(\lambda_1) - \Delta \mathrm{V}_l(\lambda_2)) + (\lambda_1 - \lambda_2) \times (T_1(\Delta \mathrm{V}_h(\lambda_2)) - \Delta \mathrm{V}_h(\lambda_2)).\end{aligned}$$

We use the fact that $T_1(\cdot)$ is a contraction mapping, thus:

$$\begin{aligned}(\Delta \mathrm{V}_h(\lambda_1) - \Delta \mathrm{V}_h(\lambda_2)) &\leq \frac{\gamma_{\mathrm{dn}} \times (\Delta \mathrm{V}_l(\lambda_1) - \Delta \mathrm{V}_l(\lambda_2))}{(r + \gamma_{\mathrm{dn}})}, \\ (\Delta \mathrm{V}_l(\lambda_1) - \Delta \mathrm{V}_l(\lambda_2)) &\leq \frac{\gamma_{\mathrm{up}} \times (\Delta \mathrm{V}_h(\lambda_1) - \Delta \mathrm{V}_h(\lambda_2))}{(r + \gamma_{\mathrm{up}})}.\end{aligned}$$

The result follows. □

E Analysis of Symmetric Markets

E.1 Lemma 4.1

Proof.

Start with the system of differential equations describing law of motion for agents' masses (we use supplementary notation from appendix A).

$$\begin{aligned}\frac{d\mu_{ln}(\lambda)}{dt} &= \gamma_{\mathrm{dn}} \times \mu_{hn}(\lambda) - \gamma_{\mathrm{up}} \times \mu_{ln}(\lambda) + \mathrm{trdnetlow}(\lambda); \\ \frac{d\mu_{lo}(\lambda)}{dt} &= \gamma_{\mathrm{dn}} \times \mu_{ho}(\lambda) - \gamma_{\mathrm{up}} \times \mu_{lo}(\lambda) - \mathrm{trdnetlow}(\lambda); \\ \frac{d\mu_{hn}(\lambda)}{dt} &= -\gamma_{\mathrm{dn}} \times \mu_{hn}(\lambda) + \gamma_{\mathrm{up}} \times \mu_{ln}(\lambda) + \mathrm{trdnethigh}(\lambda); \\ \frac{d\mu_{ho}(\lambda)}{dt} &= -\gamma_{\mathrm{dn}} \times \mu_{ho}(\lambda) + \gamma_{\mathrm{up}} \times \mu_{lo}(\lambda) - \mathrm{trdnethigh}(\lambda).\end{aligned}$$

Since the system above holds for any value of λ, and the left-hand side is always zero, we differentiate the system with respect to λ. We also note that the Markov-switching across liquidity types is independent of trading process, thus in the steady state the proportion of agents in the high-liquidity state is always equal to $\gamma_{up}/(\gamma_{up}+\gamma_{dn})$.

The system collapses to two equations after symmetry conditions in definition 4.1 are imposed:

$$\begin{aligned}
\frac{d\mu(\lambda)}{dt}=0 \quad = \quad & \gamma\times\left(\frac{F(\lambda)M_d}{2}-\mu(\lambda)\right)-\gamma\times\mu(\lambda)- \\
& -\int_0^{\lambda}\left(y\times\mu^C+\int_y^{+\infty}(y+z)\times d\left(\frac{F(\lambda)M_d}{2}-\mu(\lambda)\right)+\int_0^{+\infty}(y+z)\times d\mu(\lambda)\right)\times d\mu(\lambda)+ \\
& +\int_0^{\lambda}\left(y\times\mu^C+\int_0^{y}(y+z)\times d\mu(\lambda)\right)\times d\left(\frac{F(\lambda)M_d}{2}-\mu(\lambda)\right), \\
& \text{where } \mu^C=\frac{\gamma\,(1-M_d)}{4\gamma+M_d\int_0^{+\infty}zdF(z)}.
\end{aligned}$$

Simplifying the first equation (use integration by parts) and taking derivative with respect to λ, we obtain:

$$\begin{aligned}
&\frac{M_d}{2}\left(\left(\gamma+\lambda\mu^C-\int_0^{\lambda}\mu(z)dz+2\lambda\mu(\lambda)\right)F'(\lambda)+\lambda(F(\lambda)-1)\mu'(\lambda)\right) \\
&=\left(2\gamma+2\lambda\mu^C-2\int_0^{\lambda}\mu(\lambda)dz+\frac{1}{2}\int_{\lambda}^{+\infty}zM_dF'(z)dz+4\lambda\mu(\lambda)\right)\mu'(\lambda).
\end{aligned}$$

We denote $x=\lambda$ and $y(x)=\int_0^x\mu(z)\,dz$. The resulting equation is a second-order ODE:

$$\begin{aligned}
&\frac{M_d}{2}\left(\left(\gamma+x\mu^C-y(x)+2xy'(x)\right)F'(x)+x(F(x)-1)y''(x)\right) \\
&=\left(2\gamma+2x\mu^C-2y(x)+4xy'(x)+\int_x^{+\infty}\frac{1}{2}zM_dF'(x)dz\right)y''(x).
\end{aligned}$$

$\square$

Essay 2: Bid-Ask Spreads and the Pricing of Securitizations: 144a vs. Registered Securitizations

Joint work with Burton Hollifield and Chester Spatt

Abstract

Traditionally, various types of securitizations have traded in opaque markets. During May 2011 the Financial Industry Regulatory Authority (FINRA) began to collect transaction data from broker-dealers (without any public dissemination) as an initial step towards increasing transparency and enhancing its understanding of these markets. Securitization markets are highly fragmented and require transaction matching methods to construct bid-ask spreads. We study the relationship between bid-ask spreads and transaction characteristics, such as the size of the underlying trade and the path by which trade execution and intermediation occurs. Retail-sized transactions lead to relatively wide spreads because of the absence of competition, while institutionally-sized transactions often result in much tighter spreads. We study the contrast between Registered instruments that are freely tradable and Rule 144a instruments with much more limited disclosures that can only be purchased by sophisticated investors.

We study the structure of the dealer network and how that influences the nature of bid-ask spreads. Some dealers are relatively central in the network and trade with many other dealers, while many others are more peripheral. Central dealers receive relatively lower spreads than peripheral dealers. This could reflect greater competition and reduced bargaining power of central dealers or lower costs for the transactions which they intermediate. The order flow is more evenly divided among dealers and the customer spreads are relatively smaller for central dealers in Rule 144a than in Registered instruments.

1 Introduction

Relatively little is known about the pricing of securitizations, because these have traded traditionally in opaque markets. The importance of the shadow banking system, in general, and securitization, in particular, has been recognized strongly in the aftermath of the financial crisis. In May 2011 the Financial Industry Regulatory Authority (FINRA) used its regulatory authority to begin to collect transaction data on securitizations from broker-dealers, which it regulates.[4] This was an initial step by FINRA to increase potentially the transparency of these markets, a measure also intended to enhance understanding of the markets.

A second step by FINRA occurred five months later when it began to disseminate, in conjunction with IDC, daily price index data by collateral type. These informational releases potentially offered market participants more detailed information and transparency about valuations for various collateral types and indirectly, greater transparency about spreads and trading costs. Of course, this represents only a limited step towards full-blown transparency because it entails considerable aggregation across individual instruments in a category and involves daily rather than transaction level disclosure.[5] These steps follow FINRA's efforts to increase the transparency of the corporate bond markets a decade ago, and parallel efforts by the Municipal Securities Rule-making Board (MSRB) to increase transparency in the municipal bond markets, for which it is the Self-Regulatory Organization (SRO).

In studying securitizations we focus upon the contrast between Registered instruments, which require detailed disclosures in the issuance process, and Rule 144a instruments, which exempt private resale of restricted instruments to QIBs (Qualified Institutional Buyers) from these disclosure requirements. We focus our analysis upon ABS (”Asset-Backed Securities”), CDOs (”Collateralized Debt (Bond/Loan) Obligations”), CMBS (”Commercial-Mortgage-Backed Securities”) and CMO (”Collateralized Mortgage Obligations”) instruments due to the mix of trading of Rule 144a instruments and benchmark these against corresponding public (Registered) instruments in the ABS, CMBS and CMO cases.[6]

[4] FINRA's jurisdiction applies to broker-dealers, so under current FINRA rules all broker-dealers have been required to report trades undertaken by them, starting May 16, 2011. Our analysis is based upon these data (adjusting out identical interdealer trades between a pair of broker-dealers that are reported twice). The market design changed on October 18, 2011 with the public release of price index data by FINRA and IDC. The release of daily index valuation data represented a change in market structure and potentially increased the transparency of both valuations and spreads. We have transaction data through the end of February 2012, so our sample is of roughly comparable length between the pre-release interval (five months) and post-release interval (4.5 months). We examine how spreads changed with the dissemination of the public index data. Our full dataset has been provided to us on a confidential basis to facilitate analysis of securitization markets under opacity by FINRA. We also use the interdealer transactions data to study the structure of the trading network among dealers and the impact of the network structure on spreads.

[5] The interaction between the aggregation across instruments and the temporal aggregation further weakens the extent of transparency introduced.

[6] Since there are not 144a instruments in the TBA and MBS categories, we have not used these in our

Preliminary to our statistical analysis we discuss the economics of Rule 144a. First, we emphasize that the use of Rule 144a is a choice by the issuer and that the nature of the choice is one in which the required disclosures are more limited than for Registered securitizations. The Rule 144a instruments experience a corresponding potential reduction in issuance cost and exemption from liability. These Rule 144a instruments are designed for sophisticated (i.e., relatively informed) investors and the purchase of Rule 144a instruments would reflect self-selection on the part of the buyers, including recognition of the restrictions on re-trading for the Rule 144a instruments. This suggests relatively less interest ex post in trading the Rule 144a instruments since these are oriented to buy-and-hold investors, which can further heighten the spread from a liquidity perspective. Without Registration, the Rule 144a instruments can only be resold to QIBs. Potentially, the Rule 144a instruments are of higher quality as the issuer can sell to QIBs (without accessing the full potential market) those that it desires to sell without incurring the costs of Registration, including potential liability. On the other hand, issuers of low quality instruments could find it more appealing to issue Rule 144a instruments due to the limited required disclosure (as in models of signaling).

One focus of our empirical analysis is on descriptive comparison in trading and spreads between the Rule 144a and Registered instruments. This does not reflect analysis of the endogenous choice of Rule 144a or Registration. In particular, we note that the effect of adverse selection (information asymmetry) is ambiguous. Rule 144a instruments can have larger spreads than Registered offerings due to the more limited initial publicly available information or can have smaller spreads, if either these instruments are of higher quality or if the Rule 144a buyers have greater informational sophistication. Indeed, empirically within some asset classes Rule 144a securitizations have higher spreads than Registered securitizations, and within other asset classes Rule 144a securitizations have lower spreads than Registered securitizations. These may reflect in part substantial differences in the composition of Registered and Rule 144a markets. To limit these distortions and composi-

benchmark analysis. Similarly, we also have excluded agency CMOs from our analysis, as these do not arise for 144a instruments. We also have limited our treatment of CDOs (”Collateralized Debt Obligations”) as these are largely 144a instruments.

tion effects, we examine only non-agency CMO trading (see footnote 3), the impact of the size of transactions (there are very few retailed-sized transactions in the Rule 144a context) upon spreads (small transactions have especially large spreads) and then we exclude retail-sized transactions from our regression analyses.

Our findings suggest a number of interesting results about the nature of trading in securitization markets. Most fundamentally, trading is very fragmented and there is relatively little trading in most individual instruments, especially (but not only) for Rule 144a instruments. In fact, there are a large number of securitization issues, but many of these do not trade at all in our sample. Consequently, we do not use traditional time series techniques for estimating spreads, but instead use matching techniques to locate chains of transactions involving a buy from a customer and sell to a customer. We note that some of the absolute spreads in the ABS, CDOs, CMBS and non-agency CMO markets are surprisingly large, especially for CMOs and retail-sized matches in all other instruments. The average spread for non-agency CMO instruments is 3.46% of the mid-quote for high-yield and 2.87% for investment grade instruments. The average spread for retail-size matches in ABS instruments is 2.07% of the mid-quote for high-yield and 1.40% for investment grade instruments.

For all instruments except high-yield CMBS the Rule 144a spreads are smaller than the spreads for Registered instruments (both for retail-size and non-retail matches). The overall comparison in the spreads between Rule 144a and Registered instruments reflects the underlying composition of securitization instruments among subgroups. In interpreting the result it is important to recognize that there is considerable selection as to the use of Rule 144a versus Registered status.

For ABS, CMBS and non-agency CMO instruments there is a volume discount with respect to the spread-larger volume matches lead to lower spreads than for retail matches, and the difference is statistically significant. This finding is consistent with greater competition or ability by sophisticated investors to negotiate terms of trade with more potential counterparties. The fact that larger investors obtain better prices is reminiscent of one of the insights from the pricing of municipal bonds (Green, Hollifield, and Schürhoff [2007], Harris and Piwowar [2006]), corporate bonds (Bessembinder, Maxwell, and Venkataraman [2006], Edwards, Harris, and Piwowar [2007], and Goldstein, Hotchkiss, and Sirri [2007]).

We study the relationship between bid-ask spreads and dealer's ability to access and participate in the interdealer market. We use network analysis to measure dealers' participation and their relative importance on interdealer markets following two alternative methodologies. Under both methodologies we obtain evidence of a negative relationship between dealers' importance and spreads in general for most types of securitizations.

The results concerning the connection between the structure of the intermediary network and how it influences the nature of bid-ask spreads are especially informative. Of course, there are some intermediaries who are relatively central in the network and trade with many other dealers, while there are many others who are more tangential. More important dealers as measured by their centrality receive relatively lower spreads. The finding is consistent with the equilibrium in a search-and-bargaining model of a decentralized interdealer market in which dealers differ in their trade execution efficiency to proxy for dealer centrality in Neklyudov (2012). Here, the more connected dealers charge lower spreads because their endogenous reservation values reflect their search efficiency and they intermediate trade flows among the less efficient dealers

2 The Market for Registered and Rule 144a Securitizations

Our sample contains all trading activity between May 16, 2011 and February 29, 2012 in ABS, CDOs, CMBS and non-agency CMO instruments. These data are a sequence of trade reports, providing the trade identifier, the execution timestamp and settlement date, the side of the reporting party-either the buy side or sell side, the entered volume of the trade measured in dollars of original par balance, and the entered price measured in dollars per $100 par. The trade report allows us to determine if the trade is between a dealer and an outside customer, or between two dealers. The Appendix provides additional details on the dataset and our data-cleaning procedures.

Table 1 reports the total number of instruments in the population and the number of instruments traded with customers in the overall, pre-release, and post-release samples (these instruments had at least a buy from a customer and a sell to a customer at most 2 weeks apart). In the population there are more Rule 144a than Registered ABS and CMBS instruments, and there are more Registered than Rule 144a CDOs and non-agency CMO instruments. One interpretation is that the selection effects for CDOs and non-agency CMO instruments are different compared to ABS and CMBS instruments. Approximately the same number of instruments traded with customers at least once in the pre-release and post-release period, and many instruments traded only in one of the two sample periods.

Across all categories Registered instruments are more likely to have a buy from a customer and a sell to a customer at most two weeks apart compared to Rule 144a instruments. Perhaps the higher frequency of trading in Registered instruments reflects that a larger number of traders can hold and trade Registered instruments than can hold and trade Rule 144a instruments, as well as ex ante selection associated with the difficulty of trading the Rule 144a instruments. It also may reflect that there are fewer disclosure requirements for Rule 144a instruments, so that potential investors have less public information about them and therefore, are reluctant to trade them due to adverse selection risk.

We observe similar results within various categories of instruments. We use the collateral type to categorize ABS instruments. We split the CDOs into CDO instruments, CLO instruments and CBO instruments. We use the tranche type to categorize CMBS and CMO instruments.

Tables 2a through 3b report additional summary statistics for all types of ABS, CDOs, CMBS, and non-agency CMO instruments. In Tables 2a and 3a, we report how many instruments are investment grade or high yield,[7] how many instruments have fixed- or floating-rate coupons; indicator variables for the instruments' vintage-with vintage defined as the number of years between the trade execution date and the instrument's issue date; the instruments' average coupon rates, and the instruments' average factors. For many instruments, the principal balance can be reduced through amortization or prepayment; the factor represents the fraction of the original principal outstanding. Tables 2b and Table

[7] We classified unrated instruments as high yield rather than investment grade throughout the paper.

3b report the average number of trades per day, the average number of dealers active in each instrument, the average number of interdealer trades, and the distribution of trade sizes. We categorize trade sizes into three groups: Retail-size being trades with original par value less than \$100,000, Medium-size trades being trades with original par value between \$100,000 and \$1,000,000, and Institutional-size trades being trades with original par value greater than \$1,000,000. Registered instruments and Rule 144a instruments tend to have similar bond characteristics for all the various categories.

It is apparent from the trading frequencies reported in Table 2b and Table 3b that securitized products do not trade very frequently: For example, on average ABS instruments have 0.097 trades per day and CDOs have 0.026 trades per day. Registered instruments tend to have more trades on average than Rule 144a instruments: For example, registered ABS instruments have 0.108 trades per day, and Rule 144a ABS instruments have 0.074 trades per day. The distribution of trades across instruments is quite skewed: There are a few instruments with many trades per day, but most of the instruments in our sample do not trade very often. The trading frequency for CMBS instruments is similar to ABS and slightly larger than the frequency for non-agency CMO instruments.

For the ABS and CDOs instruments, retail-sized trades constitute the smallest fraction of total trades. There are more retail-sized trades in the Registered instruments than in the Rule 144a instruments.[8] Retail-sized trades constitute a much larger fraction of the trades in non-agency CMO instruments than in ABS instruments.

On average, there are 6.03 dealers who traded in an average ABS security, with even fewer dealers in other types of instruments. Typically there are more active dealers trading Registered instruments than trading Rule 144a instruments.

Figure 1 depicts the kernel density function of the number of distinct customer-dealer and interdealer transactions (conditional on that number being positive) in the entire sample, truncating the plot at the 95th percentile of the distribution. In the top left panel we show ABS instruments (separate graphs for Registered and Rule 144a instruments), in the

[8] Only a tiny fraction of the trade in Rule 144a instruments is retail sized (less than \$100,000 of original par volume). We would not expect substantial retail activity in these instruments, so the small matches may reflect in part order splitting by larger investors.

bottom left panel we plot CMBS instruments, in the top right panel we plot CDOs, and in the bottom right panel we plot non-agency CMO instruments. These plots and the 95th percentiles illustrate that there are not many trades in individual instruments, with especially limited trading in the Rule l44a instruments. Though we truncate from these plots those instruments with the largest number of trading records to improve the display of this density, we note that these truncated observations are potentially the most important because they correspond to the largest number of trading records and provide the most information for estimating spreads. At the same time, given the dispersed nature of the overall trading and the relatively small number of trades in individual instruments (including interdealer trades), for the most part we are unable to use structured time series methods to estimate spreads (except potentially for the most active instruments or indices). Consequently, we use a matching method to identify chains of related transactions and estimate spreads.

We include Figures 2a through 2d to illustrate the nature of trading activity in our sample. In the figures, we provide several examples of Registered and Rule 144a instruments that are highly traded in our sample. Each panel (two panels per page) depicts trading in a security. There are three subpanels within each panel-the upper subpanel shows buy and sell transactions by volumes during our sample period, the middle subpanel shows the corresponding interdealer trades by volumes and the bottom subpanel shows the corresponding transaction prices (ask, bid and interdealer) during our sample period.

The limited extent of trading highlighted by the figures illustrates some of the conceptual difficulty in estimating spreads and the importance of using matching methods, especially for less actively traded instruments. The figures illustrate the potential importance of interdealer transactions in reallocating inventory and exposures and matching buy and sell transactions at the aggregate or market level. For our formal analysis we use matching techniques to identify chains of related transactions. In some cases we may be able to match activity at a daily level (see right panel of Figure 2b, where the matching is especially striking in terms of volumes), but in other situations there will be insufficient matches at that level (and to utilize the data effectively and not excessively bias our results we need to formulate matches more broadly).[9] The bottom subpanels of the plots illustrate the positive nature of the bid-ask spread and that in some situations with relatively active instruments that the bid-ask spreads can nevertheless be quite substantial. We also note that the interdealer trades do not always lie between the customer buy and sell trades.

In many situations dealers are potentially buying or selling from existing inventory, but the nature of our data does not provide direct information identifying the initial inventory. Of course, in some cases the matching may be relatively apparent-but in most situations we only have a limited set of matches at a daily level and therefore, we consider broader matching criteria. Indeed, in at least some situations (e.g., see Figure 2b, right panel) there are considerable imbalances in trading with customers (as reflected in the figure we see indications of clustered selling) and dealer reliance on trading from pre-existing inventory.

We obtain data on Moody's ratings for all instruments that have at least a buy from a customer and a sell to a customer at most 2 weeks apart in our sample period from May 16, 2011 to February 29, 2012. Among ABS, CMBS, Rule 144a CDOs and non-agency CMOs there were 20,392 such instruments. 15,216 of these instruments have been rated by Moody's, for other instruments the Moody's ratings were not available (539 instruments were rated "NR", others had missing Moody's rating). When the Moody's rating is missing, we use the information on whether the instrument is high yield or investment grade provided by FINRA. We use the proprietary list of CUSIPs provided by FINRA to locate Moody's ratings for these instruments.

Figure 3 summarizes the distribution of the first rating observed within our sample period per security. We observe differences in rating levels for instruments traded in our sample, with relatively frequent high-grade ratings in ABS and CMBS instruments.

There were 3 Registered ABS instruments that were upgraded from high yield to investment grade during our sample period and 1 Registered ABS security that was downgraded. Similar numbers for other instrument types are: 11 and 3 for Rule 144a ABS, 105 and 2 for Rule 144a CDOs, 1 and 46 for Registered CMBS, 6 and 94 for Rule 144a CMBS,

[9] We discuss in detail the matching method we use in the Appendix called "Data Cleaning."

16 and 102 for Registered non-agency CMO, 7 and 24 for Rule 144a non-agency CMOs. These facts highlight that rating upgrades and downgrades crossing the investment grade boundary are relatively infrequent in our sample period. Overall there were more downgrades than upgrades (149 upgrades and 272 downgrades crossing the investment grade boundary); interestingly, CDOs were mostly upgraded in our sample.

Figure 4 demonstrates the trading activity around the security upgrade or downgrade dates. In this figure we consider all rating changes that do not necessarily cross the investment grade boundary, such as from A3 to A1 or from Ba1 to B3. For each such security we only consider transactions that were executed 45 days before a rating change or 31 days after. We observe 407 upgraded instruments that have at least one trade within that period and 562 downgraded instruments. Our main observation is that rating downgrades are associated with increased trading activity with customers within 10 days after the rating change, however subsequently trading volumes tend to drop (right panel of Figure 4). We do not observe such effects for instruments around the rating upgrade dates (left panel of Figure 4).

We use a multi-stage matching technique to disentangle trading activity in each instrument and organize related trades into chains of transactions. Each chain captures the movement of a particular block of volume from a customer to the interdealer network, within the interdealer network, and from the dealer network back to the customer sector. To perform sorting of this nature, we first match related interdealer and customer transactions that have the same volume moving from one party to another in a particular instrument. Second, we look for chains of transactions that may have different volume traded and thus involve volume splits as the security moves from one party to another.[10] Each chain has one buy from customer and one sell to customer, as well as several rounds of intermediation between dealers (however, a large part of the resulting sample has just one round of dealer intermediation). We are able to disentangle 75% of the total absolute turnover in ABS market, 86% in the CDOs market, 74% in CMBS market, and 80% in non-agency CMO market into complete chains that we use to compute total customer bid-

[10]We provide additional details on the matching algorithm we use in the Data Cleaning Appendix.

ask spreads.[11] The rest of the turnover in these markets corresponds to: 1) imbalanced trades with no pair of opposite trades with customers: a buy from customer and a sell to customer within a two-week horizon; 2) broken chains that do not link buy from a customer with a sell to customer based on the dealer mask (masks do not match).

2.1 Common Factors in Trading Activity

In the space of equity markets, past research has established existence of common cross-stock variation in order flows, returns and market liquidity measures (Hasbrouck and Seppi [2001]) over the short-horizon. The decentralized nature of markets for securitizations and significant illiquidity restrict our ability to borrow the methodology from the literature on equities. In the context of fragmented markets, one may think of a hazard-rate model for order arrivals, which is beyond the scope of our analysis. In this section, we perform a simpler descriptive analysis of correlations in daily numbers of different instruments traded by category. We focus on non-retail activity with transaction volumes above $100,000.

The methodology we employ is to count how many different securities in each trading day had at least one trade larger than $100,000 of original balance. The resulting number is a proxy for market activity in a given day. We drop days with less than 300 instruments traded in total across the four categories (ABS, CDO, CMBS, and non-agency CMO), because the majority of these days are around major holidays and shortened holiday season trading days. We then study the correlations across the four product categories, both overall and separately for Registered and Rule 144a instruments, the autocorrelations, and perform principal-component decomposition of variability in these measures. The table below summarizes the descriptive statistics for these measures.

[11] We use information on dealer masks to relate different trade reports with each other and construct chains of transactions.

Market	Placement	mean (st.dev)	min (max)	autocorr. ρ
ABS	Overall	149.6 (35.65)	71 (260)	0.206
	Registered	108.07 (26.54)	54 (184)	0.194
	Rule 144a	41.53 (12.5)	11 (83)	0.244
CDO	Rule 144a	26.42 (12.83)	4 (70)	0.199
CMBS	Overall	156.56 (38.57)	34 (272)	0.187
	Registered	124.39 (30.84)	33 (205)	0.200
	Rule 144a	32.17 (13.37)	1 (97)	0.130
Non-Agency	Overall	250.31 (94.17)	94 (801)	0.173
CMO	Registered	217.31 (73.78)	80 (548)	0.233
	Rule 144a	33 (48.69)	4 (511)	$0.029 \approx 0$

Legend: Overall numbers of different instruments traded on each day by product types from May 16, 2011 to February 29, 2012.

Positive autocorrelations for each of these measures suggest existence of common market-wide factors that drive the trading activity. The autocorrelation for Rule 144a non-agency CMOs is particularly low, because of large spikes in the number of instruments traded on the following dates: May 25, 2011; July 22, 2011; and December 22, 2011. On these days there were 511, 269, and 359 different instruments traded, respectively (while 33 was traded in an average day in the same). The following is the correlation matrix for these measures:

Market		Placement	[0]	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
ABS	[0]	Overall									
	[1]	Reg.	0.96								
	[2]	R144a	0.81	0.62							
CDO	[3]	R144a	0.34	0.28	0.38						
CMBS	[4]	Overall	0.55	0.54	0.42	0.35					
	[5]	Reg.	0.52	0.50	0.42	0.31	0.95				
	[6]	R144a	0.38	0.39	0.25	0.31	0.70	0.44			
Non-Agency	[7]	Overall	0.45	0.39	0.46	0.40	0.33	0.28	0.30		
CMO	[8]	Reg.	0.48	0.43	0.46	0.46	0.37	0.31	0.36	0.86	
	[9]	R144a	0.13	0.10	0.18	0.08	0.08	0.09	0.04	0.63	0.14

Legend: The table shows correlations of the overall numbers of different instruments traded on each day across product types from May 16, 2011 to February 29, 2012.

We observe generally positive and significant correlations in activity on these markets. The measures of activity for Registered and Rule 144a instruments tend to be significantly correlated for ABS and CMBS markets, with correlations of 0.62 and 0.44, respectively. These observations suggest that there may be common economic factors driving trading, however their effects are not strong.

We perform principal component decomposition of variability in these measures. Across the four markets overall, the first principal component explains 55% of variation. In Registered instruments only (excluding CDOs), the first principal component explains 61% of variation. In Rule 144a instruments the first principal component explains 42%.

The effect of the first principal components in these markets are weaker, that the results reported in Hasbrouck and Seppi [2001] for order flows in equity markets. Market fragmentation of securitizations markets may play role in this finding, as the information flow is restricted due to inherent opacity.

2.2 Bid-Ask Spreads

For each chain of transactions we compute the total client bid-ask spread by using a buy price from a customer and a sell price to a customer, ignoring dealer-to-dealer intermediation rounds in between. At the same time for each link in a chain we compute a dealer-specific spread. The total client bid-ask spread for a chain is a weighted sum of dealer-specific spreads corresponding to that chain. Since the quotes observed in our dataset are clean prices per unit of current balance, we adjust the resulting spreads for accrued interest and factor prepayments. We present detailed discussion of these adjustments in the Appendix.

For each resulting spread observation we have information on how many rounds of intermediation occurred between the two customer transactions; the average dealers' participation on the interdealer market throughout the sample; the time gap between a buy from a customer and a sell to a customer or vice versa; trade volumes; and whether any volume splitting occurred. Few of the resulting spread observations are extreme due to price data entry errors. We remove such observations from the final sample by winsorizing the upper and lower tails of spread distributions within each of the four types of instruments (ABS, CDO, CMBS, and non-agency CMO), two placement types (Registered and Rule 144a, except for CDOs category) and credit quality (investment grade and high yield). In total we modify 2% of extreme observations, controlling for major categories and subtypes.

Table 4 reports mean client bid-ask spreads computed as a percentage of the average bid and ask prices for the ABS, CDO, CMBS and non-agency CMO categories, for Registered and Rule 144a instruments. Dealers may possess potential bargaining advantages with respect to retail-sized trading, thus retail-sized trades may face especially large spreads. For this reason we distinguish spreads among trades of different sizes and adjust for differences in the trade-size composition within different types of instruments. Trades with less than $100,000 of original par generally come from retail traders, so we define a retail-size spread to be the bid-ask spread resulting from two opposite trades both having volume less than $100,000. We refer to all other spread observations as non-retail since they result from paired trades of larger volumes.

Each column of the table reports statistics on the spreads for the four different types of instruments: ABS, CDO, CMBS, and non-agency CMO in the investment grade and high yield categories. The table reports the differences in the average spreads for retail-sized and non-retail-sized trades for the different categories, along with standard errors and the F-test for equality of the average spreads between retail and non-retail sized trades. The top panel of the table reports overall spreads across categories; the second panel reports the spreads for Registered instruments; the third panel reports the spreads for the Rule 144a instruments; and the final panel reports F-tests for differences in spreads between Registered and Rule 144a instruments.

Perhaps the most striking result reported in Table 4 is the difference in spreads between retail-size and other-size trades. For all categories, retail-size spreads are significantly larger than other-size transactions. In general we confirm the finding from other fixed-income markets that retail-size trades tend to have significantly higher spreads than institutional-size transactions.

We also compare spreads across instrument types. Overall spreads are the largest for non-agency CMO instruments and overall spreads are the smallest for CMBS instruments. Average spreads are higher for Registered instruments than for Rule 144a instruments, with an exception of high-yield CMBS instruments-average spreads are lower for Registered CMBS instruments than for Rule 144a CMBS instruments. Perhaps the differences between the relative spreads for Registered and Rule 144a instruments across instrument types reflect selection effects, or that the customers in Rule 144a instruments are more sophisticated than the customers in Registered instruments.

Table 5a reports the average bid-ask spread sorted by the size of the dealers' buys from customers and sells to customers for Registered and Rule 144a ABS and CDOs instruments, sorted by the credit rating of the underlying instruments. Table 5b reports similar analysis of Registered and Rule 144a CMBS and non-agency CMO instruments.

Each cell of the table reports the average spread, the standard error of that estimate, and the number of spread observations computed for different transactions sizes, with each panel corresponding to a different instrument type: ABS or CMO instruments, Registered or Rule 144a instruments, and investment grade or high yield instruments. Each row of Tables 5a and 5b reports the average spread for all pairs of transactions with dealers' buy from customer having different sizes: Retail-less than $100,000 in par value, Medium-between $100,000 and $1,000,000 in par value, and Large-greater than $1,000,000 in par value. Each column reports the average spread for all pairs of transactions with different sizes of dealers' sales to customers. For example, the top left cell in each panel reports the average spread computed for a retail-sized dealer buy from a customer matched to a retail-sized dealer sell to a customer.

The number of observations of Retail Buys and Retail Sells shows that most of the trade in Rule 144a instruments is Large Buys and Large Sells. There are not many retail trades in Rule 144a instruments relative to the amount of retail trades in Registered instruments. Comparing the average spreads between Investment Grade instruments and High Yield instruments, the average spreads are lower for Investment Grade instruments than for High Yield instruments.

Table 6a reports descriptive statistics of spreads for non-retail transactions in our sample by category of instruments. We report the average, the standard deviation, the median, the 10th, the 25th, the 75th and the 90th percentiles of the spread distributions. The first panel of the Table is for ABS instruments, the second panel is for CDOs instruments, the third panel is for CMBS, and the fourth panel is for non-agency CMO instruments. Across all categories and both for pre-release and post-release subsamples, the mean spread is higher than the median spread, indicating that the spread distributions are skewed to the right-there are some large spreads in all categories. For all categories of instruments, the standard deviation of the spread distributions is larger than the mean, indicating a lot of dispersion in spreads. This is also evidence about spreads in the reported percentiles. The 10th percentile of the spread distribution is zero or negative for all types of instruments, indicating that dealers sometimes can make losses on their transactions.

Table 6b reports the mean, median and standard deviations of the spreads in the pre-release and post-release samples, as well as test statistics for the null hypothesis that average and median spreads are the same in the pre-release and post-release samples. We find a statistically significant decrease in average bid-ask spreads for the Registered non-agency CMO category. We observe the reverse pattern in Registered CMBS instruments and mixed results in other categories. Median spreads are largest for non-agency CMO instruments, and smallest for ABS instruments both pre-release and post-release. We compare median spreads between publicly Registered instruments and Rule 144a instruments. In the pre-release sample Registered ABS and non-agency CMOs instruments have higher median spreads than Rule 144a counterparts, with the difference between Registered and Rule 144a instruments much larger for non-agency CMO instruments. In the post-release sample this holds for CMO instruments only. Across all types of instruments, high yield instruments have higher median spreads than investment grade instruments.

In order to visualize the realized spreads, Figure 5 provides time-series plot of the realized spreads. The instruments are sorted by instrument type, and by credit rating (investment grade and high yield). The blue triangles correspond to spreads in Rule 144a instruments and the orange circles correspond to spreads in Registered instruments. The plots are consistent with the percentiles reported in Table 6a. Registered instruments tend to have more dispersion in realized spreads than the Rule 144a instruments in all categories. The plots also show the positive skewness in the realized spreads and that for all categories of instruments, dealers do sometimes make losses.

Only sophisticated investors can hold Rule 144a instruments, while both sophisticated and unsophisticated investors can hold Registered instruments. Rule 144a instruments have a smaller pool of potential owners and so the market may be more limited. Our finding that many types of Rule 144a instruments have smaller spreads than Registered instruments may reflect that sophisticated investors face lower transactions costs than unsophisticated investors. Registered non-agency CMO instruments have significantly higher average and median spreads that Rule 144a non-agency CMO instruments. Perhaps the lower spread for Rule 144a instruments relative to Registered instruments in these categories reflects that more sophisticated investors are trading the Rule 144a non-agency CMOs than the Registered non-agency CMOs and more sophisticated investors have higher bargaining power when trading with dealers than less sophisticated investors.

In order to study the importance of the underlying collateral to the spreads, Table 7a reports non-retail spreads for different types of ABS collateral, and for CDOs. We report the average spreads for overall trade, for Registered and Rule 144a instruments, and by rating (investment grade and high yield). Overall and across all collateral types, Registered ABS instruments have higher average spreads than Rule 144a instruments. For the investment grade ABS instruments, Registered ABS instruments of all collateral types have higher average spreads than Rule 144a instruments. For High Yield instruments, overall Registered ABS have a higher average spreads than overall Rule 144a ABS, but the ordering is mixed across collateral types: SBA and Student loan backed Registered instruments have higher spreads than the Rule 144a instruments, while all other collateral types have the opposite ranking.

The bottom panel of Tables 7a reports F-statistics for the null hypothesis that investment grade and high yield instruments have the same spreads across different collateral types. For the majority of collateral types, the difference between average spreads is statistically significant: High yield instruments have wider average spreads than investment grade instruments in all categories.

Table 7b reports non-retail spreads for CMBS and non-agency CMO categories for different types of underlying tranches. The table has a similar structure to Table 7a, with both CMBS instruments and the non-agency instruments sorted by tranche type.

Overall, Rule 144a CMBS have higher average spreads than Registered CMBS. Registered non-agency CMO instruments have higher average spreads than Rule 144a non-agency CMO instruments. For all tranche types of non-agency CMO instruments except support tranches and Z-tranches (SUP/Z), Registered CMO instruments have higher average spreads than Rule 144a instruments (although there are few Rule 144a SUP/Z instruments). In most subcategories, high yield instruments have higher average spreads than Investment Grade instruments.

Goldstein, Hotchkiss, and Sirri [2007] provide estimates of spreads on BBB-rated corporate bonds after the introduction of the TRACE system in 2002. They compute a round-trip spread measure similar in spirit to our measures. Table 6 in their paper reports average spreads for different trade sizes. We can compare our estimated average spreads pre-release and post-release to the spreads reported by Goldstein et al. [2007]. They report the mean spread in Panel A in Table 6 for different transactions sizes computed using a LIFO method[12] with transactions size measured in the number of $100 face value bonds. The mean spread reported in their Table 6 ranges from $2.37 per $100 of face value for transactions of less than or equal to 10 bonds, to $1.96 per $100 of face for transactions between 21 and 50 bonds, to $0.56 per $100 of face for institutional-size transactions over 1,000 bonds. From Table 4 in our study, our estimates of the retail and non-retail sized spreads both pre-release and post-release are approximately the same order of magnitude as those in the post-transparency corporate bond sample for all categories, except for non-agency CMOs. In our sample, non-agency CMO instruments have larger spreads than in the post transparency sample.

We also compare the non-retail spreads reported in Tables 6a through 7b with the spreads for corporate bonds reported by Goldstein, Hotchkiss, and Sirri [2007] in their Table 6. For ABS instruments, the spreads for Registered instruments reported in our Table 7a tend to be smaller than the spreads in the corporate bond market for institutional-sized trades, with an exception being ABS backed by Manufacturing. The spreads for Rule

[12] Goldstein et al. [2007] compute spreads matching the trade by dealer while we compute the spread aggregating over all dealers. Our spread measures are computed as a percentage of average trade prices, while their approach is dollars per unit of par. Both calculations should produce similar sized spreads as a first approximation, since the corporate bonds should have been trading close to the order of their par values.

144a instruments in Table 7a tend to be larger than institutional sized trades reported for the corporate bond market; instead the spreads for Rule 144a instruments are similar to spreads for trade sizes of 51-100 bonds in the corporate bond market. We find similar results both pre-release and post-release.

We use the regression methodology to study the relationship between characteristics of the instruments, and the structure of the dealer networks and the bid-ask spreads.

2.3 Interdealer Networks

In order to study the dealer networks, we employ network analysis and analyze properties of interdealer trading relationships. Our sample of interdealer trades allows us to determine links between different dealers and estimate relative participation measures for different market players. We employ two alternative methodologies to perform network analysis and construct variables that capture overall as well as relative importance of a particular dealer. We study how customer bid-ask spreads are related to these dealers' importance measures.

The interdealer markets we observe exhibit interdependence across different products we study in the two samples. For example, in the pre-release sample of trade records from May 16, 2011 to October 17, 2011 we observe 580 active dealers, of which 573 dealers participated at least once in interdealer trading-315 in ABS, 186 in CDOs, 228 in CMBS, and 469 in CMO-implying that many dealers participate in several markets. On average each dealer participated in 40 interdealer trades in ABS market, 12 interdealer trades in CDOs, 43 interdealer trades in CMBS, and 101 interdealer trades in non-agency CMO, either as a seller or a buyer. Over the sample, an average dealer transacted $112 million of original balance on interdealer market in ABS, $43 million in CDOs, $361 million in CMBS, and $277 million in CMO. Similar interdealer activity is observed in the post-release sample. In the post-release sample from October 18, 2011 to February 29, 2012 we observe 542 active dealers, of whom 532 dealers participated at least once in interdealer trading (275 in ABS, 164 in CDOs, 247 in CMBS, and 449 in CMO. There were 441 dealers active in both samples, and this suggests that some dealers trade only in one of the two sample periods.

On average each dealer participated in 39 interdealer trades in ABS market, 11 interdealer trades in CDOs, 45 interdealer trades in CMBS, and 85 interdealer trades in non-agency CMO, either as a seller or a buyer. Over the sample, an average dealer transacted $185 million of original balance on interdealer market in ABS, $126 million in CDOs, $283 million in CMBS, and $259 million in CMO. Figure 6 shows the break-up of total volume transacted on interdealer market by the four major product types and the two samples.

Dealers are heterogeneous both in terms of their trading with customers and interdealer market participation. Figure 7 presents the Lorenz curves computed using dealers' shares of the original order balance with customers for ABS, CDOs, CMBS and non-agency CMO, and the two placement types. We observe heterogeneity of dealers in terms of total volume traded with customers. A small number of dealers account for a major fraction of customer volume in all markets and for both placement types. There is a noticeable dispersion and skewness in interdealer market participation by different dealers. The order flow is more evenly divided among dealers in Rule 144a markets than in Registered markets.

A median dealer participated in 9.5 interdealer transactions in the pre-release sample (10 transactions in the post-release sample) and transacted in total $3 million ($5 million, respectively), while the 75th percentile of interdealer trade participation by a dealer is 69 transactions in the pre-release sample (57 transactions in the post-release) and $71 million of original balance traded ($102 million, respectively). There is also evidence that some links between different pairs of dealers are stronger than others, and some dealers have higher levels of importance to the functioning of the interdealer market and act as the key providers of interdealer liquidity.

Figure 8 summarizes the topology of the grand interdealer market for all products-its strongest links. In this figure we include links between two dealers when more than 50 trade reports were observed in the overall sample and more than $10 million of current balance in total was transacted during the sample period. Links with more than $100 million transacted are shown as solid lines.

The four broad markets we analyze are significantly interconnected. Individual dealers often participate in different markets at the same time. Some interdealer markets are generally more active than others in terms of number of interdealer trade records with the non-agency CMO market particularly active. For these reasons we measure dealers' activity in different instruments separately, then following Li and Schürhoff [2012] and Milbourn [2003], we perform normalizations of the resulting measures to preserve information on dealers' ranks in the network. For the purpose of our empirical analysis we follow two alternative methodologies. Under the first methodology we construct a single aggregate proxy for dealer-specific importance on interdealer market by performing principal component analysis and use that proxy in the fixed-effects regression. Under the second methodology for each dealer and each submarket we measure coreness and degree centrality, and use the relationship between the two variables to describe dealers' relative position in the network and resulting bargaining power. We describe both methodologies in greater detail below.

We measure the relationship between dealers by their interdealer trade. Under our first empirical methodology we compute the following centrality measures for each dealer:

- *Degree centrality* is defined as the number of closest neighboring dealers around a particular dealer in the network.
- *Eigenvector centrality* is computed using eigenvalues of the adjacency matrix (matrix describing links between dealers in the network), for each particular dealer it emphasizes connections with relatively more important dealers of the network.
- *Betweenness centrality* is equal to the total number of shortest trading paths from every single dealer to any potential counterparty that passes through this particular dealer.[13]
- *Closeness measure* is defined as the inverse of the total distance from each particular dealer to any other dealer in the network based on observed trading relationships.

[13] The betweenness centrality measure is a widely used tool in the literature on social networks, Freeman [1977]

Estimated centrality measures for dealers differ in their nature: Degree centrality is a local property taking into account only the closest sub-network of dealer's neighbors, while eigenvector centrality or betweenness centrality account for its global structure, and across different markets (e.g. some dealers are relatively more active in Registered ABS than Rule 144a non-agency CMO). Li and Schürhoff [2012] explored all of these alternative centrality measures in the context of municipal bond trading and demonstrated existence of a significant common component in these measures. We obtain similar results in our sample.

We divide all interdealer trades between May 16, 2011 and February 29, 2012 for the overall sample into seven buckets based on the four types of instruments (ABS, CDOs, CMBS, and non-agency CMO) and two placement types-Registered and Rule 144a. Within each bucket we compute the total volume transacted by all pairs of dealers, differentiated from each other by their dealer masks.[14] We estimate the following four centrality measures: 1) degree centrality (unweighted and weighted by volume transacted), 2) eigenvector centrality (unweighted and weighted by volume transacted), 3) betweenness centrality measure, and 4) the closeness measure.

All of the measures are estimated for each dealer, and the first two of these measures allow us to differently weight the links between dealers based on total volume traded over the particular sample period. We differentiate between buys from and sells to a particular dealer in the interdealer network and use directed networks in our estimation. We apply the empirical cumulative-density function transformation to each of the six centrality measures obtained, and then extract the first principal component. For each of the seven buckets we have two versions of the dealers' importance-unweighted and weighted by total volume transacted within each market. We perform principal component analysis separately for these two versions to aggregate across different markets. In our empirical analysis we use the measure weighted by total volume transacted, with the correlation between the weighted and unweighted versions at 0.98. We linearly normalize the resulting variable to a zero-to-one scale. Dealers that did not participate in interdealer trades are

[14] Dealer masks may not identify separate dealers perfectly in case when a single dealer has several trading desks having different dealer masks for reporting purposes.

assigned zero centrality value.

In our analysis of total client bid-ask spreads we use the average dealer centrality variable, which is the average aggregate centrality measure of all dealers that intermediated in a particular chain of matched transactions.

Overall we find evidence for a negative relationship between dealers' interdealer activity measured by aggregate centrality and total client bid-ask spreads. Figures 11a and 11b present scatter plots of spreads against dealers' centrality for non-retail size matches in Registered and Rule 144a instruments. Dealers who participate more actively in the interdealer market have lower inventory risk and may require lower compensation for their services. But these dealers may be generally more visible to other market participants and have a certain degree of market power-in this case we expect these dealers to charge higher compensation through customers' bid-ask spreads. We use average dealers' centrality in our regression analysis to check the validity of these conjectures when we control for other factors and characteristics as well.

Under the second methodology for each dealer we compute the following two measures:

- *Coreness measure* is defined using the k-core sub-network. The k-core sub-network is the largest sub-network in which all dealers have at least k trading partners in this sub-network. There are many sub-networks a particular dealer participates in characterized by different values of k. The dealer's coreness is the maximum k such that the dealer belongs to a k-core sub-network.

- *Coreness-Degree Residual* is defined as the difference between dealer's degree centrality and dealer's coreness.

A dealer's Degree Centrality is always larger than the dealer's Coreness. Higher Degree Centrality relative to the Coreness means that the dealer is more important as an intermediary between different groups of dealers, because the dealer is bridging different smaller sub-networks. The Coreness-Degree Residual therefore measures the relative importance of a dealer in the sub-network, and is a proxy for the dealer's local bargaining power.

We present graphical illustrations of four different scenarios for dealer's coreness and

Coreness-Degree residual in Figure 9. The figure shows sub-networks constructed using the ABS Registered market within the overall network presented in Figure 8, with a relaxed restriction on what constitutes a strong link-we do not require the volume transacted between two parties to be above $10 million in total. The dealer with 23 trading partners has the largest degree centrality in the sub-network. The second order neighborhood of that dealer is shown in the top left panel of Figure 9. That dealer's coreness is 4, meaning that the largest sub-network that this dealer participates in has all dealers with at least 4 trading partners in this sub-network.

In the Registered ABS sample of interdealer trades the maximum coreness is 4 and there are a few dealers with coreness of 4. We can think of all these dealers corresponding to the 4-core sub-network as the set of most important and frequent counterparties for the dealer with 23 partners. This dealer has links to other sub-networks as well and performs the role of a "bridge" across different parts of the interdealer market. There is also another dealer with degree 4, which is the same as its coreness-the weakest node in the 4-core sub-network. The Coreness-Degree residual captures this relative difference in dealer's local positions.

A single centrality measure cannot capture these relative differences in dealers' positions. Two dealers may have similar numbers of trading partners; however, differences in their coreness may result in different bargaining power between the dealers. A dealer with coreness similar to the degree centrality will be the least connected dealer in the main k-core sub-network he belongs to. On the other hand a dealer with coreness much smaller than degree will have the strongest outside options. We perform empirical analysis based on these two measures of dealers' standing in the network and for some of our markets we find their effects having different directions on bid-ask spreads. Figures 12a and 12b maps the average dealer bid-ask spreads against dealers' coreness and degree centrality.

2.4 Regression Analysis

Table 8 provides the definitions of the right-hand-side variables we use in the regression analysis. The dependent variable is the bid-ask spread, with one observation per pair of matched trades in the sample. We use X to denote the right-hand-side variables in the regressions. We allow the slope coefficients to be different across categories of instruments and placement types (Registered and Rule 144a). We also include fixed effects for each of the six different collateral types of ABS issues, for CDO, CBO, and CLO instruments, CMBS interest-only or principal-only (IO/PO) and all other CMBS instruments (P/I), and six different types of CMO tranches separately, which we define as subcategories. We combine CBO and CLO in a single category. Denote each category of instruments by $j \in \{1,,5\}$, each subcategory of instruments by k, and placement type by $l \in \{0,1\}$, with $l=0$ for Registered instruments and $l=1$ for Rule 144a instruments. We estimate the equation, allowing for heteroskedasticity in the residuals.[15]

$$y_{it} = \alpha_{jkl} + (X_{it})^T \beta_{jl} + \varepsilon_{it}. \tag{35}$$

We allow the regression constant to depend on the category, subcategory and placement types, and we allow the marginal effects β to differ across the five categories and two placement types.

We also perform analysis of overall categories without differentiating between Registered and Rule 144a security types. We pool together Registered and Rule 144a instruments and obtain overall marginal effects of the aforementioned factors. The estimation equation is:

$$\begin{aligned} y_{it} &= \sum_{k=1}^{6} 1_{i\in k} \times (X_{it})^T \beta_{ABS} + \sum_{k=7}^{9} 1_{i\in k} \times (X_{it})^T \beta_{CDO/CBO/CLO} + \\ &+ \sum_{k=10}^{11} 1_{i\in k} \times (X_{it})^T \beta_{CMBS} + \sum_{k=12}^{17} 1_{i\in k} \times (X_{it})^T \beta_{CMO} + \sum_{j=0}^{1}\sum_{k=1}^{17} 1_{i\in k, R144a=j}\alpha_k + \varepsilon_{it}. \end{aligned} \tag{36}$$

Table 9 reports the results from the regressions for the total client spreads. The total client spreads are computed using the complete customer-to-customer chains of matched transactions. In each group of columns, we report the point estimates of the coefficients with standard errors in parentheses below. All regressions include fixed effects for sub-

[15] We also experiment by including fixed effects for individual instruments. Our main results are robust to using the individual instrument fixed effects.

categories of instruments. We report the estimates for the overall category, estimates for Registered instruments within the category, and estimates for the Rule 144a instruments.

The point estimates of the coefficients on 4-6 Year Vintage and >6 Year Vintage are positive for all types of instruments except CDOs and Registered CMBS: Older maturity instruments tend to have higher spreads, reflecting their lack of trade, and also the possibility that there is more asymmetric information about these instruments. Across all categories of instruments, the point estimate on the Investment Grade is negative and economically significant: High yield instruments tend to have higher spreads than Investment Grade instruments.

The point estimate of the coefficient on Security-Specific Match Volume is negative for most categories of instruments. A negative coefficient on Security-Specific Volume indicates that instruments with larger trades tend to have small spreads, consistent with more actively-traded instruments having lower transactions costs. This is indeed the case for all security types except for Rule 144a CMBS.

Deviation of a Particular Match is a measure of the size of the matched transaction relative to the average transaction size in that security. The point estimates are negative across all types of instruments. A negative coefficient on Deviation of Particular Match indicates that when the matched trade is larger than typical for that instrument, the match will have a lower spread reflecting a volume discount. In typical equity markets, larger trades tend to have larger spreads, with the typical explanation that larger trades carry information so that dealers face higher adverse selection costs on larger trades. In many bond markets, smaller trades have larger spreads; with the typical explanation being that smaller trades tend to proxy for less sophisticated customers so that dealers have greater bargaining power in smaller trades and so are able to earn higher spreads on smaller trades. The securitized markets we analyze resemble bond markets with respect to volume effects. Our finding here does not depend on retail-sized trades, since those trades are removed from the regression analysis.

The effect of Floating Coupon is positive for all ABS instruments, Registered CMBS instruments and Registered CMO instruments: For these categories, instruments with floating coupons tend to have higher spreads. For CDO, CBO/CLO, Rule 144a CMBS, and Rule 144a CMO instruments floating coupon instruments tend to have lower spreads. Generally the point estimates on Investment Grade and Floating Coupon together imply that instruments with riskier cash flows tend to have higher spreads.

The point estimates on Gap in Execution Time are of mixed magnitude and sign, and are generally not statistically significant. One interpretation of a negative coefficient on Gap in Execution Time is that the dealers offer a price concession to close out a trade when the holding period is long. One interpretation of a positive coefficient on Gap in Execution Time is that the dealers in such instruments earn a higher rate-of-return the longer that the instrument is in the dealers' inventory.

The coefficients on Number of Dealers are of mixed magnitude and sign and economically small: Perhaps the mixed results on Number of Dealers indicate that the choice of the Number of Dealers in an instrument is endogenous to the size of the spread that the dealers can earn.

The point estimate on the Dealer Importance Dummy is negative and statistically significant for all categories with the exception of overall CDOs, where the positive point estimate is not statistically significant. A negative coefficient on Dealer Importance Dummy implies that the average spread is lower if the inventory passes through a dealer who is more active in the inter-dealer network. The coefficients for Rule 144a instruments are lower than the coefficients for Registered instruments: The relative benefits for customers to have orders intermediated by central dealers rather than peripheral dealers are larger in Rule 144a markets.

The point estimate on Multi Round Trade is positive except for CBO/CLO instruments, and is economically and statistically significant for most categories. A positive coefficient implies that deals that pass through many dealers as they go from a customer to another customer tend to have larger spreads. In this sense, deals with more intermediation are more costly to the customers.

Table 10 reports the results from regressions for the dealer spreads. The spreads used in the regression result from decomposing the total client spreads used in Table 9 into individual dealer spreads. For example, the two round chain: Customer to Dealer A, Dealer A to Dealer B and Dealer B to Customer yields two dealer spreads. The first spread is computed from Dealer A's purchase price from the customer and Dealer A's sale price to Dealer B, and the second spread is computed from Dealer B's purchase price from Dealer A and Dealer B's sale price to the customer. If N dealers intermediate a chain between customers, then we compute N dealer spreads.

Overall, we find similar effects of the control variables as in the total client spread regressions reported in Table 9, and we include additional control variables: Dealer's Coreness, Dealer's Degree Residual, and the two customer participation dummies-Buy from Customer and Sell to Dealer, Sell to Customer and Buy from Dealer.

The point estimate of Dealer's Coreness in Table 10 is negative for all instruments except for non-agency CMO instruments and the CDO subcategory. The negative point estimates could reflect greater competition and reduced bargaining power of more central dealers or lower trading costs on the transactions they intermediate. These findings suggest a degree of specialization in the trading of different instruments and the need to look at competition in more subtle ways. Central dealers perform a valuable function by enhancing the linkages in the network and the integration of customer activity.

The point estimate of Dealer's Degree Residual is negative for all instruments except Rule 144a CMBS instruments and Registered CMO instruments. Holding the size of the interdealer k-core sub-network constant, the higher relative position of a dealer in that sub-network captured by positive Degree Residual results in lower dealer spreads on average. The result is the opposite from the generally positive relationship between dealer's centrality and bid-ask spreads found in the literature on municipal bonds (Li and Schürhoff [2012]). The finding is consistent with the equilibrium in a search-and-bargaining model of a decentralized interdealer market in which dealers differ in their trade execution efficiency that proxy for dealer centrality in Neklyudov [2013]. Our result also highlights the importance of the decomposition of single centrality measure into the Coreness-Degree residual.

The point estimate on Multi Round Trade is positive except for Registered ABS instruments, and is economically and statistically significant for most categories. A positive coefficient implies that interdealer spreads in multi-round deals tend to be higher. The point estimate on Buy from Customer and Sell to Dealer is negative except for ABS instruments indicating that spreads are lower when the dealer is in the first link of a multi-round intermediation. Perhaps this reflects that dealers need to offer price concessions to sell to another dealer rather than a customer. The point estimate on Buy from Dealer and Sell to Customer is positive except for CDOs and Rule 144a CMO instruments indicating that spreads are higher when the dealer is in the last link of a multi-round intermediation. It is more valuable to find a customer to sell to and finish the intermediation chain rather than to sell to another dealer and keep the intermediation chain going.

3 Predictions from the Theory of OTC Markets

Generally, the negative relationship between average customer bid-ask spreads and various measures of dealers' importance is consistent with the theoretical predictions from a search model of decentralized interdealer market, developed in Neklyudov [2013]. In this paper, the more connected dealers charge lower spreads because their endogenous reservation values reflect their search efficiency and they intermediate trade flows among the less efficient dealers. In this section we discuss other links that can be established between the theory and empirical facts we document.

The seminal paper by Duffie et al. [2005] demonstrates how bid-ask spreads emerge in a model with counterparties who search for each other on a decentralized market. In this model, the spreads reflect different investor's outside options, and more sophisticated investors are facing lower spreads in equilibrium. Information-based models offer a different prediction for more sophisticated investors who may be more informed, as more informed investors face wider bid-ask spreads, as in Kyle [1985]. Another consideration is the inventory risk, that is predicted to drive spreads up for large unexpected transactions, as in Ho and Stoll [1981]. Though in the context of securitizations markets, dealers provide no commitment to trade at the posted bid and ask prices, which may imply that dealers might have more control over their inventories. On the other hand, trading opportunities are much less frequent in securitizations markets. Overall, the bid-ask spreads we measure may reflect elements of search, information, and inventory considerations.

Now we turn to the analysis of theoretical predictions about heterogenous dealer markets, developed in Neklyudov [2013], and link the developed theory with the empirical evidence.

The following factors determine the nature of equilibrium, that arises in a model of decentralized interdealer market: (i) The average magnitude of the search friction; (ii) The relative proportions of dealers and customers in the population of investors; (iii) The Nash bargaining power of a dealer; (iv) The distribution of matching capital and exposures to the search friction across dealers.

In the model, the average magnitude of the search friction, or the overall level of decentralization, is proportional to the average trading frequency on the market, for both customer and interdealer trades. Below we provide information on the number of trade records on each market we observe in our sample:

Market	Placement	Customer (Interdealer) Trade Reports	Average Volume
ABS	Registered	36,653 (8,517)	5.6M (5.5M)
	Rule 144a	12,707 (3,356)	10M (12.4M)
CDO	Rule 144a	7,273 (1,604)	12.5M (18.2M)
CMBS	Registered	40,731 (9,042)	8.9M (7M)
	Rule 144a	9,619 (1,411)	32.9M (55M)
Non-Agency CMO	Registered	147,949 (41,198)	6.6M (5.3M)
	Rule 144a	9,881 (1,499)	16M (12M)

Legend: Overall numbers of trade reports and average volumes are given by product types from May 16, 2011 to February 29, 2012.

It can be seen, that the non-agency Registered CMO market has the highest number of trades executed over our sample period. Registered instruments both in ABS and CMBS also generate larger number of trade records. These observations are consistent both on aggregate and per-security basis (per-security trading frequencies are reported in Tables 2b and 3b). This is an evidence if favor of a claim that markets in registered instruments are characterized by smaller degree of search friction. However we should note that we are not able to control for investors' willingness to trade in this context—markets with the same magnitude of search friction may have different number of transactions executed due to different exogenous investors' preferences for trading. In terms of the model, the observed trading frequencies reveal the joint effect of the frequency of changes in agents' liquidity states, and the extent of the search friction. Though one may plausibly argue that the design of the markets may react to larger willingness to trade by investors, and the severity of search friction will be reduced for markets with frequent liquidity needs.

Another observation is that there are approximately 4 times more customer trades than interdealer trades in all markets except Rule 144a CMBS and CMO, where there are 6.5 times more customer trades. With some exceptions, the trade volumes are comparable across customer and interdealer trades (yet differ across markets). In the model these numbers map to the relative proportions of dealers and customers in the population of investors. Larger proportion of customers in the population naturally results in larger number of customer trades executed. The model predicts, that when customers and dealers have equal aggregate market shares and equal exposure to liquidity risk, there are more than twice more interdealer trades in the equilibrium. This is a manifestation of a relatively more efficient interdealer market with lower exposure to search friction. Any dealer in the model encounters a larger number of other dealers than customers over a given interval of time. The empirical evidence argues in favor of much larger customer sector in the population of investors. It suggests that the market presence of customers of these products is significantly high on these markets.

We then turn to the Nash bargaining power of dealers on these markets. The theoretical finding suggests that dealers, who are capable of dealing with search friction in a more efficient way than customers, have less volatile reservation values for the asset. This in turn implies lower average bid-ask spreads for the markets where customers have relatively higher bargaining power. Moreover, when customers have significant bargaining power, bid-ask spreads are more responsive to the type and efficiency of a dealer in the cross-section of dealers. The results of our regression analysis in Table 9 suggest that on Rule 144a markets customers indeed may have greater bargaining power—the effect of Dealers' Importance dummy appears to be stronger for Rule 144a instruments. This is also consistent with our finding in Table 4 that average spreads for Rule 144a instruments are lower than corresponding spreads for Registered instruments.

Finally, we discuss the distribution of matching capital, or trade execution efficiency levels across dealers in the cross-section. Figure 7 demonstrates the proportional shares of total customer flow of different dealers using the Lorentz curve methodology. We observe than 5% of most active dealers in terms of total absolute order flow with customers account for 80-90% of customer volume in these products (with exception of CDO instruments, where the proportion is 50-60%). We observe slightly lower degree of heterogeneity of dealers in Rule 144a instruments. These observations suggest that in the cross-section of dealers in securitized products there is a substantial number of dealers with mediocre customer activity (which is significantly correlated with interdealer activity for these dealers). In the theoretical model, this would correspond to the heavily skewed distribution of trade execution efficiency with a large left tail. Empirically, the trading activity of inactive dealers is consistent with lower "matching capital" of these dealers and high exposure to the decentralized nature of the markets. This may be reflected in low customer base and low awareness about the underlying trading network, or insufficient technology to process large numbers of trades (including legal technology). The left-tail of the distribution may as well be populated by regional and geographically-peripheral dealers.

The theoretical model predicts that less efficient dealers trade only when their exogenous liquidity state changes, while more efficient dealers trade substantially more frequently. The model suggests that more efficient dealers may exploit the less efficient dealers in order to temporarily park assets when liquidity state of peripheral dealers is appropriate. Thus less efficient dealers are more likely to trade on the interdealer market, than with customers.

The panels of Figures 13a and 13b generally confirm the prediction of the model that total interdealer order flow tend to exceed the total customer order flow, especially for less active dealers. It also demonstrates well that substantial number of dealers in either markets tend to balance their total customer flows with interdealer flow. The latter feature is not accounted by a theoretical search model where agents do not prearrange both sides of their trades.

To conclude, the theoretical model provides a reasonable stylization of the observed markets. The lower spreads in Rule144a markets and higher sensitivity of spreads to the cross-sectional characteristics of dealers are consistent with customers having larger Nash bargaining power on these markets. This is consistent with our general understanding of Rule 144a instruments as ones being designed for a more sophisticated clientele. The intermediation patterns between dealers with different trade execution efficiency are consistent with the predictions of the theory. However not all features of trading are accounted for, the tendency of dealers to prearrange trades as an example.

4 Publication of Price Index Data

An important event within our sample period is the public release of price index data on a daily basis by FINRA and IDC starting in mid-October 2011 for various types of securitizations. This has the potential to lead to substantial informational changes in the market. We examined whether these indices provide market participants information about pricing and spreads, and whether that information becomes common knowledge to all market participants, including dealers. We anticipated that this could affect spreads after the initial public release of the indices (five months of such data were initially released in mid-October) and then the indices were updated on a daily basis (even without a full-blown roll-out of post-trade transaction level price reporting). Analysis of this data after its public release and comparison to an environment in which the indices were not anticipated to be released (such as prior to the initial release of index data) would allow analysis of the impact of a form of price transparency. To control for other considerations that alter the spreads, we examine both Registered and Rule 144a instruments, as this is one issue of our focus and because for categories except for the CDO/CBO/CLOs, there is more weight and trading in Registered rather than Rule 144a instruments and because the investors in Rule 144a instruments are potentially more sophisticated than those in Registered instruments.

The publication of these data began on October 18, 2011. Initially the data was published back to the start of the data collection interval and then updated daily with a one-day lag. In examining the price index data we are struck by the substantial negative first-order serial correlation in the price index-both pre- and post-release (see Figure 14). Using standard market microstructure interpretations this highlights the extent of noise in the data, which suggests the difficulty confronting market participants in extracting valuation information from the data. Conceptually, the nature of improvement in transparency at the level of individual instruments from the release of index data may have been modest, both because of the portfolio composition and the daily nature of the index. The negative serial correlation in the index points to the potential construction of spreads using time series approaches (e.g., see the Roll [1984] estimator of bid-ask spreads using the negative serial correlation in transaction prices) and is suggestive of relatively wide spreads implicit in the index data (and the underlying securitizations). Given the limited set of observations, we focus our analyses of spreads at the securitization level in our matching analyses, but time series perspectives are potentially useful as we try to understand the public index data. In other contexts (such as the equity markets) cash index returns or differences often reflect substantial positive serial correlation due to staleness in components of the pricing and strong positive cross-sectional correlation among the assets. In the current context the index construction only reflects the assets that have traded recently, so there is not an obvious rationale that would lead to underlying positive serial correlation. Indeed, this aspect of the index construction suggests an additional source of noise not present in the standard equity index, as the composition of the index here is changing because it reflects only assets that have traded recently.

The newly disseminated price index data provides us an opportunity to study the impact on spreads for Registered and Rule 144a instruments. Table 6b reports information on the spreads before and after the public dissemination of price indices, specifically whether the spreads increased or decreased from the pre- to the post-release samples for both Registered and Rule 144a instruments. The conventional view is that the spread should decrease after transparency enhancing events. We find such decrease in spreads in the Registered non-agency CMO category with the mean spreads post-release being statistically significantly smaller than the pre-release sample. However we observe the reverse pattern in Registered CMBS instruments and mixed results in other categories, that are not statistically significant.

The interpretation of the increase in spreads that we document above is not straightforward for a second reason. In particular, our graphical evidence suggests that there is a lot of variability in the spreads and not a sharp change in regime at the point at which the price index disclosure begins (see especially Figure 10, which documents the weekly moving averages of the total client bid-ask spread, and less directly, Figure 5, which offers scatter plots of the spreads). In fact, the graphical evidence suggests the plausibility of identifying changes in spread levels at a variety of alternative dates-undercutting the strength of the evidence with respect to the actual regime change.

5 Concluding Comments

In this paper, we utilize data on dealer transactions in securitizations markets to study the nature of dealer networks and how bid-ask spreads vary within the trading network. While trading among instruments is highly fragmented and relatively infrequent, trading is highly concentrated among a relatively small number of dealers. Dealer networks reflect a core-peripheral structure. We document a negative relationship between the importance and interconnectedness of dealers and their bid-ask spreads. Theoretical work studying over-the-counter markets predicts that customers that trade with more interconnected dealers with higher trade execution efficiency face lower bid-ask spreads on average in equilibrium (Neklyudov [2013]). The evidence contrasts with the empirical findings in municipal bond markets, where a positive relationship arises between dealers' importance and bid-ask spreads (Li and Schürhoff [2012]).

Our matching techniques allow us to look in more detail at how the total client bid-ask spread gets split among different parties involved in a deal. Longer chains of intermediation result in larger total spreads. Dealer spreads are especially wide on transactions that complete the chain-it is more valuable to find a customer to sell to and finish the intermediation chain rather than to sell to another dealer and keep the intermediation chain going.

We observe a smaller number of active dealers trading in an average Rule 144a instrument than in an average Registered instrument, but at the same time tighter customer bid-ask spreads. We also observe that the order flow is more evenly divided among dealers in Rule 144a instruments and that customers in Rule 144a markets face smaller bid-ask spreads when trading with more central dealers. These findings emphasize that the extent of competition differs between Registered and Rule 144a instruments.

It is important to understand the microeconomic aspects of the trading process, especially in light of the dramatic disclosure differences between Registered and Rule 144a instruments. Rule 144a securitizations have less disclosure requirements than Registered securitizations, but they could represent higher quality assets, that are held only by sophisticated investors with access to additional sources of information.

Our study points to a variety of additional directions for study. Empirical findings that emerge from the data have natural potential to inform the theory of over-the-counter markets and provide grounds for validation of different theoretical models. The nature of the data allows one to identify different counterparties and construct trading networks, offering a natural environment to perform network analysis. Network analysis has the potential to enhance our understanding of intermediation patterns for dealer markets and concentrations of risk more broadly, including systemic risks.

Appendices

F Data Cleaning

For the purpose of this study we have trading activity data ranging from May 16, 2011 to February 29, 2012 in several classes of securitized products: ABS, CDO/CBO/CLO, CMBS, CMO, MBS and TBA, as well as the database with issue characteristics for all issues subject to FINRA reporting requirement.[16] On October 18, 2011 FINRA and IDC began to disseminate the price index data, and to extend our analysis we study both the overall sample as well as separate data from the period prior to that date (referred to as pre-release sample) and the period beginning on that date (referred to as post-release sample). We limit our attention to ABS, CMBS and non-agency CMO securitizations because these classes have both Registered as well as Rule 144a placed instruments in our sample. We also present our results for CDO, CBO and CLO Rule 144a instruments separately to allow for comparisons across asset classes. In our analysis we use Moody's ratings for instruments that have at least two opposite trades with customers. For other instruments we were able to utilize the investment grade data for these instruments provided by FINRA. Moody's ratings were collected for all instruments that satisfy our minimal-trading requirement: There are at least two opposite transactions with customers at most 2 weeks apart in our sample period from May 16, 2011 to February 29, 2012. We used the proprietary list of CUSIPs provided by FINRA to locate Moody's ratings for these instruments on the corporate website.

We perform several rounds of cleaning before we obtain a workable sample of trades: 1) Adjust for trade corrections and removed cancelled trades; 2) address double-reporting issue for inter-dealer trades-both dealers were typically reporting the same trade from opposite sides; 3) match trading reports with issue-specific characteristics from the database provided by FINRA; 4) clean the data from the issues with insufficient trading activity to perform our analysis; 5) compute bid-ask spreads using an iterative cascading matching technique discussed below; 6) adjust resulting spreads for coupon and factor payments; 7) perform cleaning for outliers. Below we discuss each of these rounds of data cleaning in greater detail.

For some trade records, traders entered incorrect trade information or canceled previous transactions. Traders corrected the records by entering additional reports marked as "Corrected Trades", "Trade Cancels" or "Cancels", and "Historical Reversals" (if correction was reported not on the say trading day). In the first round of cleaning we remove all trade records that were subsequently corrected to keep only the effective transaction records, we remove all records that were cancelled and do not count them in our subsequent analyses, and we disregard all corrections when no initial trade record is reliably identified by entered volume, entered price, trade execution date and counterparty masks.

According to the FINRA reporting rule, each interdealer trade must be reported by both sides to the transaction, effectively leading to double reporting in our sample, with a few exceptions. Customer transactions and so-called "locked-in trades"[17] are always reported once. In order to cope with the double-reporting problem we implement an iterative pair-matching procedure. We look at pairs of identical transactions reported from different sides by the same counterparties. The counterparties often reported slightly different trade execution timestamps, so that we have to be careful distinguishing the second report for a particular transaction from other trading activity unrelated to it. The pair-matching procedure consists of one hundred iterative rounds of search for very similar entries in terms of entered volume, price, execution timestamps, settlement date, counterparty masks. In each round we flag trade reports that are sufficiently similar to constitute candidates for a double-entry of the same trade. Anytime we find several alternative candidate

[16] Among others the characteristics included: maturity date, coupons with update dates, type of coupon (fixed or floating), factors with update dates, type of placement (Registered or Rule 144a), description of the issue.

[17] Locked-in trades are defined in the layouts for trading data files provided by FINRA.

trades, we pick the ones closest in time according to the reported execution timestamp. Anytime we cannot identify a match based on the above criteria, we assume there was no second report for the trade. For 84.77% of all trade reports we were able to identify unique matching reports, which were subsequently removed from the sample.[18] The result of this cleaning constitutes our working sample of transactions.

We match each transaction report to the issue-specific characteristics and description from the database provided by FINRA. The database for ABS, CDOs, CMBS and non-agency CMO instruments consists of eleven time-stamped files corresponding to May 15, May 31, June 30, July 31, August 31, September 31, October 31, November 30, December 31, January 31, 2012, and February 29, 2012. Using these files we are able to reconstruct the time-series of coupon rates and prepayment factors, as well as product collateral or underlying pool types, maturity, original balance, type of placement (Registered or Rule 144a), type of coupon (fixed or floating). In the few cases when the instrument-specific characteristics (such as the product category or the type of placement) are different in different files for the same issue identifier-we take the data from the latest files available for this issue, having in mind potential data entry issues. In the very rare cases when instruments with the same CUSIP code have different symbol IDs we treat those as different instruments.

It is worth noting that most of securitizations in our sample traded very thinly during either of the two sample periods (pre-release and post-release). For example, only 2,807 out of 12,663 ABS issues, 1,219 out of 7,471 CDOs issues, 2,967 out of 13,720 CMBS issues, and 13,396 out of 78,698 non-agency CMO issues did have at least two opposite trades with customers at most two weeks apart in time. Table 1 presents more detailed information. We could compute client spreads for these instruments only.

Then we perform several steps of matching seemingly related transaction into chains. We use the complete trading sample from May 16, 2011 to February 29, 2012 to look for chains, and then tag each chain we find with the relevant pre-release or post-release sample tag. The implementation of our matching technique consists of three rounds.

In the first round we match related interdealer and customer transactions that have the same volume and each pair in a chain is no further than one month apart. For example, when we see among other trading activity three transactions in the same instrument of $1 million original balance that form a potential chain: Customer to dealer A, dealer A to dealer B, dealer B to customer, we perform two checks: 1) For each link of the potential chain there are no other alternative candidates resulting in a different branch of a chain that are closer in time based on the execution timestamp; 2) each link in the chain is no further than 1 month apart based on execution timestamp. If both conditions are satisfied, we take this chain out of the dataset and proceed with search for other chains iteratively. Different links of a single chain can be tangled in other trading activity in a given instrument, so in order to find candidates and establish links we sort our dataset by execution timestamp within each separate instrument and look for each trade record we look for candidate matches 15 record forward and 15 records backward. Note that we do not impose any timing sequence within a chain-buy from customers can follow as well as precede the sell to customer, and all seemingly related interdealer trades may happen at any point in time that satisfies the one-month maximum link span. We find most of our chains with a step size smaller than 15, so this step size limit does not constrain our results in a noticeable way. In order to search for all chains with no splits of volume we perform the aforementioned algorithm iteratively 100 times, which completely exhausts all candidate links that fall in the non-split category. The result of the first round is a set of chains of various lengths: C-D-C (1 link), C-D-D-C (2 links), etc., with the same volume moving through the chain. We find 10,871 non-split chains in ABS (1.2 links on average, 5 links maximum), 1,959 chains in CDOs (1.08 links on average, 6 links maximum), 11,298 chains in CMBS (1.15 links on average, 9 links maximum), and 30,179 chains in non-agency CMO (1.32 links on average, 7 links maximum).

In the second round we allow transaction volume to split when moving through a chain. For

[18] These numbers apply to ABS, CDO, CMBS, and non-agency CMO only.

example, when we see among other trading activity three transactions in the same instrument forming a potential chain but having different trade volumes: \$1 million customer to dealer A, \$2 million dealer A to dealer B, \$0.5 million dealer B to customer, we perform the same two checks as in the first round for the candidate links and in case these checks are satisfied we split the chain in three pieces: 1) \$0.5 million customer to dealer A; 2) \$1.5 million dealer A to dealer B; 3) \$0.5 million customer to dealer A, \$0.5 million dealer A to dealer B, \$0.5 million dealer B to customer. The last piece corresponds to a valid two-links chain we take out from the sample, while the first two pieces are returned back for further iterations of search-for-chains. This splitting is designed to treat the trading patterns when different chains branch into sub-chains or merge together and potentially have common links. Similarly to the first round we search for candidate links 15 records forward and backward each in a sorted trade sample, and perform 100 rounds. This way we find 8,719 additional chains in ABS (1.51 links on average, 9 links maximum), 794 chains in CDOs (1.43 links on average, 10 links maximum), 10,111 chains in CMBS (1.38 links on average, 15 links maximum), and 41,135 chains in non-agency CMO (1.9 links on average, 9 links maximum).

In the second round the 15 step size constraint binds for instruments with heavy trading activity and many trade records happening within a trading day. The second round ensures that we link most of the related interdealer links to trades with customers when they are less than 15 trade records away from each other. After the second round we drop all interdealer trades that have not yet been used to form a chain with any client transactions and perform LIFO matching of the opposite client transactions. This constitutes our third and final round of matching process. We keep track of all interdealer links established in prior rounds that were attached to these transactions. This way we find 3,396 additional chains in ABS (1.86 links on average, 11 links maximum), 406 chains in CDOs (1.72 links on average, 7 links maximum), 4,621 chains in CMBS (1.8 links on average, 19 links maximum), and 13,192 chains in non-agency CMO (2.3 links on average, 10 links maximum).

After the three rounds we have a sample of chains both involving splits of volume and non-split chains. We have in total 23,036 chains in ABS (1.41 links on average, 11 links maximum), 3,198 chains in CDOs (1.25 links on average, 10 links maximum), 26,124 chains in CMBS (1.35 links on average, 19 links maximum), and 84,788 chains in non-agency CMO (1.76 links on average, 10 links maximum). On average we find relatively longer chains in non-agency CMO market. In our regression analysis we refer to the number of links in a chain as number of rounds in the deal.

The complete chains we find constitute 75% of the total absolute turnover in the ABS market, 86% in the CDOs market, 74% in the CMBS market, and 80% in the non-agency CMO market. We also include broken chains in which dealer codes do not match.

Approximately 54.64% of chains we find using our matching process occur in the pre-release sample (between May 16, 2011 and October 17, 2011).

Within each chain of related transaction we adjust prices for coupon and factor payments that happened between the settlement time of a particular trade and the settlement time of the logical beginning of the chain (a buy from customer, not necessary the first trade to happen within a chain by execution time). For each chain of transactions having two opposite trades with customers, we compute two types of bid-ask spread measures: total client bid-ask spread and dealer-specific spread-both measured per \$100 of current value (capital committed). The quotes observed in our dataset are clean prices per unit of current balance, thus we adjust our bid-ask spread measures for accrued interest and factor prepayments. We use the following approach to perform these adjustments:

Firstly, the direct way to compute bid-ask spread having two quotes on the opposite sides of an intermediating trade and the full information on factor and coupon payments in between is the following. Here we consider the case when settlement date effective for the ask quote occurs after the settlement date effective for the bid quote, however the formulas generalize to allow for opposite cases (below T stands for number of calendar days in between and c is the annual dollar coupon amount per \$100 of original balance):

$$\begin{aligned} Spread &= 100 \times \frac{P_{ask} \times factor_{ask} - P_{bid} \times factor_{bid} + adj}{(P_{ask} \times factor_{ask} + P_{bid} \times factor_{bid} + adj)/2}, \\ &\quad \text{where: } adj = c \times T/360 \times factor_{bid} + factor\ prepayment. \end{aligned} \tag{37}$$

We use the following fair-pricing condition to simplify the above formula:

$$(factor\ prepayment)/P_{ask} = factor_{bid} - factor_{ask}. \tag{38}$$

Assuming the above condition holds, the bid-ask spread calculation simplifies to:

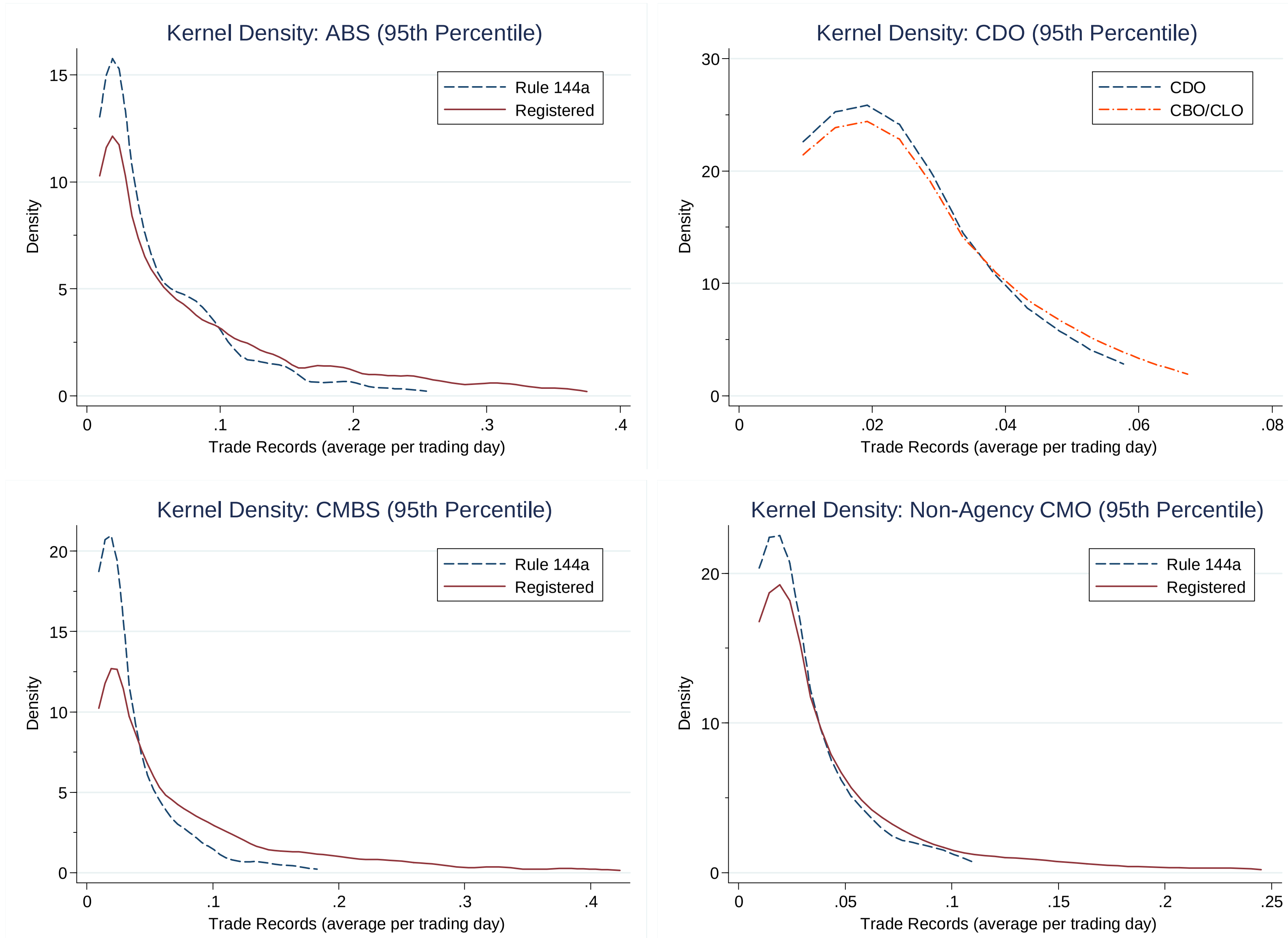
$$Spread = 100 \times \frac{P_{ask} - P_{bid} + c \times T/360}{(P_{ask} + P_{bid} + c \times T/360)/2}. \tag{39}$$

We performed both the direct spread computation and the simplified computation and did not find significant difference in terms of spread distributions. This can be explained by the fair-pricing condition outlined being a relatively good approximation for those matches that involve factor payments in between the two settlement dates. All results that follow correspond to the simplified approach.

The obtained spread observations contain outliers. In order to address this issue we winsorize 1% off each tail of the distribution of total client spreads within each subtype of instrument based on its overall type (ABS, CDOs, CMBS, non-agency CMO) and collateral sub-type, its placement type – Registered or Rule 144a, and its investment rating. The distribution characteristics of resulting total client bid-ask spreads are presented in Table 6a for the overall sample from May 16, 2011 to February 29, 2012. We compare non-retail client spread distributions for pre-release and post-release samples and present results in Table 6b.

In our analysis we use information on trade sizes measured in dollars of original par underlying pairs of trades we use to construct each spread observation. We use three buckets for trade sizes: Retail trades (R), amounting to less than \$100,000 original par, medium trades (M) between \$100,000 and \$1,000,000 original par, and institutional trades (I) amounting to more than \$1,000,000 original par. Tables 2b and 3b report proportions of trade reports falling within each bucket. In our analysis we focus on non-retail chains when both original buy from customer and sell to customer volumes were greater than \$100,000 original par (when a chain of transactions involves a split, we take into consideration the volume.

Figure 1: Distribution of Number of Trading Records per Day

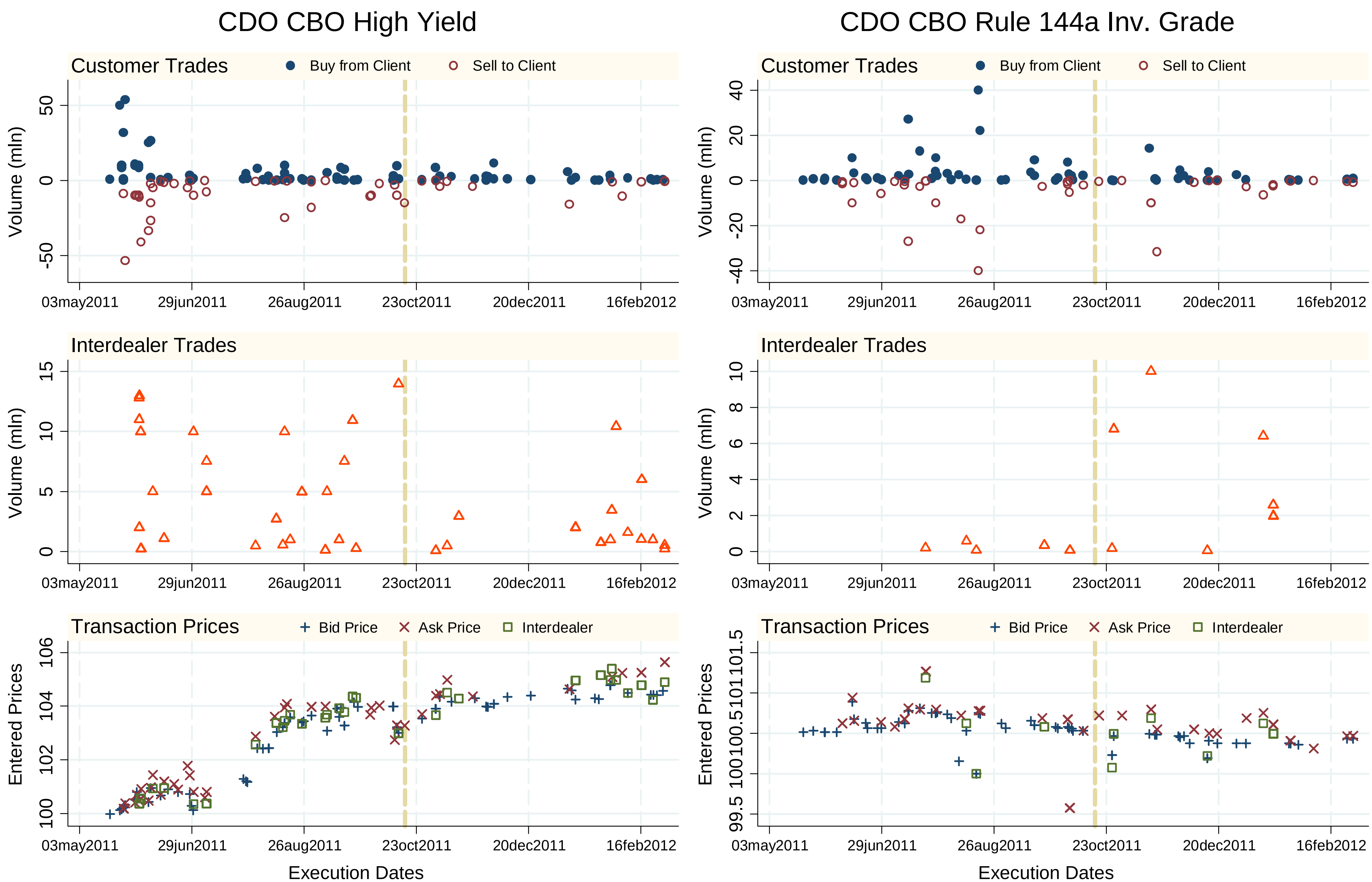


Legend: Number of trade records includes both trades with customers and interdealer trades after appropriate records cleaning (discussed in the Data section). The graphs show estimated distributions of the lower 95th percentile within each group of instruments. The distribution is estimated using epanechnikov kernel density with 1/100 bandwidth. The sample period is from May 16, 2011 to February 29, 2012.

Figure 2a: Trading Patterns of Frequently Traded ABS Instruments

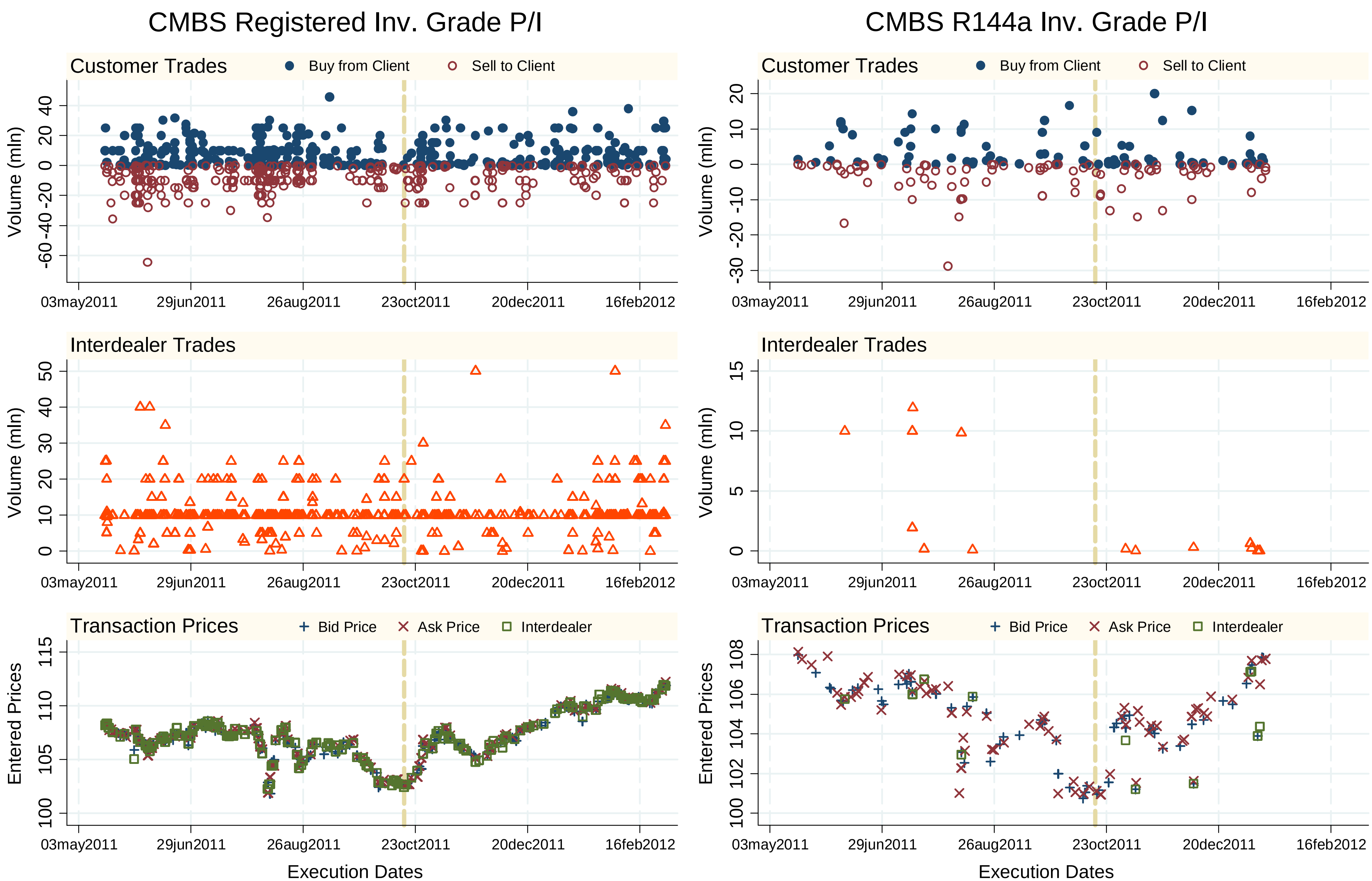
Legend: Total number of reports includes both customer and interdealer trades. Buys from customers are shown as having positive volumes traded and sells to customers are shown as having negative volume. Bold vertical line corresponds to the Index release date (October 17, 2011).

Figure 2b: Trading Patterns of Frequently Traded CDOs Instruments



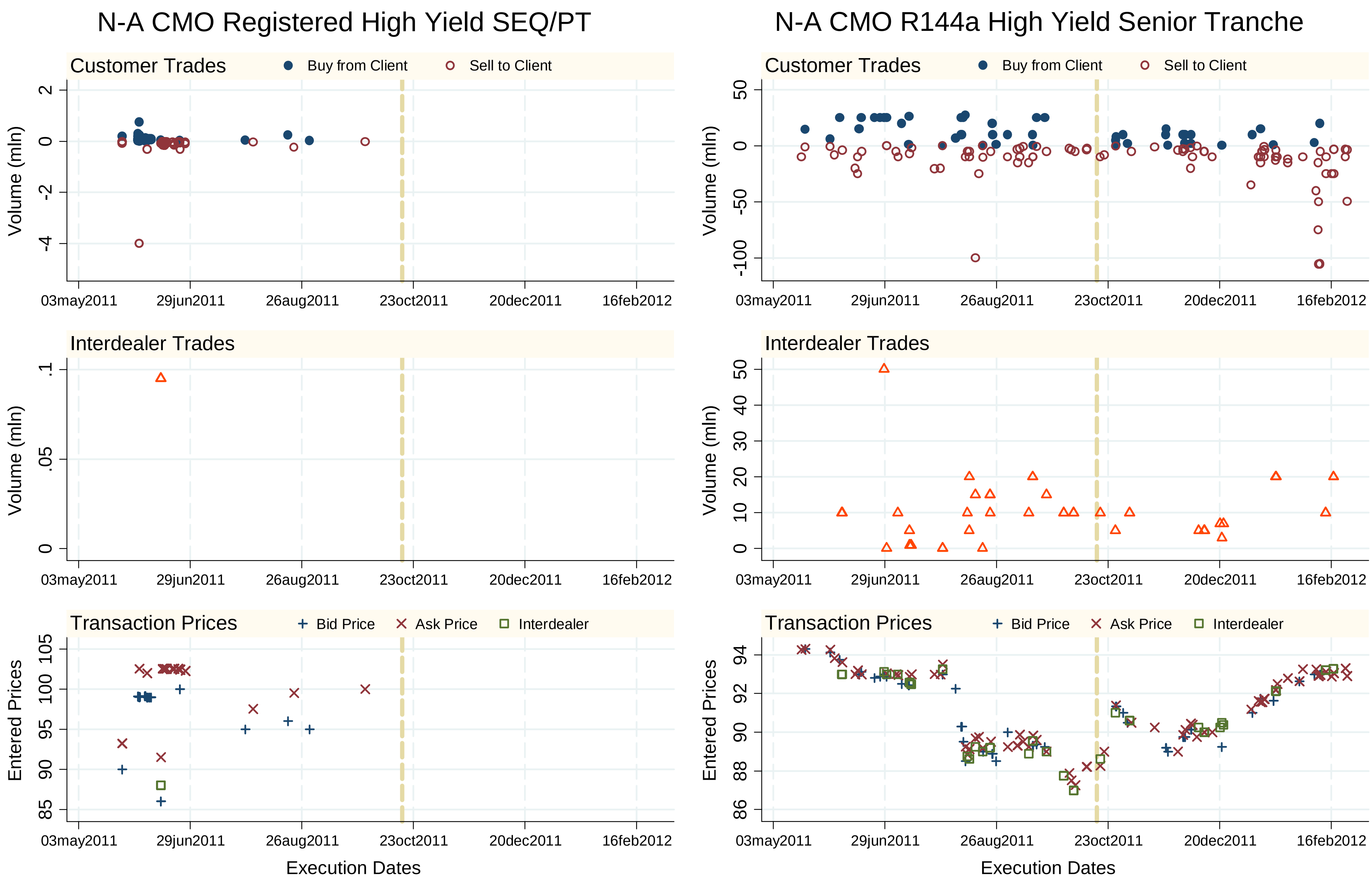
Legend: Total number of reports includes both customer and interdealer trades. Buys from customers are shown as having positive volumes traded and sells to customers are shown as having negative volume. Gray vertical line corresponds to the Index release date (October 17, 2011).

Figure 2c: Trading Patterns of Frequently Traded CMBS Instruments



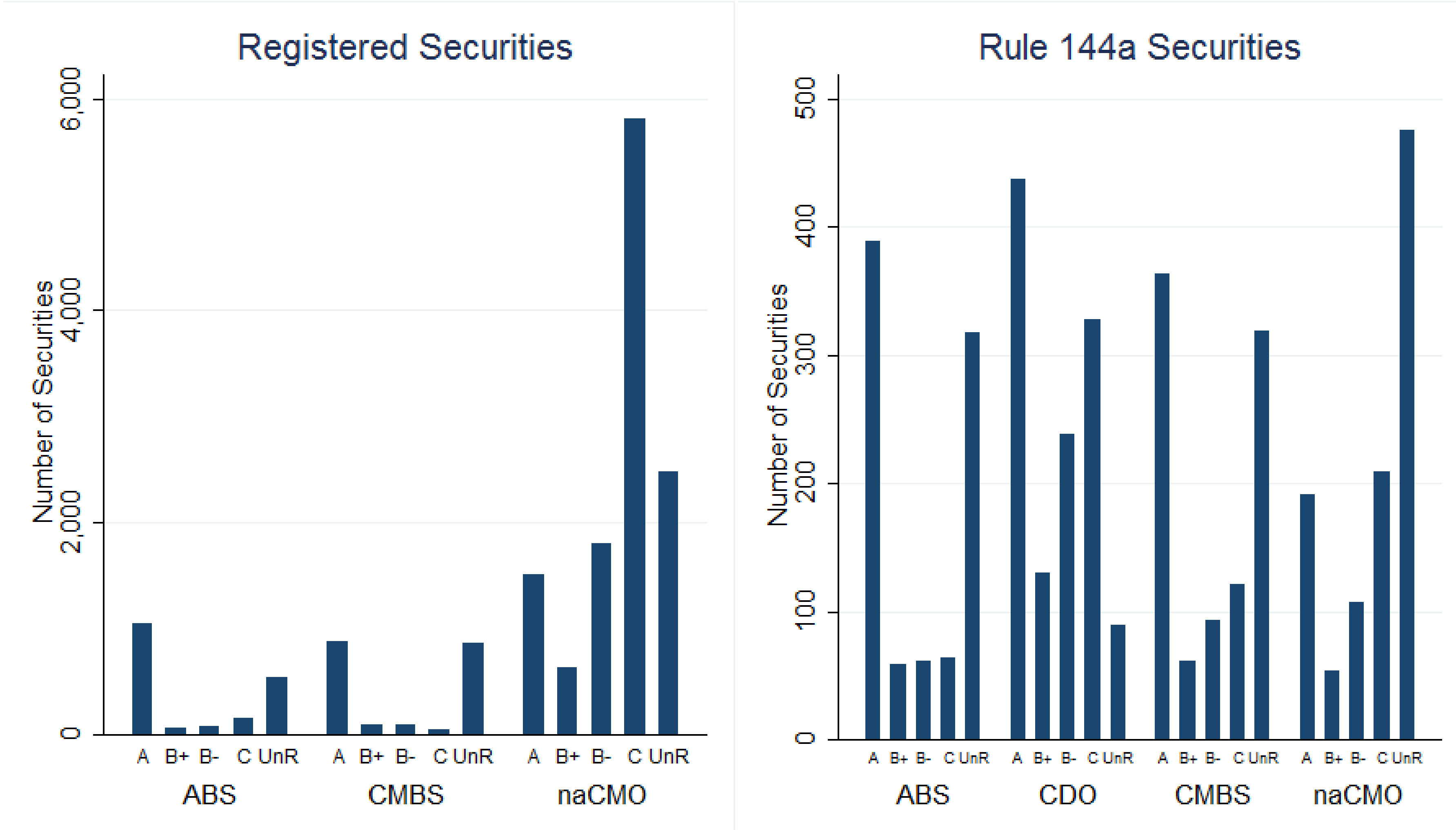
Legend: Total number of reports includes both customer and interdealer trades. Buys from customers are shown as having positive volumes traded and sells to customers are shown as having negative volume. Bold vertical line corresponds to the Index release date (October 17, 2011).

Figure 2d: Trading Patterns of Frequently Traded Non-Agency CMO Instruments



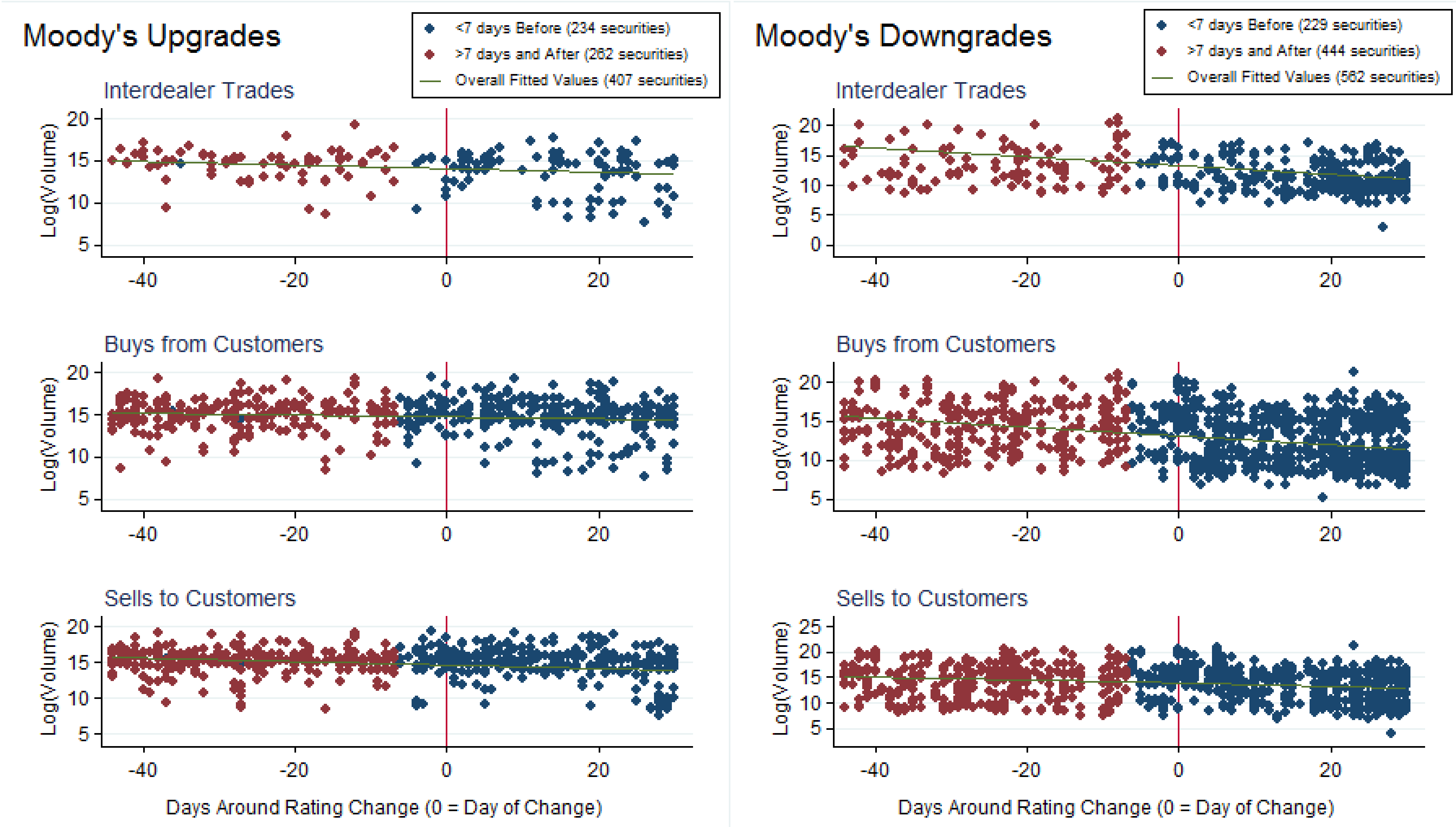
Legend: Total number of reports includes both customer and interdealer trades. Buys from customers are shown as having positive volumes traded and sells to customers are shown as having negative volume. Bold vertical line corresponds to the Index release date (October 17, 2011).

Figure 3: Distribution of Moody's Ratings in the Sample



Legend: The bars show the distribution of the first Moody's rating effective in the sample period from May 16, 2011 to February 29, 2012. A category includes Aaa, Aa1, Aa2, Aa3, A1, A2, A3. B+ category includes Baa1, Baa2, and Baa3. B- category includes Ba1, Ba2, Ba3, B1, B2, B3. C category includes Caa1, Caa2, Caa3, Ca, C. "UnR" category includes instruments rated NR, instruments for which rating is withdrawn, or instruments not found on Moody's website.

Figure 4: Trading Activity around Rating Change Dates

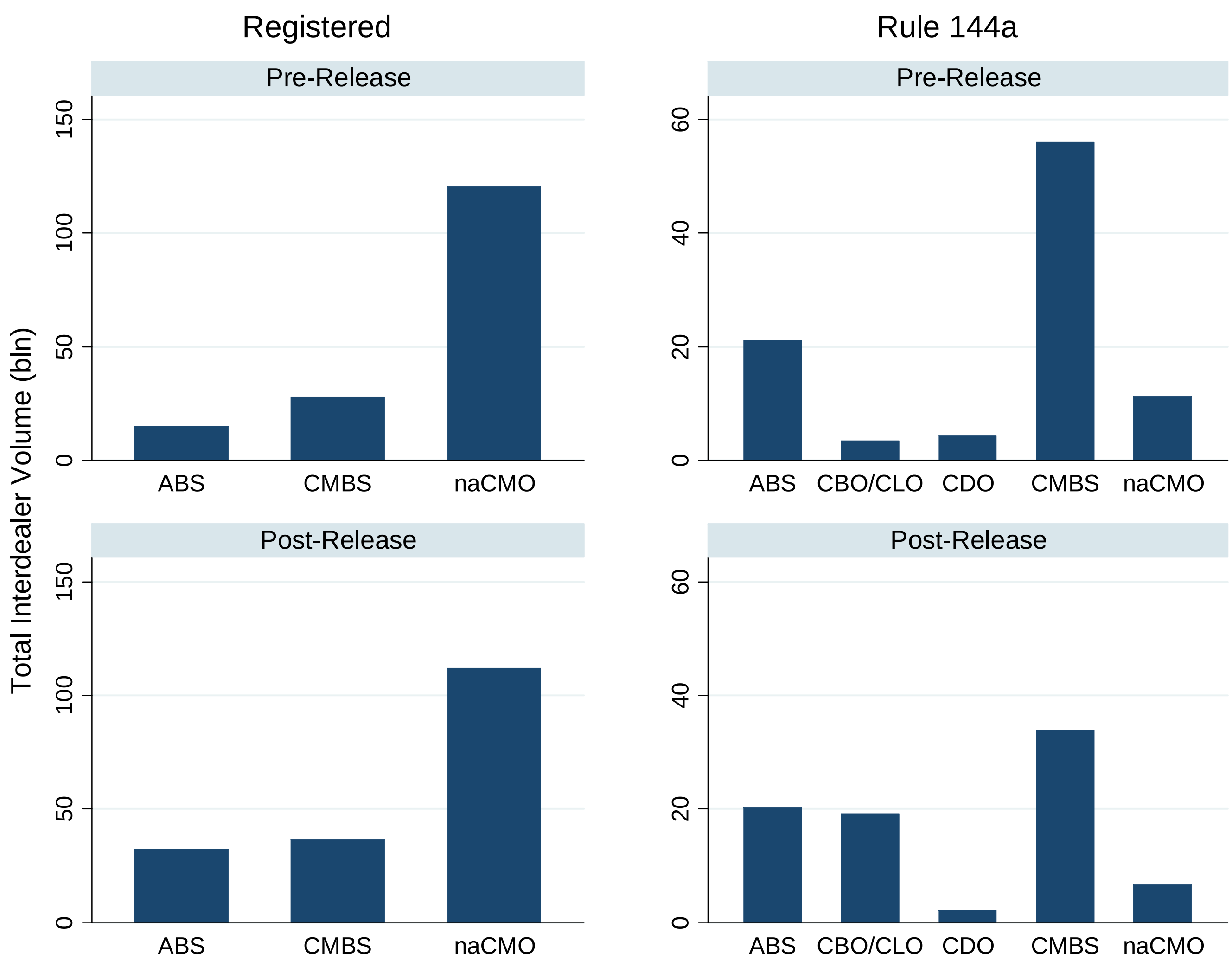


<u>Legend:</u> We look at instruments that had a Moody's upgrade and/or downgrade. For each such security we look at transactions that were executed 45 days before rating change and/or 31 days after. 7 days before rating change onward transactions are marked as "affected", they are shown as blue dots on the right part of each graph. All prior transactions are market as "before activity" (for a period of equal comparable length of 38 days, red dots). The line fits pooled sample of "before" and "after" transactions along time. An upward sloping line means volume tends to increase after the event. A downward-sloping line means volume tends to decrease.

Figure 5: Scatter Plots of Total Client Bid-Ask Spreads (Non-Retail Matches)

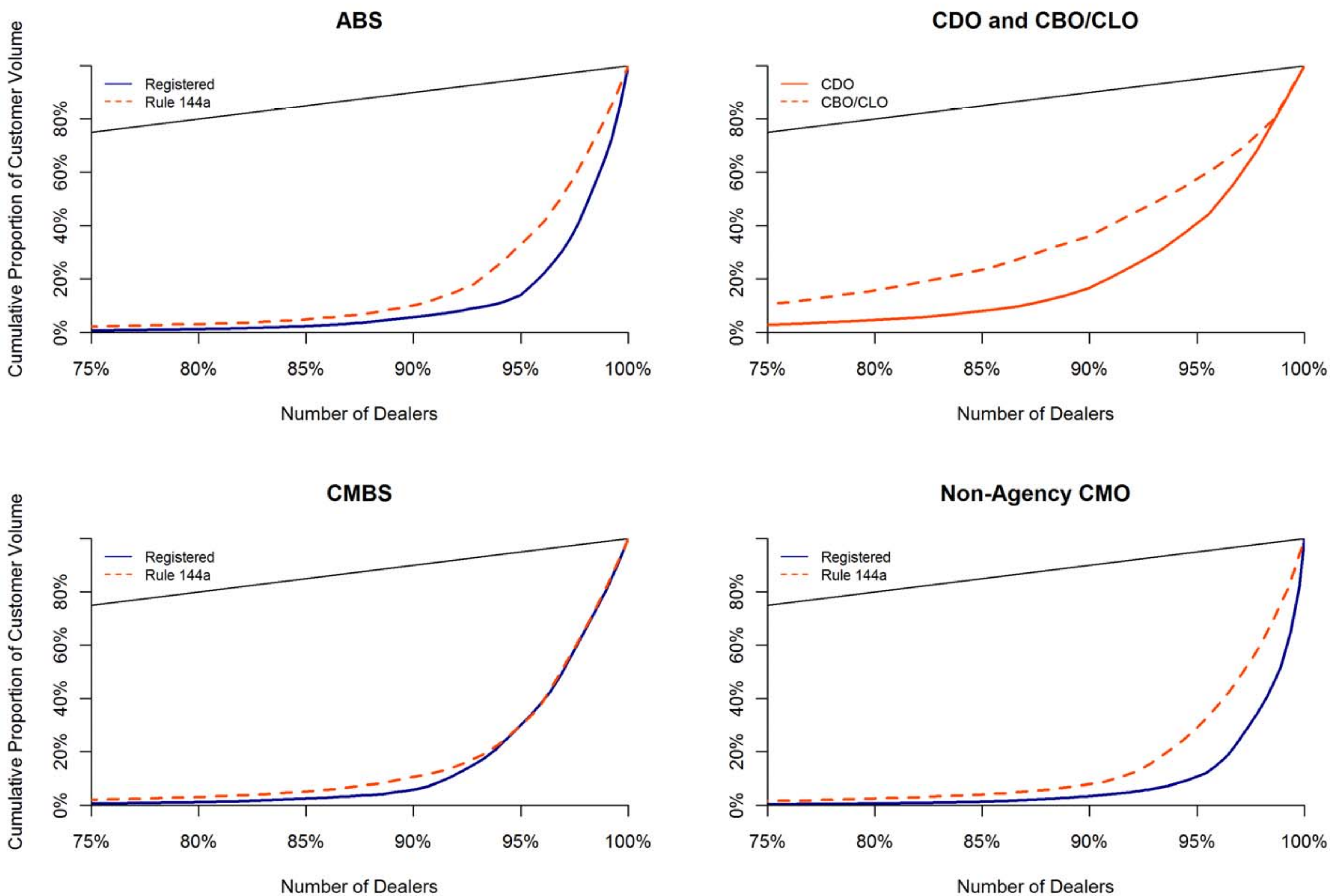
Legend: Larger size spreads are total client bid-ask spreads resulting from a chain with both buy from customer and sell to customer having volume greater than $100,000 of original balance.

Figure 6: Total Volume of Interdealer Trades by Security Types



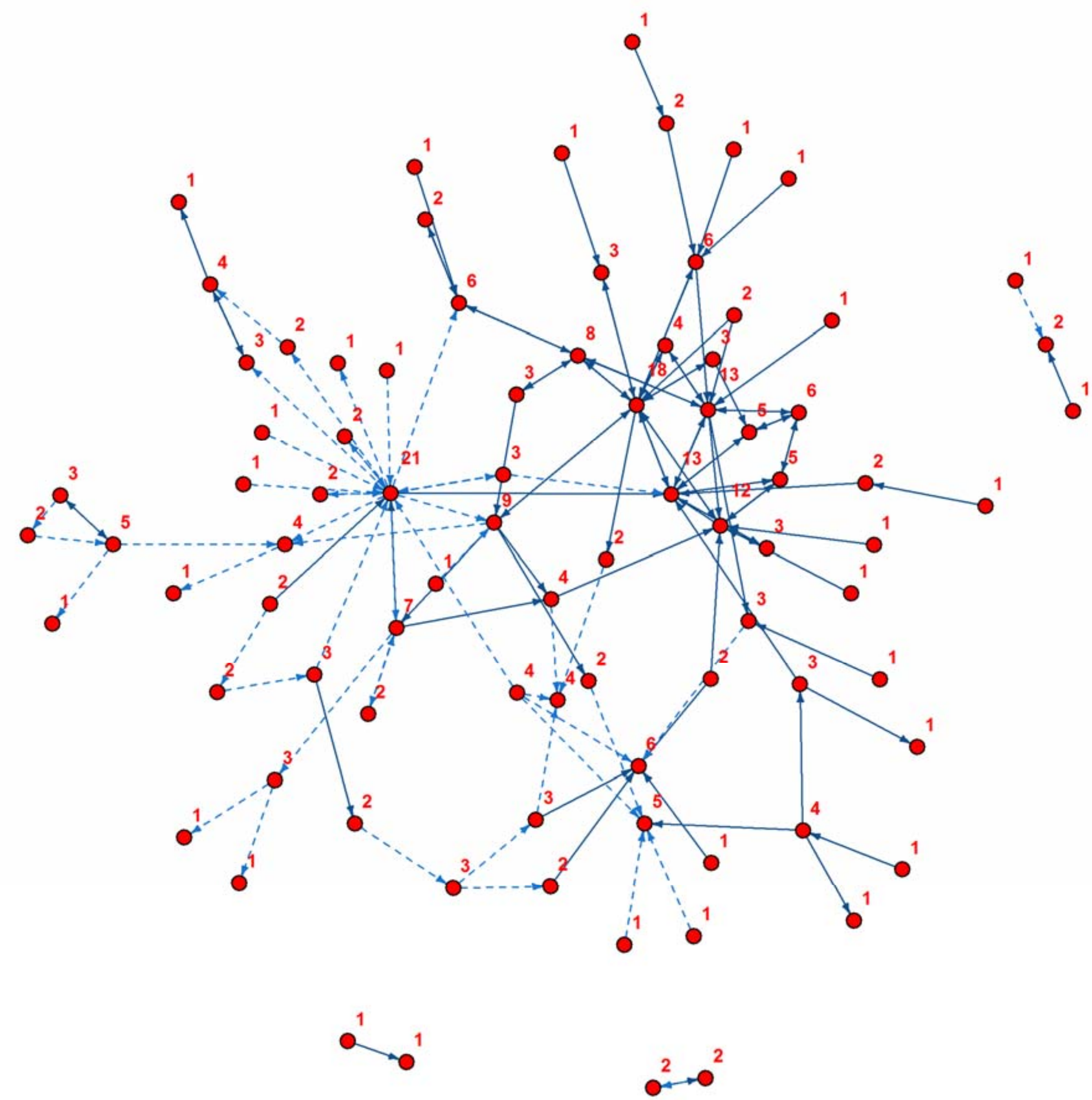
Legend: The total volume transacted on interdealer market by 580 active dealers in the pre-release subsample, 542 active dealers in the post-release subsample (441 dealers participated in both subsamples) shown by product types and type of security placement (Registered and Rule 144a). The Pre-Release Sample is from May 16, 2011 to October 17, 2011, and the Post-Release Sample is from October 18, 2011 to February 29, 2012.

Figure 7: Dealers' Shares in Original Balance with Customers (Lorenz Curves by Market)



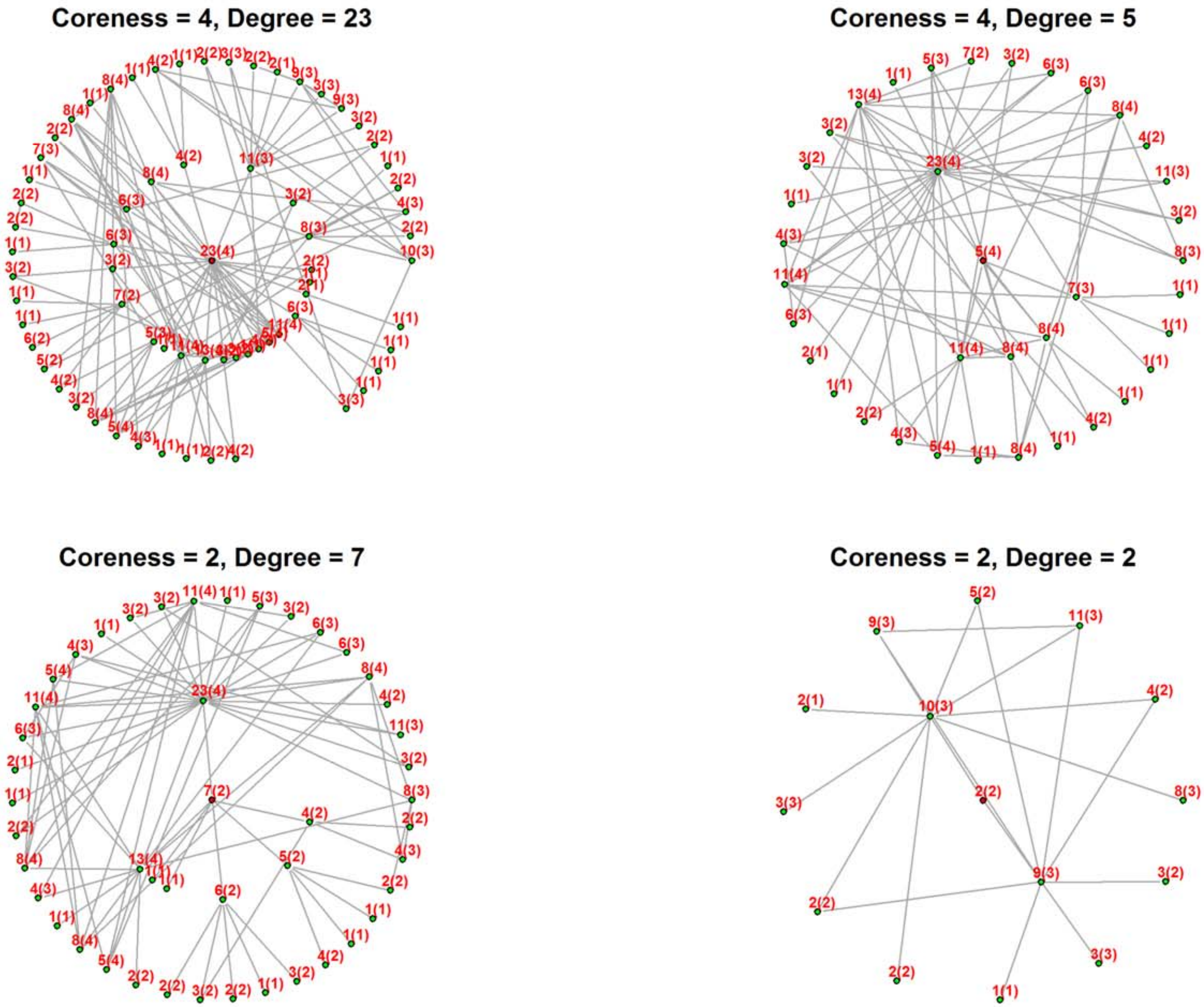
Legend: The 25% of dealers with largest volumes of original balance traded with customers are shown for each market. Numbers of Dealers in brackets correspond to dash Lorenz curves. All customer trades in instruments with at least two opposite trades at most two weeks apart in the sample period from October 17, 2011 to February 29, 2012 are used to construct Lorenz curves.

Figure 8: The Most Active Links of the Interdealer Network



Legend: Each node represents a dealer; each arrow represents the direction of order flow from one dealer to the other. Dealers are labeled by the number of trading partners (both buy and sell directed orders) in the sample from May 16, 2011 to February 29, 2012. Only trading relationships (links) with at least 50 trade reports and at least $10 million of original balance transacted are shown in the graph; links with more than $100 million transacted are shown as solid lines.

Figure 9: Examples of Dealers Coreness and Degree Centrality

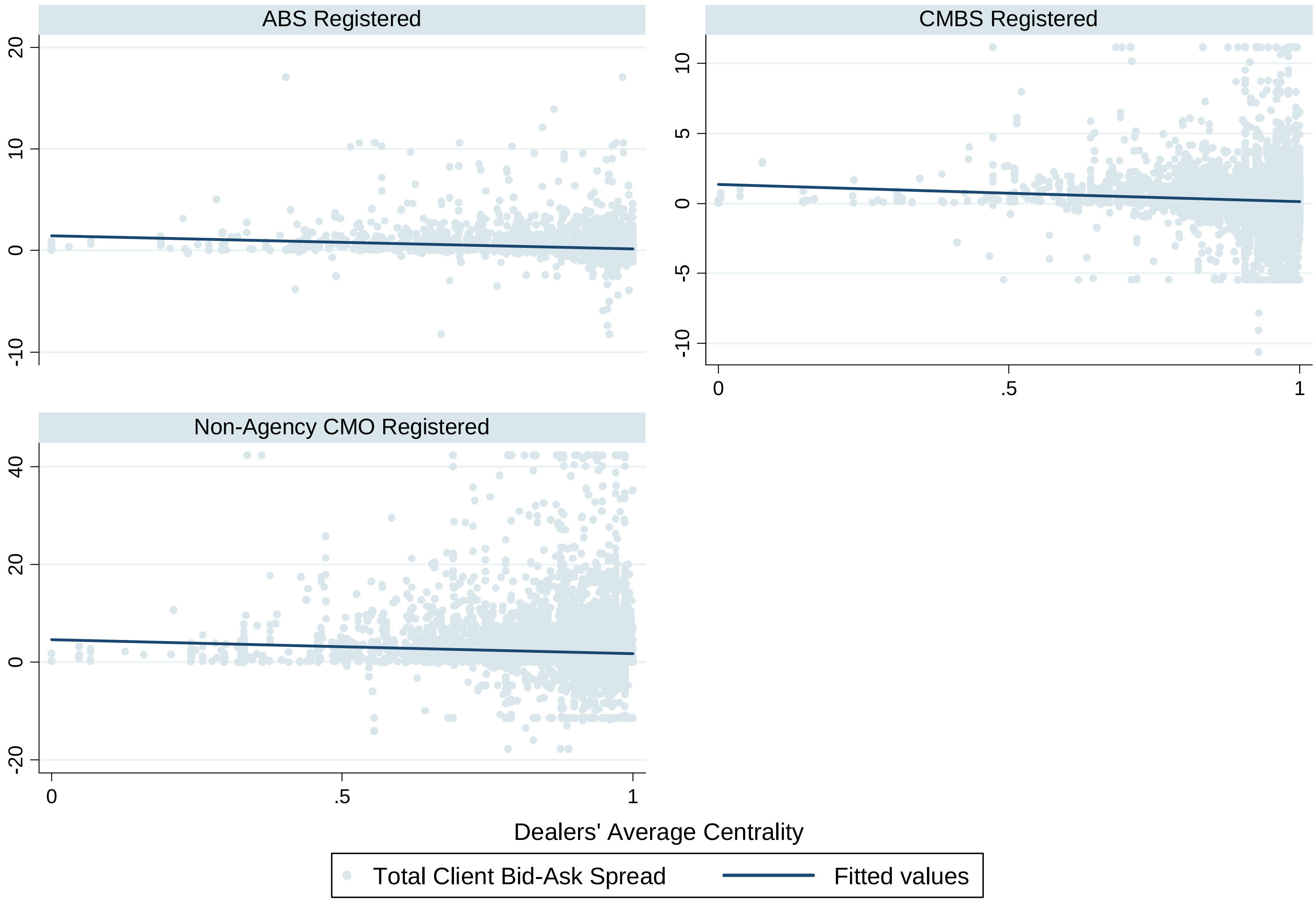


Legend: Degree centrality (undirected) shown for each dealer and coreness shown in brackets. The local neighborhoods up to the second degree (neighbors of neighbors) are presented for 4 combinations of degree and coreness of dealer in the middle (root). These neighborhoods correspond to the graph of interdealer market in Figure 6 with restriction on the volume of original balance transacted removed (each link restricted only to at least 50 transactions).

Figure 10: Weekly Moving Averages of Total Client Bid-Ask Spreads (Non-Retail Matches)

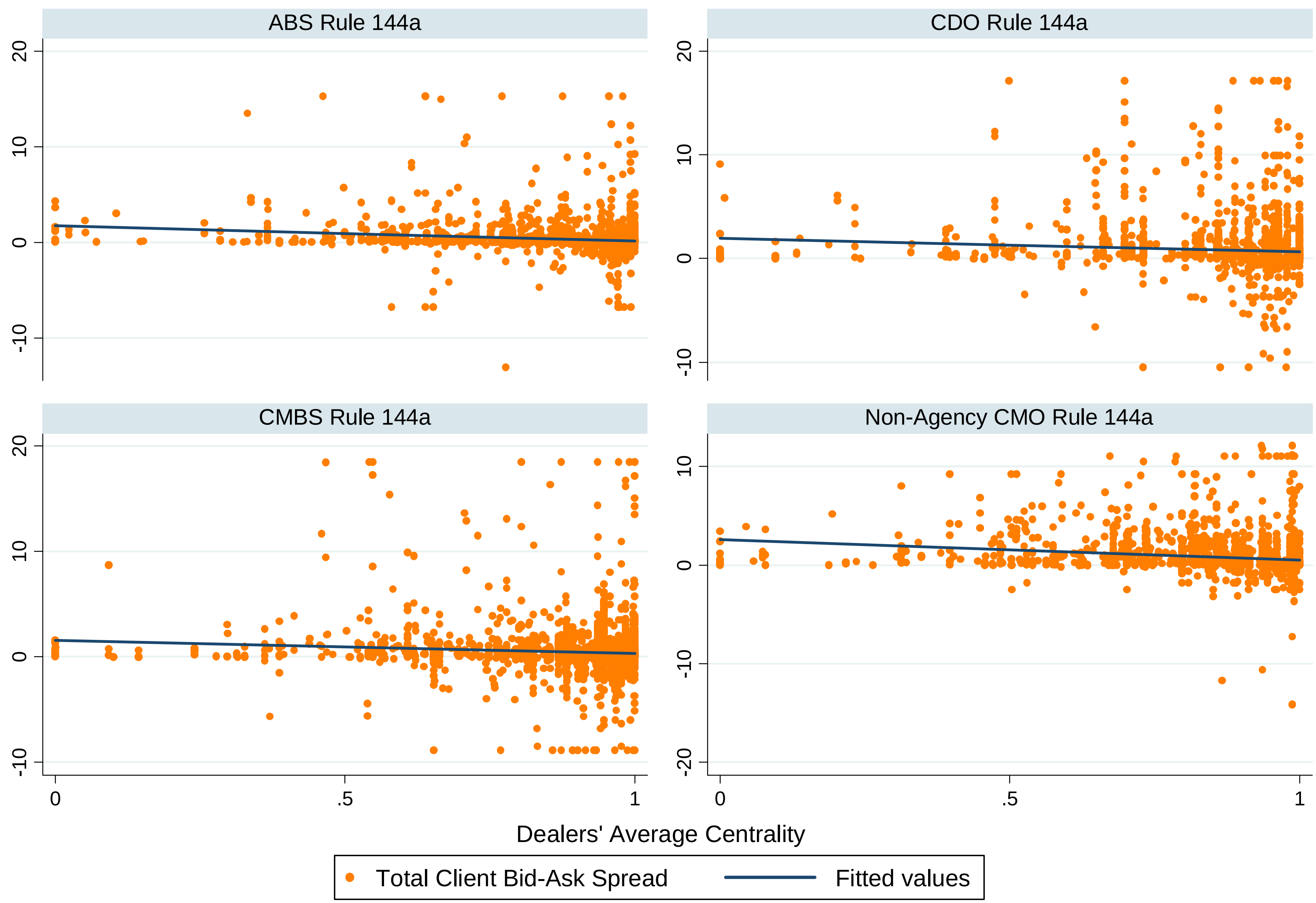
Legend: The daily moving-average client bid-ask spreads are presented with a rolling window of 7 trading days (includes 3 days forward and 3 days backward). Larger size spreads are total client bid-ask spreads resulting from a chain with both buy from customer and sell to customer having volume greater than $100,000 of original balance.

Figure 11a: Total Client Non-Retail Bid-Ask Spreads and Dealers' Centrality (Registered)



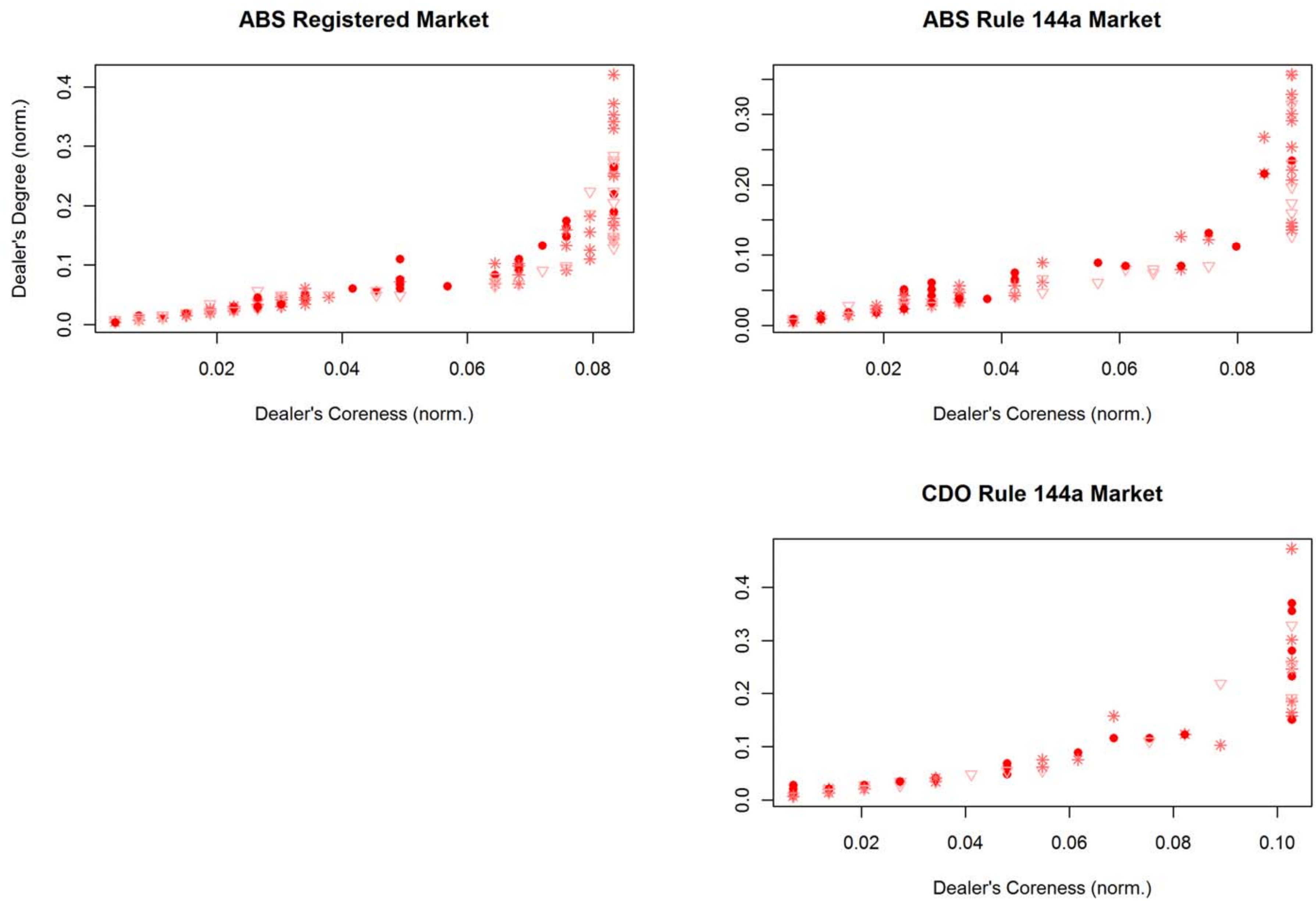
Legend: Average Dealers Centrality is the average betweenness centrality measure of all dealers that intermediated within a particular chain underlying a spread observation. Larger size spreads are total client bid-ask spreads resulting from a chain with both buy from customer and sell to customer having volume greater than $100,000 of original balance. Spreads are adjusted for coupon and factor payments.

Figure 11b: Total Client Non-Retail Bid-Ask Spreads and Dealers' Centrality (Rule 144a)



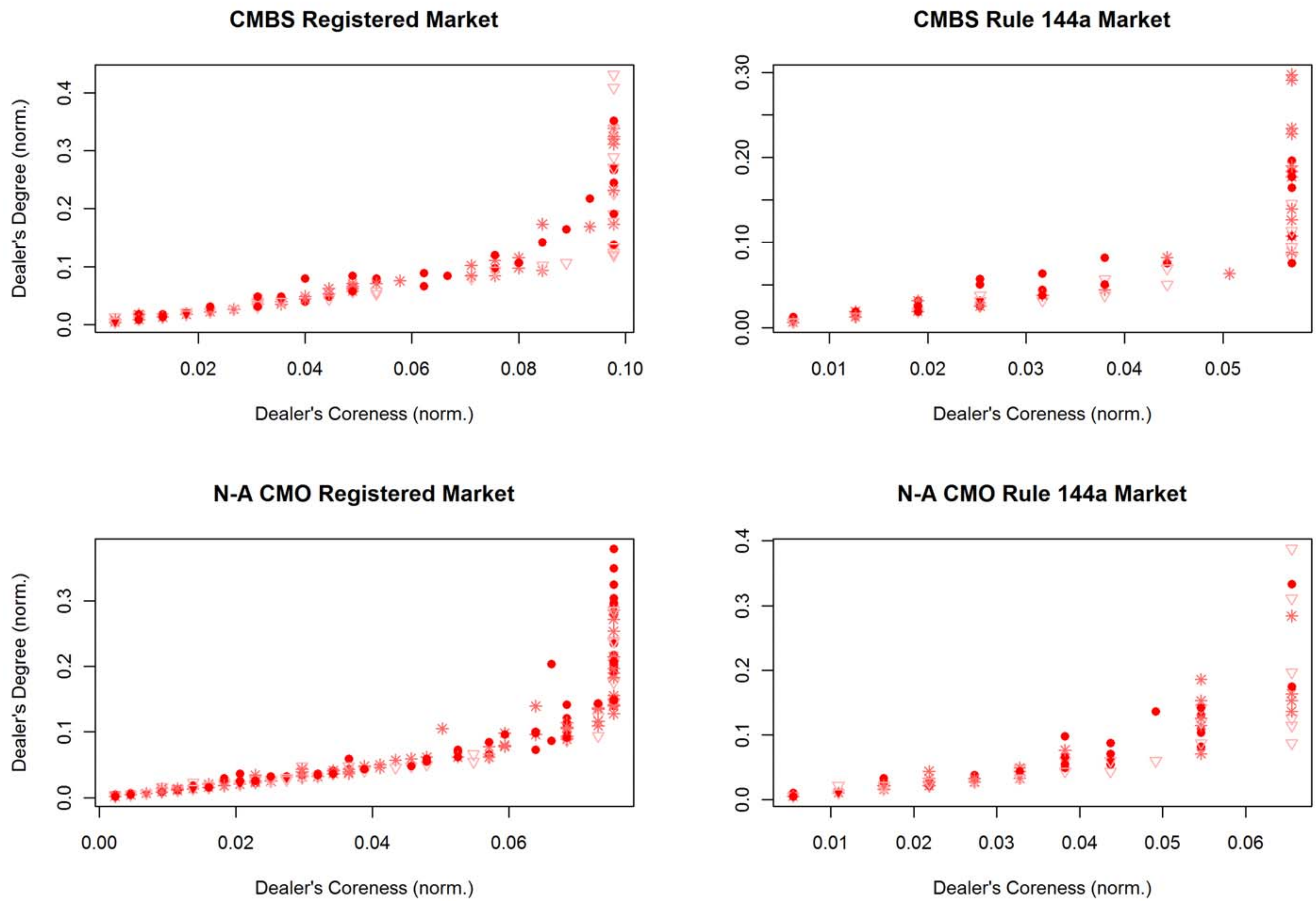
Legend: Average Dealers Centrality is the average betweenness centrality measure of all dealers that intermediated within a particular chain underlying a spread observation. Since most of transaction chains in Rule 144a issues have volume larger than $100,000 of original balance, we do not differentiate trades by size on this graph. Spreads are adjusted for coupon and factor payments.

Figure 12a: Non-Retail Dealer Bid-Ask Spreads and Dealers' Degree-Coreness



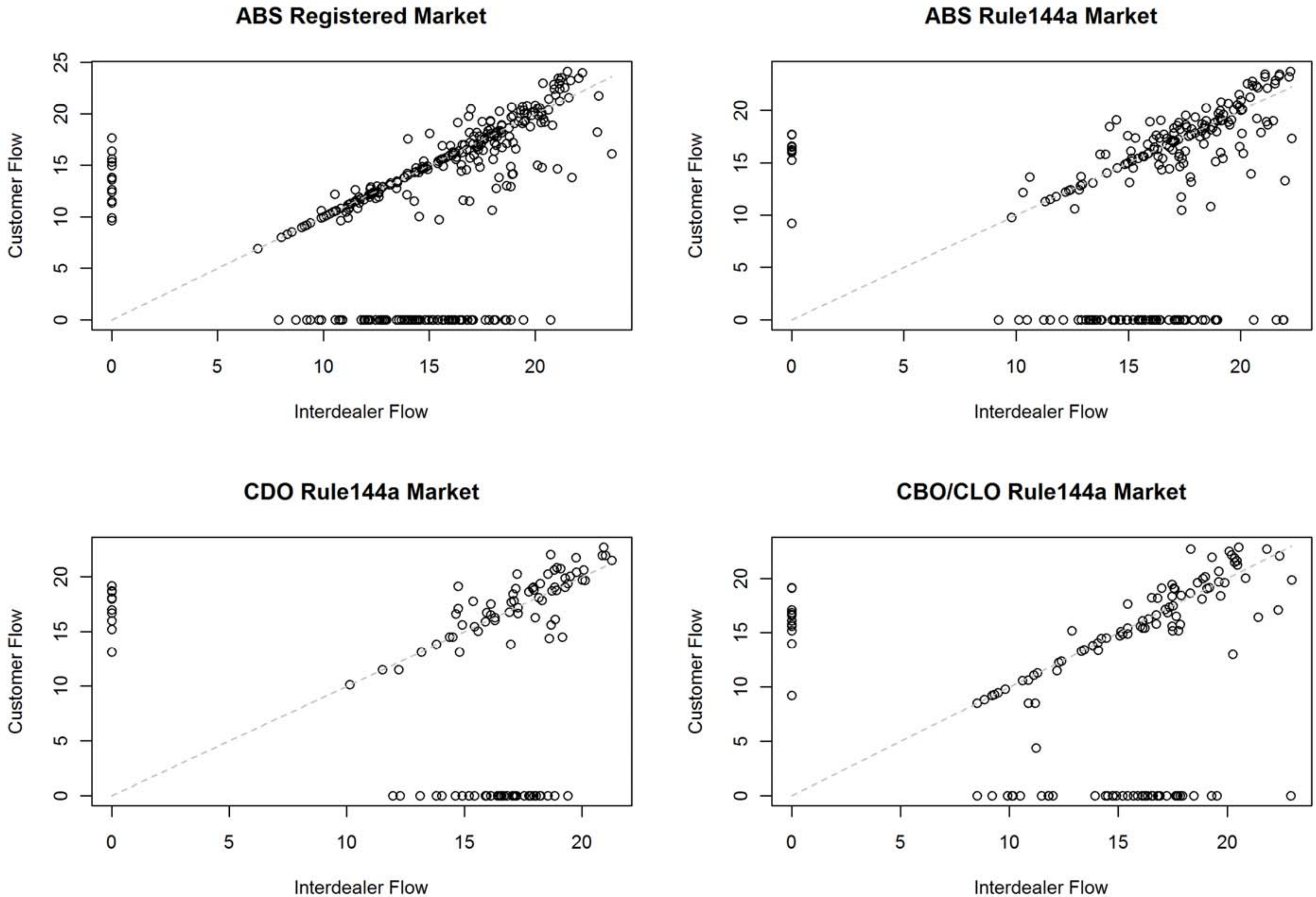
<u>Legend:</u> Each dot is a dealer with particular degree centrality and coreness in a given class of instruments. Three shades of each dot correspond to the level of average bid-ask spread charged by dealer (lighter shade means lower average bid-ask spread). Degree centrality is the number of trading partners of a dealer in the sample. Dealer's coreness is the number of trading partners in the k-core sub-network that includes that dealer (k-core is the largest sub-network where all dealers have at least k number of trading partners). Higher dealer's degree relative to his coreness means higher importance of this dealer as an intermediary between different groups of other dealers.

Figure 12b: Non-Retail Dealer Bid-Ask Spreads and Dealers' Degree-Coreness



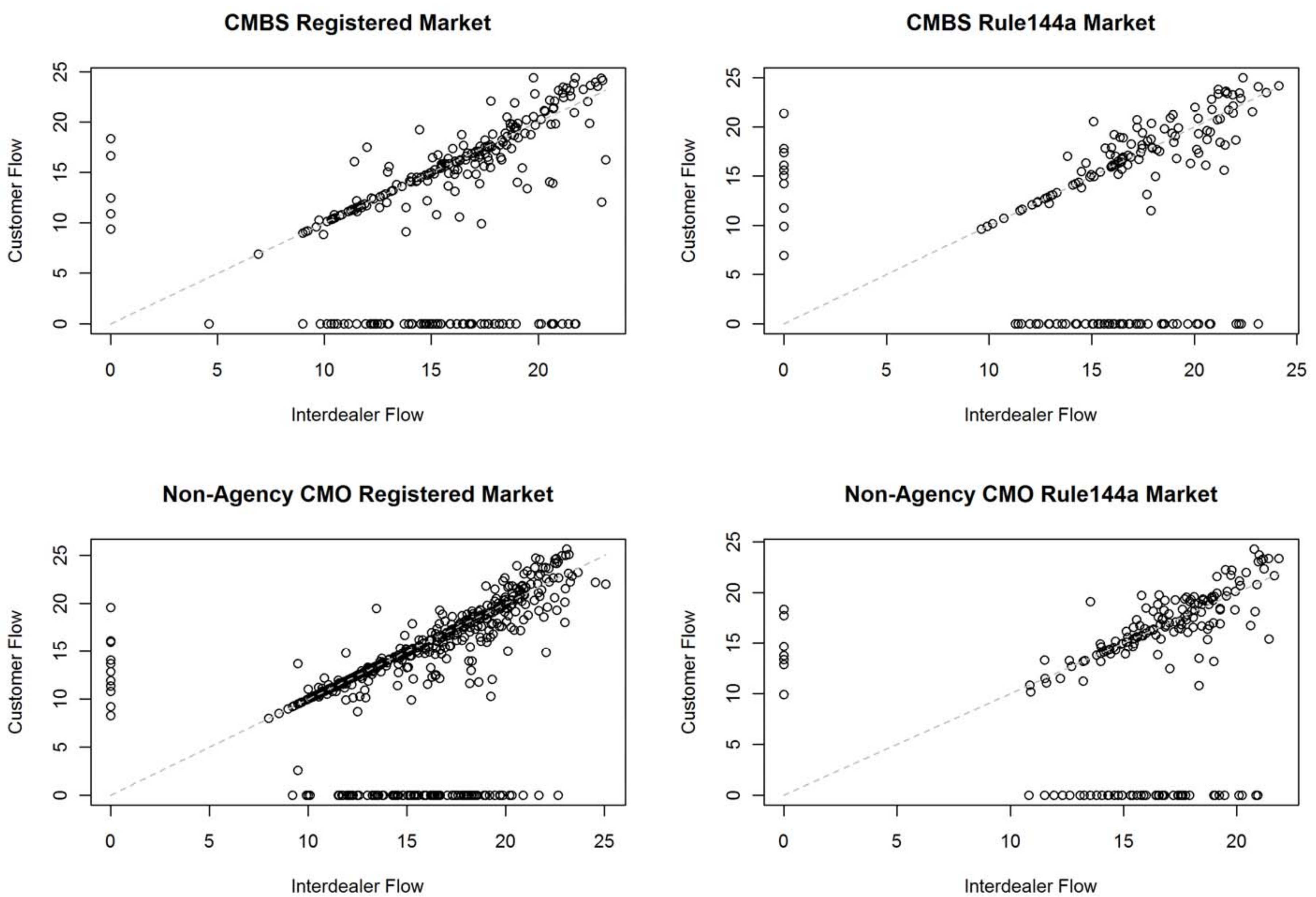
Legend: Each dot is a dealer with particular degree centrality and coreness in a given class of instruments. Three shades of each dot correspond to the level of average bid-ask spread charged by dealer (lighter shade means lower average bid-ask spread). Degree centrality is the number of trading partners of a dealer in the sample. Dealer's coreness is the number of trading partners in the k-core sub-network that includes that dealer (k-core is the largest sub-network where all dealers have at least k number of trading partners). Higher dealer's degree relative to his coreness means higher importance of this dealer as an intermediary between different groups of other dealers.

Figure 13a: Dealers' Customer and Interdealer Flows for ABS and CDO Instruments



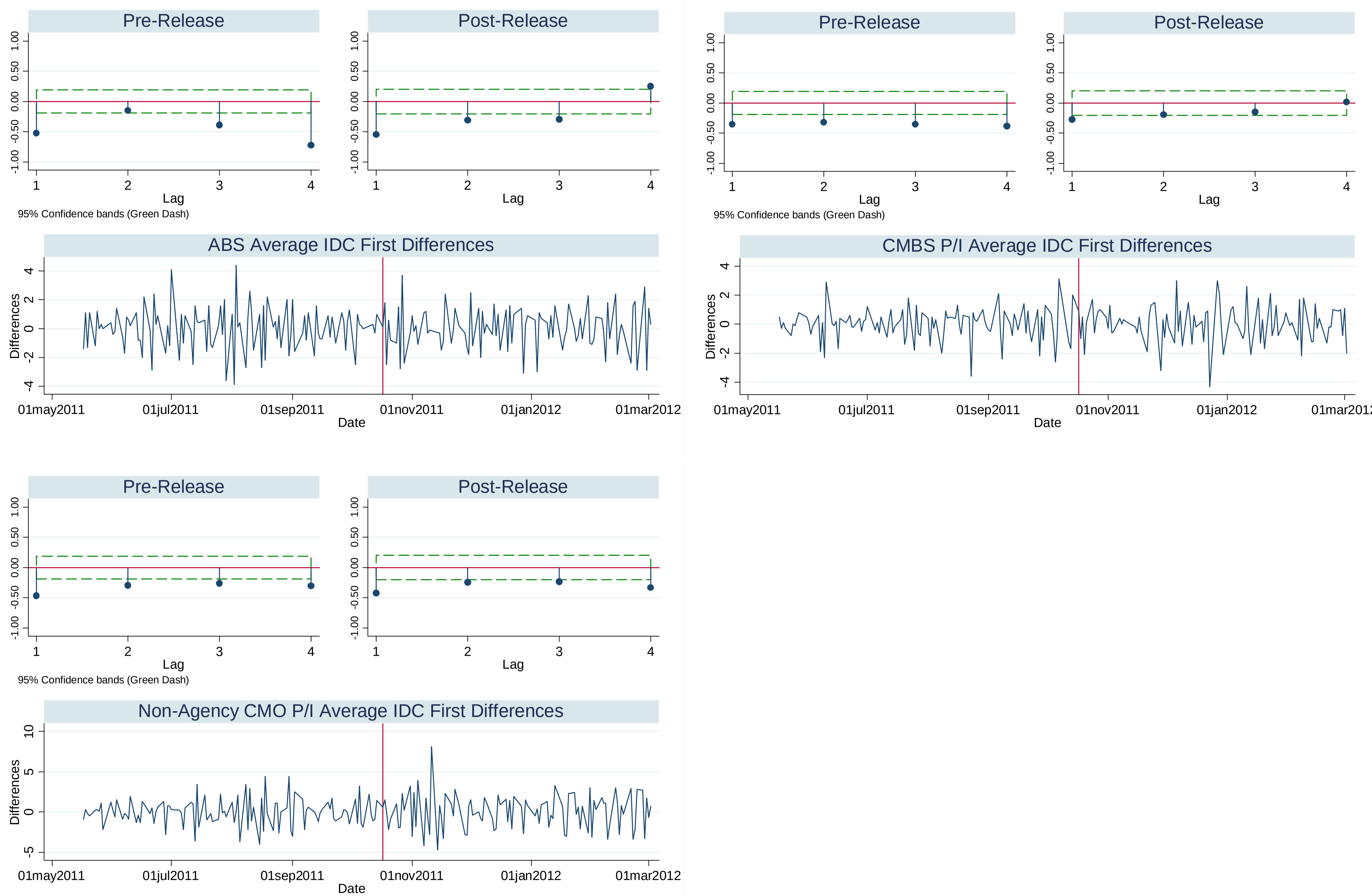
Legend: Each dot is a dealer; the coordinates are log of total order flow over the sample period from May 16, 2011 to February 2012. Interdealer order flows are shown against order flows with customers for each dealer by category and instrument placement type.

Figure 13b: Dealers' Customer and Interdealer Flows for CMBS and Non-Agency CMOs



Legend: Each dot is a dealer; the coordinates are log of total order flow over the sample period from May 16, 2011 to February 2012. Interdealer order flows are shown against order flows with customers for each dealer by category and instrument placement type.

Figure 14: Partial Autocorrelations of IDC Average Indexes



Legend: IDC Index is from the Structured Products Tables provided by FINRA and IDC publicly. The Average version of the index stands for the average (arithmetic mean) price of transactions for a particular group of instruments. The Figure presents partial autocorrelations of first differences of the index with 4 lags included in the estimation, together with the time-series plot of the index first differences.

Table 1: The Number of Instruments Traded

Category:	ABS Overall	Auto	Card	ManH	SBA	Stud	Other	CDOs Overall	CBO	CLO	CDO
Population	12,661	1,193	410	661	350	1,223	8,824	7,543	392	2,993	4,158
Registered	4,567	750	356	616	329	957	1,559	55	44	3	8
Rule 144a	8,094	443	54	45	21	266	7,265	7,488	348	2,990	4,150
Traded Pre-Release	1,994	485	227	152	172	304	654	731	53	398	280
Registered	1,425	361	211	147	169	237	300	23	22	---	1
Rule 144a	569	124	16	5	3	67	354	708	31	398	279
Traded Post-Release	1,989	513	196	113	198	290	679	718	46	474	198
Registered	1,359	371	183	109	188	224	284	24	22	---	2
Rule 144a	630	142	13	4	10	66	395	694	24	474	196
Traded Overall	2,807	645	261	213	237	417	1,034	1,251	71	749	431
Registered	1,905	466	243	206	227	328	435	29	26	---	3
Rule 144a	902	179	18	7	10	89	599	1,222	45	749	428

Category:	CMBS Overall	IO/PO	Other	Non-agency CMO Overall	IO/PO	PAC/TN	SEQ/PT	SUP/Z	Other Senior	Other
Population	13,720	1,421	12,299	78,350	8,798	4,520	29,366	1,456	15,998	18,212
Registered	5,765	628	5,137	61,687	7,906	4,487	24,505	1,280	13,432	10,077
Rule 144a	7,955	793	7,162	16,663	892	33	4,861	176	2,566	8,135
Traded Pre-Release	2,096	136	1,960	8,819	159	559	4,662	225	2,603	611
Registered	1,488	54	1,434	8,203	144	555	4,393	221	2,505	385
Rule 144a	608	82	526	616	15	4	269	4	98	226
Traded Post-Release	2,086	148	1,938	8,461	187	486	4,396	211	2,506	675
Registered	1,489	49	1,440	7,815	176	481	4,158	210	2,398	392
Rule 144a	597	99	498	646	11	5	238	1	108	283
Traded Overall	2,967	249	2,718	13,396	326	839	7,129	300	3,687	1,115
Registered	1,997	94	1,903	12,355	304	832	6,712	295	3,534	678
Rule 144a	970	155	815	1,041	22	7	417	5	153	437

Legend: The population of instruments is all issues in the FINRA database up to February 29, 2012. We define traded instruments as having at least two opposite trades with customers at most two weeks apart over the relevant sample period. The pre-release sample period is from May 16, 2011 to October 17, 2011, the post-release sample period is from October 18, 2011 to February 29, 2012, and the overall sample period is from May 16, 2011 to February 29, 2012.

Table 2a: ABS and CDOs Security Characteristics

Category:	ABS Overall	Auto	Card	ManH	SBA	Stud	Other	CDOs Overall	CBO	CLO	CDO
Traded Instruments	2,807	645	261	213	237	417	1,034	1,222	45	749	428
Registered	1,905	466	243	206	227	328	435	---	---	---	---
Inv. Grade	1,231	330	213	66	227	301	94	---	---	---	---
% floaters:	42%	11%	78%	11%	0%	100%	1%	---	---	---	---
High Yield	674	136	30	140	---	27	341	---	---	---	---
% floaters:	56%	5%	67%	9%	---	96%	92%	---	---	---	---
Rule 144a	902	179	18	7	10	89	599	1,222	45	749	428
Inv. Grade	291	115	12	4	10	78	72	655	21	529	105
% floaters:	46%	21%	75%	25%	10%	99%	29%	98%	76%	99%	95%
High Yield	611	64	6	3	---	11	527	567	24	220	323
% floaters:	82%	6%	50%	33%	---	100%	91%	95%	83%	98%	93%
Avg. Maturity	Jan-23	Feb-15	Jun-16	Feb-28	Apr-22	Dec-28	Apr-26	Oct-25	Jan-30	Jun-19	Jun-36
Registered	Aug-21	Dec-14	Jun-16	Dec-27	Apr-22	Feb-28	Apr-23	---	---	---	---
Rule 144a	Dec-25	Jul-15	Jan-17	Mar-31	Mar-22	Feb-32	Jun-28	Oct-25	Jan-30	Jun-19	Jun-36
Vintage% <4;4-6;>6	38/14/48	93/6/1	35/38/27	1/4/95	32/16/52	22/27/51	20/8/72	9/54/37	16/22/62	9/61/30	6/47/47
Registered	38/16/46	92/7/1	34/38/28	0/3/97	32/17/51	22/29/49	18/7/75	---	---	---	---
Inv. Grade	43/22/35	90/10/0	31/39/30	0/2/98	32/17/51	18/31/51	44/21/35	---	---	---	---
High Yield	30/5/65	96/2/2	53/30/17	0/4/96	---	66/12/22	11/3/86	---	---	---	---
Rule 144a	38/10/52	96/4/0	56/40/4	43/14/43	30/0/70	24/20/56	22/9/69	9/54/37	16/22/62	9/61/30	6/47/47
Inv. Grade	56/15/29	95/4/1	42/52/6	25/25/50	30/0/70	18/20/62	43/24/33	6/53/41	24/19/57	7/59/34	1/27/72
High Yield	29/7/64	98/2/0	83/17/0	67/0/33	---	64/18/18	19/7/74	11/56/33	8/25/67	16/64/20	8/53/39
Avg. Coupon Rate	3.09	2.52	1.61	6.83	5.42	1.11	3.97	1.81	2.36	1.66	2.00
Registered	3.08	2.34	1.58	6.86	5.43	0.99	3.77	---	---	---	---
Rule 144a	3.11	2.98	1.99	5.82	5.28	1.53	4.14	1.81	2.36	1.66	2.00
Avg. Factor	54.67	77.60	97.68	49.91	45.48	78.10	23.15	87.76	74.03	90.50	84.40
Registered	61.11	77.20	97.90	49.68	45.89	78.42	23.64	---	---	---	---
Rule 144a	41.06	78.64	94.74	56.81	36.17	76.93	22.79	87.76	74.03	90.50	84.40

Legend: We define traded instruments as having at least two opposite trades with customers at most two weeks apart in the sample period. For each instrument we take average of each characteristic within each instrument group. Vintage percentages represent relative percentage of instruments with less than 4 years in between first Moody's rating date and the trade execution date, in between 4 and 6 years, and more than 6 years, respectively.

Table 2b: ABS and CDO Trading Characteristics

Category:	ABS							CDOs			
	Overall	Auto	Card	ManH	SBA	Stud	Other	Overall	CBO	CLO	CDO
Avg. Trades per Day	0.097	0.132	0.215	0.033	0.091	0.069	0.072	0.026	0.056	0.025	0.025
Registered	0.108	0.139	0.194	0.033	0.089	0.067	0.103	---	---	---	---
Inv. Grade	0.117	0.140	0.202	0.032	0.089	0.069	0.124	---	---	---	---
High Yield	0.092	0.137	0.136	0.033	---	0.047	0.098	---	---	---	---
Rule 144a	0.074	0.113	0.499	0.030	0.139	0.078	0.048	0.026	0.056	0.025	0.025
Inv. Grade	0.118	0.121	0.562	0.024	0.139	0.079	0.083	0.028	0.079	0.024	0.039
High Yield	0.053	0.099	0.375	0.037	---	0.074	0.044	0.024	0.035	0.027	0.021
# of Dealers	6.03	8.25	9.94	3.02	5.27	5.71	4.59	2.38	3.44	2.34	2.33
Registered	6.74	8.51	9.90	3.06	5.26	5.67	6.40	---	---	---	---
Rule 144a	4.54	7.56	10.56	1.86	5.40	5.84	3.28	2.38	3.44	2.34	2.33
% Interdealer Trades	13.20%	11.50%	13.81%	10.91%	18.91%	17.48%	11.53%	8.57%	7.38%	8.59%	8.66%
Registered	13.62%	10.02%	13.78%	11.21%	18.79%	16.96%	13.30%	---	---	---	---
Rule 144a	12.31%	15.36%	14.24%	2.12%	21.68%	19.40%	10.25%	8.57%	7.38%	8.59%	8.66%
Trade Sizes% R/M/I	14/29/57	11/35/54	12/27/61	32/26/42	4/32/64	9/27/64	21/24/55	2/8/90	20/17/63	0/6/94	1/10/89
Registered	17/31/52	14/37/49	14/30/56	33/25/42	5/34/61	10/25/65	32/26/42	---	---	---	---
Inv. Grade	13/33/54	13/38/49	14/30/56	21/42/37	5/34/61	10/25/65	28/34/38	---	---	---	---
High Yield	27/26/47	15/33/52	20/27/53	38/18/44	---	5/27/68	33/23/44	---	---	---	---
Rule 144a	3/24/73	2/31/67	0/13/87	0/35/65	1/10/89	7/34/59	3/20/77	2/8/90	20/17/63	0/6/94	1/10/89
Inv. Grade	3/27/70	2/31/67	0/14/86	0/40/60	1/10/89	7/36/57	5/26/69	1/8/91	5/26/69	0/5/95	1/10/89
High Yield	2/21/77	2/31/67	1/11/88	0/30/70	---	2/17/81	3/19/78	4/9/87	50//48	1/9/90	1/10/89

Legend: We define traded instruments as having at least two opposite trades with customers at most two weeks apart in the sample period. For each instrument we take average of each characteristic within each instrument group. Trade sizes percentages represent proportion of retail-size trades (R) less than $100,000 of original par volume, medium-size trades (M) between $100,000 and $1,000,000 of original par volume, and institutional-size trades (I) more than $1,000,000 of original par volume.

Table 3a: CMBS and Non-Agency CMO Security Characteristics

Category:	CMBS			Non-agency CMO						
	Overall	IO/PO	Other	Overall	IO/PO	PAC/TN	SEQ/PT	SUP/Z	Other Senior	Other
Traded Instruments	2,967	249	2,718	13,396	326	839	7,129	300	3,687	1,115
Registered	1,997	94	1,903	12,355	304	832	6,712	295	3,534	678
Inv. Grade	928	42	886	2,024	34	108	1,137	23	681	41
% floaters:	32%	100%	29%	65%	76%	12%	72%	22%	60%	93%
High Yield	1,069	52	1,017	10,331	270	724	5,575	272	2,853	637
% floaters:	39%	100%	36%	71%	79%	25%	78%	31%	67%	90%
Rule 144a	970	155	815	1,041	22	7	417	5	153	437
Inv. Grade	411	104	307	110	3	2	86	---	19	---
% floaters:	71%	100%	61%	80%	67%	50%	81%	---	79%	---
High Yield	559	51	508	931	19	5	331	5	134	437
% floaters:	63%	100%	59%	85%	74%	40%	77%	40%	69%	97%
Avg. Maturity	Mar-39	Jun-40	Jan-39	Mar-35	Jan-36	Mar-35	Jul-35	Dec-34	Feb-35	Jun-33
Registered	Apr-40	Nov-40	Mar-40	Mar-35	Oct-35	Mar-35	Jun-35	Dec-34	Jan-35	Dec-32
Rule 144a	Dec-36	Mar-40	Apr-36	Dec-35	Jun-39	Dec-32	Mar-37	Jul-36	Dec-36	Mar-34
Vintage% <4;4-6;>6	34/33/33	48/22/30	33/34/33	10/42/48	17/49/34	2/54/44	9/49/42	5/43/52	12/36/52	14/10/76
Registered	31/34/36	54/21/25	30/34/36	8/44/48	15/51/34	2/54/44	7/50/43	4/43/53	11/36/53	15/12/73
Inv. Grade	6/43/51	4/41/55	6/43/51	1/17/82	0/26/74	0/19/81	1/24/75	0/15/85	1/7/92	0/3/97
High Yield	53/25/22	94/4/2	51/26/23	10/49/41	17/54/29	3/59/38	8/55/37	4/45/51	13/43/44	16/13/71
Rule 144a	39/32/29	45/22/33	38/34/28	29/23/48	45/26/29	0/67/33	41/39/20	60/40/0	44/25/31	12/6/82
Inv. Grade	32/33/35	23/31/46	35/33/32	12/45/43	0/33/67	0/50/50	14/51/35	---	6/18/76	---
High Yield	45/32/23	90/4/6	40/35/25	31/20/49	53/25/22	0/74/26	48/35/17	60/40/0	50/26/24	12/6/82
Avg. Coupon Rate	4.54	0.88	4.87	8.74	219.75	5.77	2.35	6.40	4.28	3.15
Registered	4.91	0.99	5.10	9.05	234.00	5.77	2.33	6.43	4.32	3.08
Rule 144a	3.76	0.81	4.32	2.98	3.14	5.81	2.71	4.71	3.23	3.85
Avg. Factor	85.12	67.57	86.73	52.63	41.20	69.19	58.22	72.47	43.71	31.91
Registered	85.65	60.38	86.90	53.71	39.99	69.21	58.20	71.96	43.33	42.61
Rule 144a	84.05	71.93	86.35	39.76	57.89	67.61	58.54	102.47	52.48	15.30

Legend: We define traded instruments as having at least two opposite trades with customers at most two weeks apart in the sample period. For each instrument we take average of each characteristic within each instrument group. Vintage percentages represent relative percentage of instruments with less than 4 years in between first Moody's rating date and the trade execution date, in between 4 and 6 years, and more than 6 years, respectively.

Table 3b: CMBS and Non-Agency CMO Trading Characteristics

Category:	CMBS			Non-agency CMO						
	Overall	IO/PO	Other	Overall	IO/PO	PAC/TN	SEQ/PT	SUP/Z	Other Senior	Other
Avg. Trades per Day	0.093	0.032	0.099	0.067	0.028	0.078	0.050	0.125	0.104	0.037
Registered	0.115	0.030	0.119	0.069	0.027	0.079	0.051	0.127	0.106	0.040
Inv. Grade	0.149	0.024	0.155	0.070	0.038	0.052	0.056	0.116	0.099	0.041
High Yield	0.085	0.034	0.088	0.069	0.025	0.083	0.050	0.128	0.107	0.040
Rule 144a	0.048	0.034	0.050	0.036	0.041	0.048	0.033	0.021	0.051	0.032
Inv. Grade	0.067	0.030	0.079	0.036	0.021	0.058	0.034	---	0.049	---
High Yield	0.033	0.043	0.033	0.036	0.045	0.044	0.033	0.021	0.051	0.032
# of Dealers	5.59	2.48	5.88	3.87	2.28	3.38	3.51	7.90	4.86	2.68
Registered	6.79	2.10	7.02	3.97	2.20	3.38	3.55	8.00	4.93	2.82
Rule 144a	3.13	2.72	3.21	2.70	3.36	3.43	2.74	2.00	3.14	2.47
% Interdealer Trades	9.82%	8.11%	9.98%	13.65%	14.35%	11.61%	12.66%	24.97%	15.17%	13.24%
Registered	11.10%	4.36%	11.43%	14.02%	14.27%	11.59%	12.80%	24.98%	15.51%	16.40%
Rule 144a	7.20%	10.39%	6.59%	9.28%	15.51%	14.21%	10.39%	24.67%	7.35%	8.34%
Trade Sizes% R/M/I	12/25/63	0/6/94	13/26/61	55/17/28	4/18/78	63/22/15	41/18/39	88/8/4	67/15/18	21/23/56
Registered	14/26/60	0/14/86	14/27/59	57/17/26	4/18/78	63/22/15	43/17/40	88/8/4	68/15/17	31/25/44
Inv. Grade	13/27/60	0/3/97	13/27/60	59/15/26	4/16/80	56/20/24	45/19/36	93/4/3	72/11/17	38/26/36
High Yield	16/25/59	0/20/80	16/25/59	56/17/27	4/19/77	64/22/14	42/17/41	88/8/4	68/16/16	31/25/44
Rule 144a	4/20/76	0/2/98	4/23/73	5/21/74	0/16/84	29/14/57	2/19/79	5/23/72	14/25/61	3/21/76
Inv. Grade	4/20/76	0/2/98	5/23/72	1/17/82	0/0/100	0/0/100	1/16/83	---	0/22/78	---
High Yield	2/20/78	0/2/98	3/22/75	6/21/73	0/17/83	43/22/35	3/20/77	5/23/72	16/26/58	3/21/76

Legend: We define traded instruments as having at least two opposite trades with customers at most two weeks apart in the sample period. For each instrument we take average of each characteristic within each instrument group. Trade sizes percentages represent proportion of retail-size trades (R) less than $100,000 of original par volume, medium-size trades (M) between $100,000 and $1,000,000 of original par volume, and institutional-size trades (I) more than $1,000,000 of original par volume.

Table 4: Mean Client Spreads by Transaction Sizes

	Investment Grade				High Yield			
	ABS	CDOs	CMBS	N-A CMO	ABS	CDOs	CMBS	N-A CMO
Overall	0.378	0.397	0.271	2.871	0.846	1.512	0.746	3.463
	(0.009)	(0.036)	(0.012)	(0.027)	(0.029)	(0.128)	(0.028)	(0.018)
Retail	1.400	1.197	1.023	3.828	2.066	3.711	2.868	4.333
	(0.056)	(0.614)	(0.049)	(0.034)	(0.075)	(1.482)	(0.113)	(0.021)
	1763	11	1651	6896	901	15	1099	33432
Non-Retail	0.233	0.390	0.163	1.566	0.546	1.472	0.389	2.180
	(0.006)	(0.036)	(0.011)	(0.036)	(0.029)	(0.127)	(0.023)	(0.029)
	12475	1278	11446	5052	3660	814	6532	22667
Difference	F = 433.3	F = 1.9	F = 294.3	F = 2121.2	F = 361.4	F = 2.4	F = 458.9	F = 3541.4
	p=0.000	p=0.169	p=0.000	p=0.000	p=0.000	p=0.120)	p=0.000	p=0.000
Registered	0.418		0.275	3.011	1.016		0.684	3.546
	(0.011)		(0.012)	(0.027)	(0.034)		(0.027)	(0.018)
Retail	1.423		0.995	3.829	2.116		2.761	4.337
	(0.057)		(0.048)	(0.034)	(0.075)		(0.106)	(0.021)
	1701		1554	6890	857		1062	33339
Non-Retail	0.246		0.157	1.734	0.568		0.275	2.284
	(0.007)		(0.011)	(0.040)	(0.032)		(0.020)	(0.031)
	9946		9549	4411	2099		5395	20904
Difference	F = 418.4		F = 284.6	F = 1618.7	F = 358.9		F = 530.9	F = 2942.9
	p=0.000		p=0.000	p=0.000	p=0.000		p=0.000	p=0.000
Rule 144a	0.196	0.397	0.253	0.425	0.532	1.512	1.091	1.057
	(0.016)	(0.036)	(0.035)	(0.049)	(0.053)	(0.128)	(0.101)	(0.056)
Retail	0.751	1.197	1.470	2.423	1.098	3.711	5.925	3.023
	(0.207)	(0.614)	(0.305)	(1.205)	(0.404)	(1.482)	(1.365)	(0.364)
	62	11	97	6	44	15	37	93
Non-Retail	0.182	0.390	0.190	0.407	0.516	1.472	0.933	0.953
	(0.015)	(0.036)	(0.033)	(0.048)	(0.053)	(0.127)	(0.091)	(0.054)
	2529	1278	1897	641	1561	814	1137	1763
Difference	F = 7.6	F = 1.9	F = 17.6	F = 3.3	F = 2.1	F = 2.4	F = 13.7	F = 32.0
	p=0.006	p=0.169	p=0.000	p=0.068	p=0.149	p=0.120	p=0.000	p=0.000
Reg-Rule Diff.	F = 137.0		F = 0.3	F = 2133.2	F = 59.9		F = 15.1	F = 1813.3
	p=0.000		p=0.555	p=0.000	p=0.000		p=0.000	p=0.000

Legend: A retail trade corresponds to less than $100,000 of original par traded on either side of transactions with customers in each matched pair. P-values correspond to the null hypothesis that spreads are equal to zero. The sample is from May 16, 2011 to February 29, 2012. Standard errors are shown in parentheses.

Table 5a: Mean Client Spreads by Transaction Sizes (Part 1)

ABS

	Sell Size	Investment Grade								High Yield							
		Registered				Rule 144a				Registered				Rule 144a			
Buy Size		Retail	Med.	Large	Overall	Retail	Med.	Large	Overall	Retail	Med.	Large	Overall	Retail	Med.	Large	Overall
Retail		1.339	1.322	1.616	1.361	0.597	2.411	0.029	0.790	2.170	1.956	3.168	2.242	0.917	1.865	2.337	1.190
		(0.059)	(0.259)	(0.321)	(0.060)	(0.165)	(0.880)	(0.362)	(0.210)	(0.116)	(0.148)	(0.351)	(0.095)	(0.505)	(0.843)	(1.527)	(0.460)
		1167	125	119	1411	31	7	7	45	421	117	69	607	26	2	5	33
Med.		1.711	0.276	0.287	0.330	0.923	0.386	0.258	0.352	1.640	0.563	0.788	0.749	0.773	0.593	1.281	0.731
		(0.238)	(0.013)	(0.036)	(0.015)	(0.993)	(0.062)	(0.043)	(0.045)	(0.149)	(0.054)	(0.145)	(0.051)	(0.415)	(0.087)	(0.364)	(0.100)
		138	2993	718	3849	8	488	228	724	122	613	144	879	4	286	71	361
Large		1.741	0.328	0.209	0.263	0.400	0.190	0.107	0.119	1.971	0.835	0.488	0.670	0.852	0.662	0.437	0.455
		(0.227)	(0.024)	(0.008)	(0.010)	(0.513)	(0.038)	(0.011)	(0.011)	(0.166)	(0.118)	(0.042)	(0.041)	(1.402)	(0.279)	(0.063)	(0.062)
		152	935	5300	6387	9	236	1577	1822	128	224	1118	1470	7	85	1119	1211
Overall		1.416	0.321	0.245	0.418	0.614	0.342	0.126	0.196	2.035	0.797	0.660	1.016	0.890	0.616	0.495	0.532
		(0.057)	(0.014)	(0.010)	(0.011)	(0.211)	(0.045)	(0.011)	(0.016)	(0.084)	(0.050)	(0.046)	(0.034)	(0.434)	(0.092)	(0.063)	(0.053)
		1457	4053	6137	11647	48	731	1812	2591	671	954	1331	2956	37	373	1195	1605

Rule 144a CDOs

	Sell Size	Investment Grade								High Yield							
		CDO				CBO/CLO				CDO				CBO/CLO			
Buy Size		Retail	Med.	Large	Overall	Retail	Med.	Large	Overall	Retail	Med.	Large	Overall	Retail	Med.	Large	Overall
Retail						4.010		0.062	2.036	11.429			11.429	1.782			1.782
						(0.000)		(0.000)	(1.974)	(5.714)			(5.714)	(0.562)			(0.562)
						1		1	2	3			3	12			12
Med.		4.241	0.506	0.452	0.779	0.472	0.360	0.731	0.464		3.298	1.268	2.868		0.007	-0.634	-0.124
		(0.000)	(0.250)	(0.294)	(0.287)	(0.235)	(0.121)	(0.402)	(0.139)		(0.751)	(1.634)	(0.688)		(0.520)	(1.494)	(0.508)
		2	23	2	27	2	91	35	128		41	11	52		47	12	59
Large			0.326	0.623	0.608	-0.066	0.719	0.308	0.314		4.870	2.422	2.476		1.985	0.431	0.463
			(0.412)	(0.113)	(0.109)	(0.479)	(0.367)	(0.037)	(0.037)		(2.169)	(0.208)	(0.210)		(0.690)	(0.126)	(0.125)
			12	229	241	5	18	868	891		8	355	363		7	333	340
Overall		4.241	0.444	0.621	0.625	0.578	0.420	0.324	0.337	11.429	3.555	2.387	2.589	1.782	0.263	0.394	0.417
		(0.000)	(0.214)	(0.112)	(0.102)	(0.576)	(0.117)	(0.039)	(0.037)	(5.714)	(0.716)	(0.208)	(0.207)	(0.562)	(0.468)	(0.132)	(0.128)
		2	35	231	268	8	109	904	1021	3	49	366	418	12	54	345	411

Legend: A retail trade corresponds to less than $100,000 of original par traded. An institutional trade corresponds to more than $1,000,000 of original par traded. In each cell the mean spread is shown with its standard errors in parentheses and number of observations in each category. The sample is from May 16, 2011 to February 29, 2012.

Table 5b: Mean Client Spreads by Transaction Sizes (Part 2)

CMBS

		Sell Size															
		Investment Grade								High Yield							
		Registered				Rule 144a				Registered				Rule 144a			
		Retail	Med.	Large	Overall	Retail	Med.	Large	Overall	Retail	Med.	Large	Overall	Retail	Med.	Large	Overall
Buy Size	Retail	1.129	0.678	0.861	1.038	0.978	3.248	0.328	1.379	2.825	2.406	2.667	2.776	3.569	0.070	-0.100	2.953
		(0.059)	(0.152)	(0.138)	(0.052)	(0.477)	(0.770)	(0.224)	(0.322)	(0.122)	(0.463)	(0.403)	(0.114)	(1.533)	(0.070)	(0.000)	(1.292)
		904	114	232	1250	33	20	23	76	718	68	90	876	19	3	1	23
	Med.	0.880	0.290	0.257	0.300	2.721	0.360	0.324	0.377	2.106	0.319	0.420	0.431	0.957	0.843	0.366	0.772
		(0.244)	(0.018)	(0.046)	(0.019)	(1.091)	(0.089)	(0.202)	(0.089)	(0.379)	(0.037)	(0.085)	(0.039)	(0.559)	(0.184)	(0.269)	(0.159)
		97	2115	811	3023	5	279	130	414	81	1180	321	1582	4	212	39	255
	Large	0.785	0.158	0.095	0.124	1.513	0.037	0.158	0.162	3.142	0.347	0.238	0.326	14.748	1.245	0.960	1.134
		(0.141)	(0.040)	(0.015)	(0.015)	(1.002)	(0.091)	(0.036)	(0.035)	(0.405)	(0.080)	(0.025)	(0.027)	(2.476)	(0.594)	(0.107)	(0.120)
		207	835	5788	6830	16	135	1353	1504	105	405	3489	3999	10	63	823	896
	Overall	1.050	0.268	0.140	0.275	1.298	0.392	0.175	0.253	2.797	0.412	0.309	0.684	6.640	0.926	0.932	1.091
		(0.054)	(0.018)	(0.015)	(0.012)	(0.426)	(0.079)	(0.037)	(0.035)	(0.113)	(0.040)	(0.026)	(0.027)	(1.484)	(0.194)	(0.103)	(0.101)
		1208	3064	6831	11103	54	434	1506	1994	904	1653	3900	6457	33	278	863	1174

Non-Agency CMO

		Sell Size															
		Investment Grade								High Yield							
		Registered				Rule 144a				Registered				Rule 144a			
		Retail	Med.	Large	Overall	Retail	Med.	Large	Overall	Retail	Med.	Large	Overall	Retail	Med.	Large	Overall
Buy Size	Retail	3.736	5.578	3.831	3.799	2.423			2.423	4.211	3.953	3.171	4.162	3.265	5.141	1.670	3.427
		(0.039)	(0.238)	(0.356)	(0.038)	(1.205)			(1.205)	(0.023)	(0.061)	(0.164)	(0.022)	(0.534)	(2.122)	(0.335)	(0.531)
		5419	191	101	5711	6			6	20573	2325	528	23426	41	9	5	55
	Med.	3.682	2.112	2.279	2.572		0.459	0.430	0.454	4.045	2.609	3.704	3.317	2.009	1.037	1.494	1.136
		(0.123)	(0.102)	(0.280)	(0.079)		(0.108)	(0.383)	(0.115)	(0.042)	(0.054)	(0.268)	(0.037)	(0.546)	(0.103)	(0.391)	(0.100)
		448	1015	106	1569		128	32	160	4968	5467	653	11088	27	363	34	424
	Large	4.152	3.918	1.051	2.064		0.130	0.400	0.391	5.460	4.289	1.546	2.943	3.489	1.745	0.872	0.938
		(0.077)	(0.105)	(0.038)	(0.040)		(0.206)	(0.052)	(0.051)	(0.090)	(0.091)	(0.039)	(0.037)	(0.648)	(0.262)	(0.065)	(0.064)
		731	630	2660	4021		15	466	481	4945	2990	11794	19729	11	70	1296	1377
	Overall	3.778	3.092	1.194	3.011	2.423	0.425	0.402	0.425	4.386	3.365	1.721	3.546	2.867	1.233	0.891	1.057
		(0.034)	(0.076)	(0.040)	(0.027)	(1.205)	(0.099)	(0.054)	(0.049)	(0.023)	(0.040)	(0.039)	(0.018)	(0.350)	(0.107)	(0.064)	(0.056)
		6598	1836	2867	11301	6	143	498	647	30486	10782	12975	54243	79	442	1335	1856

Legend: A retail trade corresponds to less than \$100,000 of original par traded. An institutional trade corresponds to more than \$1,000,000 of original par traded. In each cell the mean spread is shown with its standard errors in parentheses and number of observations in each category. The sample is from May 16, 2011 to February 29, 2012.

Table 6a: Distribution of Total Client Non-Retail Bid-Ask Spreads

Roundtrip Spreads:	Obs.	Mean	St. Dev.	10th Perc.	25th Perc.	Median	75th Perc.	90th Perc.
ABS	16,135	0.304	1.041	-0.024	0.006	0.057	0.303	0.894
Registered	12,045	0.302	0.871	-0.014	0.008	0.058	0.326	0.895
Rule 144a	4,090	0.310	1.427	-0.085	0.000	0.052	0.251	0.888
Investment Grade	12,475	0.233	0.691	-0.025	0.006	0.047	0.243	0.770
Registered	9,946	0.246	0.672	-0.015	0.008	0.048	0.262	0.802
Rule 144a	2,529	0.182	0.756	-0.094	0.000	0.043	0.193	0.590
High Yield	3,660	0.546	1.753	-0.016	0.004	0.115	0.531	1.548
Registered	2,099	0.568	1.459	-0.004	0.016	0.155	0.622	1.523
Rule 144a	1,561	0.516	2.084	-0.035	0.000	0.072	0.398	1.587
Overall CDO (R144a)	2,092	0.811	2.531	0.000	0.000	0.158	0.740	2.586
CDO	681	1.772	3.505	-0.003	0.066	0.535	1.965	5.556
CBO/CLO	1,411	0.347	1.708	0.000	0.000	0.121	0.424	1.339
Investment Grade	1,278	0.390	1.296	0.000	0.021	0.136	0.494	1.391
CDO	266	0.598	1.648	-0.573	0.071	0.302	0.879	2.163
CBO/CLO	1,012	0.335	1.182	0.000	0.008	0.127	0.372	1.058
High Yield	814	1.472	3.623	-0.020	0.000	0.321	1.791	5.556
CDO	415	2.525	4.121	0.000	0.000	0.829	3.293	9.201
CBO/CLO	399	0.376	2.604	-0.660	0.000	0.061	0.678	2.678
CMBS	17,978	0.245	1.470	-0.609	0.000	0.110	0.454	1.180
Registered	14,944	0.200	1.258	-0.607	0.000	0.104	0.430	1.096
Rule 144a	3,034	0.469	2.226	-0.612	0.000	0.145	0.625	1.663
Investment Grade	11,446	0.163	1.177	-0.653	-0.029	0.097	0.410	1.059
Registered	9,549	0.157	1.120	-0.644	-0.023	0.095	0.395	1.020
Rule 144a	1,897	0.190	1.428	-0.738	-0.068	0.112	0.485	1.250
High Yield	6,532	0.389	1.868	-0.518	0.000	0.133	0.535	1.418
Registered	5,395	0.275	1.468	-0.541	0.000	0.122	0.476	1.218
Rule 144a	1,137	0.933	3.079	-0.450	0.000	0.223	0.930	2.599
Non-Agency CMO	27,719	2.068	4.121	0.000	0.172	0.882	3.113	5.076
Registered	25,315	2.188	4.246	0.000	0.199	0.995	3.252	5.191
Rule 144a	2,404	0.807	2.057	0.000	0.000	0.193	1.000	2.716
Investment Grade	5,052	1.566	2.535	0.004	0.126	0.518	2.444	4.609
Registered	4,411	1.734	2.631	0.061	0.144	0.683	2.736	4.823
Rule 144a	641	0.407	1.204	0.000	0.000	0.070	0.326	1.241
High Yield	22,667	2.180	4.389	0.000	0.194	0.985	3.266	5.144
Registered	20,904	2.284	4.507	0.000	0.217	1.049	3.328	5.247
Rule 144a	1,763	0.953	2.272	0.000	0.016	0.271	1.302	3.175

Legend: Total client bid-ask spreads are computed using buy from a customer and sell to a customer at most two weeks apart in the sample. The sample is from May 16, 2011 to February 29, 2012. Bid-ask spreads are winsorized within each product sub-type, placement type and investment grade.

Table 6b: Total Client Non-Retail Bid-Ask Spreads for Pre- and Post-Release Samples

	Pre-Release				Post-Release				Difference	
	Obs.	Mean	St. Dev.	Median	Obs.	Mean	St. Dev.	Median	Mean Equality	Median Equality
ABS	8,228	0.294	0.979	0.056	7,907	0.314	1.100	0.057	F = 1.48 (p=0.22)	F = 0.16 (p=0.69)
Registered	6,337	0.302	0.808	0.061	5,708	0.302	0.936	0.054	F = 0.00 (p=0.99)	F = 4.48 (p=0.03)
Rule 144a	1,891	0.268	1.410	0.039	2,199	0.345	1.441	0.063	F = 2.96 (p=0.09)	F = 28.07 (p=0.00)
Investment Grade	6,324	0.222	0.640	0.047	6,151	0.245	0.738	0.048	F = 3.30 (p=0.07)	F = 0.37 (p=0.54)
Registered	5,152	0.238	0.632	0.050	4,794	0.254	0.713	0.047	F = 1.42 (p=0.23)	F = 1.20 (p=0.27)
Rule 144a	1,172	0.151	0.671	0.033	1,357	0.210	0.822	0.056	F = 3.95 (p=0.05)	F = 15.47 (p=0.00)
High Yield	1,904	0.534	1.646	0.117	1,756	0.558	1.862	0.112	F = 0.17 (p=0.68)	F = 0.14 (p=0.71)
Registered	1,185	0.579	1.288	0.178	914	0.553	1.655	0.127	F = 0.15 (p=0.70)	F = 4.09 (p=0.04)
Rule 144a	719	0.460	2.106	0.056	842	0.564	2.065	0.094	F = 0.95 (p=0.33)	F = 5.60 (p=0.02)
Overall CDO	1,073	0.920	2.849	0.141	1,019	0.696	2.142	0.173	F = 4.15 (p=0.04)	F = 3.03 (p=0.08)
CDO	419	1.963	3.732	0.554	262	1.466	3.089	0.475	F = 3.55 (p=0.06)	F = 0.59 (p=0.44)
CBO/CLO	654	0.251	1.806	0.093	757	0.429	1.614	0.137	F = 3.77 (p=0.05)	F = 10.26 (p=0.00)
Investment Grade	649	0.333	1.331	0.131	629	0.448	1.258	0.151	F = 2.55 (p=0.11)	F = 4.02 (p=0.05)
CDO	162	0.617	1.615	0.318	104	0.568	1.706	0.287	F = 0.05 (p=0.82)	F = 0.48 (p=0.49)
CBO/CLO	487	0.238	1.209	0.102	525	0.425	1.150	0.137	F = 6.31 (p=0.01)	F = 6.88 (p=0.01)
High Yield	424	1.818	4.065	0.321	390	1.095	3.031	0.322	F = 8.36 (p=0.00)	F = 0.00 (p=0.98)
CDO	257	2.812	4.386	0.893	158	2.057	3.614	0.757	F = 3.62 (p=0.06)	F = 0.12 (p=0.73)
CBO/CLO	167	0.288	2.924	0.000	232	0.440	2.352	0.122	F = 0.30 (p=0.58)	F = 15.20 (p=0.00)
CMBS	9,159	0.172	1.521	0.084	8,819	0.322	1.412	0.138	F = 47.17 (p=0.00)	F = 91.89 (p=0.00)
Registered	7,488	0.110	1.268	0.079	7,456	0.290	1.242	0.131	F = 76.21 (p=0.00)	F = 70.76 (p=0.00)
Rule 144a	1,671	0.445	2.321	0.120	1,363	0.498	2.103	0.191	F = 0.42 (p=0.52)	F = 12.07 (p=0.00)
Investment Grade	5,821	0.095	1.188	0.075	5,625	0.233	1.162	0.124	F = 39.25 (p=0.00)	F = 54.17 (p=0.00)
Registered	4,783	0.090	1.137	0.075	4,766	0.226	1.099	0.119	F = 35.25 (p=0.00)	F = 34.99 (p=0.00)
Rule 144a	1,038	0.122	1.397	0.075	859	0.274	1.462	0.141	F = 5.31 (p=0.02)	F = 15.48 (p=0.00)
High Yield	3,338	0.304	1.965	0.100	3,194	0.478	1.757	0.179	F = 14.24 (p=0.00)	F = 54.90 (p=0.00)
Registered	2,705	0.147	1.470	0.088	2,690	0.403	1.454	0.163	F = 41.37 (p=0.00)	F = 34.05 (p=0.00)
Rule 144a	633	0.977	3.253	0.178	504	0.879	2.846	0.265	F = 0.29 (p=0.59)	F = 4.79 (p=0.03)
Non-Agency CMO	13,832	2.192	4.678	0.894	13,887	1.945	3.474	0.873	F = 25.05 (p=0.00)	F = 0.38 (p=0.54)
Registered	12,680	2.317	4.834	1.005	12,635	2.059	3.554	0.995	F = 23.50 (p=0.00)	F = 0.25 (p=0.62)
Rule 144a	1,152	0.821	1.864	0.169	1,252	0.795	2.220	0.236	F = 0.10 (p=0.75)	F = 13.86 (p=0.00)
Investment Grade	2,617	1.766	2.815	0.550	2,435	1.350	2.174	0.486	F = 34.80 (p=0.00)	F = 1.81 (p=0.18)
Registered	2,283	1.971	2.932	0.755	2,128	1.480	2.238	0.634	F = 39.49 (p=0.00)	F = 3.11 (p=0.08)
Rule 144a	334	0.364	1.033	0.063	307	0.454	1.366	0.078	F = 0.87 (p=0.35)	F = 0.37 (p=0.54)
High Yield	11,215	2.292	5.009	0.994	11,452	2.071	3.679	0.979	F = 14.27 (p=0.00)	F = 0.32 (p=0.57)
Registered	10,397	2.393	5.156	1.060	10,507	2.176	3.754	1.042	F = 12.10 (p=0.00)	F = 0.21 (p=0.65)
Rule 144a	818	1.008	2.083	0.245	945	0.906	2.425	0.300	F = 0.90 (p=0.34)	F = 2.54 (p=0.11)

Legend: The Pre-Release Sample is from May 16, 2011 to October 17, 2011 and the Post-Release Sample is from October 18, 2011 to February 29, 2012. Total client bid-ask spreads are computed using buy from a customer and sell to a customer at most two weeks apart in the sample. The sample is from May 16, 2011 to February 29, 2012. Bid-ask spreads are winsorized within each product sub-type, placement type and investment grade.

Table 7a: Total Client Non-Retail Bid-Ask Spreads (Part 1)

Category:	ABS Overall	Auto	Card	ManH	SBA	Stud	Other	CDOs Overall	CBO	CLO	CDO
Overall	0.304	0.075	0.062	1.224	0.713	0.467	0.558	0.811	0.251	0.358	1.772
	(0.008)	(0.003)	(0.006)	(0.129)	(0.014)	(0.038)	(0.027)	(0.055)	(0.055)	(0.051)	(0.134)
Registered	0.302	0.072	0.078	1.294	0.714	0.511	0.553	---	---	---	---
	(0.008)	(0.003)	(0.007)	(0.124)	(0.014)	(0.050)	(0.026)	---	---	---	---
	12045	4001	3143	268	1522	1127	1984	---	---	---	---
Rule 144a	0.310	0.087	-0.011	-0.211	0.668	0.342	0.563	0.811	0.251	0.358	1.772
	(0.022)	(0.008)	(0.009)	(1.115)	(0.075)	(0.034)	(0.049)	(0.055)	(0.055)	(0.051)	(0.134)
	4090	1193	659	13	56	392	1777	2092	155	1256	681
Difference	F = 0.1	F = 3.0	F = 62.5	F = 1.9	F = 0.4	F = 7.8	F = 0.0	---	---	---	---
	(p=0.747)	(p=0.083)	(p=0.000)	(p=0.165)	(p=0.543)	(p=0.005)	(p=0.859)	---	---	---	---
Investment Grade	0.233	0.072	0.057	0.960	0.713	0.443	0.344	0.390	0.220	0.352	0.598
	(0.006)	(0.003)	(0.006)	(0.160)	(0.014)	(0.033)	(0.025)	(0.036)	(0.032)	(0.042)	(0.101)
Registered	0.246	0.068	0.072	0.985	0.714	0.468	0.323	---	---	---	---
	(0.007)	(0.003)	(0.007)	(0.169)	(0.014)	(0.043)	(0.022)	---	---	---	---
	9946	3287	2982	111	1522	1063	981	---	---	---	---
Rule 144a	0.182	0.088	-0.012	0.560	0.668	0.367	0.378	0.390	0.220	0.352	0.598
	(0.015)	(0.010)	(0.009)	(0.221)	(0.075)	(0.037)	(0.055)	(0.036)	(0.032)	(0.042)	(0.101)
	2529	885	645	7	56	342	594	1278	131	881	266
Difference	F = 15.0	F = 3.8	F = 55.7	F = 2.5	F = 0.4	F = 3.2	F = 0.8	---	---	---	---
	(p=0.000)	(p=0.052)	(p=0.000)	(p=0.114)	(p=0.543)	(p=0.072)	(p=0.362)	---	---	---	---
High Yield	0.546	0.088	0.179	1.415	---	0.766	0.712	1.472	0.420	0.374	2.525
	(0.029)	(0.008)	(0.030)	(0.190)	---	(0.301)	(0.042)	(0.127)	(0.315)	(0.137)	(0.202)
Registered	0.568	0.090	0.189	1.512	---	1.226	0.778	---	---	---	---
	(0.032)	(0.009)	(0.031)	(0.172)	---	(0.527)	(0.046)	---	---	---	---
	2099	714	161	157	---	64	1003	---	---	---	---
Rule 144a	0.516	0.085	0.063	-1.111	---	0.176	0.657	1.472	0.420	0.374	2.525
	(0.053)	(0.015)	(0.090)	(2.468)	---	(0.078)	(0.068)	(0.127)	(0.315)	(0.137)	(0.202)
	1561	308	14	6	---	50	1183	814	24	375	415
Difference	F = 0.7	F = 0.1	F = 1.9	F = 1.3	---	F = 3.9	F = 2.2	---	---	---	---
	(p=0.405)	(p=0.764)	(p=0.174)	(p=0.250)	---	(p=0.052)	(p=0.138)	---	---	---	---
Grade Difference	F = 111.2	F = 3.6	F = 16.6	F = 3.4	---	F = 1.1	F = 56.1	F = 67.2	F = 0.4	F = 0.0	F = 72.6
	(p=0.000)	(p=0.059)	(p=0.000)	(p=0.067)	---	(p=0.286)	(p=0.000)	(p=0.000)	(p=0.523)	(p=0.881)	(p=0.000)
Registered	F = 97.5	F = 5.0	F = 13.7	F = 4.8	---	F = 2.1	F = 79.2	---	---	---	---
	(p=0.000)	(p=0.025)	(p=0.000)	(p=0.030)	---	(p=0.149)	(p=0.000)	---	---	---	---
Rule 144a	F = 37.1	F = 0.0	F = 0.8	F = 0.5	---	F = 4.9	F = 10.2	F = 67.2	F = 0.4	F = 0.0	F = 72.6
	(p=0.000)	(p=0.847)	(p=0.384)	(p=0.511)	---	(p=0.027)	(p=0.001)	(p=0.000)	(p=0.523)	(p=0.881)	(p=0.000)

Legend: Total client bid-ask spreads are computed using buy from a customer and sell to a customer at most two weeks apart in the sample. The sample is from May 16, 2011 to February 29, 2012. Bid-ask spreads are winsorized within each product sub-type, placement type and investment grade. Standard errors are shown in parentheses.

Table 7b: Total Client Non-Retail Bid-Ask Spreads (Part 2)

Category:	CMBS Overall	CMBS IO/PO	CMBS Other	Non-Agency CMO Overall	Non-Agency CMO IO/PO	Non-Agency CMO PAC/TN	Non-Agency CMO SEQ/PT	Non-Agency CMO SUP/Z	Non-Agency CMO Other Senior	Non-Agency CMO Other
Overall	0.245	0.351	0.243	2.068	3.130	2.760	2.075	2.679	1.857	1.919
	(0.011)	(0.114)	(0.011)	(0.025)	(0.196)	(0.060)	(0.041)	(0.175)	(0.028)	(0.103)
Registered	0.200	0.156	0.200	2.188	3.346	2.768	2.137	2.675	1.942	2.853
	(0.010)	(0.248)	(0.010)	(0.027)	(0.214)	(0.060)	(0.043)	(0.179)	(0.029)	(0.165)
	14944	116	14828	25315	466	1939	13198	267	8130	1315
Rule 144a	0.469	0.478	0.468	0.807	1.110	1.006	1.174	2.849	0.479	0.591
	(0.040)	(0.097)	(0.043)	(0.042)	(0.216)	(0.495)	(0.062)	(0.698)	(0.115)	(0.061)
	3034	179	2855	2404	50	9	914	6	500	925
Difference	F = 41.6	F = 1.5	F = 37.6	F = 771.4	F = 54.5	F = 14.0	F = 160.8	F = 0.1	F = 152.7	F = 165.6
	(p=0.000)	(p=0.227)	(p=0.000)	(p=0.000)	(p=0.000)	(p=0.000)	(p=0.000)	(p=0.794)	(p=0.000)	(p=0.000)
Inv Grade	0.163	0.464	0.159	1.566	3.783	1.777	1.707	1.436	1.632	0.498
	(0.011)	(0.127)	(0.011)	(0.036)	(0.580)	(0.165)	(0.051)	(0.587)	(0.062)	(0.054)
Registered	0.157	0.407	0.156	1.734	4.345	1.811	1.771	1.436	1.693	1.109
	(0.011)	(0.331)	(0.011)	(0.040)	(0.641)	(0.168)	(0.054)	(0.587)	(0.065)	(0.115)
	9549	37	9512	4411	38	160	2671	8	1286	248
Rule 144a	0.190	0.482	0.171	0.407	0.737	0.387	0.888	---	0.630	0.056
	(0.033)	(0.131)	(0.034)	(0.048)	(0.509)	(0.219)	(0.114)	---	(0.183)	(0.021)
	1897	117	1780	641	7	4	209	---	78	343
Difference	F = 0.9	F = 0.0	F = 0.2	F = 460.0	F = 20.0	F = 31.3	F = 48.7	---	F = 30.4	F = 80.6
	(p=0.342)	(p=0.832)	(p=0.678)	(p=0.000)	(p=0.000)	(p=0.000)	(p=0.000)	---	(p=0.000)	(p=0.000)
High Yield	0.389	0.228	0.393	2.180	3.067	2.851	2.169	2.717	1.900	2.429
	(0.023)	(0.194)	(0.023)	(0.029)	(0.208)	(0.063)	(0.050)	(0.179)	(0.031)	(0.136)
Registered	0.275	0.038	0.278	2.284	3.258	2.854	2.230	2.713	1.989	3.259
	(0.020)	(0.329)	(0.020)	(0.031)	(0.225)	(0.063)	(0.053)	(0.183)	(0.032)	(0.199)
	5395	79	5316	20904	428	1779	10527	259	6844	1067
Rule 144a	0.933	0.470	0.960	0.953	1.171	1.501	1.259	2.849	0.451	0.907
	(0.091)	(0.135)	(0.096)	(0.054)	(0.238)	(0.845)	(0.073)	(0.698)	(0.132)	(0.094)
	1137	62	1075	1763	43	5	705	6	422	582
Difference	F = 49.7	F = 1.5	F = 48.2	F = 454.2	F = 40.9	F = 3.2	F = 116.3	---	F = 128.5	F = 113.9
	(p=0.000)	(p=0.228)	(p=0.000)	(p=0.000)	(p=0.000)	(p=0.075)	(p=0.000)	---	(p=0.000)	(p=0.000)
Grade Difference	F = 78.3	F = 1.0	F = 83.0	F = 178.2	F = 1.4	F = 37.2	F = 42.0	F = 4.9	F = 14.9	F = 173.9
	(p=0.000)	(p=0.309)	(p=0.000)	(p=0.000)	(p=0.242)	(p=0.000)	(p=0.000)	(p=0.028)	(p=0.000)	(p=0.000)
Registered	F = 26.0	F = 0.6	F = 28.7	F = 119.0	F = 2.6	F = 33.9	F = 36.9	F = 4.8	F = 17.0	F = 87.2
	(p=0.000)	(p=0.430)	(p=0.000)	(p=0.000)	(p=0.107)	(p=0.000)	(p=0.000)	(p=0.029)	(p=0.000)	(p=0.000)
Rule 144a	F = 58.6	F = 0.0	F = 59.8	F = 57.5	F = 0.7	F = 1.6	F = 7.5	---	F = 0.6	F = 77.4
	(p=0.000)	(p=0.947)	(p=0.000)	(p=0.000)	(p=0.423)	(p=0.248)	(p=0.006)	---	(p=0.425)	(p=0.000)

Legend: Total client bid-ask spreads are computed using buy from a customer and sell to a customer at most two weeks apart in the sample. The sample is from May 16, 2011 to February 29, 2012. Bid-ask spreads are winsorized within each product sub-type, placement type and investment grade. Standard errors are shown in parentheses.

Table 8: Definitions of Control Variables used in Regressions

4-6 Years Vintage Dummy	The number of years between the first coupon or first Moody's rating date and the trade execution date
> 6 Years Vintage Dummy	The number of years between the first coupon or first Moody's rating date and the trade execution date
Investment Grade Dummy	Dummy variable which is equal to one if the instrument is rated as investment grade
Security Specific Match Volume	The average of matched trade log(volume) for the instrument standardized by subtracting the instrument category average and dividing by the instrument category standard deviation
Deviation of Particular Match	The standardized matched log(volume) for the transaction less the average standardized matched log(volume) for the particular instrument
Floating Coupon Dummy	Dummy variable equal to one if the instrument has a floating coupon rate
Number of Trades in Sample	The total number of opposite matches found for this particular security during the sample period
Gap in Execution Time	The number of days between the two matched buy and sell transactions
Number of Dealers	The number of dealers active in the instrument
Dealers' Importance Dummy	The 5%-top most important dealer dummy based on the centrality measure: The measure of dealers' activity and participation in interdealer trades in particular product is averaged across all dealers who participated in a chain of transactions underlying each total client spread observation.
Dealer's Coreness	The dealer-specific coreness value, normalized by the size of the interdealer market within each product subcategory, demeaned and standardized within each subcategory
Dealer's Degree Residual	The difference between dealer-specific degree centrality and coreness, normalized by the size of the interdealer market within each product sub-type, demeaned and standardized within each submarket
Multi Round Trade	Dummy variable equal to one if the chain of transactions underlying the total client spread observation has more than 1 round (C-D-D-C = 2 rounds, C-D-D-D-C = 3 etc.)
Buy from Customer Sell to Dealer	Dummy variable equal to one if the dealer spread is computed using two trades, one of which is a buy from a customer, while the other is a sell to another dealer
Buy from Dealer Sell to Customer	Dummy variable equal to one if the dealer spread is computed using two trades, one of which is a buy from another dealer, while the other is a sell to a customer

Table 9: Regression for Non-Retail Total Client Spreads

	ABS			**CDOs**		**CMBS**			**Non-Agency CMO**		
Variables:	Overall	Reg.	R144a	CDO	CBO/L	Overall	Reg.	R144a	Overall	Reg.	R144a
4-6 Years Vintage	0.162 (0.030)	0.078 (0.026)	0.393 (0.106)	-0.550 (0.759)	0.137 (0.144)	0.298 (0.041)	0.178 (0.040)	0.512 (0.118)	0.807 (0.079)	0.354 (0.098)	0.662 (0.126)
> 6 year Vintage	0.184 (0.028)	0.161 (0.026)	0.207 (0.082)	-0.609 (0.750)	0.309 (0.144)	0.098 (0.036)	-0.007 (0.034)	0.415 (0.161)	0.657 (0.075)	0.176 (0.094)	0.505 (0.130)
Investment Grade	-0.135 (0.022)	-0.190 (0.028)	-0.033 (0.040)	-1.591 (0.260)	-0.049 (0.141)	-0.157 (0.029)	-0.065 (0.028)	-0.392 (0.086)	-0.527 (0.051)	-0.506 (0.053)	-0.248 (0.136)
Security Specific Match Volume	-0.149 (0.022)	-0.143 (0.023)	-0.192 (0.046)	-0.457 (0.178)	-0.092 (0.067)	-0.050 (0.037)	-0.039 (0.029)	0.030 (0.098)	-0.578 (0.035)	-0.963 (0.045)	-0.106 (0.076)
Deviation of Particular Match	-0.058 (0.009)	-0.058 (0.009)	-0.064 (0.019)	-0.031 (0.233)	-0.012 (0.089)	-0.113 (0.014)	-0.120 (0.014)	-0.063 (0.047)	-0.359 (0.051)	-0.510 (0.057)	-0.450 (0.113)
Floating Coupon	0.058 (0.017)	0.064 (0.019)	0.079 (0.045)	-0.788 (0.663)	-0.292 (0.181)	0.116 (0.026)	0.090 (0.026)	-0.094 (0.102)	0.197 (0.047)	0.320 (0.050)	-0.216 (0.118)
Number of Trades	-0.074 (0.018)	-0.035 (0.016)	-0.137 (0.046)	-0.429 (0.278)	-0.127 (0.079)	-0.143 (0.027)	-0.108 (0.021)	-0.211 (0.077)	0.119 (0.026)	-0.009 (0.029)	-0.021 (0.062)
Gap in Execution Time	0.003 (0.002)	0.004 (0.002)	-0.002 (0.005)	-0.003 (0.057)	-0.036 (0.024)	-0.010 (0.003)	-0.009 (0.003)	-0.002 (0.012)	0.094 (0.012)	0.102 (0.013)	0.020 (0.020)
Number of Dealers	0.004 (0.002)	-0.003 (0.002)	0.014 (0.008)	0.038 (0.077)	0.035 (0.028)	-0.001 (0.005)	-0.003 (0.004)	0.005 (0.016)	-0.087 (0.007)	-0.076 (0.008)	-0.033 (0.014)
Dealers' Importance	-0.291 (0.041)	-0.251 (0.040)	-0.385 (0.106)	0.135 (0.351)	-0.827 (0.185)	-0.508 (0.064)	-0.424 (0.050)	-0.798 (0.211)	-0.318 (0.064)	-0.127 (0.067)	-0.584 (0.132)
Multi Round Trade	0.217 (0.025)	0.204 (0.024)	0.256 (0.066)	0.117 (0.467)	-0.489 (0.245)	0.099 (0.035)	0.067 (0.032)	0.301 (0.151)	1.943 (0.073)	1.895 (0.078)	0.746 (0.134)
Subcategory Fixed Effects: Yes. Number of observations: 63924. R-squared: 0.268											

Legend: The regression includes fixed-effects for each of the subcategories and placement types (Registered or Rule 144a). Standard errors are reported in parentheses.

Table 10: Regression for Non-Retail Dealer Spreads

Variables:	ABS Overall	ABS Reg.	ABS R144a	CDOs CDO	CDOs CBO/L	CMBS Overall	CMBS Reg.	CMBS R144a	Non-Agency CMO Overall	Non-Agency CMO Reg.	Non-Agency CMO R144a
4-6 Years Vintage	0.146	0.070	0.431	-0.951	0.216	0.310	0.205	0.570	0.714	0.483	0.655
	(0.023)	(0.019)	(0.083)	(0.765)	(0.092)	(0.031)	(0.029)	(0.097)	(0.044)	(0.053)	(0.105)
> 6 year Vintage	0.110	0.096	0.169	-1.173	0.196	0.090	-0.002	0.400	0.616	0.367	0.381
	(0.020)	(0.017)	(0.065)	(0.747)	(0.099)	(0.028)	(0.025)	(0.128)	(0.044)	(0.053)	(0.104)
Investment Grade	-0.162	-0.177	-0.118	-1.476	-0.163	-0.173	-0.081	-0.512	-0.549	-0.467	-0.436
	(0.022)	(0.024)	(0.050)	(0.214)	(0.090)	(0.023)	(0.020)	(0.080)	(0.028)	(0.029)	(0.076)
Security Specific Match Volume	-0.115	-0.122	-0.129	-0.309	-0.115	0.002	0.018	0.052	-0.330	-0.531	-0.068
	(0.015)	(0.014)	(0.034)	(0.144)	(0.045)	(0.026)	(0.019)	(0.068)	(0.020)	(0.024)	(0.065)
Deviation of Particular Match	-0.038	-0.046	-0.017	0.176	0.064	-0.097	-0.097	-0.056	-0.298	-0.378	-0.269
	(0.006)	(0.006)	(0.015)	(0.211)	(0.067)	(0.011)	(0.010)	(0.042)	(0.028)	(0.030)	(0.077)
Floating Coupon	0.061	0.062	0.070	-0.156	-0.141	0.171	0.134	-0.020	0.196	0.262	-0.130
	(0.013)	(0.014)	(0.034)	(0.528)	(0.168)	(0.019)	(0.018)	(0.083)	(0.027)	(0.028)	(0.088)
Number of Trades	-0.055	-0.021	-0.137	-0.677	-0.130	-0.128	-0.111	-0.165	0.120	0.050	-0.111
	(0.012)	(0.011)	(0.031)	(0.228)	(0.059)	(0.019)	(0.014)	(0.068)	(0.014)	(0.015)	(0.052)
Gap in Execution Time	0.006	0.004	0.013	0.044	0.010	-0.003	-0.003	0.006	0.106	0.113	0.068
	(0.002)	(0.002)	(0.005)	(0.063)	(0.016)	(0.003)	(0.003)	(0.010)	(0.008)	(0.009)	(0.020)
Number of Dealers	0.001	-0.005	0.016	0.058	0.002	-0.003	0.000	-0.009	-0.058	-0.053	-0.009
	(0.002)	(0.002)	(0.005)	(0.069)	(0.020)	(0.003)	(0.002)	(0.013)	(0.003)	(0.004)	(0.013)
Dealer's Coreness	-0.047	-0.035	-0.071	0.280	-0.124	-0.045	-0.019	-0.096	0.148	0.149	0.063
	(0.012)	(0.011)	(0.031)	(0.138)	(0.051)	(0.015)	(0.011)	(0.049)	(0.021)	(0.022)	(0.052)
Dealer's Degree Residual	-0.039	-0.033	-0.045	-0.512	-0.035	0.012	-0.010	0.092	-0.012	0.030	-0.316
	(0.007)	(0.007)	(0.023)	(0.139)	(0.038)	(0.011)	(0.010)	(0.045)	(0.022)	(0.023)	(0.047)
Multi Round Trade	-0.031	-0.085	0.068	0.807	0.188	0.118	0.056	0.567	0.278	0.178	0.321
	(0.024)	(0.027)	(0.056)	(0.734)	(0.107)	(0.028)	(0.026)	(0.151)	(0.058)	(0.062)	(0.188)
Buy from Customer Sell to Dealer	-0.008	0.037	-0.086	-0.772	-0.332	-0.145	-0.120	-0.337	-0.317	-0.274	-0.145
	(0.031)	(0.035)	(0.070)	(0.826)	(0.125)	(0.035)	(0.031)	(0.205)	(0.064)	(0.066)	(0.233)
Buy from Dealer Sell to Customer	0.072	0.105	0.039	-0.202	-0.098	0.084	0.085	0.142	0.251	0.309	-0.162
	(0.025)	(0.029)	(0.060)	(0.768)	(0.146)	(0.033)	(0.028)	(0.192)	(0.057)	(0.059)	(0.194)
Subcategory Fixed Effects: Yes. Number of observations: 78910. R-squared: 0.297											

Legend: The regression includes fixed-effects for each of the subcategories and placement types (Registered or Rule 144a). Standard errors are reported in parentheses.

Essay 3: Information Acquisition with Overlaps and Strategic Trading Outcomes

Abstract

This paper develops a model of information acquisition and strategic trading by multiple traders with correlated signals about asset fundamentals. Traders have access to a common pool of valuable information and thus can obtain information with significant overlaps, having many bits in common. We develop a stochastic process that captures the structure of the pool of information and allows for various degrees of overlaps across traders, which generalizes the existing approaches in the literature. Finally, we study how the degree of overlaps across traders influences equilibrium information acquisition, trading strategies and overall market outcomes, such as price informativeness and market depth.

1 Introduction

The asset management and the proprietary trading industries produce massive amounts of research and information about fundamentals that drive asset prices. Information is produced and consumed by multiple competing agents, such as hedge-funds, mutual funds, trading desks, client brokerages. Often the same or very similar bits of information are produced twice, e.g. when two analysts at different firms do independent research on the same space of fundamentals. In this paper we develop a model of information acquisition and strategic trading by multiple traders who can obtain information with various degree of overlaps, having many or few bits in common. We use our model to study how the form of the overlaps influences equilibrium information acquisition and trading strategies of agents. Our model provides implications for the equilibrium price informativeness and market depth, illustrating the importance of the degree of overlaps for the way overall market functions.

In the model, multiple large risk-neutral buyers and sellers pay costs to observe an informative signal, and the properties of the signal depend on the level of investment and an exogenous degree of overlaps with others. Traders optimize their trades and take into account potential effect of their trades on prices, due to the associated adverse selection.

The information traders possess is partially revealed through their trading strategies, as in Kyle [1985].

We develop a stochastic process that captures the structure of the pool of information and allows for various degrees of overlaps across traders, which generalizes the existing approaches in the literature. Typically, agents have access to a learning technology that allows them to reduce their individual uncorrelated forecasting errors, introduced by Verrecchia [1982]. This tradition is incorporated as a special case, the *independently-overlapping* research scenario. Our approach allows us to generalize and study a *non-overlapping* scenario, which results in lower correlation of traders' signals for any level of investment in research, as well as *perfectly-overlapping* research scenario (higher correlation), and arbitrary combinations of these three scenarios.

In the paper, we trading profits determine incentives to acquire information. We study the effect of optimal information acquisition on trading behavior of agents and equilibrium market outcomes, such as market depth and price informativeness. One example of such analysis is performed by Dierker [2006] that utilizes a learning technology introduced by Verrecchia [1982]. We find that lower price informativeness is associated with higher degree of overlaps and that this effect dominates the effect of competition in trading and trading aggressiveness. Under scenario with high degree of overlaps, having more competing traders on the market may result in lower equilibrium price informativeness, while the opposite happens under low degree of overlaps. These findings illustrate the importance of the degree of overlaps for the way overall market functions.

The paper is organized as follows. Section 2 describes the information structure and research technologies and develops the intuition behind the stochastic process we use for modeling overlaps. Section 3 describes the strategic trading environment and characterizes the equilibrium. Section 4 presents our analysis of equilibrium market outcomes, such as price informativeness, market depth and order flow volatility. Section 5 concludes.

2 Information Structure and Research Technologies

The informative signal informed agent possesses has two components: Common component that tells the agent what the asset is worth, and idiosyncratic component that corresponds to the noise or forecast error. Typically in the literature on information acquisition, agents have access to a research technology that allows them to reduce individual forecasting errors that are assumed to be uncorrelated across agents. This tradition is based on Verrecchia [1982]. The assumption of uncorrelated forecast errors simplifies the analysis by making all agent's research efforts orthogonal to each other in the space spanned by these forecast errors. Moreover, if we decide to drop this assumption—it is not obvious how research efforts of agents will affect the correlation of forecast errors across agents. It turns out that there is an intuitive way to model information acquisition more generally (so that the prior tradition is nested as a special case)—to do so we propose to think about information in a different way.

Rather than thinking about an informative signal as being composed of two parts, we propose to think about the entire information set available to agents as an infinitely divisible stream of bits. This way we find alternative interpretation for Verrecchia [1982] research technology and derive a set of alternative technologies.

2.1 Research Technologies

A research technology is a mapping that describes relationship between agents' monetary expenditures on research (information production) and the results of this research—the joint distribution of informative signals and the true asset value which is the research target.

Suppose there is a single asset with payoff v, and its distribution constitutes common prior knowledge of all agents. Informed agents possess additional informative signals s_i that are correlated with v. We use this notation to introduce our definition of *research technology* below.

Definition 2.1. *A* research technology *is a mapping from informed agents' expenditures* *on research* $\mathbf{c} = (c_1 \dots c_N)$ *to the joint distribution of their informative signals and the uncertain value* v*:* $\mathcal{G}(v, s_1 \dots s_N)$*, where* s_i *is the signal* i*-th informed agent obtains,* $i \in \{1 \dots N\}$.

Example. Consider the research technology used by Verrecchia [1982]. Each informed agent observes true value $v \sim N(0, \Sigma_0)$ perturbed by normally-distributed noise ϵ_i (forecast error) with zero mean and precision $1/\sigma_i^2 \geq 0$. The noise is independent across agents. There is a cost function $TC(1/\sigma_i^2)$ associated with different levels of noise precision agents can choose. Thus the research technology is $(v, s_1 \dots s_N) \sim N(0, \Psi)$ and:

$$\Psi = \begin{pmatrix} \Sigma_0 & \Sigma_0 & \cdots & \Sigma_0 \\ \Sigma_0 & \Sigma_0 + 1/TC^{-1}(c_1) & \cdots & \Sigma_0 \\ \vdots & \vdots & \ddots & \vdots \\ \Sigma_0 & \Sigma_0 & \cdots & \Sigma_0 + 1/TC^{-1}(c_N) \end{pmatrix}.$$

2.2 Structure of Information and Cost Function

For the purpose of our analysis we propose to think about information as being composed of small pieces coming from various sources (bits of information, or fundamentals) that together constitute the universe of available information. We start building our model of information with finite number of bits of information (discrete case) and then prove existence of limiting case in which bits of information are infinitely divisible.

Suppose the true asset value is a random variable v. There are M news about fundamentals—e_i where $i \in \{1, \cdots, M\}$ that contribute to the true asset value. Fundamentals e_i can be positively correlated with each other (good news about one fundamental tend to lead to good news elsewhere).

$$v = \sum_{i=1}^{M} e_i. \tag{40}$$

All fundamentals are constructed to be identically distributed and *equally costly to reveal*. The latter assumption allows us to calculate the total cost of information acquired using the number of informative bits revealed. It is worth noting that the constant cost assumption per bit does not preclude diminishing marginal returns to a dollar spent on research—the positive correlation of bits will make first bits relatively more informative.

We want the key results to be independent of the "detail of the grid"—that is the number of fundamentals M we choose to work with. The motivation is that when we start with $M_1 = 100$ and then decide to split each piece of information into two, so that $M_2 = 200$, then revealing 50 out of initial 100 should yield the same result as revealing 100 out of 200. We refer to the necessary and sufficient condition for this as infinite-divisibility condition, which is provided below.

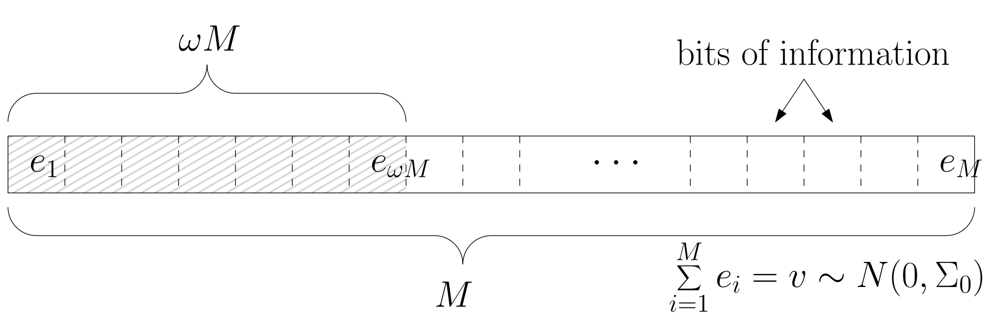
Infinite-Divisibility Condition. *When M increases, the covariance of any two fundamentals e_i and e_j decreases at a rate M^2, so that $Cov(e_i, e_j) \times M^2$ is a constant for any integer M.*

The informative signal is defined as the partial sum of revealed fundamentals (the order in which fundamentals are revealed will matter when two competing agents acquire information simultaneously). Assuming each informed agent acquires $\omega_i \times M$ sources of information (fundamentals), the informative signal is:

$$s_i = \sum_{i=1}^{\omega_i \times M} e_i. \tag{41}$$

In the paper we will refer to ω_i as the *research effort* of an informed agent. Figure 11 summarizes this structure of information.

Figure 11: Signal as a sum of bits of information



From now on we assume that all fundamentals e_i are jointly-Normally distributed with a symmetric positive definite covariance matrix. This together with infinite-divisibility condition yields the following result about properties of the signal:

Proposition 2.1. *Suppose an informed agent exerts research effort $\omega_i \in [0,1]$ and obtains signal s_i. Assume infinite-divisibility condition holds and let $\rho = Cov(e_i, e_j) \times M^2/\Sigma_0$. Then:*

$$\begin{aligned} Var(s_i) &= \omega_i \Sigma_0 (1 - (1 - \omega_i)\rho), \\ Cov(s_i, v) &= \omega_i \Sigma_0. \end{aligned} \tag{42}$$

See Appendix G.1 for proof.

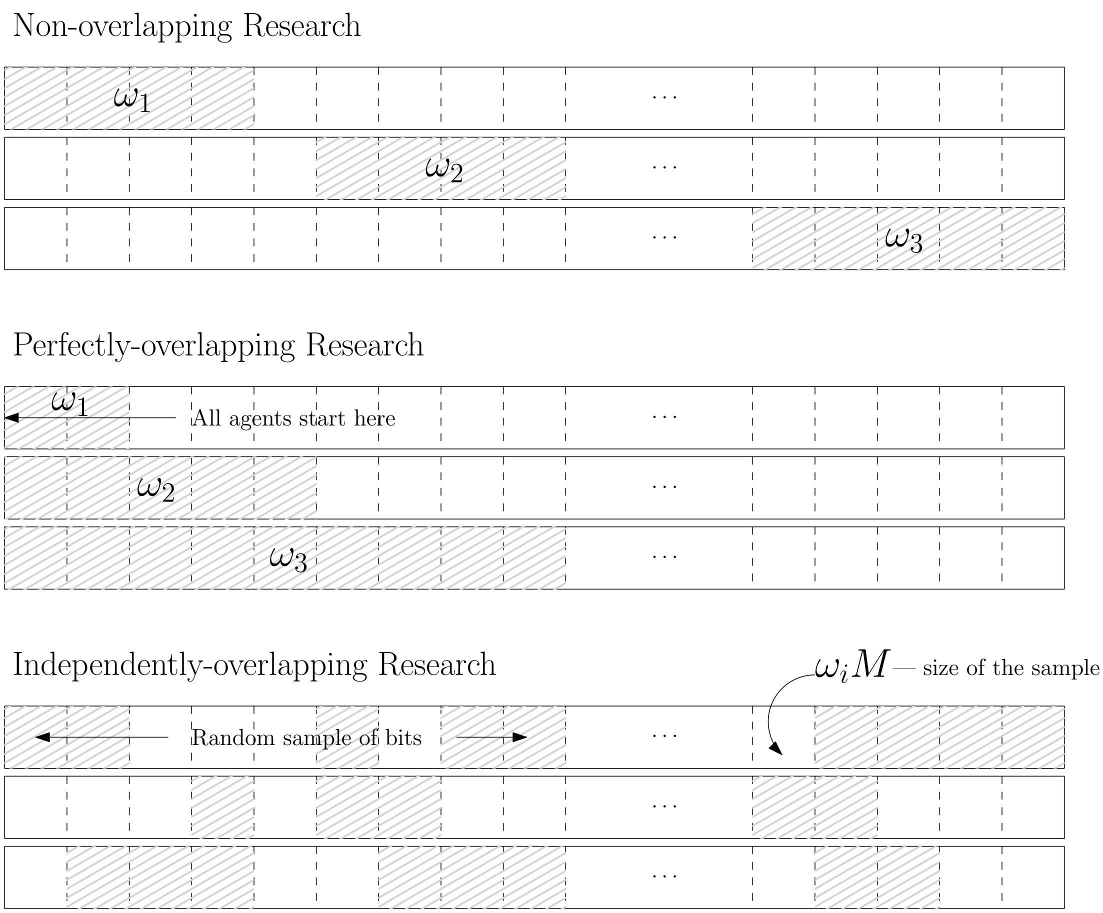
2.3 Overlaps Scenarios

When there are two or more informed agents doing research about v in the described fashion, the covariance of signals they obtain will depend on the order in which these agents reveal fundamentals and how often they overlap.

Example: Suppose $M = 6$ and there are three traders with research efforts $\omega_1 = 1/6$, $\omega_2 = 1/3$, and $\omega_3 = 1/2$. The first agent reveals one fundamental, the second agent chooses two fundamentals, and the third chooses three. It is possible that neither of the three traders overlaps with others, as when agent 1 reveals $\{e_1\}$, agent 2 reveals $\{e_2, e_3\}$ and agent 3 reveals $\{e_4, e_5, e_6\}$. We refer to this case as **non-overlapping research**. The other extreme is when all traders reveal fundamentals in the same order, as when agent 1 reveals $\{e_1\}$, agent 2 reveals $\{e_1, e_2\}$ and agent 3 reveals $\{e_1, e_2, e_3\}$. We refer to this case as **perfectly-overlapping research**. The third possible scenario occurs when each agent draws an independent random sample of fundamentals to reveal, we refer to this case as **independently-overlapping research**. Figure 12 demonstrates the three scenarios of overlaps discussed.

Definition 2.2. *Suppose there are N informed agents on the market and ω_i is the research effort of i-th agent. Suppose for $\forall i \in \{1 \dots N\}$ $\omega_i M$ is a Natural number. Denote by S_i the*

Figure 12: Possible Scenarios for Overlaps



subset of M bits of information each trader is entitled to reveal.

1. *Agents engage in* non-overlapping research *if $\forall i \neq j$ we have $S_i \cap S_j = \varnothing$. This can happen only if $\sum_{i=1}^{N} \omega_i \leq 1$.*

2. *Agents engage in* perfectly-overlapping research *if $\forall i \neq j$ such that $\omega_i \geq \omega_j$ we have $S_i \cap S_j = S_j$.*

3. *Agents engage in* randomly-overlapping research *if $\forall i : S_i$ is a simple random sample of size $\omega_i M$.*

To simplify the exposition, from now on we assume there are two agents doing research on the market ($N = 2$). Their research efforts are denoted by $\omega_2 \leq \omega_1 \leq 1$. The overlaps scenario will determine the covariance of informative signals agents obtain. The following proposition summarizes these effects for the three types of research outlined above:

Proposition 2.2. *Let two informed agents with research efforts $\omega_1 \geq \omega_2$ obtain signals s_1 and s_2. Assume infinite-divisibility condition holds and let $\rho = Cov(e_i, e_j) \times M^2/\Sigma_0$. Then the $Cov(s_1, s_2)$ is:*

$$
\begin{aligned}
Cov(s_1, s_2) &= \Sigma_0 \times \rho \times \omega_1\omega_2 - \textit{non-overlapping}, && (43)\\
Cov(s_1, s_2) &= \Sigma_0 \times \omega_2 \times (1 - (1 - \omega_1)\rho) - \textit{perfectly-overlapping}, && (44)\\
Cov(s_1, s_2) &= \Sigma_0 \times \omega_1\omega_2 - \textit{independently-overlapping}. && (45)
\end{aligned}
$$

See Appendix G.2 for proof.

An interesting result we obtain is the equivalence of independently-overlapping research technology defined above and the approach introduced by Verrecchia [1982] and commonly used in the literature on information acquisition:

Proposition 2.3. *Consider the following definition of a signal: $\widetilde{s}_i = v + \varepsilon_i$ where ε_i is agent-specific forecast error uncorrelated across agents: $Cov(\varepsilon_i, \varepsilon_j) = 0$. Precision of forecast error ε_i is proportional to agent's expenditures on research c_i: $Var(\varepsilon_i) = 1/\widetilde{TC}^{-1}(c_i)$, where $\widetilde{TC}(\cdot)$ is an increasing function. This research technology is equivalent to independently-overlapping research technology defined above (Definition 2.2).*

Proof. Define w_i and $TC(w_i)$ in the following way:

$$
\begin{aligned}
\omega_i &= \frac{\Sigma_0(1-\rho)\widetilde{TC}^{-1}(c_i)}{1 + \Sigma_0(1-\rho)\widetilde{TC}^{-1}(c_i)} \in [0, 1),\\
TC(\cdot) &: TC\left(\frac{\Sigma_0(1-\rho)\widetilde{TC}^{-1}(c_i)}{1 + \Sigma_0(1-\rho)\widetilde{TC}^{-1}(c_i)}\right) = c_i.
\end{aligned}
$$

Then rescale each agent's signal: $s_i = \omega_i \times \widetilde{s}_i = \omega_i \times (v + \varepsilon_i)$. Scaling by a constant keeps information contained in agents' signals unchanged. It is straightforward to verify that joint distribution of vector $(v, s_1, \cdots, s_N)$ is the same as under independent-overlapping research technology, thus the two research technologies are equivalent. $\square$

The result in proposition 2.3 is an interesting alternative interpretation for the research technology proposed by Verrecchia [1982]. Suppose there exists a pool of identically distributed bits of information, that may be correlated with each other. When two informed agents choose the optimal size of samples to draw from the pool and draw the samples independently of each other, this process will be equivalent to saying each agent observes the true value of the asset distorted by idiosyncratic noise, independent of other agents. The size of the sample drawn from the pool translates into the variability of the idiosyncratic noise. It is also interesting how this reframing of Verrecchia's approach allows us to generalize and study various alternative scenarios for agents' overlaps, other than independent sampling.

Finally, we want to span intermediate scenarios of overlaps that occur in between the three described above. We introduce a parameter $\gamma \in [0, 1]$ that captures severity of overlaps: $\gamma = 0$ corresponds to non-overlapping research; $\gamma = 0.5$ corresponds to independently-overlapping research; $\gamma = 1$ corresponds to perfectly-overlapping research. We use linear interpolation to describe what happens for intermediate values of γ, the following proposition summarizes results:

Proposition 2.4. *Let two informed agents with research efforts $\omega_1 \geq \omega_2$ obtain signals s_1 and s_2. Assume infinite-divisibility condition holds and let $\rho = Cov(e_i, e_j) \times M^2/\Sigma_0$. Let $\gamma \in [0, 1]$ describe the degree of overlaps in agents' research so that for $\gamma \leq 0.5$ the linear interpolation between non-overlapping and independently-overlapping scenarios is made, while for $\gamma > 0.5$ the linear interpolation between independently-overlapping and perfectly-overlapping scenarios is made. Then the $Cov(s_1, s_2)$ is:*

$$\begin{aligned} Cov(s_1, s_2) &= \Sigma_0 \times \omega_1\omega_2 \times (\rho + 2\gamma(1-\rho)), \ \textit{when } \gamma \leq 0.5, \qquad (46) \\ Cov(s_1, s_2) &= \Sigma_0 \times \omega_2 \times (\rho\omega_1 + (1-\rho)(1 + 2(\gamma-1)(1-\omega_1))), \ \textit{when } \gamma > 0.5. \end{aligned}$$

See Appendix G.3 for proof.

2.4 The Limiting Stochastic Process

In the prior discussion we used discrete number of fundamentals M, as a consequence the feasible set of research efforts was discrete as well—we relied on $\omega_i M$ being a Natural number. In this section we generalize our discussion and derive the limiting stochastic process that describes the structure of information and rationalizes any real value for agent's research effort $\omega_i \in [0, 1]$.

Definition 2.3. *Suppose that the unit interval $V = [0, 1]$ describes the universe of information available for agents to do research. Agents have acquired access to information sets $S_i \in V$ via research effort $\omega_i = \mu(S_i) \in (0, 1]$. Let $W(t)$ be Brownian motion. Then the informative signal agents obtain is defined as:*

$$s_i = \int_{S_i} dX(t), \text{ where:} \tag{47}$$

$$dX(t) = \frac{\rho}{(1-\rho)+\rho t} X(t) \times dt + \sqrt{\Sigma_0(1-\rho)} \times dW(t). \tag{48}$$

The SDE in equation 48 describes random process $X(t)$ that we use to capture the information structure in our model. Using the continuous version of the signal, we can define overlaps scenarios as related to the measure of intersection of agents' information sets. When there are two agents with information sets $S_i \in V$ and research efforts $\omega_i = \mu(S_i) \in (0, 1]$ and $\mu(S_2) \leq \mu(S_1)$, we have:

1. Non-overlapping research is defined as: $\mu(S_1 \cap S_2) = 0$,
2. Perfectly-overlapping research is defined as: $\mu(S_1 \cap S_2) = \omega_2$,
3. Independently-overlapping research is defined as: $\mu(S_1 \cap S_2) = \omega_1 \omega_2$.

The following proposition establishes equivalence between the discrete and continuous versions of informative signals defined above. The continous definition in equation (47) is more general in the sense that it does not rely on $\omega_i M$ being an integer number. It justifies the jointly Normal distribution of signals and the true asset value v with the same covariance matrix as provided by the discrete version in propositions 2.1 and 2.2.

Proposition 2.5. *The discrete version of an informative signal defined in equation (41) is equivalent to the continuous version defined in equation (47) in terms of its distributional properties $Var(s_i)$, $Cov(s_i, s_j)$, and $Cov(s_i, v)$, whenever discrete version is well-defined. See Appendix G.4 for proof.*

3 Trading Environment

We study the aforementioned research technologies within a strategic trading environment based on Kyle [1985]. The model that follows is used to demonstrate the key results of this paper, however the generalized learning technologies with overlaps discussed above can be used in alternative economic settings and models featuring uncertainty.

To simplify the exposition we use one-period trading model with a single asset traded and two competing agents with access to costly information acquisition. There is a mass of uninformed liquidity traders with no such access and a competitive market-maker intermediating the trades. We assume preferences of all agents exhibit risk-neutrality. The asset has common liquidation value $v \sim N(\overline{v}_0, \Sigma_0)$. Prior to trading each of the two agents learns a private signal—a realization of random variable s_i, which is correlated with v and another agent's signal s_j.[19] Upon observing the signals, each agent submits market order $x_i = X_i(s_i)$ to the market-maker, where $X_i(\cdot)$ is a measurable function of s_i. Liquidity traders' aggregate order flow is $u \sim N(0, \sigma_u^2)$ and is independent of all other random variables in the model. The market-maker accommodates excessive order flow $\Sigma x + u = \sum_{i=1}^{2} x_i + u$ and sets the price $p = P(\Sigma x + u)$, where $P(\cdot)$ is a measurable function of total order flow $\Sigma x + u$. Expected trading profits for each of the two agents are $E(\pi_i|s_i) = E((v-p)x_i|s_i) = E\Pi_i(X_i, X_j, P)$. Profit of one agent depends on the other agent's strategy through the total order flow and price. Below we define the trading equilibrium.

Definition 3.1. *A* trading equilibrium *is a set of functions X_1, X_2, P that satisfies two conditions:* (49) Profit Maximization: *For any trader $\forall i \in \{1, 2\}$, any alternative trading strategy X' and any realization of i-th signal s_i (the opponent's trading strategy is denoted*

[19] The joint distribution of v and traders' signals s_i will be determined by the particular learning technology.

by X_{-i}) does not yield higher expected trading profit; and (50) Market Efficiency: *Function P satisfies the fair-pricing condition:*[20]

$$E\Pi_i(X_i, X_{-i}, P) \geq E\Pi_i(X', X_{-i}, P)\ \forall i \in \{1,2\} \quad , \tag{49}$$

$$P(\Sigma x + u) = E(v|\Sigma x + u) \quad . \tag{50}$$

We assume the vector of true value and informative signals $(v, s_1, s_2)^T$ is jointly-Normally distributed and we restrict our attention to linear pricing rule $P(\Sigma x + u)$ and linear trading strategies $X_i(s_i)$. The resulting linear trading equilibrium exists and is described in the following Proposition. We use the α_i notation for the amount of information each informed agent has: We measure informational content of a signal with the relative reduction in conditional variance of true asset value v after this signal is observed:

$$\alpha_i = \frac{\Sigma_0 - Var(v|s_i)}{\Sigma_0} \in [0,1]. \tag{51}$$

Proposition 3.1. *Let ρ_{12} denote the correlation between the signals s_1 and s_2 two informed agents obtain. There exists a unique linear trading equilibrium defined by $X_i = (\beta_i/\lambda)s_i$ for each $i \in \{1,2\}$ and $P = \lambda(\Sigma x + u)$ where constants β_i and λ are:*

$$\beta_i = \sqrt{\frac{\Sigma_0}{Var(s_i)}} \times \frac{\left(2\sqrt{\alpha_i} - \rho_{12}\sqrt{\alpha_j}\right)}{4 - (\rho_{12})^2}, \tag{52}$$

$$\lambda = \sqrt{\frac{\Sigma_0}{\sigma_u^2}} \times \frac{\sqrt{\left(2\sqrt{\alpha_1} - \rho_{12}\sqrt{\alpha_2}\right)^2 + \left(2\sqrt{\alpha_2} - \rho_{12}\sqrt{\alpha_1}\right)^2}}{4 - (\rho_{12})^2}. \tag{53}$$

See Appendix H.1 for proof.

3.1 Endogenous Research Efforts

A research technology featuring a particular overlaps scenario determines distributional properties of informed agents' signals. For any chosen research efforts of informed agents a unique linear trading equilibrium will arise according to Proposition 3.1. In this section

[20]The market efficiency condition is implied by the competition for market-making business that drives expected profits to zero.

we assume that both agents choose their research efforts $\omega_i \in [0,1]$ simultaneously in the beginning of the trading game and then learn realizations of their signals s_i. We need to evaluate incentives of each informed agent to stay in a given trading equilibrium, and know what happens to the trading profit when any agent makes an unobserved deviation and obtains signal with different properties. We assume that such deviations are unobservable to all other market participants.

Definition 3.2. *Denote by $\Psi^\omega = \Psi(\omega_1, \omega_2)$ the covariance matrix of signals $s_1(\omega_1)$, $s_2(\omega_2)$, and the true value v. Denote by $(X_1^\omega, X_2^\omega, P^\omega)$ the unique linear trading equilibrium for Ψ^ω. Research intensities (ω_1, ω_2) constitute* a Nash equilibrium of the game *if $\forall \hat{\omega} \in [0,1]$ and $\forall i \in \{1,2\}$ the following condition holds:*

$$\begin{aligned} \max\nolimits_{X_i} \left[E\Pi_i(X_i, X_{-i}^\omega, P^\omega) | s_i(\hat{\omega}) \right] - c(\hat{\omega}) \leq \\ \leq E\Pi_i(X_i^\omega, X_{-i}^\omega, P^\omega | s_i(\omega_i)) - c(\omega_i). \end{aligned} \tag{54}$$

Condition 54 highlights two important points: 1) when one informed agent chooses an off-equilibrium research effort $\hat{\omega}$, all other market participants do not observe that move; 2) the deviating agent is able to reoptimize its trading strategy X_i given the new properties of the obtained signal $s_i(\hat{\omega})$. In the following lemma we derive the re-optimized trading strategy for deviating agent and the associated expected profits.

Lemma 3.1. *Suppose informed agent i enters the trading game with an arbitrary signal s_i^{new}. The opponent and the market-maker do not observe the quality of the new signal, instead they follow a given trading equilibrium for some covariance matrix Ψ (their belief about s_i may no longer be consistent with the true properties of s_i^{new}). Under these circumstances, given β_{-i} and λ determined according to Proposition 3.1, agent i's optimal trading strategy is $X_i^{\text{new}} = (\beta_i^{\text{new}}/\lambda) s_i^{\text{new}}$ where:*

$$\begin{aligned} \beta_i^{\text{new}} &= \frac{1}{2\sqrt{Var(s_i^{\text{new}})}} \left(\sqrt{\Sigma_0 \times \alpha_1^{\text{new}}} - \rho_{12}^{\text{new}} \times \sqrt{Var(s_{-i})} \times \beta_{-i} \right), \quad (55) \\ E(\pi_i^{\text{new}}) &= \frac{1}{4\lambda} \left(\sqrt{\Sigma_0 \times \alpha_1^{\text{new}}} - \rho_{12}^{\text{new}} \times \sqrt{Var(s_{-i})} \times \beta_{-i} \right)^2. \quad (56) \end{aligned}$$

See Appendix H.2 for proof.

Now we present our results on existence and uniqueness of Nash equilibria under different overlaps scenarios. For convenience of our analysis we impose restriction on the cost function $TC(\omega)$ so that a single informed agent active on the market never finds it optimal to acquire the entire information set, corresponding to $\omega = 1$. We refer to such condition as *single-agent-interior condition*.

Single-Agent-Interior Condition. *In a model with a single informed agent and a given research technology characterized by overlaps scenario $\gamma \in [0, 1]$ and weakly convex cost function $TC(\omega)$ the agent's optimal research effort is in the interior of the feasible set: $\omega_1 \in (0, 1)$. This is ensured by the following restriction on the cost function:*

$$\frac{\mathrm{d}TC}{\mathrm{d}\omega}(\omega = 1) > \frac{(1-\rho)\sqrt{\Sigma_0 \times \sigma_u^2}}{2}. \tag{57}$$

We study interior equilibria with $\omega_1, \omega_2 \in (0, 1)$ as well as corner equilibria with $\omega_1 > \omega_2 = 0$. Without loss of generality we assume $\omega_1 \geq \omega_2$. All informed agents has access to the same research technology and research is equally costly to agents. Note that our results rely on the assumption that all bits of information (fundamentals) are constructed to be identically distributed and equally costly to reveal, as discussed in section 2.2. Under this assumption we establish the result that asymmetric interior Nash equilibria do not exist when research technology is characterized by low degree of overlaps across agents ($\gamma \leq 1/2$). An alternative case may occur when some fundamentals are cheaper to acquire than others, while the informational content of all of them is the same. In this case asymmetric interior equilibria are more likely to exist, however we do not include formal analysis of these cases in this paper.

Lemma 3.2. *Under a research technology characterized by low degree of overlaps $\gamma \leq 1/2$ and linear trading and pricing rules, if for some linear cost function $TC(\omega_i)$ an interior Nash equilibrium exists with $\omega_i \in (0, 1), \forall i \in \{1, 2\}$, and $\gamma \neq \frac{\rho}{2(1-\rho)}$, then this equilibrium is symmetric so that $\omega_1 = \omega_2$.*

See Appendix H.3 for proof.

We are also interested in corner Nash equilibria, where one of the two agents willfully decides not to participate neither in research nor trading. We refer to these occurrences as endogenously-generated barriers-to-entry (however, we work with a simultaneous-move game). The next lemma locates corner equilibria in our model.

Lemma 3.3. *Assume a linear cost function $TC(\omega_i)$ that satisfies single-agent-interior condition and in a model with one informed agent the optimal research effort is $\omega^* \in (0,1)$. Under a research technology characterized by degree of overlaps γ and linear trading and pricing rules, there exists a corner Nash equilibrium with $\omega_1 = \omega^*, \omega_2 = 0$ if and only if the following holds:*

$$\rho \leq \frac{2\gamma}{1+2\gamma}, \text{ when } \gamma \leq 1/2, \tag{58}$$

$$\rho \leq \frac{(2-2\gamma)\omega^* + 2\gamma - 1}{(3-2\gamma)\omega^* + 2\gamma - 1}, \text{ when } \gamma > 1/2. \tag{59}$$

See Appendix H.4 for proof.

It should be noted that condition 59 depends on single-firm equilibrium research effort ω^*. The intuition behind this is most apparent when we consider perfectly-overlapping research technology $\gamma = 1$. The less advanced agent performs catch-up research as long as his research effort is less than of the competitor. The more advanced is the leading researcher, the longer the path to unique bits of information for the less advanced one. This idea is captured when we formalize research technologies for $\gamma > 1/2$ by taking linear interpolation in proposition 2.4.

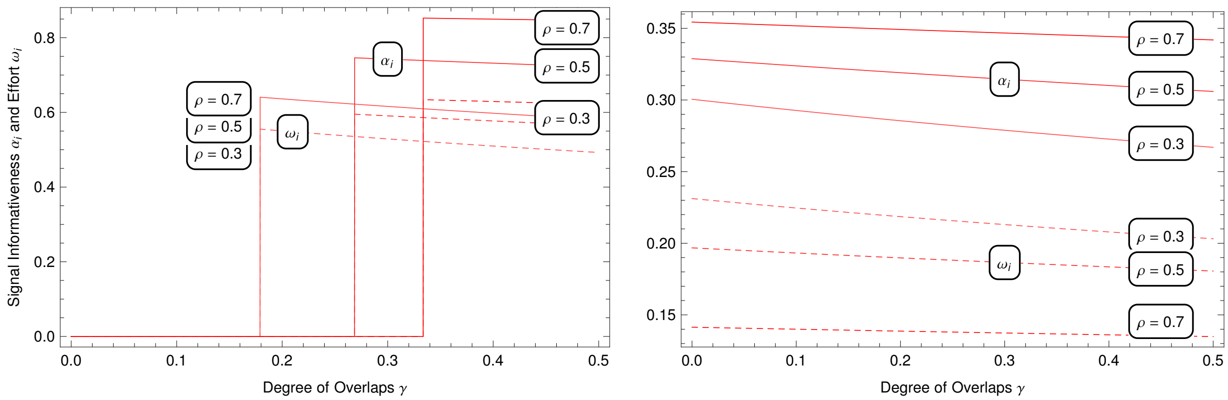
The following proposition completes the set of results on existence and uniqueness of Nash equilibria in our setting. It turns out that our specification of research technologies with high degree of overlaps ($\gamma > 1/2$) in Proposition 2.4 rules out existence of symmetric Nash equilibria. To simplify our analysis of asymmetric Nash equilibria that occur when $\gamma > 1/2$, in this paper we restrict our attention to the extreme perfectly-overlapping scenario characterized by $\gamma = 1$. This case is at the end of the spectrum of possible overlap scenarios, under which all informed agents perform research of fundamentals in the same sequence, resulting is the highest possible correlation in the informative signals they obtain.

Proposition 3.2. *Assume that a linear cost function $TC(\omega_i)$ satisfies single-agent-interior condition. Under a research technology characterized by degree of overlaps γ and linear trading and pricing rules: 1) In the class of interior Nash equilibria with $\omega_i \in (0,1), \forall i \in \{1,2\}$ there exists a unique such Nash equilibrium when $\gamma \leq 1/2$ that is symmetric: $\omega_1 = \omega_2 \in (0,1)$. 2) There exists a unique asymmetric Nash equilibrium when $\gamma = 1$.*
See Appendix H.5 for proof.

Figures 13 and 14 demonstrate optimal choices of research efforts ω and resulting proportional reduction in posterior variance of v, referred to by α. We refer to α as informational content in agents' signals, while ω is needed primarily to measure physical cost of doing research and acquisition of bits of information and fundamentals. Each of the figures has two panels: Left panel corresponds to relatively low marginal cost of research, such that a single agent would have optimally acquired all bits of information (results in no more uncertainty about v); right panel corresponds to relatively high marginal costs of research, such that a single agent would have reduced posterior variance of v only by half.

In our model parameter $\rho \in (0,1)$ relates to correlation between bits of information (fundamentals) and affects marginal (informational) returns to a dollar spent on research. We assume that the total cost of doing research is linear in the proportion of bits of information revealed by agent. Higher values of ρ mean that the first few bits of information provide some partial information about the remaining bits that were not yet acquired. This creates diminishing returns to a dollar spent on research—because partly the newly acquired bits information were already predicted by the bits acquired before, through correlation. It turns out the magnitude of this correlation has important consequences for the resulting Nash equilibria.

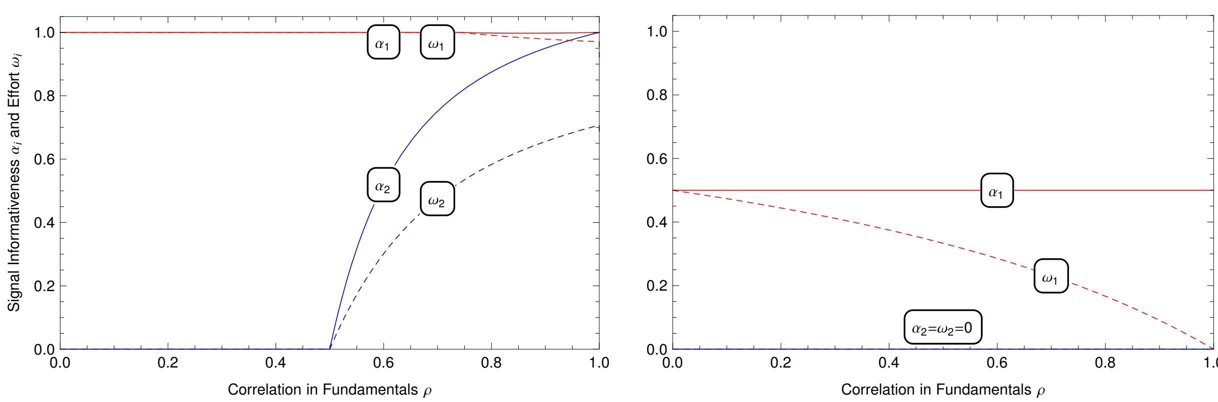
Figure 13: Optimal Choices of Research Efforts ω_i and Signal Informativeness α_i ($\gamma \leq 1/2$)



Panel A: Single-agent $\omega^* = 1$ Panel B: Single-agent $\omega^* = 0.5$

The figures illustrate how more severe overlaps reduce incentives to acquire information in equilibrium. Also, the perfectly-overlapping research presented in figure 14 below is especially interesting, because for a wide set of model parameters there are endogenous barriers to entry created for the second informed agent. When $\rho\alpha_1 \leq 1/2$ the second agent optimally decides to stay away from doing research and trading (see appendix H.5 for details).

Figure 14: Optimal Choices of Research Efforts ω_i and Signal Informativeness α_i ($\gamma = 1$)



Panel A: Single-agent $\omega^* = 1$ Panel B: Single-agent $\omega^* = 0.5$

3.2 Submodularity of Research Efforts

The strategic trading model with multiple informed traders who choose optimally their research efforts can be shown to represent a *submodular game*, in which information acquisition efforts are strategic substitutes. The type of competition across traders is similar to a Cournot competition between firms choosing quantities, which is another typical example of a submodular game, though there are important differences.

In the baseline case of the model, there are three strategic players: Two traders, who are choosing informativeness of their private signals α_i, and a market-maker, who is choosing demand sensitivity parameter λ (the market-maker's zero profit condition can be cast as a least-squares prediction problem, see Bernhardt and Taub [2008]). In case of low degree of overlaps $\gamma < 1/2$, marginal benefit of one trader's information acquisition effort is proportional to:

$$\frac{\partial E\pi_1(\alpha_1, \alpha_2, \beta_2, \lambda)}{\partial \alpha_1} = \frac{\Sigma_0(1 - (2\gamma(1-\rho) + \rho)A(\alpha_1, \alpha_2))^2}{4\lambda},$$
$$\text{where: } A(\alpha_1, \alpha_2) = \sqrt{\alpha_2}\beta_2\sqrt{Var(s_2)}.$$

Using our results in Proposition 3.1 it follows that the incentives of the first trader to acquire information are decreasing in the function $A(\alpha_1, \alpha_2)$, while this function is increasing in the informativeness of the other trader's private signal α_2. Thus, for any fixed strategy λ of the market maker, information acquisition efforts of the two traders are strategic substitutes: *A more informative signal of one trader reduces the incentive to acquire information for the other trader.* The equation above demonstrates that both trader's incentives to acquire information depend negatively on the market-maker's strategy λ: *More sensitive price response to the total order flow reduces incentives to acquire private information.*

In the following section we present our analysis of competition between informed agents and its effects on equilibrium price informativeness, market depth, price and volume volatilities.

4 Analysis

There are two forces that drive competition between informed agents and jointly determine equilibrium trading outcomes (such as price-informativeness, market depth, price and volume volatilities). The first force is trading aggressiveness of agents—their optimal choices of trading strategies given the information they possess feed back into market-maker's pricing and information revelation through price movements. It can be demonstrated that two informed agents having identically distributed signals s_1 and s_2 reveal more information through price movement compared to a single agent having the same total amount of information and a signal $s_3 : V(v|s_3) = V(v|s_1, s_2)$. The second force is competition in information acquisition among informed agents that determines their informational endowments prior to trading. The more informed agents compete on the same market, the lower are trading profits and so are incentives to acquire accurate information in the first place. This second force can counter-balance the trading aggressiveness effect and reduce the total amount of information revealed by price movements. Severity of overlaps in agents' information sets play important role in relative strengths of the two forces described above. More severe overlaps increase correlation in agents' signals and reduce the total amount of information agents possess. We present equilibrium trading outcomes under different overlaps scenarios in the following analysis.

It is important to understand first how a model with a single informed agent works in the context of our study. When there is a single informed agent on the market, trading equilibrium is characterized by $\beta_1 = \frac{\sqrt{\Sigma_0}\sqrt{\alpha_1}}{2\sqrt{Var(s_i)}}$ and $\lambda = \frac{\sqrt{\Sigma_0}\sqrt{\alpha_1}}{2\sqrt{\sigma_u^2}}$. The equilibrium trading strategy (market order) of informed agent is $(\beta_1/\lambda)s_1 = \sigma_u \frac{s_1}{\sqrt{Var(s_1)}}$ and its variance does not depend on agent's informativeness of signal α_1 (recall it is equal to proportional reduction in conditional variance of true asset value v upon observing signal s_1). In equilibrium the informed agent scales the signal so that the variance of the market order is equal to the variance of liquidity traders' total order flow u (consistent with Kyle [1985] and Dierker [2006]). The two observations to take away are: 1) When there is a single informed agent on the market, no matter what its research effort is, it masks its trades behind liquidity traders by issuing an uncorrelated market order of the same variance; 2) The competitive market maker sets its pricing rule so that in the equilibrium the more information informed agent has, the higher pricing response to aggregate order flow is.

Throughout our analysis we consider two scenarios for the marginal cost of doing research (recall that in our model we assume linear total cost function in ω, the proportion of informative bits acquired). Under the first scenario the level of marginal cost is set so that a single informed agent on the market would always find it optimal to have full amount of information $\alpha = 1$, that is to know the true asset value v. Under the second scenario a single informed agent finds it optimal to reduce posterior variance of true value v by half, that is acquire bits of information until $\alpha = 0.5$. These two scenarios serve as a benchmark for our study how particular outcome is affected when two informed agents compete.

The assumption that the total cost function is linear in the proportion of informative bits acquired by agents ω_i does not preclude diminishing returns to a dollar spent on research. Positive correlation of identically distributed informative bits captured in our parameter ρ create diminishing returns, and by changing ρ we can adjust the magnitude of this effect. Throughout our analysis we consider several alternative values of ρ.

4.1 Analysis of Price Informativeness

Once the trading period is over, an outside observer can learn information about asset value by observing prices at which transactions with market-maker took place (or total trading volume, which is informationally equivalent in the model). The informativeness of prices can be measured by relative reduction in conditional variance of the true asset value v. We denote this measure by $\mathcal{L}$:

$$\mathcal{L} = \frac{\Sigma_0 - Var(v|\Sigma x + u)}{\Sigma_0} \in [0, 1]. \tag{60}$$

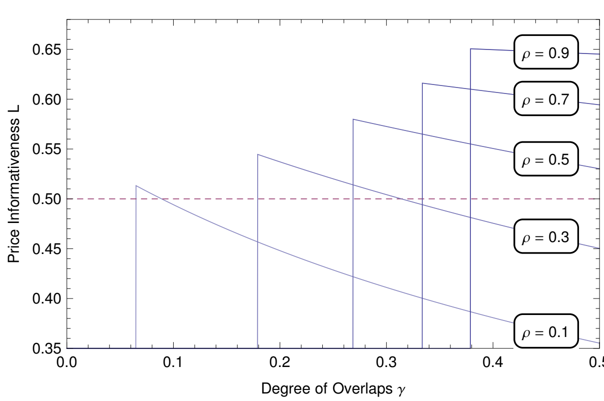
When there is a single informed agent on the market, the equilibrium price informativeness is $\mathcal{L} = \frac{\Sigma_0 - Var(v|\Sigma x + u)}{\Sigma_0} = \frac{\alpha_1}{2}$. Consistent with Kyle [1985] exactly half of insider's information gets revealed to the general public through price movements. The following lemma presents $\mathcal{L}$ for the model with two informed agents.

Lemma 4.1. *In the trading equilibrium outlined in Proposition 3.1 the equilibrium price informativeness is:*

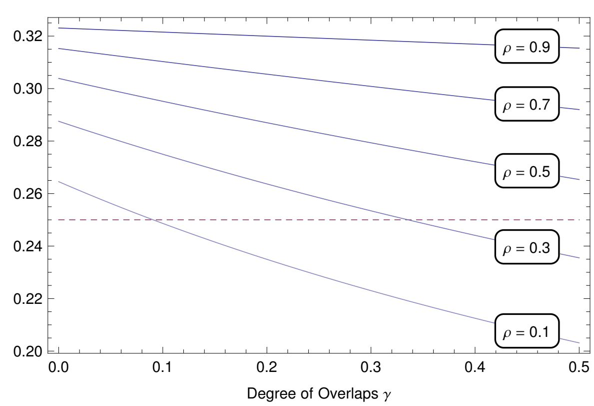
$$\mathcal{L} = \frac{2(\alpha_1 + \alpha_2) - \rho_{12}\sqrt{\alpha_1}\sqrt{\alpha_2}}{4 - (\rho_{12})^2}. \tag{61}$$

It is ambiguous how price informativeness is affected when there is an additional informed agent on the market. When α_1 and α_2 are sufficiently close to each other, price informativeness in Lemma 4.1 depends positively on the amount of information agents have and depends negatively on correlation of signals ρ_{12}. We need to evaluate how much more or less information agents acquire in a more competitive setting under a particular overlaps scenario. To answer this question we compare the two-agent trading model described above to a single-agent benchmark. As it follows from our results in section 3.1 the two sets of possible overlaps scenarios—relatively low overlaps with $\gamma \leq 1/2$ and relatively high overlaps with $\gamma > 1/2$ —must be considered separately given the way we specify correlation in agents' signals in Proposition 2.4.

Figure 15: Effect of Overlaps on Price Informativeness $\mathcal{L}$ ($\gamma \leq 1/2$)



Panel A: Single-agent $\alpha^* = 1$



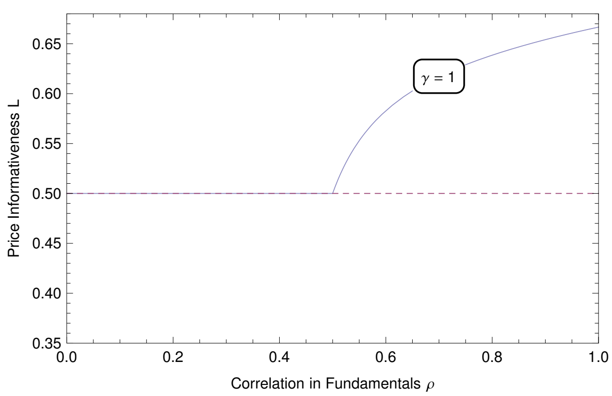
Panel B: Single-agent $\alpha^* = 0.5$

Figure 15 shows effect of overlaps on price informativeness when $\gamma \leq 1/2$: The left panel corresponds to relatively low cost of doing research (so that a single informed agent prefers to acquire the entire truth), the right panel corresponds to relatively high cost of research (single informed agent acquires a signal that drops posterior variance of true value by half). It should be noted that for the relatively low level of marginal cost, some values of γ are not feasible—this happens when two informed agents in total tend to acquire more than 100% of bits of information (e.g. two agents cannot acquire 60% of bits each and not overlap)—we do not show corresponding part of the curve for these values. Also note that this does not happen for relatively high marginal costs the way we define it.

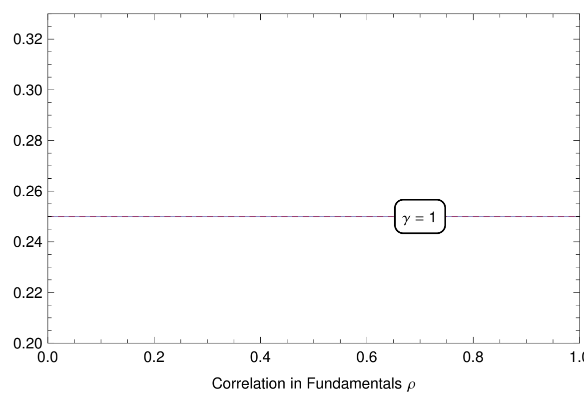
The general result we observe is that when bits of information are not highly correlated and the degree of diminishing returns in doing research is small (small values of ρ), high degree of overlaps results in lower equilibrium price informativeness when two informed agents compete (the curve is below the dashed line, which is the single agent benchmark). Low correlation in fundamentals make research a harder task—more fundamentals need to be revealed at cost to reduce posterior variance of true value v by the same amount.

Figure 16 presents similar analysis for the perfectly-overlapping research ($\gamma = 1$ case).

Figure 16: Effect of Overlaps on Price Informativeness $\mathcal{L}$ ($\gamma = 1$)



Panel A: Single-agent $\alpha^* = 1$



Panel B: Single-agent $\alpha^* = 0.5$

The finding there is that for relatively low values of ρ the second informed agent does not acquire any information whatsoever, while on the right panel corresponding to relatively high marginal costs of research this happens for all values of ρ. However, whenever ρ is high and there is potential scope for entry by the second informed agent, the price informativeness increases in equilibrium.

4.2 Analysis of Market Depth

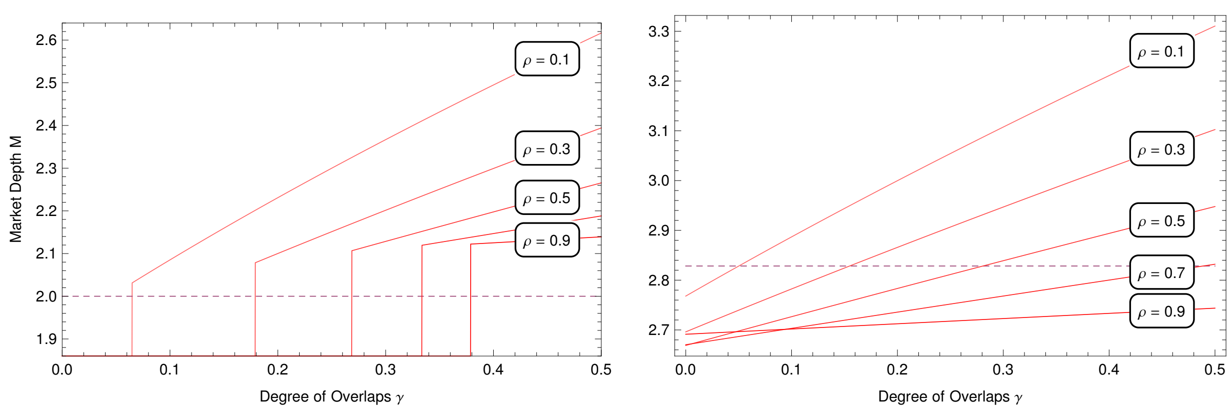
Market depth is the inverse of price sensitivity to the total order flow. We denote this measure by $\mathcal{M}$. On a deeper market larger trades can be executed without affecting the equilibrium price too much. Market depth is especially important for large institutional traders with big orders and arbitrage seekers (in the context of our model—informed agents).

When there is a single informed agent on the market, in equilibrium market depth is inversely proportional to the amount of information in agent's signal α_1: $(1/\lambda) = \frac{2\sigma_u}{\sqrt{\Sigma_0}\sqrt{\alpha_1}}$.

In the trading equilibrium outlined in Proposition 3.1 the equilibrium market depth is equal to $1/\lambda$:

$$\mathcal{M} = \frac{1}{\lambda} = \sqrt{\frac{\sigma_u^2}{\Sigma_0}} \times \frac{4 - (\rho_{12})^2}{\sqrt{\left(2\sqrt{\alpha_1} - \rho_{12}\sqrt{\alpha_2}\right)^2 + \left(2\sqrt{\alpha_2} - \rho_{12}\sqrt{\alpha_1}\right)^2}}. \tag{62}$$

Figure 17: Effect of Overlaps on Market Depth $\mathcal{M}$ ($\gamma \leq 1/2$)

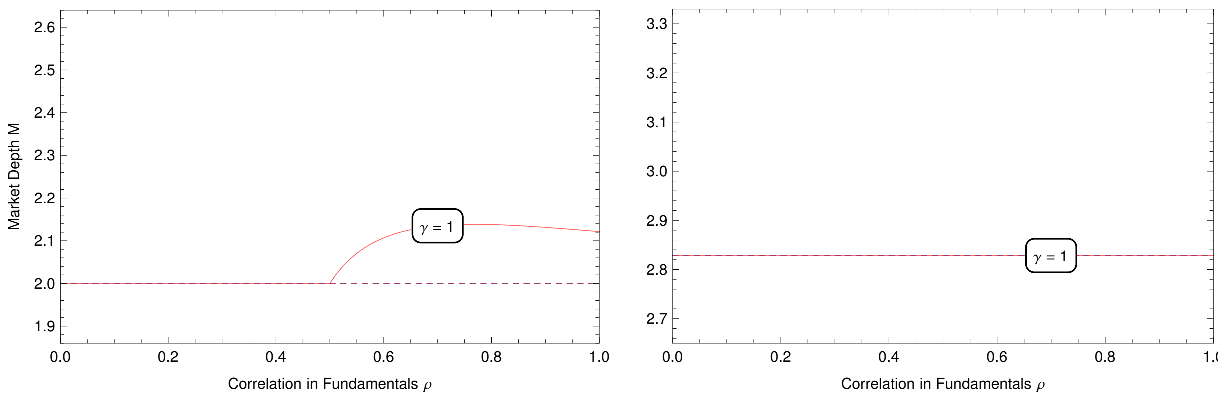


Panel A: Single-agent $\alpha^* = 1$ Panel B: Single-agent $\alpha^* = 0.5$

Figure 17 presents the effect of overlaps on market depth when $\gamma \leq 1/2$. In general we observe market depth increasing with the degree of overlaps in agent's information sets. This finding is intuitive: More overlaps increase correlation in agents' signals and make their orders more correlated with each other. This in turn reduces degree of adverse selection market maker faces and allows a deeper market to be made. Our analysis confirms this intuition for the Nash equilibrium we find.

Figure 18 presents similar analysis for the perfectly-overlapping research $\gamma = 1$.

Figure 18: Effect of Overlaps on Market Depth $\mathcal{M}$ ($\gamma = 1$)



Panel A: Single-agent $\alpha^* = 1$ Panel B: Single-agent $\alpha^* = 0.5$

4.3 Remarks on Volatility of Prices and Total Order Flow

We refer to variance of the equilibrium price level $Var(p)$ as the volatility of prices. When there is a single informed agent on the market, it is equal to: $Var(p) = \frac{\Sigma_0 \alpha_1}{2}$.

It turns out that in the trading model we consider the price informativeness measure in equilibrium scaled by the variance of true value v is always equal to the volatility of price level. This is captured by the following Lemma:

Lemma 4.2. *In the trading equilibrium outlined in Proposition 3.1 the equilibrium volatility of prices is equal to the product of equilibrium price informativeness and ex ante volatility of true asset value v:*

$$Var(p) = \Sigma_0 - Var(v|\Sigma x + u) = \Sigma_0 \times \mathcal{L}. \tag{63}$$

Proof.

$$\Sigma_0 - Var(v|\Sigma x + u) = \frac{Cov(v, \Sigma x + u)^2}{Var(\Sigma x + u)} = \left(\frac{Cov(v, \Sigma x + u)}{Var(\Sigma x + u)}\right)^2 \times Var(\Sigma x + u) = (\lambda^2) \times Var(\Sigma x + u).$$

□

So all our results about price informativeness in section 4.1 apply to volatility of prices as well.

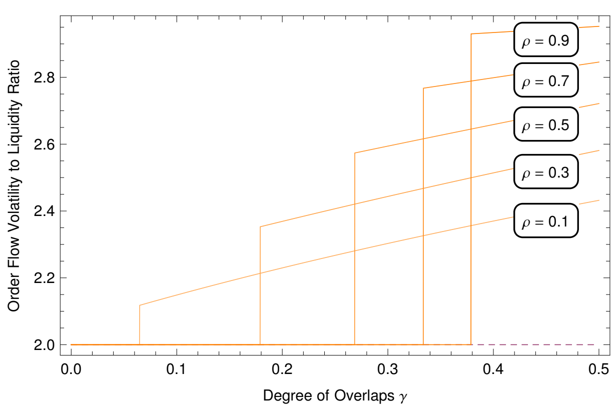
The total order flow volatility is defined as $Var(\Sigma x + u)$. The single agent benchmark for the total order flow volatility is $2\sigma_u^2$.

Lemma 4.3. *In the trading equilibrium outlined in Proposition 3.1 the equilibrium volatility of total order flow is:*

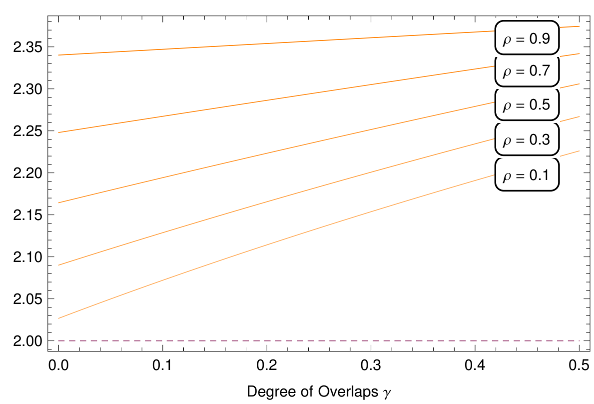
$$Var(\Sigma x + u) = \sigma_u^2 \times (4 - (\rho_{12})^2) \times \frac{2((\alpha_1 + \alpha_2) - \rho_{12}(\sqrt{\alpha_1}\sqrt{\alpha_2}))}{(2(\sqrt{\alpha_1}) - \rho_{12}(\sqrt{\alpha_2}))^2 + (2(\sqrt{\alpha_2}) - \rho_{12}(\sqrt{\alpha_1}))^2}. \quad (64)$$

Figure 19 presents the effect of overlaps on total order flow volatility when $\gamma \leq 1/2$. On the y-axis we plot the ratio of $Var(\Sigma x + u)$ and the liquidity trade variance σ_u^2, for convenience of exposition. More severe overlaps increase similarity of agents' signals and the market orders they submit. It can be observed that in equilibrium the total order flow volatility generally increases with overlaps. It reflects all of the following: 1) Optimal information acquisition choices by agents; 2) competitive market order submission; 3) correlation in market orders that amplifies volatility of total order flow.

Figure 19: Effect of Overlaps on Total Order Flow Volatility $Var(\Sigma x + u)$ ($\gamma \leq 1/2$)



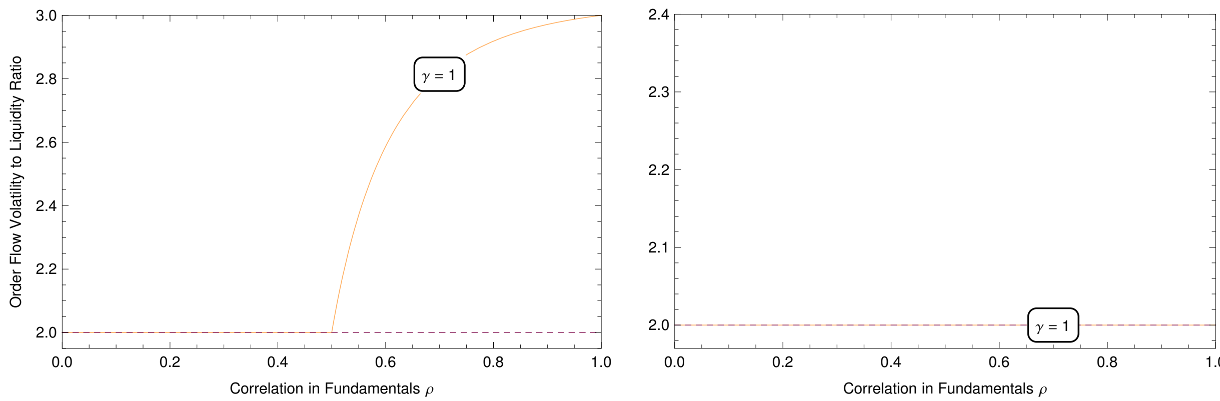
Panel A: Single-agent $\alpha^* = 1$



Panel B: Single-agent $\alpha^* = 0.5$

Figure 20 below presents similar analysis for perfectly-overlapping case when $\gamma = 1$. Note the entry deterrence-type of effect on the right panel of the figure—Nash equilibrium has no scope for the second informed agent to do research.

Figure 20: Effect of Overlaps on Total Order Flow Volatility $Var(\Sigma x + u)$ ($\gamma = 1$)



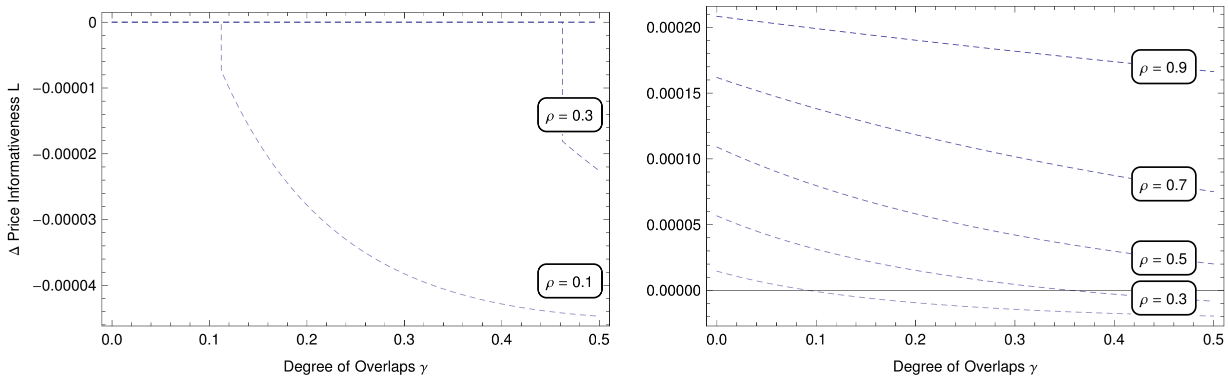
Panel A: Single-agent $\alpha^* = 1$ Panel B: Single-agent $\alpha^* = 0.5$

4.4 More Informed Agents in the Model

In this section we present our results for a trading model with N informed agents and symmetric equilibrium research efforts—under various overlaps scenarios. The underlying exercise we present in the current version of the draft is to solve a symmetric Nash equilibrium of a model with $N = 50$ informed agents and then compare it to the equilibrium with one additional informed agent ($N = 51$).

Figure 21 presents the marginal effect of an additional 51^{th} informed agent on equilibrium price informativeness under different overlaps scenarios. Since in this section we study symmetric equilibria only, we limit our attention to $\gamma \leq 1/2$—other values of γ do not sustain symmetric equilibria. The figure presents the difference in price informativeness levels due to an extra informed agent. We observe that our finding in section 4.1 is robust when we add more informed agents to the model. Note that the left panel of the figure present very limited segments of the plot—with more and more firms very low levels of overlaps γ become infeasible, due to more than 100% of bits of information being acquired by agents.

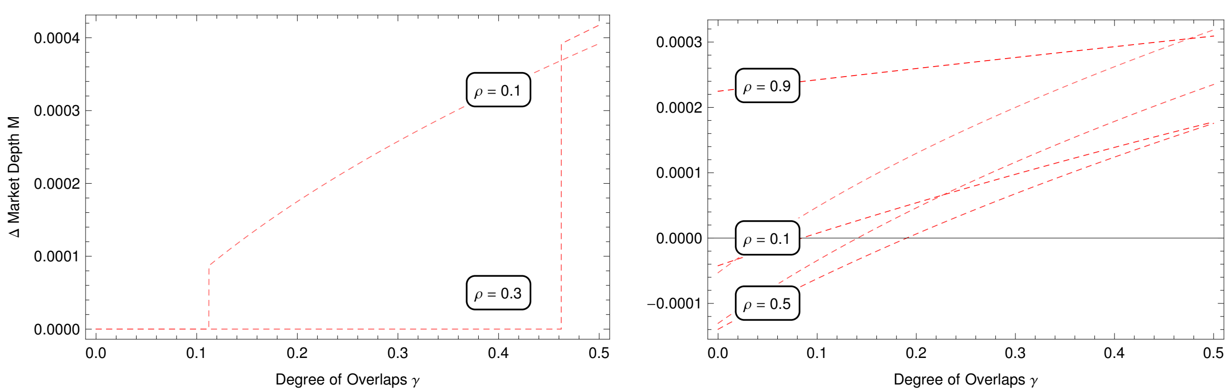
Figure 21: Effect of Overlaps on Marginal Change in Price Informativeness $\mathcal{L}$ when $N = 50$



Panel A: Single-agent $\alpha^* = 1$ Panel B: Single-agent $\alpha^* = 0.5$

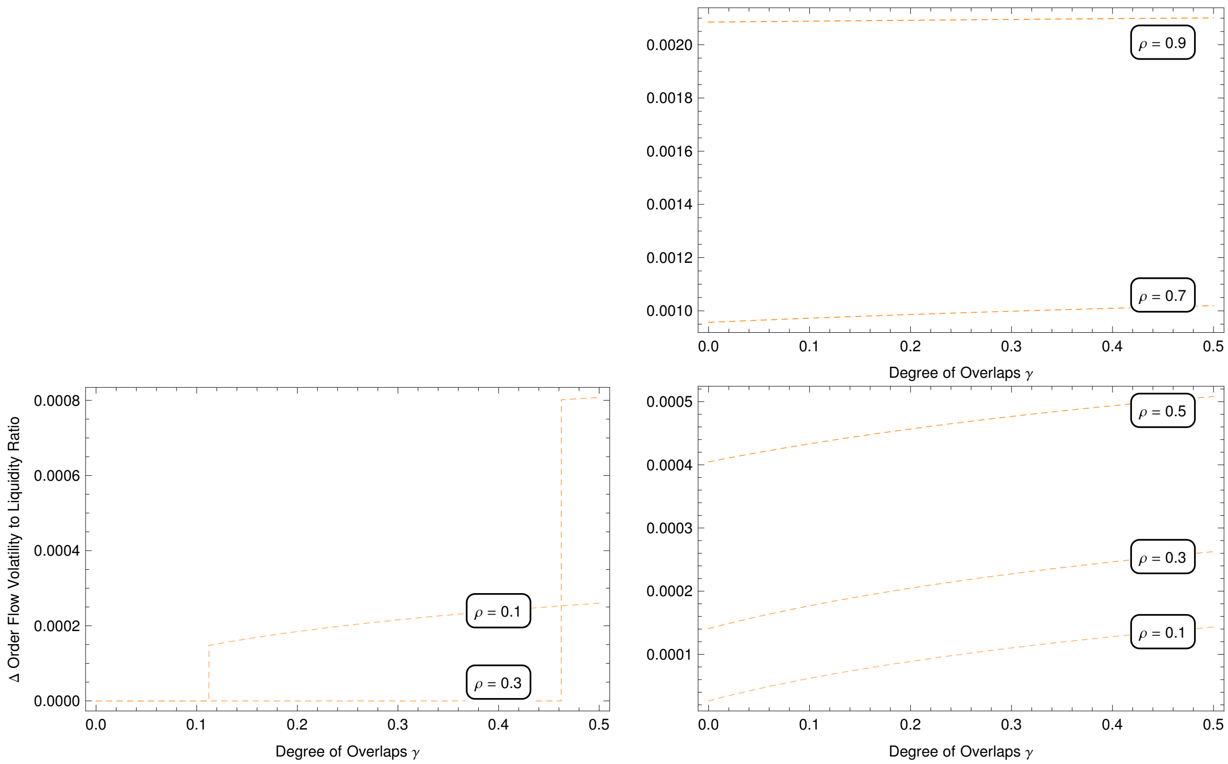
Figures 22 and 23 demonstrate similar analysis of market depth and total order flow volatility. It follows that our previous findings are robust as well. Additional informed agent generally increases market depth and total order flow volatility in the equilibrium.

Figure 22: Effect of Overlaps on Marginal Change in Market Depth $\mathcal{M}$ when $N = 50$



Panel A: Single-agent $\alpha^* = 1$ Panel B: Single-agent $\alpha^* = 0.5$

Figure 23: Effect of Overlaps on Marginal Change in Order Flow Volatility Ratio when $N = 50$



Panel A: Single-agent $\alpha^* = 1$ Panel A: Single-agent $\alpha^* = 0.5$

5 Conclusion

In this paper, we developed a framework to model multi-agent information acquisition with different scenarios of overlaps in agents' information sets. The framework nests the approach developed by Verrecchia [1982] in which agents make uncorrelated forecast errors as a special case and provides an alternative interpretation for it. The idea is to split the random variable that captures uncertainty about asset payoff into a number of identically distributed bits of information, or fundamentals, and then allow informed agents to reveal a fraction of these bits proportional to their research efforts. In the case when asset payoff is Normally distributed, we use the infinite-divisibility property of Normally distributed random variables and derive the limiting case when the number of bits in the split is infinite. The information structure is assumed to be smooth and infinitely divisible in identically distributed random variables, and agents can adjust their optimal research efforts by any small increments in a continuous fashion. Any two agents could either do research on distinct sources of information, in which case their signals would be correlated only through correlation in fundamentals. Alternatively, agents' signals could be highly similar when there is a significant overlap in the informative sources they study. These overlap scenarios together with possible intermediate cases are formalized in this paper: We characterize a mapping between agents' research efforts and the distributional properties of their informative signals under various different scenarios of overlaps.

Then we apply the developed methodology to a strategic trading model and study how competition between agents optimally choosing their research efforts and trading strategies affects equilibrium market outcomes, such as informativeness of asset prices, market depth, price and order flow volatilities. It is known in the literature that competition between informed agents generally enhances price informativeness and accuracy because more private information is revealed through informed agents' trading strategies. At the same time the competition reduces profitability of trading and creates incentives to acquire less precise information. Our model allows us to disentangle these effects and compare their relative strengths.

Appendices

G Information Structure and Research Technologies

G.1 Proposition 2.1

Proof. Equation (40) together with the $Var(v) = \Sigma_0$ implies:

$$MVar(e_i) + M(M-1)Cov(e_i, e_j) = \Sigma_0,$$
$$Var(e_i) = (1/M)(\Sigma_0 - M(M-1)Cov(e_i, e_j)). \tag{65}$$

Now use definition of a signal (41) together with the above equation (65) to calculate $Var(s_i)$ and $Cov(s_i, v)$:

$$Var(s_i) = \omega\Sigma_0 - \omega(1-\omega)M^2 Cov(e_i, e_j), \tag{66}$$
$$Cov(s_i, v) = Var(s_i) + \omega M(M - \omega M)Cov(e_i, e_j) = \omega\Sigma_0. \tag{67}$$

Equation (67) is the result we need. In order to simplify equation (66) we note that $Var(s_i)$ must not depend on M according to the infinite-divisibility condition presented in Section **??**. Thus as M increases, covariance of information bits e_i and e_j must decay at the rate M^2, in other words $Cov(e_i, e_j) = const/M^2$. We use the following normalization: $\rho = Cov(e_i, e_j) \times M^2/\Sigma_0$. Plugging this expression in equation (66) obtains the result. □

G.2 Proposition 2.2

Proof. We assume the infinite-divisibility condition holds and use the following normalization: $\rho = Cov(e_i, e_j) \times M^2/\Sigma_0$. There are two informed agents doing research, $\omega_1 \geq \omega_2$, and assume both $\omega_1 M$ and $\omega_2 M$ are Natural numbers. For non-overlapping research there are no common bits of information reflected in both traders' signals, thus:

$$Cov(s_1, s_2) = (\omega_1 M)(\omega_2 M)Cov(e_i, e_j) = \Sigma_0 \times \rho \times \omega_1\omega_2. \tag{68}$$

For perfectly-overlapping research we can rewrite the signal first agent obtains as:

$$s_1 = s_2 + \sum_{j=1}^{(\omega_1-\omega_2)M} e_j.$$

And thus we have:

$$Cov(s_1, s_2) = Var(s_2) + (\omega_2 M)(\omega_1 M - \omega_2 M)Cov(e_i, e_j).$$

Using the first equation in (2.1) to substitute for $Var(s_2)$ we obtain the result:

$$Cov(s_1, s_2) = \Sigma_0 \times \omega_2 \times (1 - (1-\omega_1)\rho). \tag{69}$$

To derive the expression for randomly-overlapping research let $\overline{\omega}M$ bits of information constitute the overlap of the two signals, $\overline{\omega} \leq \omega_2$. Similarly to perfectly-overlapping case, we can rewrite agents' signals as the sum of overlapping and non-overlapping parts, where $\overline{\omega}M$ is the size of the overlapping part. We denote the overlapping part of both signals by $\overline{s}$. Holding $\overline{\omega}$ fixed we express $Cov(s_i, s_j)$ in terms of $\overline{\omega}$:

$$Cov(s_1, s_2|\overline{\omega}) = Var(\overline{s}) + (\overline{\omega}(\omega_1 - \overline{\omega}) + \overline{\omega}(\omega_2 - \overline{\omega}) + (\omega_1 - \overline{\omega})(\omega_2 - \overline{\omega}))M^2 Cov(e_i, e_j).$$

The above expression simplifies to:

$$Cov(s_1, s_2|\overline{\omega}) = \overline{\omega}\Sigma_0(1-\rho) + \omega_1\omega_2\Sigma_0\rho. \tag{70}$$

When each agent makes independent random draws of size $\omega_i M$, the expected size of overlap is $E(\overline{\omega}) = \omega_1\omega_2$. Imagine agent 1 moves first and selects $\omega_1 M$ bits of information, and assume all numbers are Natural in the following discussion. Then agent 2 draws randomly $\omega_2 M$ bits without replacement, thus the number of bits drawn by both agents follows hypergeometric distribution with parameters $N = N, m = \omega_1 N, n = \omega_2 M$. The expected value of hypergeometric distribution is mn/N, which is equal to $\omega_1\omega_2 N$ in our case. Thus the unconditional covariance of signals is:

$$Cov(s_1, s_2) = E(\overline{\omega})\Sigma_0(1-\rho) + \omega_1\omega_2\Sigma_0\rho = \Sigma_0 \times \omega_1\omega_2. \tag{71}$$

□

G.3 Proposition 2.4

Proof. Use equation (70) expressing covariance of the two signals in terms of the size of overlap (from the proof of proposition 2.2):

$$Cov(s_1, s_2|\overline{\omega}) = \overline{\omega}\Sigma_0(1-\rho) + \omega_1\omega_2\Sigma_0\rho.$$

It follows from the definition of the three research technologies that the corresponding sizes of overlap under the three scenarios are:

1. Non-overlapping research ($\gamma = 0$): $\overline{\omega} = 0$,
2. Independently-overlapping research ($\gamma = 1/2$): $\overline{\omega} = \omega_1\omega_2$,
3. Perfectly-overlapping research ($\gamma = 1$): $\overline{\omega} = \min(\omega_1, \omega_2)$.

We take linear interpolations for intermediate overlap scenarios in the following way:

$$\overline{\omega} = \begin{cases} 2\gamma \times \omega_1\omega_2, \text{ when } 0 \leq \gamma \leq 0.5 \\ 2(1-\gamma)\omega_1\omega_2 + (2\gamma - 1)\min(\omega_1, \omega_2), \text{ when } 0.5 < \gamma \leq 1 \end{cases}.$$

Without loss of generality we assume $\omega_1 \geq \omega_2$. Plugging in expression for $\overline{\omega}$ in the above equation obtains the result. □

G.4 Proposition 2.5

Proof. It is straightforward to show that results in propositions 2.1 and 2.2 go through with the continuous definition of a signal given the process X_t satisfies the given SDE (48). Here we will present the derivation of this SDE for X_t by starting with the discrete version of a signal and taking the limiting case as the number of fundamentals goes to infinity $M \to \infty$.

Start with M identical and *independent* jointly-Normally distributed random innovations, denote by a vector $\mathbf{u}_M$. Let vector $\mathbf{e}_M$ denote M identical jointly-Normal random variables with a given covariance matrix Ψ_M (all elements of $\mathbf{e}_M$ are identically distributed, thus all off-diagonal elements of Ψ_M are the same). Denote by $Var_e = Var(e_i)$ and $Cov_e = Cov(e_i, e_j)$. Vector $\mathbf{e}_M$ captures all bits of information or fundamentals available to an informed agent. As a first step, we express a generic element e_i of vector $\mathbf{e}_M$ as a function of previous elements $e_1, \cdots, e_{i-1}$ and innovation u_i. Then we take the limit of this expression as $M \to \infty$ to obtain an SDE for a continuous time stochastic process that we refer to as X_t. Let I_m denote an $m \times m$ identity matrix, and J_m denote $m \times 1$ vector of ones:

$$\begin{aligned} \mathbf{e}_M &= \Psi_M^{1/2} \times \mathbf{u}_M, \\ \Psi_M &= (Var_e - Cov_e) \times I_M + Cov_e \times J_M J_M^T. \end{aligned} \tag{72}$$

We can use Cholesky decomposition and rewrite Ψ_M as (there exist a vector F and number E so that the following holds):

$$\Psi_M = \begin{bmatrix} \Psi_{M-1} & Cov_e \times J_{M-1} \\ Cov_e \times J_{M-1}^T & Var_e \end{bmatrix} = \begin{bmatrix} \Psi_{M-1}^{1/2} & 0 \\ F^T & E \end{bmatrix} \times \begin{bmatrix} (\Psi_{M-1}^{1/2})^T & F \\ 0 & E \end{bmatrix},$$

where:

$$\begin{aligned} F &= Cov_e \times (\Psi_{M-1}^{1/2})^{-1} \times J_{M-1}, \\ E &= \sqrt{Var_e - Cov_e^2 \times J_{M-1}^T \Psi_{M-1}^{-1} J_{M-1}}. \end{aligned} \tag{73}$$

Combining equations 72 and 73 we obtain:

$$\begin{aligned} \begin{pmatrix} \vec{\mathbf{e}}_{i-1} \\ e_i \end{pmatrix} &= \begin{bmatrix} \Psi_{i-1}^{1/2} & 0 \\ Cov_e \times J_{i-1}^T \Psi_{i-1}^{-1} \Psi_{i-1}^{1/2} & \sqrt{Var_e - Cov_e^2 \times J_{i-1}^T \Psi_{i-1}^{-1} J_{i-1}} \end{bmatrix} \times \begin{pmatrix} \vec{\mathbf{u}}_{i-1} \\ u_i \end{pmatrix}, \\ e_i &= Cov_e \times J_{i-1}^T \Psi_{i-1}^{-1} \times \vec{\mathbf{e}}_{i-1} + u_i \sqrt{Var_e - Cov_e^2 \times J_{i-1}^T \Psi_{i-1}^{-1} J_{i-1}}. \end{aligned}$$

The last equation can be simplified by noting that:

$$\begin{aligned} \Psi_{i-1}^{-1} &= \frac{1}{(Var_e - Cov_e)} \times I_{i-1} - \frac{Cov_e}{(Var_e - Cov_e)(Var_e + Cov_e(i-2))} J_{i-1} J_{i-1}^T, \\ J_{i-1}^T \Psi_{i-1}^{-1} &= \frac{1}{(Var_e - Cov_e)} \times J_{i-1}^T - \frac{Cov_e(i-1)}{(Var_e - Cov_e)(Var_e + Cov_e(i-2))} J_{i-1}^T, \\ &= \frac{1}{Var_e + Cov_e(i-2)} J_{i-1}^T. \end{aligned}$$

We obtain the following result:

$$e_i = \frac{Cov_e}{Var_e + Cov_e(i-2)} J_{i-1}^T \times \vec{\mathbf{e}}_{i-1} + u_i \sqrt{Var_e - \frac{Cov_e^2(i-1)}{Var_e + Cov_e(i-2)}}.$$

We use infinite-divisibility condition and substitute the covariance terms with $Cov_e = \Sigma_0 \rho / M^2$. We also use equation (65) from the proof of proposition 2.1 to substitute the variance terms with $Var_e = (1/M)(\Sigma_0 - M(M-1)Cov_e) = (\Sigma_0/M)(1 - \rho(M-1)/M)$:

$$e_i = \frac{\rho}{(1-\rho) + \rho(i-1)/M} \left(\frac{J_{i-1}^T \times \vec{\mathbf{e}}_{i-1}}{M} \right) + \left(\frac{u_i}{\sqrt{M}} \right) \sqrt{\Sigma_0(1-\rho) + \frac{\Sigma_0 \rho (1-\rho)}{M(1-\rho) + \rho(i-1)}}.$$

Now we let $i = t \times M$ for some $t \in (0,1)$, $\lim_{M\to\infty} 1/M = dt$, and $\lim_{M\to\infty}(J_{i-1}^T \times \vec{\mathbf{e}}_{i-1}) = X(t)$. Taking the limit as $M \to \infty$ we obtain the following SDE for $X(t)$:

$$dX(t) = \frac{\rho}{(1-\rho) + \rho t} X(t) \times dt + \sqrt{\Sigma_0(1-\rho)} \times dW(t).$$

$\square$

H Trading Environment

H.1 Proposition 3.1

Proof. Conjecture linear trading strategies $X_i = (\beta_i/\lambda)s_i$ for the two agents and linear pricing rule of the form $P = \lambda(\Sigma x + u)$. Start with the profit maximization condition (49):

$$\max_{X_i} \{E\Pi_i(X_i, X_{-i}, P)\} = \max_x \{E((v - \lambda(x + (\beta_{-i}/\lambda)s_{-i} + u)) \times x | s_i = s)\}.$$

We follow the approach of Bernhardt and Taub [2008] and rewrite the i-th agent problem as unconditional maximization with respect to trading intensity β_i:

$$\max_x \{E((v - \lambda(x + (\beta_{-i}/\lambda)s_{-i} + u)) \times x | s_i = s)\} =$$
$$\max_\beta \left\{ E\left[\left(v - \lambda \left(\left(\frac{\beta}{\lambda} \right) s_i + \left(\frac{\beta_{-i}}{\lambda} \right) s_{-i} + u \right) \right) \left(\frac{\beta}{\lambda} \right) s_i \right] \right\}.$$

Using the joint-normality of signals and the true asset value, plus independence of liquidity trading, the unconditional problem simplifies to:

$$\max_\beta \left\{ \left(\frac{\beta}{\lambda} \right) Cov(s_i, v) - \left(\frac{\beta^2}{\lambda} \right) Var(s_i) - \left(\frac{\beta\beta_{-i}}{\lambda} \right) Cov(s_i, s_{-i}) \right\}. \tag{74}$$

Assuming λ is positive, the second-order condition for the above maximization is satisfied. Thus, it is sufficient to consider the system of two first-order conditions for two informed agents:

$$\begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} = \begin{pmatrix} 2 \times Var(s_1) & Cov(s_1, s_2) \\ Cov(s_1, s_2) & 2 \times Var(s_2) \end{pmatrix}^{-1} \begin{pmatrix} Cov(s_1, v) \\ Cov(s_2, v) \end{pmatrix}.$$

From the above we obtain the expression (52) for β_i presented in the proposition. Note that given conjectured linear trading and pricing rules the β_i are determined uniquely.

Now we use the market efficiency condition (50) to determine λ. Note that if λ is determined uniquely, the initial trading intensities β_i/λ will be unique. Under the conjectured linear trading strategies the total order flow is:

$$\Sigma x + u = (\beta_1/\lambda)s_1 + (\beta_2/\lambda)s_2 + u.$$

and is jointly normally distributed with v. This implies linearity of pricing rule and the following result (market efficiency condition (50) represents a linear regression of v on $\Sigma x + u$):

$$\lambda = \frac{Cov(v, \Sigma x + u)}{Var(\Sigma x + u)} = \frac{(\beta_1/\lambda)Cov(s_1, v) + (\beta_2/\lambda)Cov(s_2, v)}{(\beta_1/\lambda)^2 Var(s_1) + (\beta_2/\lambda)^2 Var(s_2) + 2(\beta_1/\lambda)(\beta_2/\lambda)Cov(s_1, s_2) + \sigma_u^2},$$

$$(\lambda\sigma_u)^2 = \sum_{i=1}^{2} \beta_i (Cov(s_i, v) - \beta_i Var(s_i) - \beta_2 Cov(s_i, s_{-i})).$$

The first order condition for informed agent's problem 74 implies:

$$Cov(s_i, v) - \beta_i Var(s_i) - \beta_2 Cov(s_i, s_{-i}) = Var(s_i)\beta_i.$$

Plugging this result in the above equation and simplifying we obtain expression (53) for λ. The linear trading equilibrium is unique. $\square$

H.2 Lemma 3.1

Proof. Suppose agent-i's opponent and the market-maker follow equilibrium strategies β_{-i} and λ given by Proposition 3.1. Then agent-i's profit maximization problem is:

$$\max_x \left\{ E\left[\left(v - \lambda \left(x + \left(\frac{\beta_{-i}}{\lambda} \right) s_{-i} + u \right) \right) \times x \middle| s_i^{\text{new}} \right] \right\}.$$

Following the approach in Bernhardt and Taub [2008] we rewrite the above as an equivalent unconditional maximization problem:

$$\max_\beta \left\{ \left(\frac{\beta}{\lambda} \right) Cov(s_i^{\text{new}}, v) - \left(\frac{\beta^2}{\lambda} \right) Var(s_i^{\text{new}}) - \left(\frac{\beta\beta_{-i}}{\lambda} \right) Cov(s_i^{\text{new}}, s_{-i}) \right\}.$$

The first-order condition is sufficient and gives the expression (55) for β_i^{new}:

$$\begin{aligned}
\beta_i^{\text{new}} &= \frac{Cov(s_i^{\text{new}}, v) - \beta_{-i} Cov(s_i^{\text{new}}, s_{-i})}{2Var(s_i^{\text{new}})}, \\
&= \frac{1}{2\sqrt{Var(s_i^{\text{new}})}} \left(\sqrt{\Sigma_0 \times \alpha_1^{\text{new}}} - \rho_{12}^{\text{new}} \times \sqrt{Var(s_{-i})} \times \beta_{-i} \right).
\end{aligned}$$

Plugging the solution for β_i^{new} into the unconditional maximization problem we obtain the expression (56) for expected profit of agent i:

$$\begin{aligned}
E(\pi_i^{\text{new}}) &= \frac{1}{4\lambda \times Var(s_i^{\text{new}})} \left(Cov(s_i^{\text{new}}, v) - Cov(s_i^{\text{new}}, s_{-i}) \times \beta_{-i} \right)^2, \\
&= \frac{1}{4\lambda} \left(\sqrt{\Sigma_0 \times \alpha_i^{\text{new}}} - \rho_{12}^{\text{new}} \times \sqrt{Var(s_{-i})} \times \beta_{-i} \right)^2.
\end{aligned}$$

□

H.3 Lemma 3.2

Proof. Both agents have access to the same research technology characterized by overlaps parameter $\gamma \leq 1/2$ and cost function $TC(\omega)$ that is assumed to be linear in ω (all identically distributed bits of information are equally costly to obtain). In order to show the result we express the expected trading profits of informed agents in terms of their research efforts ω_1 and ω_2. We use equation (56) in Lemma 3.1 to derive the first order optimality condition necessary for a Nash equilibrium:

$$\forall i \in \{1, 2\} : \frac{\Sigma_0(1-\rho)}{4\lambda} \times \left(\frac{1 - (2\gamma(1-\rho) + \rho) \times \omega_j \beta_j}{1 - (1-\omega_i)\rho} \right)^2 = \frac{\mathrm{d}TC}{\mathrm{d}\omega}(\omega_i). \tag{75}$$

The right-hand side of the above equation is the marginal cost of information acquisition, which we assume does not depend on the research effort ω. We equate marginal trading benefits of doing research for the two agents and plug in the resulting expression equilibrium values of and β_1 and β_2 (λ cancels out). We also reexpress the result in terms of α_1 and α_2 to simplify exposition (there is a one-to-one mapping between research effort ω_i and %-conditional variance reduction measure α_i):

$$\alpha_i = \frac{\omega_i}{1 - (1-\omega_i)\rho}, \tag{76}$$

$$\alpha_2 \times \left(\frac{2(\rho - 2\gamma(1-\rho))}{4 - (2\gamma(1-\rho) + \rho)^2 \alpha_1 \alpha_2} \right) = \alpha_1 \times \left(\frac{2(\rho - 2\gamma(1-\rho))}{4 - (2\gamma(1-\rho) + \rho)^2 \alpha_1 \alpha_2} \right). \tag{77}$$

The above equation implies $\alpha_1 = \alpha_2$ when $\gamma \neq \frac{\rho}{2(1-\rho)}$. It is worth noting that the knife-edge case $\gamma = \frac{\rho}{2(1-\rho)}$ results in multiplicity of possible equilibria—for a given linear cost function $TC(\omega)$

continuum of Nash equilibria exists (one symmetric and continuum of asymmetric for any given linear cost function satisfying single-agent-interior condition). The marginal trading benefit of research efforts for each agent in this case is a symmetric function of α_1 and α_2.

We establish for a game with two informed agents that if an interior Nash equilibrium exists for $\gamma < 1/2$ and $\gamma \neq \frac{\rho}{2(1-\rho)}$, then it is symmetric, that is $\omega_1 = \omega_2$. □

H.4 Lemma 3.3

Proof. We prove the lemma by conjecturing existence of a corner equilibrium and then verifying it is a Nash equilibrium of the game. Without loss of generality suppose $\omega_1 > \omega_2 = 0$ in the corner equilibrium. We use equation (56) in Lemma 3.1 and express expected trading profits of informed agents in terms of their research efforts ω_1 and ω_2. It can be verified that trading equilibrium for a game with one informed agent is equivalent to a trading equilibrium in a game with two informed agents when one agent's research effort is zero. The two cases $\gamma \leq 1/2$ and $\gamma > 1/2$ result in the following expressions for correlation of two signals ρ_{12}:

$$\rho_{12} = \begin{cases} (2\gamma(1-\rho)+\rho)\sqrt{\alpha_1\alpha_2}, & \text{when } 0 \leq \gamma \leq 1/2 \\ \frac{(1-2(1-\gamma)(1-\alpha_1))\sqrt{\alpha_2}}{\sqrt{\alpha_1}}, & \text{when } 1/2 < \gamma \leq 1, \end{cases} \tag{78}$$
$$\text{where: } \alpha_i = \frac{\omega_i}{1-(1-\omega_i)\rho}, \forall i \in \{1,2\}.$$

Consider the case $\gamma \leq 1/2$ first. The first order optimality condition necessary for a corner Nash equilibrium is:

$$\frac{\Sigma_0(1-\rho)}{4\lambda} \times \left(\frac{1-(2\gamma(1-\rho)+\rho)\times\omega_1\beta_1}{1-\rho}\right)^2 \leq \frac{\mathrm{d}TC}{\mathrm{d}\omega}(0) = \tag{79}$$
$$= \frac{\mathrm{d}TC}{\mathrm{d}\omega}(\omega_1) = \frac{\Sigma_0(1-\rho)}{4\lambda} \times \left(\frac{1}{1-(1-\omega_1)\rho}\right)^2.$$

We plug in the above expression the trading equilibrium values of β_1 and λ that correspond to single firm doing research on the market (Proposition 3.1):

$$\beta_1 = \frac{1}{2}\left(\frac{1}{1-(1-\omega^*)\rho}\right),$$
$$\lambda = \frac{\sqrt{2\Sigma_0}}{2\sigma_u} \times \sqrt{\frac{\omega^*}{1-(1-\omega^*)\rho}}.$$

The above condition 79 simplifies to the following expression:

$$\left(\frac{1}{1-(1-\omega^*)\rho} + \frac{(\rho-2\gamma(1-\rho))\times\omega^*}{2(1-\rho)(1-(1-\omega^*)\rho)}\right)^2 \leq \left(\frac{1}{1-(1-\omega^*)\rho}\right)^2.$$

Using the single-agent-interior condition that implies $\omega^* < 1$ and also restrictions on model parameters $\rho \in [0,1)$ and $\gamma \leq 1/2$, the first order condition for the corner equilibrium is satisfied if and only if:

$$\rho - 2\gamma(1-\rho) \leq 0 \equiv \rho \leq \frac{2\gamma}{1+2\gamma}.$$

It remains to check that the necessary first order condition above is sufficient for the corner Nash equilibrium. We show that the objective functions in agents' profit maximization problems are concave (strategies of other agents held fixed and using equation (75) above):

$$\begin{aligned}\frac{\partial(E\pi_i - TC(\omega_i))}{\partial\omega_i} &= \frac{\Sigma_0(1-\rho)}{4\lambda}\times\left(\frac{1-(2\gamma(1-\rho)+\rho)\times\omega_j\beta_j}{1-(1-\omega_i)\rho}\right)^2 - \frac{\mathrm{d}TC}{\mathrm{d}\omega}(\omega_i),\\ \frac{\partial^2(E\pi_i - TC(\omega_i))}{\partial\omega_i^2} &= -\frac{\Sigma_0(1-\rho)}{4\lambda}\times\left(\frac{2\rho(1-(2\gamma(1-\rho)+\rho)\times\omega_j\beta_j)^2}{(1-(1-\omega_i)\rho)^3}\right) < 0.\end{aligned}$$

This concludes the proof for low degree of overlaps $\gamma \leq 1/2$. Now we repeat similar steps for $\gamma > 1/2$ and use corresponding functional form for the correlation between signals ρ_{12}.

The first order optimality condition necessary for a corner Nash equilibrium when $\gamma > 1/2$ is:

$$\begin{aligned}\frac{\Sigma_0(1-\rho)}{4\lambda}\times\left(\frac{1-((2\gamma-1)(1-(1-\omega_1)\rho)+2(1-\gamma)\omega_1)\beta_1}{1-\rho}\right)^2 &\leq \frac{\mathrm{d}TC}{\mathrm{d}\omega}(0) = \\ = \frac{\mathrm{d}TC}{\mathrm{d}\omega}(\omega_1) = \frac{\Sigma_0(1-\rho)}{4\lambda} &\times \left(\frac{1}{1-(1-\omega_1)\rho}\right)^2.\end{aligned} \tag{80}$$

The trading equilibrium values of β_1 and λ remain unaffected by γ because only one informed agent does research. The above condition simplifies to:

$$\left(\frac{(3-2\gamma)(1-\rho)+(2\gamma(1-\rho)+3\rho-2)\omega^*}{2(1-\rho)(1-(1-\omega^*)\rho)}\right)^2 \leq \left(\frac{1}{1-(1-\omega^*)\rho}\right)^2,$$

$$\rho \leq \frac{(2-2\gamma)\omega^*+2\gamma-1}{(3-2\gamma)\omega^*+2\gamma-1}, \text{ when } \gamma > 1/2.$$

It remains to check the sufficiency of the above condition. The objective function of the single informed agent doing research on the market is concave:

$$\begin{aligned}\frac{\partial(E\pi_1 - TC(\omega_1))}{\partial\omega_1} &= \frac{\Sigma_0(1-\rho)}{4\lambda}\times\left(\frac{1}{1-(1-\omega_1)\rho}\right)^2 - \frac{\mathrm{d}TC}{\mathrm{d}\omega}(\omega_1),\\ \frac{\partial^2(E\pi_1 - TC(\omega_1))}{\partial\omega_1^2} &= -\frac{\Sigma_0(1-\rho)}{4\lambda}\times\left(\frac{2\rho}{(1-(1-\omega_1)\rho)^3}\right) < 0.\end{aligned}$$

The objective function for the second informed agent that is at the corner consist of two parts: the catch-up part $\omega_2 < \omega^*$ and leading part $\omega_2 > \omega^*$. Instead of doing piecewise marginal analysis we use equation (56) in Lemma 3.1 to show that the total trading profits second informed agents obtains is strictly less than research costs for any research effort $\omega_2 > 0$ when the above condition holds.

$$E(\pi_2^{new}) = \frac{1}{4\lambda}\left(\sqrt{\Sigma_0\times\alpha_2^{\text{new}}} - \rho_{12}^{\text{new}}\times\sqrt{Var(s_1)\times\beta_1}\right)^2 \leq TC(\omega_2). \tag{81}$$

When one informed agent trades on the market in equilibrium, we use its first-order condition to express the relationship between research effort and total variable cost of research for the second agent in case it decides to deviate from $\omega_2 = 0$ (under linear cost assumption and single-agent interior condition):

$$TC(\omega_2) = \frac{(1-\rho)\Sigma_0}{4\lambda}\left(\frac{1}{1-(1-\omega_1)\rho}\right)^2\times\omega_2.$$

When the second informed agent exerts lower research effort than ω_1, his marginal trading profit is decreasing in ω_2, thus trading profits cannot turn positive at $0 < \omega_2 < \omega_1$ provided that marginal trading profit is already below marginal cost at zero. However once $\omega_2 \geq \omega_1$ there are potential benefits of doing break through research, and this is the case we analyze below. Plugging in corner equilibrium values of λ and β_1 in equation (81), taking $\omega_2 \geq \omega_1$ and simplifying yields an equivalent inequality:

$$(2\omega_2(1-\rho+\rho\omega_1) - \omega_1((2\gamma-1)(1-\rho)(1-\omega_2)+\omega_2))^2 < 4\omega_2^2 \times (1-\rho)(1-\rho+\rho\omega_2).$$

Note that the expression above is quadratic in ρ. When $\rho = 0$ the expression simplifies to $\omega_1((2\gamma-1)(1-\omega_2)+\omega_2)(4\omega_2 - \omega_1((2\gamma-1)(1-\omega_2)+\omega_2)) > 0$ and is true when $\omega_2 > \omega_1$ and $\gamma > 1/2$. When $\rho = 1$ the same expression simplifies to $\omega_1^2\omega_2^2 > 0$. Now if we show that when $\rho = \frac{(2-2\gamma)\omega^*+2\gamma-1}{(3-2\gamma)\omega^*+2\gamma-1}$ (the threshold in the Lemma) the above expression is negative, our result follows—for all $\rho \in [0, \frac{(2-2\gamma)\omega^*+2\gamma-1}{(3-2\gamma)\omega^*+2\gamma-1}]$ the needed inequality holds. It turns out that this holds, when ρ is equal to our threshold, the above expression is negative. It simplifies to:

$$-4\gamma^2\omega_1(\omega_2-\omega_1)^2 + 4\gamma(\omega_1^3 + 2\omega_2^3 - \omega_1\omega_2^2(1+2\omega_2)) - \omega_1^3 - 2\omega_1^2\omega_2 - 4\omega_2^3 + \omega_1\omega_2^2(3+8\omega_2) > 0.$$

The above expression is a concave quadratic polynomial in γ, the relevant range for which is $\gamma \in [0.5, 1]$. We use the region of research efforts such that $\omega_2 > \omega_1$. For convenience, let $\omega_2 = \nu\omega_1$, where $\nu > 1$. Using this reformulation for $\gamma = 0.5$ the above simplifies to $4\nu^3\omega_1^4 > 0$. For $\gamma = 1$ it simplifies to $(\nu(6+\nu(4\nu-5))-1)\omega_1^3$, which is increasing function in ν and positive when $\nu = 1$. These two facts together with concavity of the polynomial above establish the fact.

This leads us to conclude that the first order condition above is both necessary and sufficient. □

H.5 Proposition 3.2

Proof. Firstly, consider research technologies with low degree of overlaps $\gamma \leq 1/2$. Use equation (56) in Lemma 3.1 to rewrite informed agent's expected trading profits function $E(\pi_i)$ in terms of its research effort ω_i and take the first order condition of the profit maximization problem (holding ω_{-i}, λ and β_{-i} constant):

$$\frac{\Sigma_0(1-\rho)}{4\lambda} \times \left(\frac{1-(2\gamma(1-\rho)+\rho)\times\omega_{-i}\beta_{-i}}{1-(1-\omega_i)\rho}\right)^2 = \frac{\mathrm{d}TC}{\mathrm{d}\omega}(\omega_i).$$

Using result in Lemma 3.2 that in the class of interior Nash equilibria under $\gamma \leq 1/2$ only symmetric equilibria can exist, we substitute $\omega_i = \omega_j = \omega$ in the above equation. Plugging equilibrium values of λ and β_i, the above first order condition simplifies to:

$$\frac{(1-\rho)\sqrt{\Sigma_0 \times \sigma_u^2}(2(1-\rho)+(2\gamma(1-\rho)+3\rho)\omega)}{\sqrt{2}(2+2\gamma(1-\rho)+\rho)^2\sqrt{\omega}(1-(1-\omega)\rho)^{5/2}} = \frac{\mathrm{d}TC}{\mathrm{d}\omega}(\omega).$$

Our first observation is as $\omega \to 0$ the LHS of the above expression limits to $+\infty$. Thus for any finite marginal cost of doing research $\omega = 0$ is never an equilibrium. When $\omega = 1$ the LHS simplifies to $\frac{(1-\rho)\sqrt{\Sigma_0\times\sigma_u^2}}{\sqrt{2}(2+2\gamma(1-\rho)+\rho)} < \frac{(1-\rho)\sqrt{\Sigma_0\times\sigma_u^2}}{2} < \frac{\mathrm{d}TC}{\mathrm{d}\omega}(\omega = 1)$, the latter implied by the single-agent-interior condition. Thus $\omega = 1$ is never an equilibrium. It remains to show that for any given constant RHS there is a unique solution for $\omega \in (0, 1)$. Below we show that LHS is a decreasing function of ω, which establishes the result.

We show this by differentiating the LHS with respect to ω. The denominator is always positive, while the numerator is a concave quadratic polynomial in ω that needs to be negative for our result:

$$-4(2\gamma(1-\rho)+3\rho)\rho \times \omega^2 + (1-\rho)(2\gamma(1-\rho)-9\rho)\times\omega - 2(1-\rho)^2 < 0.$$

The polynomial is negative both when $\omega = 0$ and $\omega = 1$. It attains its optimal value when $\omega = \frac{(1-\rho)(2\gamma(1-\rho)-9\rho)}{8(2\gamma(1-\rho)+3\rho)\rho}$. When the optimal value is attained outside the $[0, 1]$ domain, the two checks at endpoints above are sufficient for the result. When $\gamma \geq \frac{9\rho}{2(1-\rho)}$ and $\gamma \leq \frac{3\rho(3+5\rho)}{2(1-\rho)(1-9\rho)}$ the optimal value is inside the $[0,1]$ domain, so we check the value of polynomial at the optimum. It is negative whenever $4\gamma^2(1-\rho)^2 - 100\gamma(1-\rho)\rho - 15\rho^2 < 0$, which holds under the above restrictions on γ (verified numerically). This completes the proof of the $\gamma \leq 1/2$ case.

Now consider the perfectly-overlapping research technology $\gamma = 1$ in the second part of the Proposition. Again, we use equation (56) in Lemma 3.1 to rewrite informed agent's expected trading profits function $E(\pi_i)$ in terms of its research effort ω_i and take the first order condition of the profit maximization problem (holding ω_{-i}, λ and β_{-i} constant). We use the formula for correlation of informed agents' signals ρ_{12} that corresponds to the perfectly-overlapping research technology $\gamma = 1$ and without loss of generality we assume $\omega_1 \geq \omega_2$. The first order condition for the two informed agents is:

$$\omega_1 \geq \omega_2 :$$

$$\frac{\partial(E\pi_1)}{\partial\omega_1} = \frac{\Sigma_0(1-\rho)}{4\lambda}\left(\frac{1}{1-(1-\omega_1)\rho} - \frac{\omega_2}{\omega_1}\beta_2\right)\left(\frac{1}{1-(1-\omega_1)\rho} + \frac{\omega_2}{\omega_1}\beta_2\right) = \frac{\mathrm{d}TC}{\mathrm{d}\omega}(\omega_1),$$

$$\frac{\partial(E\pi_2)}{\partial\omega_2} = \frac{\Sigma_0(1-\rho)}{4\lambda}\left(\frac{1-\beta_1+\beta_1(1-\omega_1)\rho}{1-(1-\omega_2)\rho}\right)^2 = \frac{\mathrm{d}TC}{\mathrm{d}\omega}(\omega_2).$$

It can be shown that $\frac{\partial(E\pi_1)}{\partial\omega_1}(\omega) > \frac{\partial(E\pi_2)}{\partial\omega_2}(\omega)$, while $\frac{\partial(E\pi_1)}{\partial\omega_1}$ has at most one point where it changes direction. Although the first informed agent's maximization problem is not concave, the first order condition is still sufficient. Any candidate Nash equilibrium with positive $\omega_1 > 0$ and $\omega_2 > 0$ must satisfy both first order conditions above. We assume linear variable costs of research $\frac{\mathrm{d}TC}{\mathrm{d}\omega}(\omega_1) = \frac{\mathrm{d}TC}{\mathrm{d}\omega}(\omega_2)$, thus we can equate marginal trading profits of two agents and obtain relationship between ω_1 and ω_2 in equilibrium:

$$(-2\rho(1-\rho(1+\omega_1))) \times \omega_2^2 + 2(1-\rho)(3\rho\omega_1 - (1-\rho)) \times \omega_2$$
$$+\omega_1(4(1-\rho)^2 - (1-\rho(1-\omega_1))^2) = 0.$$

We solve the above equation for ω_2. It turns out that when $\omega_1\rho > 1-\rho$ we have positive $0 < \omega_2 < \omega_1$. When one of the conditions is not satisfied, we have $\forall\omega_2 \in [0,1]$ the first agent with higher research effort $\omega_1 > \omega_2$ has $\frac{\partial(E\pi_1)}{\partial\omega_1}(\omega_1) > \frac{\partial(E\pi_2)}{\partial\omega_2}(\omega_2)$, thus only corner solution is possible for ω_2:

$$\begin{aligned} \text{when } \omega_1\rho &> 1-\rho : \\ \omega_2 &= \frac{-(1-\rho)(3\omega_1\rho - 1 + \rho) + (\omega_1\rho + 1 - \rho)\sqrt{(\omega_1\rho - 1 + \rho)^2 + \rho^2\omega_1^2}}{2\rho(\omega_1\rho - 1 + \rho)}, \quad (82) \\ \text{when } \omega_1\rho &\leq 1-\rho : \\ \omega_2 &= 0. \quad (83) \end{aligned}$$

The latter case when $\omega_1\rho \leq 1-\rho$ is consistent with the result in Lemma 3.3 after plugging in $\gamma = 1$. It is interesting that when this condition does not hold, the level of first agent's research effort ω_1 uniquely determines equilibrium level of second agent's effort ω_2 according to equation (82). When $\omega_1\rho \leq 1-\rho$ the existence and uniqueness of the corner equilibria is straightforward to establish. When $\omega_1\rho > 1-\rho$ we establish existence and uniqueness using numerical methods. The underlying idea is to pick any linear cost function satisfying single-agent-interior condition and demonstrate that equation (82) pins down ω_1 uniquely. Single-agent interior condition ensures that the equilibrium is interior $\omega_1 < 1$.

This concludes the proof of the proposition. □

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