ESSAYS ON OVER-THE-COUNTER MARKETS

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This dissertation consists of three essays studying on over-the-counter trading (OTC henceforth). In Chapter 1, I model the formation of the inter-dealer network in an OTC market, and study how the network affects prices and volumes in the market. The model explains the empirically observed core-periphery network with dealers' capacity of providing liquidity. Specifically, dealers with large capacity comprise the core of the network, connecting them to all other dealers, while dealers who have small capacity operate at the periphery. In addition, my model matches the empirical finding on the negative relation between markups and order sizes. Furthermore, I show that there may be structural breaks in this negative relationship as variations in order sizes may alter the inter-dealer network. These results suggest that empirical studies on OTC markets should control for the stability of an inter-dealer network to avoid model misspecification.

Chapter 2 evaluates how a centralized market could provide an incentive for OTC dealers to reduce opacity in trading. In this chapter, opacity is modeled as Knightian uncertainty faced by investors. I find that while a competitive centralized market provides an incentive for dealers to reduce opacity in an OTC market, a noncompetitive centralized market does the opposite. Competition between the competitive centralized market and the OTC market forces dealers in the latter to reduce opacity. With the noncompetitive centralized market, opportunities for collusion provide an incentive for dealers to increase opacity. Dealers do not have the incentive to reduce opacity in this case.

In Chapter 3, we test the model implications in Chapter 2 with an empirical study on the corporate bond markets, and find consistent results. We find that transaction costs of bonds traded only in OTC markets are significantly different from (10 basis points larger than) bonds traded both in OTC markets and the NYSE market. Since the latter contains pre-trade information from the NYSE market, this finding suggests that pre-trade transparency reduces bonds' trading costs. This result implies that pre-trade transparency benefits investors but hurts dealers, as the major part of dealers' profits comes from investors' trading costs. We also find that pre-trade transparency increases bonds' values. Bonds with the NYSE pre-trade transparency have significantly lower bond yields than bonds without the pre-trade transparency. Our findings are robust to endogeneity of firms' bond listing decisions on the NYSE.

BIOGRAPHICAL SKETCH

Zhuo Zhong earned his Bachelor or Arts in Economics from Xiamen University in 2005. In the same year, he entered the graduate school of Xiamen University and was enrolled in the dual-masters program held by Singapore Management University and Xiamen University. He received a Master of Arts in Finance from Singapore Management University in 2007 and a Master of Arts in Finance from Xiamen University in 2008. After that, Zhuo Zhong continued his graduate studies in the Department of Economics at Cornell University and would earn his Ph.D. degree in Economics in August 2014.

献给我的父母钟兴国和曾碧霞，春晖寸草，无以为报！

献给周亭，让我们一起成就梦想！

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PREFACE

Over-the-counter (OTC henceforth) markets are important ingredients of the modern financial world. Unlike an exchange market, trading in an OTC market is done directly between two parties. This bilateral trading offers greater flexibility on terms of a trade, which helps process non-standardized transactions. As a result, financial assets traded in OTC market are those requiring customization or traded in enormous amounts, e.g., asset-backed securities, credit derivatives, interest rate products, corporate bonds, municipal bonds, etc.

Customization of OTC assets implies that direct matches between buyers and sellers would be challenging. Most OTC trades involve dealers who act as intermediaries between buyers and sellers. Dealers are the most active participants in OTC trading. However, not many studies try to investigate dealers' strategies and behaviors in OTC markets. With the goal of filling this gap, my first chapter studies how dealers influence OTC trading. In Chapter 1, I study the inter-dealer network in an OTC market. I ask what determines the network of inter-dealer trading and how the network affects prices in an OTC market.

While Chapter 1 focuses on trades among dealers, my second and third chapters investigate trades between investors and dealers. In Chapter 2, I study the relation between opacity and OTC trading. I find that opacity increases traders' search costs in OTC trading. While traders suffer from opacity, dealers profit from it. Since dealers control most information in OTC markets (for example quotes), it is doubtful if one could have a mechanism that incentivizes dealers to release more information, thereby reducing opacity. Thus, in this chapter I evaluate how a centralized market could affect the opacity of an OTC market. I show that a competitive centralized market provides an incentive for dealers in the OTC market to reduce opacity, whereas a noncompetitive centralized market does not.

Chapter 3 tests the model implication in Chapter 2 with an empirical study on the corporate bond markets. We construct two groups of bonds with similar characteristics except that one group trades in both OTC and the NYSE markets and the other trades only in OTC markets. Since the NYSE market provides pre-trade information, the first group is more pre-trade transparent than the second group. Then we analyze the transaction costs, variances of transaction costs, and yields between these two groups. We find that transaction costs of bonds traded only in OTC markets are significantly different from (10 basis points larger than) bonds traded both in OTC markets and the NYSE market. The result is consistent with the model implication in Chapter 2.

Chapter 1 The Network of Inter-Dealer Trading in an Over-the-Counter Market

1.1 Introduction

Over-the-counter (OTC) markets have grown exponentially in the last decade. As OTC markets grow, researchers have increasingly investigated the trading structure of these markets. Research interest is further stimulated by the recent financial crisis, which has brought attention to the OTC market for subprime mortgage derivatives. However, studies on OTC markets overlook an important element — inter-dealer trading. Since dealers act as intermediaries in OTC markets, inter-dealer trades should affect trades between dealers and other market participants, and hence affect the entire market. To provide new insights into how inter-dealer trades influence OTC trading, this chapter studies an important aspect of inter-dealer trades, the dealers' trading network. Specifically, I ask several questions. How does such a network form? What determines a dealer's position within the network? How does the network affect price determination in an OTC market?

To address these questions, I construct a theoretical model to study how dealers strategically form an inter-dealer network, and I then examine how such an inter-dealer network affects other aspects of an OTC market. In my model, OTC dealers form an inter-dealer network and trade through the network to share their inventory risks. The more links a dealer has, the more benefits the dealer obtains from risk-sharing. But the more links a dealer has, the greater are the costs he has to bear for maintaining his links. The linking cost includes the cost of hedging counterparty risk. For example, in the CDS markets collateral is used pervasively in transactions as a protection in case one party fails to deliver his commitment. Preparing collateral could be costly because of funding liquidity. A dealer with many links faces a larger linking cost, as he has to prepare a larger collateral pool in the event of trading.[1] The trade-off between the benefit of risk-sharing and the cost of linking determine the shape of the inter-dealer network. At one extreme, when the linking cost is trivial compared with the risk-sharing benefit, the inter-dealer network is a complete network. In a complete network, all dealers are connected. At the other extreme, when the linking cost is overwhelming, the inter-dealer network is an empty network, one in which no dealer is connected with any other dealer. Between these two extremes, inter-dealer networks can exhibit connectedness to varying degrees depending on the risk-sharing benefit and the linking cost.

Inter-dealer networks affect OTC trading insofar as the number of links a dealer has influences his markup (the difference between the price for which a dealer buys a security and

[1] The linking cost also includes the due diligence effort, telecommunication costs, data subscription fees to inter-dealer brokers, and the time human traders in a broker-dealer firm spent on interacting with his linked parties, etc.

the price at which he sells it), trading volume, and inventory risk. For example, in a more connected network, a dealer has more links, earns a higher markup, trades at higher volume, and is exposed to lower inventory risk. In such a network, having more links gives a dealer greater market power in the inter-dealer market, which enables the dealer to sell at a higher price to (or buy at a lower price from) other dealers. Since a markup is proportional to its corresponding inter-dealer price, this highly connected dealer charges a higher markup. Having more links also provides a dealer with more opportunities to trade in the inter-dealer market. As a result, the dealer completes more trades and manages his inventory risk more effectively.

My model resonates with recent empirical studies which show that inter-dealer networks have a significant influence on OTC trading. Hollifield, Neklyudov, and Spatt (2012) study the inter-dealer network of securitization markets (e.g., asset-backed securities, collateral debt obligations, commercial mortgage-backed securities, and collateral mortgage obligations) and Li and Schürhoff (2012) study the inter-dealer network operating in the municipal bond markets. Both studies document that the structure of the inter-dealer network correlates with dealers' markups in OTC trading. Moreover, they show that inter-dealer networks across OTC markets exhibit structural similarity in spite of trading distinct classes of assets. This common structure is the core-periphery structure. That is, some dealers are closer to the center of a network than others.

In the abovementioned empirical studies, inter-dealer networks are treated as exogenously determined. This limits the capacity of the analyses to explain why inter-dealer networks form the observed core-periphery structure, and how the core-periphery network is related to prices in OTC trading. In principle, inter-dealer networks should be jointly determined with prices and trading volumes in equilibrium, since these are outcomes based on dealers' decisions. This suggests that theoretical models are needed to explain the formation of inter-dealer networks. More importantly, such theoretical models should generate new empirical implications by treating inter-dealer networks as endogenously determined rather than exogenously determined as in past empirical studies. The theoretical model I construct in this chapter satisfies these conditions.

Using differences in dealers' capacity of providing liquidity, my model explains the core-periphery feature of an inter-dealer network. Large-capacity dealers who can accommodate large orders comprise the core, while small-capacity dealers who only accommodate small orders become the periphery. This gives a novel testable empirical prediction regarding a dealer's location in a network: a dealer's capacity of liquidity provision positively determines his centrality (a measure that captures how central a dealer is in a network).

In addition, I show that the unconditional relationship between investors' trading prices and dealers' centrality is ambiguous. Dealers with high centrality do not necessarily offer better prices to investors than dealers with low centrality. However, this relationship is determined when it is conditioned on the size of the investor order. On orders with the same size, high-centrality dealers offer investors more favorable prices than low-centrality dealers. This conditional relationship between investors' trading prices and dealers' centrality is consistent with empirical findings in Hollifield, Neklyudov, and Spatt (2012). The above suggests that the order size is an important control variable in determining how centrality is related to investors' trading prices.

Another novel empirical implication arising from my model involves potential structural breaks in the price-size and price-volatility relationships in OTC markets. Changes in order sizes or volatility can alter the fundamental structure of an economy, which in the setup of this work is the inter-dealer network. As a result, sudden structural jumps emerge in these relationships. Based on this result, I suggest that empirical studies examining OTC markets should control for the stability of an inter-dealer network in order to avoid model misspecification. Empirical research should, for example, include a measure of a network's connectedness as an additional control variable interacting with other control variables in the regression model.

To the best of my knowledge, my study is the first to study strategic formation of an inter-dealer network arising from dealers' risk-sharing needs. My model not only confirms existing empirical findings, but also provides new empirical implications pertaining to OTC markets. Malamud and Rostek (2013) have also studied dealers who share risks through inter-dealer networks. While they focus on dealers' strategic interactions in simultaneous trading on the network, I emphasize the formation process of the network. Although I model the rise of an inter-dealer network from a risk-sharing perspective, I do not rule out other possible forces that may generate such a network. For example, sharing information is a possible incentive for building a dealers' network.

My study is also the first to apply the risk-sharing idea of the network formation literature to a specific type of financial market, the OTC market. This approach provides the advantage of identifying the relationship between agents' payoffs and primitive parameters, e.g., order sizes and volatility, as the trading protocol and needs are concrete and specific. As a result, I can explore issues that have not yet received much attention. For example, I consider how order sizes and volatility contribute to determining a network as well as how they affect equilibrium outcomes such as prices and quantities traded through the network.

In the next section, I review the related literature. Section 1.3 presents the benchmark model and Section 1.4 analyses the equilibrium results. In Section 1.5, I extend the benchmark model to a case in which dealers' capacity of providing liquidity varies and show the core-periphery network that emerges in equilibrium. Section 1.6 discusses the implications of the model for "hot potato" trading, which involves trades that occur between successive dealers. The empirical implications are summarized in Section 1.7. Finally, I conclude in Section 1.8.

1.2 Literature Review

Inter-dealer trading has been an important subject in market microstructure studies for a long time. Ho and Stoll (1983) point out that inter-dealer trading benefits dealers, since dealers are better able to manage their inventory risks by trading among themselves instead of filling an investor order with uncertain arrival. Viswanathan and Wang (2004) show that inter-dealer trading also benefits investors. In their model, an investor prefers trading with one dealer and letting that dealer unwind his extra inventory later in the inter-dealer market rather than splitting up the order and trading with multiple dealers. Thus, inter-dealer trading is beneficial to both dealers and investors. Both papers model the incentive for inter-dealer trading as the sharing of inventory risks. Based on this risk sharing idea, others build models to study issues such as price formation, information transmission, and transparency in multi-dealer markets (see Biais (1993), Lyons (1997), Naik, Neuberger, and Viswanathan (1999), de Frutos and Manzano (2002), Yin (2005), and Cao, Evans, and Lyons (2006)). Empirical evidence supports risk-sharing as the main driver behind inter-dealer trading. Reiss and Werner (1998) and Hansch, Naik, and Viswanathan (1998) find that dealers on the London Stock Exchange use the inter-dealer market primarily to share their inventory risks. In the foreign exchange market, Lyons (1995) finds that dealers control risk by systematically laying off inventory to other dealers.

Another thread of literature to which this work contributes, studies price determination in

OTC markets. Duffie, Garleanu, and Pedersen (2005, 2007) study how search and bargaining determine prices in OTC markets.[2] Spulber (1996), employing an alternative type of search model, shows that prices in decentralized markets (OTC markets) are determined by dealers' transaction costs.[3] In addition, dealers' transaction costs also affect OTC market structure. Atkeson, Eisfeldt, and Weill (2013) show that market entry costs help to determine the structure of OTC trading, and thereby prices charged in OTC trading. Past studies also show that dealers' strategies influence price determination. For example, Zhu (2012) shows that repeated visits to the same dealer results in a less favorable price for the trader. Empirically, the price of an asset in OTC trading seems to depend on order sizes and transparency of the market environment. Green, Hollifield, and Schürhoff (2007) find that a dealer earns smaller markups on larger trades in municipal bond markets. This negative relationship between order sizes and markups is also found in corporate bond markets by Schultz (2001) and Randall (2013). Bessembinder, Maxwell, and Venkataraman (2006), Goldstein, Hotchkiss, and Sirri (2007), and Edwards, Harris, and Piwowar (2007) estimate the bid-ask spread in the OTC market for corporate bonds, finding that more transparent bonds have smaller bid-ask spreads. Recently, new empirical studies (Li and Schürhoff (2012) and Hollifield, Neklyudov, and Spatt (2012)) have discovered a new factor that affects prices in OTC markets, namely the inter-dealer network.

Finally, my study adds to the growing literature on network studies in financial markets. Compared with the rich applications of network theory that have been made to other areas in

[2] Vayanos and Wang (2007), Vayanos and Weill (2008), and Weill (2008) extend the original model to study OTC markets with multiple assets. Lagos and Rocheteau (2009) relax the assumption on constraint asset holdings in the original model, which enables market participants to accommodate trading frictions by adjusting their asset positions.

[3] This type of search model also receives extended treatment in the literature. Rust and Hall (2003) extend the original model by introducing a centralized market to compete with decentralized markets. Zhong (2013) incorporates Knightian uncertainty into the search process to study the impact of transparency on OTC markets.

economics, the application of network theory to financial markets has only just begun.[4] Blume et al. (2009) and Gale and Kariv (2007) study how a network intermediates trades in a decentralized market. Gofman (2011) assesses the efficiency of resource allocation through the trading network in an OTC market. Malamud and Rostek (2013) develop a general framework for studying dealers' strategic interactions in decentralized markets. The decentralized market in their model is represented by a hypergraph (an abstract network, loosely speaking). Many past studies also focus on information acquisition from a network and its impact on financial markets. Han and Yang (2012) extend the rational expectation equilibrium model to study the information network in a financial market. Babus and Kondor (2012) study information transmission through inter-dealer networks in OTC markets by extending the model in Vives (2011) to games in networks. In addition to using network models to study OTC markets, others apply network models to the inter-bank market to analyze the contagion risk in the banking system (see Leitner (2005), Babus (2013), Blume et al. (2013), and Elliott, Golub, and Jackson (2013)). There is also a growing body of empirical studies that explore networks' implications on a variety of topics ranging from return predictability to CEOs' wages (see Cohen and Frazzini (2008), Cohen, Frazzini, and Malloy (2008), and Engelberg, Gao, and Parsons (2012)).

1.3 The Model

1.3.1 The Environment

Suppose there are $N \geq 2$ dealers in an OTC market. All dealers have the same mean-variance utility function over their wealth W, and all dealers have the same risk-aversion parameter $\rho >$

[4] Economic research on networks has tapped into various fields, such as job hunting in labor economics, decentralized market trading in microeconomics, and international alliance and trading agreements in macroeconomics. Jackson (2008) and Easley and Kleinberg (2010) provide excellent surveys of network applications in economic research.

0. That is,

$$U(W) = E(W) - \frac{\rho}{2} Var(W). \tag{1.1}$$

The initial endowment, consisting of a portfolio of m units of a risk-free asset and I units of a risky asset, is identical for all dealers. In this initial endowment, the risk-free asset has a constant value of 1, while the risky asset has a random value v following a normal distribution $\boldsymbol{N}(\bar{v}, \sigma^2)$.

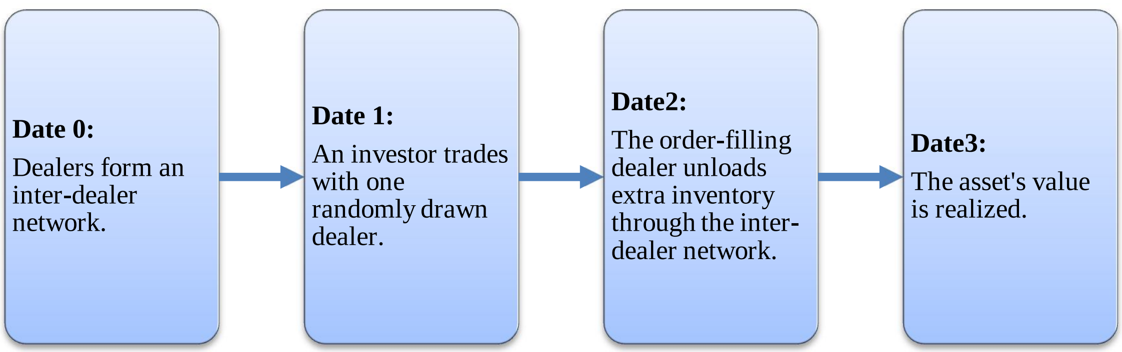

Figure 1.1: The Timeline

Figure 1.1 illustrates this timeline within the model. The timeline goes as follows. At date 0, dealers strategically form an inter-dealer network by building or severing links between each other. At date 1, an investor arrives and wants to trade an order of size z. Only one dealer in the network meets this investor, with a probability of meeting of λ, which is the matching rate. Assume that $\sum_N \lambda \leq 1$, which means that there is a probability of $1 - \sum_N \lambda$ that the arriving investor does not trade with any other dealer. The matching rate is assumed to be the same for all dealers. The price of the investor-dealer transaction is p^0. At date 2, the dealer who fills the investor's order at date 1 re-trades with other dealers to adjust his inventory risk. However, this order-filling dealer can trade only with those dealers who are connected to him. In this inter-dealer trade, the order-filling dealer solicits bids from his connected dealers, and then chooses the price that clears the market. To differentiate that price from the investor-dealer price p^0, I denote the price in the inter-dealer market as p. Finally, at date 3, the value of the risky asset is realized. In Section 1.6, I extend the model to consider multiple rounds of inter-dealer trading before the value of the asset is realized. By doing so, I am able to generate implications on "hot potato" trading in inter-dealer markets.

Assuming that the risk-aversion parameter, the initial endowment, the distribution of the risky asset's value, the matching rate, and the cost of adding links are common knowledge to all dealers, I solve the equilibrium by backward induction. Unless otherwise specified, in the rest of this chapter the arriving investor is regarded as a seller. (By symmetry, this would be similar to solving the equilibrium when the arriving investor is a buyer.)

1.3.2 The Inter-Dealer Trade at Date 2

In an inter-dealer market, a given dealer is able to contact several other dealers to explore their interest in trading through inter-dealer brokers. Typically, a dealer who has filled an investor's order solicits bids from other dealers. Then, as soon as the order-filling dealer receives quotes from interested dealers he chooses the price to clear the market. Past studies use search-theoretic models to capture such an inter-dealer trade (see Duffie, Garleanu, and Pedersen (2005, 2007) and Lagos and Rocheteau (2009)). Those studies postulate that an order-filling dealer sequentially searches for another dealer with whom to conduct a bilateral trade. Recently, empirical studies by Saunders, Srinivasan, and Walter (2002), Dunne, Hau, and Moore (2010), and Hendershott and Madhavan (2013) suggest that inter-dealer trading in OTC markets has become more like multilateral trading than bilateral trading. Services from inter-dealer brokers and the evolution of inter-dealer markets into limit-order book alike systems enable the order-filling dealer to approach other dealers at the same time rather than searching sequentially among dealers. To capture this multilateral feature of inter-dealer trading, I model the inter-dealer trade as an auction of shares, as in Viswanathan and Wang (2004).[5]

To reflect that an order-filling dealer trades only through his inter-dealer network, I modify the model in Viswanathan and Wang (2004) by restricting the order-filling dealer to soliciting bids only from his connected dealers. Specifically, if dealer i fills the investor's order at date 1, he then announces an auction at date 2 to all his connected dealers. In the auction, dealer i's connected dealers submit their demand schedules, which are combinations of prices and quantities, to dealer i. After dealer i collects those demand schedules, he chooses the price and quantity to clear the market.

Following Viswanathan and Wang (2004), in such an inter-dealer trade auction, dealer i's equilibrium strategy is

$$\left\{\left(\underbrace{I + z - X_i^A}_{\text{quantity supply}}, \underbrace{p_i}_{\text{the inter-dealer price}}\right) : X_i^A = (\overline{v} - p_i)\gamma + \frac{I + z}{n_i}\right\}, \tag{1.2}$$

where X_i^A is dealer i's risky holding after the inter-dealer trade, n_i is the number of links dealer i has, and $\gamma = (n_i - 1)/(n_i \rho \sigma^2)$ is the price elasticity. Let dealer j be a dealer who is linked to dealer i; dealer j's equilibrium strategy is

[5] The share auction is also called a uniform-price double auction. In such an auction, each player (the dealer in my model) bids for his residual supply and the market-clearing condition determines the price. This trading structure is used extensively in the literature to study the impact of strategic player interactions on asset prices (e.g., Kyle (1989), Vives (2011), and Malamud and Rostek (2013)).

$$\left\{\left(\underbrace{X_j^B}_{\text{quantity demand}}, \underbrace{p_i}_{\text{the inter-dealer price}}\right) : X_j^B = (\overline{v} - p_i)\gamma - \frac{n_i - 1}{n_i} I\right\}, \tag{1.3}$$

where X_j^B is the quantity demanded by dealer j. The market-clearing condition, which requires that $I + z - X_i^A = \sum_{j:j \text{ is linked with } i} X_j^B$, indicates that the inter-dealer price is

$$p_i = \overline{v} - \rho\sigma^2 \left(I + \frac{z}{n_i + 1}\right). \tag{1.4}$$

Viswanathan and Wang (2004) prove that the above strategies (Eq.(1.2), Eq.(1.3)) and price (Eq.(1.4)) constitute a unique linear equilibrium in the inter-dealer trade. In the linear equilibrium, dealer i's risky holding after the inter-dealer trade is

$$X_i^A = I + \frac{2z}{n_i + 1}, \tag{1.5}$$

and dealer j receives

$$X_j^B = \frac{n_i - 1}{n_i} \frac{z}{n_i + 1}, \tag{1.6}$$

shares of the risky asset from the inter-dealer trade. Dealers who are not connected with dealer i maintain their risky holdings as before. Eq.(1.6) indicates that the minimum number of links for ensuring that the inter-dealer trade occurs is 2, since $n_i < 2$ implies that $X_j^B \leq 0$. In other words, if the order-filling dealer connects to only one other dealer, no inter-dealer trade occurs.

Both dealer i and dealer j benefit from the inter-dealer trade. For dealer i, his welfare increases by

$$Eu\left(W\left(X_i^A\right)\right) - Eu\left(W(I + z)\right) = \frac{\rho\sigma^2 z^2}{2} \frac{n_i - 1}{n_i + 1} \geq 0. \tag{1.7}$$

And for dealer j, his welfare increases by

$$Eu\left(W\left(I + X_j^B\right)\right) - Eu\big(W(I)\big) = \frac{\rho\sigma^2 z^2}{2}\frac{n_i - 1}{n_i^2(n_i + 1)} \geq 0. \tag{1.8}$$

These benefits become more prominent when the risk increases (that is, increases in ρ, σ, and z), which reinforces the idea that the inter-dealer trade is a channel through which dealers share inventory risks. The benefit for dealer i increases with the number of links he has, whereas the benefit for dealer j decreases with the number of dealer i's links. This reflects the fact that dealer i uses his market power to extract more benefits from risk-sharing, since he can increase his selling price by exerting his market power (see Eq.(1.4)).

1.3.3 The Investor-Dealer Trade at Date 1

In an OTC market, direct trades between investors are rare, since each investor has his unique needs. In most cases, investors trade with OTC dealers. Having said that, it should be noted that investors cannot trade with multiple OTC dealers simultaneously. The lack of a centralized venue where dealers and investors can post their quotes implies that investors and dealers must search their counterparties for trades in OTC markets.[6] As a result, even though inter-dealer trades have evolved into multilateral trading, trades between investors and dealers remain bilateral.

Following precedent in the literature, I use a search-and-bargaining model to characterize the bilateral trading relationship between investors and dealers. To emphasize the influence of the inter-dealer network, I simplify the search problem. In particular, the probability that a dealer is matched with an incoming investor equals his matching rate λ. The matching rate measures the intensity of a dealer's search for an investor, and could be related to his publicity in an OTC market, his expertise in the asset traded, or his reputation regarding the services he has provided.[7]

[6] Although some inter-dealer markets have adopted limit-order book systems in which dealers can post their quotes, those systems are usually not accessible to investors.

[7] Neklyudov (2012) considers the matching rate as the proxy for a dealer's location since it represents a dealer's

When an investor meets a dealer, they bargain over the price. Following Nash (1950), the price is the solution of the following bargaining problem

$$\max_{p_i^0}\left(Eu\left(W\left(X_i^A\right)\right)-Eu\left(W(I)\right)\right)^q\left(z\left(p_i^0-M_0+M_1\sigma^2\right)\right)^{1-q} \tag{1.9}$$

where $p_i^0-M_0+M_1\sigma^2$ is the per unit utility gain for the investor if he sells and q represents the dealer's bargaining power.[8] The investor's gains from the trade can arise from aspects such as the search cost, his information about the asset, his risk aversion, and so on.[9] To ensure that the investor is willing to sell, I assume that $0<M_0-M_1\sigma^2<\bar{v}-\rho\sigma^2\left(I+\frac{z}{2}\right)$.

If there exists an inter-dealer trade at date 2, then the order-filling dealer's gains from trade, $Eu\left(W\left(X_i^A\right)\right)-Eu\left(W(I)\right)$, which equals $z\left(p_i-p_i^0\right)$. p_i is the inter-dealer price from Eq.(1.4). Hence, the solution to the bargaining problem involving an inter-dealer trade is

$$p_i^0=(1-q)p_i+q\left(M_0-M_1\sigma^2\right). \tag{1.10}$$

Eq.(1.10) implies that the investor-dealer's price, p_i^0, is proportional to the inter-dealer's price, p_i. In other words, when dealer i realizes that he can unload the extra inventory at a higher price in the inter-dealer market, he is more inclined to fill the investor's order at a higher price.

If there is no inter-dealer trade at date 2, then the order-filling dealer's final risky holding is $I+z$. This indicates that the order-filling dealer obtains $Eu\left(W(I+z)\right)-Eu\left(W(I)\right)$ in gains from trade, which equals $z\left(\bar{v}-\rho\sigma^2\left(I+\frac{z}{2}\right)-p_i^0\right)$. Under this case, the solution of the bargaining problem is

execution efficiency.

[8] For tractability, I assume that q is such that $\frac{2}{1-q}$ is an integer.

[9] One can replace this reduced-form assumption by explicitly modeling the seller's decision; e.g., a seller having a liquidity shock maximizes his mean-variance preference. This setting does not change the result of the model, but it adds considerable complexity and introduces more parameters.

$$p_i^0 = (1-q)\left(\bar{v} - \rho\sigma^2\left(I + \frac{z}{2}\right)\right) + q(M_0 - M_1\sigma^2). \tag{1.11}$$

In all,

$$p_i^0 = \tag{1.12}$$

$$\begin{cases} (1-q)\left(\overline{v} - \rho\sigma^2\left(I + \dfrac{z}{n_i + 1}\right)\right) + q(M_0 - M_1\sigma^2), & \text{when there exists inter-dealer trading,} \\ (1-q)\left(\overline{v} - \rho\sigma^2\left(I + \dfrac{z}{2}\right)\right) + q(M_0 - M_1\sigma^2), & \text{when there is no inter-dealer trading.} \end{cases}$$

1.3.4 Network Formation at Date 0

In Sections 1.3.2 and 1.3.3, I show that the inter-dealer price, the investor-dealer price, and volumes of inter-dealer trades depend on the equilibrium number of a dealer's links. In this section, I show that the equilibrium network determines the equilibrium number of a dealer's links. In particular, I demonstrate how the trade-off between the risk-sharing benefit and the linking cost determines the equilibrium network, and hence prices and volumes in OTC trading.

At date 0, dealers strategically form and sever links with each other. While it takes mutual consent to build a link, it takes just one side to sever a link. For every link the dealer adds, there is a cost. Specifically, the average cost of adding links is

$$\text{Average Cost}(n) = \frac{c}{n+1}, \tag{1.13}$$

in which n is the total number of links and c captures the magnitude of the average cost. The average cost function captures the idea of economies of scale. That is, the average cost decreases when more links are built. In reality, the linking cost for a dealer comes from the cost of managing counterparty risk such as the funding cost of preparing collateral, the cost of telecommunication, fees to inter-dealer brokers for obtaining other dealers' quotes and trading through inter-dealer brokers, and the opportunity cost of maintaining the additional link. Some portion of a dealer's linking cost is similar to a fixed cost, e.g., the telecommunication cost. Those fixed costs are spread out when dealers build more links. Thus, it is reasonable to assume that the linking cost exhibits economies of scale.

A natural approach to modeling network formation is defining a non-cooperative game among dealers, and such a non-cooperative game generates an equilibrium outcome as a graph. An equilibrium network is such a graph, consisting of a set of nodes and pairs of links that connect those nodes. Hence, the equilibrium network G is written as $(\mathcal{N}, \mathcal{E})$. $\mathcal{N}$ is the set of all dealers, i.e., $\mathcal{N} = \{1, 2, 3, \dots, N\}$, and $\mathcal{E}$ is the set of all links among those dealers, i.e., $\mathcal{E} = \{ij\text{: for some } i, j \in \mathcal{N}\}$.

Although it is appealing to study network formation within a game-theoretical framework, there are problems. There are, for example, various ways to specify such a game, such as the simultaneous link-announcement game in Myerson (1977) and the sequential link-announcement game in Aumann and Myerson (1988). In addition, as pointed out by Jackson and Wolinsky (1996), some standard game-theoretic equilibrium notions are not suitable for the study of network formation, since those notions do not reflect communication and coordination in the formation of networks.

To circumvent the abovementioned problems, network theorists study properties of networks that are of interest to them and can be satisfied in the equilibria of some network-formation games. In this spirit, I define an equilibrium inter-dealer network formed at date 0 using the strong stability concept from Jackson and van den Nouweland (2005):

Definition 1.1

A network G' *is obtainable from* G *via deviation by* $\mathcal{N}' \subset \mathcal{N}$ *if*

i) $ij \in G'$ *and* $ij \notin G$ *implies* $\{i, j\} \subset \mathcal{N}'$, *and*

ii) $ij \in G$ *and* $ij \notin G'$ *implies* $\{i, j\} \cap \mathcal{N}' \neq \emptyset$.

In the above, $ij \in G$ *means that* i *and* j *are linked in network* G, *whereas* $ij \notin G$ *means that* i *and* j *are not linked in network* G.

Definition 1.1 says that changes in a network can be made by a coalition $\mathcal{N}'$ without the consent of any dealers outside of $\mathcal{N}'$. Specifically, i) indicates that any new links that are built involve only dealers in $\mathcal{N}'$; ii) indicates that at least one dealer involved in any deleted link is in $\mathcal{N}'$.

Definition 1.2

Let $U_i(G)$ *be the payoff for dealer* i *in network* G. *Network* G *is strongly stable if, for any* $\mathcal{N}' \subset \mathcal{N}$, G' *is obtainable from* G *via deviations by* $\mathcal{N}'$, *and* $i \in \mathcal{N}'$ *such that* $U_i(G') > U_i(G)$, *there exists* $j \in \mathcal{N}'$ *such that* $U_j(G') < U_j(G)$.

Definition 1.2 states that one cannot find a coalitional deviation from a strongly stable network in which all relevant dealers are better off and with some are strictly better off. Strong stability requires that the network formed be coalition-proof. That is, a coalitional move from any subset of dealers cannot make all of them better off without hurting some dealers in this subset.

Requiring that a network exhibit strong stability imposes a requirement that is stricter than most other network stability requirements, since a strongly stable network makes tighter predictions due to coalitional considerations. Thus, strong stability is more robust than other definitions of an equilibrium network. In addition, the concept of being coalition-proof, which is used for cases in which players can communicate before they play a game, is particularly applicable to describing the equilibrium of an inter-dealer network. In an inter-dealer market, communications among dealers are almost inevitable.

Another appealing feature of strong stability is that a strongly stable network is the outcome of a pure strategy Nash equilibrium from Myerson's (1977) simultaneous link-announcement game. More importantly, such a strongly stable network is the Pareto-efficient outcome of this simultaneous link-announcement game (see Jackson and van den Nouweland (2005) and Jackson (2008)).

To simplify the notation, let $c^* = \frac{c}{\rho\sigma^2 z^2}$ be the relative cost. Given a network G, dealer i's payoff $U_i(G)$ is

$$U_i(G) = \overbrace{\lambda Eu\left(W(X_i^A)\right)}^{i \text{ fills the order}} + \overbrace{\sum_{j:ij\in G} \lambda Eu\left(W\left(X_j^B + I\right)\right)}^{i'\text{s connected dealer fills the order}} \tag{1.14}$$

$$+ \overbrace{\left(1 - \lambda - \sum_{j:ij\in G} \lambda\right) Eu\big(W(I)\big)}^{\text{neither } i \text{ nor his connected dealers fill the order}}$$

$$- \frac{\overbrace{cn_i}^{\text{total cost of links}}}{n_i + 1}$$

$$= \begin{cases} \rho\sigma^2 z^2 \left(\dfrac{c^* - \lambda q}{n_i + 1} + \displaystyle\sum_{j:ij\in G} \lambda \frac{1}{2} \frac{n_j - 1}{n_j^2 (n_j + 1)} \mathbf{1}_{[n_j \geq 2]} + \left(\frac{\lambda q}{2} - c^*\right) \right) + U_0, & n_i \geq 1 \\ U_0, & n_i = 0 \end{cases},$$

where n_i is the number of links dealer i has in network G, $\mathbf{1}_{[n_j \geq 2]}$ is an indicator function that takes 1 when $n_j \geq 2$ and 0 otherwise, and U_0 is the payoff when dealer i has no link,

$$U_0 = \lambda qz(\bar{v} - \rho\sigma^2 I - M_0 + M_1\sigma^2) + Eu\big(W(I)\big) - \frac{1}{2}\lambda\rho\sigma^2 qz^2. \quad (1.15)$$

Since all dealers are identical ex-ante, a strongly stable network in equilibrium should be symmetric. That is, all dealers should obtain the same level of payoff. If not, then some dealers enjoy higher payoffs than others. In such cases, dealers with lower payoffs could deviate together with those connected to a higher payoff dealer to provide an improving deviation. Thus, the original network would not be strongly stable. **Proposition 1.1** formalizes this intuition.

Proposition 1.1

Let a connected component be a sub-graph in which any two nodes are either directly connected or indirectly connected through a path consisting of several links. In a strongly stable network, all dealers in the same connected component, which has more than one connection, have the same number of connections. If such a strongly stable network consists of more than one connected component, then dealers in distinct components obtain identical payoffs.

The symmetry of a strongly stable network suggests that the total number of dealers, N, affects the existence of such a network. For example, when N is 6, symmetric networks are those in which every dealer has 2, 3, or 5 links. Any discontinuity between links in a symmetric network implies that no strongly stable network involving those links exists. In the above case, when N is 6, there is no strongly stable network in which every dealer has 4 links. To avoid such a discontinuity, I assume that N equals 2^k, where k is an integer greater than one. Under this assumption, a symmetric network can have links the number of which equals any integer between 2 and $2^k - 1$.

In **Proposition 1.2**, I characterize a strongly stable network in equilibrium. Together with Eq.(1.2), Eq.(1.3) and Eq.(1.4), which characterize the inter-dealer equilibrium, and Eq.(1.10), which characterizes the price of the investor-dealer trade, **Proposition 1.2** describes the equilibrium of the model.

<u>Proposition 1.2</u>

The following describes a strongly stable network in equilibrium.

i) *If* $c^* > \frac{\lambda(1+q)^2}{8}$*, then the strongly stable network is an empty network.*

ii) *If* $c^* < \min\left\{\lambda\left(\frac{2N-1}{2(N-1)^2} + q - \frac{1}{2}\right), \frac{\lambda(1+q)^2}{8}\right\}$*, then the strongly stable network is a complete network.*

iii) *If* $\lambda\left(\frac{2N-1}{2(N-1)^2} + q - \frac{1}{2}\right) \leq c^* \leq \frac{\lambda(1+q)^2}{8}$*, the strongly stable network is such that all dealers have the same number of links, and the number equals* $\left\llbracket \frac{1+\sqrt{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)} \right\rrbracket$.[10]

iv) *If none of the above conditions is satisfied, then there is no strongly stable network in equilibrium.*

In equilibrium, risky asset holdings, the inter-dealer price, and the investor-dealer price depend on the number of dealers' links. Specifically, under i), there is no inter-dealer network. Hence, there is no inter-dealer trade. The investor-dealer price is

$$p_{i)}^{0} = (1-q)\left(\overline{v} - \rho\sigma^2\left(I + \frac{Z}{2}\right)\right) + q(M_0 - M_1\sigma^2). \tag{1.16}$$

Under ii), the price in the inter-dealer trade is

$$p_{ii)} = \overline{v} - \rho\sigma^2\left(I + \frac{Z}{N}\right), \tag{1.17}$$

and the price in the investor-dealer trade is

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10 $\left\llbracket \frac{1+\sqrt{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)} \right\rrbracket = \arg\max_{n\in\left\{\left\lfloor \frac{1+\sqrt{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)} \right\rfloor, \left\lfloor \frac{1+\sqrt{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)} \right\rfloor+1\right\}} \left(c^* - \lambda q + \frac{\lambda}{2} - \frac{\lambda}{2n}\right)\frac{1}{n+1}$, where $\left\lfloor \frac{1+\sqrt{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)} \right\rfloor$ represents the largest integer no larger than $\frac{1+\sqrt{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)}$.

$$p_{ii)}^{0} = (1-q)p_{ii)} + q(M_0 - M_1\sigma^2). \quad (1.18)$$

Under iii), the inter-dealer price is

$$p_{iii)} = \overline{v} - \rho\sigma^2 \left(I + \frac{z}{\left\llbracket \frac{1 + \sqrt{2\left(\frac{c^*}{\lambda} - q + \frac{1}{2}\right) + 1}}{2\left(\frac{c^*}{\lambda} - q + \frac{1}{2}\right)} \right\rrbracket + 1} \right), \quad (1.19)$$

and the price in the investor-dealer trade is

$$p_{iii)}^{0} = (1-q)p_{iii)} + q(M_0 - M_1\sigma^2). \quad (1.20)$$

Figure 1.2 shows a complete network as an equilibrium network corresponding to **Proposition 1.2 (ii)**, while Figure 1.3 shows a 4-link symmetric network as an equilibrium network, which corresponds to **Proposition 1.2 (iii)**. The total number of dealers in Figure 1.2 and 1.3 is eight.

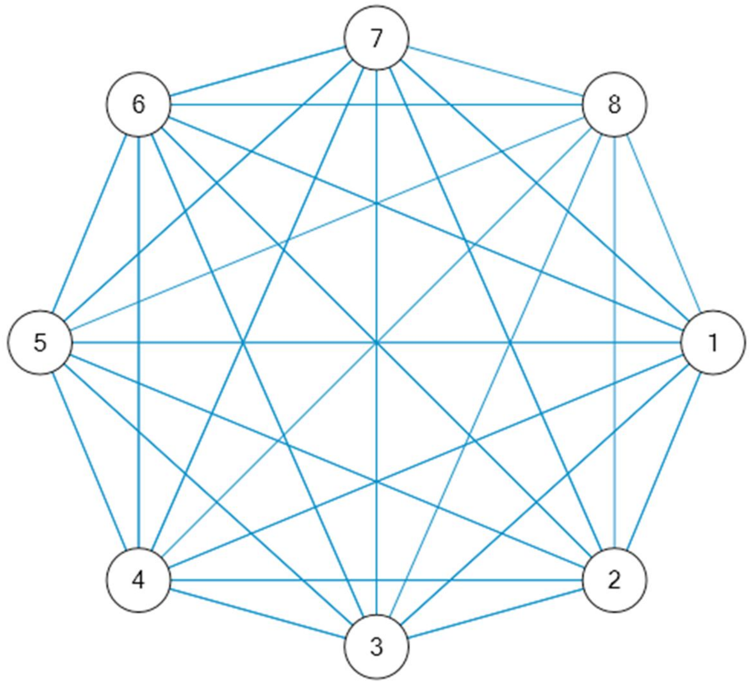


Figure 1.2: A Strongly Stable Network that is Complete

The above figure shows an equilibrium network that is complete. In the complete network all dealers are connected. Every dealer has seven links.

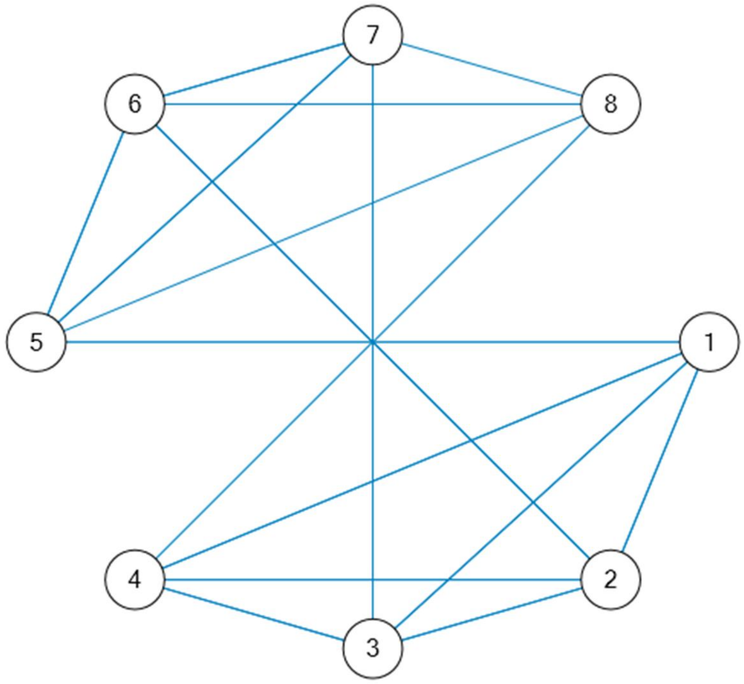


Figure 1.3: A Strongly Stable Network with Four Links

The above figure shows an equilibrium network in which every dealer has four links

Proposition 1.2 indicates that the trade-off between the linking cost and the risk-sharing benefit determines the equilibrium of a network. A dealer becomes more connected when the benefit from risk-sharing increases or when the linking cost decreases. The following proposition formalizes this statement.

Proposition 1.3

The number of links made by a dealer increases when the relative cost c^* decreases, that is, i) when the order size increases, ceteris paribus; ii) when volatility increases, ceteris paribus; or iii) when the linking cost decreases, ceteris paribus.

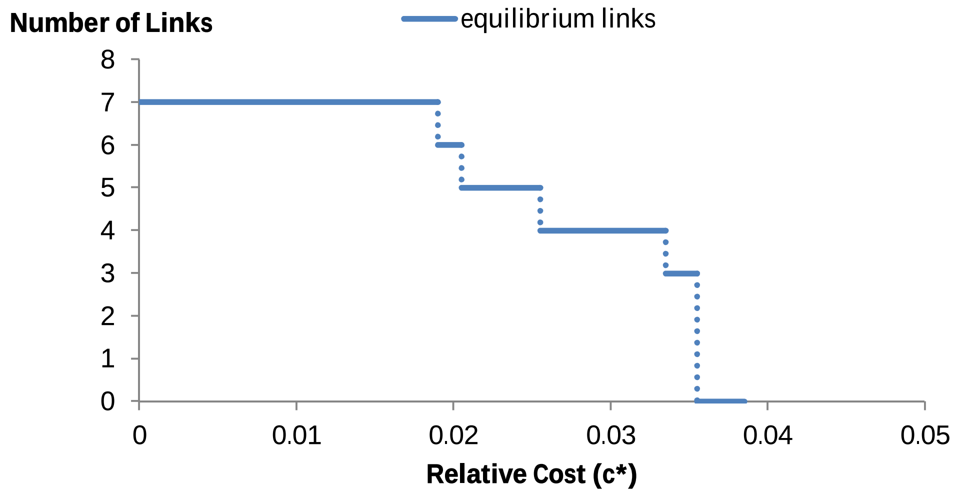


Figure 1.4: Equilibrium Number of Links and Relative Cost

Figure 1.4 depicts the relationship between the equilibrium number of links and the relative cost. The relative cost is $c^* = \frac{c}{\rho\sigma^2 z^2}$. *Parameters chosen are* $N = 8, \lambda = \frac{1}{8}, \rho = 1, \sigma = 1, z = 1,$ *and* $q = \frac{1}{2}$.

Figure 1.4 shows the negative relationship between the number of links and the relative cost as stated in **Proposition 1.3**. **Proposition 1.3** implies that larger orders give rise to more connected inter-dealer markets. This seems to be consistent with anecdotal evidence from dealer markets. For example, in the foreign exchange market, the bulk of the trading volume comes from inter-dealer trades, and those trades usually consist of larger orders. In stock trading, the upstairs market, where broker-dealer firms trade with each other, almost exclusively carries out block trades. **Proposition 1.3** provides a testable empirical prediction pertaining to the inter-dealer network of an OTC market. The connectedness of an inter-dealer network is positively related to order sizes and volatility in an OTC market.

1.4 Comparative Statics Analysis of an Inter-Dealer Network

Proposition 1.3 suggests two ways, or layers, in which primitives such as order sizes and volatility can affect equilibrium. At the first layer, primitives change equilibrium outcomes when an equilibrium network does not change. At the second layer, primitives change the equilibrium network, which then changes equilibrium outcomes. I refer to the first layer as the local property and the second layer as the global property. In the following sections, I first show the results of a comparative analysis of the local property and then illustrate results regarding the global property. Finally, I discuss the connection between local and global properties.

1.4.1 The Local Property of an Inter-Dealer Network

To investigate the local property of an equilibrium network, I fix the equilibrium network and then investigate how order sizes and volatility affect equilibrium prices. An important equilibrium price is the markup for an order-filling dealer. The markup measures the order-filling dealer's profitability in making the market for investors. The markup is the price difference between the price at which the order-filling dealer buys an asset from an investor and the price at which he sells it to other dealers. That is,

$$\text{markup} = p_i - p_i^0 = q(p_i - M_0 + M_1\sigma^2). \tag{1.21}$$

<u>Proposition 1.4</u>

Given an equilibrium network, the inter-dealer price, the investor-dealer price, and the markup decrease with the order size.

When the order size increases, inventory risk also increases. Meanwhile, the order-filling dealer's risk-sharing ability is fixed insofar as the network is fixed. To unload extra inventory, the order-filling dealer has to sell it at a lower price in the inter-dealer market. The lower inter-dealer price reduces the investor-dealer price. The order-filling dealer decreases his price when buying an asset from an investor in the anticipation of a lower price for off-loading a large order in the inter-dealer market. However, due to bargaining, the order-filling dealer is not able to transfer completely the decrease in the inter-dealer price to the investor. This reduces the order-filling dealer's profitability because he must accept a smaller markup.

The negative relationship between markups and order sizes conforms to empirical findings for corporate and municipal bond markets (see Randall (2013) and Green, Hollifield, and Schürhoff (2007)). More importantly, my model offers an alternative explanation to those offered in past studies. Past studies argue that larger orders are from sophisticated investors who have greater bargaining power and hence lead to smaller markups for dealers. I show that, even if dealers have the same bargaining power as investors (when $q = \frac{1}{2}$), the negative relationship between markups and order sizes persists because of the increasing cost to dealers of unloading large inventory volume in the inter-dealer market. That said, my explanation for this negative relationship does not contradict the explanation based on bargaining power. Eq.(1.10), makes it obvious that a decrease in dealers' bargaining power, q, decreases the markup. Thus, a larger order associated with a smaller dealer's bargaining power decreases the markup.

<u>Proposition 1.5</u>

The inter-dealer price and the investor-dealer price decrease with volatility. If $M_1 > \rho\left(I + \frac{z}{n_i+1}\right)$, then the markup increases with volatility; otherwise the markup decreases with volatility.

As the previous discussion of the relationship between inter-dealer prices and order sizes suggests, when volatility increases, a traded asset becomes more risky, which intensifies the order-filling dealer's risk-sharing need. Consequently, the inter-dealer price decreases, which leads to a decrease in the investor-dealer price. However, the impact of volatility on the markup is different from the impact of an order size on the markup. Besides affecting the markup from the dealer side, volatility also affects the markup from the investor's side. Specifically, when volatility increases the investor's utility for holding the asset $M_0 - M_1\sigma^2$ decreases, which implies that the investor is more willing to sell the asset. This results in a further decrease in the investor-dealer price. When the investor's willingness to sell is relatively strong (when $M_1 > \rho\left(I + \frac{z}{n_i+1}\right)$), the drop in the investor-dealer price exceeds the drop in the inter-dealer price, and hence the markup increases. The relationship between price markups and volatility depends on the investor's altitude towards risk.

1.4.2 The Global Property of an Inter-Dealer Network

In Section 1.4.1, I discussed relationships between equilibrium outcomes and order sizes and relationships between equilibrium outcomes and volatility within a fixed equilibrium network. In this section, I consider the global property of an equilibrium network. In other words, I examine what happens to equilibrium outcomes such as prices and trading volumes when the equilibrium network changes.

Proposition 1.6

If the number of links that an order-filling dealer has increases, he sells at a higher inter-dealer price, buys at a higher investor-dealer price, and earns a larger markup.

In an inter-dealer trade, the order-filling dealer solicits bids from his connected dealers. If the network becomes more connected, the order-filling dealer links to more dealers. The bidding competition becomes more intense, and hence drives the inter-dealer price in favor of the order-filling dealer. Consequently, the order-filling dealer is willing to buy at a higher price from the seller. However, the order-filling dealer increases the investor-dealer price only to the extent that his profit still increases. That is, his markup goes up.

Trading volumes for a dealer involve two parts. The first part is the trading volume when he is an order-filling dealer; the second part is the trading volume when one of his connected dealers is an order-filling dealer. Specifically, dealer i's expected number of trades is

$$\lambda + \sum_{j:ij\in G} \lambda = (n_i + 1)\lambda. \tag{1.22}$$

And dealer i's expected trading volume is

$$\lambda\left(I + z - X_i^A\right) + \sum_{j:ij\in G} \lambda X_j^B = 2\lambda\left(1 - \frac{2}{n_i + 1}\right)z. \tag{1.23}$$

In the above, both equalities are obtained as $n_i = n_j$ because dealer i and dealer j have the same number of links when they are connected in an equilibrium network (see **Proposition 1.1**).

Proposition 1.7

The more links a dealer has in an inter-dealer network, the more trades he makes and the greater is his trading volumes.

Proposition 1.7 states that more trades take place when the network becomes more connected. This is not surprising, as more links increase a dealer's probability of participating in risk-sharing trades with other dealers.

To see if a more connected network improves risk-sharing, I examine the risk of a dealer's inventory in equilibrium. The expected risky holding for dealer i is

$$EX_i = \lambda X_i^A + \sum_{j:ij\in G} \lambda\left(I + X_j^B\right) + \left(1 - \lambda - \sum_{j:ij\in G} \lambda\right)I \tag{1.24}$$

And the variance of the risky holding is

$$Var(X_i) = \lambda {X_I^A}^2 + \sum_{j:ij\in G} \lambda\left(I + X_j^B\right)^2 + \left(1 - \lambda - \sum_{j:ij\in G} \lambda\right)I^2 - (EX_i)^2 \tag{1.25}$$

Proposition 1.8

The variance of a risky holding decreases as the number of links a dealer has increases.

Based on **Proposition 1.8**, a more connected network reduces dealers' inventory risks. Together, **Proposition 1.7** and **1.8** imply that a more connected network achieves better risk-sharing among dealers, which accompanies higher trading volumes in the inter-dealer market. The positive relationship between a network's connectedness and trading volumes and the negative relationship between connectedness and inventory risks yield two testable empirical predictions from my model.

1.4.3 The Connection between Local Properties and Global Properties

As discussed at the beginning of Section 1.4, changes in primitives have two layers of impacts on equilibrium. One affects equilibrium outcomes directly, while the other exerts influence through changing the equilibrium network's structure. Because of the second impact, the local property of the network is not stable. In other words, relationships between prices and order sizes, or between prices and volatility, can exhibit structural breaks as variations in order sizes and volatility can also change the structure of the equilibrium network.

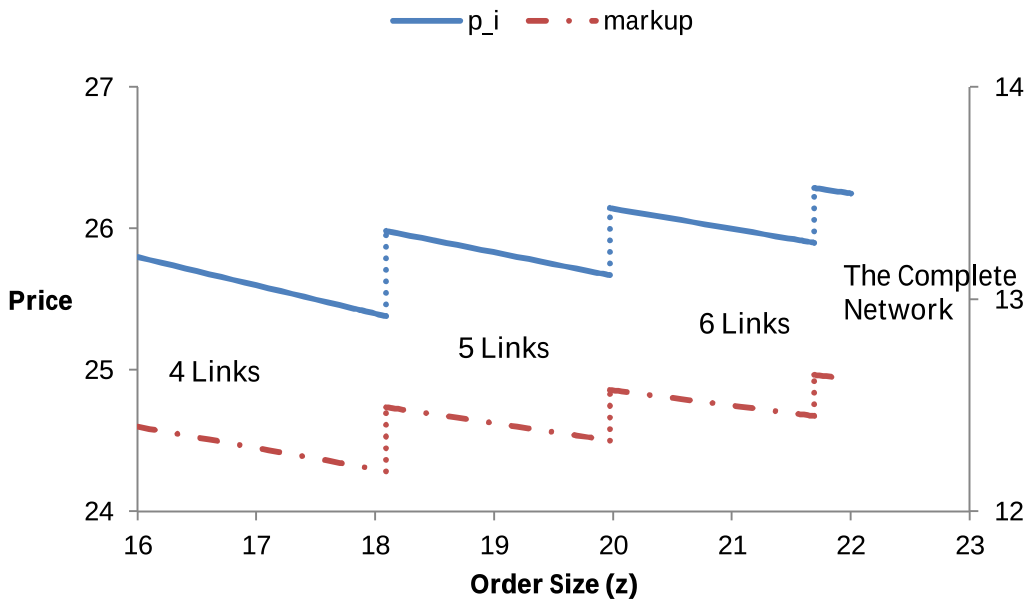


Figure 1.5: The Relationship between Prices and Order Sizes

Figure 1.5 depicts structural breaks in the negative relationship between inter-dealer prices and order sizes, and the negative relationship between markups and order sizes. Parameters chosen are $c = 9, \lambda = \frac{1}{8}, \rho = 1, \sigma = 1, I = 1, \overline{v} = 30, q = \frac{1}{2}, M_0 = 0, M_1 = 1,$ *and* $z \in [16, 22]$. *The structural break occurs at* $z = 18.09, 19.97,$ *and* 21.69.

Figure 1.5 shows that the negative relationship between markups and order sizes exhibits jumps as the order size increases. Such jumps occur when the network becomes more connected, i.e., the number of a dealer's links increases. As shown in **Proposition 1.6**, the markup and the inter-dealer price increase when the network becomes more connected, and the jumps shown in Figure 1.5 reflect this increase. The same pattern exists in relationships between prices and volatility (see Figure 1.6).

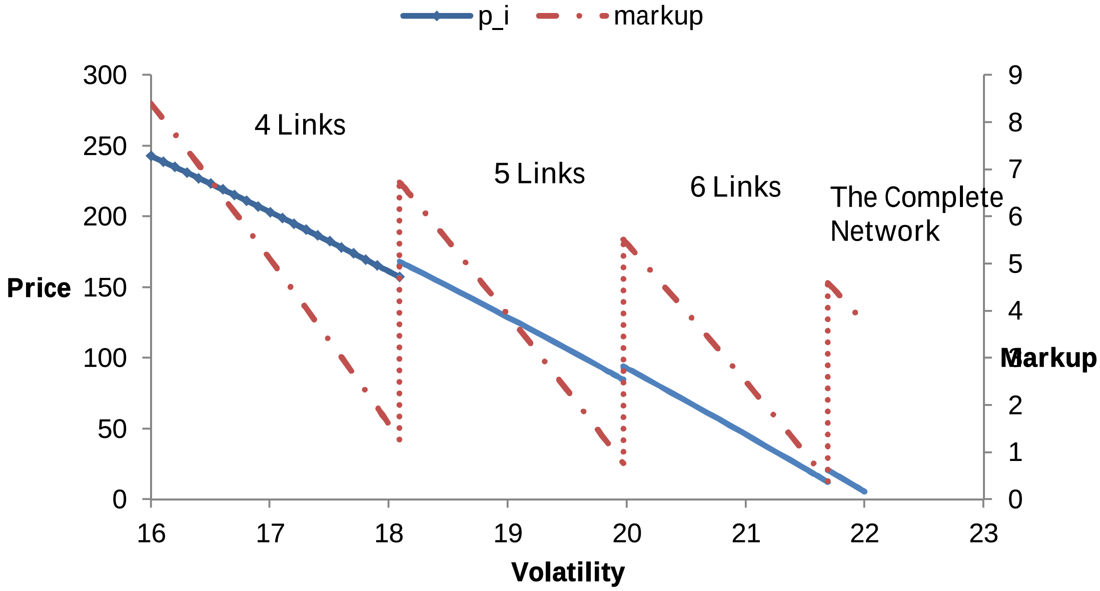


Figure 1.6: The Relationship between Volatility and Order Sizes

Figure 1.6 depicts structural breaks in the negative relationship between inter-dealer prices and volatility, and the negative relationship between markups and volatility. Parameters chosen are $c = 9, \lambda = \frac{1}{8}, \rho = 1, z = 1, I = 1, \overline{v} = 30, q = \frac{1}{2}, M_0 = 482, M_1 = 1$, *and* $\sigma \in [16, 22]$. *The structural break occurs at* $\sigma = 18.09, 19.97$, *and* 21.69.

The above discussion suggests that empirical research on OTC markets should take into account the stability of the underlying network. Otherwise, the regression model used runs the risk of model misspecification, since the regression model may suffer from structural breaks. For example, empirical research should include a measure of a network's connectedness as an additional control variable interacting with other important explanatory variables in a regression model. In Section 1.7, I discuss this empirical implication more thoroughly, together with other implications of the model.

1.5 Core-Periphery Inter-Dealer Networks

In the previous model I assume that dealers are homogeneous. This assumption reduces the model's complexity. In the model dealers have to decide only how many links to make, but they do not have to decide with whom they should connect, since all dealers are the same ex-ante. In this section, I introduce heterogeneity among dealers into the model. Dealers are different in their capacity of providing liquidity to investors. Specifically, there are three types of dealers. The first type consists of dealers with small capacity $s_S = \underline{z}$. Those dealers are small or regional banks who can only accommodate retail-sized orders, i.e., the size of the order is no larger than $\underline{z}$. The second type consists of dealers with medium capacity $\underline{z} + s_M$. The third type dealer has large capacity $\underline{z} + s_L$. Large-capacity dealers are those big banks who are able to provide liquidity to both retail investors (with small orders) and institutional investors (with huge orders).

In addition to introducing differences in dealers' capacity of liquidity provision, I relax the assumption that the size of the investor order is constant. I assume that the size of the investor order is random and follows a Pareto distribution.[11] This assumption together with the above assumption that dealers have different capacity determines a dealer's probability of trading with an investor. Specifically, at date 1, an investor arrives and wants to trade an order of size $z \sim Pareto(\underline{z}, 1)$.[12] The investor meets with one dealer in the network with probability λ. If the order size z is smaller than the chosen dealer's capacity, then the dealer fills the investor order. Otherwise, no investor-dealer trade occurs. Hence, for a large-capacity dealer, his probability of trading with an investor equals $\lambda \times \Pr\left[z \le \underline{z} + s_L\right] = \lambda\left(1 - \frac{\underline{z}}{\underline{z}+s_L}\right)$; for a medium-capacity

[11] The assumption that the order size follows a Pareto distribution does not affect any implication in the model. For any distribution, large capacity dealers always have the highest probability of trading with an investor, since large capacity dealers are able to accommodate any orders that medium or small capacity dealers accommodate. The probability of trading is the key driver that gives rise to the core-periphery equilibrium network. That being said, using Pareto distribution significantly reduces redundancy in the mathematical derivation.

[12] $z \sim Pareto(\underline{z}, 1)$ means that z follows a Pareto distribution with a scale parameter $\underline{z}$ and a shape parameter 1. The probability density function for z is

$$f(z) = \begin{cases} \frac{\underline{z}}{z^2}, \text{ if } z \ge \underline{z} \\ 0, \text{ otherwise} \end{cases}.$$

dealer, his probability of trading with an investor equals $\lambda\left(1-\frac{\underline{z}}{\underline{z}+s_M}\right)$; for a low-capacity dealer, his probability of trading with an investor is zero.

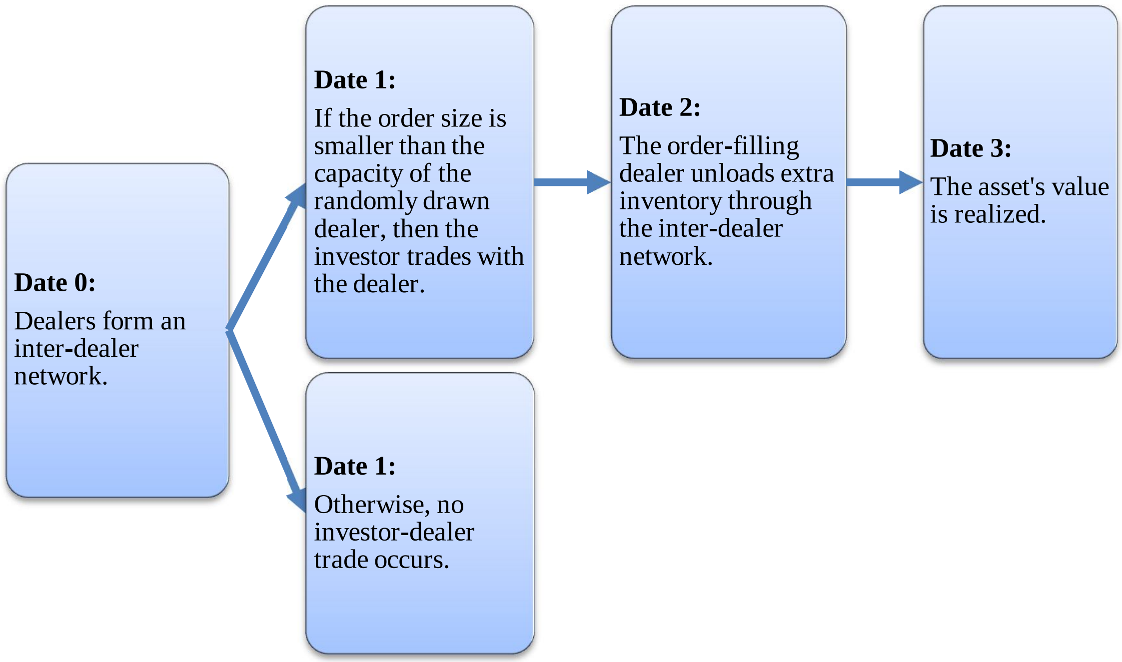


Figure 1.7: The Timeline of the Extended Model

Figure 1.7 gives the timeline of the extended model. At date 0, dealers form an inter-dealer network. At date 1, a randomly selected dealer meets with the investor. They trade if the order size is smaller than the dealer's capacity. Otherwise, they don't trade. At date 2, the dealer who fills the order at date 1 starts to re-trade through his inter-dealer network. At date 3, the asset's value is realized

Figure 1.7 gives the timeline of this extended model. It is similar to the model in Section 1.3 except for two differences. The first difference is that the size of the investor order is random, and it follows a Pareto distribution. The second difference is that at date 1, an investor-dealer trade occurs if the order size is smaller than the capacity of the selected dealer. Otherwise, no investor-dealer trade occurs. All the rest is the same as the benchmark model (see Figure 1.1).

With capacity as the only device of heterogeneity that differentiates dealers, I show that the equilibrium network is asymmetric. An asymmetric network means that dealers do not have the same number of links. The core-periphery structure is a special case of this asymmetric network. Additionally, I show that differences in capacity create a vacillating relationship between investor-dealer prices and dealers' centrality (measured by the number of a dealers' links).

Denote $\tilde{c} = \frac{c}{\lambda\rho\sigma^2\underline{z}}$. Given a network G, the payoff for dealer i is, $\underline{z}$

$$
\begin{aligned}
&U_i(G) \qquad (1.26)\\
&= \int_{\underline{z}}^{\infty}\Bigg(\overbrace{\lambda\mathbf{1}_{[z\leq\underline{z}+s_i]}Eu\left(W(X_i^A)\right)}^{i\text{ fills the order}}\\
&+\overbrace{\sum_{j:ij\in G}\lambda\mathbf{1}_{[z\leq\underline{z}+s_j]}Eu\left(W\left(X_j^B+I\right)\right)}^{i'\text{s connected dealer fills the order}}\Bigg)f(z)dz\\
&+\overbrace{\left(1-\lambda\left(1-\frac{\underline{z}}{\underline{z}+s_i}\right)-\sum_{j:ij\in G}\lambda\left(1-\frac{\underline{z}}{\underline{z}+s_j}\right)\right)Eu\big(W(I)\big)}^{\text{neither } i \text{ nor his connected dealers fill the order}}\\
&-\quad\frac{\overbrace{cn_i}^{\text{total cost of links}}}{n_i+1}\\
&=\begin{cases}\lambda\rho\sigma^2\underline{z}\left(\dfrac{\tilde{c}-s_iq}{n_i+1}+\displaystyle\sum_{j:ij\in G}\frac{1}{2}s_j\frac{n_j-1}{n_j^2(n_j+1)}\mathbf{1}_{[n_j\geq 2]}+\left(\frac{s_iq}{2}-\tilde{c}\right)\right)+U_0, & n_i\geq 1\\ U_0, & n_i=0\end{cases},
\end{aligned}
$$

and where U_0 is dealer i's payoff when he has no link. U_0 is defined as follows,

$$
\begin{aligned}
U_0 &= \lambda q(\overline{v}-\rho\sigma^2 I-M_0+M_1\sigma^2)\ln\frac{\underline{z}+s_i}{\underline{z}}+Eu\big(W(I)\big) \qquad (1.27)\\
&\qquad -s_i\frac{\lambda\rho\sigma^2 q\underline{z}}{2}.
\end{aligned}
$$

Proposition 1.9

Let n_{s_L}, n_{s_M}, and n_{s_S} be the number of links for large-capacity dealers, medium-capacity dealers, and small-capacity dealers, respectively. Then, in a strongly stable network,

$$n_{s_L} \geq n_{s_M} \geq n_{s_S}. \tag{1.28}$$

Proposition 1.9 indicates that the equilibrium network when dealers have different capacity in providing liquidity is asymmetric. Some dealers have more links than others. I show that centrality measured by the number of links a dealer has is positively determined by the dealer's capacity. A dealer who has larger capacity and is more capable of accommodating investors' orders has more links. The dealer with large capacity has greater risk-sharing needs, since he has a greater likelihood of facing a liquidity shock. Such a liquidity shock occurs if the dealer fills the order from an incoming investor. As a result, the large-capacity dealer is inclined to build more links. At the same time, connecting with the large-capacity dealer implies more chances for other dealers to participate in risk-sharing activities, which means greater benefits. Hence, other types of dealers are also inclined to connect to the large-capacity dealer. This mutual consent leads to the equilibrium in which the large-capacity dealer has the greatest number of links.

Since the core-periphery network is a special case of the asymmetric network, **Proposition 1.9** explains the core-periphery structure of the inter-dealer network found in empirical studies (Hollifield, Neklyudov, and Spatt (2012) and Li and Schurhoff (2012)). In a core-periphery network, some dealers operate at the core of the network, connecting to all dealers, while peripheral dealers connect to no one but those at the core. Consequently, core dealers have more links than peripheral dealers. **Proposition 1.9** suggests that large-capacity dealers comprise the core and have more links than peripheral dealers, who are those small-capacity dealers.

As a large-capacity dealer has a higher probability of trading than other dealers, **Proposition**

1.9 also justifies the model in Neklyudov (2012). In that paper, the author studies the impact of the core-periphery structure using a dealer's matching rate, which is essentially a dealer's probability of trading, as the proxy for a dealer's centrality in the network. My model supports this idea of approximating a dealer's centrality with his matching rate. I show that dealers with high matching rates have higher centrality than dealers with low matching rates, which is an equilibrium consequence of strategic network formation.

To focus on the core-periphery network and illustrate the vacillating relationship between investor-dealer prices and dealers' centrality, I restrict $\tilde{c}$ such that $s_M q \le \tilde{c} \le s_L \min\left\{q, \frac{1}{2}\frac{N_{s_L}-2}{\left(N_{s_L}-1\right)^2 N_{s_L}}\right\}$. N_{s_L} is the total number of large-capacity dealers. $N_{s_M} = 2^k$ $(k \ge 1)$ is the total number of medium-capacity dealers, and $N_{s_M} > N_{s_L} > 2$.

<u>Proposition 1.10</u>

When dealers have varying capacity s_L, s_M, and s_S, a strongly stable network in equilibrium is as follows. Dealers with the large capacity s_L form the core of the network and connect to all dealers; dealers with the small capacity s_S form the periphery and connect only to those at the core; dealers with the medium capacity s_M connect to all large-capacity dealers and other $n^*_{s_M} - N_{s_L}$ medium-capacity dealers. $n^*_{s_M}$ is

$$n^*_{s_M} = \arg\max_{n_{s_M} \in \mathbb{N}} \left(\tilde{c} - s_M q + \frac{s_M}{2} - s_M \frac{n_{s_M}\left(N_{s_L}+1\right) - N_{s_L}}{2n^2_{s_M}}\right)\frac{1}{n_{s_M}+1}. \quad (1.29)$$

Proposition 1.10 shows the equilibrium network that exhibits the core-periphery structure as found in empirical studies. Figure 1.8 gives an example of this core-periphery network. In Figure 1.8, there are 20 dealers (3 large-capacity dealers, 8 medium-capacity dealers, and 9 small-capacity dealers). Only large-capacity dealers operate at the core of the network, while small-capacity dealers are the periphery of the network.

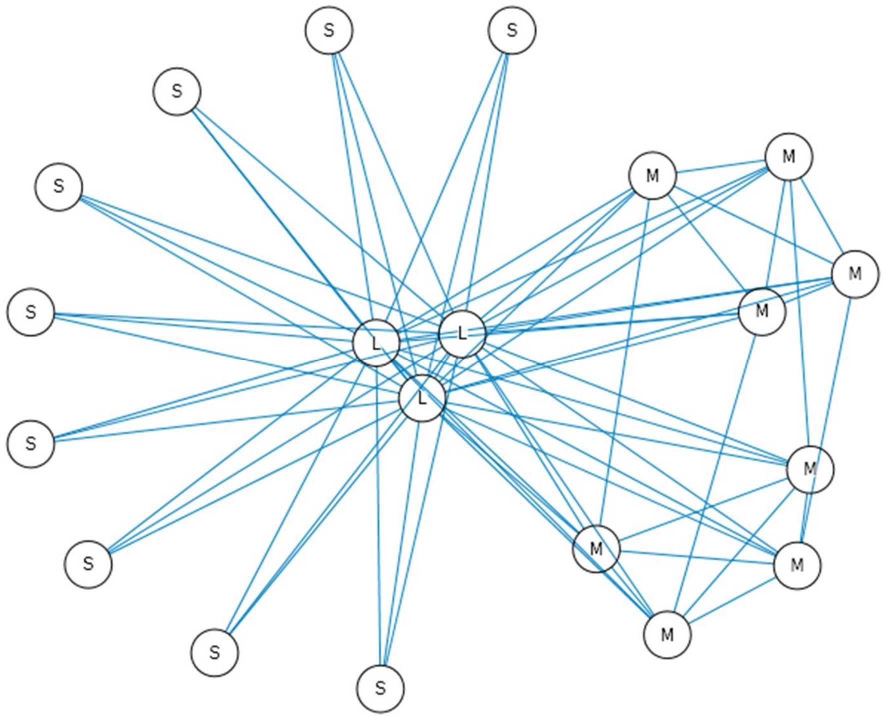


Figure 1.8: A Core-Periphery Network

Figure 1.8 shows a core-periphery network in which large-capacity dealers comprise the core of the network and small-capacity dealers become the periphery. L represents the large-capacity dealer, M represents the medium-capacity dealer, and S represents the small-capacity dealer. In equilibrium, each L has 19 links, each M has 7 links, and each S has only 3 links.

In the core-periphery network, core dealers do not necessarily offer more favorable prices to investors. Two opposite forces affect the investor-dealer price that a core dealer offers. On one side, a core dealer has more links, thereby greater market power in inter-dealer trading. Greater market power in the inter-dealer market enables the core dealer to sell at a higher price, and hence to buy from an investor at a higher price. On the other side, a dealer becomes the core because of his large capacity, which implies he fills larger orders than other dealers. Larger orders overburden the dealer's inventory rebalancing in inter-dealer trading, and hence worsen the dealer's price in the inter-dealer market. Consequently, the large-capacity dealer buys from an investor at a lower price. In short, the cross-sectional relationship between investor-dealer prices and dealers' centrality is ambiguous. **Proposition 1.11** illustrates this undetermined relationship.

<u>Proposition 1.11</u>

Denote $\bar{p}^0_{s_L}$ and $\bar{p}^0_{s_M}$ as the average investor-dealer price from large-capacity dealers and medium-capacity dealers, respectively. If $\frac{\left(1+\frac{z}{s_L}\right)\ln\left(1+\frac{s_L}{z}\right)}{\left(1+\frac{z}{s_M}\right)\ln\left(1+\frac{s_M}{z}\right)} \leq \frac{N}{n^*_{s_M}+1}$, *then* $\bar{p}^0_{s_L} \geq \bar{p}^0_{s_M}$. *Otherwise,* $\bar{p}^0_{s_L} < \bar{p}^0_{s_M}$. *In the above,* $n^*_{s_M}$ *is defined in* ***Proposition 1.10*** *and N is the total number of dealers.*

Proposition 1.11 gives the condition under which large-capacity dealers buy from investors at higher prices, and under which large-capacity dealers buy at lower prices. Since a dealer's capacity positively determines his centrality, **Proposition 1.11** suggests that the relationship between investor-dealer prices and dealers' centrality vacillates between positive and negative. Figure 1.9 further illustrates this ambiguous relationship between investor-dealer prices and dealers' centrality by following the example in Figure 1.8. In the figure, a medium-capacity dealer has 7 links and a large-capacity dealer has 19 links in equilibrium. The large-capacity dealer has higher centrality than the medium-capacity dealer. In the upper panel of the figure, the relationship investor-dealer prices and centrality is positive. This occurs when the difference in capacity between high centrality dealers and low centrality dealers is small. That is, $\frac{\left(1+\frac{z}{s_L}\right)\ln\left(1+\frac{s_L}{z}\right)}{\left(1+\frac{z}{s_M}\right)\ln\left(1+\frac{s_M}{z}\right)} \leq \frac{N}{n^*_{s_M}+1}$. However, when the difference in capacity is big, the relationship becomes negative, which is illustrated in the bottom panel of the figure. This occurs when

$$\frac{\left(1+\frac{z}{s_L}\right)\ln\left(1+\frac{s_L}{z}\right)}{\left(1+\frac{z}{s_M}\right)\ln\left(1+\frac{s_M}{z}\right)} > \frac{N}{n_{s_M}^*+1}.$$

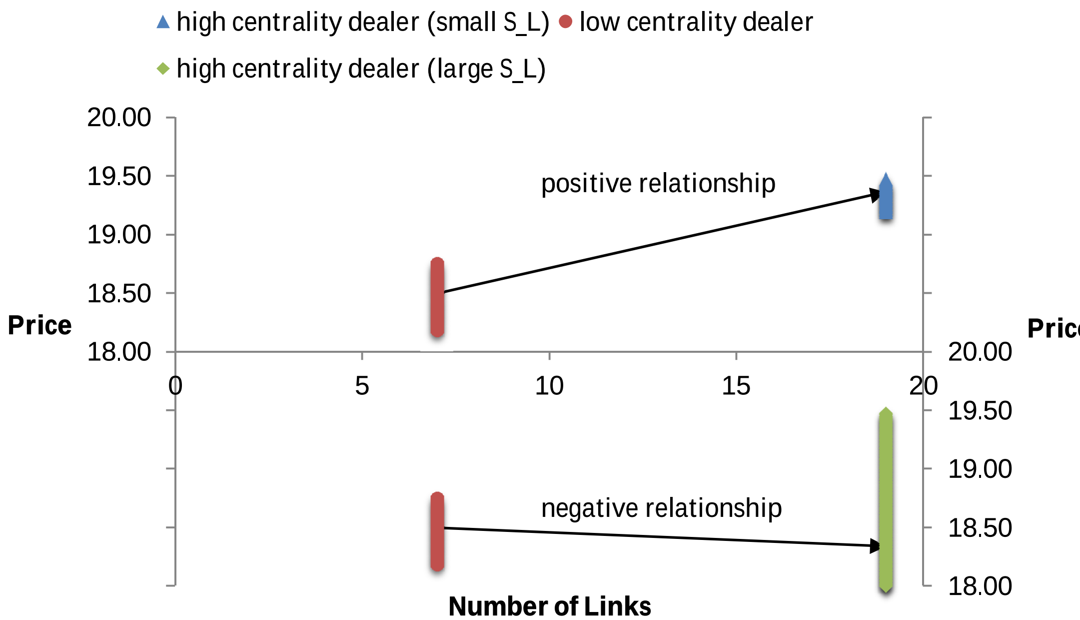


Figure 1.9: The Relationship between Investor-Dealer Prices and Centrality

Figure 1.9 shows that the relationship between investor-dealer prices and dealers' centrality (which measures how central a dealer is in the network) is undetermined. In the upper panel of the figure, the relationship is positive. This occurs when the difference in capacity between high centrality dealers and low centrality dealers is small. That is, $\frac{\left(1+\frac{z}{s_L}\right)ln\left(1+\frac{s_L}{z}\right)}{\left(1+\frac{z}{s_M}\right)ln\left(1+\frac{s_M}{z}\right)} \leq \frac{N}{n_{s_M}^*+1}$*. However, when the difference in capacity is big, the relationship between investor-dealer prices and centrality is negative. This occurs when* $\frac{\left(1+\frac{z}{s_L}\right)ln\left(1+\frac{s_L}{z}\right)}{\left(1+\frac{z}{s_M}\right)ln\left(1+\frac{s_M}{z}\right)} > \frac{N}{n_{s_M}^*+1}$*. Parameters chosen are* $= 20, N_{s_L} = 3, N_{s_M} = 8, c = 20, \lambda = \frac{1}{36}, q = \frac{1}{10}, \rho = 1, I = 1, \bar{v} = 31, M_0 = 10, M_1 = 0, \sigma = 6, z \sim Pareto(20,1), s_M = 9$, $s_L(small) = 10$ *and* $s_L(large) = 380$. *Based on* ***Proposition 1.10****, this set of parameters implies that* $n_{s_M}^* = 7$.

Though the relationship between investor-dealer prices and dealers' centrality is undetermined, the conditional relationship between them is determined. When conditioning on the size of the investor order, high-centrality dealers offer better prices than low-centrality dealers. That is, when z_i is fixed, $p_i^0 = (1-q)\left(\bar{v} - \rho\sigma^2\left(I + \frac{z_i}{n_i+1}\right)\right) + q(M_0 - M_1\sigma^2)$ is positively determined by n_i. This is consistent with Hollifield, Neklyudov, and Spatt (2012), which shows that investors get more favorable prices when trading with core dealers. The above suggests that the size of the investor order is an important control variable in determining how dealers' centrality is related to investor-dealer prices.

1.6 "Hot Potato" Trading in an Inter-Dealer Market

So far in this study, transactions among dealers take place only when an order-filling dealer initiates an auction in the inter-dealer market. This setup helps to demonstrate that risk-sharing drives network formation, since the sole role played by dealers in the inter-dealer market is risk-sharing. However, such one-shot trading limits the analysis of strategies that could be deployed by dealers, since dealers who connect to the order-filling dealer can only be buyers when the order-filling dealer sells (or sellers when the order-filling dealer buys). In reality, one of the strategies deployed by dealers is intermediary or "hot potato" trading. "Hot potato" trading occurs when a dealer who has traded with the order-filling dealer continues to trade with other dealers who do not connect with the order-filling dealer. In so doing, this dealer serves as the intermediary between the order-filling dealer and dealers who are not in the order-filling dealer's network.

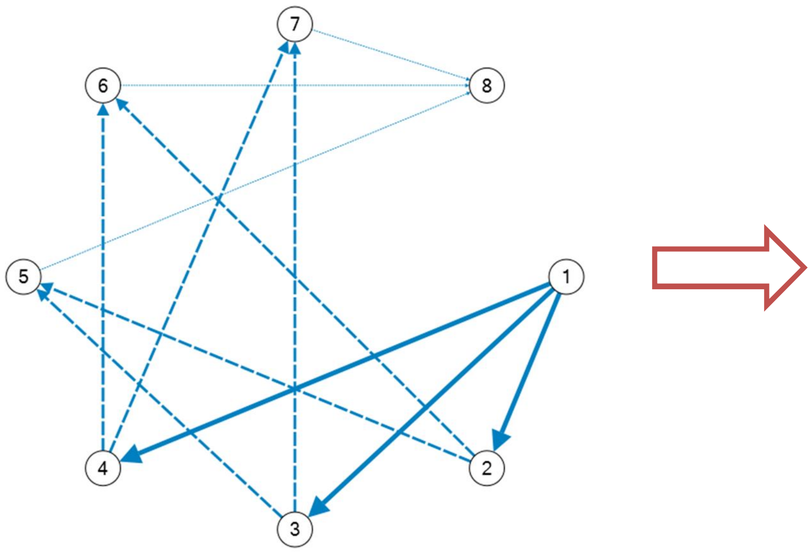
To analyze "hot potato" trading in an inter-dealer network, I relax the one-shot trading assumption, and allow dealers who trade with the order-filling dealer to also trade in their own networks simultaneously. Specifically, let dealer i be the order-filling dealer and dealer j be one of i's connected dealers. When dealer i starts an auction, dealer j not only submits his orders to i, he also solicits bids from his connected dealers j' (to focus sharply on "hot potato" trading, I consider only the case in which j' does not connect to dealer i). Similarly, dealer j' submits his orders to j, and in the meantime solicits bids from his connected dealers, and so forth. One can visualize this setup as consisting of multiple rounds of trading that occur instantaneously. That is, in a short period of time the order-filling dealer trades with his connected dealers in the first round, and then those order-filling-connected dealers trade in their own networks in the second round, and so forth.

Unlike the model with one-shot trading only, the above setup allows dealers to continue trading in an inter-dealer network. However, this general setup complicates the analysis of the equilibrium at date 2. Since trades continue through the network, a dealer's strategy depends not only on who he connects to (as in the one-shot setup) but also on who his connected dealers connect to and who his connected dealers connected dealers connect to, and so forth. Fortunately, the equilibrium at date 2 is still solvable, and it is characterized on another network derived from the inter-dealer network. Let us denote this derived network as the "trading-sets network." **Definition 1.3** and **1.4** show how a "trading-sets network" is derived from an inter-dealer network.

Definition 1.3

Given the flow of trades in an inter-dealer network, dealers in an inter-dealer network are grouped into various trading sets. In each trading set, there is a dealer, called the initiator, who trades in the previous round of trading, and there are other dealers, called participants, who do not participate in previous rounds but participate in the current round initiated by the initiator. Furthermore, if a trading set has only one participant who is not a participant in any other trading set, then the trading set is considered as an empty set. If this unique participant in the trading set is also the only participant in other trading sets, then these trading sets are grouped into one set consisting of only one participant but many initiators.

Definition 1.3 indicates that a trading set can take only two forms. One form includes many participants but a unique initiator; the other has many initiators but a unique participant. Figure 1.10 provides an example of the grouping for a symmetric network with three links. In those trading sets, numbers before the semicolons stand for initiators and numbers after the semicolons stand for participants. In Figure 1.10, the arrow on a link indicates the flow of trades.



Trading Set1 = {1; 2, 3, 4}

Trading Set2 = {2; 5, 6}

Trading Set3 = {3; 5, 7}

Trading Set4 = {4; 6, 7}

Trading Set5 = {5, 6, 7; 8}

Figure 1.10: Trading Sets derived from a Symmetric Network with Three Links

Figure 1.10 provides an example of dealers in an inter-dealer network that is grouped into trading sets. In the figure, the arrow represents the direction of the flow of trades. The thickest line represents the first round of trading. The dashed line represents the second round of trading. The thinnest line represents the final round of trading. In the trading set brackets, the numbers before the semicolons stand for the initiator and the numbers after the semicolons stand for the participants

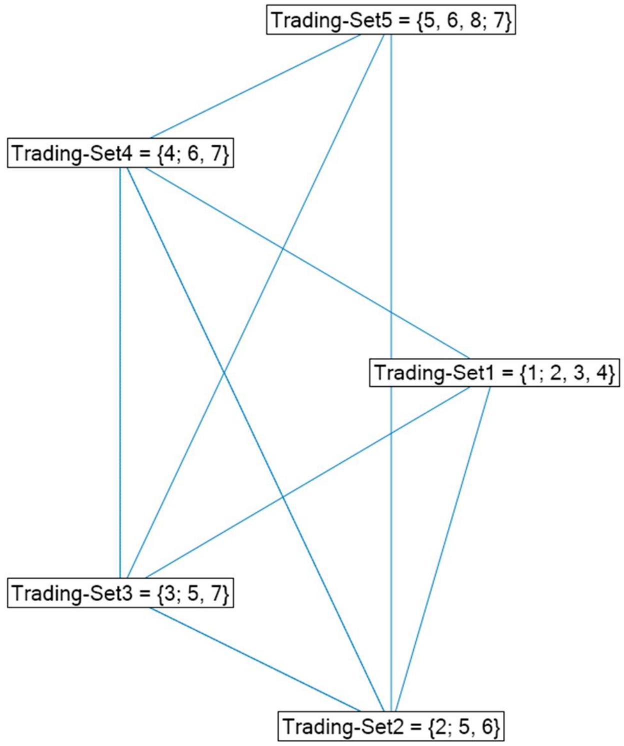


Figure 1.11: A "Trading-Sets Network" derived from an Inter-Dealer Network

Figure 1.11 shows a "trading-sets network" that is derived from the inter-dealer network shown in Figure 8. In Figure 8, trading set 1 connects to trading set 2 but not to trading set 5, since the intersection between trading set 1 and 2 contains a common dealer, dealer 2, but the intersection between trading set 1 and trading set 5 is empty

Definition 1.4

Two trading sets are connected if their intersection is not empty.

While **Definition 1.3** defines how nodes (trading sets) in a "trading-sets network" are derived from an inter-dealer network, **Definition 1.4** defines how links in a "trading-sets network" are derived. Figure 1.11 gives an example of a "trading-sets network" derived from an inter-dealer network. It is obvious that with a given flow of trades in an inter-dealer network the grouping of trading sets is unique. Since links between trading sets are determined only by members of those sets, a "trading-sets network" is uniquely derived from an inter-dealer network through **Definition 1.3** and **Definition 1.4**. This means that characterizing the date 2 equilibrium when dealers continually trade along an inter-dealer network is equivalent to characterizing the equilibrium when dealers trade in the derived "trading-sets network."

As in Section 1.3.2, initiators trade with participants strategically in each trading set. When the market in each trading set clears, it generates a unique price associated with the corresponding trading set. In other words, inter-dealer trading occurs in various fragmented markets (trading sets), and these fragmented markets are linked when they have common members (dealers).

In each of these trading sets dealers are divided into two classes, initiators and participants. This fits the model description in Malamud and Rostek (2013), in which exactly two classes of dealers trade in each trading set.[13] In fact, **Definition 1.3** and **Definition 1.4** map the dealers' network into the "trading-sets network" which is first studied by Malamud and Rostek (2013).

The equilibrium in inter-dealer trading is that every dealer (say dealer k) submits a vector of demand schedules (q_k) to all trading sets (say $\mathbb{M}_k$ sets) he belongs to, and his vector of demand schedules is

$$q_k(\Lambda_k) = \left(\rho\sigma^2 \mathbb{I}_{\mathbb{M}_k\times\mathbb{M}_k} + \Lambda_k\right)^{-1}\left(\bar{v}\mathbb{I}_{\mathbb{M}_k\times 1} - \mathbb{p}_{\mathbb{M}_k\times 1} - \rho\sigma^2 I_0 \mathbb{I}_{\mathbb{M}_k\times\mathbb{M}_k}\right),$$

where Λ_k is dealer k's price impact and $\mathbb{p}_{\mathbb{M}_k\times 1}$ is a vector of equilibrium prices in $\mathbb{M}_k$ sets.[14] To be more specific, Λ_k is the $\mathbb{M}_k \times \mathbb{M}_k$ Jacobian matrix $D_q\mathbb{p}$, in which entry (r, s) stands for the price change in set s caused by a demand change in set r. In equilibrium, Λ_k is determined by the market-clearing condition. Although solving the equilibrium is equivalent to finding every dealer's price impact, the actual work of solving for those price impacts (solving N matrices with $\mathbb{M}_k \times \mathbb{M}_k$ dimensions) is non-trivial, let along specifying how the network and Λ_k are jointly

[13] See **Example 1 (ii)** in Malamud and Rostek (2013).

[14] $\mathbb{I}_{\mathbb{M}_k\times\mathbb{M}_k}$ is an $\mathbb{M}_k$ by $\mathbb{M}_k$ matrix with all entries equal to 1.

determined in the network formation process.

To circumvent this difficulty, I focus on the property regarding "hot potato" trading that is persistent in any strongly stable network.

Proposition 1.12

Denote a dealer as a monopolistic dealer if his connected dealers belong to distinct connected components. In any strongly stable network, monopolistic dealers always buy and sell at different prices gaining non-zero markups in "hot potato" trading. In contrast, if a pair of dealers has more than two unconnected common neighbors, then this pair of dealers and all their common neighbors receive zero markups in "hot potato" trading.[15]

Proposition 1.12 identifies which dealer in the inter-dealer network receives non-zero markups for "hot potato" trading. Interestingly, the dealer with the most links does not necessarily enjoy non-zero markups. In fact, this dealer may receive zero markups for "hot potato" trading. For example, in Figure 1.12, dealer 6 has the highest number of links but he always receives zero markups since he has exactly two common neighbors with every dealer he connects to. The dealer who always receives non-zero markups is the one who reaches different groups of dealers, for example dealer 7 in Figure 1.12. This dealer is called the monopolistic dealer, as his ability to access unconnected parts of the inter-dealer network provides him with local monopoly power in "hot potato" trading.

[15] Neighbors of a dealer are his connected dealers.

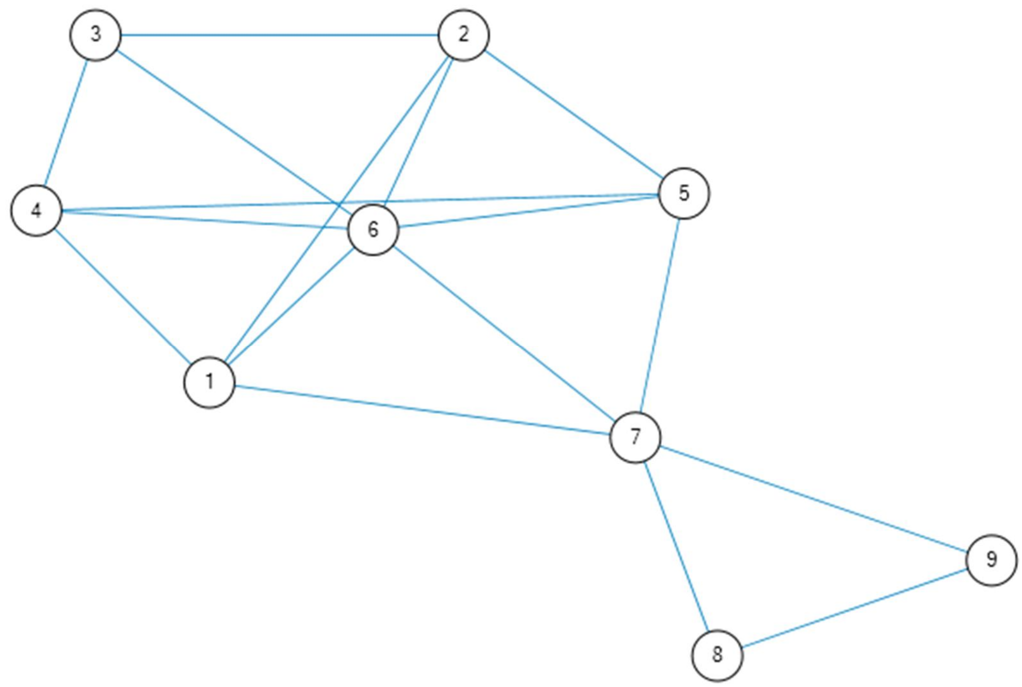


Figure 1.12: An Inter-Dealer Network in which Dealer 7 is the Monopolistic Dealer

In Figure 1.12, if there is "hot potato" trading, dealer 7 is the monopolistic dealer with non-zero markups, even though he has fewer links than dealer 6. In fact, dealer 6 gets zero markups in "hot potato" trading.

Proposition 1.12 is an extension of the study by Malamud and Rostek (2013). Their model implies that a dealer who acts as a "monopolistic bridge" in a "trading-sets network" is the one with non-zero markups. **Proposition 1.12** extends their results to identify the "monopolistic bridge" in an inter-dealer network. This helps empirical research to identify which dealer has local monopoly power in "hot potato" trading.

1.7 Empirical Implications

My model offers novel testable hypotheses in addition to confirming findings from past empirical studies. As an inter-dealer network is formed to share risks among dealers, the connectedness of the network is closely related to volatility and order sizes that characterize dealers' inventory risks.

Hypothesis 1.1:

An asset with high volatility has a more connected inter-dealer network than an asset with low volatility.

Hypothesis 1.2:

An asset traded in large order sizes has a more connected inter-dealer network than an asset traded in small order sizes.

The above hypotheses are novel empirical predictions obtained from endogenizing the formation of an inter-dealer network. However, the empirical design involved in testing those hypotheses requires statistics that measure the connectedness of an inter-dealer network. In the network literature, several statistics have been proposed to describe the connectedness of a network including average path length, cliquishness, a clustering coefficient, cohesiveness, etc.[16] In econometrics, Diebold and Yilmaz (2011) propose statistics based on variance decompositions to measure the connectedness of a network of financial firms.

Based on my model, the connectedness of an inter-dealer network determines prices and trading volumes in an inter-dealer market. In a more connected inter-dealer market, dealers trade more and gain higher markups. This yields the following hypotheses:

Hypothesis 1.3:

In a more connected inter-dealer network, dealers generate larger trading volumes and face smaller inventory risks.

Hypothesis 1.4:

In a more connected inter-dealer network, dealers earn higher markups.

My model explains the observational finding regarding core-periphery networks in OTC

[16] See Jackson (2008) and Easley and Kleinberg (2010) for more details.

markets with varying capacity of providing liquidity among dealers. Dealers with large capacity of providing liquidity are more central in a network than dealers with small capacity. As a result, my model provides an additional testable implication:

Hypothesis 1.5:

A dealer with larger capacity of liquidity provision has higher centrality.

As mentioned above, here the empirical design would entail constructing measures for each dealer's centrality in a network. Past studies in the network literature have used degree centrality, closeness centrality, betweenness centrality, eigenvector related measures, etc., to capture dealers' centrality.[17] One proxy for a dealer's capacity would be the size of the dealer. A large dealer is more likely to be capable of accommodating huge orders than a small dealer.

An important empirical implication of the model pertains to sudden jumps in relationships between prices and primitive parameters, e.g., volatility and order sizes. Such jumps occur as an inter-dealer network changes along with continuous changes in primitive parameters (see Figures 1.5 and 1.6). This implies that when an asset whose volatility or order sizes change over time is involved, empirical studies should consider testing for structural breaks since the corresponding inter-dealer network may have changed over time. The potential structural break in an inter-dealer network implies that time-series data on prices and trading volumes may not be stationary. With respect to cross-sectional studies, my model implies that an inter-dealer network entails another layer of heterogeneity that should be controlled for. For example, assets traded in larger orders differ from assets traded in smaller orders not only in terms of the order size but also in terms of the structure of corresponding inter-dealer networks. Thus, statistics that describe inter-

[17] Hollifield, Neklyudov, and Spatt (2012) and Li and Schürhoff (2012) use degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality to measure dealers' centrality in the inter-dealer network. Refer to Jackson (2008) for further elaboration of centrality measures in network studies.

dealer networks, e.g., the clustering coefficient, should be included as additional control variables in a regression model. In all, the structure of the inter-dealer network is an important state variable that should not be overlooked in empirical OTC studies.

1.8 Conclusion

In this chapter, I investigate inter-dealer network formation in an OTC market. I assume that dealers form inter-dealer networks to share inventory risks. In equilibrium, the benefit from such risk-sharing and the cost of linking determine the shape of a network. An equilibrium network pins down outcomes such as prices and trading volumes. Furthermore, I show that differences in dealers' capacity of liquidity provision imply that dealers with large capacity have high centrality, whereas dealers with small capacity have low centrality. Hence, an equilibrium network exhibits the core-periphery structure. My model not only matches empirical findings in OTC markets, it also generates novel empirical implications. I demonstrate that empirical models that fail to control for the connectedness of an inter-dealer network may suffer from structural breaks.

In my model, dealers strategically form an inter-dealer network to share inventory risks. The inter-dealer network serves as the channel for dealers to rebalance their inventory. This feature differs from Babus and Kondor (2012), in which they assume that dealers use the network to share information. In reality, dealers are likely to use the inter-dealer network for both risk-sharing and information-sharing purposes. As a result, future research should emphasize the interaction between the inventory model and the information model in the formation of an inter-dealer network as well as the trading in this network market.

Chapter 2 Reducing Opacity in Over-the-Counter Markets

2.1 Introduction

OTC markets are often opaque, meaning that they fail to publicly disclose information regarding trades. In the 2008-2009 financial crisis, opacity in OTC derivative markets was blamed for hampering the price discovery process, thereby deterring investors from trading. Having experienced the detrimental impact of opacity, in the post crisis era many policy makers call for reforms to reduce opacity in OTC markets.[18] One of the ongoing reforms is to trade standard OTC products in centralized markets.[19] This can lead to the coexistence of centralized and OTC

[18] See G20 Pittsburgh Summit Declaration, September 2009, G20 Toronto Summit Declaration, June 2010, and Communiqué of Finance Ministers and Central Bank Governors of the G20, October 2011.
[19] In the United States, the Dodd-Frank act requires trading standard swaps in "swap execution facilities", where

trading. How does this coexistence affect market making and trading in OTC markets? Furthermore, as dealers may benefit from opacity (see Madhavan (1995) and Yin (2005)), does a centralized market provide an incentive for dealers to reduce opacity (as it is supposed to)? These questions are important for understanding the economics of transparency as well as for guiding reforms that attempt to increase transparency in OTC markets.

I develop a model where a centralized market operates simultaneously with an opaque OTC market. In the centralized market, a finite number of market makers compete for order flows by posting bid-ask spreads. In a competitive centralized market, the winning market maker sets his spread to deter potential entrance of other market makers. On the other hand, in a noncompetitive centralized market, the winning market maker, who is not bound by the potential entrance of other maker makers, sets his spread to maximize profits. I find that whether the centralized market is competitive or not generates different impacts on the OTC market. While a competitive centralized market causes dealers' profits to decrease under greater opacity, a noncompetitive centralized market leads to the opposite result. The change in the relation between opacity and dealers' profits is due to the change in the relation between the centralized market and the OTC market. Specifically, when the centralized market is noncompetitive, there are opportunities for cooperation between these two markets. Based on these findings, I suggest that regulators should adopt market structures that boost competition among market makers, e.g., the electronic limit order book, as the primary industrial organization for the centralized market.

The model developed in this chapter extends Spulber (1996) and Rust and Hall (2003) by incorporating opacity in the OTC market. In the benchmark model, I analyze an economy that consists of the OTC market only. I show that greater opacity leads to larger bid-ask spreads in the

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multiple participants can trade on publicly available prices made by other participants. In Europe, the MiFID II requires trading derivatives on organized venues, known as "organized trading facilities."

OTC market. This result implies that reducing opacity decreases trading costs, thereby increasing market efficiency. However, the welfare analysis indicates that dealers oppose reducing opacity because of smaller profits. The driving force behind these results is that opacity makes investors' outside options ambiguous, and hence, reduces the value of search. Thus investors search less. Fewer searches lead to increases in investors' trading costs. Since investors' losses are dealers' gains, dealers profit from opacity.

To explore the impact of centralized trading, I extend the benchmark model to include an additional market — a centralized market. When the centralized market is competitive, the bid-ask spread in it depends only on the transaction costs of other market makers, and hence, is independent of OTC trading. As a result, the centralized market attracts investors who have to trade but would like to avoid trading ambiguously in the OTC market. Under greater opacity, dealers lose their customers to the centralized market, which decreases their profits.

However, the noncompetitive centralized market changes the above relation between dealers' profits and opacity. The natural monopoly in the centralized market adjusts its bid-ask spread along with changes in dealers' bid-ask spreads. Specifically, the bid-ask spread in the noncompetitive centralized market is positively correlated with the bid-ask spreads in the OTC market. This dependence implies that dealers and the monopoly can collude to increase investors' trading costs so as to profit from opacity.

In addition, I explore how opacity affects the survival of both the centralized market and the OTC market. I find that greater opacity increases the ability of the centralized market to survive regardless of its competitiveness. However, opacity is not the key determinant of the viability of the OTC market. The comparison between transaction costs in the OTC market and the centralized market (both competitive and noncompetitive) determines if the OTC market is eliminated in the case of a centralized market. In short, when market makers in the centralized market have substantially lower transaction costs than dealers in the OTC market, the OTC market cannot survive in equilibrium.

I model opacity in OTC markets by Knightian uncertainty, meaning that the odds of future states are unknown. Knightian uncertainty assumes that the decision maker has a set of priors rather than a unique prior. Thus, the degree of Knightian uncertainty can be measured by the size of the set of priors. Past studies have shown that Knightian uncertainty may arise if the decision maker has vague information (Ellsberg (1961)); if the decision maker has insufficient knowledge (Easley and O'Hara (2009, 2010a, 2010b)); or if the decision maker has adopted incorrect models (Hansen and Sargent (2001)). Since opacity means that some trading information (e.g. quotes, prices, and order flows) is unavailable or unreliable, investors in OTC markets only have vague information, and hence, face Knightian uncertainty.

I describe trading in OTC markets with a search model.[20] First, most OTC markets are dealer markets. In dealer markets, trades are conducted through bilateral negotiations with investors. As terms of bilateral trades are not public, investors have to search among dealers for price information. Hence, a model in which economic agents search for the optimal deal captures these bilateral trades. Second, Yin (2005) shows that search costs are crucial in analyzing fragmented markets, which include OTC markets, even for infinitesimal amounts. This is because the friction created by search significantly changes price behaviors between fragmented markets and centralized markets.

Dealers in my model adjust their bid-ask spreads to maximize profits under inventory

[20] Spulber (1996) and Rust and Hall (2003) use the same framework to describe trading in dealership markets, of which OTC markets are special examples. Duffie, Garleanu, and Pedersen (2005, 2007), and Lagos and Rocheteau (2009) adopt a different search framework to model OTC trading. I discuss the differences in Section 2.2.

constraints. Hence, my model falls into the category of inventory-based market microstructure models (e.g. Amihud and Mendelson (1980), and Ho and Stoll (1981)), which is different from the information-based market microstructure models (e.g. Glosten and Milgrom (1985), and Easley and O'Hara (1987)). Investors in my model are "liquidity traders" rather than "informed traders."

In the next section, I review the related literature. In Section 2.3, I set out the benchmark model, in which only an OTC market operates in the economy. In Section 2.4, I extend the benchmark model to include a centralized market. In Section 2.5, I discuss the empirical implications of my model and conclude.

2.2 Related Literature

Since OTC markets are typical examples of fragmented markets, my study builds on the market fragmentation and transparency literature. Biais (1993), de Frutos and Manzano (2002), and Yin (2005) compare equilibrium outcomes, such as spreads and investors' strategies, between fragmented markets and centralized markets to investigate how transparency affects market trading. Madhavan (1995) shows how large investors can benefit from a fragmented market that requires less disclosure of trades. Pagano and Roell (1996) compare a market structure based on auctions with a dealer market and find that investors have lower transaction costs under greater transparency. Those studies consider fragmented markets as completely opaque, and study fragmented markets and the centralized market separately. Implications in those studies are obtained by comparing fragmented markets with the centralized market. Gehrig (1993) and Rust and Hall (2003) explore the implication under the coexistence of fragmented markets and a centralized market. However, they do not consider how the coexistence of two market structures can improve transparency in fragmented markets, since they do not allow fragmented markets to have varying degrees of opacity.

This study also contributes to the growing literature on ambiguity or Knightian uncertainty in market microstructure research. In a series of papers, Easley and O'Hara (2009, 2010a, 2010b) show how Knightian uncertainty can affect market trading, and how certain designs of the market microstructure can lessen Knightian uncertainty, and hence, increases market participation and liquidity. Easley, O'Hara, and Yang (2012) model opacity in hedge funds trading with ambiguity and demonstrate how regulations over opaque trading affect the welfare of market participants.

My work also links to search models that characterize OTC markets. Duffie, Garleanu, and Pedersen (2005, 2007) model bilateral trading in OTC markets with a search and bargaining model. Lagos and Rocheteau (2009) further extend the search and bargaining model to allow for different trade sizes. In those models, both investors and dealers search and prices are set through bilateral negotiations. On the other hand, Spulber (1996) and Rust and Hall (2003) provide another line of search models that characterizes OTC trading. In their models, only investors search and prices are dealers' quotes. Though differ in modeling details, both types of models capture OTC trading with a search mechanism that assumes investors search in the market to trade.

2.3 The Search Equilibrium in an OTC Market

In this section, I extend the search model in Spulber (1996) by adding Knightian uncertainty. This extended model is used as the benchmark to characterize the OTC market. In the benchmark, only the OTC market operates. The economy consists of a continuum of buying investors (buyers) and a continuum of selling investors (sellers). Investors' types depend on their valuations of the asset. Denote v^B as the buyer's valuation and v^S as the seller's valuation, and assume both $v^B$and v^S follow the uniform distribution over $[0,1]$. This assumption summarizes the heterogeneity of the investors. I do not explore this heterogeneity, since the paper focuses on the trading structure not the asset valuation. The economy also consists of a continuum of dealers. Dealers connect the buys and sells in the OTC market, and are heterogeneous in their transaction costs. Denoting the dealer's transaction cost with k, I assume k follows a uniform distribution over $[\underline{k},1]$, where $\underline{k}$ denotes the transaction cost for the most efficient dealer. Heterogeneity among transaction costs reflects the fact that dealers adopt different technologies, or use different pricing models for assets traded, or have different costs to finding counterparties for unloading extra inventory.[21]

Investors engage in a sequential search process due to fragmentation in the OTC market. Furthermore, they search with Knightian uncertainty due to opacity in the OTC market. That is, investors' prior knowledge is a set of distributions over dealers' quotes. In addition, investors adopt maxmin preferences to make their trading decisions. An alternative approach would be to consider opacity as risk over investors' search processes. However, this alternative approach requires investors to have a prior over all possible distributions of dealers' quotes. As investors rarely observe any dealer's quote, let alone the distribution of dealers' quotes, this alternative approach seems less realistic. In addition, the assumption of Knightian uncertainty and maxmin preferences has the interpretation that investors' adopt robustness over their decisions. That is, since investors are aware of opacity in the market, they control their risk of model misspecification by choosing the worst outcome derived from the set of priors.

[21] In Chapter 1, I show that a dealer's location and connectedness in the inter-dealer network affects his cost of unloading inventory. A more connected dealer faces less cost in unloading inventory as his markup increases with his numbers of links.

The set of priors for investors is an ϵ-*contamination* of historical distributions over bid and ask prices.[22] In particular, for any given ϵ, buyers have the following set of priors,

$$\boldsymbol{P^B}(\epsilon) \equiv \{(1-\epsilon)P_a + \epsilon\mu : \mu \in \boldsymbol{M}\}, \tag{2.1}$$

where P_a is the historical distribution of ask prices and $\boldsymbol{M}$ is the set of all probability measures on the Borel set of real numbers. Sellers have the following set of priors,

$$\boldsymbol{P^S}(\epsilon) \equiv \{(1-\epsilon)P_b + \epsilon\mu : \mu \in \boldsymbol{M}\}, \tag{2.2}$$

where P_b is the historical distribution of bid prices. In either $\boldsymbol{P^B}(\epsilon)$ or $\boldsymbol{P^S}(\epsilon)$, when ϵ is zero, the set reduces to a unique prior, which indicates no Knightian uncertainty, and as ϵ grows, the degree of Knightian uncertainty increases. As Knightian uncertainty represents opacity in the OTC market, ϵ becomes the measure of opacity in the OTC market. Larger ϵ indicates greater opacity. In addition, since the core of the ϵ-*contamination* set is the distribution of historical prices, the ϵ-*contamination* set implies that investors construct their priors by reducing the accountability of historical prices. The more opaque the OTC market is, the less informative historical prices are, and hence, investors reduce the accountability of historical prices by enlarging the set of priors.[23]

2.3.1 Investors' Decisions

For any given ϵ, a buyer maximizes his minimal expected future payoff,

$$\min\left\{\int I(a)dP : P \in \boldsymbol{P^B}(\epsilon)\right\}, \tag{2.3}$$

where $I(a)$ is the discounted future payoff. More specifically,

---

[22] The ϵ-*contamination* refers to the procedure of introducing a set of priors, which indicates that an $\epsilon \times 100\%$ chances the hypothetical prior is wrong. To be more specific, the set of priors $\boldsymbol{P}(\epsilon)$ is

$$\boldsymbol{P}(\epsilon) \equiv \{(1-\epsilon)P_0 + \epsilon\mu : \mu \in \boldsymbol{M}\},$$

where P_0 is the hypothetical prior and μ is any probability distribution in the relevant space.

[23] The model assumes that the ϵ-*contamination* equates to Knightian uncertainty, though the former is a special case of the latter.

$$I(a) = \begin{cases} \beta^t(\nu^B - a), & \text{if he trades at time } t; \\ 0 & \text{, otherwise,} \end{cases} \tag{2.4}$$

in which β is the discount factor.

By Schmeidler (1989), the buyer's objective function equals the Choquet integral of discounted future payoff $I(a)$ with respect to a convex probability capacity θ_a, which means

$$\min\left\{\int I(a)dP : P \in \boldsymbol{P^B}(\epsilon)\right\} = \int I(a)d\theta_a. \tag{2.5}$$

θ_a is, for any given measurable set E,

$$\theta_a(E) = \begin{cases} (1-\epsilon)P_a(E), & \text{if } E \neq \Omega; \\ 1 & \text{, if } E = \Omega, \end{cases} \tag{2.6}$$

in which Ω represents all asks.

As shown in Nishimura and Ozaki (2004), the Bellman equation associated with the above problem is,

$$V^B(a, \nu^B) = \max\left\{0, \nu^B - a\ , \beta \int V^B(\hat{a}, \nu^B)d\theta_a\right\}. \tag{2.7}$$

In Eq.(2.7), $V^B(a)$ is the value function for the buyer who has an ask offer a at hand, and $\hat{a}$ is his next randomly received ask if he continues to search. $V^B(a)$ reflects the choices that the buyer has: (i) do nothing; (ii) accept the dealer's ask; (iii) reject the ask price and continue to search. Obviously, if the buyer has $\nu^B \leq \underline{a}$ ($\underline{a}$ is the lower bound of the ask prices offered by dealers), he will never trade or search.[24] When $\nu^B > \underline{a}$, the optimal search strategy for the buyer is to accept any ask greater than his reservation buying price. The reservation buying price $r^B(\nu^B)$ is the solution to the following equation,

[24] For technical reasons, I assume that when a trader is indifferent between trading in the market or not, he chooses not to trade. That is, when a buyer has valuation $\nu^B = \underline{a}$ he quits, and when a seller has valuation $\nu^S = \overline{b}$ he quits. $\overline{b}$ is the upper bound of bids offered by dealers.

$$\nu^B = r^B(\nu^B) + \frac{\beta}{1-\beta}\int_{\underline{a}}^{r^B(\nu^B)} \theta_a[a \leq \hat{a}]d\hat{a}. \tag{2.8}$$

According to Nishimura and Ozaki (2004), Eq.(2.8) is equal to the following equation,

$$\nu^B = r^B(\nu^B) + \frac{\beta(1-\epsilon)}{1-\beta}\int_{\underline{a}}^{r^B(\nu^B)} P_a[a \leq \hat{a}]d\hat{a}. \tag{2.9}$$

Applying the Implicit Function Theorem, $r^B(\nu^B)$ is a strictly increasing function of ν^B on the interval $(\underline{\nu}^B, 1]$. The lower bound of the interval $\underline{\nu}^B$ denotes the valuation of the marginal buyer whose gain from trading is zero, i.e., $\underline{\nu}^B = \underline{a} = r^B(\underline{\nu}^B)$.

Similarly, I derive the seller's reservation price, which is the solution of the following equation

$$\nu^S = r^S(\nu^S) - \frac{\beta(1-\epsilon)}{1-\beta}\int_{r^S(\nu^S)}^{\overline{b}} P_b[b \geq \hat{b}]d\hat{b}. \tag{2.10}$$

$r^S(\nu^S)$ strictly increases on the interval $[0, \overline{\nu}^S)$, $\overline{\nu}^S$ denotes the valuation of the marginal seller whose gain from trading is zero, i.e., $\overline{\nu}^S = \overline{b} = r^S(\overline{\nu}^S)$.

2.3.2 Dealers' Decisions

Since ν^B is uniformly distributed on $(\underline{\nu}^B, 1]$ and $r^B(\nu^B)$ is monotone on the interval $(\underline{\nu}^B, 1]$, by change of variables, the density of the reservation buying prices is

$$f^B(r^B) = \frac{1-\beta+F_a(r^B)(1-\epsilon)\beta}{(1-\beta)(1-\underline{\nu}^B)}. \tag{2.11}$$

Analogously, the density of the reservation selling prices is

$$f^S(r^S) = \frac{1-\beta+\left(1-F_b(r^S)\right)(1-\epsilon)\beta}{(1-\beta)\overline{\nu}^S}. \tag{2.12}$$

A dealer posts stationary bid and ask to maximize his expected discounted profits. In the meantime, the dealer has to maintain his inventory position, which means that his expected demand must equal his expected supply.[25]

As N is the total population of dealers operating in the market, $\frac{1-\underline{\nu}^B}{N} f^B(r^B)$ represents the density of buyers for every dealer. The number of buyers who have reservation price r^B visiting the dealer is as follows: 1 at date-0, $P_a[a \geq r^B]$ at date-1, $P_a^2[a \geq r^B]$ at date-2, ..., $P_a^t[a \geq r^B]$ at date-t. If the dealer sets the ask to a, then the market demand at time t is

$$D_t(a) = \frac{1-\underline{\nu}^B}{N} \int_a^{\overline{a}} P_a^t[a \geq r^B] f^B(r^B) dr^B \tag{2.13}$$

$$= \frac{1}{N} \int_a^{\overline{a}} \frac{\left(1 - F_a(r^B)\right)^t (1 - \beta + F_a(r^B)(1-\epsilon)\beta)}{1-\beta} dr^B,$$

in which $\overline{a}$ is the upper bound of asks in the OTC market.

By an analogous derivation, the date-t supply associated with the bid price b is,

$$S_t(b) = \frac{1}{N} \int_{\underline{b}}^{b} \frac{F_b^t(r^S)\left(1 - \beta + \left(1 - F_b(r^S)\right)(1-\epsilon)\beta\right)}{1-\beta} dr^S, \tag{2.14}$$

where $\underline{b}$ is the lower bound of bids in OTC markets.

Given demand $D_t(a)$ and supply $S_t(b)$, the dealer's objective is

$$\max_{\mathrm{a,b}} \sum_{t=0}^{\infty} \beta^t \left(a D_t(a) - (b+k) S_t(b)\right), \tag{2.15}$$

subject to

$$D_t(a) = S_t(b). \tag{2.16}$$

In the above, the dealer matches his demand with his supply. The interpretation is that the dealer

[25] Spulber (1996), Rust and Hall (2003), Duffie, Garleanu, and Pedersen (2005, (2007), and Lagos and Rocheteau (2009) use the same assumption in their search models.

tries to maintain a preferred inventory level. Whenever the dealer is off his preferred inventory level because of trading with investors, he tries to retain the preferred level by trading with investors on the opposite side of the market.

2.3.3 The Stationary Search Equilibrium

Proposition 2.1 describes the stationary search equilibrium in the OTC market, in which investors maximize their minimum expected payoffs, and dealers maximize their expected profits.

Proposition 2.1 [The Benchmark Equilibrium]

For any given ϵ, there exists a continuously differentiable symmetric equilibrium pricing policy, $a(k), b(k)$, with $a(k)$ increasing and $b(k)$ decreasing in k for all $\underline{k} \leq k < k^*$, where k^* denotes the marginal dealer whose profit margin and trading volume are zeros. The pricing policy functions satisfy

$$a(k) = e^{-\int_k^{k^*} Y(z)dz}\left(\frac{k^* + 1}{2} + \int_k^{k^*}\left(-\frac{1}{4} + \frac{1+z}{2}Y(z)\right)e^{\int_z^{k^*} Y(u)du}dz\right), \quad (2.17)$$

$$b(k) = 1 - a(k), \quad (2.18)$$

$$k^* = a(k^*) - b(k^*), \quad (2.19)$$

in which

$$Y(z) = \frac{\beta}{2(k^* - \underline{k})}\left(\frac{1}{1 - \frac{\beta(k^* - z)}{k^* - \underline{k}}} - \frac{1 - \epsilon}{1 - \beta + \frac{z - k}{k^* - \underline{k}}(1 - \epsilon)\beta}\right), \quad (2.20)$$

and k^* is the solution to the following equation

$$1 = \frac{k^* + 1}{2} + \frac{\beta(1-\epsilon)}{1-\beta}\left(\frac{k^* + 1}{2} - \frac{1}{k^* - \underline{k}}\int_{\underline{k}}^{k^*} a(k)dk\right). \tag{2.21}$$

In the stationary equilibrium, the historical distributions of prices coincide with the equilibrium distributions of prices. The equilibrium obtained above is conceptually similar to the rational expectations equilibrium as the equilibrium prices confirm investors' set of priors. However in terms of the equilibrium outcomes, the equilibrium is different from the rational expectations equilibrium. In equilibrium, investors' predictions on prices systematically deviate from the equilibrium prices, whereas in the rational expectations equilibrium, investors' predictions on prices are self-fulfilling. These systematic deviations in the equilibrium of this model depend on opacity in the OTC market. When the OTC market is fully transparent, the equilibrium becomes the rational expectations equilibrium obtained in Spulber (1996).

2.3.4 Comparative Statics

The price system in **Proposition 2.1** is non-linear, and therefore, the analytical solution for the price system does not generally exist. Hence, I show the comparative statics numerically. Setting $\beta = 0.9$ and $\underline{k} = 0.005$, I solve the equilibrium with ϵ ranging from 0 to 0.5.[26]

[26] I obtain similar results with other assigned parameter values.

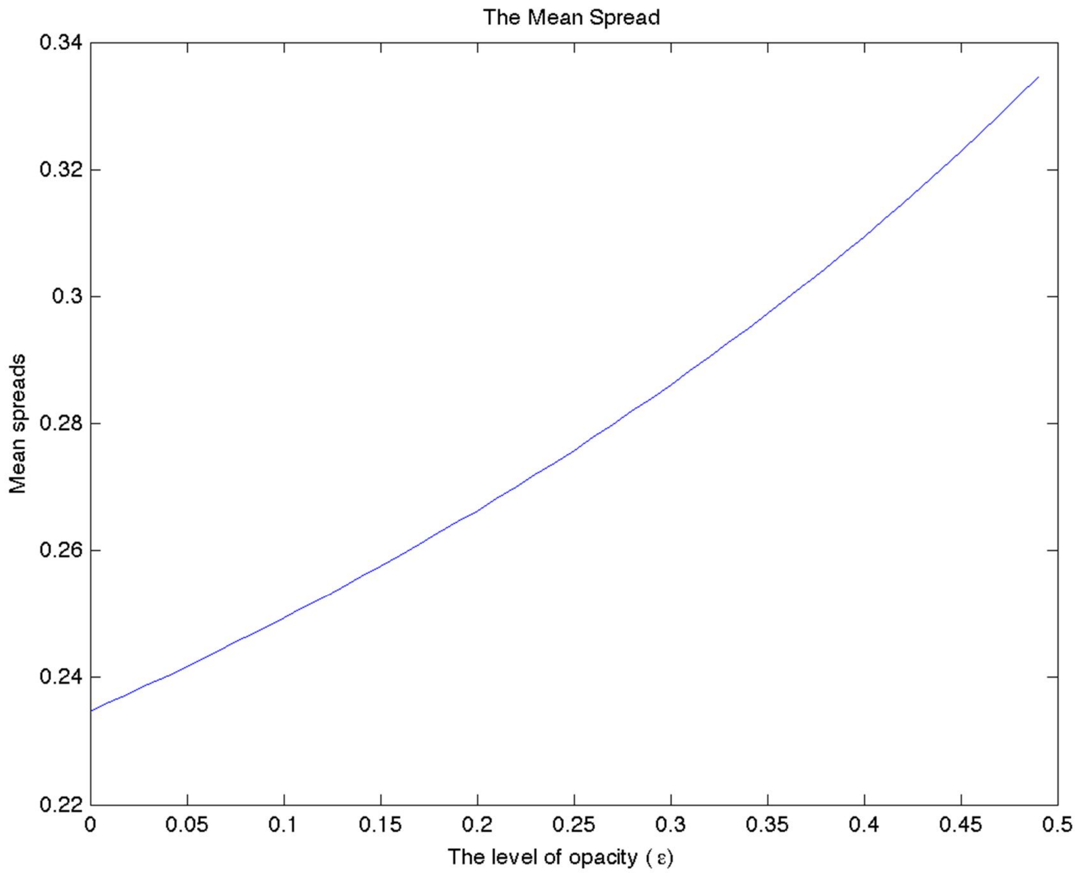

Figure 2.1: Comparative Statics of the Average Bid-Ask Spread

Figure 2.1 shows the comparative statics of the average bid-ask spread in the search equilibrium of ***Proposition 2.1*** *with respect to* ϵ. *The parameters are* $\beta = 0.9$, *and* $\underline{k} = 0.005$.

Figure 2.1 shows that the average bid-ask spread in the OTC market increases as ϵ increases. As ϵ represents the degree of opacity in the OTC market, the increasing ϵ indicates greater opacity in the OTC market. Thus, Figure 2.1 shows that when the OTC market becomes more opaque, the average bid-ask spread increases.

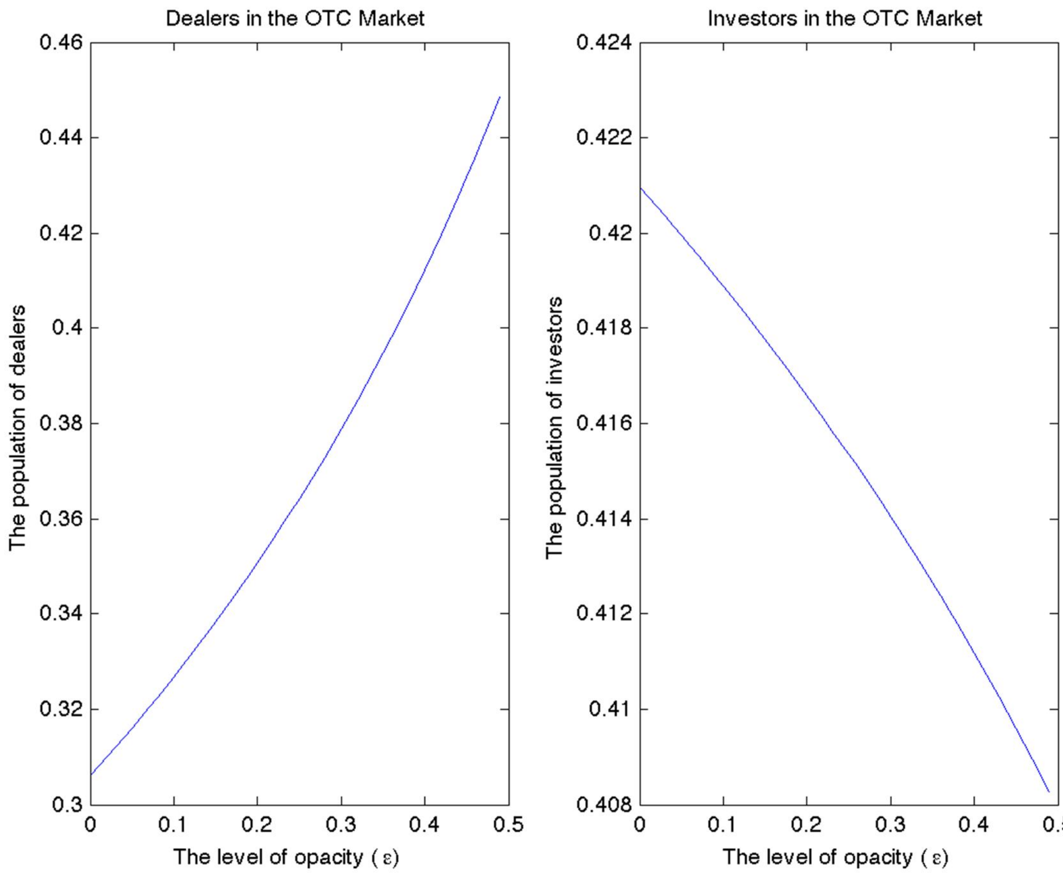

Figure 2.2: Comparative Statics of the Total Population of Dealers and Investors

Figure 2.2 shows the comparative statics of the total population of dealers and investors in equilibrium of ***Proposition 1*** *with respect to* ϵ*. The parameters are the same as in Figure 2.1. The left panel plots the total population of dealers in equilibrium, and the right panel plots the total population of investors in equilibrium.*

Figure 2.2 illustrates how changes in ϵ alter the demography in the economy. The left panel of Figure 2.2 shows that the total population of dealers in the OTC market increases as ϵ increases, whereas the right panel of Figure 2.2 shows the total population of investors in the OTC market decrease as ϵ increases. This means that the impact of opacity on the OTC market is two fold. On one hand, greater opacity encourages the participation of dealers; on the other hand, greater opacity discourages the participation of investors.

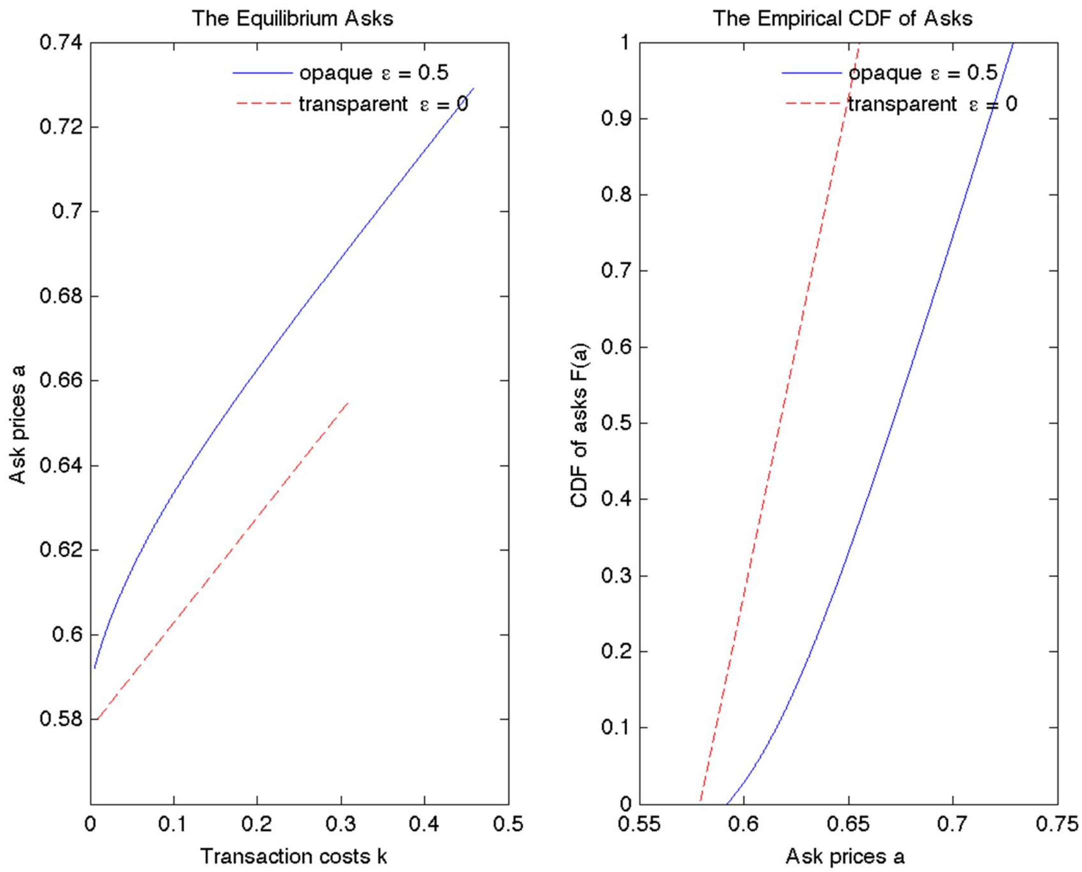

Figure 2.3: The Ask Price in the Opaque OTC Market versus in the Transparent OTC Market

Figure 2.3 compares the equilibrium asks between the opaque OTC market ($\epsilon = 0.5$) and the transparent OTC market ($\epsilon = 0$). Solid lines illustrate the asks when the OTC market is opaque, while dashed lines show the asks when the OTC market is transparent. The left panel shows the equilibrium asks, and the right panel shows the empirical cumulative density functions of the asks.

To decompose comparative results in Figure 2.1 and Figure 2.2, I compare the ask prices when the OTC market is transparent (that is, when $\epsilon = 0$) with the ask prices when the OTC market is opaque (that is, when $\epsilon > 0$). Figure 2.3 shows the results from this comparison. In the right panel of Figure 2.3, I find that the cumulative density function of asks shifts toward the right when $\epsilon > 0$. The shift means that buyers are more likely to receive higher asks from dealers when the OTC market is opaque, i.e., $\epsilon > 0$. Since in equilibrium, $b(k) = 1 - a(k)$, the dealer who increases his ask also decreases his bid. Hence, when the OTC market is opaque, all operating dealers' bid-ask spreads become larger. Consequently, the increasing bid-ask spreads discourage investors to trade, since their trading costs increase.

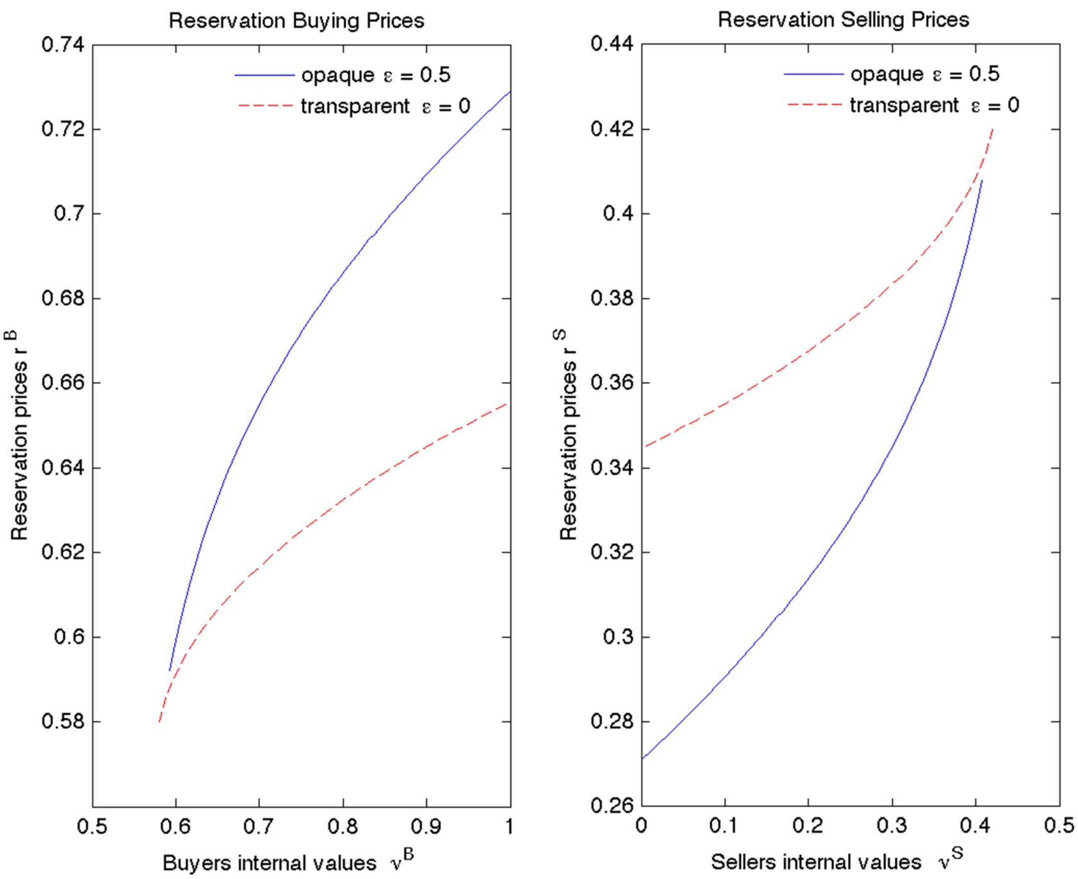

Figure 2.4: Reservation Prices in the Opaque OTC Market versus in the Transparent Market

Figure 2.4 compares investors' reservation values between the opaque OTC market ($\epsilon = 0.5$) and the transparent OTC market ($\epsilon = 0$). Solid lines show the reservation values when the OTC market is opaque, and dashed lines show the reservation values when the OTC market is transparent. The left panel illustrates buyers' reservation buying prices, and the right panel illustrates sellers' reservation selling prices

The force driving results in Figure 2.3 is the decrease of the search value in the opaque OTC market. In Figure 2.4, I compare investors' reservation values between different opacity regimes in the OTC market. I show that buyers' reservation buying prices are higher, and sellers' reservation selling prices are lower, when $\epsilon > 0$. That is, buyers are willing to buy at higher prices and sellers are willing to sell at lower prices when the OTC market is opaque. These results imply that the search value is lower in the opaque OTC market. The OTC market opacity increases investors' uncertainty on outside options.[27] As investors become uncertain about their outside options, they are willing to accept worse offers. As a result , bid-ask spreads increase with the degree of opacity.

2.3.5 The Welfare Analysis

I define the gains from trade as the sum of investors' surplus

$$\int_{\underline{\nu}^B}^{1} (\nu^B - r^B(\nu^B) d\nu^B + \int_0^{\overline{\nu}^S} (r^S(\nu^S) - \nu^S) d\nu^S. \tag{2.22}$$

Figure 2.5 shows how changes in ϵ change investors' total surplus and dealers' total profits. The left panel of Figure 2.5 shows that as ϵ increases, investors' surplus decreases. This means that the gains from trade decrease under greater opacity. While investors suffer from opacity, dealers benefit from opacity. In the right panel of Figure 2.5, I show dealers' total profits increase as ϵ increases. The result that dealers are better off in the opaque OTC market is consistent with Madhavan (1995) and Yin (2005).

[27] Uncertainty here refers to Knightian uncertainty.

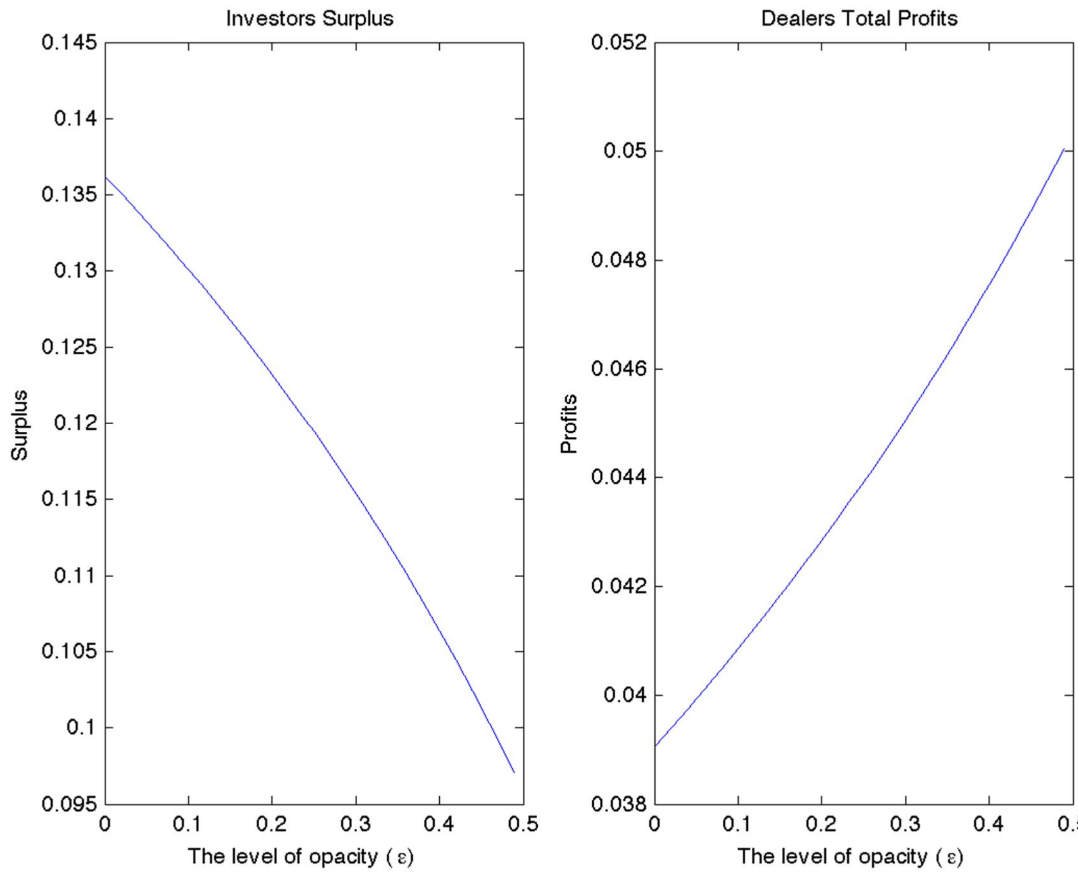

Figure 2.5: Comparative Statics on the Welfare of the Participants

Figure 2.5 shows the comparative statics of the welfare in equilibrium of ***Proposition 2.1*** *with respect to* ϵ*. Parameters are the same as in Figure 2.1. The left panel plots investors' surplus, and the right panel plots dealers' total profits.*

The welfare analysis indicates that though reducing opacity decreases trading costs and increases market efficiency, it harms the dealers in the OTC market. As a result, dealers who are vital in connecting buys and sells in the OTC market, oppose reducing opacity.

2.4 Stationary Search Equilibriums with a Centralized Market

In this section, I show that having a competitive centralized market to compete with the OTC market provides incentives for dealers to reduce the opacity of the latter. In the model, the centralized market is a trading venue. On the venue, there are m market makers with transaction costs $K_1, K_2, \dots, K_m$. To endogenize those market makers, I assume that those market makers are randomly chosen from OTC dealers to operate in the centralized market. It is convenient to visualize this assumption as policy makers grant some OTC dealers licenses to make market in the centralized market. Those dealers who receive permission set up two trading desks, with one in charge of OTC trading and the other in charge of centralized trading. Each trading desk maximizes its own profits. To differentiate dealers' intermediary services on the centralized market from their intermediation services in the OTC market, the dealers' trading desks on centralized trading are referred to as "market makers." In the centralized market, market makers post publicly available asks and bids.

2.4.1 Investors' Decisions under the Existence of the Centralized Market

Investors have an additional option that is to trade in the centralized market. This additional option changes investors' trading decisions. Specifically, a buyer who has not yet chosen to search has three options: (i) do nothing; (ii) buy a unit of asset in the centralized market at price a_c; (iii) search for a better price in the OTC market. Hence, the buyer's value function before he searches is

$$W^B(a_c, v^B) = \max\left\{0, v^B - a_c, \beta \int V^B(\hat{a}, a_c, v^B) d\theta_a\right\}, \tag{2.23}$$

in which $V^B(\hat{a}, a_c, v^B)$ denotes the value function for the buyer when he searches in the OTC market and $\hat{a}$ is the next random ask received. Once the buyer starts to search in the OTC market, he has the fourth option of accepting the current ask, a. The buyer's value function when he searches is

$$V^B(a, a_c, \nu^B) = \max\left\{0, \nu^B - a, \nu^B - a_c, \beta \int V^B(\hat{a}, a_c, \nu^B) d\theta_a\right\}. \tag{2.24}$$

Similarly, the seller's value function before he searches is

$$W^S(b_c, \nu^S) = \max\left\{0, b_c - \nu^S, \beta \int V^S(\hat{b}, b_c, \nu^S) d\theta_b\right\}, \tag{2.25}$$

in which $V^S(\hat{b}, b_c, \nu^S)$ denotes the value function for the seller if he decides to search in the OTC market and $\hat{b}$ is the next random bid received. And the seller's value function when he searches is

$$V^S(b, b_c, \nu^S) = \max\left\{0, b - \nu^S, b_c - \nu^S, \beta \int V^S(\hat{b}, b_c, \nu^S) d\theta_b\right\}, \tag{2.26}$$

in which b is the current bid.

From buyers and sellers' value functions when they search (Eq.(2.24) and Eq.(2.26)), if all dealers' asks are lower than the centralized market's ask, and if all bids are higher than the centralized market's bid, then in equilibrium no trader trades in the centralized market. On the other hand, if no dealer can offer an ask lower than the centralized market's ask, and if no dealer can bid higher than the centralized market's bid, then in equilibrium all investors trade in the centralized market. The intermediate stage is when some but not all dealers are able to offer lower asks and higher bids than the centralized market. In this case, some investors trade in the centralized market and some trade in the OTC market. I start the analysis from this intermediate stage equilibrium, since the other two are extreme cases of the intermediate stage equilibrium.

2.4.2 The Equilibrium in which an OTC Market Coexists with a Centralized Market

2.4.2.1 Investors' Decisions

As discussed above, no dealer can survive by posting an ask a higher than the ask from the centralized market a_c. Thus, a_c is the upper bound of asks in the OTC market. Let $\underline{a}$ be the lower bound of asks in the OTC market. The buyer's value function when he searches (Eq.(2.24)) implies that any buyer with $v^B \leq \underline{a}$ will never trade. Hence, $\underline{a}$ determines the marginal buyer. That is, $\underline{a} = \underline{v}^B$ where $\underline{v}^B$ is the marginal buyer's valuation of the asset.

For the buyer whose reservation value equals a_c when he searches, let $\overline{v}^B$ be his valuation of the asset. **Proposition 2.2** describes buyers' optimal strategies in choosing which market to trade in.

<u>Proposition 2.2</u>

A buyer's optimal strategy depending on his type v^B is as follows:

i) if $v^B \in [\overline{v}^B, 1]$, then it is optimal for the buyer to bypass the OTC market and purchase the asset immediately from the centralized market at the ask price a_c;

ii) if $v^B \in (\underline{v}^B, \overline{v}^B)$, then it is optimal for the buyer to trade in the OTC market;

iii) if $v^B \in [0, \underline{v}^B]$, then it is not optimal for the buyer to trade in the centralized market or in the OTC market.

When $v^B \in (\underline{v}^B, \overline{v}^B)$, the buyer's optimal search strategy is a reservation price policy with the reservation price implicitly defined as

$$v^B = r^B(v^B) + \frac{\beta(1-\epsilon)}{1-\beta}\int_{\underline{a}}^{r^B(v^B)} P_a[a \leq \hat{a}]d\hat{a}. \tag{2.27}$$

By the Implicit Function Theorem, $r^B(v^B)$ is monotone on $(\underline{v}^B, \overline{v}^B)$. Thus, Eq.(2.27) implies

$$\overline{v}^B = a_c + \frac{\beta(1-\epsilon)}{1-\beta}\int_{\underline{a}}^{a_c} P_a[a \leq \hat{a}]d\hat{a}. \tag{2.28}$$

Likewise, **Proposition 2.3** describes sellers' optimal strategies in choosing which market to trade in. In **Proposition 2.3**, $\underline{v}^S$ denotes the seller with reservation value equal to the centralized market's bid, b_c, and $\overline{v}^S$ is the marginal seller whose gain from trading is zero.

Proposition 2.3

A seller's optimal strategy depending on his type v^S is as follows:

i) if $v^S \in [\overline{v}^S, 1]$, then it is not optimal for the seller to trade in the centralized market nor in the OTC market;

ii) if $v^S \in (\underline{v}^S, \overline{v}^S)$, then it is optimal for the seller to trade in the OTC market;

iii) if $v^S \in [0, \underline{v}^S]$, then it is optimal for the seller to bypass the OTC market and sell the asset immediately in the centralized market at the bid price b_c.

From the above, when $v^S \in (\underline{v}^S, \overline{v}^S)$, the seller's optimal search strategy is a reservation price policy, and the reservation price is implicitly defined as the follows,

$$v^S = r^S(v^S) - \frac{\beta(1-\epsilon)}{1-\beta} \int_{r^S(v^S)}^{\overline{b}} P_b[b \geq \hat{b}] d\hat{b}. \tag{2.29}$$

Similarly, $r^S(v^S)$ is a strictly increasing function of v^S on the interval $(\underline{v}^S, \overline{v}^S)$ by the Implicit Function Theorem. Thus, $\underline{v}^S$ is defined as

$$\underline{v}^S = b_c - \frac{\beta(1-\epsilon)}{1-\beta} \int_{b_c}^{\overline{b}} P_b[b \geq \hat{b}] d\hat{b}. \tag{2.30}$$

2.4.2.2 Dealers' Decisions

With an analogous derivation in Section 2.3, the demand and supply for a dealer at time t are,

$$D_t^D(a) = \frac{1}{N^D} \int_a^{a_c} \frac{\left(1 - F_a(r^B)\right)^t \left(1 - \beta + F_a(r^B)\right)(1-\epsilon)\beta}{1-\beta} dr^B, \tag{2.31}$$

$$S_t^D(b) = \frac{1}{N^D} \int_{b_c}^{b} \frac{F_b^t(r^S)\left(1 - \beta + \left(1 - F_b(r^S)\right)\right)(1-\epsilon)\beta}{1-\beta} dr^S, \tag{2.32}$$

in which N^D is the total population of the surviving dealers. With the constraint of keeping demand equal to supply, a dealer maximizes his expected discounted profits. That is,

$$\max_{a,b} \sum_{t=0}^{\infty} \beta^t \left(a D_t^D(a) - (b + k) S_t^D(b) \right), \tag{2.33}$$

subject to

$$D_t^D(a) = S_t^D(b). \tag{2.34}$$

2.4.2.3 Market Makers' Decisions and the Competitiveness of the Centralized Market

All market makers post asks and bids in the centralized market, and all asks and bids are public. Publicly available prices imply that only one market maker intermediates in the centralized market. The most efficient market maker (who has the lowest transaction cost) charges a bid-ask spread that is less than or equal to the next most efficient market maker's transaction cost to become the single market maker in the centralized market. Call this single market maker the "winning market maker." Denoting $K_{(2)}$ as the second order statistic of $\{K_1, K_2, \dots, K_m\}$, the bid-ask spread in the centralized market satisfies the following condition,

$$a_c - b_c \leq K_{(2)}. \tag{2.35}$$

From **Proposition 2.2**, market demand for the centralized market is,

$$D^C(a_c) = 1 - \nu^B(\underline{a}, a_c) = 1 - a_c - \frac{\beta(1-\epsilon)}{1-\beta} \int_{\underline{a}}^{a_c} P_a[a < \hat{a}] d\hat{a}. \tag{2.36}$$

From **Proposition 2.3**, market supply for the centralized market is,

$$S^C(b_c) = \nu^S(b_c, \overline{b}) = b_c - \frac{\beta(1-\epsilon)}{1-\beta} \int_{b_c}^{\overline{b}} P_b[b > \hat{b}] d\hat{b}. \tag{2.37}$$

The winning market maker chooses a_c and b_c to maximize his expected discounted profits. That is,

$$\max_{a_c,b_c} a_c D^C(a_c) - \left(b_c + K_{(1)}\right) S^C(b_c), \tag{2.38}$$

subject to

$$D^C(a_c) = S^C(b_c), \tag{2.39}$$

$$a_c - b_c \leq K_{(2)}, \tag{2.40}$$

in which $K_{(1)}$, the winning market maker's transaction cost, is the first order statistic of $\{K_1, K_2, \ldots, K_m\}$.

Two sets of solutions arise from the above maximization problem. The first set is the corner solution, in which the inequality (2.40) binds. This indicates that the centralized market is competitive. The winning market maker has to post a bid-ask spread equaling $K_{(2)}$ to deter the entry of other market makers. The second set is the interior solution, in which the inequality (2.40) is not binding. This indicates that the centralized market is not competitive. The most efficient market maker, the winning market maker, becomes a natural monopoly whose action does not depend on other market makers. Unlike the corner solution where the bid-ask spread equals $K_{(2)}$, the bid-ask spread in this case depends on $K_{(1)}$. Hence, given $\underline{k}$, ϵ, and β, whether the winning market maker's profit maximization is the corner solution or the interior solution depends on $K_{(1)}$ and $K_{(2)}$.

2.4.2.4 Stationary Search Equilibriums

Depending on market makers' transaction costs, there are two equilibriums. In the following, I first describe the equilibrium when the winning market maker is forced to choose the corner solution because of competition. I then show the equilibrium when the winning market maker chooses the interior solution, as the centralized market is not competitive. Finally, I compare these two equilibriums.

Proposition 2.4 characterizes the equilibrium when the winning market maker's profit maximization generates the corner solution.

<u>Proposition 2.4 [The Corner Equilibrium]</u>

For any given ϵ, there exists a continuously differentiable symmetric equilibrium pricing policy, $a(k)$ and $b(k)$, with $a(k)$ increasing and $b(k)$ decreasing in k for all $\underline{k} \leq k < K_{(2)}$. The pricing policy functions satisfy,

$$a(k) = e^{-\int_k^{K_{(2)}} Y(z)dz} \left(\frac{K_{(2)} + 1}{2} + \int_{k_d}^{K_{(2)}} \left(-\frac{1}{4} + \frac{(1+z)}{2} Y(z) \right) e^{\int_z^{K_{(2)}} Y(u)du} dz \right), \tag{2.41}$$

$$b(k) = 1 - a(k), \tag{2.42}$$

in which

$$Y(z) = \frac{\beta}{2\left(K_{(2)} - \underline{k}\right)} \left(\frac{1}{1 - \frac{\beta\left(K_{(2)} - z\right)}{K_{(2)} - \underline{k}}} - \frac{1-\epsilon}{1 - \beta + \frac{z - \underline{k}}{K_{(2)} - \underline{k}}(1-\epsilon)\beta} \right), \tag{2.43}$$

The centralized market prices are

$$a_c = \frac{K_{(2)} + 1}{2}, \tag{2.44}$$

$$b_c = 1 - a_c. \tag{2.45}$$

Proposition 2.5 characterizes the equilibrium where the winner's profit maximization generates the interior solution.

Proposition 2.5 [The Interior Equilibrium]

For any given ϵ, there exists a continuously differentiable symmetric equilibrium pricing policy, $a(k)$ and $b(k)$, with $a(k)$ increasing and $b(k)$ decreasing in k for all $\underline{k} \leq k < k^{**}$, where k^{**} denotes the marginal dealer whose profit and trading volumes are zero. The pricing policy functions satisfy,

$$a(k) = e^{-\int_k^{k^{**}} Y(z)dz} \left(\frac{k^{**}+1}{2} + \int_{k_d}^{k^{**}} \left(-\frac{1}{4} + \frac{(1+z)}{2} Y(z)\right) e^{\int_z^{k^{**}} Y(u)du} dz\right), \tag{2.46}$$

$$b(k) = 1 - a(k), \tag{2.47}$$

$$k^{**} = a(k^{**}) - b(k^{**}), \tag{2.48}$$

in which

$$Y(z) = \frac{\beta}{2(k^{**} - \underline{k})}\left(\frac{1}{1 - \frac{\beta(k^{**} - z)}{k^{**} - \underline{k}}} - \frac{1-\epsilon}{1 - \beta + \frac{z - \underline{k}}{k^{**} - \underline{k}}(1-\epsilon)\beta}\right). \tag{2.49}$$

The centralized market prices are

$$a_c = a(k^{**}), \tag{2.50}$$

$$b_c = 1 - a_c. \tag{2.51}$$

k^{**} is defined as follows

$$k^{**} = \arg\max_{\tilde{k}\in(\underline{k},K_{(2)})} \left(\tilde{k} - K_{(1)}\right)\left(1 - \frac{\tilde{k}+1}{2} - \frac{\beta(1-\epsilon)}{1-\beta}\left(\frac{\tilde{k}+1}{2} - \frac{1}{\tilde{k}-\underline{k}}\int_{\underline{k}}^{\tilde{k}} a(k)dk\right)\right), \tag{2.52}$$

in which $\tilde{k}$ represents the winning market maker's bid-ask spread.

To determine cases under which each equilibrium will manifest, I first solve the interior equilibrium but without the competitive constraint, i.e., $a_c - b_c \leq K_{(2)}$. Let k_u^{**} denote the solution. If $k_u^{**} \geq K_{(2)}$, then the corner equilibrium will manifest, as other market makers can undercut the winning market maker's unconstrained spread k_u^{**}. If $k_u^{**} < K_{(2)}$, then the interior equilibrium will manifest.

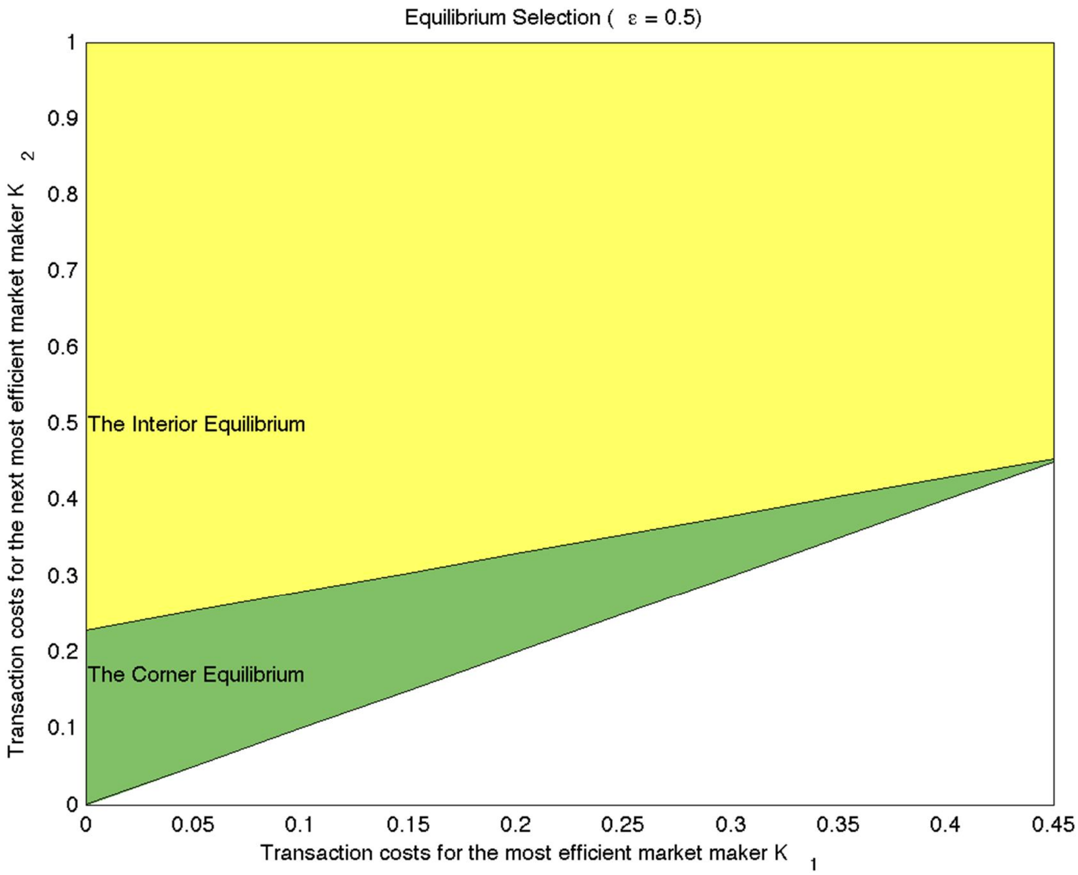

Figure 2.6: Equilibrium Selection when the Centralized Market Coexists with the OTC Market

Figure 2.6 shows equilibrium selection when both the OTC market and the centralized market operate in the economy. When $K_{(1)}$ and $K_{(2)}$ lie in the green region, the equilibrium is the corner equilibrium. When $K_{(1)}$ and $K_{(2)}$ lie in the yellow region, the equilibrium is the interior equilibrium. Parameters are $\epsilon = 0.5, \beta = 0.9$.

Given $\underline{k}, \epsilon$, and β fixed, k_u^{**} depends only on $K_{(1)}$. Thus, the pair of $K_{(1)}$ and $K_{(2)}$ determines which equilibrium emerges. With $\epsilon = 0.5, \underline{k} = 0.005$, and $\beta = 0.9$, Figure 2.6 shows for which pairs of $K_{(1)}$ and $K_{(2)}$ the corner equilibrium emerges, and for which pairs of $K_{(1)}$ and $K_{(2)}$ the interior equilibrium emerges.

2.4.2.5 Comparative Statics in the Corner Equilibrium

Setting $\beta = 0.9, \underline{k} = 0.005, K_{(1)} = 0.29$, and $K_{(2)} = 0.3$, I solve the equilibrium with ϵ ranging from 0 to 0.5.[28]

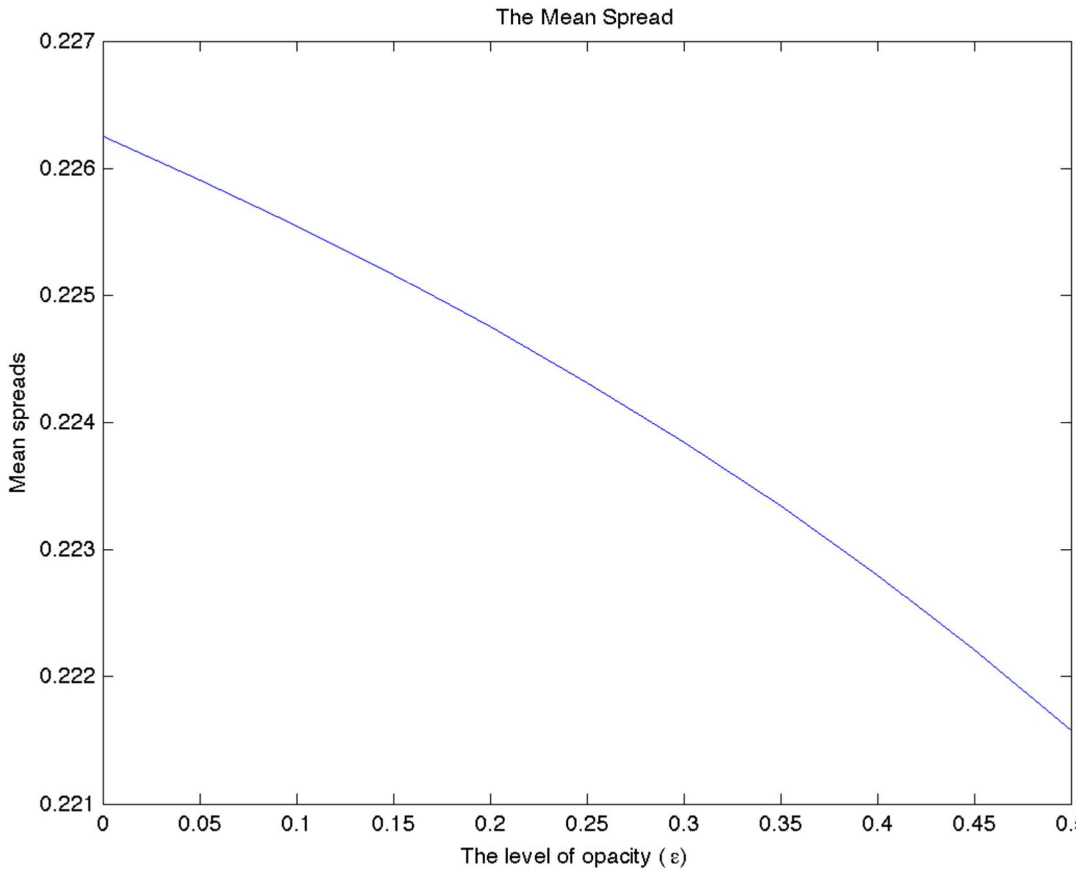

Figure 2.7: Comparative Statics of the Average Bid-Ask Spread in the Corner Equilibrium

Figure 2.7 shows the comparative statics of the average bid-ask spread in corner equilibrium with respect to ϵ. The parameters are β = 0.9, $\underline{k}$ = 0.005, $K_{(1)}$ = 0.29, and $K_{(2)}$ = 0.3.

Figure 2.7 shows that the average bid-ask spread in the OTC market decreases as ϵ increases. This means that the average spread shrinks when the OTC market becomes more opaque. This result differs from the finding in Section 2.3, where greater opacity enlarges the average spread (see Figure 2.1).

[28] Numerical results are robust to parameter choices.

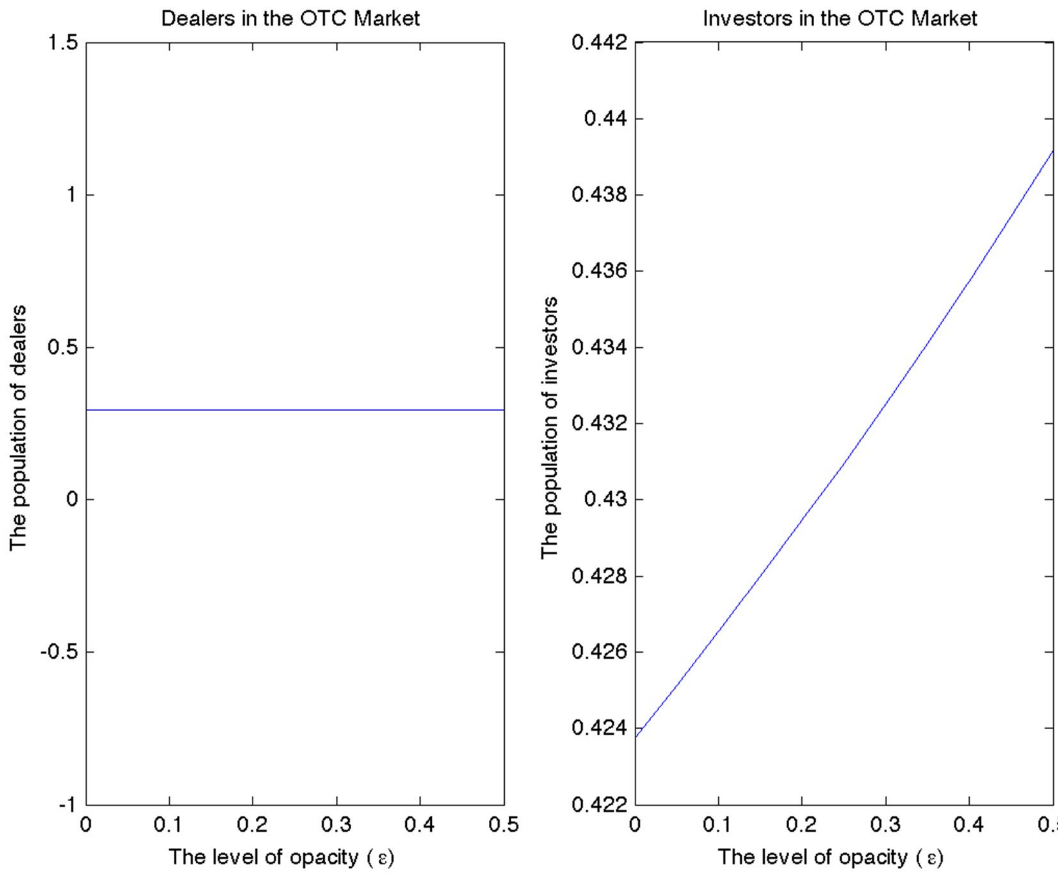

Figure 2.8: Comparative Statics of the Demographics in the Corner Equilibrium

Figure 2.8 shows the comparative statics of the demographics in the corner with respect to ϵ. The parameters are the same as in Figure 2.7. The left panel plots the total population of dealers in equilibrium, and the right panel plots the total population of investors in equilibrium

In Figure 2.8, I show that how dealers and investors respond to changes in ϵ. The left panel of Figure 2.8 shows that the total population of dealers is independent of changes in ϵ, while the right panel of Figure 2.8 shows that the total population of investors increases as ϵ increases. The increase in the total population of investors with larger ϵ implies that more investors participate in trading when the OTC market gets more opaque. These results again differ from the finding in Section 2.3, where greater opacity discourages investors to participate.

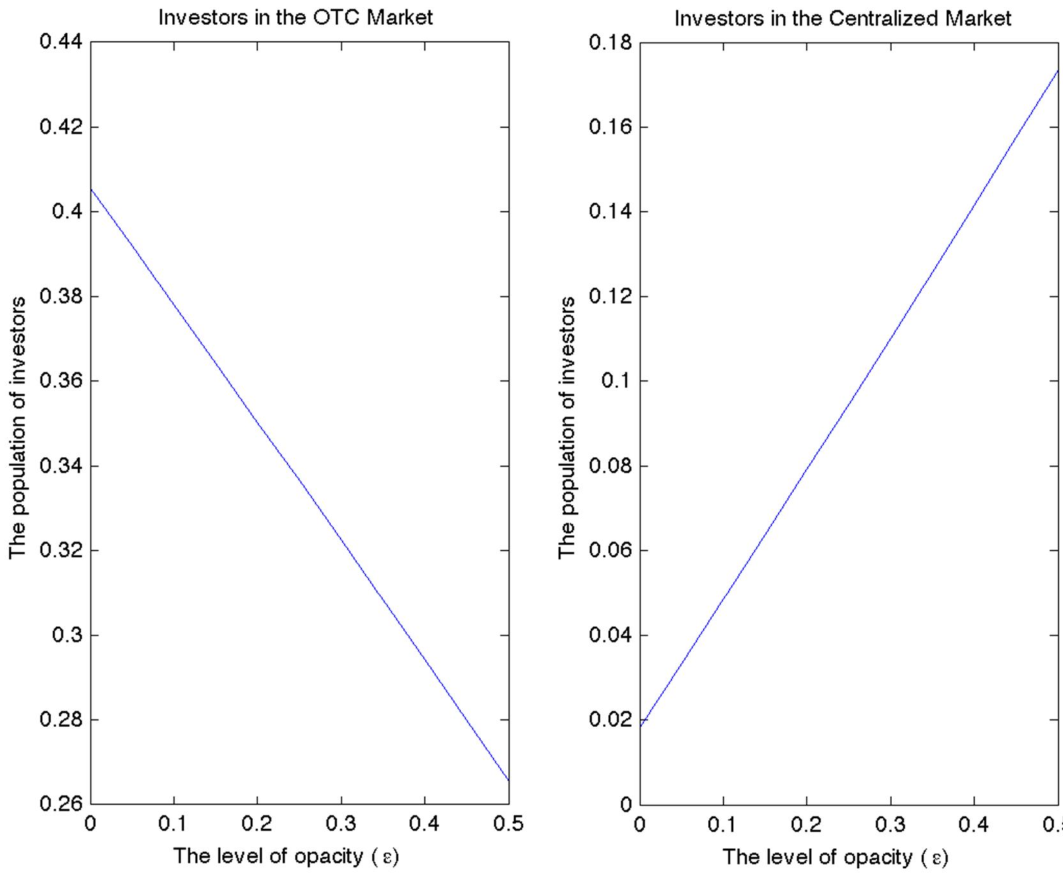

Figure 2.9: Comparative Statics of Investors' Participation in the Corner Equilibrium

Figure 2.9 shows the comparative statics of investors' distribution between the OTC market and the centralized market in the corner equilibrium with respect to ϵ. The parameters are the same as in Figure 2.7. The left panel plots the total population of investors in the OTC market, and the right panel plots the total population of investors in the centralized market

To understand different results obtained here, I compute the distribution of investors between the OTC market and the centralized market under different degrees of opacity (ϵ). From the left panel in Figure 2.9, trades in the OTC market decrease as ϵ increases, whereas the right panel in Figure 2.9 shows that trades in the centralized market increase as ϵ increases. This implies that investors migrate to the centralized market when the OTC market gets more opaque.

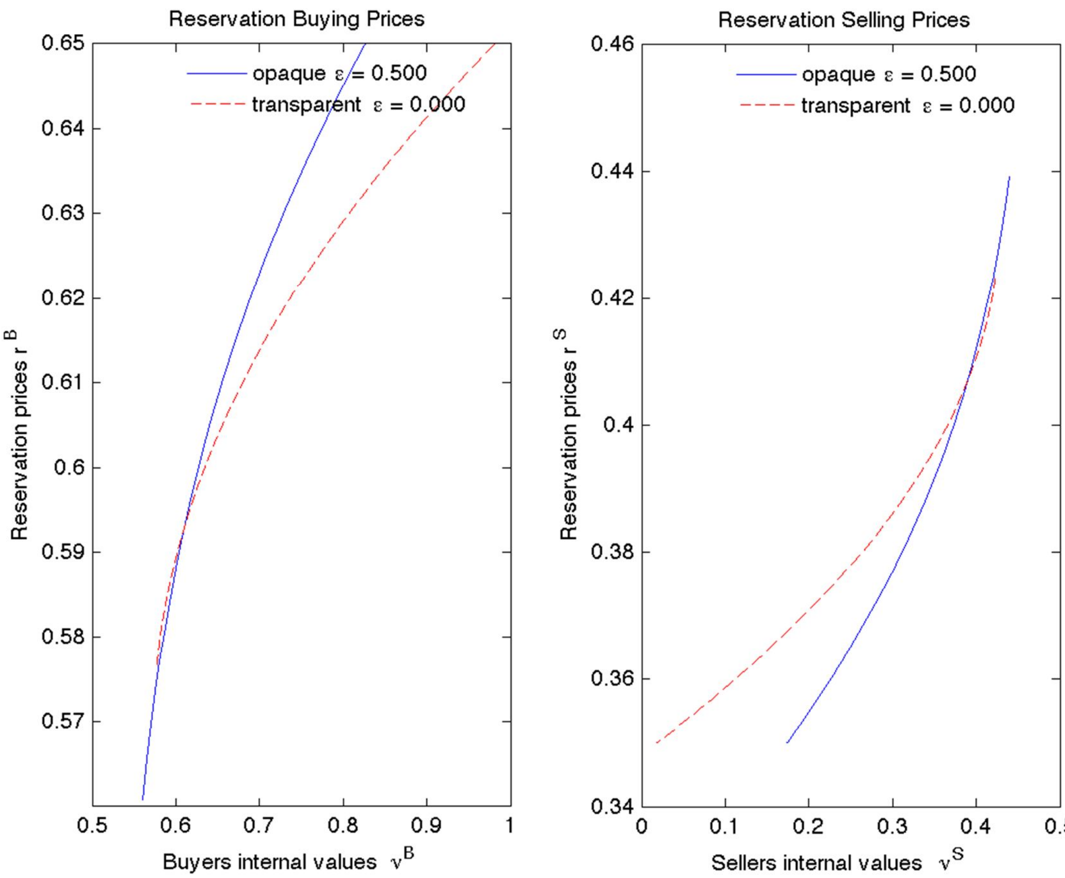

Figure 2.10: Reservation Prices in the Corner Equilibrium

Figure 2.10 compares investors' reservation values between the opaque OTC market ($\epsilon = 0.5$) and the transparent OTC market ($\epsilon = 0$) in the corner equilibrium. Solid lines show the reservation values when the OTC market is opaque, and dashed lines show the reservation values when the OTC market is transparent. The left panel plots buyers' reservation buying prices, and the right panel plots sellers' reservation selling prices

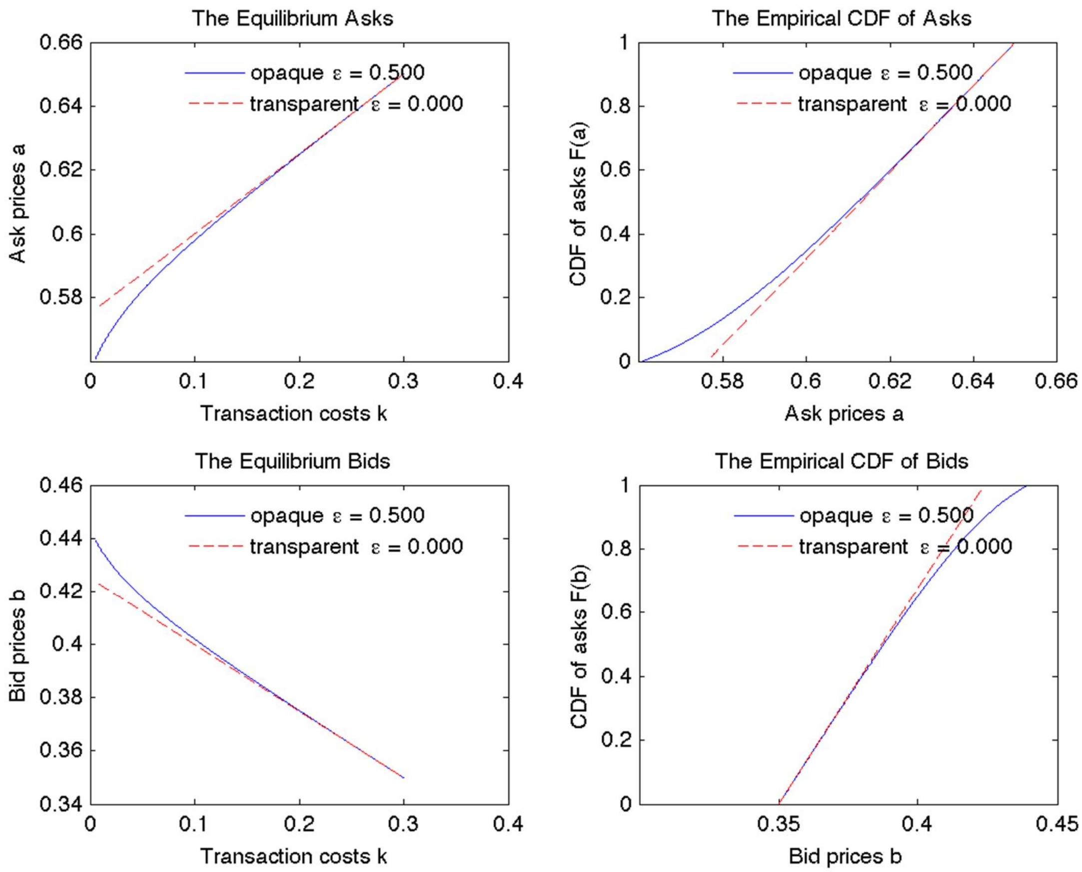

Figure 2.11: The Ask and Bid Price in the Corner Equilibrium

Figure 2.11 compares the asks and bids between the opaque OTC market ($\epsilon = 0.5$) and the transparent OTC market ($\epsilon = 0$) in the corner equilibrium. Solid lines are the asks and bids under the opaque OTC market, and dashed lines are the asks and bids under the transparent OTC market. The left part are the asks (the upper plot) and bids (the bottom part), and the right part are empirical cumulative density functions of the asks (the upper plot) and bids (the bottom part).

The migration of investors highlights how the existence of the centralized market affects equilibrium outcomes. Analogous to the benchmark model in Section 2.3, when the OTC market becomes more opaque, the value of search decreases which leads to changes in investors' reservation values (as shown in Figure 2.10). However, in contrast to the benchmark model, investors here have an additional option — trading in the centralized market. Thus, when the search value decreases, rather than negotiating with dealers under ambiguous outside options, investors choose to trade in the centralized market. Furthermore, Figure 2.10 shows that high valuation buyers and low valuation sellers suffer the most from greater opacity. Hence, most migrants are high valuation buyers and low valuation sellers. The remaining buyers in the OTC market are with low valuations, and the remaining sellers are with high valuations. This forces dealers to lower their asks and increase their bids to accommodate the remaining investors. In addition, dealers want to attract more trading with smaller bid-ask spreads. Figure 2.11 verifies these changes in dealers' asks and bids.

Defining the gains from trade as the sum of investors' surplus

$$\underbrace{\int_{\bar{v}^B}^{1}(v^B - a_c)dv^B + \int_{0}^{\underline{v}^S}(b_c - v^S)dv^S}_{Gains\ from\ Trading\ in\ the\ Centralized\ Market} \tag{2.53}$$

$$+ \underbrace{\int_{\underline{v}^B}^{\bar{v}^B}\left(v^B - r^B(v^B)\right)dv^B + \int_{\underline{v}^S}^{\bar{v}^S}(r^S(v^S) - v^S)dv^S}_{Gains\ from\ Trading\ in\ the\ OTC\ Market},$$

I show the welfare changes of investors, dealers, and the winning market maker in Figure 2.12.

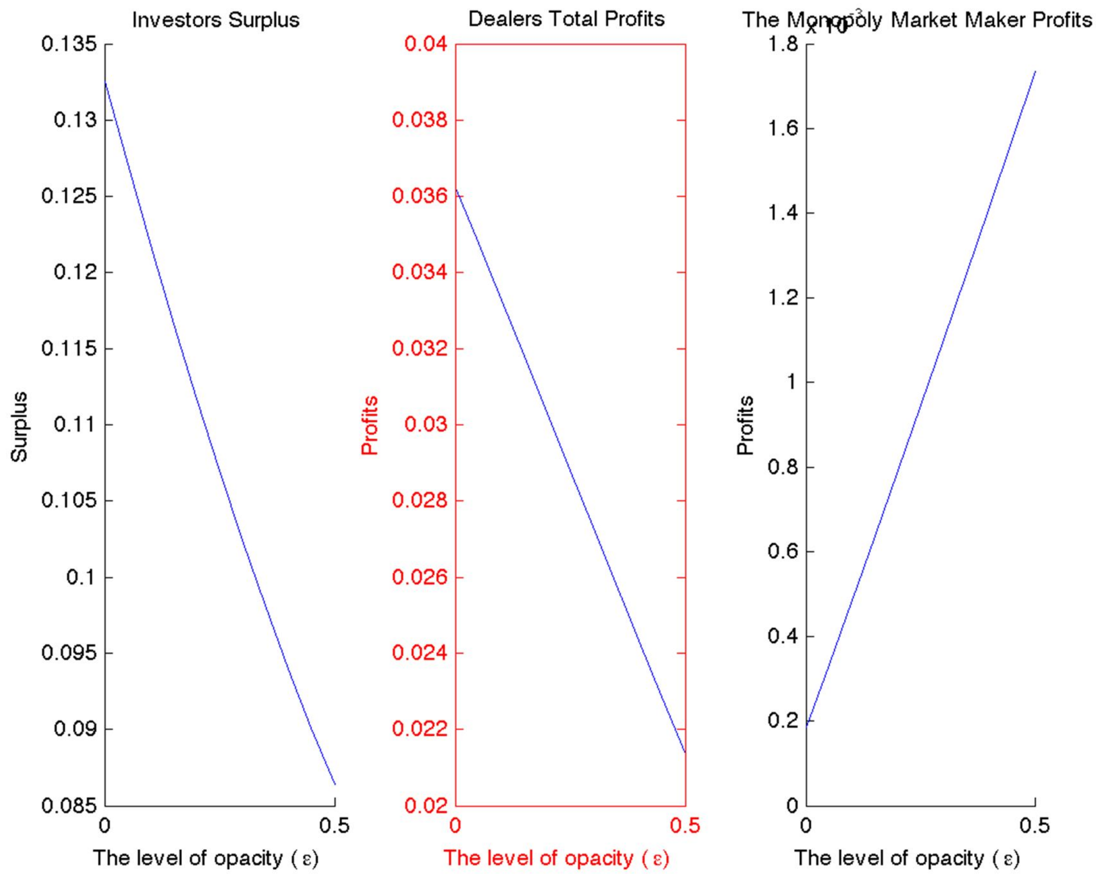

Figure 2.12: Comparative Statics of the Welfare in the Corner Equilibrium

Figure 2.12 shows the comparative statics of the welfare in the corner equilibrium with respect to ϵ. Parameters are the same as in Figure 2.7. The left panel plots investors' surplus, the middle panel plots dealers' total profits, and the right panel plots the market maker's profits

The left panel of Figure 2.12 shows that the gains from trade decrease as ϵ increases. This is because opacity makes it more costly to trade. The middle panel of Figure 2.12 shows that dealers' total profits decrease as ϵ increases. This is because dealers have less volume and smaller bid-ask spreads. The right panel of Figure 2.12 shows the winning market maker's profits increase as ϵ increases. This is because more investors migrate to the centralized market due to greater opacity in the OTC market. These results indicate that when there is a competitive centralized market in equilibrium, greater opacity implies losses not only to investors, but also to dealers. Hence, introducing a competitive centralized market to the economy is an effective approach to provide an incentive for dealers to reduce opacity in the OTC market.

2.4.2.6 Comparative Statics for the Interior Equilibrium

Setting $\beta = 0.9, \underline{k} = 0.005, K_{(1)} = 0.009$, and $K_{(2)} = 0.3$, I solve the equilibrium with ϵ ranging from 0 to 0.5.[29]

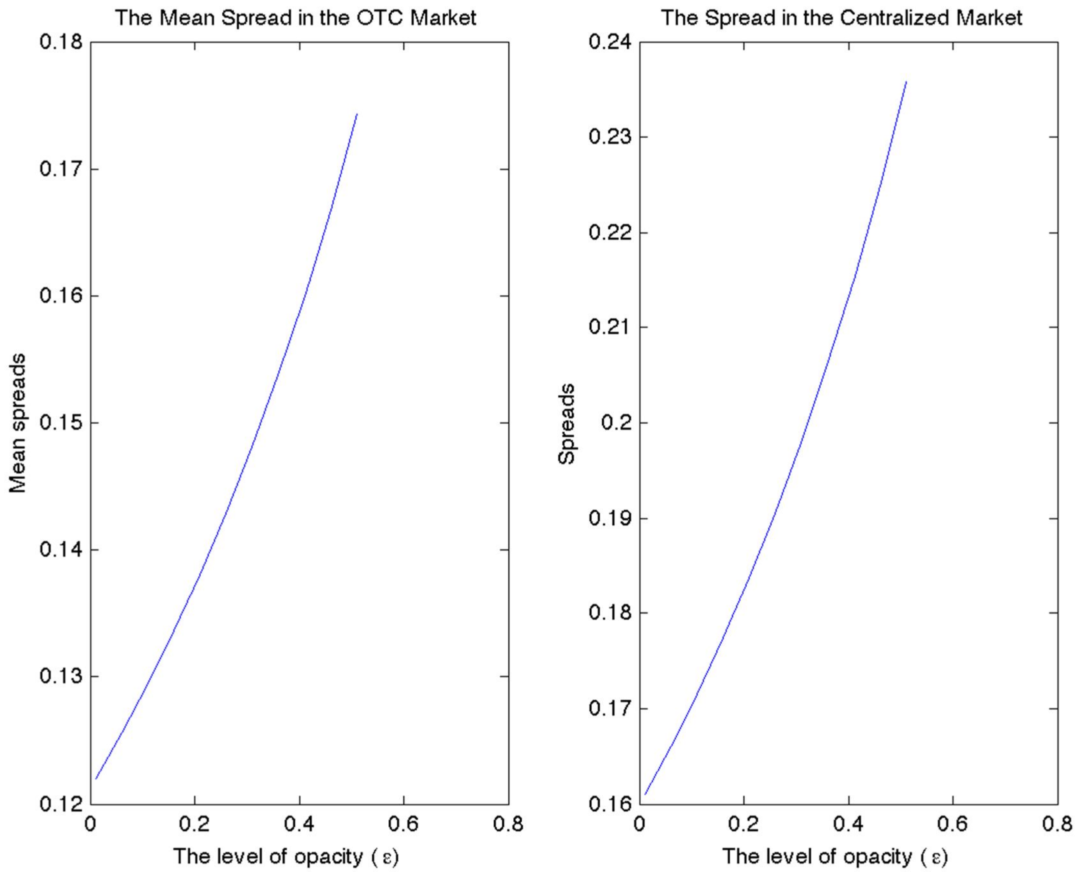

Figure 2.13: Comparative Statics of the Average Bid-Ask Spread in the Interior Equilibrium

Figure 2.13 shows the comparative statics of the average bid-ask spread in the interior equilibrium with respect to ϵ. The parameters are $\beta = 0.9, \underline{k} = 0.005, K_{(1)} = 0.009$, and $K_{(2)} = 0.3$.

Figure 2.13 shows that how the average bid-ask spread in the OTC market and the spread in

[29] Numerical results are robust to parameter choices.

the centralized market change with different ϵ. Unlike in the corner equilibrium, the OTC market's average spread in the interior equilibrium increases under greater opacity. In addition, greater opacity increases the spread in the centralized market.

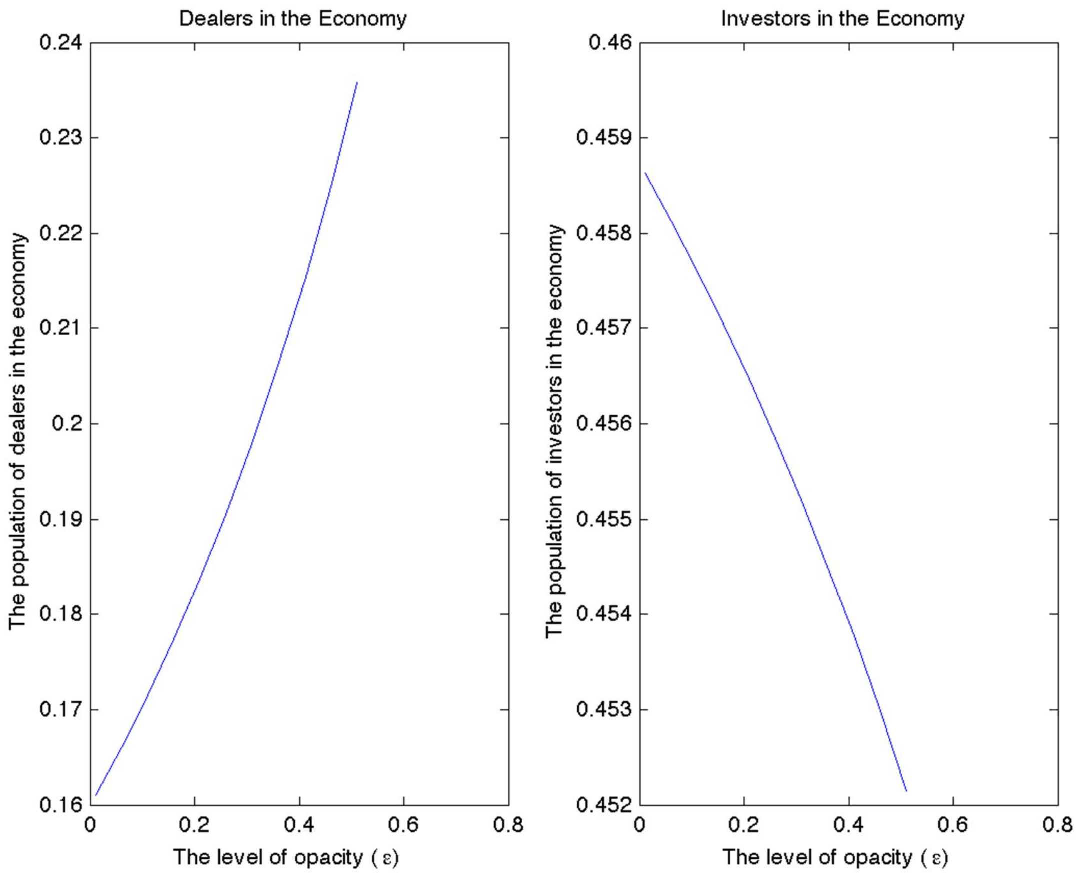

Figure 2.14: Comparative Statics of the Demographics in the Interior Equilibrium

Figure 2.14 shows the comparative statics of the demographics in the interior equilibrium with respect to ϵ. The parameters are the same as in Figure 2.7. The left panel plots the total population of dealers in equilibrium, and the right panel plots the total population of investors in equilibrium.

In Figure 2.14, I show how dealers and investors respond to changes in ϵ. Again, unlike findings in the corner solution equilibrium, in the interior equilibrium, greater opacity leads to less participation from investors, but more participation from dealers.

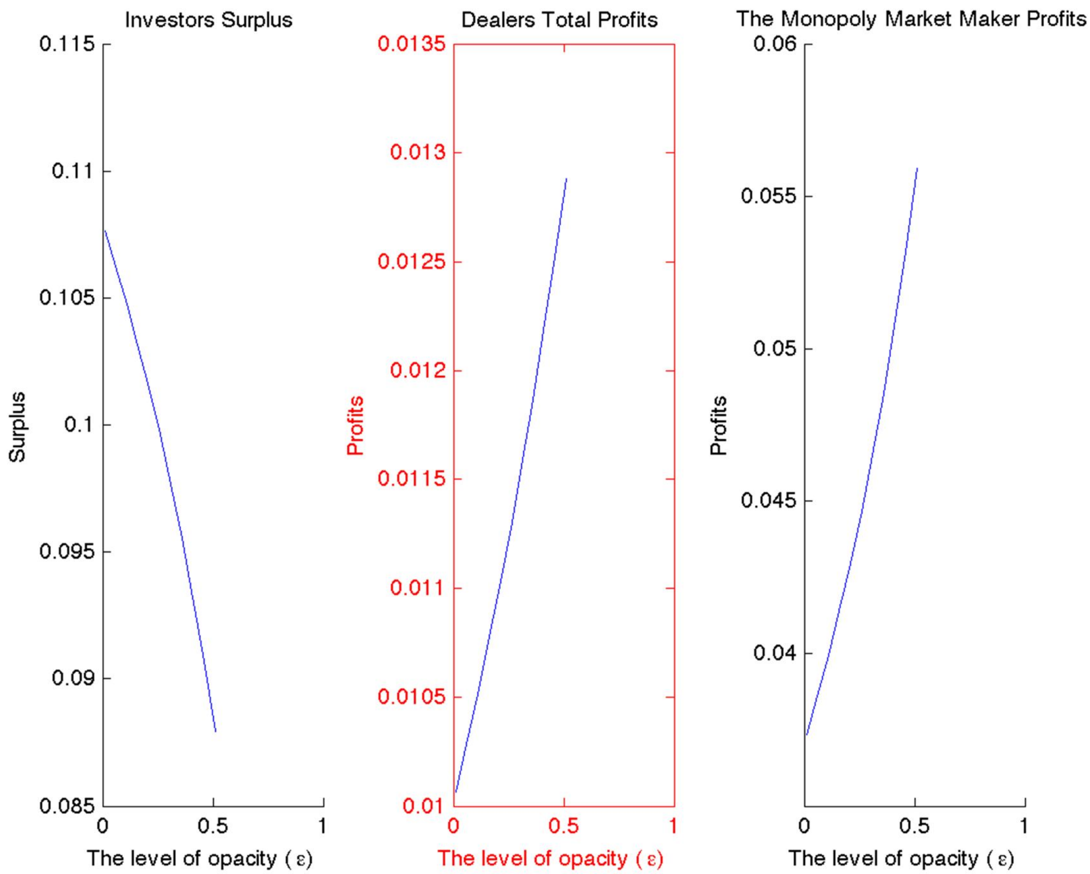

Figure 2.15: Comparative Statics of the Welfare in the Interior Equilibrium

Figure 2.15 shows the comparative statics of the welfare in the interior equilibrium with respect to ϵ. Parameters are the same as in Figure 2.7. The left panel plots investors' surplus, the middle panel plots dealers' total profits, and the right panel plots the market maker's profits.

Figure 2.15 shows the changes in the welfare of investors, dealers, and the winning market maker. Similar to the corner solution equilibrium, investors' total surplus decreases as ϵ increases (see the left panel of Figure 2.15). This is because the impact of opacity on investors is the same as before. The middle panel of Figure 2.15 shows that dealers' total profits increase as ϵ increases. The right panel of Figure 2.15 shows the winning market maker's profits increase as ϵ increases. These results indicate that when the centralized market is not competitive, its existence in equilibrium does not provide an incentive for dealers to reduce opacity in the OTC market.

2.4.2.7 Comparing the Corner Equilibrium with the Interior Equilibrium

Different results obtained from the corner equilibrium and the interior equilibrium are due to the impact of opacity on the winning market maker. In the interior equilibrium, the winning market maker does not fear the entry of other market makers, which enables him to charge the unconstrained ask and bid with the spread equals k_u^{**}. This spread depends on spreads in the OTC market, and hence, opacity in the OTC market. This dependency offers opportunities for the winning market maker to collude with dealers in the OTC market. Under greater opacity, with the expectation that dealers in the OTC market would enlarge their bid-ask spreads, the winning market maker enlarges his bid-ask spread correspondingly. Increasing spreads in both the OTC market and the centralized market discourage investors to participate, whereas, in the corner solution equilibrium, the winning market maker's spread is independent to dealers'. This makes the centralized market as a safe haven for investors to avoid opacity in the OTC market. As a result, under greater opacity, the OTC market loses market share to the centralized market.

2.4.3 The Equilibrium in which the Centralized Market Fails to Survive

As mentioned previously, the equilibrium in which the OTC market coexists with the centralized market is the intermediate stage equilibrium. It is possible that the centralized market loses all trades to the OTC market, and hence, fails to survive. In this equilibrium, establishing the centralized market is futile to incentivize dealers in the OTC market to reduce opacity, since the centralized market does not survive in equilibrium.

The condition for this equilibrium, in which the centralized market fails to survive, is illustrated by **Proposition 2.6**.

Proposition 2.6

A centralized market fails to survive in equilibrium if and only if $K_{(1)} > k^*$*, where* k^* *is defined in* ***Proposition 2.1****. The equilibrium is the same as in* ***Proposition 2.1****.*

Figure 2.1 shows that k^* increases in ϵ. As k^* represents the upper bound for the centralized market to survive. This implies that greater opacity in the OTC market makes it easier for the centralized market to survive in equilibrium. More specifically, when the OTC market has high opacity, the centralized market survives even if market makers have high transaction costs.

Proposition 2.6 suggests that stricter regulations, which raise transaction costs, would not dominate the centralized market's viability if the OTC market has great opacity. This sheds light on the dispute between regulators over the strictness of rules on Swap-Execution-Facilities (SEFs, henceforth).[30] Some policy makers are afraid that stricter rules may impair the viability of SEFs as stricter rules raise transaction costs. According to **Proposition 2.6**, if OTC markets on swaps have great opacity, SEFs with stricter rules still survive in equilibrium.

Admittedly, the ultimate goal for SEFs is to replace OTC markets on standardized swaps, but is beyond the scope of this analysis. To understand how the centralized market, e.g., a SEF, can replace an OTC market, I analyze the other equilibrium, in which the OTC market fails to survive.

2.4.4 The Equilibrium in which the OTC Market Fails to Survive

In this subsection, I show the condition for the centralized market to replace the OTC market in equilibrium. The key determinant is the comparison of the transaction cost between the centralized market and the OTC market. However, in one special case, the opacity of the OTC

[30] SEFs are under the regulation of both the CFTC and the SEC. The two agencies have disagreed on rules over SEFs. In short, the industry deems the CFTC's proposed rules to be stricter than the SEC's. For example, the CFTC requests swap traders to obtain at least five quotes before they trade, whereas the SEC requests traders to obtain at least one quote.

market also has influence on the takeover.

2.4.5 The OTC Market Fails to Survive in the Corner Equilibrium

As shown in Subsection 2.4.2, when the centralized market is competitive, the winning market maker's optimal choice is to post his bid-ask spread at the next most efficient market maker's transaction cost, i.e., $K_{(2)}$. The equilibrium is the corner equilibrium. The condition that the centralized market replaces the OTC market in the corner equilibrium is described as follows,

Proposition 2.7

In the corner equilibrium, the OTC markets fail to survive if and only if $\underline{k} > K_{(2)}$. *The equilibrium prices are*

$$a_c = 1 - b_c = \frac{K_{(2)} + 1}{2}. \tag{2.54}$$

Proposition 2.7 implies that for a competitive centralized market to successfully replace the OTC market, market makers' transaction costs must be lower than dealers' transaction costs. More precisely, the next most efficient market maker's transaction cost, which is the spread in the centralized market, must be lower than the most efficient dealer's transaction cost. This suggests that to replace the OTC swap market with the SEF, which is a competitive market, market makers in the SEF must have lower transaction costs than dealers in the OTC swap market. From this perspective, stricter rules on the SEF do not favor the takeover, even though they do not impair the SEF's viability.

As the OTC market fails to survive in equilibrium, and the winning market maker in the centralized market charges a fixed spread to deter the entrance of other market makers, opacity in the OTC market does not exert any influence on the equilibrium outcomes. However, opacity in the OTC market impacts the condition for the OTC market to survive, when the entrance threat from another market maker is not credible, i.e., the centralized market is not competitive.

2.4.6 The OTC Market Fails to Survive in the Interior Equilibrium

When the centralized market is noncompetitive, the winning market maker faces no entrance threat from other market makers. The winning market maker posts a bid-ask spread that is his interior solution for profit maximization. The equilibrium obtained is the interior equilibrium. The condition for the centralized market to replace the OTC market in the interior equilibrium is more complex. As shown in Rust and Hall (2003), when the OTC market fails to survive in the interior equilibrium, two pricing strategies arise for the winning market maker in the centralized market. The first is that the winning market maker charges a price which equals the lower bound of dealers' transaction costs to deter the entrance of dealers. This is known as the limited price. The second is that the winning market maker charges the price that does not consider the impact on OTC dealers. In this scenario, the winning market maker ignores OTC dealers' strategies, since the threat of OTC dealers' entrances is not credible. The equilibrium selection depends only on the lower bound of dealers' transaction costs, and is known as the unlimited price.

<u>Proposition 2.8 [Limited Prices by the Market Maker]</u>

In the interior equilibrium, the OTC market fails to survive if and only if

$$\left(k^{**} - K_{(1)}\right)\left(1 - \frac{k^{**}+1}{2} - \frac{\beta(1-\epsilon)}{1-\beta}\int_{\underline{k}}^{k^{**}} a(k)dk\right) \leq \frac{\left(\underline{k} - K_{(1)}\right)\left(1-\underline{k}\right)}{2}, \tag{2.55}$$

*in which k^{**} is defined in **Proposition 2.5**. Under the condition (2.25), the equilibrium prices are*

$$a_c = 1 - b_c = \frac{\underline{k}+1}{2}. \tag{2.56}$$

Proposition 2.9 [Unlimited Prices by the Market Maker]

If and only if $\frac{K_{(1)}+1}{2} < \min\{\underline{k}, K_{(2)}\}$, *then the equilibrium prices are*

$$a_c = 1 - b_c = \frac{K_{(1)} + 3}{4}. \quad (2.57)$$

The upper panel of Figure 2.16 shows the region of the lower bound of dealers' transaction costs, $\underline{k}$, for the OTC market to survive in the interior equilibrium. In addition, the upper panel of Figure 2.16 illustrates the equilibrium selection when the OTC market fails to survive. The lower panel of Figure 2.16 shows how changes in ϵ affects the viability of the OTC market. Specifically, the OTC market survives with higher transaction costs when ϵ is large. When the OTC market has great opacity, the noncompetitive centralized market is less likely to replace it, since the noncompetitive centralized market prefers to keep the OTC market in order to profit from opacity. However, when transaction costs in the OTC market are substantially larger than transaction costs in the centralized market, the centralized market finds it more profitable to replace the OTC market (see the upper panel of Figure 2.16).

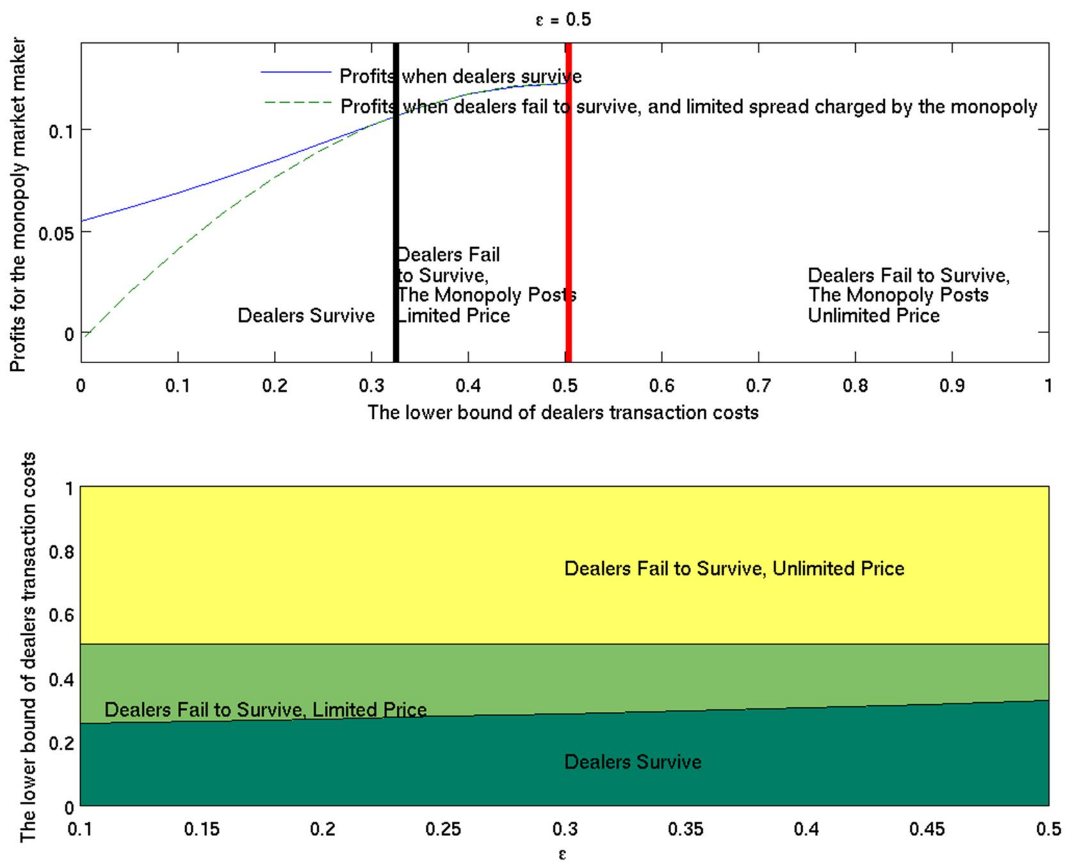

Figure 2.16: Equilibrium Selection on when the OTC Survives and when it Fails to Survive

The upper panel of Figure 2.16 shows the equilibrium selection when the OTC market survives or fails to survive in the economy ($\epsilon = 0.5$). *The lower panel shows the comparative statics of the lower bound of dealers transaction costs, with which the OTC market can survive. Let* $K_{(2)} = 1$ *to focus on the interior equilibrium.* $K_{(1)} = 0.009$ *and* $\beta = 0.9$.

The analysis on the viability of the OTC market under the noncompetitive centralized market sheds lights on the OTC corporate bond market. In the OTC corporate bond market, banks are major dealers that provide intermediary services. The "Volker Rule," which limits the proprietary trading from banks, increases banks transaction costs. As a result, transaction costs in the OTC corporate bond market increases once the "Volker Rule" is enforced. From the upper panel of Figure 2.16, the increase in transaction costs in the OTC corporate bond market increases the likelihood that a noncompetitive centralized market replaces the OTC market on the corporate bond. In fact, BlackRock has recently planned to launch its “Aladdin” matching platform on trading corporate bonds, which is likely to be a noncompetitive centralized market, to compete with the OTC corporate bond market.[31]

2.5 Concluding Remarks

Based on this chapter, I suggest that setting up a centralized market may be an efficient way to provide an incentive for dealers to choose for less opaque OTC markets. This is because the migration of order flows to the centralized market under greater opacity leads to smaller profits for dealers in OTC markets. However, the centralized market has to be competitive to generate competitive pressure on OTC markets. Results support recent reforms in OTC derivative markets aiming to reduce opacity in those markets.

My model provides some empirical implications. First, when an OTC market is the only intermediary in the economy, greater opacity in the OTC market increases the average bid-ask spread. Second, when a centralized market and an OTC market coexist in the economy, the correlation between degrees of opacity and prices can be used to test if the centralized market competes or colludes with the OTC market. Specifically, the centralized market, which competes with the OTC market, predicts that greater opacity decreases the average bid-ask spread in the OTC market, but does not change the bid-ask spread in the centralized market. Conversely, the centralized market, which colludes with the OTC market, predicts that greater opacity increases both the OTC market and the centralized market's bid-ask spreads.

To test these empirical implications, one needs to construct proxies to measure opacity. The

[31] BlackRock Inc. is planning to launch a trading platform this year that would let the world's largest money manager and its peers bypass Wall Street and trade bonds directly with one another (see Wall Street Journal, Apr 12th, 2012).

availability of an OTC asset's pre-trade and post-trade information is a good proxy for opacity. But, this approach is likely to be plagued by endogeneity, since the availability of information is an endogenous choice of relevant agencies. Alternatively, one can use the complexity of an OTC asset. The more complex an asset is, the larger opacity it adds to investors because investors face more uncertainty in both valuing the asset and searching for counterparties.

There are some limitations of this model. Investors in the model are liquidity investors rather than informed investors. This limits my model to analyze information asymmetry in OTC trading. Also there are continuum investors and dealers in my model. In reality, most OTC trades occurred among finitely many large institutions. Accommodating those limitations could potentially provide additional insights on OTC trading.

Chapter 3 Pre-Trade Transparency in Over-the-Counter Markets: An Empirical Test in the Corporate Bond Markets[32]

3.1 Introduction

The availability of quote information, which is defined as pre-trade transparency, is very limited to investors in OTC markets. Consequently, the search process can be potentially costly to investors in OTC markets because of the sequential search and bilateral bargaining that characterizes consummation of trades (see Duffie (2010, 2012)). However, little evidence exists as to whether, and if so, how pre-trade transparency/opacity influences information search costs, and thus the transaction costs in OTC markets. In this chapter, we study a specific but an

[32] This chapter is adapted from the paper I collaborate with Fan Chen from University of Oklahoma.

important type of OTC markets, the corporate bond markets. We examine the impact of pre-trade transparency on corporate bond transaction costs. By doing so, our research adds to the understanding of the influence of pre-trade transparency on OTC markets.

To guide our empirical research and explain the pre-trade transparency mechanism influencing OTC trading, we use the search model constructed in Chapter 2. In the model, traders' lack of pre-trade information is modeled as traders facing Knightian uncertainty. Unlike risk, where the odds of future states are known, Knightian uncertainty refers to the situation in which the odds of future states are unknown. The lack of pre-trade information and the awareness of this deficiency in OTC markets indicates the vagueness of information possessed by traders, which gives credence to Knightian uncertainty in this search process. In Chapter 2, the model shows that pre-trade information enhances a traders' willingness to search, which implicitly improves their bargaining capabilities. As a result, dealers have to lower their ask prices and increase their bid prices in order to secure trades. In other words, dealers have to compete for traders more aggressively. This results in not only smaller bid-ask spreads, but also less dispersion among bid-ask spreads. We test these model implications through an empirical study on U.S. corporate bonds using the OTC bond transaction data from TRACE.

In the U.S., the majority of corporate bonds are traded in OTC markets, but some are traded on both OTC and NYSE markets. The NYSE's Bonds (previously known as the Automated Bond System) operates the largest centralized corporate bond market in the U.S. and is organized as an electronic limit order book system providing comprehensive pre-trade transparency. Thus, bonds traded both on OTC and NYSE markets are more pre-trade transparent relative to bonds that are only traded in OTC markets. Bond traders benefit from the pre-trade quote information in NYSE Bonds since their bargaining power increases when they trade with dealers.

Accordingly, the increases in bargaining power benefits bond traders on the OTC market by reducing their transaction costs.

Based on this feature we conduct an observational study. First, we construct a group of bonds traded on both OTC and NYSE, identified as the OTC-NYSE group, and then we employ propensity score matching to identify a matched group of bonds that trade only in OTC, namely OTC-only group. Since we focus only on bond transactions occurred on the OTC market, the availability of the pre-trade quote, which is provided by the limit order book, is the only one relevant difference between these two groups of bonds in regards of trading environments. Finally, we analyze the transaction costs, variances of transaction costs, and yields between these two groups.

Consistent with model implications, we find smaller bond bid-ask spreads and smaller standard deviation of bid-ask spreads in the OTC-NYSE group compared to OTC-only group. Our findings are robust to a multitude of tests. In the univariate analysis, where bonds are matched by issuers, the OTC-NYSE group has on average 24 basis points smaller effective bid-ask spreads than the OTC-only group. The standard deviation of bid-ask spreads are also significantly smaller for the OTC-NYSE group of bonds. These findings are consistent across different rating categories. After acquiring a sample of OTC-only bonds with firm and bond characteristics similar to OTC-NYSE bonds via propensity score matching, the mean and standard deviation of bid-ask spreads of the OTC-NYSE group remain statistically and economically lower than the matched OTC-only group. The average effective bid-ask spread is 10 basis points lower on OTC-NYSE group of bonds. In our sample period from 2008 to 2011, OTC-only bond transactions between dealers and traders are roughly $1,058 billion per year. Therefore, if NYSE pre-trade transparency had been offered as part of OTC trading, traders would have saved approximately $1,058 million per year on transaction costs. A potential endogeneity issue for our empirical design of matching groups is that firms may choose to list bonds with smaller transaction costs on both OTC and NYSE markets. We address this concern with two-stage least square regressions utilizing a firm's accounting standard and the listing status of a firm's equity as instruments. Those factors affect a firm's decision on where to list its bonds but are not likely to correlate with bonds' bid-ask spreads. Our regression results provide evidence that bonds' transaction costs, as measured by bid-ask spreads, are negatively correlated with the presence of NYSE pre-trade transparency with a p-value less than 0.01.

The reduction in bond transaction costs is also significant for sophisticated institutional traders. In a truncated sample, we focus specifically on institutional sized trades (trade size>$100,000) and find that bonds' bid-ask spreads are negatively related to whether a bond is listed on both OTC and NYSE. As institutional traders are likely to be informed traders, this suggests that improving pre-trade information favors traders over dealers.[33] Pre-trade information is more likely to help traders enhance their bargaining capabilities than to help dealers to discern informed trading. If it were the latter that dominated, then we should observe a positive relation between bonds' bid-ask spreads and whether a bond is listed on both OTC and NYSE, which we did not.

Furthermore, NYSE pre-trade transparent bonds tend to have lower yields, suggesting that an improvement in pre-trade transparency causes a significant reduction in bond yields and thus adds value to bonds. Pre-trade transparency reduces bonds' transaction costs, thereby increasing bonds' liquidity. The increase of bond value associated with improving pre-trade transparency is the premium of improved liquidity.

[33] Anand, Chakravarty, and Martell (2005) argue that institutional traders are more likely to be informed traders in the corporate bond markets.

We are aware of other papers that have examined the impact of trade transparency on transaction costs in the corporate bond markets (see Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2007), and Goldstein, Hotchkiss, and Sirri (2007)). Our paper differs from these recent papers in the following aspects. First, these studies use the introduction of TRACE reporting system to test the relation between corporate bonds trading and market transparency. More specifically, they focus on the influence of improving post-trade transparency, which is the release of transaction information following a trade. However, the focus of our study is on the influence of improving pre-trade transparency, which is the release of quote information. Given the bilateral trading nature in OTC markets, it is critical to examine whether and if so, how the pre-trade transparency impacts transaction costs in OTC markets. Second, Edwards, Harris, and Piwowar (2007) show a regression result that listing on the NYSE can reduce bonds' transaction costs, but they do not discuss it in details nor adjust for the endogeneity problem, as it is not the focus of their paper. We extend their study by resolving the endogeneity issue with the propensity score matching method and an instrumental regression. Lastly, we show that the improved pre-trade transparency in corporate bond markets favors traders over dealers as both volatility of bid-ask spreads and institutional sized trades' bid-ask spreads decrease, indicating more competition among dealers and that potential informed traders face smaller bid-ask spreads.

The next section provides a review of related literature. In Section 3.3, we conduct an empirical study on the corporate bond market to test the implications of our model. Sections 3.4 and 3.5 provide further discussions of our paper's implications. Finally, Section 3.6 concludes this chapter.

3.2 Related Literature

The relationship between pre-trade transparency and market quality is important to the design of markets. This relationship provides implications on market liquidity, informational efficiency, inter-market competition, and ultimately the welfare of market participants. However, academia has yet to reach a consensus on major issues in these areas. Baruch (2005) develops a model in which liquidity demanders and suppliers have differing degrees of access to the limit order book. The model predicts that liquidity demanders benefit from access to the book while liquidity suppliers benefit when the book is closed. Boehmer, Saar, and Yu (2005) find that the introduction of the NYSE's OpenBook service, which provides limit order book information, decreases the price impact of orders and improves the informational efficiency of prices. Eom, Ok, and Park (2007) find that market stability and informational efficiency of the price are improved when the Korea Exchange increases the number of publicly disclosed quotes. On the other hand, Madhavan, Porter, and Weaver (2005) find that increased pre-trade transparency leads to higher trading costs and volatility after the Toronto Stock Exchange disseminated real-time information on its limit order book to the public.

The influence of pre-trade transparency has also been investigated via experimental studies. Bloomfield and O'Hara (1999) show that pre-trade transparency has no impact on informational efficiency, bid-ask spreads, and trader welfare. Whereas Flood et al. (1999) conclude that pre-trade opacity leads to more dispersed opening spreads and lower trading volume due to higher search costs.

Besides studies on the equity market, past studies also examine the impact of transparency on OTC markets. Most of those research focus on the corporate bond markets. They use the release of the TRACE data as a natural experiment and find that transparency improves the OTC market's liquidity (see Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2007), and Goldstein, Hotchkiss, and Sirri (2007)). TRACE contains only information related to traded prices but doesn't contain information regarding quotes (pre-trade information), therefore, studies using TRACE focus specifically on post-trade transparency. Carrion (2009) studies how pre-trade transparency affects bond trading costs by comparing the costs on the NYSE versus those in OTC markets.

3.3 An Empirical Study on the Corporate Bond Markets

The search model in Chapter 2 illustrates that pre-trade transparency affects OTC trading through enhancing traders bargaining capability. We test the empirical implications resulting from the model. More specifically, we conduct an empirical analysis on the corporate bond markets to test if the average and standard deviation of bid-ask spread decrease as pre-trade transparency increases.

3.3.1 Data and Sample

Our initial sample ranges from November 1st, 2008, to March 31st, 2011, and includes 40,977 bonds with 26,658,403 trades and $7.6 trillion of volume. Firm characteristics data is obtained from COMPUSTAT, bond transactions data from the Trade Reporting and Compliance Engine (TRACE), and bond characteristics data from the Mergent Fixed Income Securities Database (FISD). An important file for the analysis is the "ISSUE EXCHANGE" master file that is retrieved from FISD. This file documents the exchange(s) (if any) where the bonds are listed. For a debt security to be listed on the NYSE, the debt issue must have a minimum market value or principal amount of $5,000,000. Additionally, the debt security must have an investment grade rating to a senior issue or a rating that is no lower than an S&P rating of "B". The credit rating is not required if the issuer of the debt security has equity securities listed on the NYSE. Through June 30, 2011, all bonds listed on NYSE Bonds are subject to an initial listing fee of $15,000. Effective July 1, 2011, all bonds listed on NYSE Bonds are subject to an initial listing fee of $5,000 and an annual listing fee of $5,000. According to NYSE Bonds trading guideline, any debt securities listed on the NYSE are eligible to trade on NYSE Bonds trading platform.[34] Based on the "ISSUE EXHANGE" file, we are able to identify OTC traded bonds also traded on the NYSE. Since TRACE reports trades with very few bond characteristics, Mergent's FISD database is employed to secure comprehensive bond attributes, such as coupon, maturity, and ratings. FISD reports an exhaustive list of 35,779 bond characteristics that are available. Table 3.1 describes the sample selection procedure.

[34] http://www.nyse.com/bonds/nysebonds/1095449059236.html

Table 3.1: Sample Composition

The sample period is from November 1, 2008 to March 31, 2011. This table describes the composition of the final sample. From TRACE we collect bond trade data. Bond characteristics, such as coupon, maturity and ratings, are obtained from Mergent's FISD database. The filtering conditions applied rule out bonds that are: (i) put-able; (ii) with abnormal prices (less than $10 or greater than $200); (iii) subsequently corrected; (iv) affected by price reversions and (v) traded less than 9 times over the sample period. To estimate a bond's daily bid-ask spread, we further require bonds to have at least one buy and one sell within a day. Lastly, all but NYSE listed bonds are discarded.

	# of Bonds	# of Trades	Size($s)	Yield(%)	Coupon(%)	Dollar Volume (Billions)
Data downloaded from TRACE(Starting from Nov 1, 2008 to March 31, 2011)	40,977	26,658,403	285,916.96	8.98	N.A.	7,621.94
After filtering conditions:	25,884	24,958,872	276,633.09	8.04	5.90	6,904.32
Sell	25,146	9,058,715	279,239.83	6.90	5.90	2,529.54
Inter-Dealer	25,167	10,019,697	206,389.84	8.32	5.92	2,067.92
Buy	24,263	5,880,460	392,306.06	9.35	5.85	2,306.86
Sample(only buy and sell plus NYSE)						
OTC-only	16,670	8,776,241	291,459.79	8.83	5.03	2,557.92
OTC-NYSE	4,187	4,698,929	396,650.13	5.91	6.10	1,863.83
Sell	20,857	8,225,185	280,275.13	6.89	5.90	2,305.31
Buy	20,857	5,249,985	403,132.08	9.23	5.88	2,116.44

We filter the data by eliminating 739 put-able bonds, 869 bonds with abnormal prices (prices greater than \$200 or less than \$10), bond trading with subsequent corrections, bonds' trading side are not indicated, and bond trading affected by price reversions.[35] To exclude rarely traded bonds, we require the bond trade at least 9 times during the sample period, which eliminates 8,287 bonds from our sample. These filtering conditions leave a sample of 25,884 bonds and 24,958,872 trades. To compute same-bond-same-day effective bid-ask spreads, we further require bonds to have at least one buy and one sell transaction within a day as in Hong and Warga (2000), Chakravarty and Sarkar (2003) and Goldstein, Hotchkiss, and Sirri (2007). Bonds that cannot be identified in the "ISSUE EXCHANGE" master file are also excluded from the sample. Lastly, we drop all inter-dealer transactions and bonds listed on an exchange other than the NYSE.[36] The final sample used for the empirical analysis contains 20,857 bonds responsible for 13,475,170 trades and roughly \$4.4 trillion of volume. Table 3.2 provides descriptive statistics for the 20,857 bonds in the sample.

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[35] Note the bond return from time t to time $t+1$ as R_t^{t+1}; a price reversal happens if $R_{-1}^{0} < -10\%$ and $R_0^1 > -0.5R_{-1}^{0}$ or if $R_{-1}^{0} > 10\%$ and $R_0^1 < -0.5R_{-1}^{0}$. We adjust our filter rule from Bessembinder et al. (2009). Bessembinder et al. (2009) define large return reversals as 20% or more price change which is reversed over 20% in the next observation. Our results are qualitatively the same when applying their rules to our sample.

[36] The empirical results are not affected at all even if we include those bonds listed on exchanges other than the NYSE, e.g., the Frankfurt Stock Exchange and the Luxembourg Stock Exchange.

Table 3.2: Sample Summary Statistics

This table presents the number of observations, mean, median, and standard deviation of all variables in the main sample. Definitions of variables can be seen in the Appendix B.

Variable	# of Obs	Mean	Median	Std Dev
Bid-ask Spread	20,857	0.0097	0.01	0.01
Firm size (log millions)	17,889	11.4508	11.49	2.30
Leverage	17,886	0.2229	0.17	0.19
Firms' accounting standard-IFRS	20,857	0.0284	0.00	0.17
Firms' accounting standard-Domestic	20,857	0.8002	1.00	0.40
Issuer is in finance industry	20,857	0.6574	1.00	0.47
Issuer is a utility	20,857	0.0610	0.00	0.24
Issuers' equity is private	20,857	0.1425	0.00	0.35
Issue size (sq. root of millions)	20,857	11.0846	5.43	11.22
Moody's bond rating	20,857	9.8220	7.00	7.56
Years to maturity (years)	20,857	11.8303	10.00	9.51
Global bond	20,857	0.1166	0.00	0.32
Variable rate bond	20,857	0.1334	0.00	0.34
Foreign bond	20,857	0.0001	0.00	0.01
Senior bond	20,857	0.0770	0.00	0.27
Rule144a bond	20,857	0.0021	0.00	0.05

The average (median) bid-ask spread is 97 basis points. 66% (6%) of bond issuers are classified as finance (utilities), though bond issuers are from a wide array of industries. Thus, we partition the bonds into three industry categories: Finance, Utilities, and Other for the multiple regression analysis. Private companies are able to issue publicly traded debt if they satisfy disclosure requirements similar to public companies. We identify public companies by matching the issuer's CUSIP in TRACE to equity's first 6-digit NCUSIP in the Center for Research in Security Prices (CRSP) data set.[37] In aggregate, we classify only 14.3% of sample bonds are issued by private firms. The mean (median) maturity of the sample bonds is 11.8 (10.0) years.

[37] Unlike CUSIPs for stocks, CUSIPs for bond is somehow permanent. Cusip for issuer could be changed through the time, for many reasons, such as a slight change in company name. However, when issuers changed their name, the cusips for their bonds will not change (cusips for their stocks will change though.) In Mergent, issuer_cusip reflects the historical value. In CRSP, NCUSIP is a security's historical cusip.

3.3.2 The Estimation of Effective Bid-ask Spreads

Since the quotation data for corporate bond trading is generally unobtainable, we are forced to estimate effective bid-ask spreads using transaction records. Hong and Warga (2000), Chakravarty and Sarkar (2003) and Goldstein, Hotchkiss, and Sirri (2007) all calculate the "traded bid-ask spreads" over a one-day window in the corporate bond market. Specifically, this approach takes the average of the differences between selling prices and buying prices on the same day as the effective bid-ask spread. We estimate the effective bid-ask spread for a particular bond as the time series average of its traded bid-ask spreads in a one-day window. The traded bid-ask spread is the difference between the average daily selling price and average daily buying price divided by their sum:

1. Denoting i to each individual bond and t to time periods, we have

$$Spread_{it} = \frac{\overline{Sell}_{it} - \overline{Buy}_{it}}{\overline{Sell}_{it} + \overline{Buy}_{it}}, \tag{3.1}$$

where $\overline{Sell}_{it}$ and $\overline{Buy}_{it}$ are the average daily selling price and buying price, respectively.

2. Taking the time series average of $Spread_{it}$, we have

$$Spread_i = \sum_{t=1}^{T_i} \frac{Spread_{it}}{T_i}, \tag{3.2}$$

where T_i is the time length of the bonds in our sample.

3.3.3 The Empirical Design

Though the OTC market of corporate bonds has achieved greater post-trade transparency since the unveiling of the TRACE reporting system on July 01, 2002, the market still lacks of pre-trade transparency. There is no centralized and extensive report of pre-trade information such as real-time quote data in this market before NYSE Bonds is introduced.[38] In contrast to the OTC market's bilateral trading feature, NYSE Bonds is the largest centralized corporate bond market in the U.S. functioning through an electronic limit order book system.[39] The NYSE Bonds trading platform provides real-time full market-by-order depth, best limit quotes, and trades to all its participants. Pre-trade pricing data on individual corporate bonds is updated every 10 seconds. Firm and executable bids and offers entered by members or sponsored participants are displayed on a full order book (NYSE BondBook) with full depth of market.

The NYSE Bonds system provides the opportunity to test if pre-trade transparency has any effect on OTC trading. We design an observational study by constructing two groups of bonds. The first group, which is the treatment group (the OTC-NYSE group), consists of bonds traded on both OTC and NYSE markets. The second group, which is the control group (the OTC-only group), consists of bonds traded only in the OTC market. The objective is to compare effective bid-ask spreads and variance of the effective bid-ask spread between these two groups. As with all observational studies, our main challenge in drawing conclusions from this comparison is the endogeneity problem, as the assignment of bonds into the treatment and the control groups is not random. Therefore, we need to control for the endogeneity that bonds with smaller spreads are chosen by their issuers to trade on both OTC and NYSE markets. We address this concern in the next subsection. Based on the model in Chapter 2, our null hypothesis is,

[38] There are some potential data sources providing quote data, like proprietary market information vendors (e.g., Bloomberg Trade Order Management Solutions (TOMS)) or private electronic trading networks (e.g., Tradeweb, MarketAxess, Goldman Sachs GSessions, and BlackRock Aladdin Trading Network). These data sources are fragmented and have other limitations. For example, GSessions only operates each Tuesday and Thursday, in two five-minute sessions each day. The quotes provided in these systems are representative rather than firm. The depth at each quote is not informative to investors and investors are not identical since it is costly to purchase access to these trading systems.

[39] The NYSE conducts two daily bond auctions – an Opening Bond Auction at 4:00 a.m. ET and a Core Bond Auction at 9:30 a.m. ET. Orders not executed in either auction become eligible for continuous trading immediately after the auction.

Hypothesis 3.1

The average and standard deviation of effective bid-ask spreads in the OTC-NYSE group are smaller than the average and standard deviation of effective bid-ask spreads in the OTC-only group.

3.3.4 Empirical Results on the Difference in Bid-ask Spreads between Bonds with and without NYSE Pre-Trade Information

In this subsection, we report univariate and regression results of comparing the mean and standard deviation of bid-ask spreads of the OTC-NYSE and the OTC-only group. We address sample selection bias in several different ways. First, we focus on bonds issued by the same firm to control for firm characteristics. Second, propensity score matching is used to reduce selection bias by equating the OTC-NYSE and OTC-only group of bonds based on individual firm and bond characteristics. The advantage of this method is the ability to compare the difference in the mean and standard deviation of bonds' bid-ask spreads between OTC-NYSE and OTC-only bonds when controlling for firm and bond characteristics. Finally, we conduct multiple regression analysis to examine the statistical significance of the relationship between the NYSE pre-trade transparency and the size of bond bid-ask spreads. Estimates are provided for two-stage least squares estimation with a firm's accounting standard and the equality listing status of a firm as instrumental variables. We find consistent results for all the procedures above. Our results suggest that pre-trade transparency reduces the mean and standard deviation of effective bid-ask spreads in corporate bond trading. This result is consistent with the model implications in Chapter 2.

3.3.4.1 Bonds Issued by the Same Firm

In Table 3.3, we compare the average effective bid-ask spreads of bonds issued by the same firm.

the average bid-ask spread for OTC-NYSE group bonds is 24 basis points lower than those of OTC-only group bonds, and the difference is statistically significant (p-value=0.00). In addition, we obtain consistent results across different credit rating categories. We find that the difference in the bid-ask spreads of non-investment-grade bonds is 51 basis points, which is much greater than the difference in superior bonds (difference of 22 basis points) and other investment-grade bonds (difference of 20 basis points). Both differences are significant with p-values less than 0.01.

Table 3.3: Effective Bid-Ask Spreads Matched by Issuers

This table presents the differences of bid-ask spreads between OTC-only bonds with OTC-NYSE bonds, at the issuer level across ratings. Moody's bond ratings are used to measure a bond's credit rating. If bonds are unrated by Moody's, S&P ratings are used in their place. OTC-only (OTC-NYSE) bonds indicate bonds listed in the over-the-counter markets (both over-the-counter market and the NYSE market). The bid-ask spread is estimated as the time series average of its traded bid-ask spreads in a one-day window. For each bond, the effective (traded) bid-ask spread is the difference between the average daily selling price and average daily buying price divided by their sum. Superior bonds include bonds that have a moody rating of Aaa, Aa1, Aa and Aa2 during the sample period. Other investment grade bonds consist of bonds that have a rating between Baa3 and Aa3. Bonds rated as or below Baa3 belong to non-investment grade bonds category. The bid-ask spread is winsorized at the 1st and 99th percentiles. tt-test (Wilcoxon) is used to test the difference of mean (median) bid-ask spreads between the two groups of bonds. Anova and Kruskal Wallis tests are used to test the difference of standard deviation of bid-ask spreads. The p-value of each test is reported.

	OTC-only				OTC-NYSE				Difference (P-Value)			
	# of Bonds	Mean (bps)	Std Dev (10^{-2})	Coupon (%)	# of Bonds	Mean (bps)	Std Dev (10^{-2})	Coupon (%)	tt-test	Wilcoxn	Anova	Kruskal Wallis
Total	9,487	105	0.74	4.95	3,061	81	0.56	5.90	0.00	0.00	0.00	0.00
Superior Bonds (Aa2 and up)	635	79	0.76	3.29	124	47	0.42	4.28	0.00	0.00	0.00	0.00
Investment Bonds (Aa3-Baa3)	6,064	100	0.63	5.03	2,092	80	0.53	5.70	0.00	0.00	0.00	0.00
Non-Investment Bonds	1,826	131	1.02	5.37	533	80	0.71	7.40	0.00	0.00	0.00	0.00

Results in Table 3.3 suggest that pre-trade information decreases bid-ask spreads in corporate bond trading. This reduction is more evident for low-credit-rating bonds relative to high-credit-rating bonds. In addition, we also find the same pattern for the standard deviation of bid-ask spreads. On average, the standard deviation is significantly smaller for OTC-NYSE bonds than OTC-only bonds across different rating categories in Table 3.3. The difference of bid-ask spreads is more significant for non-investment rating bonds than other bonds.

The number of bonds within the OTC-only bonds in Table 3.3 is far greater than that of OTC-NYSE bonds, suggesting that fewer bonds are traded on the NYSE than in OTC markets. Also, the coupon rate between the OTC-only group and OTC-NYSE group differs dramatically. It could be that firms choose bonds that are more liquid to trade on the NYSE. These findings suggest that the lower level and standard deviation for OTC-NYSE group of bonds may be due to the significant difference of bond characteristics between the two groups. In the next subsection, we use propensity-score matching to control for both bond and firm features.

3.3.4.2 Bonds Matched by Propensity Scores

We utilize propensity-score matching to acquire a sample of bonds with characteristics similar to the bonds traded both in OTC markets and on the NYSE for the sample. First, we run a logistic regression to determine which factors influence firms' listing decisions. Using the estimated coefficients, we can obtain the predicted probability (propensity score) for each bond. Then we match each OTC-NYSE bond to an OTC-only bond based on the closest propensity score. Table 3.4 presents results of the logistic regression and propensity-score matching.

Table 3.4: Effective Bid-Ask Spreads Differences by Propensity Score Matching

Panel A presents results of logistic regressions for the determinants of a firm's listing decisions. The probability is modeled as 1 when a bond listed in both the OTC market and NYSE. Logistic represents the logistic model with a set of independent variables below. Definitions of independent variables can be found in the Appendix B. Using the estimated coefficients in Panel A, the predicted probability (propensity score) for each bond is estimated and used to acquire a sample of OTC-only bonds with characteristics similar to bonds (based on the closest propensity score) traded both in OTC markets and on the NYSE in Panel B. The mean and standard deviation of estimated bid-ask spreads are reported in Panel B. The bid-ask spread is winsorized at the 1st and 99th percentiles. tt-test (Wilcoxon) is used to test the difference of mean (median) bid-ask spreads between the two groups of bonds. Anova and Kruskal Wallis tests are used to test the difference of standard deviation of bid-ask spreads. The p-value of each test is reported.

Panel A: Dependent Variable: Listed on NYSE YES/NO		
Model:	Logistic	
	Coefficient	P-value
Firm size (log millions)	-0.19	0.00
Leverage	0.21	0.10
Firms' accounting standard-IFRS	1.16	0.00
Firms' accounting standard-Domestic	0.52	0.00
Issuer is in finance industry	-0.14	0.02
Issuer is a utility	0.16	0.03
Issuers' equity is private	2.62	0.00
Issuers' equity is listed in NYSE	2.08	0.00
Issue size (sq. root of millions)	0.06	0.00
Moody's bond rating	-0.05	0.00
Years to maturity	0.02	0.00
Global bond	0.38	0.00
Variable rate bond	-2.80	0.00
Foreign bond	0.60	0.71
Senior bond	-0.66	0.00
Rule144a bond	-1.70	0.03
Intercept	-2.13	0.00
Pseudo R-square	0.20	
# of Bonds	17,886	

Panel B: Propensity Scoring Matched Bid-ask Spread Difference		
	OTC-only	OTC-NYSE
Spread-Mean (bps)	87	77
S.D. $*10^{-2}$	0.63	0.54
tt-test for differences	0.00	
Wilcoxon-test for differences	0.00	
ANOVA	0.00	
Kruskal-Wallis	0.00	
# of Bonds	3,843	

We attempt to model firms' bond listing decisions from two avenues: firm characteristics and bond features. There has been no research on how firms decide to list bonds on the NYSE versus in OTC markets. Thus, we construct our model based on basic intuition and on studies of foreign firms' preferences on the U.S. bond market. We control for the following firm characteristics: size, leverage ratio, equity listing status, and accounting standard. In Appendix B, we present our variables of choice and their definitions.

Panel A in Table 3.4 provides our logistic regression results of firms' decisions to list bonds on the NYSE. The dependent variable is binary in nature with a value of 1 if a bond is listed on the NYSE and 0 otherwise. We find that firms who choose to list bonds on the NYSE are small firms or highly leveraged firms. Small or highly leveraged firms should experience more difficulty selling bonds in the debt market than large or low leverage firms. For instance, small firms have poorer information disclosure and less coverage than large companies (see Lang and Lundholm (1993, 1996)). This could increase the costs for small firms raising funds solely from OTC markets. Higher leverage firms pose greater risks to bond investors than low leverage firms. Therefore, these firms may attempt to promote the sale of their bonds by listing bonds both on the NYSE and in OTC markets to reach a greater number of investors. Gao (2011) finds that firms adopting International Financial Reporting Standards prefer to list bonds on the U.S. public bond market but she does not specify whether it is in OTC markets or on the NYSE. To investigate whether firms' accounting standards impact firms' listing choice in bond markets, we assign a dummy variable to firms adopting International Financial Reporting Standards in the logistic regressions. In Panel A of Table 3.4, we find that accounting standards have a positive effect on the choice to list debt on the NYSE given that both two coefficients are positive and highly significant. This result signifies that firms adopting International Financial Reporting

Standards are more likely to list their bonds on the exchange. Bond issuers' industry category may affect bond-listing choice. Bond issuers in the utilities industry tend to issue bonds in the exchange, while issuers in the finance industry tend to issue bonds in the OTC markets.

The effect of a firm's equity listing status affects its debt listing choice. We find that listing equities on the NYSE encourages firms to list their bonds on the NYSE since having equities on the NYSE may reduce the information disclosure cost of listing bonds on the NYSE. This evidence is consistent with the notions that (1) the NYSE may not place any additional disclosure requirements on firms who already trade equities on the exchange as they already satisfy NYSE disclosure requirements for listing stock, and (2) the additional reporting costs associated with stringent disclosure requirements on bonds imposed by the NYSE are marginal for firms with equities listed on the NYSE. In addition, we also find private firms are more likely to issue bonds on the NYSE.

We use the abovementioned variables to control for a firm's characteristics in its bond-listing choice. We also control for a variety of a bond's characteristics in modeling the listing choice of a bond. We find bonds with larger issuance sizes, longer maturity, higher credit ratings, or without variable rates are more likely to be listed on the NYSE. Besides that, global bonds are also more likely to be listed on the NYSE. Senior bonds and Rule 144a bonds are less likely to be listed on the NYSE.

Large or long-maturity debt offerings can be more costly and difficult to issue as issuers try to efficiently raise capital by selling debt. Apparently, listing bonds in both markets can help issuers raise funds more efficiently given the increase in investor base issuers can reach.

We find that the probability of listing bonds on the NYSE is negatively correlated with Moody's bond rating. This correlation indicates that the probability increases as credit quality increases. This relation continues to hold when we use an indicator variable for investment-grade bonds as a proxy for bonds' credit quality. This reflects the clientele effect, as higher rated bonds are usually associated with lower risks, so they are more preferred by retail investors, who prefer to trade on the exchange.

Variable interest payment bonds, with coupon payments adjusting to a schedule or a reference index (for example, LIBOR or Treasury bond interest rates), are less likely to be listed on the NYSE. This finding indicates that typically bonds with complicated instruments that are more complex for retail investors to value are not traded on the NYSE. Since the majority of traders on the NYSE are retail investors, complex bonds might not be favored on the NYSE and hence will tend to suffer from a liquidity shortage.

A separating equilibrium can help to signal the quality of foreign firms who choose to access the U.S. capital markets (see Karolyi (2006)). We find evidence that global bonds are more likely to be listed on the NYSE than domestic bonds. However, not all types of bonds from foreign issuers are likely to be listed on the NYSE. Rule 144a bonds issued by foreign firms, which are traded only by large institutions (Qualified Institutional Buyers (QIBS)), are less likely to be listed on the exchange. This finding is consistent with the clientele effect as most institutional investors trade in OTC markets.

Panel B of Table 3.4 reports the comparison results after matching bonds by their propensity scores. We find that the average effective bid-ask spread for bonds traded both in OTC markets and on the NYSE is 10 basis points lower than bonds traded only in OTC markets. The difference is statistically significant. Our data shows that in the sample period, approximately $1,058 billion per year is traded on bonds for which pre-trade quote information is not available.[40] These results indicate that traders could save a minimum of $1,058 million per year on transaction costs if pre-trade transparency were to be enforced. In Panel B, we also find that the standard deviations of bid-ask spreads for bonds having NYSE pre-trade transparency are smaller than bonds without the pre-trade transparency. Both parametric and non-parametric tests indicate this difference is statistically significant.

3.3.4.3 Multiple Regressions on the Impact of NYSE Pre-Trade Transparent Information

In the previous subsection, we examine the economic significance of the bid-ask spread difference between bonds with and without NYSE pre-trade transparency. In this subsection, we run multiple regressions to examine the statistical significance of the relation between the NYSE pre-trade transparency and bonds' bid-ask spreads when controlling other factors that may influence bid-ask spreads. We start this analysis with an OLS regression in Table 3.5. In addition to the OLS specification, we provide regression results using two-stage least square estimation (2SLS). The dependent variables, except as noted, in the regression are effective bid-ask spreads which is the time-series average of the difference between the average daily selling price and average daily buying price divided by their sum. P-values of estimated coefficients are reported in parenthesis. Consistent with our theoretical model predictions, we find that NYSE pre-trade transparency is negatively correlated with bonds' bid-ask spreads, all else being equal.[41]

[40] In the sample period from November 1, 2008 to March 31, 2011, the sum of buy- and sell-sized trading volume in the OTC markets is $2,558 billion. Thus, the annual trading volume is approximately $1,058 billion.

[41] To control the effect of trade size on bond spreads, we consider the impact of retail-sized investors' trading on bid-ask spreads in unreported results and find qualitatively similar results. We include the percentage of retail-sized trades and trading volume in our regressions, respectively. We find a positive relationship between bid-ask spreads and the proportion of retail-sized trades and trading volume, indicating that small trades occur at higher transaction costs than do trades of institutional investors.

Table 3.5: Effective Bid-Ask Spreads and NYSE Pre-Trade Transparency

This table reports regression results for the relation between a bond's effective bid-ask spread and whether a bond is listed on the NYSE. The sample period is from November 1, 2008 to March 31, 2011. The dependent variable, except as noted, is the estimated effective bid-ask spread, which is the time series average of the difference between the average daily selling price and average daily buying price divided by their sum. Prob of Being Listed on the NYSE is the propensity score computed from the logistic models in Table 3.4. All other independent variables are defined as in Appendix B. In the OLS model, we use a dummy variable of 1 to represent whether a bond is listed on the NYSE in the OLS regression. In the remaining table, we present regression estimates using a two-stage least squares (2SLS) method. All estimated coefficients reported are multiplied by 100. The bid-ask spread is winsorized at the 1st and 99th percentiles. P-values are reported in parentheses.

Model	OLS		2SLS-Logistic			
Dependent variable	Bid-ask spread		Listed on the NYSE=1/0		Bid-ask Spread	
Listed on the NYSE	-0.10	(0.00)			-0.16	(0.04)
Prob of Beling Listed on the NYSE			75.62	(0.00)		
Firm size (log millions)	0.01	(0.00)	-0.24	(0.16)	0.01	(0.00)
Leverage	0.18	(0.00)	0.53	(0.74)	0.54	(0.00)
Issuer is in finance industry	-0.15	(0.00)	-1.17	(0.18)	0.18	(0.00)
Issuer is a utility	-0.24	(0.07)	1.32	(0.31)	-0.14	(0.00)
Issuers' equity is private	0.54	(0.00)	3.65	(0.63)	-0.23	(0.08)
Issue size (log millions)	-0.02	(0.00)	0.21	(0.00)	-0.02	(0.00)
Moody's bond rating	-0.01	(0.00)	-0.09	(0.02)	-0.01	(0.00)
Years to maturity	0.02	(0.00)	0.09	(0.01)	0.02	(0.00)
Global bond	-0.09	(0.00)	2.05	(0.04)	-0.09	(0.00)
Variable rate bond	-0.11	(0.00)	-4.57	(0.00)	-0.12	(0.00)
Foreign bond	-0.72	(0.06)	1.43	(0.95)	-0.71	(0.06)
Senior bond	-0.11	(0.00)	-2.88	(0.02)	-0.12	(0.00)
Rule144a bond	-0.33	(0.01)	-6.21	(0.42)	-0.35	(0.01)
Intercept	0.58	(0.00)	6.55	(0.00)	0.60	(0.00)
Adj. R-square	0.23		0.19		0.22	
# of Bonds	17,886		17,886			

The first two regressors in Table 3.5 characterize the level of NYSE pre-trade transparency in corporate bond markets, respectively. From the OLS model, the effect of a bond being listed on the NYSE on the bid-ask spread is significantly negative. The coefficient for the issuance size is negative and statistically significant at the 0.01 level, indicating that large issues are cheaper to trade than small issues. This result is consistent with Edwards, Harris, and Piwowar (2007). Bonds with a greater maturity are considered to possess greater risk compared to short term bonds, thus it should cost more to trade longer term bonds. We find consistent evidence with this notion, as long-term bonds have larger bid-ask spreads than short term bonds. Different types of bonds issued by the firm may also impact bond trading costs. The estimated coefficients for global bonds are significantly negative. The lower transaction costs for global bonds could be due to the competition of bond transactions across different countries. Senior bonds have a priority claim in firms' residual assets when the firm faces bankruptcy and is more desired by investors. Therefore, a senior bond tends to have a lower transaction cost. Foreign bonds, issued by foreign firms, are more favored by investors in the market, which brings more liquidity to the bonds. This, in turn, makes foreign bonds cheaper to trade.

As discussed in Section 3.4.4.1, our findings of the difference of bid-ask spreads between the OTC-only and the OTC-NYSE group bonds could be due to the sample selection bias. This means that omitted factors could simultaneously determine both bid-ask spread and firms' listing choice. Thus, we employ two-stage least squares (2SLS) estimation to resolve the potential endogeneity issue. We use firms' accounting standards and the listing status of a firm's equity as the instrument variables. We believe those instruments are likely to affect a firm's decision on listing its bonds, but are not likely to correlate with bonds' spreads. The next paragraph details our procedure of estimation.

We first estimate the logistic model as in our propensity score matching on firms' bond listing decisions with instruments and other exogenous variables (results are in Panel A Table 3.4). Then we use the fitted probability as the new and the only instrument variable in our 2SLS estimation. The advantage of this method is that the misspecification of logistic model in the first stage regression is irrelevant in the IV regression provided that the dummy variable for NYSE listing is partially correlated with the fitted probabilities (see Wooldridge (2002) for detail discussion).

The 2SLS model in Table 3.5 examines the relation between bonds' bid-ask spreads and the NYSE pre-trade transparency using the 2SLS specification. We first report results for the first stage regression predicting the fitted value of being listed on the NYSE using probability of bonds being listed on the NYSE from the logistic regression as the new instrumental variable. The instrument is positively significant, indicating relevance. The joint F-tests of significance is 490 with p-values less than 0.01, indicating weak instruments are not a concern. Hausman tests indicate that the 2SLS regression provides more consistent estimated coefficients than the OLS regression.

In Table 3.5, Columns 5 and 6 report results from the second stage regression using probability estimated from the logistic model as the new instrumental variable. In this specification, the coefficient on bonds listed on the NYSE is negative with a p-value less than 0.01, which confirms the causal interpretation of NYSE pre-trade transparency on a bond's bid-ask spread. In addition, we find that the magnitude of the coefficient estimates in 2SLS regressions (-0.16×10^{-2}) increases compared to estimated coefficients in OLS model (-0.10×10^{-2}). All other control variables except for dummy variables indicating if a firm is in finance industry and if a firm is private have the same signs as the OLS specification.

Overall, regression results in Table 3.5 indicate that the NYSE pre-trade transparent bonds have lower transaction costs (smaller bid-ask spreads) compared to more opaque bonds even after controlling for other factors that impact bond transaction costs.

3.4 The Empirical Implications for Informed Traders

In the market microstructure literature, a sophisticated trader who has more information faces larger bid-ask spreads since dealers protect themselves against information asymmetry (see Glosten and Milgrom (1985) and Easley and O'Hara (1987)). Following this intuition, Pagano and Roell (1996) show that pre-trade transparency decreases bid-ask spreads as information asymmetry is eased, though not necessarily for all trade sizes. While they emphasize that pre-trade transparency enhances dealers' ability to discern informed trading, the model in Chapter 2 emphasizes that pre-trade transparency refines traders' information sets, leading to more bargaining power. This difference leads to different empirical predictions. Given that institutional traders have superior information in trading, Pagano and Roell (1996) predict that institutional-sized trades of pre-trade transparent bonds should have larger bid-ask spreads because institutional traders' information rents are reduced when more pre-trade information is provided. In contrast, my model predicts the opposite as pre-trade information increases institutional traders' bargaining ability, which implies smaller bid-ask spreads for them.

To test this prediction, we restrict the sample of bond transactions to institutional-sized trades (trade size>$100,000).[42] On average, the institutional-sized trades have smaller bid-ask spread than total sample trades (compared with Panel A of Table 3.4). This finding may suggest that institutional traders negotiate better prices than do retail traders. In the Panel A of Table 3.6,

[42] We follow Edwards, Harris and Piwowar (2007) to define institutional-sized trades as trades with a size greater than $100,000.

we find that the average effective bid-ask spreads are smaller on OTC-NYSE bonds (NYSE pre-trade transparent bonds) than OTC-only bonds for institutional-sized trades.

Table 3.6: Institutional Traders' Effective Bid-Ask Spreads and NYSE Pre-Trade Transparency

This table reports results for the relation between a bond's bid-ask spread and whether a bond is listed on the NYSE for the sample limiting to institutional-sized trades (trade size>$100,000). Panels A and B report propensity score matching and regression results, respectively. The estimated effective bid-ask spread in Panel A is computed as the time series average of the difference between the average daily selling price and average daily buying price divided by their sum. The bond bid-ask spread is winsorized at the 1st and 99th percentiles. tt-test (Wilcoxon) is used to test the difference of mean (median) bid-ask spreads between the two groups of bonds. Anova and Kruskal Wallis tests are used to test the difference of standard deviation of bid-ask spreads. Panel B reports regression estimates using a two-stage least squares (2SLS) method. Definitions of other independent variables can be seen in Appendix B. All estimated coefficients reported in Panel B have been multiplied by 100. P-values are reported in parentheses.

Panel A: Propensity Scoring Matched Bid-ask Spread Difference		
	OTC-only	OTC-NYSE
Spread-Mean (bps)	39	37
S.D.*10^{-2}	0.39	0.38
tt-test for differences	0.05	
Wilcoxon-test for differences	0.00	
ANOVA	0.00	
Kruskal Wallis	0.00	
# of Bonds	3,265	

Panel B: Dependent Variable is Bid-ask Spread						
Model:	OLS		2SLS-Logistic			
Dependent variable	Bid-ask spread		Listed on the NYSE=1/0		Bid-ask Spread	
Listed on the NYSE	-0.02	(0.09)			-0.08	(0.10)
Prob of Beling Listed on the NYSE			89.71	(0.00)		
Firm size (log millions)	0.02	(0.00)	-0.13	(0.58)	0.02	(0.00)
Leverage	0.18	(0.00)	-0.01	(1.00)	0.34	(0.00)
Issuer is in finance industry	-0.08	(0.00)	-0.16	(0.89)	0.18	(0.00)
Issuer is a utility	-0.09	(0.47)	0.30	(0.85)	-0.08	(0.00)
Issuers' equity is private	0.34	(0.00)	1.14	(0.90)	-0.09	(0.50)
Issue size (log millions)	-0.01	(0.00)	0.05	(0.32)	-0.01	(0.00)
Moody's bond rating	0.00	(0.34)	-0.08	(0.25)	0.00	(0.73)
Years to maturity	0.01	(0.00)	0.02	(0.56)	0.01	(0.00)
Global bond	-0.02	(0.21)	0.96	(0.43)	-0.01	(0.40)
Variable rate bond	0.00	(0.80)	-2.84	(0.09)	-0.02	(0.40)
Foreign bond	-0.42	(0.21)	0.32	(0.99)	-0.42	(0.21)
Senior bond	-0.05	(0.05)	-1.05	(0.55)	-0.05	(0.03)
Rule144a bond	-0.03	(0.83)	-2.60	(0.77)	-0.04	(0.73)
Intercept	0.14	(0.00)	4.69	(0.18)	0.16	(0.00)
Adj. R-square	0.14		0.19		0.13	
# of Bonds	10,748		10,748			

Consistent with our model prediction of smaller bid-ask spreads for institutional traders provided with more pre-trade information, we find smaller spreads in institutional sized trades. OTC-NYSE bonds are two basis points smaller than OTC-Only bonds in Panel A of Table 3.6. For informed traders (institutional traders), the standard deviation of bid-ask spreads of OTC-NYSE bonds is also smaller than OTC-Only bonds. The standard deviation of bid-ask spreads is smaller for OTC-NYSE bonds. All of these differences are statistically significant. Panel B of Table 3.6 continues to provide support the finding that OTC-NYSE bonds are more liquid after controlling for the sample selection bias with the 2SLS regression. This finding is evidenced by the negatively significant coefficient for the indicator variable of bonds being listed on the NYSE in the second stage regressions. However, the impact is only significant at the 0.1 significance level. This suggests though institutional traders do benefit from pre-trade transparency, the effect is less prominent than other traders. Institutional traders are sophisticated enough so that pre-trade information only enriches their information sets marginally.

Collectively, these results provide supporting evidence for our search model, while not finding any supporting evidence of the information asymmetry model. Thus, the primary mechanism of pre-trade transparency affecting bonds' liquidity is through increasing traders' bargaining ability rather than increasing dealers' ability to discern informed orders. This implies that improving pre-trade transparency favors traders over dealers.

3.5 Transparency and Valuation in the Corporate Bond Market

In Section 3.3.4, we find that corporate bonds with NYSE pre-trade transparency have higher liquidity than those without NYSE pre-trade transparency. The increase in liquidity should add value to NYSE pre-trade transparent bonds, since investors value liquidity.[43] In Panel A of Table 3.7, we find that OTC-NYSE bonds on average have lower yields (higher prices) than OTC-Only bonds in the propensity-score matching specifications. For instance, OTC-NYSE bonds have an average yield of 5.95%, which is significantly smaller than OTC-only bonds' mean yield of 7.27% in the propensity-score matched sample. The approximately 1.2% difference in yields between OTC-NYSE bonds and OTC-only bonds looks puzzling, as it implies too large of an economic importance.[44] This could imply that our propensity-score matching sample is not perfect. There are some unknown features that should be controlled are not controlled.

Though our propensity-score matching method is not perfect, it does not affect our conclusion on pre-trade transparency significantly lowers cost of debt capital than otherwise identical firms. Our 2SLS regression (using the same instrumental variables as in previous sections), which is immune to the misspecification of the logistic model (the propensity-score matching model), shows that OTC-NYSE bonds have significantly smaller yield than OTC-Only bonds. This is evidenced by the negatively significant coefficient for the indicator variable of bonds being listed on the NYSE. However, we should be cautious in interpreting the economic significance of pre-trade transparency on bonds' value.

[43] Amihud and Mendelson (1986) find that illiquid securities should compensate security investors with a liquidity premium. Lo, Mamaysky, and Wang (2004) argue that illiquidity leads to lower security prices and larger yield spreads given the same future cash flows since investors demand an ex-ante risk premium. Chen, Lesmond, and Wei (2007) find that illiquid bondholders are compensated with higher yield spreads and bonds' yield spreads decrease when liquidity improves.

[44] The current yield difference between high-yield bonds and investment grade bonds is roughly 1.8% based on Bloomberg bond indices.

Table 3.7: Bond Yield Differences by Propensity Score Matching

This table reports results for the relation between a bond's yield and whether a bond is listed on the NYSE for the total sample. Panels A and B report propensity score matching and regression results, respectively. Using the logistic model as described in Panel A of Table 4, the predicted probability (propensity score) for each bond is estimated and used to acquire a sample of OTC-only bonds with characteristics similar to bonds (based on the closest propensity score) traded both in OTC markets and on the NYSE in Panel A. For the missing bond yields, we use the trade price reported on TRACE and coupon and maturity date from FISD to compute a bond's yield-to-maturity. For multiple bond trading occurring within the same day, we compute trade-size weighted average of bond yields. Bond yields are winsorized at the 1st and 99th percentiles. tt-test (Wilcoxon) is used to test the difference of mean (median) yields between the two groups of bonds. Anova and Kruskal Wallis tests are used to test the difference of standard deviation of yields. Panel B reports regression estimates using a two-stage least squares (2SLS) method. Definitions of other independent variables can be seen in Appendix B. Estimated coefficients reported in the first stage regressions of Panel B are multiplied by 100. P-values are reported in parentheses.

Panel A: Propensity Scoring Matched Bond Yield Difference		
	OTC-only	OTC-NYSE
Yield-Mean (%)	7.27	5.95
S.D.$\times$ 100	8.47	4.89
tt-test for differences	0.00	
Wilcoxon-test for differences	0.00	
ANOVA	0.00	
Kruskal Wallis	0.00	
# of Bonds	3,850	

Panel B: Dependent Variable is Bond Yields						
Model:	OLS		2SLS-Logistic			
Dependent variable	Bond Yield		Listed on the NYSE=1/0		Bond Yield	
Listed on the NYSE	-1.47	(0.00)			-8.74	(0.00)
Prob of Beling Listed on the NYSE			76.04	(0.00)		
Firm size (log millions)	-0.04	(0.31)	-0.25	(0.15)	-0.12	(0.01)
Leverage	0.94	(0.00)	0.56	(0.72)	8.38	(0.00)
Issuer is in finance industry	-2.45	(0.00)	-1.05	(0.23)	0.63	(0.01)
Issuer is a utility	0.43	(0.82)	1.34	(0.30)	-2.04	(0.00)
Issuers' equity is private	8.21	(0.00)	3.59	(0.64)	1.52	(0.44)
Issue size (log millions)	-0.04	(0.00)	0.21	(0.00)	0.02	(0.06)
Moody's bond rating	0.34	(0.00)	-0.09	(0.02)	0.31	(0.00)
Years to maturity	0.06	(0.00)	0.09	(0.01)	0.09	(0.00)
Global bond	-0.88	(0.00)	2.09	(0.04)	-0.24	(0.38)
Variable rate bond	-1.00	(0.00)	-4.52	(0.00)	-2.37	(0.00)
Foreign bond	1.70	(0.75)	1.39	(0.95)	2.12	(0.70)
Senior bond	-0.10	(0.74)	-2.87	(0.02)	-0.97	(0.00)
Rule144a bond	-3.73	(0.04)	-6.19	(0.39)	-5.60	(0.00)
Intercept	3.04	(0.04)	6.50	(0.00)	5.01	(0.00)
Adj. R-square	0.11		0.19		0.03	
# of Bonds	17,854		17,854			

In the model in Chapter 2, the mechanism that pre-trade transparency affects liquidity is through the reduction of traders' perceived Knightian uncertainty. Hence, the result in Table 3.7 implies that reducing Knightian uncertainty can increase the value of a bond. This provides an empirical support of Easley and O'Hara (2010) in which they show that an asset's value increases when its associated Knightian uncertainty decreases.

3.6 Conclusion

Given the significant importance of OTC markets in financial markets and the bilateral trading nature in OTC markets, a motivating question arises, "Whether, and if so, how pre-trade transparency affects OTC trading?" Our empirical evidence from the corporate bond markets shows that pre-trade transparency in an OTC market decreases the mean and standard deviation of bid-ask spreads for traders who trade in the market.

Our empirical findings are robust to endogeneity of firms' bond listing decisions on the NYSE. After controlling for endogeneity with propensity-score matching, the average effective bid-ask spread of OTC-NYSE bonds is 10 basis points smaller than the average effective bid-ask spread of OTC-only bonds. The 10-basis-point difference suggests that approximately $1,058 million could be saved on transaction costs if pre-trade information were revealed in the corporate bond markets. Using a firm's accounting standard and the equality listing status of a firm as instrumental variable, we still find bonds' bid-ask spreads are negatively correlated with the presence of NYSE pre-trade transparency.

In contrast to the prediction of Pagano and Roell (1996), our empirical evidence shows that improved pre-trade transparency increases traders' bargaining ability rather than dealers' ability to discern informed orders. Bond bid-ask spreads for institutional-sized trades on OTC-NYSE bonds are significantly smaller than OTC-only bonds after controlling bond and firm characteristics. This finding is robust across various univariate and multivariate tests.

Consistent with the notion that improved liquidity should add value to securities, we find that OTC-NYSE bonds have significantly lower bond yields than OTC-only bonds. Controlling for the endogeneity of firms' bond listing decisions on the NYSE with an IV regression, we document a negative relationship between bond yields and NYSE pre-trade transparency. Therefore, the improved pre-trade transparency adds value to OTC-NYSE bonds. However, the economic magnitude of the yield difference (approximately 1.2%) is puzzling. This mystifying yield premium indicates a potential area for future research.

Appendix A: Proofs of Propositions in Chapter 1 and 2

Proof of Proposition 1.1

Proof:

Suppose G is a strongly stable network, in which dealers in the same component have uneven links. Let dealer j be the one with the maximal number of links in this component. Then there exists a pair of unconnected dealers i and i', both of whom are connected with j and at least one of whom has fewer links than j (let's say i has fewer links than j). Consider a deviation such that both i and i' cut their connections with j and then build a link between themselves. Denote the obtainable network via this deviation as G'. Since $1 < n_i < n_j$ and $1 < n_{i'} \leq n_j$,

$$U_i(G') - U_i(G) = \frac{1}{2}\frac{n_{i'}}{n_{i'}+1}\left(\frac{1}{n_{i'}+1} - \frac{1}{n_{i'}+2}\right) - \frac{1}{2}\frac{n_j}{n_j+1}\left(\frac{1}{n_j+1} - \frac{1}{n_j+2}\right) \geq 0 \quad \text{(A1)}$$

and

$$U_{i'}(G') - U_{i'}(G) = \frac{1}{2}\frac{n_i}{n_i+1}\left(\frac{1}{n_i+1} - \frac{1}{n_i+2}\right) - \frac{1}{2}\frac{n_j}{n_j+1}\left(\frac{1}{n_j+1} - \frac{1}{n_j+2}\right) > 0. \quad \text{(A2)}$$

The deviation is an improving deviation, since i' is strictly better off and i is weakly better off. Hence, G cannot be a strongly stable network.

The above shows that dealers in the same component have the same number of links. Now suppose that a strongly stable network $\tilde{G}$ has components of varying sizes and that, for i and i' from distinct components, $U_i(\tilde{G}) > U_{i'}(\tilde{G})$. Consider a deviation such that i' cuts all his links, all i's connected dealers (call them y) cut their links with i, and i' then builds links with those y dealers. The deviation replaces i's position in the network with i'. The new network is called $\tilde{G}'$.

In $\tilde{G}'$, $U_y(\tilde{G}') = U_y(\tilde{G})$, since nothing is changed for them. But $U_{i'}(\tilde{G}') > U_{i'}(\tilde{G})$, since i' replaces i's position in the network and $U_i(\tilde{G}) > U_{i'}(\tilde{G})$. The deviation is an improvement, which contradicts to the proposition that $\tilde{G}$ is a strongly stable network.

Q.E.D.

Proof of Proposition 1.2

Proof:

The following lemma is useful in my proof of **Proposition 1.2**.

Lemma A.1

In a strongly stable network no connected dealer has exactly one link.

Proof:

Suppose G is a strongly stable network such that for connected dealers i and j, $n_i = 1$ and $n_j \geq 1$. Since

$$U_j(G) - U_j(G - ij) \tag{A3}$$
$$= \begin{cases} \rho\sigma^2 z^2 \left((\lambda q - c^*) \left(\frac{1}{n_j} - \frac{1}{n_j + 1} \right) \right), & n_j \geq 2 \\ \rho\sigma^2 z^2 \left(-\frac{c^*}{2} \right), & n_j = 1 \end{cases},$$

if $n_j = 1$ or $\lambda q < c^*$, then cutting the connection between i and j will be an improving deviation. The above indicates that $n_i = 1$ and $n_j = 1$ cannot exist in a strongly stable network. The above also indicates that when $\lambda q < c^*$, the network G (with i having only one link) cannot be strongly stable.

Based on the above discussion, the remaining case to consider if G is strongly stable is one in which $\lambda q \geq c^*$ and $n_j > 1$. When $n_j > 1$, let j' be another dealer connecting to j. Let G' be an obtainable network from G via the deviation of cutting the connection between j and j' and building the link between i and j'. If $\lambda q \geq c^*$,

$$U_i(G') - U_i(G) \tag{A4}$$
$$= \rho\sigma^2 z^2 \left((\lambda q - c^*) \left(\frac{1}{2} - \frac{1}{3}\right) + \lambda \frac{1}{2} \frac{n_{j'}}{n_{j'} + 1} \left(\frac{1}{n_{j'} + 1} - \frac{1}{n_{j'} + 2}\right) \mathbf{1}_{[n_{j'}+1 \geq 2]} \right) > 0,$$

and

$$U_{j'}(G') - U_{j'}(G) \tag{A5}$$
$$= \lambda\rho\sigma^2 z^2 \left(\frac{1}{2}\frac{1}{2}\left(\frac{1}{2} - \frac{1}{3}\right) - \frac{1}{2}\frac{n_j}{n_j + 1}\left(\frac{1}{n_j + 1} - \frac{1}{n_j + 2}\right) \right) \geq 0.$$

Thus, the deviation is an improving deviation, which indicates that G cannot be a strongly stable network when $\lambda q \geq c^*$ and $n_j > 1$.

Q.E.D.

Lemma A.1 implies that a connected strongly stable network is such that all connected dealers have the same number of links and this number is greater than one. If G is a strongly stable network, then $U_i(G)$ can be rewritten as

$$\begin{cases} \rho\sigma^2 z^2 \left(\left(c^* - \lambda q + \frac{\lambda}{2} - \frac{\lambda}{2n_i} \right) \frac{1}{n_i + 1} + \frac{\lambda q}{2} - c^* \right) + U_0, & n_i \geq 2 \\ U_0, & n_i = 0 \end{cases}, \tag{A6}$$

which implies

$$U_i(G) - U_0 = \max\left\{ \rho\sigma^2 z^2 \frac{n_i}{n_i + 1} \left(-\frac{\lambda}{2}\left(\frac{1}{n_i} - \frac{1 - q}{2}\right)^2 + \frac{\lambda(1 + q)^2}{8} - c^* \right), 0 \right\}. \tag{A7}$$

Based on Eq.(A7), for any n_i, when $c^* > \frac{\lambda(1+q)^2}{8}$, $U_i(G) - U_0 < 0$. Thus, a strongly stable network should be an empty network when $c^* > \frac{\lambda(1+q)^2}{8}$.

Now suppose the strongly stable network is an empty network when $c^* < \frac{\lambda(1+q)^2}{8}$. Consider an obtainable deviation in virtue of which all dealers build $\hat{n} = \frac{2}{1-q}$ links. Then the change in a dealer's payoff is $\rho\sigma^2 z^2 \frac{\hat{n}}{\hat{n}+1}\left(\frac{\lambda(1+q)^2}{8} - c^*\right) > 0$. Thus, the deviation is an improvement in those dealers' payoffs. The discussion above proves that when $c^* < \frac{\lambda(1+q)^2}{8}$, the empty network cannot be strongly stable. To find out the equilibrium number of links for each dealer in a connected network, we have to consider the following continuous function $F(n)$:

$$F(n) = \left(c^* - \lambda q + \frac{\lambda}{2} - \frac{\lambda}{2n}\right)\frac{1}{n+1}, \tag{A8}$$

and $n \in [0, N-1]$. Taking the derivative of $F(n)$, we have

$$\frac{dF(n)}{dn} = \left(-2\left(c^* - \lambda q + \frac{\lambda}{2}\right)n^2 + 2\lambda n + \lambda\right)\frac{1}{2n^2(n+1)^2}. \tag{A9}$$

$F(n)$ achieves the maximum at $n^* = \frac{\lambda + \sqrt{2\lambda\left(c^* - \lambda q + \frac{\lambda}{2}\right) + \lambda^2}}{2\left(c^* - \lambda q + \frac{\lambda}{2}\right)}$, as $\frac{dF(n^{*-})}{n} > 0, \frac{dF(n^{*+})}{n} < 0$, and $\frac{dF(n^*)}{n} = 0$. In addition, we have

$$\frac{dn^*}{dc^*} = -\frac{\lambda}{\sqrt{2\lambda\left(c^* - \lambda q + \frac{\lambda}{2}\right) + \lambda^2}}\left(\frac{1}{2\left(c^* - \lambda q + \frac{\lambda}{2}\right)}\right) - \frac{\lambda + \sqrt{2\lambda\left(c^* - \lambda q + \frac{\lambda}{2}\right) + \lambda^2}}{2\left(c^* - \lambda q + \frac{\lambda}{2}\right)^2} < 0. \tag{A10}$$

Based on the analysis of $F(n)$, when $c^* < \frac{\lambda(1+q)^2}{8}$, the strongly stable network is such that every dealer has $\left\lfloor\frac{\lambda + \sqrt{2\left(c^* - \lambda q + \frac{\lambda}{2}\right) + \lambda}}{2\left(c^* - \lambda q + \frac{\lambda}{2}\right)}\right\rfloor$ or $\left\lfloor\frac{\lambda + \sqrt{2\left(c^* - \lambda q + \frac{\lambda}{2}\right) + \lambda}}{2\left(c^* - \lambda q + \frac{\lambda}{2}\right)}\right\rfloor + 1$ links, whichever gives the dealer greater utility.[45] Formally speaking, the equilibrium number of links when $c^* < \frac{\lambda(1+q)^2}{8}$ is $\left[\!\left[\frac{1+\sqrt{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)}\right]\!\right]$, in which

(A11)

$$\left[\!\left[\frac{1+\sqrt{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)}\right]\!\right] = \underset{n\in\left\{\left\lfloor\frac{1+\sqrt{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)}\right\rfloor,\left\lfloor\frac{1+\sqrt{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)}\right\rfloor+1\right\}}{\operatorname{argmax}} \left(c^* - \lambda q + \frac{\lambda}{2} - \frac{\lambda}{2n}\right)\frac{1}{n+1}.$$

When $c^* = \frac{\lambda(1+q)^2}{8}$, then $n_i^* = \frac{2}{1-q}$ and $U_i(G) = U_0$. In this case, I define the strongly stable network as the connected network with $\frac{2}{1-q}$ links for every dealer.

To close the proof, I summarize the shape of the strongly stable network and the condition for its existence as follows. If $\left[\!\left[\frac{1+\sqrt{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)}\right]\!\right] \geq N-1$ or $c^* \leq \frac{\lambda(1+q)^2}{8}$, i.e., $c^* \leq \min\left\{\lambda\left(\frac{2N-1}{2(N-1)^2}+q-\frac{1}{2}\right), \frac{\lambda(1+q)^2}{8}\right\}$, then G is a complete network. If $\lambda\left(\frac{2N-1}{2(N-1)^2}+q-\frac{1}{2}\right) \leq c^* \leq \frac{\lambda(1+q)^2}{8}$, then the strongly stable network G has $\left[\!\left[\frac{1+\sqrt{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)}\right]\!\right]$ links. If $c^* > \frac{\lambda(1+q)^2}{8}$, then the strongly stable network is an empty network. If none of the above conditions is satisfied, there is no strongly stable network.

Q.E.D.

[45] $\left\lfloor\frac{\lambda+\sqrt{2\left(c^*-\lambda q+\frac{\lambda}{2}\right)+\lambda}}{2\left(c^*-\lambda q+\frac{\lambda}{2}\right)}\right\rfloor$ is the largest integer no larger than $\frac{\lambda+\sqrt{2\left(c^*-\lambda q+\frac{\lambda}{2}\right)+\lambda}}{2\left(c^*-\lambda q+\frac{\lambda}{2}\right)}$.

Proof of Proposition 1.3

Proof:

We first show that the equilibrium number of links weakly increases when the relative cost c^* decreases. From **Proposition 1.2**, we know when $c^* > \frac{\lambda(1+q)^2}{8}$, the strongly stable network is an empty network. When c^* decreases such that $c^* \leq \min\left\{\lambda\left(\frac{2N-1}{2(N-1)^2}+q-\frac{1}{2}\right), \frac{\lambda(1+q)^2}{8}\right\}$, the strongly stable network is the complete network. When $\lambda\left(\frac{2N-1}{2(N-1)^2}+q-\frac{1}{2}\right) \leq c^* \leq \frac{\lambda(1+q)^2}{8}$, every dealer has $\left[\!\left[\frac{1+\sqrt{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)}\right]\!\right]$ links. Thus, to show that the equilibrium number of links weakly increases when the relative cost decreases, we have to show only that $\left[\!\left[\frac{1+\sqrt{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c^*}{\lambda}-q+\frac{1}{2}\right)}\right]\!\right]$ weakly increases when c^* decreases.

Consider $c_1^* < c_0^*$, then Eq.(A10) shows that $\left\lfloor\frac{1+\sqrt{2\left(\frac{c_1^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c_1^*}{\lambda}-q+\frac{1}{2}\right)}\right\rfloor \geq \left\lfloor\frac{1+\sqrt{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)}\right\rfloor$. Due to the definition of $[\![.]\!]$, $\left\lfloor\frac{1+\sqrt{2\left(\frac{c_1^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c_1^*}{\lambda}-q+\frac{1}{2}\right)}\right\rfloor > \left\lfloor\frac{1+\sqrt{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)}\right\rfloor$ implies $\left[\!\left[\frac{1+\sqrt{2\left(\frac{c_1^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c_1^*}{\lambda}-q+\frac{1}{2}\right)}\right]\!\right] > \left[\!\left[\frac{1+\sqrt{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)}\right]\!\right]$. Hence, we focus on the case in which $\left\lfloor\frac{1+\sqrt{2\left(\frac{c_1^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c_1^*}{\lambda}-q+\frac{1}{2}\right)}\right\rfloor = \left\lfloor\frac{1+\sqrt{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)}\right\rfloor$.

Let $n_0^* = \left\lfloor\frac{1+\sqrt{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)}\right\rfloor$. Suppose that when $\lambda\left(\frac{2N-1}{2(N-1)^2}+q-\frac{1}{2}\right) \leq c^* \leq \frac{\lambda(1+q)^2}{8}$, the equilibrium number of links strictly increases in c^*. Then $c_1^* < c_0^*$ implies $\left[\!\!\left[\frac{1+\sqrt{2\left(\frac{c_1^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c_1^*}{\lambda}-q+\frac{1}{2}\right)}\right]\!\!\right] <$ $\left[\!\!\left[\frac{1+\sqrt{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)}\right]\!\!\right]$. Since $\left\lfloor\frac{1+\sqrt{2\left(\frac{c_1^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c_1^*}{\lambda}-q+\frac{1}{2}\right)}\right\rfloor = \left\lfloor\frac{1+\sqrt{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)}\right\rfloor = n_0^*$, it has to be the case that $\left[\!\!\left[\frac{1+\sqrt{2\left(\frac{c_1^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c_1^*}{\lambda}-q+\frac{1}{2}\right)}\right]\!\!\right] = n_0^*$ and $\left[\!\!\left[\frac{1+\sqrt{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)}\right]\!\!\right] = n_0^* + 1$. That is, the equilibrium number of links equals n_0^* when the relative cost is c_1^*, but it equals $n_0^* + 1$ when the relative cost is c_0^*. This implies that

(A12)

$$\left(c_1^* - \lambda q + \frac{\lambda}{2} - \frac{\lambda}{2n_0^*}\right)\frac{1}{n_0^*+1} > \left(c_1^* - \lambda q + \frac{\lambda}{2} - \frac{\lambda}{2n_0^*+2}\right)\frac{1}{n_0^*+2} \Leftrightarrow c_1^* > \frac{1}{n_0^*},$$

and

(A13)

$$\left(c_0^* - \lambda q + \frac{\lambda}{2} - \frac{\lambda}{2n_0^*}\right)\frac{1}{n_0^*+1} < \left(c_0^* - \lambda q + \frac{\lambda}{2} - \frac{\lambda}{2n_0^*+2}\right)\frac{1}{n_0^*+2} \Leftrightarrow c_0^* < \frac{1}{n_0^*}.$$

Eq.(A12) and Eq.(A13) imply that $c_1^* > \frac{1}{n_0^*} > c_0^*$ contradicting our set-up. Hence, when $c_1^* < c_0^*$, $\left[\!\!\left[\frac{1+\sqrt{2\left(\frac{c_1^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c_1^*}{\lambda}-q+\frac{1}{2}\right)}\right]\!\!\right] \geq \left[\!\!\left[\frac{1+\sqrt{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)+1}}{2\left(\frac{c_0^*}{\lambda}-q+\frac{1}{2}\right)}\right]\!\!\right]$.

Overall, **Proposition 1.2** implies that an equilibrium network becomes increasingly connected when c^* decreases. To prove **Proposition 1.3**, we have only to show that c^* decreases when σ or z increases, ceteris paribus, and c^* decreases when c increases, ceteris paribus. This is true, since

$$\frac{dc^*}{d\sigma} = -\frac{2c}{\rho\sigma^3 z^2} < 0, \tag{A14}$$

$$\frac{dc^*}{dz} = -\frac{2c}{\rho\sigma^2 z^3} < 0, \tag{A15}$$

and

$$\frac{dc^*}{dc} = \frac{1}{\rho\sigma^2 z^2} > 0. \tag{A16}$$

Q.E.D.

<u>Proof of Proposition 1.4</u>

Proof:

Fixing an equilibrium network, we have

$$\frac{dp_i}{dz} = -\frac{\rho\sigma^2}{n_i + 1} < 0, \tag{A17}$$

$$\frac{dp_i^0}{dz} = -(1-q)\frac{\rho\sigma^2}{n_i + 1} < 0, \tag{A18}$$

$$\frac{d\text{markup}}{dz} = -q\frac{\rho\sigma^2}{n_i + 1} < 0. \tag{A19}$$

Q.E.D.

Proof of Proposition 1.5

Proof:

Given a fixed equilibrium network, we have

$$\frac{dp_i}{d\sigma} = -2\rho\sigma\left(I + \frac{z}{n_i + 1}\right) < 0, \tag{A20}$$

$$\frac{dp_i^0}{d\sigma} = -2(1-q)\rho\sigma\left(I + \frac{z}{n_i + 1}\right) < 0, \tag{A21}$$

$$\frac{d\text{markup}}{d\sigma} = -2q\rho\sigma\left(I + \frac{z}{n_i + 1}\right) + 2qM_1\sigma. \tag{A22}$$

If $M_1 \geq \rho\left(I + \frac{z}{n_i+1}\right)$, then $\frac{d\text{markup}}{d\sigma} \geq 0$. Otherwise, $\frac{d\text{markup}}{d\sigma} < 0$.

Q.E.D.

Proof of Proposition 1.6

Proof:

We want to show that p_i, p_i^0, and the markup increase in n_i. Without loss of generality, we let $n_i < n_i'$. Then

$$p_i(n'_i) - p_i(n_i) = \lambda\rho\sigma^2 z^2\left(\frac{1}{n_i + 1} - \frac{1}{n'_i + 1}\right) > 0 \Rightarrow p_i(n_i') > p_i(n_i). \tag{A23}$$

Since $p_i^0 = (1-q)p_i + q(M_0 - M_1\sigma^2)$, it is obvious that $p_i^0(n_i') > p_i^0(n_i)$. Similarly, as markup $= q(p_i - M_0 + M_1\sigma^2)$, markup$(n_i')$ > markup(n_i).

Q.E.D.

Proof of Proposition 1.7

Proof:

The number of trades is

$$\lambda + \sum_{j:ij\in G} \lambda = (n_i + 1)\lambda, \tag{A24}$$

which obviously increases in n_i.

Since, in an equilibrium network, when dealer i and dealer j are linked they have the same number of links, the volume of trades is

$$\left(I + z - X_i^A\right) + \sum_{j:ij\in G} \lambda X_j^B = \lambda\left(1 - \frac{2}{n_i + 1}\right)z + n_i\lambda\frac{n_i - 1}{n_i}\frac{z}{n_i + 1} \quad \text{(A25)}$$

$$= 2\lambda\left(1 - \frac{2}{n_i + 1}\right)z,$$

which also increases in n_i.

Q.E.D.

Proof of Proposition 1.8

Proof:

The expected risky holding is

$$EX_i = \lambda X_i^A + \sum_{j:ij\in G} \lambda\left(I + X_j^B\right) + \left(1 - \lambda - \sum_{j:ij\in G} \lambda\right)I \quad \text{(A26)}$$

$$= \lambda\left(I + \frac{2z}{n_i + 1}\right) + \sum_{j:ij\in G} \lambda\left(I + \frac{n_j - 1}{n_j}\frac{z}{n_j + 1}\right) + \left(1 - \lambda - \sum_{j:ij\in G} \lambda\right)I$$

$$= \lambda z + I.$$

The variance if the risky holding is

$$Var(X_i) = EX_i^2 - (EX_i)^2 \quad \text{(A27)}$$

$$= \lambda\left(I + \frac{2z}{n_i + 1}\right)^2$$

$$+ \sum_{j:ij\in G} \lambda\left(I + \frac{n_j - 1}{n_j}\frac{z}{n_j + 1}\right)^2$$

$$+ \left(1 - \lambda - \sum_{j:ij\in G} \lambda\right) I^2 - (\lambda z + I)^2$$

$$= \lambda\left(I + \frac{2z}{n_i + 1}\right)^2 + n_i\left(I + \frac{n_j - 1}{n_j}\frac{z}{n_j + 1}\right)^2 + (1 - \lambda - n_i\lambda)I^2$$

$$- (\lambda z + I)^2.$$

We have only to prove that the claim is true for $n_i$and $n_i + 1$, and then by induction we infer that the claim is true for any $n_i < n_j$.

$$Var\big(X_i(n_i)\big) - Var\big(X_i(n_i + 1)\big) \qquad \text{(A28)}$$

$$= \lambda\left(I + \frac{2}{n_i + 1}z\right)^2 - \lambda\left(I + \frac{2}{n_i + 2}z\right)^2$$

$$+n_i\lambda\left(\left(I + \frac{n_i - 1}{n_i}\frac{z}{n_i + 1}\right)^2 - \left(I + \frac{n_i}{n_i + 1}\frac{z}{n_i + 2}\right)^2\right)$$

$$-\lambda\left(I + \frac{n_i}{n_i + 1}\frac{z}{n_i + 2}\right)^2 + \lambda I^2.$$

Since

$$\lambda\left(I + \frac{2}{n_i + 1}z\right)^2 - \lambda\left(I + \frac{2}{n_i + 2}z\right)^2 \qquad \text{(A29)}$$

$$= \lambda z\frac{2}{(n_i + 1)(n_i + 2)}\left(2I + 2z\frac{2n_i + 3}{(n_i + 1)(n_i + 2)}\right),$$

$$n_i\lambda\left(\left(I + \frac{n_i - 1}{n_i}\frac{z}{n_i + 1}\right)^2 - \left(I + \frac{n_i}{n_i + 1}\frac{z}{n_i + 2}\right)^2\right) \qquad \text{(A30)}$$

$$= \lambda z\frac{n_i - 2}{(n_i + 1)(n_i + 2)}\left(2I + z\frac{2n_i^2 + n_i - 2}{n_i(n_i + 1)(n_i + 2)}\right)'$$

and

$$-\lambda\left(I+\frac{n_i}{n_i+1}\frac{z}{n_i+2}\right)^2+\lambda I^2 \tag{A31}$$
$$=-\lambda z\frac{n_i}{(n_i+1)(n_i+2)}\left(2I+z\frac{n_i}{(n_i+1)(n_i+2)}\right),$$

we have

$$\frac{Var\big(X_i(n_i)\big)-Var\big(X_i(n_i+1)\big)}{\lambda z^2} \tag{A32}$$
$$=4\frac{2n_i+3}{(n_i+1)^2(n_i+2)^2}+\frac{(n_i-2)(2n_i^2+n_i-2)}{n_i(n_i+1)^2(n_i+2)^2}$$
$$-\frac{n_i^2}{(n_i+1)^2(n_i+2)^2}$$
$$=\frac{n_i^3+5n_i^2+2n_i+4}{n_i(n_i+1)^2(n_i+2)^2}>0.$$

Q.E.D.

Proof of Proposition 1.9

Proof:

Obviously, a small-capacity dealer never connects to his own kind, as there is only a linking cost but no risk-sharing benefit. This implies that small-capacity dealers connect only to large-capacity or medium-capacity dealers. Hence, $n_{s_S}\le n_{s_M},n_{s_L}$.

Now, suppose that G is a strongly stable network such that $n_{s_M}>n_{s_L}$. Let dealer i be one of s_M's connected dealers who does not connect to s_L. Consider another network G' obtained via replacing the $s_M i$ link with the $s_L i$ link. Then, we have

$$U_i(G')-U_i(G) \tag{A33}$$
$$=s_L\lambda\rho\sigma^2\underline{z}\left(1-\frac{1}{n_{s_L}+1}\right)\left(\frac{1}{n_{s_L}+1}-\frac{1}{n_{s_L}+2}\right)$$
$$-s_M\lambda\rho\sigma^2\underline{z}\left(1-\frac{1}{n_{s_M}+1}\right)\left(\frac{1}{n_{s_M}+1}-\frac{1}{n_{s_M}+2}\right)$$
$$>0,$$

$$U_{s_L}(G') - U_{s_L}(G) \tag{A34}$$

$$= \lambda\rho\sigma^2\underline{z}(s_L q - \tilde{c})\left(\frac{1}{n_{s_L}+1} - \frac{1}{n_{s_L}+2}\right)$$

$$+ \frac{s_i\lambda\rho\sigma^2\underline{z}}{2}\left(1 - \frac{1}{n_i+1}\right)\left(\frac{1}{n_i+1} - \frac{1}{n_i+2}\right)$$

$$\geq \lambda\rho\sigma^2\underline{z}(s_M q - \tilde{c})\left(\frac{1}{n_{s_M}} - \frac{1}{n_{s_M}+1}\right)$$

$$+ \frac{s_i\lambda\rho\sigma^2\underline{z}}{2}\left(1 - \frac{1}{n_i+1}\right)\left(\frac{1}{n_i+1} - \frac{1}{n_i+2}\right).$$

For G to be a strongly stable network it has to be the case that cutting the link between s_M and i cannot make s_M better off. This means that $\lambda\rho\sigma^2\underline{z}(s_M q - \tilde{c})\left(\frac{1}{n_{s_M}} - \frac{1}{n_{s_M}+1}\right) + \frac{s_i\lambda\rho\sigma^2\underline{z}}{2}\left(1 - \frac{1}{n_i+1}\right)\left(\frac{1}{n_i+1} - \frac{1}{n_i+2}\right) > 0$, which implies that $U_{s_L}(G') > U_{s_L}(G)$. Thus, G' makes both s_L and i better off, which means G cannot be a strongly stable network.

Q.E.D.

<u>Proof of Proposition 1.10</u>

Proof:

The following lemma is helpful in the proof.

<u>Lemma A.2</u>

In a strongly stable network, if large-capacity dealers connect to small-capacity dealers, then large-capacity dealers also connect to medium-capacity dealers.

Proof:

Let dealer s_L be the large-capacity, dealer s_M be the medium-capacity, and dealer s_S be the small-capacity. Suppose that G is a strongly stable network, in which s_L and s_S are connected but s_L and s_M are not connected. Let n_{s_L}, n_{s_M}, and n_{s_S} be the number of links s_L, s_M, and s_S have, respectively. Let G' be an obtainable network from G via deviation of connecting s_L and s_M.

Then,

$$U_{s_M}(G') - U_{s_M}(G) \tag{A35}$$

$$= \lambda\rho\sigma^2 \underline{z}(s_M q - \tilde{c})\left(\frac{1}{n_{s_M}+1} - \frac{1}{n_{s_M}+2}\right)$$

$$+ \frac{s_L \lambda\rho\sigma^2 \underline{z}}{2}\left(1 - \frac{1}{n_{s_L}+1}\right)\left(\frac{1}{n_{s_L}+1} - \frac{1}{n_{s_L}+2}\right)$$

$$\geq \lambda\rho\sigma^2 \underline{z}\, s_M q\left(\frac{1}{n_{s_M}+1} - \frac{1}{n_{s_M}+2}\right)$$

$$+ s_L \frac{\lambda\rho\sigma^2 \underline{z}}{2}\left(1 - \frac{1}{n_{s_L}+1}\right)\left(\frac{1}{n_{s_L}+1} - \frac{1}{n_{s_L}+2}\right)$$

$$- \tilde{c}\lambda\rho\sigma^2 \underline{z}\left(\frac{1}{n_{s_S}+1} - \frac{1}{n_{s_S}+2}\right).$$

Since G is a strongly stable network. Consider G'', another network that is obtainable from G via the deviation of cutting the link between s_L and s_S. Then,

$$U_{s_S}(G'') - U_{s_S}(G) \tag{A36}$$

$$= -s_L \frac{\lambda\rho\sigma^2 \underline{z}}{2}\left(1 - \frac{1}{n_{s_L}+1}\right)\left(\frac{1}{n_{s_L}+1} - \frac{1}{n_{s_L}+2}\right)$$

$$+ \tilde{c}\lambda\rho\sigma^2 \underline{z}\left(\frac{1}{n_{s_S}+1} - \frac{1}{n_{s_S}+2}\right) \leq 0.$$

Otherwise, G is not strongly stable. Eq.(A36) implies that $U_{s_M}(G') - U_{s_M}(G) > 0$ in Eq.(A35). That is, s_M is strictly better off with if deviates to G'. As $\tilde{c} \leq s_L q$ implies that dealer s_L is also better off, that is,

$$U_{s_L}(G') - U_{s_L}(G) \tag{A37}$$

$$= \lambda\rho\sigma^2 \underline{z}(s_L q - \tilde{c})\left(\frac{1}{n_{s_L}+1} - \frac{1}{n_{s_L}+2}\right)$$

$$+ s_M \frac{\lambda\rho\sigma^2 \underline{z}}{2}\left(1 - \frac{1}{n_{s_M}+1}\right)\left(\frac{1}{n_{s_M}+1} - \frac{1}{n_{s_M}+2}\right)$$

$$\geq 0,$$

deviation from G to G' is an improving deviation. Hence, G cannot be strongly stable.

Q.E.D.

Since $\tilde{c} < s_L q$, any two high-matching dealer must be connected in the strongly stable network. Thus, $n_{s_L} \geq N_{s_L} - 1$, where N_{s_L} is the number of large-capacity dealers. Since $\tilde{c} < \frac{s_L}{2} \frac{N_{s_L}-2}{(N_{s_L}-1)^2 N_{s_L}}$, low-capacity dealers always connect with large-capacity dealers. By **Lemma A.2**, any medium-capacity dealer must also connect with all large-capacity dealers. Therefore, large-capacity dealers comprise the core of the network and connect to all dealers in the strongly stable network.

Since any medium-capacity dealer connects to all high-capacity dealers, all medium-capacity dealers have at least N_{s_L} links. Since all medium-capacity dealers are identical, **Proposition 1.1** still applies. The payoff function for a medium-capacity dealer m is

$$U_m(G) = \lambda\rho\sigma^2\underline{z}\left(\tilde{c} - s_M q + \frac{s_M}{2} - s_M \frac{n_{s_M}(N_{s_L}+1) - N_{s_L}}{2n_{s_M}^2}\right)\frac{1}{n_{s_M}+1} - c - Eu(W(I)) + s_L N_{s_L} \frac{\lambda\rho\sigma^2\underline{z}}{2} \frac{(N-2)}{(N-1)^2 N}. \tag{A38}$$

Let

$$n_{s_M}^* = \arg\max_{n_{s_M}\in\mathbb{N}} \left(\tilde{c} - s_M q + \frac{s_M}{2} - s_M \frac{n_{s_M}(N_{s_L}+1) - N_{s_L}}{2n_{s_M}^2}\right)\frac{1}{n_{s_M}+1}, \tag{A39}$$

where $n_{s_M}^*$ is the number of links a medium-capacity dealer has in equilibrium.

Q.E.D.

Proof of Proposition 1.11

Proof:

Since $\bar{p}^0_{s_L} - \bar{p}^0_{s_M} = \left(\frac{\underline{z}+s_L}{s_L}\int_{\underline{z}}^{\underline{z}+s_L} p^0_{s_L} f(z)dz - \frac{\underline{z}+s_M}{s_M}\int_{\underline{z}}^{\underline{z}+s_M} p^0_{s_M} f(z)dz\right) =$

$(1-q)\rho\sigma^2\underline{z}\left(\frac{\left(1+\frac{\underline{z}}{s_M}\right)\ln\left(1+\frac{s_M}{\underline{z}}\right)}{n^*_{s_M}+1} - \frac{\left(1+\frac{\underline{z}}{s_L}\right)\ln\left(1+\frac{s_L}{\underline{z}}\right)}{N}\right)$, it is obvious if $\frac{N}{n^*_{s_M}+1} \geq \frac{\left(1+\frac{\underline{z}}{s_L}\right)\ln\left(1+\frac{s_L}{\underline{z}}\right)}{\left(1+\frac{\underline{z}}{s_M}\right)\ln\left(1+\frac{s_M}{\underline{z}}\right)}$, then $p^0_{s_L} \geq p^0_{s_M}$. Otherwise, $p^0_{s_L} < p^0_{s_M}$.

Q.E.D.

Proof of Proposition 1.12

Proof:

Definition A.1

A cycle in a "trading-sets network" is a path consisting of more than two non-repeated trading sets and the starting set is the same as the ending set.

Lemma 3 [Theorem 4.2 in Malamud and Rostek (2013)]

Any two trading sets in the "trading-sets network" have the same prices if and only if these two sets are on the same cycle.

Proof:

See Malamud and Rostek (2013).

Q.E.D.

Definition A.2

A link in a "trading-sets network" is a bridge if cutting it would cause its ending points to lie in separate components.

Lemma A.4

A monopolistic dealer in an inter-dealer network is a bridge in the "trading-sets network" derived from the inter-dealer network.

Proof:

Suppose a monopolistic dealer is not a bridge in the "trading-sets network." Then removing the monopolistic dealer does not increase the number of components in the "trading-sets network." This means that all trading sets that include the monopolistic dealer are still connected, even when the monopolistic dealer is removed. To see if dealers in those trading-sets are connected in the inter-dealer network, we do the following.

i) Label those trading-sets in sequence from 1 to m.

ii) Start from set 1, and then find its connected sets.

iii) Start from those connected sets identified in step 2, and then find their connected sets.

iv) Repeat step 3 until all trading sets are exhausted.

Based on **Definition 1.3** and **1.4**, the above algorithm shows that dealers in the same trading set are connected, and dealers in trading sets identified in step 3 are also connected. Since all those trading sets are connected, step 4 eventually ends, which means that all dealers in those trading sets are connected. This contradicts the definition of the monopolistic dealer, whose neighbors belong to separate components. Hence, a monopolistic dealer is a bridge in the "trading-sets network."

Q.E.D.

Lemma A.3 is used to prove the second half of **Proposition 1.12**. If a pair of dealers have more than two unconnected common neighbors, then in the "trading-sets network" this pair of dealers and their unconnected common neighbors construct a cycle. By **Lemma A.3**, prices along the cycle are the same, which means that any of those dealers buys and sells at the same price in distinct trading sets. That is, the markup for "hot potato" trading is zero. The first half of **Proposition 1.12** is proved by **Lemma A.4**, which states that a monopolistic dealer is a bridge in the "trading-sets network." Hence, the monopolistic dealer can never be in a cycle. **Lemma A.3** then implies that the monopolistic dealer always charges non-zero markups.

Q.E.D.

Proof of Proposition 2.1

Proof:

Denote $D(a) = \sum_t \beta^t D_t(a)$ and $S(b) = \sum_t \beta^t S_t(b)$. Given that $D_t(a)$ is a continuous and decreasing function on $[\underline{a}, \overline{a}]$, it is easy to see that $D(a)$ is continuous and decreasing on $[\underline{a}, \overline{a}]$. We note that, from the value function of the buyers

$$V^B(a) = \max\left\{0, v^B - a, \beta \int V^B(\hat{a}) d\theta_a\right\}, \tag{A40}$$

$\underline{a} = \underline{v}^B$ and $\overline{a} = r^B(1)$. Similarly, we have $S(b)$ continuous and increasing on $[\underline{b}, \overline{b}]$, in which $\underline{b} = r^S(0)$ and $\overline{b} = \overline{v}^S$. As $D_t(a) = S_t(b)$, we have $D(a) = S(b)$. Then, define the inverse functions $A(q)$ and $B(q)$ mapping from q to prices.

From the inverse function theorem, we have

$$A'(q) = \left(\frac{\partial D}{\partial a}\right)^{-1} = \left(-\frac{1-\beta + F_a(a)(1-\epsilon)\beta}{N(1-\beta)\left(1-\beta\left(1-F_a(a)\right)\right)}\right)^{-1}, \tag{A41}$$

$$B'(q) = \left(\frac{\partial S}{\partial b}\right)^{-1} = \left(\frac{1-\beta + \left(1-F_b(b)\right)(1-\epsilon)\beta}{N(1-\beta)\left(1-\beta F_b(b)\right)}\right)^{-1}. \tag{A42}$$

As $a(k)$ increases in k and $b(k)$ decreases in k, we have

$$F_a(a) = P_a[\hat{a} < a] = P_k[\hat{k} < k] = \frac{k - \underline{k}}{k^* - \underline{k}}, \tag{A43}$$

$$1 - F_b(b) = P_b[\hat{b} < b] = P_k[\hat{k} < k] = \frac{k - \underline{k}}{k^* - \underline{k}}, \tag{A44}$$

where k^* is the marginal dealer whose profit margin and trading volume are zeros. Thus, the total population of dealer N equals to $k^* - \underline{k}$.

Plugging $F_a(a)$ and $F_b(b)$ into $A'(q)$ and $B'(q)$ respectively, we obtain

$$A'(q) = -B'(q) = \left(-\frac{1 - \beta + \frac{k - \underline{k}}{k^* - \underline{k}}(1 - \epsilon)\beta}{N(1 - \beta)\left(1 - \frac{\beta(k^* - k)}{k^* - \underline{k}}\right)} \right)^{-1}. \tag{A45}$$

For the dealer with transaction cost k, he chooses q to maximize the expected profit $(A(q) - B(q) - k)q$. The optimality condition implies,

$$A(q) - B(q) - k = \big(B'(q) - A'(q)\big)q. \tag{A46}$$

Thus, we obtain

$$A\big(q(k)\big) - B\big(q(k)\big) - k \tag{A47}$$

$$= \frac{2(k^* - \underline{k})(1 - \beta)\left(1 - \frac{\beta(k^* - k)}{k^* - \underline{k}}\right)q(k)}{1 - \beta + \frac{k - \underline{k}}{k^* - \underline{k}}(1 - \epsilon)\beta} - k.$$

Substituting $q(k) = D\big(a(k)\big)$ into Eq.(A47), we get

$$a(k) - b(k) - k \tag{A48}$$

$$= \frac{2\left(1 - \frac{\beta(k^* - k)}{k^* - \underline{k}}\right)}{1 - \beta + \frac{k - \underline{k}}{k^* - \underline{k}}(1 - \epsilon)\beta} \int_{a(k)}^{r^B(1)} \frac{1 - \beta + F_a(r^B)(1 - \epsilon)\beta}{1 - \beta\big(1 - F_a(r^B)\big)} dr^B.$$

Since, for any k, $D\big(a(k)\big) = S\big(b(k)\big)$, it implies that $\frac{\partial D}{\partial k} = \frac{\partial S}{\partial k}$. Since $A'(q) = -B'(q)$, we have

$\frac{\partial a}{\partial k} = -\frac{\partial b}{\partial k}$. Thus,

$$a(k) + b(k) = C, \tag{A49}$$

in which C represents a constant.

From the buyer's reservation value, we have

$$\begin{aligned} 1 &= r^B(1) + \frac{\beta(1-\epsilon)}{1-\beta}\int_{\underline{a}}^{r^B(1)} P_a[a < \hat{a}]d\hat{a} \\ &= r^B(1) + \frac{\beta(1-\epsilon)}{1-\beta}\int_{\underline{k}}^{k^*} \frac{k-\underline{k}}{k^*-\underline{k}} a'(k)dk, \end{aligned} \tag{A50}$$

where the second equality is obtained by performing a change of variables. Likewise, we have

$$\begin{aligned} 0 &= r^S(0) - \frac{\beta(1-\epsilon)}{1-\beta}\int_{r^S(0)}^{\overline{b}} P_b\left[b > \hat{b}\right]d\hat{b} \\ &= r^S(0) + \frac{\beta(1-\epsilon)}{1-\beta}\int_{\underline{k}}^{k^*} \frac{k-\underline{k}}{k^*-\underline{k}} b'(k)dk. \end{aligned} \tag{A51}$$

From the above, it is obvious that $1 = r^B(1) + r^S(0)$. Since $a(k^*) = \overline{a} = r^B(1)$ and $b(k^*) = \underline{b} = r^S(0)$, we have $a(k^*) + b(k^*) = 1$. This implies $C = 1$, and hence,

$$b(k) = 1 - a(k). \tag{A52}$$

Plugging the Eq.(A52) into the optimality condition (Eq.(A47)) and differentiating with respect to k, we arrive at the following differential equation

$$a'(k) - \frac{a(k)\beta X(k)}{2\left(k^* - \underline{k}\right)} = \frac{1}{4} - \frac{(1+k)\beta X(k)}{4(k^* - \underline{k})}, \tag{A53}$$

in which

$$X(k) = \frac{1}{1 - \frac{\beta(k^* - k)}{k^* - \underline{k}}} - \frac{1 - \epsilon}{1 - \beta + \frac{k - \underline{k}}{k^* - \underline{k}}(1 - \epsilon)\beta}. \tag{A54}$$

The solution for the above differential equation is

$$a(k) = e^{-\int_k^{k^*} Y(z)dz}\left(\frac{k^* + 1}{2} + \int_k^{k^*}\left(-\frac{1}{4} + \frac{1 + z}{2}Y(z)\right)e^{\int_z^{k^*} Y(u)du}dz\right), \tag{A55}$$

in which

$$Y(z) = \frac{\beta X(z)}{2(k^* - \underline{k})}. \tag{A56}$$

Thus, Eq.(A56) determines the equilibrium asks, and the equilibrium bids equal $1 - a$.

To determine the equilibrium k^*, we apply $k^* = a(k^*) - b(k^*)$ to the buyer's reservation value $r^B(1)$ and get

$$1 = \frac{k^* + 1}{2} + \frac{\beta(1 - \epsilon)}{1 - \beta}\left(\frac{(k^* + 1)}{2} - \frac{1}{k^* - \underline{k}}\int_{\underline{k}}^{k^*} a(k)dk\right). \tag{A57}$$

Q.E.D.

<u>Proof of Proposition 2.2</u>

Proof:

The buyer follows a reservation pricing strategy when he searches in the OTC market. This means that

$$\nu^B - r^B(\nu^B) = \beta\int V(\hat{a}, a_c, \nu^B)d\theta_a. \tag{A58}$$

Plugging Eq. (A58) into the buyer's value function before he starts to search, Eq.(2.23), we have

$$W^B(a_c, \nu^B) = \max\{0, \nu^B - a_c, \nu^B - r^B(\nu^B)\}. \tag{A59}$$

Since $r^B(\nu^B)$ increases in ν^B, and since $a_c = r^B(\overline{\nu}^B)$, we have for any $\nu^B \geq \overline{\nu}^B$,

$$r^B(\nu^B) \geq a_c \qquad \text{(A60)}$$

which implies that

$$\nu^B - a_c \geq \nu^B - r^B(\nu^B) \qquad \text{(A61)}$$

whereas, for any $\nu^B < \overline{\nu}^B$,

$$r^B(\nu^B) < a_c \qquad \text{(A62)}$$

which implies that

$$\nu^B - a_c < \nu^B - r^B(\nu^B). \qquad \text{(A63)}$$

Thus, for any buyer with $\nu^B \geq \overline{\nu}^B$, he is better off buying the asset in the centralized market, whereas for any buyer with $\nu^B < \overline{\nu}^B$, he is better off to buy the asset in the OTC market. Moreover, if the buyer has $\nu^B \leq \underline{\nu}^B = \underline{a}$, then

$$\nu^B - a \leq 0, \forall a \in [\underline{a}, \overline{a}]. \qquad \text{(A64)}$$

Since $\overline{a} = a_c$, Eq. (A64) implies that the buyer loses if he trades either in the OTC market or in the centralized market. Thus, for any buyer with $\nu^B \leq \underline{\nu}^B$, he is better off not to trade in any market.

Q.E.D

<u>Proof of Proposition 2.3</u>

Proof:

This is similar to the proof of **Proposition 2.2**, since sellers and buyers are symmetric.

Q.E.D

Proof of Proposition 2.4

Proof:

The derivation of the price system in the OTC market is the same as in the proof of **Proposition 2.1** except for the marginal dealer. Specifically, the winning market maker charges the bid-ask spread equal to the next most efficient market maker's transaction cost $K_{(2)}$. Since all surviving dealers have to undercut the bid-ask spread posted by the winning market maker, $K_{(2)}$ defines the marginal dealer's transaction cost. That is,

$$k^{**} = K_{(2)}. \tag{A65}$$

The inventory constraint applied to the winning market maker implies that

$$1 - a_c - \frac{\beta(1-\epsilon)}{1-\beta}\int_{\underline{a}}^{a_c} P_a[a < \hat{a}]d\hat{a} = D^C(a_c) = S^C(b_c) \tag{A66}$$

$$= b_c - \frac{\beta(1-\epsilon)}{1-\beta}\int_{b_c}^{\overline{b}} P_b[b > \hat{b}]d\hat{b}.$$

From Eq. (A43) and Eq. (A44), we have

$$P_a[\hat{a} < a] = P_b[\hat{b} > b] = P_k[\hat{k} < k] = \frac{k - \underline{k}}{k^{**} - \underline{k}}. \tag{A67}$$

Therefore,

$$a_c = 1 - b_c = \frac{K_{(2)} + 1}{2}. \tag{A68}$$

Q.E.D

Proof of Proposition 2.5

Proof:

Similar to the proof of **Proposition 2.4**, the derivation of the price system in the OTC markets is the same as in the proof of **Proposition 2.1** except for the marginal dealer. Since the winning market maker does not fear the entrance of the next most efficient market maker, he posts the bid-ask spread that maximizes his expected profits. Consequently, the marginal dealer is no longer the one with transaction cost equal to $K_{(2)}$, but the one with transaction cost equal to the winning market maker's profit maximizing spread.

Since the winning market maker's inventory constraint implies that $a_c = 1 - b_c$. Defining $\tilde{k}$ as the winning market maker's bid-ask spread, I rewrite the winning market maker's profit maximization as follows,

$$\max_{\tilde{k}}(\tilde{k} - K_{(1)})\left(1 - \frac{\tilde{k} + 1}{2} - \frac{\beta(1-\epsilon)}{1-\beta}\left(\frac{\tilde{k} + 1}{2} - \frac{1}{\tilde{k} - \underline{k}}\int_{\underline{k}}^{\tilde{k}} a(k)dk\right)\right). \tag{A69}$$

If $\tilde{k} \geq K_{(2)}$, then the next most efficient market maker enters and undercuts the winning market maker's bid-ask spread. If $\tilde{k} \leq \underline{k}$, then no dealers survive in equilibrium. Hence, the interior equilibrium arises, if $\tilde{k} \in (\underline{k}, K_{(2)})$. Therefore, the marginal dealer k^{**} is defined by the $\tilde{k}$ that maximizes Eq. (A78) and is in the interval of $(\underline{k}, K_{(2)})$.

Q.E.D

<u>Proof of Proposition 2.6</u>

Proof:

When all bid-ask spreads in the OTC market in **Proposition 2.1** are smaller than the transaction cost of the most efficient market maker, the establishment of the centralized market is futile. All trades go to the OTC market. Therefore, the condition for the centralized market to survive is $K_{(1)} < k^*$.

Q.E.D

Proof of Proposition 2.7

Proof:

In the corner equilibrium, the bid-ask spread in the centralized market equals to $K_{(2)}$. If no dealer is able to undercut this spread, i.e. $K_{(2)} < \underline{k}$, then the OTC market fails to survive in equilibrium.

Q.E.D

Proof of Proposition 2.8

Proof:

In the interior equilibrium, if no dealer is able to undercut the winning market maker's profit maximizing spread, the winning market maker can set a spread equal to $\underline{k}$ to become the only trading intermediary in the economy as long as $\underline{k} \geq K_{(1)}$. When the winning market maker becomes the only trading intermediary, **Proposition 2.2** and **Proposition 2.3** show that the demand in the centralized market is $1 - a_c$, and the supply in the centralized market is b_c. The winning market maker's profit maximization becomes

$$\max_{a_c} \left(2a_c - 1 - K_{(1)}\right)(1 - a_c). \quad \text{(A70)}$$

The unconstrained optimal choice of a_c is $\frac{K_{(1)}+3}{4}$, and the spread is $\frac{K_{(1)}+1}{2}$.

If $\underline{k} \leq \frac{K_{(1)}+1}{2}$, then the winning market maker cannot set his ask price at the unconstrained optimal choice $\frac{K_{(1)}+3}{4}$. In this case, the quadratic objective function (Eq.(A79)) implies that the optimal ask price is $\frac{\underline{k}+1}{2}$, which generates a spread equal to $\underline{k}$.

When the winning market maker charges limited prices, his profit is $\frac{(\underline{k}-K_{(1)})(1-\underline{k})}{2}$. Hence, the winning market maker charge limited prices to eliminate dealers in the OTC market if and only if

$$\left(k^{**} - K_{(1)}\right)\left(1 - \frac{k^{**}+1}{2} - \frac{\beta(1-\epsilon)}{1-\beta}\int_{\underline{k}}^{k^{**}} a(k)dk\right) \tag{A71}$$

$$\leq \frac{\left(\underline{k} - K_{(1)}\right)\left(1 - \underline{k}\right)}{2}.$$

Q.E.D

<u>Proof of Proposition 2.9</u>

Proof:

From the proof of **Proposition 2.8**, if $\underline{k} > \frac{K_{(1)}+1}{2}$, then the winning market maker sets his ask price to the unconstrained profit maximization choice, i.e, $a_c = \frac{K_{(1)}+3}{4}$.

Q.E.D

Appendix B: Variable Names in Chapter 3

Table B.1: Variable Definitions in Chapter 3

Variable	Description
Firm size (log millions)	Natural logarithm of total assets in the fiscal year prior to the bond issue
Leverage	Ratio of long-term debt over total asset in the fiscal year prior to the bond issue
Firms' accounting standard-IFRS	Binary variable equal to 1 when the accounting standard that a company uses in presenting its financial statements is International Financial Reporting Standards
Firms' accounting standard-Domestic	Binary variable equal to 1 when the accounting standard that a company uses in presenting its financial statements is Domestic
Issuer is in finance industry	Binary variable equal to 1 when the issuer belongs to the finance industry
Issuer is a utility	Binary variable equal to 1 when the issuer belongs to the utility industry
Issuers' equity is private	Binary variable equal to 1 when the issuer is a private firm
Issue size (sq. root of millions)	Square root of the par value of debt initially issued.
Moody's bond rating	A value of 1 (2,3,…) is assigned to Moody’s rating of Aaa (Aa1, Aa2,…)
Years to maturity	The number of years before the bond is expired
Global Bond	Binary variable equal to 1 when the issue is offered globally
Variable rate bond	Binary variable equal to 1 when the coupon type for the issue is variable
Foreign bond	Binary variable equal to 1 when the issue is denominated in a foreign currency.
Senior bond	Binary variable equal to 1 when the security is a senior issue of the issuer.
Rule144a bond	Binary variable equal to 1 when the issue is a private placement exempt from registration under SEC Rule 144a.
Listed on the NYSE	Binary variable equal to 1 when the bond is listed on the NYSE

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