Three Essays on US Corporate Bond Market and Canadian Newspaper Market

by

Chengjie Diao

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Abstract

This thesis presents an empirical study of the US Corporate Bond market and the consolidation of the Canadian Community Newspaper Market. First, we focus on the effects of post-crisis regulations designed to reduce risk exposure on dealers' trading behaviors and market liquidity. A simple model is developed to illustrate the relationship between dealers' trading behaviors and market liquidity, specifically predicting that optimizing relationships with long-term trading partners enables dealers to maintain the same level of liquidity while reducing inventory risk. Empirical regression analysis, using the Trace Academic dataset, was conducted to test this hypothesis. The findings support the notion that since the implementation of the Dodd-Frank Act, dealers have indeed optimized their trading partnerships to provide consistent liquidity levels under regulatory pressure, thereby enhancing market efficiency.

The thesis also delves into the origins of the centrality premium in the US corporate bond market, which operates on an over the counter basis. In this market, dealers are positioned within a network, with more connected, central dealers at the core and less connected, peripheral dealers at the edges. A common observation is that core dealers typically charge higher markups than their peripheral counterparts, resulting in a centrality premium. The study investigates the factors contributing to this premium. It reveals that core dealers capitalize on their search efforts, retain bonds for longer periods, and engage with higher-valued clients, leading to a greater trading surplus.

Finally, I explore the consolidation of the Canadian community newspaper market. In 2017, Postmedia and Metroland engaged in a swap involving dozens of newspapers across several local regional markets, followed by closing most of the swapped publications. This led to an increased concentration in these markets, potentially resulting in anti-competitive impacts. My investigation delves into the details of advertising rates before and after this event. My findings reveal that while there is indeed a spike in the average advertising rate in the treatment markets following the event. However, this is attributable to the strategic shutdown of lower-rate newspapers following the swap. There is no evidence of always existing newspapers increasing rates after the swap events.

Co-Authorship

The second chapter for this thesis is co-authored with Evan Dudley (Smith Business School, Queen's University) and Amy Sun (Department of Economics, Queen's University).

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Chapter 1

Introduction

This thesis presents an empirical analysis of two distinct markets: the US corporate bond market and the consolidation of the Canadian community newspaper market. In the US, the corporate bond market operates as an over-the-counter format, involving thousands of dealers who act as market makers and provide liquidity. Unlike stocks, many bonds trade infrequently, some may only be traded once a year. This infrequency results in the rarity of the double coincidence of wants, necessitating dealers to maintain inventory to balance temporary disparities between buy and sell orders to ensure liquidity. Post-financial crisis, a set of regulations aimed at reducing dealers' risk has imposed strict controls on their inventory, raising concerns from academia and industry about liquidity. The subsequent chapter investigates the impact of these post-crisis regulations on dealers' trading behaviors and their subsequent effect on liquidity.

When dealers hold bonds in inventory, they are subject to risks such as price volatility risk. For example, if a dealer needs to borrow funds to purchase bonds from a customer, these bonds sometimes work as collateral. If prices shift in an unfavorable direction, dealers may be subject to margin requirements. To reduce these kinds of risks, a series of regulations, including Basel III, the Dodd-Frank Act, and the Volcker Rule, were signed into law after the financial crisis. These regulations discourage dealers from holding inventory. As a result, many academic studies, such as those by Bessembinder (2018) and Dick-Nielsen and Rossi (2019), claim that these regulations are harmful to liquidity. Contrary to these publications, the next chapter focuses on an overlooked aspect, arguing that these regulations encourage dealers to optimize their long-term trading partners (which are also dealers) according to the correlation of their clients' liquidity demands.

Consider three dealers: A, B, and C. Each has its own client base that relies on them for trading. As O'Hara (2018), shows, clients tend not to randomly search among all dealers but instead rely on a small subset of dealers for repeated trades. Suppose dealers A and B are long-term trading partners, but the liquidity demands from A's and C's client bases are less correlated than the correlation between dealer A and B. The model of next chapter illustrates that dealers A and C can achieve a higher trading surplus after absorbing the liquidity demand from their respective client bases than what is possible between dealers A and B. By forming or strengthening their trading relationships, dealers A and C can provide higher liquidity with less inventory risk.

To verify the hypothesis that these regulations have changed dealers' trading behaviors, specifically whether they optimize their trading relationships according to this correlation after the regulations were signed into law, I utilized the Trace academic dataset. This dataset enabled me to identify each dealer's transactions with other dealers and their client base. I discovered a structural break after the Dodd-Frank Act was signed into law: dealers have strengthened their relationships with partners who have less correlated liquidity demands from their client base. This suggests that these regulations potentially shift dealers' behavior, motivating them to provide liquidity with reduced inventory risk. This finding contributes to a more thorough understanding of the consequences of post-crisis regulations, aiding in better judgment of these policies and deepening the understanding of financial microstructure.

In the second chapter of this thesis, we investigate the origins of the centrality premium within the US corporate bond market. This premium refers to the additional markup that core dealers impose compared to peripheral dealers. As previously discussed, this market operates under an Over-The-Counter (OTC) format, where dealers serve as intermediaries for making the market, and clients engage with these dealers for trading. In addition, dealers engage in intensive trading with each other, managing inventory and facilitating liquidity. They also form trading relationships with multiple dealers.

These interdealer relationships, combined with heterogeneous relations with various clients, create a dealers' network. This network exhibits a core-peripheral structure, where more connected dealers in the center function as the core, and less connected, peripheral dealers are located at the edge. Literature indicates that core dealers charge a significantly higher markup for making the market compared to peripheral dealers.

Potential explanations for the centrality premium include factors such as bargaining power, the provision of immediacy, and compensation for providing liquidity. To investigate the source of the centrality premium, we analyze it in the context of liquidity provision, focusing on a channel that combines search and inventory costs. We construct a structural model to demonstrate this. The model suggests that after acquiring bonds from a client and holding them in inventory, core dealers exert more effort in searching and retain the inventory for a longer period to find clients who place a higher valuation on the bonds. As a result, they charge a higher premium compared to peripheral dealers.

To further investigate the behavior of core and peripheral dealers in terms of search and inventory management, we employed the Trace Academic Dataset for our model. This model classifies bonds into two categories: GIT (Guaranteed Intraday Trades) and Non-GIT (Non-Guaranteed Intraday Trades), based on the decisions of the dealers. In the case of lower quality bonds, such as junk bonds, dealers sometimes set a very low threshold for buyers to ensure these bonds are sold on the same day they were acquired. GIT bonds are characterized by a strategy where both core and peripheral dealers set a sufficiently low valuation threshold. This threshold is the lowest acceptable value below which any potential buyer's valuation would lead to unsuccessful negotiations. For instance, when a dealer aims to sell a bond, they require the buyer's valuation of this bond to meet or exceed this minimum value threshold to enable a successful trade. This approach is designed to ensure the sale of the bonds within the same day they are acquired.

Our findings indicate that the centrality premium is higher for GIT bonds compared to Non-GIT bonds. Core dealers exert more effort in searching for higher-valued clients, especially for GIT bonds. Consequently, they charge a significantly higher centrality premium for GIT bonds than for Non-GIT bonds. This distinction highlights the differing strategies and market behaviors between core and peripheral dealers in the bond market. This chapter enhances the understanding of the centrality premium by exploring the search and inventory management channels, thereby offering a more comprehensive insight into financial microstructure.

The third chapter examines the consolidation of the Canadian community newspaper market. Operating under a two-sided market structure, these newspapers generate revenue from both readers' subscriptions and advertising profits. Unlike daily newspapers, most community newspapers are free, making advertising the primary source of income. However, the readership side is still essential, as advertisers place significant value on the number of readers a newspaper can reach.

Like other newspapers, Canadian community newspapers have been hit hard by the technological boom. With the rise of internet platforms, they are losing readers and revenue. The Canadian community newspaper market is concentrated, with around 50% of newspapers owned by two large corporations: Postmedia and Metroland. In 2017, these two companies swapped dozens of community newspapers in several regional markets, thereby avoiding competition in local markets, and then shut down most of the swapped newspapers. This action has led to concerns about anti-competitive impacts between the two companies. For example, if two companies avoid contacts in local regional markets, they may raise advertising rates because of higher market power.

To investigate whether the two companies raised advertising rates after the swap event, we conducted a difference-in-differences regression for each market where at least one newspaper was swapped. This was done to determine whether the mean advertising rate in these affected markets increased post-event. To address potential endogeneity issues, such as certain market characteristics influencing both the advertising rate and the decision to swap, or exhibiting unique time trends, we employed a matching strategy. This involved creating control markets based on demographic and structural characteristics. The regression results indicate a significant increase in the mean advertising rate for markets affected by the swap. However, this increase is attributed not to anti-competitive effects, but to the closure of lower-rated newspapers by the companies to reduce operational costs, subsequently driving down the mean advertising rate post-event. When considering only the newspapers that persisted before and after the swap events (always existing newspapers) of the two companies, there was no significant increase in the rate for these markets. This suggests no evidence of anti-competitive behavior, such as the newspapers owned by the two companies increasing rates post-swap due to higher market power.

Although many studies have focused on daily newspapers, there are relatively few publications that examine community newspapers. Canadian community newspapers play a crucial role in fundraising for local regional projects, connecting community members, and supporting local businesses. This chapter bridges this gap by analyzing a far-reaching event that leads to an overall higher advertising rate environment and the closure of many community newspapers. Although the always existing newspapers have not increased rates due to anti-competitive behavior, the closure of lower-rated newspapers in these local regional markets eliminates more affordable advertising options for local businesses. This suggests the importance of policies to support or subsidize Canadian community newspapers.

Chapter 2

Dealers' Relationship, Capital Commitment and Liquidity

2.1 Introduction

The US corporate bond market is massive and growing, with over \$10 trillions outstanding in 2022. Despite this, it is still a relatively decentralized OTC market. Insurance companies, mutual funds, and pension funds that are the main clients in this market, rely on dealers (major investment banks or other financial institutions) to trade. As a result, understanding dealers' role in the financial microstructure is essential as dealers' behavior seriously impacts market liquidity (easiness to trade without negatively impacting price). There are two important functions of dealers in this market: first, dealers' network serves as intermediaries to connect different counterparties. The client-to-dealer and dealer-to-dealer trading relations are both non-random and long-term, forming a decentralized network that connects different market identities. Even though there are emerging platforms that allow clients to circumvent dealers to trade with each other directly, most of the time, when a client needs to trade, she still approaches a dealer first. So dealers' networks are the most important channels for one party to reach another. Second, dealers provide liquidity by absorbing temporary order imbalances into their inventories. Furthur, many bonds have low trading frequency, and double coincidences of wants are rare occurrences. Even if such coincidences happen, the decentralized market structure may hinder the two counterparties from connecting with each other. Although a number of papers in recent years studys the interaction between dealers' trading behavior and liquidity, there is still a need for further understanding of the roles of dealers' behavior on liquidity.

To gain a deeper understanding of the roles that dealers may play in influencing liquidity, this paper raises one potentially overlooked link that connects liquidity and dealers' behavior in the US corporate bond market: we argue that dealers have optimized the relationship with long-term trading partners with regard to the correlation of order imbalance from their client base after the crisis, and this allows them to provide higher liquidity with less capital commitment. If two dealers have client bases whose trades display less positively correlated directions (e.g., -0.5 compared to 0.5 or 0.5 compared to 1), and if these two dealers strengthen their trading relationship, both dealers can offer enhanced liquidity to their respective clients without increasing their inventory risk. This leads to a more efficient market.

The literature has established that dealers' willingness to commit capital (absorbing the temporary order imbalance between buy and sell orders into inventory and bearing the risk accordingly) is crucial to maintain liquidity. If dealers are unwilling to commit capital, clients who wish to trade in the same direction as the majority of the market may experience difficulty in executing their trades. After the financial crisis, several regulations (such as the Dodd-Frank Act, Basel 2.5 and 3, and the Volcker Rule) were enacted, aimed at reducing dealers' inventory risk (such as liquidity risk when a dealer needs cash but cannot immediately sell a bond). According to Bessembinder et al. (2018), these regulations have increased the cost of committing capital, resulting in a significant decline in dealers' aggregate capital commitment during the post-crisis period. Given this, practitioners and academics predicted a significant reduction in liquidity in the post-crisis period. However, the effects of these regulations on liquidity are ambiguous, as some papers (Bessembinder et al. (2018) and Trebbi and Xiao. (2017)) conclude that liquidity remains robust or is even improved, while others suggest that liquidity has significantly decreased during certain events such as bond downgrading (Dick-Nielsen and Rossi, (2019)).

The previously mentioned link (dealers strengthening ties with partners whose clients have less positively correlated trades) could be a possible explanation for this ambiguity.

One challenge in empirically illustrating this link is that liquidity is not directly observable, and can only be inferred from imperfect measures such as spreads and trading volumes. Different measures of liquidity sometimes yield different conclusions. Moreover, pure empirical work lacks theoretical micro-foundations. To delineate the mechanims better, this paper proposes a simple model featuring two dealers who are long-term trading partners (representing dealer pairs with strong relationships in the real market), which allows us to construct a measure of liquidity that directly reflects how easily clients can trade with less price impact. In the model, each of the two dealers has a loyal client (representing the client base of this dealer) who relies on this dealer to trade. In the first period, each client approaches her home dealer (the dealer she is loyal to) to sell q units of a bond (buy if q is less than zero). Afterward, the two dealers trade with each other to share their inventory risk and incur some cost if the absolute change of inventory is not zero at the last period. The correlation between the two q's from the two clients is an exogenous characteristic between these two dealers. The model shows that the lower the correlation, the higher the liquidity each dealer can provide to her client under the same level of capital commitment. Intuitively, a lower correlation means that when one of the dealers' clients has a higher selling pressure, the other dealer's client tends to have a relatively higher buying pressure compared to a higher correlated pair of dealers. This implies that one dealer tends to absorb less order imbalance (compared to a higher correlated situation) whenever the other dealer absorbs more, leading to increased willingness of interdealer trade to share inventory risk, which further increases dealers' willingness to trade with clients and improves liquidity.

The model's setup is grounded in existing literature. Hendershot et al. (2019) propose a theoretical model that supports long-term trading relationships between clients and dealers. According to their model, dealers place value on the concentration of a client's trades with them, leading to a willingness to charge a lower markup if the client engages with fewer other dealers. This friction prevents clients from randomly searching for dealers, as it is detrimental to the existing dealers' established relationships. O'Hara et al. (2016) provide empirical evidence supporting this notion, demonstrating that insurance companies tend to repeatedly trade with a select group of dealers rather than engaging with all available dealers.

O'Hara et al. (2016) find that, throughout their study period, the median number of dealers with whom insurance companies trade is five (mean of 11), despite the market having thousands of dealers. The research also reveals that nearly all companies rely on a single dealer to trade a specific bond, providing strong evidence of dealers specializing in trading specific bonds. Additionally, they find compelling evidence that large central dealers price discriminate against less active traders, suggesting that concentrating trades with smaller dealers may benefit less active traders in securing a larger share of the dealer's business.

These findings provide a strong theoretical foundation and empirical support for the presence of frictions that discourage clients from randomly approaching less familiar dealers for trading, even in the presence of widely recognized dealers with extensive market connections.

In this paper, our model represents the client base of a dealer using a representative client who can only trade with that specific dealer. The purpose is to capture the challenges clients face when attempting to trade with unfamiliar dealers and align with the observation that clients heavily rely on their most familiar dealer for trading. While in reality, clients have the ability to search for other dealers, albeit with frictions that may arise from game theoretical behaviors rather than being exogenous given. However, our model does not account for all potential factors or origins of frictions in a market with numerous variables. A simpler setup allows us to focus specifically on the impact of correlation of client order imbalance on dealers' long-term trading relationships while ensuring the model remains tractable.

The financial crisis significantly impacted dealers' trading behavior. During and after the crisis, many dealers reorganized their corporate structure. This often involved expanding or establishing new risk control departments to place greater emphasis on supervising the risks associated with holding financial assets. In addition to internal adjustments, a slew of external regulations was discussed and subsequently enacted, specifically targeting dealers' inventory risks. Notable among these are Basel 2.5, Basel 3, and the Dodd-Frank Act (more detail about these regulations to be dicussed in the following).These regulations collectively increase the inventory costs for dealers. As a consequence, dealers might be compelled to find ways to provide liquidity while minimizing fluctuations in their inventory levels.

Drawing from the model's intuition outlined in this paper, we posit that dealers, in the aftermath of the crisis, have strengthened their trading relationships with counterparts exhibiting lower correlations. According to the model, such an adaptation would enhance liquidity. Yet, when this strategic shift is set against the backdrop of the heightened capital commitment costs introduced by post-crisis regulations — which negatively impact liquidity — It provides an explanation for the unclear results regarding the effects of post-crisis regulations on liquidity in the following period. Despite many researchers suggesting a decrease in liquidity, the market continues to operate effectively. Other factors, such as grace periods granted for compliance with new regulations, could also influence the observed outcomes. The aim of this paper is not to claim strict causality, given the myriad confounding factors, this might not be feasible. Nonetheless, this paper provides valuable insights into liquidity by presenting potential explanations.

In the post-crisis period, have dealers strengthened their trading relations with lower correlated partners? We first investigate the institutional details and conclude that both the increased cost of committing capital and specific requirements from post-crisis regulations should motivate dealers to devote more effort to optimize their trading relations after the crisis. Basel 2.5 and 3 introduced stricter regulations on metrics like capital ratio requirements on different tiers and Value at Risk. The Dodd-Frank Act further pressured dealers to minimize inventory risk by mandating that dealers undergo stress tests based on severe macroeconomic conditions. Additionally, the Volcker Rule, a component of the Dodd-Frank Act, scrutinizes dealers' trading flows, profit standard deviations, and inventory fluctuations. The Volcker Rule seeks to curtail dealers' proprietary trading, yet, as Duffie (2016) points out, market-making activities inherently fall under the umbrella of proprietary trading. To differentiate between the two, it requires dealers to show evidence that they are absorbing the order imbalance from the client side when they commit a significant amount of capital. Dealers are also required to anticipate the trading demands of their counterparts ahead of time. Such stipulations probably encouraged dealers to invest more effort in understanding these correlations following the crisis. The increased costs associated with capital commitment, stemming from these regulations, further motivate dealers to grasp these correlations and fine-tune their trading connections. One piece of evidence underscoring these motivations is the emergence of fintech companies in the bond market post-crisis that promote their ability to provide insights on the industry jargon "axe" (data pinpointing the preferred trading direction of counterparties), highlighting a significant interest in this specific information.

Secondly, we conduct a regression analysis to verify whether dealers have strengthened their long-term trading relationships with less correlated partners following the crisis. The empirical analysis is based on the TRACE Academic dataset from June 2002 to December 2012, which is the most comprehensive dataset in the US corporate bond market. We observe the price, quantity, trade time, and buy or sell directions for all transactions subject to reporting requirements (almost all transactions involving a dealer in the US corporate bond secondary market are required to report to FINRA within 15 minutes after execution). Moreover, this dataset includes a masked identifier for each dealer, allowing for the identification of bilateral transactions between any two dealers.

We construct the dependent variable, bilateral trading shares, as a measure of the strength of long-term relationships formed between a pair of dealers (following the approach of Di Maggio, Kermani, and Song (2016)). We then calculate the daily client order imbalance for each dealer by summing over all bonds that clients sold to this dealer minus all bonds clients bought from this dealer for each day, and use the correlation of daily client order imbalances for each dealer pair as the key independent variable. This construction is similar to Cocco, Gomes, and Martins (2009). Their study concludes that pairs of banks with a lower correlation between the funds that customers withdraw from each bank tend to have a higher share of interbank loans with each other. In contrast, we examine the impact of the correlation of client order imbalance on the trading shares of dealer pairs in the US corporate bond market. For scrutinty, we address two sources of endogeneity problems. The first source of endogeneity arises from factors that do not change over time, resulting in persistent endogeneity throughout time. For example, some dealers may specialize in trading similar bonds and attract clients with similar investment strategies. As a result, their client order imbalances are positively correlated, and their bilateral trading share with each other is higher than that of other dealers simply because they trade similar bonds and rely on each other to obtain or unload inventory. This source of endogeneity problems arises from the similarity between dealers' characteristics, and we address this issue by including control variables that capture dealers' similarity, such as the similarity of the bond sets that two dealers traded and the difference of eigen centrality between two dealers to capture the difference of connectivity. We also add dealer fixed effect to mitigate this endogeneity issue. The second source of endogeneity arises from factors that vary over time, such as market shocks. For instance, in times of market turbulence, clients may trade in similar directions, resulting in a higher correlated order imbalance. At the same time, dealers' bilateral trading share may increase due to a higher demand to manage inventory or decrease suddenly due to the breakdown of cooperation in inventory management if the shock is too severe. To address this issue, we lag the independent variable (correlation of the client order imbalance) by one period and include time dummies. We acknowledge that the secondary market involves many complex factors, and these techniques may not be sufficient to entirely solve the endogeneity problem. Therefore, our results should be interpreted with caution. However, as with other empirical studies, it is improbable to fully eliminate all endogeneity issues in the secondary market. Nevertheless, our paper still provides valuable insights into the market microstructure, contributing to a better understanding of the market dynamics.

The regression results suggest that dealers have strengthened their trading shares with partners that have lower correlations after the crisis, which supports the hypothesis proposed in this paper.

This paper is organized as follows: Section 2 reviews the related literature. Section 3 introduces the data used in our analysis. We discuss the model in section 4 and present the empirical results in seciton 5. Section 6 concludes.

2.2 Related Literature

This paper primarily relates to the literature that examines liquidity in the US corporate bond market. Bessembinder et al. (2018) studies the effect of post-crisis regulations on dealers' capital commitment and liquidity. The authors find that dealers' capital commitment have significantly declined due to the regulations. However, the effects of these regulatory reforms on liquidity are unclear, as they do not find significant evidence of liquidity deterioration after the regulations were implemented. Trebbi and Xiao (2017) conducts a comprehensive investigation of liquidity measures in the US corporate bond market and concludes that liquidity remained robust and, according to some measures, was even improved after the financial crisis and the implementation of post-crisis regulations. Adrian, Fleming, Shachar, and Vogt (2017) finds that some liquidity measures had deteriorated, while others remained robust after the financial crisis, indicating mixed evidence regarding the effects of regulatory reforms. On the other hand, some strands of literature concludes that liquidity in the US corporate bond market has declined significantly during specific events. For instance, Dick-Nielsen and Rossi (2017) finds that the cost for clients to trade bonds immediately during some events such as index exclusion and bond downgrading had significantly increased after the crisis, suggesting deteriorating liquidity due to the post-crisis regulations. Instead of examining pre- and post-crisis liquidity as previous literature has done, this paper aims to offer overlooked explanations for the ambiguous conclusions on the impacts of the post-crisis regulations on liquidity found in some existing literature.

This paper is also relevant to the literature about dealers' behavior and dealer networks. Goldstein and Hochkiss. (2020) examines the challenges that dealers face in providing liquidity and finds that, after the crisis, dealers searched harder for counterparties to offset buy and sell orders in order to avoid carrying inventory overnight. This suggests that dealers adapted their trading behavior in response to the increased cost of committing capital. While the they concludes that dealers searched harder randomly for counterparties to avoid committing capital, the focus of this paper is on how dealers address the increased cost of capital commitment by optimizing their long-term relationships with other dealers. Another closely related paper is Chang and Zhang. (2021), which presents a theoretical model that suggests dealers' networks can endogenously respond to the increased cost of committing capital due to post-crisis regulations, potentially mitigating the reduction of liquidity to excessively low levels without such a response. In their model, smaller and less connected peripheral dealers that do not have relationships with large and more connected core dealers will pay a fixed cost to form new connections with core dealers in response to the increased cost of committing capital. While the main idea of this paper is similar to Chang and Zhang (2021), it explores a different aspect of dealers' behavior by examining how dealers endogenously optimize their relationships based on the correlation of client order imbalances - an area that is not addressed in their paper. Furthermore, this paper is also related to empirical works on the relationships between clients and dealers, as well as between dealers themselves. O'Hara, Wang, and Zhou. (2016) conducts an empirical investigation of the relationships between insurance companies and dealers, and finds that instead of trading with all dealers, each insurance company only trades repeatedly with a limited number of dealers. Their empirical findings were rationalized by the theoretical model developed by Hendershott et al. (2020), which suggests that dealers offer discounts to loyal clients. As a result, clients tend to concentrate their trading activities on a small subset of dealers. Di Maggio, Kermani, and Song. (2016) empirically investigates the relationships between dealers and finds that dealers to dealers' relationships are non-random and have a significant impact on the liquidity that dealers are able to provide to their clients. The disruption of existing relationships, such as the bankruptcy of an important partner dealer, can greatly increase transaction costs. This paper is based on these empirical findings and underscores a potential yet overlooked link related to the long-term client-to-dealer and dealer-to-dealer relationships, which can impact liquidity. Moreover, their paper focuses on the observation that dealers' relationships are relatively stable over time and play a crucial role in the liquidity provided by these dealers. Any disruption to this stable relationship, such as the bankruptcy of trading partners, significantly diminishes the dealer's ability to provide liquidity. While this paper emphasizes the stability of these relationships, it also recognizes that increased regulatory pressure and technological advancements can lead to the optimization of these relationships, ultimately benefiting market liquidity.

2.3 Data

We rely on the Trace Academic dataset from June 2002 to December 2012. To ensure the reliability and validity of our analysis, we exclude convertible bonds, bond issued globally, asset-backed securities, yankee bonds (US denominated bond issued by foreign institutions), foreign currency-denominated bonds and bonds with other features that make their cash flows more complicated or variable. In summary, our analysis mainly focuses on plain vanilla bonds. Furthermore, in line with Goldstein and Hotchkiss (2020), we only include bonds that have been traded at least once with a notional value of $100000 or higher. Since institutional investors are the dominant players in the bond market, our focus is on those bonds that have been traded at least once at or above the institutional size (with notional value of above \$100000). We identify 18519 bonds that satisfy these criteria.

The sample comprises more than 3000 different dealers, with many of them trading infrequently. Since we are interested in studying the correlation between client order imbalance and dealer behavior, it would be problematic if many dealers only trade sporadically (problematic to calculate the correlation). To address this issue, we include only the top 10 percent of dealers ranked by eigen vector centrality, which identifies the most connected large dealers. Moreover, we exclude dealers that have never traded with clients or held overnight inventories, since these dealers are primarily interdealer brokers and are not the focus of our study. Of course, interdealer brokers play an important role in facilitating interdealer trade and consequently contribute to market liquidity. However, the focus of this paper is on the relationship between the correlation of client order imbalance and dealers' relationships, and their effect on market liquidity, which does not involve interdealer brokers. This leaves us with a total of 342 dealers, and these dealers account for approximately 93.8 percent of the aggregate trading volume in our data sample. This pattern is consistent with the core-periphery structure found in the existing literature, where a small number of large dealers occupy a significant share of the market.

During the sample period, the market experienced several shocks, including the dot-com bubble, the financial crisis, and the European debt crisis, which may have led to dealers entering or exiting the market. As we do not observe dealers enter or exit, we use the first quarter dealer trades as the entry time for this dealer, and the last quarter this dealer trade as the exit time for this dealer. We define the variable "ActiveDays" as the number of days between the periods this dealer last trade and this dealer first trade and refer to this period as this dealer's active period. Furthermore, we constructe a variable 'TradedDays' to represent the number of days this dealer traded at least once. To measure the level of trading activity for each dealer, we calculate a new variable "%TradedDays" by dividing "TradedDays" by "ActiveDays". Table 1 summarizes these three variables.

According to Table 1, around 75% of the dealers in our sample remain in the market for at least 3150 days. Considering our dataset spans roughly 10 years, or approximately 3650 days, this statistic suggests that the majority of the dealers are present in the market for nearly the entire duration of our dataset. The median number of days that each dealer traded at least once is 1311, and the median percentage of traded days out of the active period across each dealer is approximately 42%. So for most dealers in the sample, at least half of the active period does not involve any transaction. This finding is consistent with the fact that corporate bonds are not actively traded, and it is possible for a bond to trade multiple times in some days, particularly if there is a shock from the clients' side or other parts of the market, while remaining inactive during other periods. Similarly, it is possible for dealers to trade many times in response to shocks from their clients' side or other parts of the market, while remaining inactive during other periods. Given the potential for trading activity to be influenced by shocks in the market or from clients, it is interesting to study the correlation of dealers' client order imbalances. In the bond market, clients tend to rush to trade in the same direction if there are shocks in the market. However, if two dealers' clients have different characteristics and investment strategies, one dealer's clients may tend to trade while the other's may not, leading to zero or even negative correlation, then it is desirable for these two dealers to strengthen their relationship compared to the higher correlated dealer pairs.

We further investigate the bilateral trading shares in this sample. For each dealer and quarter, we construct a variable $Share_{A,B,t} = \frac{AggV_{A,B,t}}{TotalDV_{A,t}}$, where the variable $AggV_{A,B,t}$ represents the aggregate trading volume in notional value between dealer A and B for quarter t, and $TotalDV_{A,t}$ represents the total volume in notional value that dealer A trades with all other dealers for quarter t. Thus, $Share_{A,B,t}$ is a measure of the proportion of the aggregate trading volume between dealer A and B for quarter t, relative to the total volume that dealer A trades with all other dealers for the same quarter. Both $Share_{A,B,t}$ and $Share_{B,A,t}$ reflect the strength of the relationship between dealer A and B. It should be noted that $Share_{B,A,t}$ may not be equal to $Share_{A,B,t}$ in general, as this variable is not necessarily symmetric. In particular, if dealer B is larger than dealer A, dealer B may have a larger trading share on dealer A than dealer A has on dealer B (Di Maggio, Kermani, and Song (2016) and Cocco, Gomes, and Martins. (2009) use similar definitions of variable to measure inter-relationship).

Table 2 summarizes the $Share_{A,B,t}$ values for each dealer pair. It is noteworthy that for around 90% of the data, the $Share_{A,B,t}$ value is 0, indicating that many dealer pairs do not trade with each other across many quarters. We account for this in the empirical analysis by including a dummy variable to indicate whether a dealer pair trades with each other for each specific quarter. However, regardless of whether we include this dummy variable, we obtain similar results. To further understand the statistics, we also summarize the trading shares for the sub sample with $Share_{A,B,t} \neq 0$. The trading shares are relatively small, with a median of around 0.0037. This variable is generally lower than the sample from Di Maggio, Kermani, and Song (2016), which is reasonable as we only include the top 10% connected large dealers and these dealers are likely more diversified in terms of trading relations, while Di Maggio, Kermani, and Song (2016) includes all dealers. Despite the small average value of these trading shares, the authors have concluded that trading relationships with counterparties, as measured by trading shares, exert a significant influence on dealers' willingness to provide liquidity to those counterparties. While optimizing trading relations solely based on the correlation discussed in this paper with a single dealer may not have a strong enough impact on the liquidity provided by that dealer, optimizing trading shares for all long-term trading partners is likely to play a substantial role. This approach has the potential to enhance the overall market's aggregate liquidity provided by dealers, especially if all dealers adopt a similar process.

For each pair of dealers, we calculate the correlation of their daily client order imbalance

$\rho_{A,B,t}$ for each quarter t. First, for each day and dealer A and B, we calculate the daily client order imbalance as the notional value of all bonds clients sold to this dealer, minus the notional value of all bonds clients bought from this dealer. We then calculate the correlation using all days from June 2002 up to the last day of quarter t. If either dealer is not active after June 2002, we exclud the days before the date when both dealers became active. Futher, if either dealer exited the market before the quarter t, $\rho_{A,B,t}$ is undefined and excluded from the analysis. Finally, any $\rho_{A,B,t}$ is undefined if either dealer A or dealer B does not have variation of client order imbalance from the first day of June 2002 to the last day of quarter t, and is excluded from the analysis. We choose to utilize all days from June 2002 up to the last day of quarter t instead of solely focusing on the days in the previous quarter for several reasons. Firstly, the primary objective of this paper is to examine the impact of long-term correlation, rather than restricting our analysis to the previous quarter alone, and dealers who invest effort and conduct research to infer this correlation from past trading history are likely to utilize all available data. Relying solely on the previous quarter may introduce biases stemming from specific time periods that do not adequately represent the long-term correlation under investigation. Additionally, since numerous bonds and dealers are not very actively traded, including all days enables us to explore the entire range of variations and attain more precise results in our empirical analysis.

Table 3 summarizes the distribution of $\rho_{A,B,t}$ for all pairs of dealer quarters with well-defined $\rho_{A,B,t}$. The distribution of $\rho_{A,B,t}$ is skewed to the left, with the 1st percentile at -0.1233, the 50th percentile at 0.0013, and the 99th percentile at 0.1435. This skewness is consistent with the fact that clients tend to rush to trade in the same direction when there are market shocks, leading to a greater likelihood of positive correlations in client order imbalances for each pair of dealers.

Table 4 presents preliminary evidence supporting the hypothesis proposed in this paper. It illustrates the relationship between the bilateral trading shares of two dealers and the long-term correlation of their order imbalances. In line with the discussion in the previous section, we anticipate a decrease in the correlation between these two variables over the four examined periods, with an expectation of a structural break subsequent to the enactment of the Dodd-Frank Act. Consistent with our expectations, Table 4 reveals a declining trend in correlation throughout the periods, with the most significant decrease occurring after the Dodd-Frank Act's implementation.To furthur investigate, we use a simple model to delineate the underlying mechanism and conduct regression analysis to provide a more thorough investigation.

Table 2.1: Dealer Trading Activity Summary

Percentiles	TotalDaysThisDealer	TradedDaysThisDealer	%TradedDaysThisDealer
1%	678	127	4.83
5%	1293	256	8.76
10%	1936	389	12.78
25%	3150	763	27.73
50%	3826	1311	42.41
75%	3837	2143	63.28
90%	3842	2610	67.46
95%	3882	2631	68.36
99%	4121	2645	68.67
N	342	342	342

TotalDaysThisDealer is the number of days between the dealer's first and last trade in the quarter. *TradedDaysThisDealer* is the number of days the dealer traded at least once. *%TradedDaysThisDealer* is calculated as *TotalDaysThisDealer* divided by *TradedDaysThisDealer*, providing a measure of the dealer's trading activity.

Table 2.2: Dealer Trading Shares Summary

Percentiles	$Share_{A,B,t}$	$Share_{A,B,t}$ (Nonzero Subsample)
1%	0.00000	0.00001
5%	0.00000	0.00007
10%	0.00000	0.00017
25%	0.00000	0.00076
50%	0.00000	0.00373
75%	0.00000	0.01587
90%	0.00016	0.05137
95%	0.00493	0.09914
99%	0.05727	0.37671
N	5014746	443238

Summary of $Share_{A,B,t}$, where $Share_{A,B,t}$ is the trading volume between dealer A and B in quarter t divided by the trading volume between dealer A and all dealers in quarter t. To further understand the distribution, we also summarize the percentiles within the subsample with $Share_{A,B,t} \neq 0$.

2.4 Model

2.4.1 Model Setup

This section focuses on the model and comparative statistics. The setup involves two dealers who are long-term partners and rely on each other to share inventory after absorbing order imbalances from trading with their own clients. This arrangement is consistent with the fact that both dealer-to-dealer relationships and client-to-client relationships are nonrandom and long-term, as noted by Di Maggio et al. (2016) and Hendershott et al. (2020). The model's intuition is straightforward: if the correlation between order imbalances from each dealer's clients is lower, then when one dealer faces higher selling pressure (or lower buying pressure) from their clients, the other dealer is more likely to experience lower selling pressure (or higher buying pressure). This makes the two dealers more willing to trade with each other and share inventory risk, compared to when the correlation is higher. Consequently, if the correlation is lower, each dealer is more willing to trade with their long-term partner dealer, resulting in lower capital commitment on average across different days. Conversely, knowing that they can easily share inventory

Table 2.3: Summarize of the correlation of client order imbalance

Percentiles	$\rho_{A,B,t}$
1%	-0.1233
5%	-0.0524
10%	-0.0322
25%	-0.0108
50%	0.0013
75%	0.0176
90%	0.0436
95%	0.0667
95%	0.1435
N	1940792

$\rho_{A,B,t}$ is the correlation calculated based on the daily order imbalance from Jun 2002 to the last date of quarter t. Summary is across each dealer pairs for each quarter.

Table 2.4: Correlations of Dealer Pair Trading Shares per Quarter for Lagged Long-Term Correlation Order Imbalance Over 1, 4, and 8 Quarters.

	$\rho_{A,B,[0,t-1]}$	$\rho_{A,B,[0,t-4]}$	$\rho_{A,B,[0,t-8]}$
Pre Crisis	-0.0009	0.0009	0.0033
Crisis Period	-0.0024	0.0016	0.0013
Post Crisis before Dodd Frank Signed into Law	-0.0058	-0.0076	-0.0006
Dodd Frank Signed into Law	-0.0084	-0.0084	-0.0072

Correlation of bilateral trading shares with lagged long-term correlation of order imbalance over various quarters: $\rho_{A,B,[0,t-1]}$ denotes the correlation lagged by one quarter, $\rho_{A,B,[0,t-4]}$denotes the correlation lagged by four quarters, and so on. Lagging long-term correlation of order imbalance is employed to mitigate simultaneity issues.

risk with their long-term partner dealers, each dealer is more willing to trade with their own clients, leading to higher liquidity and lower capital commitment.

We follow a simliar set up with the Colliard, Foucault and Hoffmann (2021). Time is discretized into three periods (t=1, 2, 3). There are two dealers, A and B, represent long-term partners who rely on each other to share inventory risk, two representative clients: client a and b, each of whom is loyal (only trade with) to dealer A and B, respectively and one bond pays $v \sim N(0, \sigma_v^2)$ at the last period t=3.

At period 1, client a bargains and sells q_A(buy if $q_A < 0$) to dealer A, client b bargains and sells q_B to dealer B, where q_A and q_B have a correlation $\rho_{A,B}$. The correlation $\rho_{A,B}$ represents the long-term correlation between q_A and q_B for each day (e.g., day 1, day 2, etc.). Both dealers know $\rho_{A,B}$, but only dealer A observes q_A and not q_B, and vice versa for dealer B.

In period 2, dealer A and B trade to share their inventory risk, and each dealer will incur inventory cost if $\Delta I \neq 0$ at $t = 3$.

The model is solved backward. At t=3, the bond payment and inventory cost are realized, and each dealer receives a payment.

$$v\Delta I_i - \omega_i \sigma_v^2 \Delta I_i^2 - k_i(\Delta I_i)^2, i \in A, B \tag{1}$$

Here, ω_i represents the exogenous risk tolerance for each dealer, and the term $\omega_i \sigma_v^2 \Delta I_i^2$ is the cost associated with risk aversion. The higher the randomness of the bond payment σ_v^2, the higher this cost. The term $k_i(\Delta I_i^2)$ represents the total cost of committing capital, which is an increasing function of the absolute change of inventory (same set up under Colliard, Foucault and Hoffmann (2021)) , and k_i represents the idiosyncratic component of the cost to commit capital for each dealer.

At t=2, dealer A sells q_d (or buys if $q_d < 0$) units of bond to dealer B at price p_d, where q_d and p_d are determined through bargaining between dealer A and B. We follow a Kalai bargaining setup, where the goal is to maximize the aggregate surplus subject to the ratio of surplus for each party being equal to the ratio of each party's bargaining power.

Dealer A's surplus from interdealer trade is:

$$\underbrace{p_d q_d - \omega_A \sigma_v^2 (q_A - q_d)^2 - k_A (q_A - q_d)^2}_{\text{Value to Trade with Dealer B}} - \underbrace{(-\omega_A \sigma_v^2 q_A^2 - k_A q_A^2)}_{\text{Value Not Trade}} \tag{2}$$

Dealer B's surplus from interdealer trade is:

$$\underbrace{-p_d q_d - \omega_B \sigma_v^2 (q_B + q_d)^2 - k_B (q_B + q_d)^2}_{\text{Value to Trade with Dealer A}} - \underbrace{(-\omega_B \sigma_v^2 q_B^2 - k_B q_B^2)}_{\text{Value Not Trade}} \tag{3}$$

The dealers' bargaining problems are:

$$\max_{p_d, q_d} Aggregate\ Surplus: \ (2) + (3) \tag{4}$$

such that:

$$\frac{p_d q_d - \omega_A \sigma_v^2 (q_A - q_d)^2 - k_A (q_A - q_d)^2 - (-\omega_A \sigma_v^2 q_A^2 - k_A q_A{}^2)}{-p_d q_d - \omega_B \sigma_v^2 (q_B + q_d)^2 - k_B (q_B + q_d)^2 - (-\omega_B \sigma_v^2 q_B^2 - k_B q_B{}^2)} = \frac{\theta}{1 - \theta} \tag{5}$$

In this model, θ and $1 - \theta$ symbolize the bargaining powers of Dealer A and Dealer B, respectively. The model posits that ϑ is an exogenous factor, and the allocation of the aggregate surplus between the two parties is proportional to their respective bargaining powers.

Given the problem of interdealer trade, we can obtain the solution of interdealer price and quantity: p_d^* and q_d^*.

At $t = 1$, client a approaches dealer A to trade q_A units of bonds. We focus on client a and dealer A since the problem for client b and dealer B is the same:

The gain for client a is:

$$p_A q_A^r - v_A^r q_A^r \tag{6}$$

Here, the superscript r in q_A^r represents the realized value of the random variable q_A on this day, and v_A^r represents the realized value of client a's valuation for this bond on this specific date. In the real world, client a represents the group of clients that remain loyal to dealer A. Therefore, v_A^r is a representative valuation and can be different across different days depending on the number of sellers and buyers within this client base (for example, how many clients need to trade and how urgently each client needs to trade due to reasons such as cash demand or adjustment of investment strategy for business reasons).

The expected surplus for dealer A, given $q_A = q_A^r$ is:

$$\underbrace{E(V(p_A, q_A^r)|q_A = q_A^r)}_{\text{Value to Trade with Client}} - \underbrace{E(V(0)|q_A = q_A^r)}_{\text{Value Not Trade}} \tag{7}$$

Dealer A's valuation of agreeing to trade with client a is:

$$\begin{aligned} E(V(p_A, q_A|q_A = q_A^r) = & \underbrace{-p_A q_A^r + \int p_d^*(\Phi) q_d^*(\Phi) f_{\rho_{A,B}}(dq_B|q_A = q_A^r)}_{\text{Expected Proceeds from Interdealer Trade}} \\ & \underbrace{-\omega_A \sigma_v^2 \int (q_A^r - q_d^*(\Phi))^2 f_{\rho_{A,B}}(dq_B|q_A = q_A^r)}_{\text{Expected Cost of Risk Aversion}} - \underbrace{k_A \int (q_A^r - q_d^*(\Phi))^2 f_{\rho_{A,B}}(dq_B|q_A = q_A^r)}_{\text{Expected Inventory Cost}} \end{aligned} \tag{8}$$

where $\Phi = (q_A^r, q_B, k_A, k_B, \theta, \sigma_v, \omega_A, \omega_B)$.

Dealer A's valuation of refusing to trade with client a is:

$$\begin{aligned} E(V(0, 0|q_A = q_A^r) = & \underbrace{-p_A q_A^r + \int p_d^*(\Phi_0) q_d^*(\Phi_0) f_{\rho_{A,B}}(dq_B|q_A = q_A^r)}_{\text{Expected Proceeds from Interdealer Trade}} \\ & \underbrace{-\omega_A \sigma_v^2 \int (0 - q_d^*(\Phi_0))^2 f_{\rho_{A,B}}(dq_B|q_A = q_A^r)}_{\text{Expected Cost of Risk Aversion}} - \underbrace{k_A \int (0 - q_d^*(\Phi_0))^2 f_{\rho_{A,B}}(dq_B|q_A = q_A^r)}_{\text{Expected Inventory Cost}} \end{aligned} \tag{9}$$

where $\Phi = (0, q_B, k_A, k_B, \theta, \sigma_v, \omega_A, \omega_B)$.

The problem for dealer A and client a is to maximize the aggregate surplus:

$$\max_{p_A} \mathbb{E}(V(p_A^*, q_A^r)|q_A = q_A^r) - \mathbb{E}(V(0)|q_A = q_A^r) + p_A q_A^r - v_A^r q_A^r \tag{10}$$

such that

$$\frac{\mathbb{E}(V(p_A^*, q_A^r)|q_A = q_A^r) - \mathbb{E}(V(0)|q_A = q_A^r)}{p_A^* q_A^r - v_A^r q_A^r} = \frac{\mu_A}{1-\mu_A} \tag{11}$$

q_A represents the quantity of trade demanded by client a, which is designed to capture the effects of exogenous shocks on Dealer A's client base (to maintain tractability, this paper assumes that client a does not split orders). Dealer A and client a then engage in price bargaining to determine the price p_A. Since there are two equations but only one unknown in the Kalai bargaining setting, it is equation (11) that must be satisfied. Equation (11) provides the solution for price p_A^*, but for the bargaining problem to be successful, the aggregate surplus must be greater than zero, which establishes a threshold for client a's valuation necessary for successful bargaining:

$$\tilde{v}_A(\Phi) = \frac{\mathbb{E}(V(p_A^*, q_A^r)|q_A = q_A^r) - \mathbb{E}(V(p_A, 0)|q_A = q_A^r) + p_A^* q_A^r}{q_A^r} \tag{12}$$

This threshold specifies that for dealer A to agree to trade with client a, if client a requires selling ($q_a > 0$), dealer A requires that client a's valuation cannot be too high to exceed this threshold, otherwise, the bargaining will fail. There is no lower threshold as a lower v_a^r yields higher surplus for the dealer when the client wants to sell. Conversely, if client a requires buying ($q_a < 0$), dealer A requires that client a's valuation cannot be too low to fall below this threshold (whether $\tilde{v}_A(\Phi)$ is an upper or lower threshold depends on the sign of q_a^r and is undefined if $q_a^r = 0$). This threshold is endogenously determined by $\rho_{A,B}$, dealers' risk aversion, and the cost of committing capital, and it measures dealer A's willingness to trade with client. Thus, it can be interpreted as a measure of liquidity.

The cost of capital commitment is measured as the expected change in absolute inventory, using a similar setup to Bessembinder et al. (2018):

$$E|\Delta I_A| = \int |q_A^r - q_d^*(\Phi)| f(dq_B | q_A = q_A^r) \tag{13}$$

2.4.2 Dealers' Long Term Relationship and Market Friction

Di Maggio et al. (2016) demonstrated that dealers establish long-term trading relationships within the interdealer network, utilizing these close partnerships to manage inventory risk. The collapse of a major trading partner can result in dealers with close relationships facing a depletion of inventory management resources. This scenario is evidenced by the elongation of intermediation chains and a marked rise in the cost of providing liquidity.

While dealers are capable of seeking partners for inventory management, various frictions impede their ability to trade randomly with each other. It is common for dealers to engage in price discrimination when interacting with unfamiliar trading partners. Despite a trend towards market centralization via electronic trading. Traditional trading methods, such as phone negotiations for price setting, remain predominant, thereby the search costs for dealers looking for random trading partners are still high. Because it is costly to make repeated phone calls and time-consuming to bargain the price with other dealers. Prior studies have demonstrated that dealers depend extensively on their close trading partners for inventory management, especially during periods of market stress. Additionally, liquidity on electronic trading platforms often diminishes during these times of market turmoil. Consequently, establishing long-term trading relationships with close partners is essential for dealers to effectively manage their inventory risk. Further, the disclosure of immediate trading needs during random searching, stemming from inventory management problems within the interdealer market, poses a risk by potentially attracting predatory traders. On the other hand, a long-term trading partner with a solid history of transactions is less prone to spreading sensitive information or engaging in predatory actions against a dealer facing difficulties. Long-term trading relationships emerges as dealers establish repeated interactions over time. Miguel, Lobo, and Viswanathan (2007) developed a theoretical model illustrating how long-term trading relationships are maintained through repeated cooperation. When faced with episodic shocks that require immediate trading action, dealers turn to their cooperative trading partners to facilitate transactions. repeated cooperation between trading partners decreases the likelihood of predatory trading during periods when one is faced with shocks related to inventory management.

To simplify the analysis, this paper does not explicitly model the structure of these long-term trading relations. Instead, we model the reliance of close trading partners, where a pair of dealers exclusively rely on each other to manage inventory risk. This simplification allows us to extend the model to incorporate the correlation of liquidity demand from their client base under a tractable structural model. Building a structural model that both explicitly models the long-term trading relationship and the correlation of each dealer's clients' liquidity demand is interesting for future research.

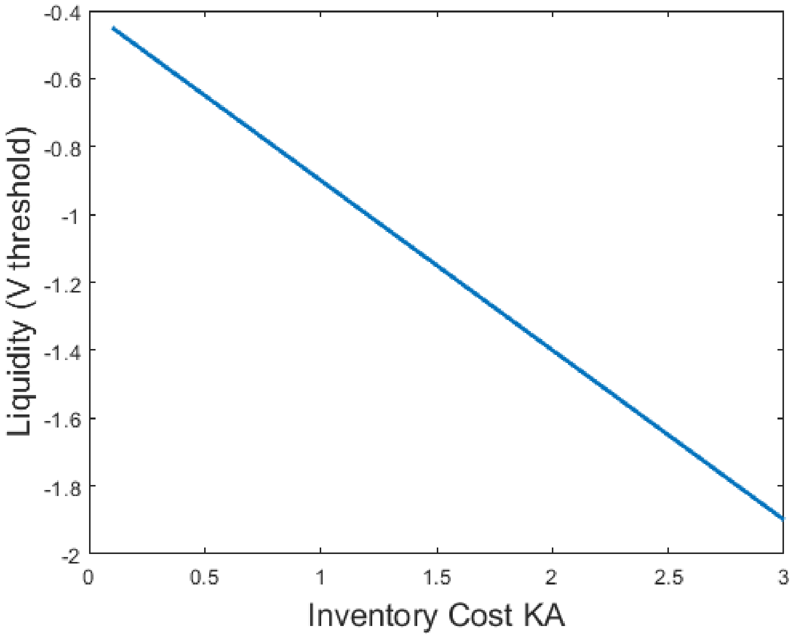
Long-term trading relationships among dealers do evolve over time, especially during and after periods of crisis and regulatory change. However, the development of these interdealer long-term trading relationships over time is still insufficiently examined. A key contribution of this paper is to identify and analyze a specific aspect through which dealers optimize their long-term trading relationships. This optimization has the potential to elevate market efficiency and warrants recognition and support from regulatory authorities.

Some studies suggest that, in recent years, some clients are evolving into liquidity providers for dealers. However, in the majority of instances, dealers continue to act as liquidity providers for clients. Dealers impose significantly higher markups on their clients than they do on other dealers, highlighting the substantial bargaining power dealers wield over their clients. This paper concentrates on the traditional framework in which clients seek out dealers to procure liquidity. Enriching the model to include dealers actively soliciting liquidity from their client base constitutes a compelling and valuable direction for subsequent research.

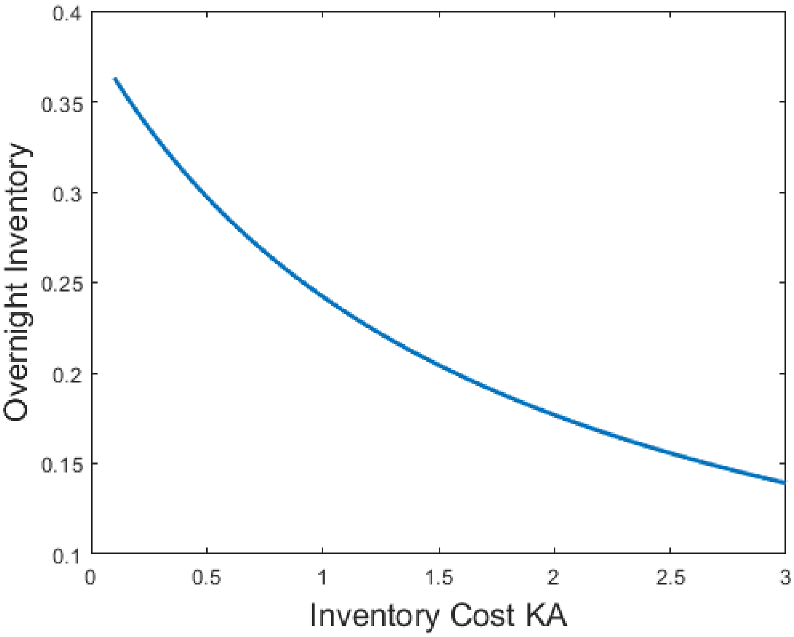
2.4.3 Model Predictions

With these measures of capital commitment and liquidity, the model addresses the question of how the cost of capital commitment k_A and the correlation of client order imbalance $\rho_{A,B}$ affect liquidity and capital commitment. Figures 1 and 2 display the associated comparative statistics. A higher k_A leads to lower liquidity and capital commitment, consistent with traditional inventory models, while a lower $\rho_{A,B}$ leads to higher liquidity but lower capital commitment. It remains to be shown whether $\rho_{A,B}$ declined after the crisis. If this is the case, a declining $\rho_{A,B}$ may explain why liquidity is ambiguous after the crisis. The role of the model is to delineate the increased trading gains when dealers trade with lower correlated partners and the model does not explicitly simulate how dealers optimize their long-term trading relationships in response to regulatory changes. We suggest that the enhanced inventory regulations introduced by the Dodd-Frank Act may motivate dealers to exert additional effort—for instance, by conducting more thorough research into their partners' trading patterns—to optimize these relationships and forge stronger ties with less correlated trading partners. Given the potential gain from trading with lower correlated partners, the desire to vigorously optimize their trading relations should be clear. Before the Dodd-Frank Act, while inventory regulations were more lenient, there was less incentive for dealers to pursue this strategy vigorously.

As a result, we anticipate that dealers have increased their trading shares with less correlated partners (the lower the correlation, the higher the trading share) throughout the four periods listed in Table 5, with the most significant structural break occurring during the Dodd-Frank Act period. The following empirical section tests this hypothesis with a carefully specified regression model.

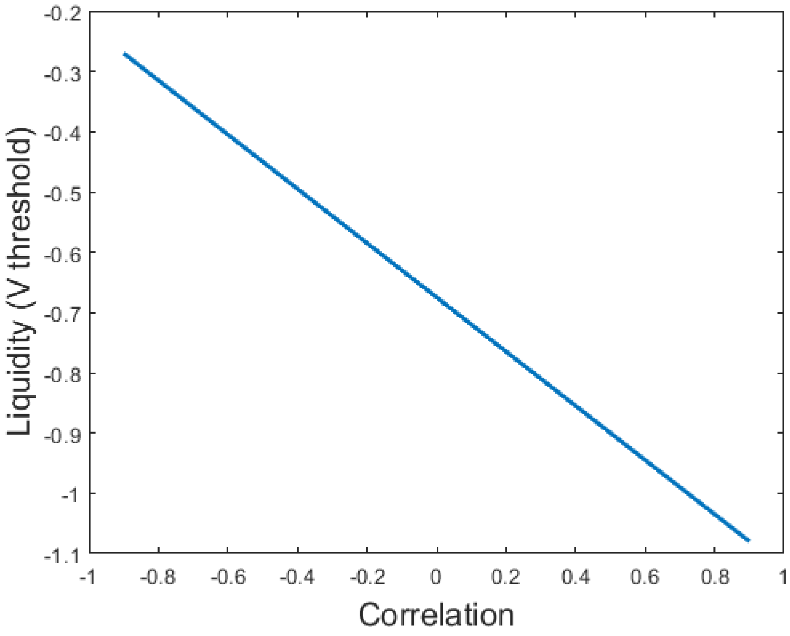


(a) Liquidity and Inventory Cost

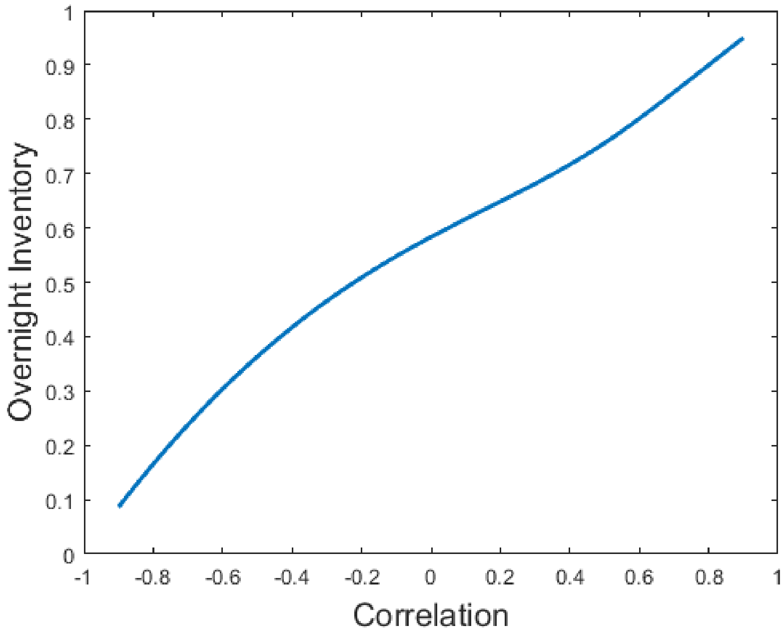


(b) Capitalcommitment and Inventory Cost

Figure 2.1: Liquidity, Capital Commitment and Inventory Cost



(a) Liquidity and Correlation



(b) Capitalcommitment and Correlation

Figure 2.2: Liquidity, Capital Commitment and Correlation of Client Order Imbalance

2.5 Empirical Analysis

Before the Dodd-Frank Act was signed into law, the regulation on inventory was slack. it is likely that the dealers were not willing to devote enough effort to learn this correlation (learning these correlations involves hiring researchers, purchasing data, keeping intensive contacts for information exchange). However, after the Dodd-Frank Act was signed into law, inventory cost is high. Since the model suggests that two dealers with lower correlated client order imbalances lead to a higher trading surplus compared to higher correlated partners, strict regulations will probably push dealers to learn this correlation and strive to strengthen the trading relationship with lower correlated trading partners.

To explore whether dealers have strengthened trading relationships with less correlated partners following the enactment of the Dodd-Frank Act. This paper runs a regression similar with Cocco, Gomes, and Martins (2009), using bilateral trading shares as a measure of trading relation for each pair of dealer and calculates the correlation of daily client order imbalance (the amount clients sold to this dealer minus the amount clients bought from this dealer for this day). The regression result suggests that trading shares between dealer pairs with a lower historical correlation of client order imbalance have increased significantly after the crisis. Under the mechanisms proposed by the model, this suggests even though the cost of committing capital has increased significantly after the crisis, a lower correlation between client order imbalance in the post crisis period should to some extent counteract the pressure on liquidity from a higher cost of committing capital, which could result amibiguous conclusions on the post-crisis liquidity.

In the model, there are only two dealers, dealer A and dealer B, representing a pair of long term partners. In reality, dealer A and B correspond to dealer pairs with strong trading relations (following Di Maggio et al (2016)) we use the bilateral trading shares as a measure of the srength of trading relaitons. The higher the trading share, the higher the relations. We want to investigate whether dealers have strengthened the trading relations with others with a lower correlation of client order imbalance.

We get the data from Trace Academics, which is one of the most comprehensive data sets covering the transactions in the US corporate bond market. We run the following equation:

$$\begin{aligned} S_{A,B,t} = \gamma_1\ \rho_{A,B,[0,t-1]} &+ \gamma_2\ \rho_{A,B,[0,t-1]} * Crisis \\ &+ \gamma_3\ \rho_{A,B,[0,t-1]} * PostCrisisBeforeDodd \\ &+ \gamma_4\ \rho_{A,B,[0,t-1]} * DoddFrank + X_{A,B,t} \\ &+ DealerADummy + DealerBDummy + TimeDummy + \epsilon_{A,B,t} \end{aligned}$$

The correlations $\rho_{A,B[0,t-1]}$ are calculated using the correlation from the first date of the data set to the last date of quarter $t-1$ of daily client order imbalance (the aggregate quantity of bonds that clients sold to this dealers minus the aggregate quantity clients bought on this day). Following Di Maggio et al (2016), we lag one period to reduce endogeneity problem.

We seek to understand wether, for the pair of dealers A and B, a lower correlation of order flow compared to other pairs (for example, lower than the correlation between dealer A and C, or between dealer A and D, etc.) leads to a higher trading share of B on A. The sign and statisitcal signficance of γ_1 will give us a hint for this question. If a lower correlation leads to a higher trading share, we expect to see γ_1 to be signifcantly negative. Moreover, we aim to explore whether post-crisis regulations have impacted the structure of correlations contributing to bilateral trading shares. Our focus lies on the coefficients γ_2, γ_3, and especially γ_4. The coefficient γ_4 enables us to infer how the enactment of the Dodd-Frank Act has affected the contribution of correlations on trading shares. We acknowledge preemptive effects where dealers respond to anticipated regulatory policy and take actions in advance could exist. It is plausible that the impact of the Dodd-Frank Act came before it was formally signed into law. However, we still anticipate that this specification will unveil some structural breaks attributable to the Act. The Dodd-Frank variable is a dummy variable that takes a value of 1 after the Act was signed into law, albeit the actual implementation lagged. As a result, we can interpret the Dodd-Frank dummy as an indicator that the regulation was definitively established, signaling a time when dealers should have believed that regulatory reform is firm.

The regression capitalizes on cross-sectional variations to discern the impact of correlation on trading shares, hence we do not incorporate dealer pair dummies into the regression. Including a dummy for each dealer pair would eliminate all cross-sectional variation and inflate the regression coefficients, especially considering there are 342 dealers with a total of 116964 possible dealer pairs. We accommodate both sides of each pair by incorporating a dealer A dummy and dealer B dummy, along with a time dummy for each time period, aiming to mitigate endogenous factors as much as possible. Given that dealer characteristics such as dealer centrality, market shares, and bond specialization tend to remain relatively stable over time, we choose not to include them as their inclusion could obstruct the identification of coefficients due to the dealer dummy variables. In order to mitigate the endogeneity problems arising from the bilateral relations between dealers A and B, additional controls $X_{A,B,q}$ are introduced, representing the exogenous characteristics shared between these dealers. For instance, if both dealers specialize in similar bonds, they are likely to attract clients with alike investment strategies, resulting in a high degree of correlation. This resemblance in bond specialization might also prompt dealers A and B to engage in more trades with one another. In addressing these issues, we are taking into account the commonality of the traded bond set for both dealers A and B. For example, if dealer B and A trade different kinds of bonds, however, the interseaction of bonds both two dealer trades occuplies a high percentage of the number of bonds for each dealers' bonds sets. These two dealers are likely to form a strong relations as they share important commanlity in bonds specialzation.

We recognize the existence of innumerable confounding factors in one of the world's largest secondary markets where traders interact with a variety of entities including companies, governments, banks, and NGOs across different countries. The market comprises participants with diverse business models, including hedge funds, investment banks, and pension funds, all of whom engage in trades within this secondary market. Consequently, the objective of this paper is to propose a possible explanation rather than establishing precise causality. However, we attempt to alleviate the endogeneity issues by lagging variables over different periods, adding dealer and time dummies, and controlling for the commonality of the bond sets between the two dealers in each dealer pair.

The regression results are presented in Table 6. To test for robustness, we run seperate regressions by lagging the correlation of order imbalance by 1 quarter, 4 quarters, and 8 quarters, respectively. Lagging this variable allows the model From the first regression, γ_1 is negative, indicating that a lower correlation leads to a higher trading share between dealer A and dealer B in a dealer pair. This result is intuitive. As the model suggests, if historically two dealers have tended to trade in less correlated directions, there will be a higher trading surplus between them for sharing inventory risk compared to a situation with a higher correlation. Suppose there is another dealer, C, and Dealer A and C have a higher correlation compared with Dealer A and B. Then, when Dealer A suffers a higher liquidity demand from her clients, Dealer B will suffer a lower liquidity demand from her clients than Dealer C, leading to a higher aggregate trading surplus between Dealer A and B than between Dealer A and C. So, it is favorable for dealers to strengthen long-term partnerships with lower-correlated trading partners. Doing so allows them to minimize inventory fluctuations while still effectively providing liquidity to their respective clients. For regression 2 and 3, γ_1, which represents the long-term correlations lagged by 4 and 8 quarters, is not significant. These regressions are intended as robustness checks and lagging over such extended periods of 4 to 8 quarters might contribute to the insignificance of γ_1. However, γ_4, intended to capture the impact of the introduction of the Dodd-Frank Act into law, is significantly negative across all regression specifications. This supports the hypothesis that dealers aim to strengthen their trading relationships with partners that have lower correlations to reduce capital commitments and inventory fluctuations. The results hold even when lagging correlation variables for up to 2 years. Furthur, for the three regression specifications, most of the γ_2 and γ_3 consistently show negative values. These variables are designed to identify structural breaks during the crisis and the post-crisis period before the Dodd-Frank Act was enacted. Their negative values further suggest that during these challenging times, dealers aimed to reduce inventory fluctuations and minimize capital commitments by trading more with partners having lower correlations.

In addition to accounting for the common bond sets between each pair of dealers, we have incorporated various control factors aimed at capturing the nuances of interactions between the two dealers. These factors encompass disparities in centrality, trading shares, the duration of their trading history, standard deviation in order imbalance, and differences in average bond grading. These additional controls do not alter the results pertaining to γ_1, γ_2,γ_3 and γ_4. Particularly noteworthy is the robustness of the significant negative values observed for γ_4 across various control settings and lagging periods, underscoring the consistency of our findings. To ensure conciseness, we do not include all coefficients of control variables in the regression results.

Table 2.5: Regression Results: Analysis of Trading Shares and Correlation of Order Imbalance for each Period

	(1)	(2)	(2)
γ_1	-0.0014*** (0.0004)	-0.0007 (0.0004)	0.0011 (0.0007)
γ_2	-0.0022** (0.0009)	-0.0007 (0.0009)	-0.0031*** (0.0010)
γ_3	-0.0022 (0.0017)	-0.0038*** (0.0011)	-0.0030** (0.0012)
γ_4	-0.0039*** (0.0009)	-0.0042*** (0.0010)	-0.0057*** (0.0011)
Dealer A Dummy	Yes	Yes	Yes
Dealer B Dummy	Yes	Yes	Yes
Time Dummy	Yes	Yes	Yes
Observations	3487842	3221012	2862367
R squared	0.1217	0.1232	0.1273
	***p<0.01, **p<0.05, *p<0.1		

The main variable of interest, the correlation of order imbalance, is lagged over different periods to check for robustness. Regression 1 lags the correlation of order imbalance by 1 quarter, Regression 2 lags the correlation of order imbalance by 4 quarters, and Regression 3 lags the correlation of order imbalance by 8 quarters. The dependent variable is $Share_{A,B,t}$, which is the trading share between the two dealers for quarter t.

2.6 Conclusion

In the aftermath of the financial crisis, regulatory initiatives aimed at mitigating dealers' risk were introduced, focusing on dealers' trading behavior and inventory management. These regulations had a significant impact on the behavior of dealers in the US corporate bond market. Bessembinder et al. (2018) demonstrated a substantial reduction in dealers' capital commitment, reflecting their decreased willingness to allow inventory fluctuations to provide liquidity. Surprisingly, the effects of post-crisis regulations on the liquidity of the US corporate bond market remain somewhat ambiguous. Some studies suggest no change or even enhancement of liquidity, while others conclude that liquidity deteriorated.

In this paper, we have introduced a straightforward model designed to explore the potential connection between dealers' trading relationships, inventory fluctuations, and the liquidity they offer. According to our model, when dealers increase their engagement with partners displaying lower correlated order flow, they can enhance liquidity levels while keeping inventory fluctuations at similar levels. Empirical analysis of transaction data lends support to this hypothesis, demonstrating a significant shift in dealers' preferences toward trading more frequently with lower correlated partners, especially after the implementation of the Dodd-Frank Act.

The hypothesis raises the possibility that stricter regulations regarding dealers' inventory, despite facing substantial criticism for potential negative effects on liquidity, may yield some positive outcomes. Specifically, these regulations might incentivize dealers to enhance their trading relationships, strengthening their ties with other dealers who tend to trade in opposing directions. While these regulations may reduce dealers' willingness to commit capital for facilitating liquidity provision, they may also exert pressure on dealers to optimize their relationships with other dealers. This optimization can result in an enhanced trading network and decreased inventory fluctuations required for liquidity provision, shedding light on why conclusions regarding post-crisis liquidity are somewhat uncertain. In contrast to classical models that propose that higher costs associated with inventory fluctuation and capital commitment negatively impact market liquidity, our model emphasizes a counterbalancing mechanism that offsets the decline in liquidity.

This research also underscores the importance of fostering more efficient and interconnected markets. Following the financial crisis, various mechanisms were introduced to the market, such as electronic trading platforms that enable "all to all" trading (allowing clients to trade directly with each other), challenging the traditional role of dealers. Additionally, innovations in financial technologies have reduced the cost of finding trading partners.

However, despite the proliferation of new trading protocols, it is noteworthy, as indicated by numerous academic studies and practitioner reports, that the traditional method of trading bonds—contacting familiar dealers and relying on long term trading partners—still holds significant influence and continues to dominate the market. While this paper does not delve into the reasons why dealers and clients persist with traditional trading methods despite the availability of new alternatives, it does suggest that stricter regulations on dealers' inventory, while potentially impacting liquidity, can compel the optimization of relationships with long-term trading partners.

Chapter 3

Search and Inventory in the Over-the-Counter Market

3.1 Introduction

Trading in over-the-counter (OTC) markets is often described in terms of a network structure in which some dealers are more central than others. An empirical regularity across many markets is the presence of a centrality premium, whereby dealers who are more central charge more for transacting the same security. This premium exists in the OTC market for corporate bonds, in the foreign exchange market, in overnight bank lending, in debt securitizations (in the form of a discount) and in the municipal bond market. Given the size and importance of these markets, understanding the centrality premium is important for fostering transparency and efficiency in off-exchange markets.[1]

What is the source of this premium? Possible explanations involve bargaining power, trading speed and efficiency, or compensation for liquidity provision. We examine this question in the context of corporate bond trading. Corporate bonds trade in OTC markets, in which dealers and customers negotiate transaction terms bilaterally. This market is characterized by infrequent trading of many bond issues, and concentrated trading among a few participants called dealers, who intermediate between institutional clients (Babus **and** Peter Kondor 2018). An unresolved question is why trading costs tend to be higher in dealer-oriented markets compared to peer-to-peer exchange-based markets (Hendrik Bessembinder, Spatt **and** Kumar Venkataraman 2020a)?

To answer this question, we examine the pricing of roundtrip transactions in the U.S. corporate bond market. In a roundtrip, a dealer buys and then sells the bond possibly at a later date, and usually at a higher price than the purchase price. Roundtrip spreads consist of the difference between the sale and purchase price by a dealer on sequential buy and sell orders, of (possibly) different amounts in the same bond over one or multiple days. Consistent with prior findings, we find a substantial and pervasive centrality premium. Roundtrip spreads are larger by several basis points for core dealers than peripheral dealers, on both intraday roundtrips (*i.e.*, purchases and sales completed in the same day) and

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[1] See Di Maggio, Kermani **and** Z. Song (2017a) and Colliard, Foucault **and** Hoffmann (2021a) for evidence on the centrality premium in the corporate bond market, Hasbrouck **and** R. M. Levich (2021) for the foreign exchange market, Gabrieli **and** Georg (2014) for overnight bank lending, R. C. Green, Hollifield **and** Schürhoff (2007) for debt securitizations, and D. Li **and** Schürhoff (2019) for the muncipal bond market.

multiple day roundtrips. We show both theoretically and through structural estimation that the centrality premium in this market is driven by the difference between core and peripheral dealers in searching effectively for counterparties to trade with. The premium is thus closely related to the provision of liquidity. Core dealers exert higher search effort than peripheral dealers, but hold out for higher-value clients than peripheral dealers after taking a bond into inventory. The net effect is that core dealers earn higher roundtrip spreads. Thus core dealers play a unique role in facilitating liquidity flow in the corporate bond market.

In order to formalize this intuition, we construct a dynamic model of endogenous search effort and roundtrip spreads that characterizes dealers' optimal trading behavior and identifies the sources of the dealer centrality premium. Our model features (i) dealer and bond heterogeneity, (ii) costly inventory, and (iii) endogenous search effort of dealers in finding clients. Dealers are heterogeneous in terms of their position in the network. Core dealers, *i.e.*, those closer to the network center, have an advantage relative to peripheral dealers in contacting clients: exerting effort to find clients is less costly for core dealers. Bonds are heterogeneous in terms of periodic coupon, survival rate and quantity traded.

In each period, upon random arrival of a client-seller, the dealer negotiates with the client-seller over the bid price. If the dealer successfully acquires this bond, it then immediately makes a decision on how much effort to exert in searching for a client-buyer for this bond. Search costs strictly increase with effort. If the dealer successfully meets with a client-buyer, it negotiates with the client-buyer over the ask price. The dealer sells the bond if both parties agree on the price. If the dealer does not meet a client-buyer, the dealer contacts a fellow dealer immediately (at no cost) and negotiates with the latter for the ask price. If the negotiation (either with a potential client-buyer or another dealer) is unsuccessful, the dealer holds the bond in inventory and tries the search and bargaining procedure again in the next period, until a successful sale of the bond.

With this, our model naturally gives rise to endogenous intraday and multiday roundtrips and generates endogenous roundtrip spreads for both dealer-to-client (D2C) trades and dealer-to-dealer (D2D) trades. As a baseline, we assume that no dealer has any advantage in bargaining power relative to each other, while all dealers enjoy a greater bargaining power relative to their clients. This leads to a result that a dealer will always exert a positive amount of effort in searching for a client for any bond it holds.

We also prove theoretically that bonds of sufficiently low quality (conditional on acquisition) are guaranteed to sell in an intraday roundtrip by dealers of any centrality. We call these Guaranteed Intraday Trades (GIT). The intuition is the following: for an acquired bond that is sufficiently low in quality (*i.e.*, high default risk or low coupon rate relative to the dealer's inventory costs and cost of funds), it is optimal for a dealer, core or peripheral, to sell it in an intraday fashion to avoid incurring inventory costs on a low-value bond. Proving the existence of GITs identifies core dealers' strength in search as a key source of the centrality premium.

We structurally estimate this model with U.S. corporate bond transaction data. Bargaining power and inventory costs are held constant across core and peripheral dealers in order to identify search. Despite these restrictions, estimates of the average centrality premium are close to the average observed centrality premiums in the data. Core dealers differ in both search effort and willingness to hold bonds in inventory: these dealers exert more search effort than peripheral dealers, hold out for higher-value clients once the bond is in inventory, and sell the same bond at a higher price than peripheral dealers, *i.e.*, the same bond is traded with a higher roundtrip spread. A natural consequence is that it is easier for clients to sell bonds to a core dealer in the sense that the gains from trade are larger for core than peripheral dealers.

Core dealers' advantage in search is best understood by differentiating between GITs and non-GIT trades. We show counterfactually that core dealers exert greater search effort per unit of bond than peripheral dealers on guaranteed intraday trades. Despite holding these bonds in inventory exactly the same amount of time as peripheral dealers (one day), core dealers earn an 11 bps centrality premium. We also find that core dealers provide greater liquidity than peripheral dealers in that the former are more likely to buy from a client and take into inventory non-GIT.

While bargaining power and inventory costs are held constant across dealers in the estimation, we vary these metrics counterfactually to quantify core dealers' advantage in search. This sensitivity analysis reveals that core dealers' advantage in search is equivalent to a 6.8% advantage in bargaining power in the D2C market and a 21.5% advantage in marginal inventory costs over peripheral dealers.

Our paper relates to prior literature that shows that the decision to take a bond into inventory is related to its liquidity (Dick-Nielsen, Rossi **and** I. Goldstein 2018, Ellul, Jotikasthira **and** Lundblad 2011 and Hendrik Bessembinder, Jacobsen **andothers** 2018a). Core dealers in our framework trade "slower" in the sense that their advantage in search allows them to be more selective in whom they sell to. On the one hand, it is true that core dealers enjoy a higher contact rate in finding counterparties as search is less costly for them. On the other hand, core dealers also find it optimal to set a higher threshold for ask prices for a bond with a given quality and a given trade size. The latter effect dominates and implies that core dealers hold bonds in inventory longer than peripheral dealers, which makes core dealers appear to trade slower.

Previous work theoretically addresses the centrality premium. For example, Babus **and** Peter Kondor (2018) study information diffusion in a model of OTC trades and show that core dealers tend to learn more, trade more at lower costs and earn higher expected profit. Glode **and** Opp (2020) make a similar point and show theoretically that well-connected core traders earn rents from expertise acquisition in OTC markets when gains to trade are uncertain. In contrast, our model illustrates that core dealers' advantage in searching for counterparties implies a centrality premium in an environment without asymmetric information and learning.

Our paper complements models of search frictions in asset trading such as Duffie, Garleanu **and** Pedersen (2005), Lagos and Rocheteau (2009), Lagos, Rocheteau **and** Weill (2011), and others surveyed in Weill (2020a). Often in these papers, investors have random contacts with dealers at an exogenous rate and prices are bargained bilaterally. Dealers are assumed to offload inventories through a frictionless inter-dealer market. The papers closest to our work are by Hugonnier, Lester **and** Weill (2020b) and Liu (2020). Hugonnier, Lester **and** Weill (2020b) generalize the benchmark search-theoretic model of OTC markets by Duffie, Garleanu **and** Pedersen (2005) and allow for a decentralized inter-dealer market with arbitrary heterogeneity in dealers' valuations (or, equivalently, inventory costs). Their model is tractable and provides closed-form, theoretical formulas for key statistics analysed in empirical studies of OTC markets. Liu (2020) proposes and structurally estimates a model with dealers choosing search intensities. The main finding is that dealers with medium private valuations endogenously intermediate trades of other dealers, and there is considerable trading inefficiency associated with the OTC market.

Similar to these two papers, we develop a tractable structural model based on a rich set of market characteristics. Nevertheless, our paper differs both in terms of the theoretical structure and the findings. We focus on understanding the dealer centrality premium. Because the ability to process large trades can be one of the advantages of core dealers, it is important to allow for continuous trade sizes and inventory trade-offs, instead of the 0-1 asset position considered by Hugonnier, Lester **and** Weill (2020b) and Liu (2020). This generates endogenous behaviors of core and peripheral dealers that vary in search intensities and roundtrip spreads. Our results contrast with the role bargaining and inventory costs play in models of OTC markets that emphasize dealer market power (R. C. Green, Hollifield **and** Schürhoff 2007) or inventory-bearing capacity (Eisfeldt **andothers** 2023).

This paper is organized as follows. Section 2 discusses the data, how we measure roundtrip spreads and how we identify core and peripheral dealers. Section 3 documents the empirical regularity of the centrality premium, and how it varies by dealer's holding period. In section 4, we present the theoretical model environment. Section 5 investigates the sources of the centrality premium through structural estimation. Section 6 concludes.

3.2 Data

Bond transaction prices and amounts are based on the Academic Version of TRACE with observations between January 1, 2010 and October 31, 2012. We focus on this earlier period because very few trades were executed on electronic trading platforms prior to 2012.[2] Including such transactions would make inferences from calibrating a dealer-inventory model more difficult. Hendershott **and** Madhavan (2015a) and O'Hara **and** Xing (2021) provide stylized facts on electronic trading *vs.* traditional dealer-to-client trading.

We exclude any transaction within 60 days of offering date and maturity, any convertible bonds, and bonds that do not trade at least once starting 60 calendar days after the bond offering date. We also exclude transactions involving bonds that have a missing maturity, perpetual bonds, bonds with maturity dates less than one month away from the trade date, and bonds with a missing coupon rate. Raw transaction data is cleaned using the algorithm described in Dick-Nielsen (2009).

In order to identify roundtrip trades, we follow M. Goldstein **and** E. Hotchkiss (2020) and proceed in three stages. First, we match the buy trade and sell trade for a given bond with the same quantity, from the same dealer on the same day. If more than two sell trades can be matched with the initial buy trade, we match the buy to the sell trade that is closest in time. After a pair of trades have been matched, they are set aside and labelled as part of an intraday roundtrip, and the above process repeats, until there are no trades with the same quantity for the same bond and dealer on the same day that can be matched. Second, we match the buy trades and sell trades within the same day, for the same bond and same dealer, allowing one buy trade to be matched with several subsequent sell trades, with a dealer's sell orders summing up to the quantity of the initial buy order. If adding one sell order leads to the aggregate sell amount exceeding the initial buy amount, then the last sell order is split into two parts, with the first part matched to the initial buy order so that the sum of sells is equal to the quantity of the buy, while the remaining part is left in the data to be matched with other buy orders. Third, we match the initial buy trade for the same bond for a given dealer with sell trades transacted within 60 days after the transaction date of the initial buy trades, as described in step 2 above, according to a first-in first-out rule.

Following these steps, we exclude roundtrip trades, where the initial buy transaction

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[2] The share of electronic trading was less than 10% of total volume in 2011 and 2012 (O'Hara **and** Xing 2021).

size is less than \$100,000 in notional value. We further exclude roundtrips initiated by inter-dealer trades since our focus is on *client-initiated roundtrips*. Note that intraday roundtrips can either be inititated by a sale or a purchase order by a client. Multiday roundtrips are always initiated by a buy order (*i.e.*, client sells to dealer). These steps yield 1,161,026 roundtrip trades involving 13,440 unique CUSIPs.

Bond prices are expressed as a percentage of par value.[3] We define the roundtrip spread as the weighted sell price minus the initial buy price, where the selling price is weighted by the trade quantity of each sell order. Thus a roundtrip spread of 15 bps, indicates that the difference between the sale and purchase prices was 0.15% of par value. Whenever a roundtrip lasts more than one day, we calculate the weighted average holding period for each bond, where the weights are determined with the amount sold on each transaction date associated with a given roundtrip.

We also classify roundtrips by who the bonds are sold to. If any amount of the roundtrip is sold to a client, then this roundtrip is classified as a Dealer-to-Client (D2C) roundtrip. If all of the amount of the roundtrip is sold to a dealer, then the roundtrip is classified as a Dealer-to-Dealer (D2D) roundtrip. Only about 10% of roundtrips end up being sold to both clients and dealers.

We measure bond liquidity as the number of trades during the 30-day period before the initial buy order of each roundtrip trade ($TradeCount$). We rank the bonds' liquidity into 10 deciles according to $TradeCount$, where Decile 1 consists of the least frequently traded bonds and Decile 10 the most frequently traded bonds.

We also define variables at the dealer level that measure dealer trading and inventory-taking activity. $PastDaysTraded$ and $PastDaysInventory$ summarize the trading history for each bond of a given dealer. $PastDaysTraded$ equals the number of times a given dealer traded this bond in the year prior to the start of the roundtrip. $PastDaysInventory$ equals the number of days the dealer took this bond into inventory in the year prior to the start of the roundtrip. Variable definitions are provided in Appendix A.

We measure the core-periphery structure following Colliard, Foucault **and** Hoffmann (2021a).[4] For each quarter, we define a dealer as connected to another dealer if the two dealers trade at least once within this quarter. Core dealers are defined as members of the largest "clique", where a clique consists of any subset of dealers that are connected to all other members of this subset in a given quarter. Any dealer not defined as a core dealer is classified as a peripheral dealer. On average in a given calendar quarter, there are 37 core

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[3] Transaction prices correspond to the clean price, which equals the economic value of the bond minus accrued interest.

[4] We thank Jean-Edouard Colliard for providing the code for identifying core dealers. This code is sourced from Jean-Edouard Colliard's website at https://sites.google.com/site/jecolliardengl/research?authuser=0.

dealers and 1,099 peripheral dealers. Appendix A reports transition probabilities from core to peripheral status and *vice versa.* Core and peripheral dealer status are stable over time.

Table 3.1 provides some summary statistics. Almost a third of trades are between 1M and 5M in notional amount. There is variation in liquidity as measured by past 30-day trade counts ($TradeCount$): some bonds may not trade at all over the past 30 days, while other bonds trade over 11,000 times over a given 30-day period. However, the median bond trades infrequently, with a trade-count of just 128 times over the past 30 days, or approximately 4 times a day. The mean roundtrip spread is 29 basis points, and the median is 15 bps. Roundtrip trades completed in more than one day (*i.e.*, multiple-day roundtrips) have on average a higher spread (32 basis points) than intraday roundtrip trades (24.5 basis points), implying dealers charge significantly higher spread to take the overnight inventory risk. How long do dealers hold the bonds in inventory on average? The average holding period is 8.5 days, while the average holding period equals 14.7 days conditional on a multi-day roundtrip. More than half (62%) of the roundtrips observed in the sample are executed by core dealers.

Table 3.2 Panel A reports mean and medians for spreads and holding periods by dealer type. Core and peripheral dealer trade sizes and trade count deciles are similar, with core dealers trading slightly less liquid bonds than peripheral dealers. Core dealers earn a centrality premium, as evidenced by the higher average and median spreads on both intraday and multiday roundtrips. The next section shows that this premium is persistent over the sample period.

Core dealers also differ in how long they hold on to bonds that are taken into inventory. The average holding period is 10 days for core dealers and 5.9 days for peripheral dealers. Longer holding periods can be explained by core dealers' lower propensity to engage in intraday roundtrips: core dealers engage in intraday trips 31% of the time, compared with 61% for peripheral dealers. Conditional on engaging in a multiday roundtrips, holding periods are about equal at about 15 days for both types of dealers. Core dealers differ in the frequency at which they trade a given bond. As shown, core dealers trade any given bond 50 days per year on average, compared with only 28 days for peripheral dealers (*Past days traded*).

Panel B splits the sample into intraday and multi-day trades. Core dealers execute about 45% of intraday trades and 74% of multiday trades, suggesting that core dealers supply liquidity by holding bonds in inventory overnight. Intraday and multiday trades have similar trade counts (median trade decile is 5 for both types), but bonds traded intraday tend to be less traded in the previous year by the trading dealer (median of 15 times for intraday trades *vs* 35 for multiday trades). This feature suggests that bonds held in inventory overnight may be easier for the dealer to trade. Current intraday trades are taken into inventory (*Past days inventory*) less often in the prior year than multiday trades (median of 0 for intraday trades *vs* 7 days for multiday trades). Bonds that trade intraday are likely to have traded intraday in the previous year by the dealer.

3.2.1 Centrality Premium in Roundtrip Spreads

Figure 3.3 plots the difference between median core and median peripheral spreads for intraday and multiday roundtrips. As shown, the centrality premium exists for both types of roundtrips. This premium is always positive in the case of intraday roundtrips, and more often positive than negative for multiday roundtrips. Thus, core dealers earn higher roundtrip spreads than peripheral dealers on both intraday roundtrips and multiday roundtrips.

Glode **and** Opp (2020) predit that trading skill is correlated with the surplus earned by dealers in OTC markets. The centrality premium may thus be related to the holding period if core dealers are more skilled at managing the inventory risk associated with certain bonds. If so, then we would expect the centrality premium to increase with the holding period. Figure 3.4 plots the centrality premium by holding period, measured in weeks. There appears to be no discernible pattern as the premium remains relatively flat up to 7 weeks. The premium rises in week 8. However, the number of roundtrips lasting eight weeks is low. The flat relation between holding period and the centrality premium is inconsistent with a core dealer advantage in terms of inventory costs.

We next investigate whether this premium varies with bond liquidity. Figure 3.5 plots the centrality premium for intraday and multiday trades by decile of trade count. Decile 1 is comprised of bonds with the lowest trade count, and decile 10 is comprised of bonds with the highest trade count. As shown by the blue line with circles, centrality premiums are decreasing in trade counts for intraday roundtrips, but not multiday roundtrips.

The subsets of bonds traded by core and peripheral dealers may be different in terms of credit rating, liquidity and tenor. Certain types of bonds may only trade through intraday trades, which can lead to differences in roundtrip spreads on bonds traded intradaily *vs* over several days. Does the centrality premium persist when we control for both bond features and selection into overnight inventory? We provide estimates of a two-step selection model in Appendix B that takes into account bond features and dealers' decision to hold the bond into overnight inventory. Core dealers charge approximately 7.8 bps more on intraday roundtrips than peripheral dealers, and 7.4 bps more than peripheral dealers on multiple-day roundtrips, controlling for trade size, bond age, *etc.* The centrality premiums on the two types of roundtrips are not significantly different from each other.

What is then the source of this premium if it persists after controlling for both selection into inventory and observable bond features? In order to answer this question, we formulate a model of search and inventory management. The framework allows us to activate/deactivate dealer characteristics such as market power in the dealer-to-client market, and measure the efficiency of a dealer's search technology, as well as dealer inventory costs.

3.3 Model Environment

Having documented the presence of a centrality premium in roundtrip spreads, we construct a theoretical framework that incorporates a dealer's inventory choice and search activity. We describe the model environment and characterize the optimal decisions. Later in the next section, we structurally estimate our model with roundtrip transaction data.

The modelling framework differs from the standard OTC search setup along three dimensions. First, we do not assume constant contact rates as in Duffie, Garleanu **and** Pedersen (2005). Relaxing this assumption permits endogenous search intensities to vary with the status of the dealer in the network. Second, we allow for a continuum of trade amounts instead of assuming a binary 0-1 position in the asset. This allows us to factor in dealer inventory positions and costs into the estimation process. In particular, dealer search intensity can vary with the size of the position held in inventory. Third, we do not assume a flow utility of holding on to a bond. Instead, the value of holding the bond is a function of the coupon rate, the dealer's cost of funds and inventory costs.

Time is discrete and continues forever. The economy consists of a continuum of risk-neutral dealers and clients. Each dealer is characterized by its centrality denoted by $d \in [0,1]$, which is the distance of this dealer from the center of the dealer network. Thus a dealer with a greater d is more peripheral relative to the whole network. In each period, a dealer takes a random draw on the opportunity to acquire some bond with characteristics (q, θ, α), where q is the size of the issuance, θ is the periodic coupon and α is the survival rate of the bond in each period. That is, the bond loses its value with probability $1-\alpha$. The variables (q, θ, α) are *i.i.d.* from respective distributions with supports $\left[\underline{q}, \bar{q}\right]$, $\left[\underline{\theta}, \overline{\theta}\right]$, and $[\underline{\alpha}, \bar{\alpha}]$. To acquire the bond, the dealer negotiates with the client over the *bid price.*

Upon acquiring this bond, the dealer chooses an *effort*, $e \in [0, \infty]$, to search for a client buyer. Let $s\left(e; d\right)$ be the search cost associated with effort level e for a given dealer centrality d, where $s\left(0; d\right) = 0$ and $s\left(\infty; d\right) = \infty$ for all d, $\partial s/\partial e > 0$ with $\lim_{e \to 0} \partial s/\partial e = 0$ and $\lim_{e \to \infty} \partial s/\partial e = \infty$, and $\partial s/\partial d > 0$. Moreover, $\partial^2 s/\partial e^2 > 0$ and $\partial^2 s/\partial d \partial e > 0$. That is, given d the greater the search effort, the greater the search cost. Similarly, given

e the more peripheral the dealer, the higher the search cost as d is a measure of the connectedness of a dealer with the rest of the network. Through exerting effort e, the dealer's probability of matching with a client with a capacity[5] of q and below is given by $F(q;e)$, where $F(q;0) > 0$, $\partial F/\partial e < 0$ and $\partial^2 F/\partial e^2 \geq 0$. With the latter two assumptions, the probability of matching with a client of $\geq q$ is given by $[1 - F(q;e)]$, which is strictly increasing and concave in effort e. This renders the marginal benefit of increasing effort strictly decreasing as the effort rises. Dealers with lower d have superior search technology in terms of the cost of one additional unit of effort. Structural estimation of these functions quantifies the magnitude of this advantage of core dealers over peripheral dealers.

If the dealer does not get to meet a client of $\geq q$, then it will approach another dealer in the network for a possible trade within the period. If the negotiation (either with a potential client-buyer or another dealer)[6] fails, then the dealer holds this bond as inventory to the next period, which involves an exogenous, per-unit cost of $k > 0$ per period. When meeting with a potential buyer, being either a client or another dealer, the dealer negotiates with the counterparty over the *ask price*. If the dealer manages to acquire and sell the bond within the same period, we call it an *intraday roundtrip*. All other trades are *multiday roundtrips*. The bond survival shock hits at the end of each period.

Timing of events. The timing of events in a typical time period is given by the following:

1. Bond coupons are paid to the bondholder at the beginning of a period.
2. Dealer is approached by a client seller in the dealer-to-client (D2C) market. If the dealer successfully acquires the bond, it will decide how much effort to exert in searching for a client-buyer to trade.
3. A successful contact with a client of $\geq q$ leads to either a successful sale or no trade. If no trade, then the dealer holds the bond in inventory into the next period.
4. If no successful contact with a client of $\geq q$, the dealer will contact another dealer to trade in the inter-dealer market (D2D). Similarly, a contact with a dealer leads to

---

[5] The capacity of a client can be interpreted as various financial and regulatory constraints that limit the demand for a certain bond by a client.

[6] Note that the assumption is that the dealer can only engage in one negotiation per period. It can choose to search for a client counterparty. If a meeting with a client does not happen, the dealer can reach out to another dealer at no cost and engage in a negotiation. The contact with another dealer does not occur if the dealer has met with a client but failed the negotiation. Excluding the prospect of multiple negotiations a day over a particular bond transaction helps greatly simplify the analysis and save computation time in the estimation process. Moreover, perhaps it is not as restrictive an assumption as it might seem, from a realistic point of view, because negotiations take time to carry out and each dealer works with numerous transactions everyday.

either a successful sale or no trade. If no trade, then the dealer holds the bond in inventory into the next period.

5. Bond default events are realized at the end of a period for bonds held in inventory.

For a successful intraday roundtrip, the dealer actively goes through three stages: negotiation with a seller, decision on search effort, and negotiation with a buyer (a client or a dealer). Next we introduce the respective buying and selling negotiations, before investigating the optimal choice of search effort.

3.4 Dealer Search and Inventory Cost

3.4.1 Price Negotiations

Bid-price negotiation (client selling to dealer)

Let us first consider the negotiation between the dealer and a *client-seller*. The latter has a valuation $\left(v + \frac{\theta}{1-\alpha\beta}\right) q$ for the bond for any q below its capacity, where v is *i.i.d.* from a distribution of CDF $F_v(v)$ with support $[\underline{v}, \bar{v}]$. The value v is an idiosyncratic component that determines the gains from trade (or trade surplus) between sellers and buyers. The term $\frac{\theta}{1-\alpha\beta}$ represents the fundamental value of the bond and is the present value of perpetuity with discount factor $\alpha\beta$. The term α represents the bond's survival rate (the inverse of the default rate) and β is a function of the risk-free rate. Let $\sigma \in (0.5, 1)$ be the bargaining power of the dealer to trade with a client. Moreover, b represents the negotiated bid-price with a client. The client-seller's trade surplus is the sales revenue less the value of holding onto the bond, which is given by:

$$bq - \left(v + \frac{\theta}{1-\alpha\beta}\right) q. \tag{14}$$

The dealer's trade surplus is the value of owning the bond less the purchase payment. It is thus given by

$$V(d; q, \theta, \alpha) - bq,$$

where $V(d; q, \theta, \alpha)$ is the dealer's value of owning the bond with characteristics (q, θ, α), given the dealer's centrality d. We will characterize $V(d; q, \theta, \alpha)$ later when we study the dealer's search choice. Thus the total surplus is given by

$$V(d; q, \theta, \alpha) - \left(v + \frac{\theta}{1-\alpha\beta}\right) q.$$

The negotiation splits the total trade surplus according to the bargaining powers:

$$(1-\sigma)[V(d;q,\theta,\alpha)-bq]=\sigma\left[b-\left(v+\tfrac{\theta}{1-\alpha\beta}\right)\right]q. \tag{15}$$

Therefore, the optimal choice of b is given by

$$b(v,d,q,\theta,\alpha)=\frac{1}{q}(1-\sigma)V(d;q,\theta,\alpha)+\sigma\left(v+\frac{\theta}{1-\alpha\beta}\right). \tag{16}$$

A trade will occur if and only if the total trade surplus is non-negative. That is,

$$V(d;q,\theta,\alpha)\geq\left(v+\frac{\theta}{1-\alpha\beta}\right)q,$$

which requires the client-seller to have

$$v\leq\frac{1}{q}V(d;q,\theta,\alpha)-\frac{\theta}{1-\alpha\beta}\equiv\tilde{v}_b(d,q,\theta,\alpha). \tag{17}$$

The last term $\tilde{v}_b(d,q,\theta,\alpha)$ represents the *bid-price sale threshold.* Without loss of generality, we focus on a client-seller approaching the dealer. Although a bidding negotiation could also be initiated by another dealer, the bid-price sale threshold for a D2D case would still be $\tilde{v}_b(d,q,\theta,\alpha)$ as is with the D2C. As is seen above, the derivation of $\tilde{v}_b(d,q,\theta,\alpha)$ does not depend on the respective bargaining powers of the seller and the bidding dealer.

Ask-price negotiation in the dealer-to-client market (D2C)

We now consider the negotiation between the dealer and a *client-buyer.* The latter has a valuation $\left(v_c+\frac{\theta}{1-\alpha\beta}\right)q$ for the bond, where v_c is *i.i.d.* from a distribution with CDF $F_v(v)$ with support $[\underline{v},\bar{v}]$. Recall that $\sigma\in(0.5,1)$ is the bargaining power of the dealer to trade with a client. Moreover, p_c represents the negotiated ask-price with a client. Similar to the bid-price negotiation, the client-buyer's trade surplus is given by

$$\left(v_c+\frac{\theta}{1-\alpha\beta}\right)q-p_cq \tag{18}$$

and the dealer's trade surplus is given by

$$p_cq-\alpha[\beta V(d;q,\theta,\alpha)-kq]. \tag{19}$$

If an agreement is not reached and the bond survives the current period with probability α, then the dealer will continue to hold the bond and incur the inventory cost kq. Again, the negotiation splits the surplus between a dealer and a client-buyer according to

$$(1-\sigma)[p_cq-\alpha\beta V(d;q,\theta,\alpha)+\alpha kq]=\sigma\left[\left(v_c+\tfrac{\theta}{1-\alpha\beta}\right)q-p_cq\right] \tag{20}$$

Thus the D2C ask price p_c is given by

$$p_c\left(v_c, d, q, \theta, \alpha\right) = \sigma\left(v_c + \frac{\theta}{1-\alpha\beta}\right) + (1-\sigma)\frac{\alpha}{q}\left[\beta V\left(d; q, \theta, \alpha\right) - kq\right]. \tag{21}$$

For a trade to take place, the total surplus must be non-negative, which requires

$$v_c \geq \alpha\left[\frac{\beta}{q}V\left(d; q, \theta, \alpha\right) - k\right] - \frac{\theta}{1-\alpha\beta} \equiv \tilde{v}\left(d, q, \theta, \alpha\right), \tag{22}$$

where we have defined $\tilde{v}\left(d, q, \theta, \alpha\right)$ as the dealer*'s net ask-price trade threshold*, or the net trade threshold $\tilde{v}$ for short. Note that the gross trade threshold equals $\tilde{v} + \frac{\theta}{1-\alpha\beta}$, which is the break-even value from the perspective of the dealer.

Ask-price negotiation in the inter-dealer market (D2D Market)

If the dealer fails to find a match in the D2C market, it will turn to the inter-dealer market and search for a dealer counterparty. The negotiation between the dealer and a dealer-buyer is similar to the one with a client-buyer, except that the bargaining power is now $\sigma = 0.5$. Thus, the negotiated ask-price with a dealer-buyer (*i.e.*, the inter-dealer price), denoted by p_d, is given by (21) with $\sigma = 0.5$:

$$p_d\left(v_d, d, q, \theta, \alpha\right) = 0.5\left(v_d + \frac{\theta}{1-\alpha\beta}\right) + 0.5\frac{\alpha}{q}\left[\beta V\left(d; q, \theta, \alpha\right) - kq\right] \tag{23}$$

where v_d is the dealer-buyer's random draw from the same distribution $F_v\left(v\right)$. Similar to (22), a trade between two dealers takes place iff the dealer-buyer's valuation satisfies $v_d \geq \tilde{v}\left(d, q, \theta, \alpha\right)$.

3.4.2 Optimal Search Behavior

Upon acquiring a bond of characteristics (q, θ, α), the dealer chooses $e \geq 0$ in effort to search for a client-buyer and maximize the expected value of holding the bond at the beginning of a period, $V(d,q,\theta,\alpha)$:[7]

$$V(d,q,\theta,\alpha)=\max_{e\geq 0}\left\{\begin{array}{c}\theta q+[1-F(q;e)]\int_{\tilde{v}(d,q,\theta,\alpha)}^{\bar{v}}p_c\left(v_c,d,q,\theta,\alpha\right)qdF_v\left(v_c\right)\\ +F(q;e)\int_{\tilde{v}(d,q,\theta,\alpha)}^{\bar{v}}p_d\left(v_d,d,q,\theta,\alpha\right)qdF_v\left(v_d\right)\\ +F_v\left(\tilde{v}\left(d,q,\theta,\alpha\right)\right)\alpha[\beta V(d,q,\theta,\alpha)-kq]-s(e;d)\end{array}\right\}. \tag{24}$$

The first term in the objective function is the coupon for the current period. The next three terms cover all possible scenarios in terms of selling the bonds: With probability $1-F(q;e)$, the dealer meets with a client-buyer of capacity $\geq q$. The dealer gets to sell the bonds to this buyer if the latter has a valuation no less than $\tilde{v}\left(d,q,\theta,\alpha\right)$. The sales revenue is $p_c\left(v_c,d,q,\theta,\alpha\right)q$. With probability $F(q;e)$, the dealer does not meet a client-buyer of sufficient capacity[8] and thus contacts another dealer of capacity $\geq q$. The sale goes through if the dealer-buyer has a valuation no less than $\tilde{v}\left(d,q,\theta,\alpha\right)$. Obviously, there is no sale within the period if neither the client-buyer nor the dealer-buyer has a valuation below $\tilde{v}\left(d,q,\theta,\alpha\right)$. Thus these bonds go into the dealer's inventory with probability $F_v\left(\tilde{v}\left(d,q,\theta,\alpha\right)\right)$,in which case the dealer incurrs a cost k per unit of bonds in inventory. Assume an interior solution. The first-order condition on the optimal choice of $e>0$ is given by:

$$F_e\left(q;e\right)\left[\int_{\tilde{v}(d,q,\theta,\alpha)}^{\bar{v}}p_d\left(v_d,d,q,\theta,\alpha\right)qdF_v\left(v_d\right)-\int_{\tilde{v}(d,q,\theta,\alpha)}^{\bar{v}}p_c\left(v_c,d,q,\theta,\alpha\right)qdF_v\left(v_c\right)\right]=s_e\left(e;d\right)$$

where

$$\begin{aligned}&\int_{\tilde{v}(d,q,\theta,\alpha)}^{\bar{v}}p_c\left(v_c,d,q,\theta,\alpha\right)qdF_v\left(v_c\right)\\ =\;&\sigma q\int_{\tilde{v}(d,q,\theta,\alpha)}^{\bar{v}}v_c dF_v\left(v_c\right)\\ &+\left[1-F_v\left(\tilde{v}\left(d,q,\theta,\alpha\right)\right)\right]\left(\frac{\sigma\theta q}{1-\alpha\beta}+\left(1-\sigma\right)\alpha\left[\beta V\left(d;q,\theta,\alpha\right)-kq\right]\right)\end{aligned}$$

---

[7] We assume that the dealer treats each batch of bonds it acquires independently. As a result, the dealer's search policy for a given bond and trade amount q is not affected by how many units of this bond he already holds in inventory. In this sense, each trading day is identical in expectation. While this feature may seem restrictive in the sense that dealer search policies may vary with the level of inventory, this assumption facilitates estimation by leading to a closed-form expression for the likelihood of each observation. For the model estimation, we circumvent this restriction by controlling for each dealer's past trading history of each bond with *PastDaysTraded* and *PastDaysInventory*. Finally, it is important to note that this assumption does not take away the role of inventory from this setting. Indeed, the dealer's choices of search, acquisition and unloading of bonds all depend on the cost of taking bonds into inventory.

[8] Order-splitting is not allowed here to improve model tractability.

and

$$
\begin{aligned}
& \int_{\tilde{v}(d,q,\theta,\alpha)}^{\bar{v}} p_d\left(v_d, d, q, \theta, \alpha\right) q dF_v\left(v_d\right) \\
= \; & 0.5q \int_{\tilde{v}(d,q,\theta,\alpha)}^{\bar{v}} v_d dF_v\left(v_d\right) \qquad (25) \\
& + \left[1 - F_v\left(\tilde{v}\left(d,q,\theta,\alpha\right)\right)\right] \left(\frac{0.5\theta q}{1-\alpha\beta} + 0.5\alpha\left[\beta V\left(d; q, \theta, \alpha\right) - kq\right]\right). \qquad (26)
\end{aligned}
$$

It follows that

$$
\begin{aligned}
& \int_{\tilde{v}(d,q,\theta,\alpha)}^{\bar{v}} p_d\left(v_d, d, q, \theta, \alpha\right) q dF_v\left(v_d\right) - \int_{\tilde{v}(d,q,\theta,\alpha)}^{\bar{v}} p_c\left(v_c, d, q, \theta, \alpha\right) q dF_v\left(v_c\right) \\
= \; & \left(0.5 - \sigma\right) q \left[\int_{\tilde{v}(d,q,\theta,\alpha)}^{\bar{v}} v dF_v\left(v\right) - \left[1 - F_v\left(\tilde{v}\left(d,q,\theta,\alpha\right)\right)\right] \tilde{v}\left(d,q,\theta,\alpha\right)\right], \quad \text{given (22)} \\
= \; & \left(0.5 - \sigma\right) q \int_{\tilde{v}(d,q,\theta,\alpha)}^{\bar{v}} \left[v - \tilde{v}\left(d,q,\theta,\alpha\right)\right] dF_v\left(v\right).
\end{aligned}
$$

Therefore, the FOC boils down to

$$
F_e\left(q; e\right)\left(0.5 - \sigma\right) q \left[\int_{\tilde{v}(d,q,\theta,\alpha)}^{\bar{v}} \left[v - \tilde{v}\left(d,q,\theta,\alpha\right)\right] dF_v\left(v\right)\right] - s_e\left(e; d\right) = 0. \qquad (27)
$$

This result is very intuitive. On deciding whether to exert effort to search for a client-buyer, the dealer compares the respective expected prices from a client-buyer and a dealer-buyer, which is essentially the additional trade surplus due to differences in bargaining powers associated with the two types of trades. With this, we have the following proposition:

Proposition 1 *For any given $\tilde{v} < \bar{v}$, there exists a unique optimal choice $e^* \in (0, \infty)$ to the maximization problem in (24). Moreover, $\partial e^* / \partial \tilde{v} < 0$. For any given $\tilde{v} \geq \bar{v}$, the optimal search effort is $e^* = 0$.*

Proof. Define the left-hand side of (27) as $LHS\left(e\right)$. Given $\tilde{v} < \bar{v}$, we have

$$
\int_{\tilde{v}}^{\bar{v}} \left[v - \tilde{v}\right] dF_v\left(v\right) > 0.
$$

Moreover, given $\sigma > 0.5$, $F_e < 0$, $F_{ee} \geq 0$ and $s_{ee}\left(e; d\right) > 0$, we have the following properties:

$$\begin{aligned} LHS\,(0) &= F_e\,(q,0)\,(0.5-\sigma)\,q\int_{\tilde{v}}^{\bar{v}}[v-\tilde{v}]\,dF_v\,(v)>0 \\ LHS\,(\infty) &= F_e\,(q,\infty)\,(0.5-\sigma)\,q\int_{\tilde{v}}^{\bar{v}}[v-\tilde{v}]\,dF_v\,(v)-s_e\,(\infty;d)=-\infty \\ LHS'\,(e) &= F_{ee}\,(q,e)\,(0.5-\sigma)\,q\int_{\tilde{v}}^{\bar{v}}[v-\tilde{v}]\,dF_v\,(v)-s_{ee}\,(e;d)<0. \end{aligned} \tag{28}$$

Therefore, there exists a unique solution $e^* \in (0,\infty)$ to (27). Moreover, we have

$$\frac{\partial LHS}{\partial \tilde{v}} = F_e\,(q;e)\,(0.5-\sigma)\,q\left[-\int_{\tilde{v}}^{\bar{v}} dF_v\,(v)\right]<0. \tag{29}$$

Therefore, an increase in a given $\tilde{v}$ will shift the function $LHS\,(e)$ down and thus cause the optimal effort choice of e to decrease. That is, $\partial e^*/\partial \tilde{v} < 0$. Finally, if $\tilde{v} \geq \bar{v}$, then $LHS\,(0) = 0$ and $LHS\,(e) < 0$ for all $e > 0$. Obviously the optimal choice is $e^* = 0$ in this case. ■

In addition to the existence and uniqueness of the optimal search effort, Proposition 1 reveals the optimal behavior in terms of a dealer's choice of search effort. First, whether or not the dealer exerts effort to search for a client-buyer critically depends on how high the ask-price sale threshold is. For a threshold sufficiently high, that is, $\tilde{v}\,(d,q,\theta,\alpha) \geq \bar{v}$, no potential buyer, client or dealer, has such high valuation for the bond and thus it is pointless to search for a client buyer. A dealer can only benefit from the search for a client-buyer if there is a possibility to meet a buyer who is willing to purchase the bond. Secondly, Proposition 1 establishes that the search effort is always strictly positive as long as $\tilde{v}\,(d,q,\theta,\alpha) < \bar{v}$. This result is intuitive. The dealer is strictly better off trading with a client-buyer than with a dealer-buyer because he enjoys a higher bargaining power in the former case. As a result, the dealer will always exert some effort and try to connect with a client-buyer first. Overall, Proposition 1 is important in helping us understand the optimal search behavior.

To further characterize analytical results, we now assume that v_d, v_c and v follow independently distributed uniform distributions. This assumption will also help estimate the model, where we use this assumption to compute roundtrip spreads and infer parameter values. Given the optimal level of effort e^*, the value function is given by

$$V(d,q,\theta,\alpha)=\left\{\begin{array}{c}\theta q+[1-F(q;e^*)]\,q\int_{\tilde{v}(d,q,\theta,\alpha)}^{\bar{v}}p_c\left(v_a,d,q,\theta,\alpha\right)dF_v\left(v_a\right)\\ +F(q;e^*)q\int_{\tilde{v}(d,q,\theta,\alpha)}^{\bar{v}}p_d\left(v_a,d,q,\theta,\alpha\right)dF_v\left(v_a\right)\\ +F_v\left(\tilde{v}\left(d,q,\theta,\alpha\right)\right)\alpha[\beta V(d,q,\theta,\alpha)-kq]-s(e^*;d)\end{array}\right\}. \tag{30}$$

We can solve for $(\tilde{v}^*, e^*)$ from the two equations (27) and (30). We have the following proposition:

Proposition 2 *For any given (d,q,θ,α), there exists a unique pair of $\tilde{v}^* < \bar{v}$ and $e^* > 0$ that solve*

$$F_e\left(q;e\right)\left(0.5-\sigma\right)\frac{q\left(\bar{v}-\tilde{v}\right)^2}{2\left(\bar{v}-\underline{v}\right)}=s_e\left(e;d\right) \tag{31}$$

and

$$\tilde{v}=\frac{2A\bar{v}+B-\sqrt{\left(2A\bar{v}+B\right)^2-4A\left(A\bar{v}^2+D\right)}}{2A}, \tag{32}$$

where

$$\begin{aligned} A &\equiv \sigma+F(q;e)\left(0.5-\sigma\right)\\ B &\equiv \frac{1-\alpha\beta}{\alpha\beta}2\left(\bar{v}-\underline{v}\right)\\ D &\equiv 2\left(\bar{v}-\underline{v}\right)\left[\theta\left(1-\frac{1}{\alpha\beta}\right)-\frac{k}{\beta}-\frac{s(e;d)}{q}\right].\end{aligned}$$

The optimal threshold and search effort, $\tilde{v}(d,q,\theta,\alpha)$ and $e(d,q,\theta,\alpha)$, are given by

$$\tilde{v}(d,q,\theta,\alpha)=\begin{cases}\tilde{v}^*, & \textit{if } \tilde{v}^*>\underline{v}\\ \underline{v}, & \textit{if } \tilde{v}^*\leq\underline{v}\end{cases}$$

$$e(d,q,\theta,\alpha)=\begin{cases}e^*, & \textit{if } \tilde{v}^*>\underline{v}\\ \underline{e}^*, & \textit{if } \tilde{v}^*\leq\underline{v}\end{cases}$$

where $\underline{e}^*$ solves

$$\left(\bar{v}-\underline{v}\right)qF_e\left(q;e\right)\left(0.5-\sigma\right)=2s_e\left(e;d\right). \tag{33}$$

Finally, the optimal bond value is given by

$$V(d,q,\theta,\alpha)=\frac{q}{\alpha\beta}\left(\tilde{v}(d,q,\theta,\alpha)+\frac{\theta}{1-\alpha\beta}+\alpha k\right). \tag{34}$$

The proof of this proposition, as well as other proofs in the rest of this paper, are available in Appendix C. Proposition 2 establishes an important result, that is, a dealer finds it optimal to *actively* search for a client-buyer for any bond that it holds, *i.e.*, $e\left(d,q,\theta,\alpha\right) > 0$ for all (d,q,θ,α). This is driven by the fact that all else equal, the dealer has a strictly higher gain from trade against a client-buyer than against a dealer-buyer.

3.4.3 Roundtrip Spreads

A *roundtrip spread* refers to the difference between the ask-price and the bid-price of the same bond held by a dealer. We now solve for the roundtrip spreads in the dealer-to-client and dealer-to-dealer markets. Let us first recall the bid price and the ask price in the D2C market are given by equations (16) and (21). It follows that

$$p_c - b = \sigma(v_c - v) - (1-\sigma)[(1-\alpha\beta)V/q + \alpha K/q]. \tag{35}$$

Given (34), the above implies

$$p_c - b = \sigma(v_c - v) - \tilde{v}(1-\sigma)\left[\frac{1}{\alpha\beta} - 1\right] - (1-\sigma)\left[\frac{1}{\alpha\beta} - 1\right]\left(\frac{\theta}{1-\alpha\beta}\right) - \frac{(1-\sigma)}{\beta}k. \tag{36}$$

Similarly, the roundtrip spreads in the D2D market, $p_d - b$, is obtained from (16) and (23):

$$p_d - b = [0.5v_d - \sigma v] - \tilde{v}(1-\sigma)\left[\frac{1}{\alpha\beta} - \frac{0.5}{1-\sigma}\right] - (1-\sigma)\left[\frac{1}{\alpha\beta} - 1\right]\left(\frac{\theta}{1-\alpha\beta}\right) - \frac{(1-\sigma)}{\beta}k \tag{37}$$

Roundtrip spreads have four components. For instance, in equation (36) the first term represents the differential valuation of the bond by the dealer-buyer and the client-seller. The second term represents future costs for holding the bond in inventory. In the data, this effect increases roundtrip spreads in the D2C market as the term $\tilde{v}$ is decreasing in inventory costs according to estimates described in the next section. The sign of the corresponding effect in the D2D market (equation 37) depends on dealer bargaining power σ. The third term is related to the characteristics of the bond. The last term represents the current cost of holding the bond in inventory, which decreases the spread. The effects of the third and fourth terms are more muted, the higher the dealer's bargaining power σ in the client market.

The inventory cost affects the spread through two channels: inventory costs for the current period as measured by the last term, and inventory costs that will be incurred in the future, measured with the second term in both expressions. On the one hand, higher future inventory costs lower $\tilde{v}$ and exert an upward pressure on the spread in order to compensate the dealer for providing immediacy and holding the bond in inventory. On the other hand, given the opportunity to sell the bond in either the D2C or D2D market, trading now helps avoid the immediate inventory cost, which puts downward pressure on the spread. So, the overall effect on the spread is a trade-off between these two effects.

Given the expressions of the spreads, we have the following proposition, which helps to understand more about the nature of intraday roundtrips (*i.e.*, bonds acquired and sold within the same period) and multiday roundtrips (*i.e.*, bonds acquired and sold in different periods):

Proposition 3 *A dealer's optimal search effort has the following properties: (i) For any dealer and bond of* (d, q)*, if the bond has* (θ, α) *satisfying*

$$\sigma \left(\bar{v} - \underline{v}\right) + 2 \left(\theta + \underline{v}\right) \left(1 - \frac{1}{\alpha\beta}\right) \leq 2 \frac{k}{\beta}, \tag{38}$$

then this bond is such that $\tilde{v}(d, q, \theta, \alpha) = \underline{v}$*, which means it is guaranteed to sell within the same period of being acquired by the dealer;*

(ii) The set of trades that have a strictly positive probability of selling in a multiday roundtrip is a strict subset of the set of trades with a strictly positive probability of selling in an intraday roundtrip.

This proposition highlights an important aspect of the optimal dealer search behavior. Bonds with $\tilde{v}(d, q, \theta, \alpha) = \underline{v}$ are guaranteed to sell in an intraday roundtrip. Let us call them *guaranteed intraday trades*. Condition (38) identifies the features of bonds such that all dealers find optimal to trade in guaranteed intraday roundtrips. Note that this condition tends to hold for bonds with lower θ and α. Intuitively, these bonds are of low enough value, either because of low coupon relative to β, or high risk, or both, that it is optimal for any dealer to sell them to any buyer at a sufficiently low price, implying a guaranteed intraday trade ($\tilde{v}(d, q, \theta, \alpha) = \underline{v}$). In other words, these bonds are not of sufficiently high value for the dealers to risk incurring inventory costs and holding them on a multi-period basis.[9]

Not all intraday roundtrips are guaranteed. Bonds with $\tilde{v}(d, q, \theta, \alpha) > \underline{v}$ have a strictly positive probability of being sold in any given period and can therefore also end up in an intraday roundtrip. However, an intraday roundtrip does not occur with 100% probability for bonds with $\tilde{v}(d, q, \theta, \alpha) > \underline{v}$. Therefore, the set of bonds found in multiday roundtrips

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[9] This comes with a caveat that the reason why such a bond was acquired by the dealer in the first place is because the client-seller's valuation for it was very low.

is a strict subset of the set of bonds that end up in intraday roundtrips. Identifying guaranteed intraday trades is thus an important step toward understanding the centrality premium. In the quantitative analysis we show how such trades can help us identify how core dealers' advantage in search contributes to the centrality premium.

3.5 Structural Estimation

We next structurally estimate the model to see if we can generate the differences in roundtrip spreads observed between core and peripheral dealers.

To match the model to the data, the search function F, search cost function s and inventory cost function K must be parametrized. We parametrize the search function $F(q;e)$ as

$$F(q;e) = [1 - exp(-\gamma(X,e)q)] \tag{39}$$

$$\gamma(X,e) = \exp(\gamma_1 + \gamma_2 PastDaysTraded + \gamma_3 e). \tag{40}$$

The function F satisfies the properties listed in Section 3.3 as long as $\gamma_3 < 0$ and provided that $\gamma(X,e)$ is not too large, i.e., $1/q >= \gamma(X,e) \ \forall \ (q,X,e)$, a condition we verify empirically based on the parameter estimates.

Search costs are parametrized as

$$s(e;d) = de^2 \tag{41}$$

which satisfies the assumptions of Section 2.

We measure the distance d to the core with dealers' eigenvector measure of centrality (v_e). This measure of centrality is based on each dealer's degree centrality (i.e., the number of connections to other dealers) as well as the degree centrality of the dealers to whom each dealer is connected (Jackson 2008). As might be expected, core dealers have larger measures of centrality than peripheral dealers: the average eigenvector measure for core dealers is 0.0058 compared to 0.0032 for peripheral dealers.[10] We assume that d is a decreasing concave function of v_e, parametrized as follows,

$$d := exp(-\phi_1 v_e \times 100)$$

,

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[10] Eigenvector centrality is normalized so that the Euclidian distance measure of the vector equals 1. There is one element in this vector for each dealer in the sample, and we measure the vector quarterly.

where $\phi_1 \geq 0$ is a parameter to be estimated.[11]

Instead of the linear inventory cost that we assumed for analytical tractability, we parametrize a generalized inventory cost:

$$K = exp(\kappa_1) + exp(\kappa_2)q + \kappa_3 exp(\kappa_4 PastDaysInventory + \kappa_5 DecTradeCount) \quad (42)$$

so that inventory costs have both a fixed and a variable component. We allow both the bond's liquidity (measured with $DecTradeCount$) and the number of times a dealer took the bond into inventory in the past year ($PastDaysInventory$) to affect inventory costs.

Because the gross trade threshold is $\tilde{v} + \frac{\theta}{1-\alpha\beta}$, we assume that the net trade threshold $\tilde{v}$ has support $(\underline{v}, \overline{v})$ centered around zero. We parametrize the integration bounds v_u and v_l as $v_u = exp(\lambda_1 + \lambda_3 T)$ and $v_l = -exp(\lambda_2 + \lambda_4 T)$. The variable T indicates the bond's maturity in years.

Bargaining power is parametrized as $\sigma = \Phi(\psi_1)$ where Φ is the standard cumulative normal distribution.

Estimation of parameter vector $\mathit{\Psi} = (\gamma_1, \gamma_2, \gamma_3, \kappa_1, \kappa_2, \kappa_3, \kappa_4, \kappa_5, \lambda_1, \lambda_2, \lambda_3, \lambda_4, \phi_1, \psi_1)$ is with maximum likelihood (MLE). MLE is a feasible estimator in our setting because the model solution provides an expression for the likelihood. Using equations (36) and (37) and given $\mathit{\Psi}$, we can infer the value of z_i from observed roundtrip spreads, where

$$z_i = \begin{cases} \sigma(v_c - v) & \mathbf{1}(D2C) = 1 \\ 0.5 v_d - \sigma v & \mathbf{1}(D2D) = 1 \end{cases} \quad if \qquad (43)$$

The likelihood of observation i is then

$$L(\gamma, \sigma, e, \kappa, d, \underline{v}, \overline{v}; z_i) = f(z_i)^{\mathbf{1}(D2C)} g(z_i)^{\mathbf{1}(D2D)} \qquad (44)$$

where $f(z_i)$ and $g(z_i)$ equal the convolution of two uniform distributions. See Appendix D for a full derivation.[12]

Coupon rates θ and survival rates α are obtained from MERGENT/FISD and Standard and Poor's. Default rates are based on bond credit ratings in MERGENT/FISD. Ratings are matched to Standard and Poor's historical default rates. The discount factor β is set to the inverse of the daily risk-free total rate of return, i.e., $\beta = 1/(1+r))$.

Finally, we derive approximate closed-form expressions for optimal effort and trade thresholds to ease the computational burden of estimating the system of equations in

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[11] We obtain similar results if we assume a different mapping function based on the standard normal cumulative distribution function.

[12] In our setting, estimation by MLE is preferred over other methods (*e.g.*, GMM) because MLE is feasible and offers efficiency gains over other estimators.

Proposition 2. Details are provided in the Internet Appendix.

3.5.1 Model Identification

The data and model are sufficiently rich to identify each of the key parameters in the vector $\varPsi = (\gamma_1, \gamma_2, \gamma_3, \kappa_1, \kappa_2, \kappa_3, \kappa_4, \kappa_5, \lambda_1, \lambda_2, \lambda_3, \lambda_4, \phi_1, \psi_1)$. Dealers respond in terms of roundtrip spreads to variation in trade size, the trading frequency of the bond and bond features such as credit risk and maturity. To see this, suppose two bonds differ in terms of deciles of past trading frequency ($TradeCount$). This difference affects roundtrip spreads through two channels. The direct channel involves the effect of trade counts on inventory costs K. This effect is proportional to the parameter κ_5 in equation (42). The indirect channel involves the dealer's future inventory costs and effort level, as determined by the endogenous effort e and trading threshold $\tilde{v}$ choices. Different levels of trade count deciles and thus levels of K imply different values for the pair $(e^*, \tilde{v}^*)$, which affect estimated roundtrip spreads through equations (23) and (24). Intuitively, the estimation process minimizes the distance between observed roundtrip spreads and estimated roundtrip spreads by varying κ_5, e^* and $\tilde{v}^*$. Identification comes from observed roundtrip spreads' responsiveness to bond features that vary across observed trades.

We are also able to identify the effect on roundtrip spreads of dealer features (*e.g.*, centrality, past days traded and past days in inventory). Suppose two dealers trade the same bond in the same quantity, but the dealers differ in terms of their distance d from the core. Dealers closer to the core have lower search costs s, which affect dealer choices of the pair $(e^*, \tilde{v}^*)$. Dealers with lower d will exert more search effort (higher effort) and sell to a client with higher valuation in expectation (higher $\tilde{v}^*$). Thus variation in d affects roundtrip spreads both directly and indirectly. The direct effect occurs through the dealer's choice of $\tilde{v}^*$, where higher trade thresholds decrease roundtrip spreads in the D2C market. The indirect effect occurs through dealers' choice of effort, which increases the probability of selling in the D2C market where bargaining power is the highest. Since effort is determined jointly with the trade threshold, effort indirectly affects roundtrip spreads through its influence on $\tilde{v}^*$.

Identification of bargaining power σ stems from variation in roundtrip spreads across markets (*e.g.*, D2C vs D2D markets). Consider a bond purchase from a client by dealer d in amount q. Upon purchase the dealer can search for a client buyer or sell to another dealer. From the perspective of this dealer, he is trading off inventory costs against search costs. The reward from search stems from a greater share of the surplus from transacting with a client (with whom the dealer has higher bargaining power) instead of another dealer. Variation in where roundtrips are executed is thus a function of bargaining power differences across D2C and D2D markets. Bargaining power σ is identified by differences in roundtrip spreads across D2C and D2D markets for similar trades by dealers with the same centrality.

3.5.2 Parameter Estimates

Table 3.3 reports Maximum Likelihood estimates. Standard errors are based on the asymptotic variance of the MLE estimator.[13]

Increasing effort reduces the magnitude of γ since γ_3 is negative. This implies that greater effort increases the probability of finding a client for a given trade size. Bonds that are traded more often by a dealer, as measured by $PastDaysTraded$, are easier to match with client buyers (negative γ_2). Bonds with greater maturity have more variablity in idiosyncratic valuations, as both λ_3 and λ_4 are positive. Because κ_3 is positive and both κ_4 and κ_5 are negative, inventory costs vary negatively with past days inventory and trade count deciles, implying that bonds that were taken more often into inventory in the past by the dealer and are traded more frequently across all dealers have lower inventory costs.

As shown, the bargaining power estimate in the client market implies bargaining power of 98%, substantially higher other estimates provided in the literature. For example, Hendershott, D. Li **andothers** (2020b) estimate bargaining power in the dealer-to-client market to be 87%. However, their sample is based on corporate bond transactions by insurance companies. Insurance companies are large and sophisticated buyers of corporate bonds, whereas the average client in the TRACE data may be less so and therefore have less bargaining power relative to the larger dealers.

Panel B reports some key moments from our dataset. The first moment is the average of the difference between the expected roundtrip spread and the observed roundtrip spread. Estimated roundtrip spreads are approximately 30 bps higher than observed roundtrip spreads (i.e., 0.30%). This difference is about the same for roundtrip spreads observed in the D2C market and D2D markets.

We also verify that the second derivative $\frac{\delta^2 F}{\delta^2 e} \geq 0$. This is true in 91.5% of roundtrips in our sample, and the percentage is slightly higher for roundtrips in the D2C market than those in the D2D market. Recall that this assumption is required to guarantee a unique effort level (see proof of proposition 1). The third set of moments measures the difference between expected and estimated holding periods in days, i.e., the time between the first leg of each roundtrip and the last leg. Here we underestimate the average holding period by about 7 days, and the difference between estimated and observed days is stronger in

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[13] We use the diagonal elements of the inverse of the outer product of the scores to estimate the standard errors. See Chapter 13 of Wooldridge (2010).

the D2C market than the D2D market (8 days vs 5 days).

Table 3.4 reports average search costs, inventory costs and total surplus in the D2C market. Inventory costs per unit of notional amount average 136 bps per million per day. The average total surplus in the D2C market (expressions (18)+(19)) scaled by notional amount equals 142 bps. Comparing daily inventory costs with search costs indicates that dealers have strong incentives to engage in search.

Table 3.4 also reports the average net trade threshold $\tilde{v}$ times 10,000. As shown, this average is negative and equals -45.5 bps, but there is variation as the standard deviation equals 10 bps. Perhaps surprisingly, inventory policies, as captured by $\tilde{v}$ do not differ much between core and peripheral dealers.[14]

The expected spread on each roundtrip ($E[sprd(bps)]$) equals the probability-weighted sum of the roundtrip spreads in the D2C and D2D markets. As shown, estimated roundtrip spreads are approximately 64 bps. Peripheral dealers earn significantly lower spreads in expectation, with the expected spread equals to 54bps. Breaking down these spreads by type of market (D2C or D2D), reveals that both dealer types charge the same spread in each market. The difference in expectations stems from the higher probabilty of placing bonds in the D2C market by core dealers. These dealers are 13% more likely to sell to a client than to another dealer than peripheral dealers, reflecting the greater effort core dealers put into search.

Dealer effort levels vary considerably within both groups of dealers. For example, the average effort is 0.67 for core dealers with a standard deviation of 1.64, yet the median effort 0.11. This result implies that most trades require little in the way of search effort, with some trades requiring substantial amounts of effort.

The expected holding periods in days is 1 day for both core and peripheral dealers. As discussed above, the calibrated estimates underestimate the average length of the holding period. Partitioning by type of dealer reveals that the model underestimates core dealer holding periods and overestimates peripheral dealer holding periods: observed holding periods average 4.78 for core dealers and 0 days for peripheral dealers.

3.5.3 Explaining the Centrality Premium

Can the calibrated estimates reproduce the centrality premium? To answer this question, we plot observed roundtrip spreads by trade count decile and compare them with estimated roundtrip spreads. For each decile of trade count we subtract the mean observed peripheral

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[14] The value of $\tilde{v}$ lies in the interval $[\underline{v}, \overline{v}]$, which represents the support for the distribution of buyer net idiosyncratic value $\tilde{v}$. Recall that the dealer's gross idiosyncratic value is $\tilde{v} + \frac{\theta}{1-\alpha\beta}$. Since the support for $\tilde{v}$ can span the number zero, the trade threshold $\tilde{v}$ can be negative.

dealer spread from the mean observed core dealer spread. We do the same for the model-implied roundtrip spreads, and plot the two time series in Figure 3.5.

Panel A reports the centrality premium by trade count decile for intraday trades. Centrality premiums are decreasing in trade count as in the data, but the premium is overstated by several basis points for all trade count deciles. Panel B plots observed and estimated centrality premiums for multiday roundtrips. The difference between observed and estimated multi-day premiums matches well for trade count deciles 1-7, but is lower than in the data for trade count deciles 8, 9 and 10. A possible explanation for this discrepancy is the large variation in the holding periods for multiday trades within trade count deciles. For intraday trades, the holding period is less than 1 day by construction.

We conclude from Figure 3.5 that the centrality premium can exist without differences in bargaining power or inventory costs between core and peripheral dealers. Can search instead explain the centrality premium? To answer this question, we scale search costs $s(e; d)$ by the trade amount in millions, and report averages separately for core and peripheral dealers. As shown in Table 3.4, mean search costs equal 23.9 bps for core dealers and 5.1 bps for peripheral dealers, implying that core dealers search more than peripheral dealers. In order to better understand where core dealers are directing their search, Figure 3.6 reports median search costs for intra-day and multi-day roundtrips by trade count decile. As shown, core dealers incur higher search costs than peripheral dealers for the least traded bonds (deciles of trade count 1, 2 and 3). For example, core dealers incur about 5-6 times more search costs (5-6 bps) for bonds in trade count decile 2 than peripheral dealers (1 bp). Comparing intra-day and multi-day trades also reveals that core dealers search harder for bonds that spend less time in inventory; this is not surprising as higher search efforts lead to a higher probability of finding a client buyer in the D2C market on the day a bond is purchased by a dealer.

3.5.4 Counterfactual Roundtrip Spreads

To further investigate core dealers' advantage in search we consider the subset of trades consisting of all intraday and multiday roundtrips executed by core dealers. We use model estimates to determine the corresponding counterfactual roundtrip spread, had a peripheral dealer undertaken the exact same roundtrip.

There are 718,986 roundtrips executed by core dealers. We split this subset into three groups based on trade-count decile: below 3 (trades rarely), between 4 and 7 (trades sometimes) and 8 or greater (trades often). For each of these subgroups we estimate the effort level, trade threshold and roundrip spreads in either the D2C and D2D market charged by the core dealer. We then repeat the same exercise assuming that a peripheral dealer undertakes the same transaction. We assume that the counterfactual peripheral dealer has a distance to core measure of $d = 0.0704$, which corresponds to the average eigenvector measure of centrality for peripheral dealers (0.0032). Estimated core dealer spreads and estimated peripheral dealer counterfactuals are reported in Table 3.5.

Table 3.5 shows that it is easier for a client to sell to a core dealer than a peripheral dealer. Core dealers have higher values of the (net) bid-sale threshold $\tilde{v_b}$. Recall that selling clients must value the bond below this threshold in order for gains to trade to be present. The higher this threshold, the more likely a dealer and a high-valuation client will trade. Comparing this threshold across core and peripheral dealers shows that it is more advantageous for clients to sell bonds that trade rarely to core dealers than to peripheral dealers. The bid threshold is 91.37 for core dealers, compared to 91.33 for peripheral dealers.

Comparing actual and counterfactual effort and spreads reveals that the centrality premium arises through core dealers' choice of effort level and their choice of the trade threshold. The former is a *search channel* and the latter an *inventory channel.* Core dealers generally choose higher effort levels, and this difference increases the chance of selling bonds in the D2C market, where the dealers' bargaining power is greater. Take for example bonds that trade sometimes. Core dealers exert effort of 0.72 compared with a counterfactual effort of 0.09 for peripheral dealers on the same bonds. Search costs incurred by core dealers are correspondingly higher (25.8 bps vs 3.2 bps) , despite their advantage in search. Core dealers' probability of selling in the D2C market is greater (90%) than peripheral dealers (counterfactual probability of 77%). Although peripheral dealers earn the same roundtrip spread as core dealers in the D2C market, they earn less in expectation than core dealers because, 1) peripheral dealers have a lower selling probability in the D2C market where bargaining power is highest and, 2) peripheral dealer roundtrip spreads conditional on selling in the D2D market are slightly lower (3.19 vs. 3.17 bps). These two effects combined reduce the roundtrip spread peripheral dealers earn for the *same bond* and trade size. This describes the centrality premium through the search channel.

Higher effort levels allow core dealers to set higher trade thresholds $\tilde{v}$ despite the lower chance of a successful negotiation with a client. Recall that client buyers must value the bond above this threshold for there to be gains to trade. Intuitively, core dealers have a higher probability of placing the bond in the D2C market because of greater search effort.

Equation (37) shows how core dealer trade thresholds $\tilde{v}$ increase roundtrip spreads in the D2D market relative to peripheral dealers. Even though both dealers incur similar inventory costs K, they differ in terms of future inventory policy. Because core dealers have slightly higher $\tilde{v}$ and roundtrip spreads are increasing in $\tilde{v}$ in the D2D market, core dealers earn a centrality premium in this market by virtue of their longer-duration inventory policy. The centrality premium therefore increases with $\tilde{v}$. This describes the centrality premium through the inventory channel. These two channels combined allow core dealers to earn between 5.9 and 12.5 bps in centrality premium on roundtrips (Panel B).

3.5.5 Guaranteed Intraday Trades

To further understand core dealers' advantage in search, we use the structural parameter estimates to examine how core and peripheral dealers price and trade guaranteed intraday trades. These trades are guaranteed not to be taken into inventory by either type of dealer, and can thus provide further evidence on core and peripheral dealers' search policies.

Proposition 3 and condition (38) show that there are transactions that both core and periphery dealers will find optimal to execute on an intraday basis. These trades are characterized by trading thresholds $\tilde{v}(d, q, \theta, \alpha) = \underline{v}$ for given features of dealer and trade (d, q, θ, α).

With this, we first set out to identify such bonds from data. For each transaction, we compare trade thresholds for the dealer who transacted the bond and a counterfactual dealer (either core or peripheral). We assume that each counterfactual dealer is the average dealer in terms of their distance from the core in the correponding subset: counterfactual core dealers have a distance measure $d = 0.0704$ corresponding to the average value of the eigenvector in their group. Counterfactual peripheral dealers have a distance measure $d = 0.0082$ based on the average value of eigenvector centrality among peripheral dealers. When both the actual and counterfactual trade thresholds equal $\underline{v}$, then the trade is labelled as a GIT.[15] Non-GITs are bonds that are either traded in multiday roundtrips by all dealers, or traded as intraday by some dealers but multiday by others. We expect GIT's to generate a centrality premium for core dealers.[16]

Panel A of Table 3.6 reports mean and median bond features for GIT and non-GIT transactions. GITs tend to be smaller in size based on the notional amount of the bond traded, and have lower trade-counts. GITs are also less frequently traded by the trading dealer. As shown, dealers take GIT-bonds an average of 7.1 times in inventory in the preceding year prior to the trade, compared with 18 times for non-GITs. Also, bonds involved in GIT's are traded by the dealer 33 days prior to the GIT date, compared with

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[15] Condition (38) is a sufficient but not necessary condition for a bond to qualify as a GIT for both core and peripheral dealers. The set of bonds identified as GITs in this section is at least as large as the set implied by this condition.

[16] The GITs are identified based on the estimated values of the net trade threshold, $\tilde{v}$. GITs are identified with some error, and thus in the data, some of the bonds so labeled as GITs may have stayed in the inventory more than one day.

73.5 days for non GITs. Bonds involved in GITs also tend to be shorter in maturity and have smaller amounts outstanding. GIT bonds are held in inventory a median of one day, compared with 4.2 days for non-GIT bonds.

We next run the following counterfactual analysis: for each GIT, we first assume the trade is executed by a core dealer and compute the pair $(e^*, \tilde{v}^*)$. We then reprice the same trade assuming the trade is executed by a peripheral dealer and report the corresponding pair $(e^*, \tilde{v}^*)$. Since $\tilde{v}^*$ the trade threshold is the same for both core and peripheral dealers, core and peripheral dealers only differ in terms of search effort, search costs and the probability of selling to a client in the D2C market.

Counterfactual estimates are reported in Table 3.7. As expected, core dealers exert higher average effort levels than peripheral dealers on GITs (Panel A). The additional effort increases search costs (28.3 *vs* 4.7 bps), but also generates a higher probability of selling in the D2C market (84% *vs* 68%). Peripheral dealers rely more on the dealer network when providing liquidity to their clients: the probability of selling in the D2D market is 32% for peripheral dealers and 16% for core dealers. From equations (36) and (37), roundtrip spreads on GITs are the same for both dealer types. Thus, differences in the expected spread between core and peripheral dealers are a sole function of effort. Higher effort by core dealers leads to a higher probability of selling GIT bond in the D2C market where bargaining power is greatest. Consequently, core dealers earn a centrality premium of approximately 11.4 bps (= 61.8-50.4) on roundtrip spreads associated with GIT trades.

Panel B reports counterfactual pricing of non-GIT bonds. Core and peripheral dealers have very similar levels of effort, and because effort levels are low, search costs are correspondingly low for both types of dealers. However, core dealers differ in terms of their inventory policy with respect to non-GIT bonds. Cores are more likely to purchase a bond from a client with a high valuation (higher v_b) and they are more likely to sell to a client with a higher valuations (higher $\tilde{v}$).[17] The centrality premium for non-GIT bonds is a low 1.2 bps (69.9-68.7), reflecting the similar search efforts of both types of dealers.

3.5.6 Sensitivity Analysis

Table 3.8 reports the results of a sensitivity analysis in which select parameter values vary while all other parameters remain at their estimated values.

We first vary bargaining power in the D2C market. The expressions (36) and (37) predict that the centrality premium is increasing in bargaining power. Consistent with

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[17] Therefore, it is worth noting that although core dealers appear to be cream skimming when selling a bond that they own, they serve a broader set of clients when buying in response to a customer sell order.

this prediction, decreasing both dealer's bargaining power simultaneously reduces the centrality premium. The reason is that higher bargaining power increases the reward to search, which is to core dealers' advantage.

We next vary the marginal benefit of effort. For the least traded bonds, more rewards to effort increase the centrality premium as core dealers have lower search costs per unit of effort. This result is very intuitive. The greater the marginal benefit of effort, as measured by a more negative value of parameter γ_3 in the search function F, the greater the centrality premium. The centrality premium for more frequently traded bonds is less sensitive to changes in this parameter.

We next examine differences in bargaining power between core and peripheral dealers. What happens to the centrality pemium when core dealers have less bargaining power than peripheral dealers? Holding peripheral dealer bargaining power fixed, decreasing core dealer bargaining power to 92.1% from the estimated 98.9% reduces the centrality premium to zero for the least traded bonds. We conclude that core dealers' advantage in search is equivalent to a 6.8% (=98.9%-92.1%) advantage in bargaining power in the D2C market. Core dealers' advantage in search is smaller for more frequently traded bonds.

We perform a similar comparison for marginal inventory costs. Increasing core dealers' marginal cost of inventory $exp(\kappa_2)$ in equation (42) from the estimated value of 0.0130 to 0.0158 eliminates the centrality premium for the least traded bonds. We conclude that core dealers' advantage in search is equivalent to a 21.5% (= $(0.0158 - 0.0130)/0.0130$) advantage in marginal inventory cost.

3.5.7 Estimates Excluding Dealer Inventory History

Core dealers may have superior inventory-management skills compared to peripheral dealers, perhaps because of larger investments in technology due to inventory size and/or greater transaction volumes (Eisfeldt **andothers** 2023). A possible explanation for the differences between core and peripheral dealers in terms of spreads and inventory policy is that the former dealers have greater inventory-bearing capacity, as measured by the number of times they took a bond into inventory in the past. We further explore the inventory channel and calibrate a version of the model in which the inventory cost function K (equation 42) omits information on past inventory decisions by the dealer (*i.e.*, $PastDaysInventory$ is omitted from K), thus ensuring that both core and peripheral dealers face exactly the same inventory costs for each bond-trade size pair. This parametrization shuts down any superior technology advantage in inventory management by core dealers that may be reflected in past decisions to take a bond into inventory. We re-estimate the model with this more parsimonious inventory function. Estimated moments and centrality premiums are close to the baseline estimates. For example, the difference in expected roundtrips between the baseline model and the parsimonious model is less than 1 bp.

3.6 Conclusion

We examine the sources of the centrality premium in the OTC market for corporate bonds. We find that this premium arises from core dealers' advantage in search rather than differences in bargaining power or an advantage in holding bonds in inventory. Structural estimation of a simple model of search shows that core dealers exert more search effort per unit of bond traded when searching for a buyer. Core dealers' advantage in search manifests itself in guaranteed intraday trades, where both core and peripheral dealers trade intraday with certainty: despite identical holding periods, core dealers earn a premium over peripheral dealers. Core dealers also supply more liquidity than peripheral dealers for non-guaranteed intraday trades, *i.e.*, trades that have a positive probability of being held in inventory overnight. Core dealers are more likely to purchase these bonds and hold them in inventory than peripheral dealers, despite identical inventory costs.

Figures

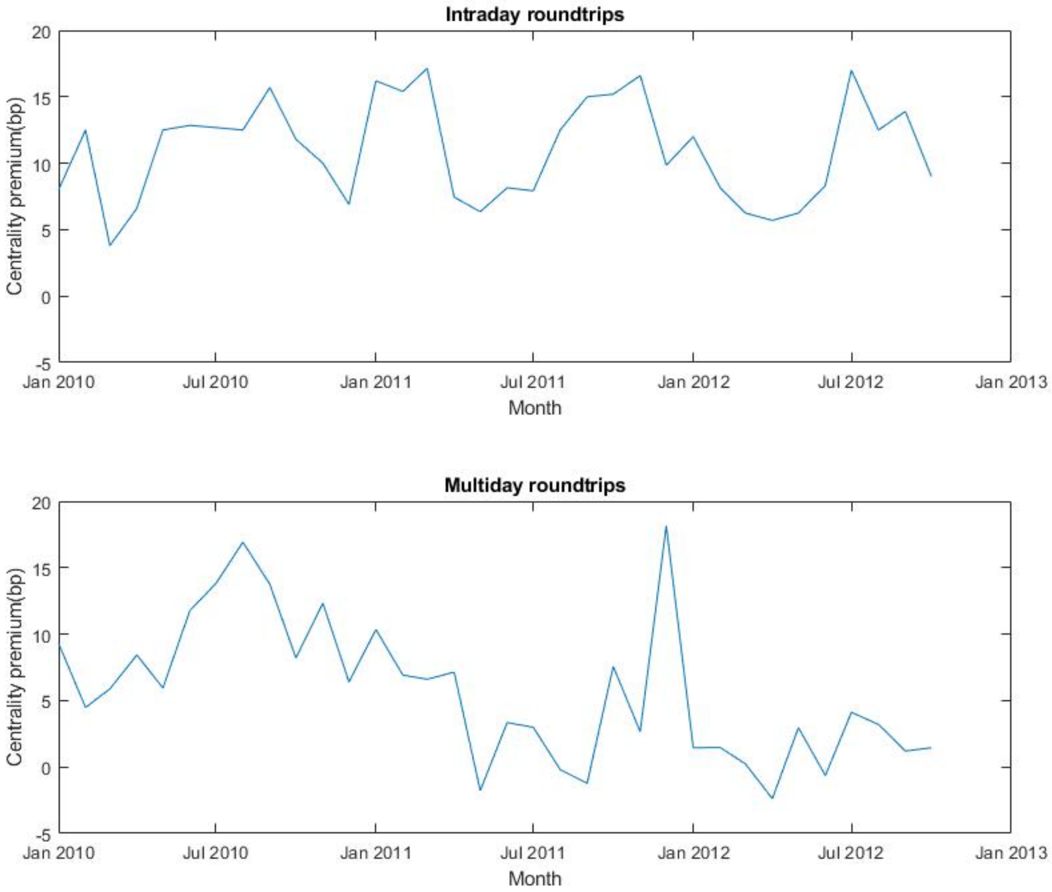

Figure 3.3: Centrality premium over time. This figure plots the monthly centrality premiums in basis points for intraday and multiday roundtrips. The centrality premium equals the difference between the median core dealer roundtrip spread and median peripheral dealer roundtrip spread, where the medians are calculated month-by-month. Dealers are classified as either core or periphery dealers as described in the text. Roundtrip spreads are defined as the difference in the trade-weighted sale price and purchase price of a given quantity of bonds by a dealer. The sample spans all client-initiated roundtrips between January 1, 2010 and October 31, 2012.

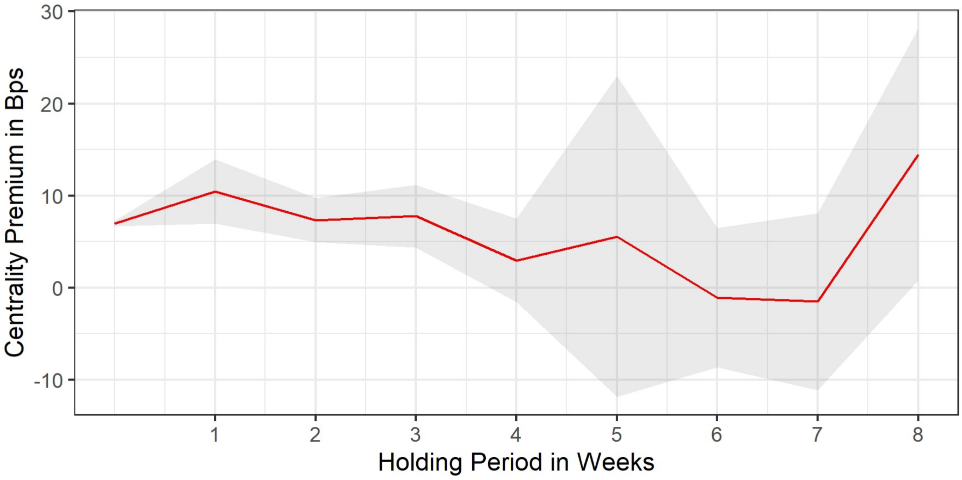

Figure 3.4: Centrality premium by holding period. This figure reports the centrality premium by holding period. Holding periods are measured in weeks and the centrality premium is defined as the difference between mean core and mean peripheral dealer roundtrip spreads. Holding periods are rounded up to the nearest week. The grey shaded area represents a 95% confidence interval around the mean.

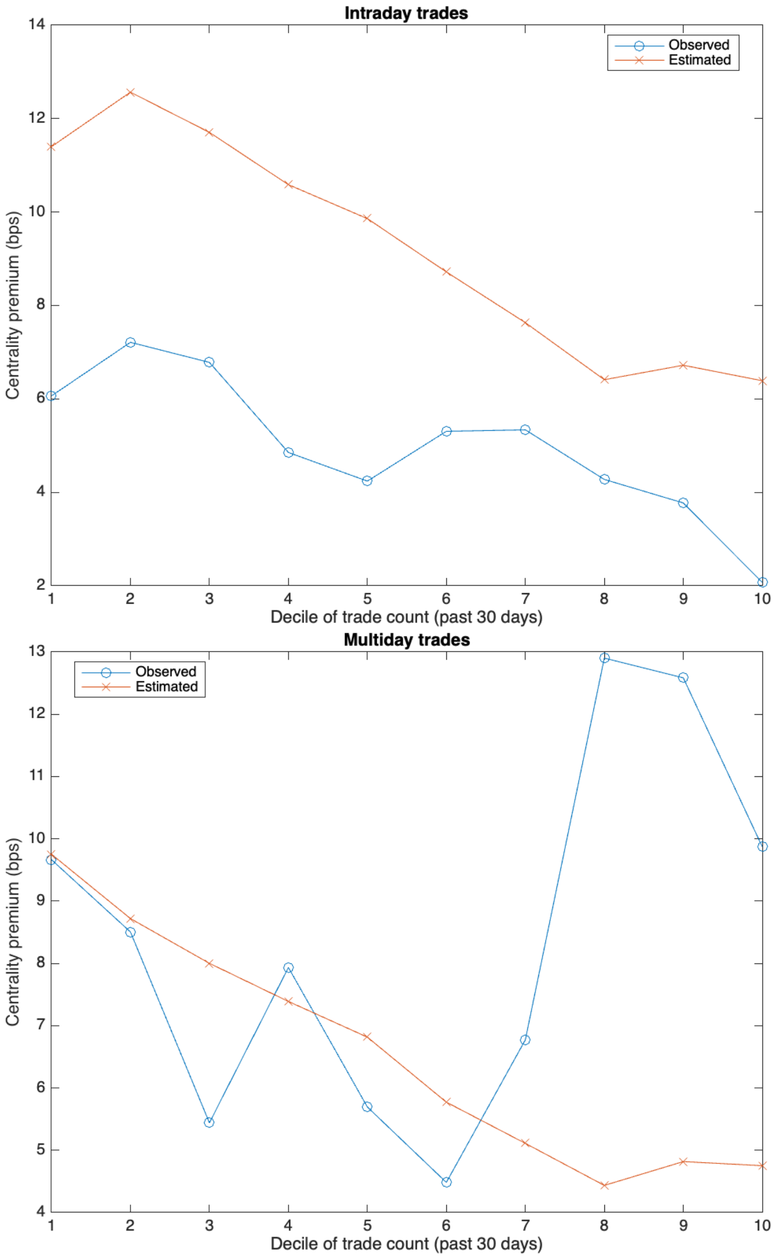

Figure 3.5: Centrality premium by trade count decile. This figure plots the centrality premium in basis points for intraday and multiday roundtrips by decile of trade count. Trade count deciles rank bonds by the number of trades over the prior 30 days; Decile 1 = Low trade count, Decile 10 = High trade count. For each type of roundtrip, the centrality premium equals the difference between the mean roundtrip for core dealers minus the mean roundtrip for peripheral dealers. Dealers are classified as either core or periphery dealers as described in the text. Roundtrip spreads are defined as the difference in the trade-weighted sale price and purchase price of a given quantity of bonds by a dealer. The sample spans all client-initiated roundtrips between January 1, 2010 and October 31, 2012. Estimated premiums are based on roundtrips spreads implied by equations (23) and (24) and estimated parameters from the model.

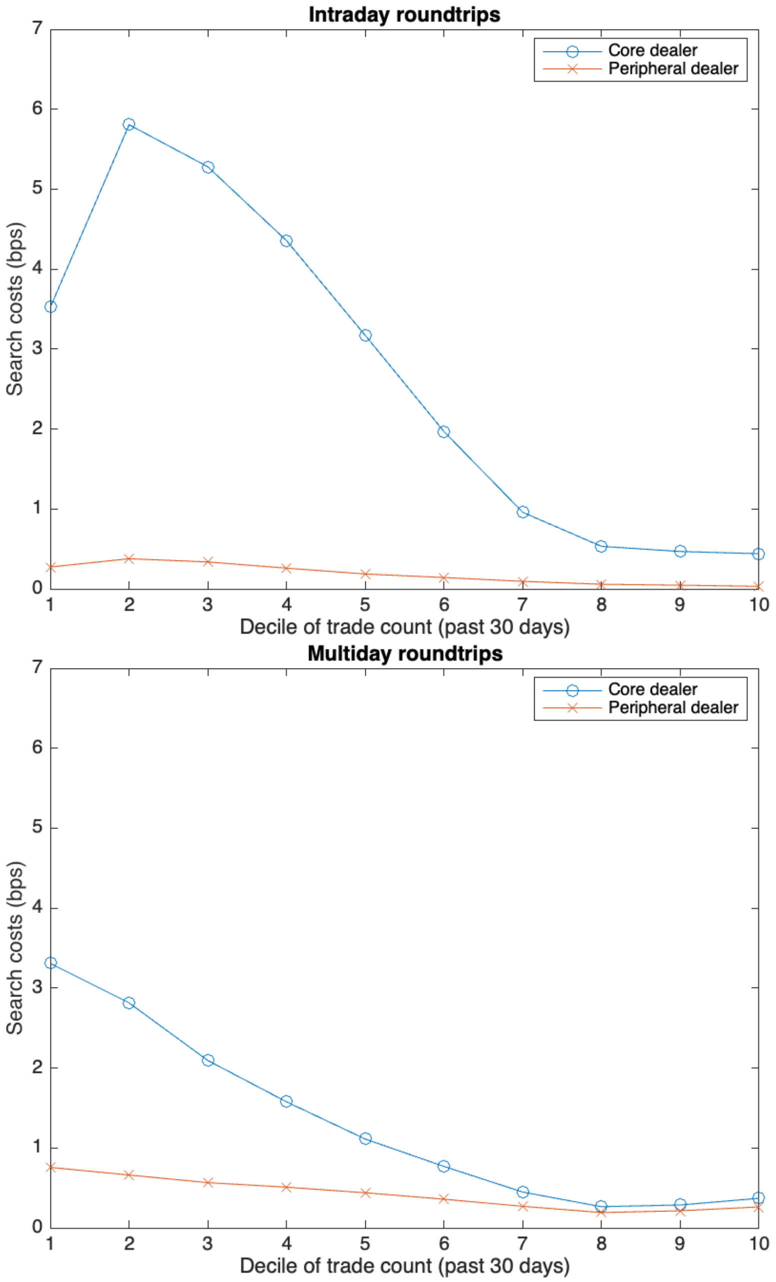

Figure 3.6: Dealer search costs. This figure reports median search costs by dealer type and trade count decile. Search costs are defined as $(s/q) \times 10,000$ where q the trade size in millions, and $s = de^2$.

Tables

Table 3.1: Summary statistics. This table reports summary statistics on the sample of roundtrips. The data spans the period January 1, 2010 to Ocother 31, 2012, and consists of all buyer-initiated roundtrip trades. The roundtrips spread is the price difference between the size-weighted sale price and the purchase price. Variables are defined in Table A.1.

Variable	**mean**	**sd**	**p25**	**p50**	**p75**	**min**	**max**	**N**
Spread	29.01	112.70	0.00	15.40	50.00	-578.00	623.04	1161026
Spread(intraday)	24.52	40.38	0.00	13.10	30.00	-575.00	622.00	492469
Spread(multiday)	32.31	144.32	-16.25	18.24	83.81	-578.00	623.04	668557
Holding	8.48	12.63	0.00	1.91	13.00	0.00	60.00	1161026
Holding (multiple day)	14.73	13.60	4.00	10.00	22.00	0.00	60.00	668557
Dummy: sameday roundtrip	0.42	0.49	0.00	0.00	1.00	0.00	1.00	1161026
Buyvolume less than 1M	0.16	0.37	0.00	0.00	0.00	0.00	1.00	1161026
Buy volume btwn 1M & 5M	0.32	0.47	0.00	0.00	1.00	0.00	1.00	1161026
Buy volume > 5M	0.10	0.30	0.00	0.00	0.00	0.00	1.00	1161026
Core dealer	0.62	0.49	0.00	1.00	1.00	0.00	1.00	1161026
Eigenvector×100	0.47	0.15	0.37	0.50	0.58	0.00	0.76	1161026
Maturity	8.39	9.67	2.80	5.43	8.90	0.17	100.02	1161026
Age	3.47	3.17	1.17	2.57	4.67	0.17	66.28	1161026
Size	1219.62	1008.93	500.00	1000.00	1746.00	0.00	8000.00	1161026
Trade count	277.72	466.85	52.00	128.00	314.00	0.00	11320.00	1161026
Trade count decile	4.98	2.77	3.00	5.00	7.00	1.00	10.00	1161026
Dealer volume decile	9.97	0.25	10.00	10.00	10.00	2.00	10.00	1161026
Past days traded	41.81	45.72	8.00	26.00	60.00	0.00	255.00	1161026
Past days inventory	9.42	14.40	0.00	3.00	13.00	0.00	138.00	1161026

Table 3.2: Core vs peripheral dealer roundtrips. This table reports summary statistics for select variables, conditional on the roundtrip being executed by a core *vs.* peripheral dealer. (Panel A), or a intraday *vs.* a multi-day trade (Panel B). The sample is comprised of all roundtrips between January 1, 2010 and October 31, 2012. Spreads are in basis points. Variables are defined in Table A.1.

Panel A: Core vs peripheral dealers

	Core dealer		**Peripheral dealer**	
Variable	**Mean**	**Median**	**Mean**	**Median**
	(1)	(2)	(3)	(4)
Trade size (M)	2.46	0.90	2.27	0.85
Spread (bp)	32.26	20.50	23.73	11.40
Spread(same day)	27.40	21.70	22.16	10.00
Spread(multiple day)	34.43	19.90	26.19	13.10
Holding	10.07	4.78	5.90	0.00
Holding (multiple day)	14.57	10.00	15.19	11.00
Dummy: sameday roundtrip	0.31	0.00	0.61	1.00
Trade count decile	4.90	5.00	5.11	5.00
Past Days traded	50.0	35.0	28.5	14.0
Past Days inventory	11.6	6.0	5.8	0.0
Eigenvector×100	0.56	0.57	0.32	0.35
N	718986		442040	

Panel B: Intraday vs multi-day trades

	Intraday		**Multi-day**	
Variable	**Mean**	**Median**	**Mean**	**Median**
	(1)	(2)	(3)	(4)
Trade size (M)	2.45	1.00	2.35	0.80
Dummy: core dealer	0.45	0.00	0.74	1.00
Spread	24.52	13.10	32.31	18.24
Holding	0.00	0.00	14.73	10.00
Size between 0.5M and 1M	0.15	0.00	0.17	0.00
Size between 1M and 5M	0.33	0.00	0.31	0.00
Size greater than 5M	0.10	0.00	0.10	0.00
Trade count decile	5.07	5.00	4.91	5.00
Past days traded	31.86	15.00	49.13	35.00
Past days inventory	5.10	0.00	12.60	7.00
Eigenvector×100	0.40	0.40	0.51	0.53
N	492469		668857	

Table 3.5: Counterfactual roundtrips. Panel A reports average counterfactual estimates of spreads, effort and trade thresholds on 718,986 roundtrip transactions undertaken by core dealers. Panel B reports differences in means across core and peripheral dealers for selected variables. For each transaction we estimate core dealer effort and trade thresholds as well as expected roundtrip spreads. We then redo the same exercise assuming the dealer is a peripheral dealer (counterfactual). Effort is e^*, and $Search\,costs(bps)$ equals search costs s divided by the trade size times 10,000. $Bid(\%)$ is the dealer's purchase price expressed as a percentage of par value. $Pr(D2C)$ and $Pr(D2D)$ are the probabilities in % of selling the bond to either a client or a dealer, respectively. $Sprd(D2C)$ and $Spr(D2D)$ are the expected roundtrip spreads in the D2C and D2D markets. ($E[sprd(bps)]$) equals the expected roundtrip spread based on the spreads and probabilities for the D2C and D2D markets. The variable $\tilde{v}$ designates the dealer's net trade threshold, and the variable $\tilde{v}_b$ is the (net) bid-price sale threshold.

Panel A: Core vs Peripheral Dealer

Bond trading frequency	**Trades rarely**		**Trades sometimes**		**Trades often**	
Trade count decile	**(1,3)**		**(4,7)**		**(8,10)**	
	Core	**Periph**	**Core**	**Periph**	**Core**	**Periph**
Effort(e^*)	0.54	0.07	0.72	0.09	0.80	0.10
Search costs(bps)	19.24	2.44	25.83	3.20	28.01	3.46
Bid(%)	145.35	145.35	140.67	140.67	142.23	142.23
Ask(%)	146.09	146.09	141.40	141.40	142.96	142.96
$\tilde{v} \times 10^4$	-45.51	-45.55	-45.72	-45.80	-45.19	-45.26
$\tilde{v}_b \times 10^4$	91.37	91.33	91.56	91.48	92.45	92.38
E[Holding(days)]	1.0009	1.0008	1.0036	1.0034	1.0067	1.0064
Pr(D2C)(%)	76.79	59.09	89.99	77.41	93.79	85.39
Pr(D2D)(%)	23.12	40.83	9.66	22.27	5.56	13.98
Sprd(D2C)(bps)	73.93	73.93	73.66	73.66	73.28	73.28
Sprd(D2D)(bps)	3.24	3.23	3.19	3.17	3.12	3.10
E[sprd(bps)]	57.51	45.00	66.57	57.67	68.87	62.95
N	263751		300206		155029	

Panel B: Differences (Core - Peripheral)

Trade count decile			
Trade size			
Holding period (days)	0.0001	0.0002	0.0003
Pr(D2C)(%)	17.7	12.6	8.4
Pr(D2D)(%)	-17.7	-12.6	-8.4
Search costs (bps)	16.79	22.62	24.55
Effort(e^*)	0.47	0.63	0.70
Rountrip spread (bps)	12.52	8.89	5.93

Table 3.3: Model estimates. This table reports model parameter estimates (Panel A) and moment estimates (Panel B). Estimates are based on 1,161,026 roundtrip trades observed between January 1, 2010 and October 31, 2012. Panel A reports Maximum Likelihood Estimates (MLE) along with standard errors (SE). Panel B reports average values of each quantity; D2C and D2D indicate that the average is taken over the corresponding subset of transactions for each heading.

Panel A: Parameter estimates

Variable	**Coeff** (1)	**SE** (2)
Search function parameters		
γ_1	5.771	0.01072
γ_2	-1.900	0.04706
γ_3	-2.598	0.85664
Bond issue parameters		
λ_1	-3.764	0.00000
λ_2	-5.160	0.00001
λ_3	0.005	0.00000
λ_4	-0.029	0.00005
Inventory function parameters		
κ_1	-8.224	0.00003
κ_2	-4.346	0.00000
κ_3	-1.489	0.05361
κ_4	-5.924	3.49174
κ_5	-11.223	0.07981
Centrality parameter		
ϕ_1	8.292	1.27200
Bargaining power parameter		
ψ_1	2.28377	0.00097
NegLogLikelihood	-4193380	

Panel B: Moment estimates

	Moment	**N**
Est. spread - Obs. Spread (bps)	31.23	1161026
D2C market	30.19	776047
D2D market	33.32	384979
$Pr\left(\frac{\delta^2 F}{\delta^2 e} >= 0\right)$	91.5%	1161026
D2C market	93.8%	776047
D2D market	90.1%	384979
Est. holding - Obs. Holding (days)	-6.90	1161026
D2C market	-8.62	776047
D2D market	-5.17	384979

Table 3.4: Implied moment estimates. This table reports mean and median implied model moments based on estimates reported in Table 3.3. The expected spread (*E[sprd(bps)]*) equals expected spread across the D2C or D2D markets using the estimated probabilities *Pr(D2C)(%)* and *Pr(D2D)(%)* of selling in each market respectively. $Surplus(D2C)(bps)$ equals the total surplus in the D2C market divided by the trade size times 10,000. Search costs are parametrized as $s = de^2$ and *Search costs (bps)* equals s divided by the trade size times 10,000. The inventory cost function is given by $K = exp(\kappa_1) + exp(\kappa_2)q + \kappa_3 exp(\kappa_4 PastDaysInventory + \kappa_5 TradeCount)$ and *Inventory costs* equal this amount scaled by the trade size time 10,000. Holding periods are predicted (*E[holding(days)]*). *D2C spread* and *D2D spread* are the predicted roundtrip spreads conditional on trading in either the D2C or D2D markets. The values of effort (e^*) and the net trade threshold ($\tilde{v}$) are based on the estimation output. The net bid-sale threshold $\tilde{v}_b$ represents the net valuation threshold below which clients must value the bond in order for there to exist gains to trade between the client and dealer.

	Core dealers			**Peripheral dealers**		
	Mean (1)	**Median** (2)	**SD** (3)	**Mean** (4)	**Median** (5)	**SD** (6)
E[sprd(bps)]	63.74	67.13	14.36	54.53	61.59	18.31
Pr(D2C)(%)	86.0%	92.3%	20.5%	72.9%	83.4%	27.3%
Pr(D2D)(%)	13.7%	6.9%	20.6%	26.8%	16.5%	27.5%
D2C spread(bps)	73.68	74.63	4.13	73.70	74.60	4.38
D2D spread(bps)	3.19	4.44	3.68	3.12	4.33	3.80
E[holding(days)]	1.00	1.00	0.01	1.00	1.00	0.01
Effort(e^*)	0.67	0.11	1.64	0.14	0.02	0.44
$\tilde{v} \times 10^4$	-45.53	-48.24	10.44	-45.46	-48.50	10.91
$\tilde{v}_b \times 10^4$	91.68	88.54	12.13	91.91	88.54	12.60
Search costs(bps)	23.88	1.55	66.44	5.08	0.25	17.80
Inventory costs(bps)	135.52	132.44	6.38	135.67	132.66	6.44
Centrality(d)	0.0118	0.0089	0.01	0.1424	0.0539	0.20
Surplus(D2C)(bps)	144.19	143.94	2.28	144.39	143.98	2.46
Bargaining power(σ)	0.989	0.989	0.000	0.989	0.989	0.000

Table 3.6: Guaranteed Intraday Trades. This table reports summary statistics for Guaranteed Intraday Trades (GITs) vs Non-Guaranteed Intraday trades (Non-GITs). GITs are defined as transactions for which $\tilde{v}$ is equal to $\underline{v}$ for both core and peripheral dealers. Based on this feature, these bonds are guaranteed to be traded on an intraday basis. Non-guaranteed intraday trades have $\tilde{v} > \underline{v}$ for core or peripheral dealers.

	GIT trades			**Non-GIT trades**		
Variable name	**mean**	**median**	**SD**	**mean**	**median**	**SD**
Roundtrip spread (bps)	29.2	17.5	108.6	28.4	10.4	126.6
Trade count decile	4.5	4.0	2.7	6.6	7.0	2.3
Trade size (M)	2.8	1.0	6.8	1.0	0.6	2.2
Maturity (years)	7.7	5.3	8.0	11.1	6.1	13.8
Amount outstanding(M)	953.3	750.0	786.2	2203.0	2000.0	1125.0
Past days inventory	7.1	2.0	11.4	18.0	12.0	19.9
Past days traded	33.2	20.0	38.6	73.5	62.0	55.0
Holding (days)	8.1	1.0	12.5	9.8	4.2	12.9
N		913615			247411	

Table 3.7: Core vs Peripheral Pricing of Guaranteed Intraday Trades. Panel A conducts a counterfactual analysis by comparing GITs assuming in turn that they are priced by core dealers and peripheral dealers. Couterfactual core dealer have a distance to core of $d = 0.0082$ and counterfactual peripheral dealers have a distance measure $d = 0.0704$. *Search costs*(bps) equals search costs s divided by the trade size times 10,000. Panel B reports the same type of counterfactual analysis on non-guaranteed intraday trades.

Panel A: Core vs Peripheral dealer pricing of GITs

	Core			**Peripheral**		
Variable name	**mean**	**median**	**SD**	**mean**	**median**	**SD**
E[sprd(bps)]	61.76	65.17	15.94	50.42	57.48	18.35
Pr(D2C)	0.84	0.91	0.23	0.68	0.76	0.28
Pr(D2D)	0.16	0.09	0.23	0.32	0.24	0.28
Spread(D2C)	73.32	74.72	4.01	73.32	74.72	4.01
Spread(D2D)	2.70	4.31	3.67	2.70	4.31	3.67
E[holding(days)]	1.00	1.00	0.00	1.00	1.00	0.00
Bid (% of par)	142.29	151.55	62.19	142.29	151.55	62.19
Effort (e^*)	0.78	0.21	1.63	0.13	0.03	0.34
$\tilde{v} \times 10^4$	-46.97	-49.18	8.66	-46.97	-49.18	8.66
$\tilde{v}_b \times 10^4$	90.56	87.97	10.96	90.56	87.97	10.96
Search costs (bps)	28.34	4.58	66.34	4.74	0.63	13.70

Panel B: Core vs Peripheral dealer pricing of non-GITs

	Core			**Peripheral**		
Variable name	**mean**	**median**	**SD**	**mean**	**median**	**SD**
E[sprd(bps)]	69.91	69.28	3.53	68.65	68.61	3.85
Pr(D2C)	0.93	0.93	0.03	0.91	0.92	0.06
Pr(D2D)	0.06	0.05	0.03	0.08	0.07	0.06
Spread(D2C)	75.05	74.37	4.72	75.05	74.37	4.72
Spread(D2D)	4.91	4.72	3.45	4.84	4.62	3.43
E[holding(days)]	1.01	1.01	0.01	1.01	1.01	0.01
Bid (% of par)	145.84	154.37	53.68	145.84	154.36	53.69
Effort (e^*)	0.11	0.04	0.24	0.02	0.01	0.04
$\tilde{v} \times 10^4$	-39.97	-44.71	14.65	-40.24	-44.95	14.67
$\tilde{v}_b \times 10^4$	96.33	91.18	15.57	96.07	90.89	15.61
Search costs (bps)	1.34	0.22	4.77	0.22	0.03	0.84

Table 3.8: Sensitivity Analysis. This table presents the results of comparative statics with respect to key parameters. Each row displays the level of the centrality premium for different levels of a key parameter holding the trade count decile group constant. Highlighted columns represent the estimated values of the parameter that varies in each panel. The bargaining power panels vary the value of $\Phi(\psi_1)$. The marginal benefit of effort panel varies the parameter γ_3. The marginal cost of inventory panel varies the value of $exp\{\kappa_2\}$. In each panel, all other parameters are fixed at their estimated value. Bonds that trade rarely have a trade count in the bottom three deciles. Bonds that trade sometimes have trade count deciles between 4 and 7, and bonds that trade often have trade counts between 8 and 10.

D2C bargaining power

$\Phi(\psi_1)$:	92.1%	93.8%	95.1%	96.3%	97.2%	97.9%	98.5%	98.9%	99.2%
Bond category									
Trades rarely	10.8	11.4	11.8	12.1	12.4	12.6	12.8	12.9	13.0
Trades sometimes	7.5	7.8	8.1	8.2	8.4	8.5	8.6	8.7	8.7
Trades often	5.6	5.8	5.9	6.0	6.1	6.2	6.2	6.3	6.3

Marginal benefit of effort

	High marginal benefit								Low marginal benefit
γ_3:	-4.598	-4.098	-3.598	-3.098	-2.598	-2.098	-1.598	-1.098	-0.598
Bond category									
Trades rarely	13.7	13.9	14.0	13.7	12.9	11.4	9.0	5.9	3.3
Trades sometimes	7.1	7.6	8.1	8.5	8.7	8.5	7.5	5.5	2.8
Trades often	4.8	5.1	5.5	5.9	6.3	6.5	6.2	5.2	3.2

Core dealer bargaining power in D2C market

$\Phi(\psi_1)$:	92.1%	93.8%	95.1%	96.3%	97.2%	97.9%	98.5%	98.9%	99.2%
Bond category									
Trades rarely	0.0	3.2	5.8	8.0	9.7	11.1	12.1	12.9	13.5
Trades sometimes	-5.1	-1.7	1.2	3.5	5.3	6.7	7.8	8.7	9.3
Trades often	-7.5	-4.0	-1.2	1.1	2.9	4.3	5.4	6.3	6.9

Core dealer marginal inventory cost

	Low marginal cost								High marginal cost
$exp\{\kappa_2\}$:	0.012	0.013	0.014	0.016	0.018	0.019	0.021	0.024	0.026
Bond category									
Trades rarely	17.7	12.9	6.8	-0.1	-7.8	-16.5	-26.1	-36.8	-48.8
Trades sometimes	12.9	8.7	2.4	-4.9	-12.9	-21.9	-31.9	-42.9	-55.2
Trades often	10.2	6.3	0.0	-7.4	-15.6	-24.7	-34.8	-46.0	-58.4

3.7 Appendix A: Supplementary Tables and Figures

Table A.1: Variable Definitions. This table describes the variables used in the empirical analysis reported in Tables 3.1 and B.1.

Variable	Description
Spread	Roundtrip spread in bps (see text for more details)
Spread(same day)	Roundtrip spread cond. On same-day roundtrip
Spread(multiple day)	Roundtrip spread cond. On multiple day roundtrip
Holding	Dealers' holding period in days
Holding (multiple day)	Holding period cond. on multiple day roundtrip
Dummy: sameday roundtrip	Dummy variable, same-day roundstrip
Buyvolume less than 1M	Dummy variable, 1 if the initial buy volume is less than 1 Million but greater than 0.5M
Buy volume btwn 1M & 5M	Dummy variable, 1 if initial buy volume is Between 1 Million and 5 Million
Buy volume > 5M	Dummy variable, 1 if dealer initial buy volume is above 5 Million
Core dealer	Dummy core dealer (0 if periphery dealer) (see text for more details)
Eigenvector	Dealer eigenvector measure of centrality
Maturity (T)	Bond maturity in years
Age	Bond age in years
Size	The Size of Primary Issue of the Bond
Trade count	Nb. of times bond traded in previous 30 days
Trade count decile	Decile of trade count in the past 30 days (Low count = 1 - High count = 10)
Dealer volume decile	Rank of aggregate trading volume of this dealer
Past days traded	Nb. of days dealer traded bond in prior year
Past days inventory	Nb. of days dealer took bond into inventory in prior year

Table A.2: Core-periphery transition matrix. The transition probability is estimated using the data from January 1, 2010 to 31 October 2012. To calculate the transition probability we count the number of core or peripheral dealer-quarters and identify the subset of dealer-quarters that change status in the next calendar quarter. For example, the probability of staying a core dealers of 79.6% is calculated by dividing the number of dealers who remain core dealers in the next period by the total number of core dealer-quarters. The transition probability from core to the periphery, and core to not trading next period, are calculated in the same way. Similarly, the transition probability for the peripheral dealers is calculated in a same way.

From/To:	Core Next Period	Peri Next Period	NoTrade Next Period
Core This Period	79.60%	20.20	0.20
Peri This Period	0.89	87.91	11.19

3.8 Appendix B: Two-Stage Selection Model

This Appendix estimates the centrality premium in a multivariate setting that controls for dealers' decision to hold the bonds in inventory overnight. As in M. Goldstein **and** E. Hotchkiss (2020), we proceed in two stages. The first stage is a probit regression to analyze the probability that a dealer engages in an intraday rountrip. The second stage examines the relation between dealer core-peripheral status and roundtrip spreads, taking into account the inventory decision in the first stage. We estimate,

$$Pr(intraday) = \alpha + \beta_1 X_{Bond} + \beta_2 X_{Dealer} + \gamma Z + \epsilon, \tag{B.1}$$

where X_{Bond} and X_{Dealer} represent sets of bond and dealer characteristics, respectively. The variable Z consists of instruments ($PastDaysTraded$ and $PastDaysInventory$) that identify the selection equation. Both variables are divided by 252 in the regression specification. Column (1) of Table 2 shows that bonds that trade less frequently in the previous month have a higher probability to be taken into overnight inventory. Sepcifically, the coefficients on the trade count decile 1-5 are all negative. Dealer trading history also matters. For example, the coefficient on $PastDaysInventory$ implies that dealers who took a given CUSIP into overnight inventory in the past are more likely to do so again. Dealers are more likely to complete the roundtrip trades within the same day for the trades with a larger size (*Buy volume >5*). Dealers are less likely to take into overnight inventory older bond issues and bonds with a smaller issue size.

We run the second-stage spread regression for the intraday round-trip trades and multiday round-trip trades separately.

$$Spread = \alpha + \beta_0 Core + \beta_1 X_{Bond} + \beta_2 X_{Dealer} + \beta_3 * Mills + u_1, \tag{B.2}$$

where $Mills$ denotes the Heckman selection term from the first-stage regression, and $Core$ is a binary variable indicating a core dealer.

Table B.1: Two-stage selection model. This table reports two-stage Heckman regressions with the roundtrip spread (intraday or multiday) as the dependent variable. All variables are defined in the Appendix. Column (1) reports the selection-equation estimates, in which the dependent variable equals one for an intraday roundtrip. Column (2) reports intraday roundtrip spreads, and column (3) reports estimates for multiday roundtrip spreads. Both regressions have credit rating fixed effects. Standard errors are based on bootstrapping with replacement.

	Selection	**Intraday**	**Multiday**
	(1)	**(2)**	**(3)**
Core dealer		7.922***	8.040***
		(0.120)	(0.586)
Dealer volume decile	-1.302***	-17.196***	-54.493***
	(0.011)	(0.174)	(3.224)
Dummy: trade count decile = 1	-0.362***	-3.173***	-6.592***
	(0.005)	(0.205)	(0.696)
Dummy: trade count decile = 2	-0.426***	-4.583***	-12.134***
	(0.004)	(0.202)	(0.642)
Dummy: trade count decile = 3	-0.366***	-4.811***	-12.076***
	(0.004)	(0.200)	(0.622)
Dummy: trade count decile = 4	-0.295***	-4.399***	-11.585***
	(0.004)	(0.193)	(0.605)
Dummy: trade count decile = 5	-0.209***	-3.567***	-8.575***
	(0.004)	(0.192)	(0.605)
Buyvolume less than 1M	0.023***	-10.296***	-14.437***
	(0.004)	(0.163)	(0.505)
Buy volume btwn 1M & 5M	0.149***	-12.029***	-23.046***
	(0.003)	(0.132)	(0.420)
Buy volume > 5M	0.234***	-11.584***	-21.991***
	(0.004)	(0.194)	(0.621)
Log(age)	0.089***	3.733***	7.234***
	(0.001)	(0.057)	(0.183)
Log(size)	-0.096***	-4.798***	-13.844***
	(0.002)	(0.071)	(0.313)
Log(maturity)	0.017***	7.443***	20.701***
	(0.001)	(0.055)	(0.174)
Past days traded/252	0.076***		
	(0.011)		
Past days inventory/252	-7.617***		
	(0.037)		
Constant	13.612***	214.246***	648.224***
	(0.113)	(1.744)	(32.749)
Mills		1.114***	-6.779***
		(0.238)	(0.991)
Rating FE	Yes	Yes	Yes
N	1161029	492469	668560
ChiSq stat.		44835.9	62962.6

As shown, the Mills terms are statistically significant, indicating that selection into intraday trades is an important determinant of the spread. Roundstrip spreads decline in trade size, as measured by the size of the first leg of the roundtrip. Bond of older age and longer time to maturity are associated with higher roundtrip spreads.

Core dealers ($Core = 1$) charge a significantly higher spread than peripheral dealers for both intraday and multiday roundtrips, suggesting a centrality premium in roundtrip spreads controlling for both selection into inventory and bond characteristics.

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3.9 Appendix C: Proofs and Derivations

Proof of Proposition 2: To make derivation simpler, let us simplify notations in the following way:

$$\begin{aligned}\tilde{v} &= \tilde{v}\left(d, q, \theta, \alpha\right) \\ V &= V\left(d; q, \theta, \alpha\right) \\ p_c\left(v_c\right) &= p_c\left(v_c, d, q, \theta, \alpha\right) \\ p_d\left(v_d\right) &= p_d\left(v_d, d, q, \theta, \alpha\right). \end{aligned} \tag{C.1}$$

Moreover, we do the following preliminary derivations: First,

$$\tilde{v} = \alpha\left(\frac{\beta}{q}V - k\right) - \frac{\theta}{1-\alpha\beta}$$

$$\Rightarrow V = \frac{q}{\alpha\beta}\left(\tilde{v} + \frac{\theta}{1-\alpha\beta} + \alpha k\right). \tag{C.2}$$

Next,

$$\begin{aligned} & \int_{\tilde{v}}^{\bar{v}} p_c\left(v_c\right) q dF_v\left(v_c\right) \\ = & \int_{\tilde{v}}^{\bar{v}} \left(\sigma\left(v_c + \frac{\theta}{1-\alpha\beta}\right) q + (1-\sigma)\,\alpha\left[\beta V - kq\right]\right) dF_v\left(v_c\right), \quad \text{given (21)} \\ = & \sigma q \int_{\tilde{v}}^{\bar{v}} v_c dF_v\left(v_c\right) + \left[1 - F_v\left(\tilde{v}\right)\right]\left(\frac{\sigma\theta q}{1-\alpha\beta} + (1-\sigma)\,\alpha\left[\beta V - kq\right]\right) \end{aligned}$$

$$\begin{aligned} & \int_{\tilde{v}}^{\bar{v}} p_d\left(v_d\right) q dF_v\left(v_d\right) \\ = & \int_{\tilde{v}}^{\bar{v}} \left(0.5\left(v_d + \frac{\theta}{1-\alpha\beta}\right) q + 0.5\alpha\left[\beta V - kq\right]\right) dF_v\left(v_d\right), \quad \text{given (23)} \\ = & 0.5q \int_{\tilde{v}}^{\bar{v}} v_d dF_v\left(v_d\right) + \left[1 - F_v\left(\tilde{v}\right)\right]\left(\frac{0.5\theta q}{1-\alpha\beta} + 0.5\alpha\left[\beta V - kq\right]\right) \end{aligned}$$

$$
\begin{aligned}
& \int_{\tilde{v}}^{\bar{v}} p_d\left(v_d\right) q dF_v\left(v_d\right) - \int_{\tilde{v}}^{\bar{v}} p_c\left(v_c\right) q dF_v\left(v_c\right) \\
= \; & 0.5q \int_{\tilde{v}}^{\bar{v}} v_d dF_v\left(v_d\right) + \left[1 - F_v\left(\tilde{v}\right)\right] \left(\frac{0.5\theta q}{1-\alpha\beta} + 0.5\alpha\left[\beta V - kq\right] \right) \\
& -\sigma q \int_{\tilde{v}}^{\bar{v}} v_c dF_v\left(v_c\right) - \left[1 - F_v\left(\tilde{v}\right)\right] \left(\frac{\sigma\theta q}{1-\alpha\beta} + \left(1-\sigma\right)\alpha\left[\beta V - kq\right] \right) \\
= \; & \left(0.5-\sigma\right) q \int_{\tilde{v}}^{\bar{v}} v dF_v\left(v\right) + \left[1 - F_v\left(\tilde{v}\right)\right] \left(\frac{\left(0.5-\sigma\right)\theta q}{1-\alpha\beta} + \left(\sigma - 0.5\right)\alpha\left[\beta V - kq\right] \right) \\
= \; & \left(0.5-\sigma\right) q \left[\int_{\tilde{v}}^{\bar{v}} v dF_v\left(v\right) - \left[1 - F_v\left(\tilde{v}\right)\right] \tilde{v}\left(d, q, \theta, \alpha\right) \right], \qquad \text{given (22)} \\
= \; & \left(0.5-\sigma\right) q \int_{\tilde{v}}^{\bar{v}} \left[v - \tilde{v}\right] dF_v\left(v\right).
\end{aligned}
\tag{C.3}
$$

Given e, the dealer's value function is given by

$$
\begin{aligned}
V = \; & \theta q + \left[1 - F(q;e)\right] \int_{\tilde{v}}^{\bar{v}} p_c\left(v_c\right) q dF_v\left(v_c\right) + F(q;e,d) \int_{\tilde{v}}^{\bar{v}} p_d\left(v_d\right) q dF_v\left(v_d\right) \\
& + F_v\left(\tilde{v}\right) \alpha\left(\beta V - kq\right) - s(e;d) \\
= \; & \theta q + \int_{\tilde{v}}^{\bar{v}} p_c\left(v_c\right) q dF_v\left(v_c\right) + F(q;e) q \left[\int_{\tilde{v}}^{\bar{v}} p_d\left(v_d\right) dF_v\left(v_d\right) - \int_{\tilde{v}}^{\bar{v}} p_c\left(v_c\right) q dF_v\left(v_c\right) \right] \\
& + F_v\left(\tilde{v}\right) \alpha\left(\beta V - kq\right) - s(e;d) \\
= \; & \theta q + \int_{\tilde{v}}^{\bar{v}} p_c\left(v_c\right) q dF_v\left(v_c\right) + F(q;e)\left(0.5-\sigma\right) q \int_{\tilde{v}}^{\bar{v}} \left[v - \tilde{v}\right] dF_v\left(v\right) \\
& + F_v\left(\tilde{v}\right) \alpha\left(\beta V - kq\right) - s(e;d) \\
= \; & \theta q + \sigma q \int_{\tilde{v}}^{\bar{v}} v_c dF_v\left(v_c\right) + \left[1 - F_v\left(\tilde{v}\right)\right] \left(\frac{\sigma\theta q}{1-\alpha\beta} + \left(1-\sigma\right)\alpha\left(\beta V - kq\right) \right) \\
& + F(q;e)\left(0.5-\sigma\right) q \int_{\tilde{v}}^{\bar{v}} \left[v - \tilde{v}\right] dF_v\left(v\right) + F_v\left(\tilde{v}\right) \alpha\left(\beta V - kq\right) - s(e;d) \\
= \; & \theta q + \sigma q \int_{\tilde{v}}^{\bar{v}} v_c dF_v\left(v_c\right) + \left[1 - F_v\left(\tilde{v}\right)\right] \left(\frac{\sigma\theta q}{1-\alpha\beta} + \alpha\left(\beta V - kq\right) - \sigma\alpha\left(\beta V - kq\right) \right) \\
& + F(q;e)\left(0.5-\sigma\right) q \int_{\tilde{v}}^{\bar{v}} \left[v - \tilde{v}\right] dF_v\left(v\right) + F_v\left(\tilde{v}\right) \alpha\left(\beta V - kq\right) - s(e;d) \\
= \; & \theta q + \sigma q \int_{\tilde{v}}^{\bar{v}} v_c dF_v\left(v_c\right) + \left[1 - F_v\left(\tilde{v}\right)\right] \left(\alpha\left(\beta V - kq\right) - \sigma q \tilde{v}\right) \\
& + F(q;e)\left(0.5-\sigma\right) q \int_{\tilde{v}}^{\bar{v}} \left[v - \tilde{v}\right] dF_v\left(v\right) + F_v\left(\tilde{v}\right) \alpha\left(\beta V - kq\right) - s(e;d) \\
= \; & \theta q + \alpha\left(\beta V - kq\right) + \sigma q \int_{\tilde{v}}^{\bar{v}} v dF_v\left(v\right) - \left[1 - F_v\left(\tilde{v}\right)\right] \sigma q \tilde{v} \\
& + F(q;e)\left(0.5-\sigma\right) q \int_{\tilde{v}}^{\bar{v}} \left[v - \tilde{v}\right] dF_v\left(v\right) - s(e;d)
\end{aligned}
\tag{C.4}
$$

At this point, we can use (C.2) to replace V in the above equation and obtain:

$$\begin{aligned}\frac{1-\alpha\beta}{\alpha\beta}q\left[\tilde{v}+\frac{\theta}{1-\alpha\beta}+\alpha k\right] &= \theta q-\alpha kq-s(e;d)+\sigma q\int_{\tilde{v}}^{\bar{v}}vdF_v\left(v\right)-\left[1-F_v\left(\tilde{v}\right)\right]\sigma q\tilde{v}\\ &\quad +F(q;e)\left(0.5-\sigma\right)q\int_{\tilde{v}}^{\bar{v}}\left[v-\tilde{v}\right]dF_v\left(v\right),\end{aligned}$$

which simplifies to

$$\begin{aligned}0 &= \theta\left(1-\frac{1}{\alpha\beta}\right)-\frac{k}{\beta}-\frac{s(e;d)}{q}+\sigma\int_{\tilde{v}}^{\bar{v}}vdF_v\left(v\right)-\left[1-F_v\left(\tilde{v}\right)\right]\sigma\tilde{v}\\ &\quad +F(q;e)\left(0.5-\sigma\right)\int_{\tilde{v}}^{\bar{v}}\left[v-\tilde{v}\right]dF_v\left(v\right)-\frac{1-\alpha\beta}{\alpha\beta}\tilde{v}. \qquad \text{(C.5)}\end{aligned}$$

Let

$$C\equiv\theta\left(1-\frac{1}{\alpha\beta}\right)-\frac{k}{\beta}-\frac{s(e;d)}{q}. \qquad \text{(C.6)}$$

Then we have

$$\sigma\int_{\tilde{v}}^{\bar{v}}vdF_v\left(v\right)-\sigma\left[1-F_v\left(\tilde{v}\right)\right]\tilde{v}+F(q;e)\left(0.5-\sigma\right)\int_{\tilde{v}}^{\bar{v}}\left[v-\tilde{v}\right]dF_v\left(v\right)-\frac{1-\alpha\beta}{\alpha\beta}\tilde{v}+C=0. \qquad \text{(C.7)}$$

Recall that given $F_v\left(v\right)$ is a uniform distribution, we derive the following:

$$\int_{\tilde{v}}^{\bar{v}}vdF_v\left(v\right)=\frac{1}{\bar{v}-\underline{v}}\int_{\tilde{v}}^{\bar{v}}vdv=\frac{1}{\bar{v}-\underline{v}}\cdot\left.\frac{v^2}{2}\right|_{\tilde{v}}^{\bar{v}}=\frac{\bar{v}^2-\tilde{v}^2}{2\left(\bar{v}-\underline{v}\right)} \qquad \text{(C.8)}$$

$$\left[1-F_v\left(\tilde{v}\right)\right]\tilde{v}=\tilde{v}\left(1-\frac{\tilde{v}-\underline{v}}{\bar{v}-\underline{v}}\right)=\frac{\tilde{v}\left(\bar{v}-\tilde{v}\right)}{\bar{v}-\underline{v}} \qquad \text{(C.9)}$$

$$\int_{\tilde{v}}^{\bar{v}}\left(v-\tilde{v}\right)dF_v\left(v\right)=\int_{\tilde{v}}^{\bar{v}}\frac{v-\tilde{v}}{\bar{v}-\underline{v}}dv=\frac{1}{\bar{v}-\underline{v}}\int_{\tilde{v}}^{\bar{v}}vdv-\tilde{v}\frac{\bar{v}-\tilde{v}}{\bar{v}-\underline{v}}=\frac{\left(\bar{v}-\tilde{v}\right)^2}{2\left(\bar{v}-\underline{v}\right)}. \qquad \text{(C.10)}$$

Substituting all of the above into the dealer's value function, we obtain

$$\sigma\frac{\bar{v}^2-\tilde{v}^2}{2\left(\bar{v}-\underline{v}\right)}-\sigma\frac{\tilde{v}\left(\bar{v}-\tilde{v}\right)}{\bar{v}-\underline{v}}+F(q;e)\left(0.5-\sigma\right)\frac{\left(\bar{v}-\tilde{v}\right)^2}{2\left(\bar{v}-\underline{v}\right)}-\frac{1-\alpha\beta}{\alpha\beta}\tilde{v}+C=0. \qquad \text{(C.11)}$$

Re-arranging the above yields

$$\left[\sigma+F(q;e)\left(0.5-\sigma\right)\right]\left(\bar{v}-\tilde{v}\right)^2-\frac{1-\alpha\beta}{\alpha\beta}2\left(\bar{v}-\underline{v}\right)\tilde{v}+2\left(\bar{v}-\underline{v}\right)C=0. \qquad \text{(C.12)}$$

Let

$$\begin{aligned} A &\equiv \sigma + F(q;e)\,(0.5-\sigma) = \sigma\,[1-F(q;e)] + 0.5F(q;e) > 0 \\ B &\equiv \frac{1-\alpha\beta}{\alpha\beta} 2\,(\bar{v} - \underline{v}) > 0 \\ D &\equiv 2\,(\bar{v} - \underline{v})\,C = 2\,(\bar{v} - \underline{v}) \left[\theta\left(1 - \frac{1}{\alpha\beta}\right) - \frac{k}{\beta} - \frac{s(e;d)}{q}\right]. \end{aligned} \tag{C.13}$$

Then (C.12) becomes

$$A\,(\bar{v} - \tilde{v})^2 - B\tilde{v} + D = 0, \tag{C.14}$$

which can be re-arranged to

$$A\tilde{v}^2 - (2A\bar{v} + B)\,\tilde{v} + A\bar{v}^2 + D = 0. \tag{C.15}$$

The solutions to the above quadratic equation are

$$\tilde{v} = \frac{2A\bar{v} + B \pm \sqrt{(2A\bar{v} + B)^2 - 4A\,(A\bar{v}^2 + D)}}{2A}. \tag{C.16}$$

Note that $B > 0$, and thus the larger root of $\tilde{v}$ is strictly greater than $\bar{v}$, which would imply no trades with a buyer and thus does not serve our purpose. Therefore, we are left with a unique root,

$$\tilde{v}^* = \frac{2A\bar{v} + B - \sqrt{(2A\bar{v} + B)^2 - 4A\,(A\bar{v}^2 + D)}}{2A}. \tag{C.17}$$

This root exists as long as

$$(2A\bar{v} + B)^2 - 4A\left(A\bar{v}^2 + D\right) \geq 0,$$

that is,

$$B^2 + 4A\,(\bar{v}B - D) \geq 0. \tag{C.18}$$

From Proposition 1, we know that $e^* > 0$ if $\tilde{v} < \bar{v}$. Thus to ensure $e^* > 0$, we require $\tilde{v} < \bar{v}$, i.e.,

$$\frac{2A\bar{v} + B - \sqrt{(2A\bar{v} + B)^2 - 4A\,(A\bar{v}^2 + D)}}{2A} < \bar{v}. \tag{C.19}$$

Given $A > 0$, this boils down to

$$B < \sqrt{(2A\bar{v} + B)^2 - 4A\,(A\bar{v}^2 + D)}. \tag{C.20}$$

Given $B > 0$, the above requires

$$(2A\bar{v} + B)^2 - 4A\left(A\bar{v}^2 + D\right) - B^2 > 0, \tag{C.21}$$

which reduces to

$$\bar{v}B - D > 0.$$

Substituting in the expressions for B and D, respectively, yields

$$\bar{v}\frac{1-\alpha\beta}{\alpha\beta}2\left(\bar{v} - \underline{v}\right) - 2\left(\bar{v} - \underline{v}\right)\left[\theta\left(1 - \frac{1}{\alpha\beta}\right) - \frac{k}{\beta} - \frac{s(e;d)}{q}\right] > 0. \tag{C.22}$$

The above simplies to

$$\left(\bar{v} + \theta\right)\left(\frac{1}{\alpha\beta} - 1\right) + \frac{k}{\beta} + \frac{s(e;d)}{q} > 0. \tag{C.23}$$

Given $1 - \alpha\beta > 0$ and $s(e;d) \geq 0$, the above, i.e., $\bar{v}B - D > 0$, holds for any $e \geq 0$. Moreover, this implies the existence condition (C.18) also holds for any $e \geq 0$. In sum, the root $\tilde{v}$ as specified in (C.17) exists and satisfies $\tilde{v} < \bar{v}$ for all $e \geq 0$. Then given $\tilde{v}^* < \bar{v}$, $e^* > 0$ can be uniquely solved from (27) according to Proposition 1. Given uniform distribution, it boils down to $e^* > 0$ solving

$$F_e\left(q;e\right)\left(0.5 - \sigma\right)\frac{q\left(\bar{v} - \tilde{v}\right)^2}{2\left(\bar{v} - \underline{v}\right)} = s_e\left(e;d\right). \tag{C.24}$$

Note that the optimal threshold is effectively bounded below given the support of the distribution. Therefore, if $\tilde{v}^* \leq \underline{v}$, then $\tilde{v}(d,q,\theta,\alpha) = \underline{v}$ and $e(d,q,\theta,\alpha) = \underline{e}^*$, where $\underline{e}^*$ solves (33). Finally, given $\tilde{v}(d,q,\theta,\alpha)$, the value $V(d,q,\theta,\alpha)$ can be easily derived from (22).

Proof of Proposition 3:

For part (i), note that all potential buyers will agree to trade a bond with $\tilde{v}(d,q,\theta,\alpha) = \underline{v}$, be they clients or dealers. Therefore, a dealer is able to sell such bonds within the same period of acquiring, either to a client-buyer or a dealer-buyer. Then Proposition 1 implies that a dealer's search effort is the highest for all of its bond holdings such that $\tilde{v}^* \leq \underline{v}$ because $\partial e^*/\partial\tilde{v} < 0$. Next, recall from Proposition 2 that $\tilde{v}^* \leq \underline{v}$ requires

$$\frac{2A\bar{v} + B - \sqrt{\left(2A\bar{v} + B\right)^2 - 4A\left(A\bar{v}^2 + D\right)}}{2A} \leq \underline{v}. \tag{C.25}$$

This boils down to

$$2A\bar{v} + B - 2A\underline{v} \leq \sqrt{\left(2A\bar{v} + B\right)^2 - 4A\left(A\bar{v}^2 + D\right)}$$

$$\left[2A\bar{v} + B - 2A\underline{v}\right]^2 \leq \left(2A\bar{v} + B\right)^2 - 4A\left(A\bar{v}^2 + D\right)$$

$$\left(2A\bar{v} + B\right)^2 - 4A\underline{v}\left(2A\bar{v} + B\right) + 4A^2\underline{v}^2 \leq \left(2A\bar{v} + B\right)^2 - 4A\left(A\bar{v}^2 + D\right)$$

$$A\bar{v}^2 + D + A\underline{v}^2 - 2A\underline{v}\bar{v} - \underline{v}B \leq 0$$

$$A\left(\bar{v} - \underline{v}\right)^2 + D - \underline{v}B \leq 0$$

$$A\left(\bar{v} - \underline{v}\right)^2 + 2\left(\bar{v} - \underline{v}\right)\left[\theta\left(1 - \frac{1}{\alpha\beta}\right) - \frac{k}{\beta} - \frac{s(e;d)}{q}\right] - \underline{v}\frac{1 - \alpha\beta}{\alpha\beta}2\left(\bar{v} - \underline{v}\right) \leq 0$$

$$A\left(\bar{v} - \underline{v}\right) + 2\left(\theta + \underline{v}\right)\left(1 - \frac{1}{\alpha\beta}\right) - 2\frac{k}{\beta} \leq 2\frac{s(e;d)}{q}$$

$$\left[\sigma - F(q;e)\left(\sigma - 0.5\right)\right]\left(\bar{v} - \underline{v}\right) + 2\left(\theta + \underline{v}\right)\left(1 - \frac{1}{\alpha\beta}\right) - 2\frac{k}{\beta} \leq 2\frac{s(e;d)}{q}. \tag{C.26}$$

The left-hand side of the above strictly decreases in $F(q;e)$. Thus the highest possible value of LHS is given by probability $F(q;e) = 0$. Similarly, the lowest possible value of the right-hand side is zero given that the search cost is non-negative. Therefore, condition (C.26) holds for a dealer of any centrality d and any effort choice e, that is, $\tilde{v}^* \leq \underline{v}$ for any (d,e) if

$$\sigma\left(\bar{v} - \underline{v}\right) + 2\left(\theta + \underline{v}\right)\left(1 - \frac{1}{\alpha\beta}\right) \leq 2\frac{k}{\beta}. \tag{C.27}$$

This implies that all dealers will choose to make sure bonds with sufficiently low θ and α are sold within the same period in which they have been acquired.

For part (ii), let us first identify the respective sets of bonds involved in intraday and multiday roundtrips. Note that the probability of a bond being sold in a given period is $1 - F_v\left(\tilde{v}\left(d,q,\theta,\alpha\right)\right)$. Also recall that Proposition 2 that $\tilde{v}^* < \bar{v}$ for any given dealer and any bond acquired by the dealer. Therefore, the probability of the bond being sold in a given period is strictly positive, *i.e.*, $1 - F_v\left(\tilde{v}\left(d,q,\theta,\alpha\right)\right)$ given $\tilde{v}^* < \bar{v}$. Thus it implies that all bonds newly acquired by a dealer have a strictly positive probability of being in an intraday roundtrip. Let $\mathit{\Omega}\left(d\right)$ denote the set of all bonds acquired by a particular dealer d. Then the set of bonds that may end up in an intraday roundtrip is simply $\mathit{\Omega}\left(d\right) = \{(q,\theta,\alpha) : \tilde{v}(d,q,\theta,\alpha) \geq \underline{v}\}$. However, we know from part (ii) that all bonds such that $\tilde{v}^* \leq \underline{v}$ will be sold in an intraday roundtrip because $1 - F_v\left(\tilde{v}(d,q,\theta,\alpha) = \underline{v}\right) = 1$. As a result, all bonds that are involved in multi-day roundtrips must be those such that $\tilde{v}^* > \underline{v}$.

3.10 Appendix D: Maximum Likelihood Function

The likelihood function of the roundtrip spreads is the convolution of two uniform distributions. Let $z_1 = x - y$,where $y = \sigma v | v < v_b$ and $x = \sigma v_c | v_c > \tilde{v}$. Since v_c and v follow a uniform distribution, it follows that x and y also follow uniform distributions with support $[\sigma\tilde{v}, \sigma\overline{v}]$ and $[\sigma\underline{v}, \sigma v_b]$, respectively. Let $\Delta v = \overline{v} - \underline{v}$. Note that z_1 has support $[\sigma(\tilde{v} - v_b), \sigma(\overline{v} - \underline{v})]$. Let $I_{(a,b)}(x)$ denote an indicator function with a value of 1 whenever x lies in the interval (a, b) and 0 otherwise. We use the following result from Mood, Graybill **and** Boes (1974) on the convolution of two uniform distributions,

$$f(z) = \int_{-\infty}^{\infty} \frac{I_{(a,b)}(x) I_{(c,d)}(x - z)}{(b - a)(d - c)} dx$$

$$= \frac{1}{(b - a)(d - c)} \big([z + d - a] I_{(a-d,b-d)}(z) + [b - c - z] I_{(a-c,b-c)}(z) \big) \tag{D.1}$$

Letting $a = \sigma\tilde{v}$, $b = \sigma\overline{v}$, $c = \sigma\underline{v}$ and $d = \sigma v_b$, the density f of z_1 is

$$f(z) = \int_{-\infty}^{\infty} f_x(x) f_y(x - z) dx = \frac{1}{\sigma^2(\overline{v} - \tilde{v})(v_b - \underline{v})} \int_{-\infty}^{\infty} I_{(\sigma\tilde{v},\sigma\overline{v})}(x) I_{(\sigma\underline{v},\sigma v_b)}(x - z) dx$$

$$= \frac{1}{\sigma^2(\overline{v} - \tilde{v})(v_b - \underline{v})} \Big([z + \sigma(v_b - \tilde{v})] I_{(\sigma(\tilde{v}-v_b),\sigma(\overline{v}-v_b))}(z) + [\sigma(\overline{v} - \underline{v)} - z] I_{(\sigma(\tilde{v}-\underline{v}),\sigma(\overline{v}-\underline{v}))}(z) \Big) \tag{D.2}$$

Similarly, let $z_2 = w - y$ where $w = 0.5 v_d | v_d > \tilde{v}$ and $y = \sigma v | v < v_b$. Both w and y follow uniform distributions with support $[0.5\tilde{v}, 0.5\overline{v}]$ and $[\sigma\underline{v}, \sigma v_b]$, respectively. Using an analogous argument, the density g of z_2 is

$$g(z) = \int_{-\infty}^{\infty} f_w(w) f_y(w - z) dw = \frac{1}{0.5\sigma(\overline{v} - \tilde{v})(v_b - \underline{v})} \int_{-\infty}^{\infty} I_{(0.5\tilde{v},0.5\overline{v})}(w) I_{(\sigma\underline{v},\sigma v_b)}(w - z) dw$$

$$= \frac{1}{0.5\sigma(v_b - \underline{v})(\overline{v} - \tilde{v})} \big([z + \sigma v_b - 0.5\tilde{v}] I_{(0.5\tilde{v}-\sigma v_b,0.5\overline{v}-\sigma v_b)}(z) + [0.5\overline{v} - \sigma\underline{v} - z] I_{(0.5\tilde{v}-\sigma\underline{v},0.5\overline{v}-\sigma\underline{v})}(z) \big) \tag{D.3}$$

Define

$$z_i = \begin{cases} \sigma(v_c - v) & \multirow{2}{*}{if} \ \mathbf{1}(D2C) = 1 \\ 0.5v_d - \sigma v & \quad \mathbf{1}(D2D) = 1 \end{cases}$$

The likelihood of observation i is thus

$$L(\gamma, \sigma, e, \kappa, d, \underline{v}, \overline{v}; z_i) = f(z_{1i})^{\mathbf{1}(D2C)} g(z_{2i})^{\mathbf{1}(D2D)}. \tag{D.4}$$

3.11 Internet Appendix

Linear Approximation to the Two-Equation System

This section describes how we solve equations (C.17) and (C.24) in the optimization process. We first linearize both equations using a first-order Taylor series expansion and then solve for effort iteratively based on the closed form expression for the trade threshold.

Consider the following system,

$$G(e^*, \tilde{v}^*) = F_e\left(q; e^*\right)(0.5 - \sigma)\frac{q\left(\bar{v} - \tilde{v}^*\right)^2}{2\left(\bar{v} - \underline{v}\right)} - 2de^* = 0$$

$$H(e^*, \tilde{v}^*) = \tilde{v}^* - \frac{2A\bar{v} + B - \sqrt{\left(2A\bar{v} + B\right)^2 - 4A\left(A\bar{v}^2 + D\right)}}{2A} = 0$$

Because effort e enters both equations in a non-linear fashion, solving this system is costly in terms of computing time. In order to ease the computational burden we linearize both equations around a point $(\hat{e}, \hat{v})$ using first-order Taylor series expansion, and then solve for e^* and v^* iteratively.

3.11.1 Step 1: Taylor series expansion

$$\begin{aligned}
0 = G((\hat{e} + h_1, \hat{v} + h_2) &= G(\hat{e}, \hat{v}) + \frac{\delta G(\hat{e}, \hat{v})}{\delta e}h_1 + \frac{\delta G(\hat{e}, \hat{v})}{\delta v}h_2 \\
0 = H((\hat{e} + h_1, \hat{v} + h_2) &= H(\hat{e}, \hat{v}) + \frac{\delta H(\hat{e}, \hat{v})}{\delta e}h_1 + \frac{\delta H(\hat{e}, \hat{v})}{\delta v}h_2
\end{aligned}$$

where

$$
\begin{aligned}
G_e &:= \frac{\delta G(e,v)}{\delta e} = exp\left\{-\gamma(X,e)q\right\} q^2\gamma(X,e)\gamma_3^2(0.5-\sigma)0.5\frac{(\overline{v}-\tilde{v})^2}{(\overline{v}-\underline{v})}\left[1-q\gamma(X,e)\right]-2d \\
G_{v:=} & \frac{\delta G(e,v)}{\delta v} = -q\frac{(\overline{v}-\tilde{v})^2}{(\overline{v}-\underline{v})}exp\left\{-\gamma(X,e)q\right\} q\gamma(X,e)\gamma_3(0.5-\sigma) \\
H_e &:= \frac{\delta H(e,v)}{\delta e} = (0.5B)^{-2}\frac{\delta A}{\delta e} \\
& \quad +\frac{1}{2}\left\{\frac{A}{2}\left[(2A\overline{v}+B)^2-4A\left(A\overline{v}^2+D\right)\right]^{(-1/2)}\right\} \\
& \quad \times\left(4(2A\overline{v}+B)\overline{v}\frac{\delta A}{\delta e}-4\left(A\overline{v}^2+D\right)\frac{\delta A}{\delta e}-4A\overline{v}^2\frac{\delta A}{\delta e}-4A\frac{\delta D}{\delta e}\right)/A^2 \\
& \quad -\frac{1}{2}\left\{\left[(2A\overline{v}+B)^2-4A\left(A\overline{v}^2+D\right)\right]^{0.5}\frac{\delta A}{\delta e}\right\}/A^2 \\
H_v &:= \frac{\delta H(e,v)}{\delta v} = 1
\end{aligned}
$$

and where

$$
\begin{aligned}
\frac{\delta A}{\delta e} &= F_e(q;e)(0.5-\sigma) \\
\frac{\delta D}{\delta e} &= \frac{-1(\overline{v}-\underline{v})}{q}2de
\end{aligned}
$$

Solving for $h_1$and h_2,

$$
\begin{aligned}
h_1 &= \frac{(\hat{G}_v\hat{H}-\hat{G})}{\hat{G}_e-\hat{H}_e\hat{G}_v} \\
h_2 &= -\hat{H}_e\frac{(\hat{G}_v\hat{H}-\hat{G})}{(\hat{G}_e-\hat{H}_e\hat{G}_v)}-\hat{H}
\end{aligned}
$$

where the ^ indicate that the expression is evaluated at the point $(\hat{e},\hat{v})$ =(0, 0.01).

3.11.2 Step 2: Iteration

Denote by $\hat{A}_j$ and $\hat{D}_j$ the values of A, D at the point $(\hat{e_j},\hat{v_j})$, with $(\hat{e_1},\hat{v_1}) = (0+h_1, 0.01+h_2)$. The trade threshold and effort are then solved for iteratively using,

$$\hat{v}_{j+1} = \frac{2\hat{A}_j\bar{v} + \hat{B}_j - \sqrt{\left(2\hat{A}_j\bar{v} + B\right)^2 - 4\hat{A}_j\left(\hat{A}_j\bar{v}^2 + \hat{D}_j\right)}}{2A^*}$$

$$\hat{e}_{j+1} = \left(F_e\left(q;\hat{e_j}\right)\left(0.5 - \sigma\right)\frac{q\left(\bar{v} - \tilde{v}\right)^2}{2\left(\bar{v} - \underline{v}\right)}\right)\left(2d\right)^{(-1)}$$

Convergence is achieved after two iterations.

Chapter 4

Consolidation and Advertising Rates: A Study of the Impact of Newspaper Ownership Swap on Community Newspapers in Ontario

4.1 Introoudction

Despite the considerable focus on daily newspapers for their thorough coverage of national and international events, academic research on community newspapers in Canada is surprisingly scant. However, these local publications play a pivotal role in conveying regionally pertinent information. They serve as vital platforms for local government activities, advertisements, fundraising efforts for community projects and elections, and fostering regional business. Additionally, they carry immense cultural significance, representing a treasured heritage of Canadian society. Community newspapers also contribute to connections within local households, ensuring that multifaceted local news spreads across the residents in these areas, fostering closer networking. These functions cannot be easily replaced by daily newspapers that primarily concentrate on international and national events. Despite the proliferation of numerous online news platforms in recent decades, community newspapers continue to hold a crucial position in reaching specific households, particularly among elderly individuals who may choose not to use or lack experience in accessing the internet. As a result, community newspapers serve as a significant intermediary for disseminating news to this subgroup of the population.

In 2017, a notable event occurred: Postmedia and Metroland exchanged dozens of ommunity newspapers, subsequently shutting down most of them in various regional markets of Ontario, resultling loss in approximate 244 jobs. Prior to these events, a significant number of regional markets had newspapers operated by both Postmedia and

Metroland. However, following the occurrence of these events, many of these markets underwent a change, with only one newspaper remaining in operation, owned by either Postmedia or Metroland (CBC News, 2017). This change transpired due to the ownership swap strategy implemented by Postmedia and Metroland. Under this strategy, the companies engaged in the exchange of newspaper ownership across various markets. Despite their claimed objective of cutting down costs by focusing on the areas where they primarily operated their business and discontinuing business in the less focused areas, it is suspicious that they wanted to prevent situations where a single market had newspapers operated by both Postmedia and Metroland. By doing so, the two companies can eliminate potential market overlap or competition between them within the same geographic area. This large-scale closure has the potential to stifle competition, increase market concentration, and alter the industry's market structure. Given that a majority of community newspapers operate on a free distribution model and generate revenue primarily from advertisements, undertaking a comprehensive analysis of the event's repercussions on the advertising side becomes crucial. This is particularly important considering the substantial role that community newspapers play in advertising for local businesses within their respective regions. Therefore, it is important for us to specifically examine how this event directly impacted advertising rates within the local markets that were affected.

We aim to ascertain whether the ownership swap led to higher advertising rates in the regions that underwent these changes, particularly for newspapers owned by Postmedia and Metroland. If there is a change, we seek to understand the reasons behind it. Is it a result of the two companies cutting down their operating costs, or is it because the swap led to a reduction in competition? This consideration is crucial because if the event resulted in increased advertising rates, it could lead to concerns about local businesses losing access to newspapers that offered more affordable rates. This potential scenario could potentially harm businesses in these markets. Furthermore, if there is a significant competition effect, people worry that the anti-competitive behavior is harmful to other newspapers owned by companies other than Postmedia or Metroland.

To address these inquiries, we obtain advertising rate and circulation data for Ontario from 2013 to 2019 from sources including Adoreach and News Media Canada. The data from News Media Canada enable us to observe information regarding the market, name, and ownership of community newspapers. Meanwhile, Adoreach provides the rates for posting advertisements per line. Subsequently, we identify the census subdivision within which each newspaper operates and integrate data with demographic information from CHASS. By merging these three, we create a cohesive dataset that allows us to explore variations in advertising rates across different newspaper ownerships and markets.

Our primary challenge lies in the fact that local markets display distinct characteristics, including population, age, education levels, and others. Moreover, the selection of local markets for swapping newspapers is likely not random. This can lead to potential discrepancies in the demographic characteristics between the markets where the event (swap) takes place and those that remain unaffected. These demographic attributes likely play a crucial role in determining advertising rates. Furthermore, markets with significant variations in demographic data are unlikely to follow a common time trend, an assumption that is essential for accurately identifying the treatment effect in a difference-in-differences regression setup. To tackle this challenge, we are implementing the matching strategy outlined in Smith and Todd (2004). Specifically, we are utilizing market characteristic data to compute propensity scores. These scores allow us to select markets unaffected by the event, based on the similarity of their propensity scores, creating a set of control markets, which helps us eliminate markets with differing parallel trends.

Our approach deviates from the traditional matching strategy, where each treatment is paired with a single control entity. Instead, we opt for matching each market in the treatment group with multiple markets. Subsequently, we calculate the average of these matched markets, creating a synthetic control group. This method is simliar to the one imployed by Abadie and Gardeazabal (2003), which creates synthetic controls from existing controls by average or weighted averaging of the markets. This approach proves advantageous in further reducing bias in market characteristics, as compared to the practice of matching each treatment market with only one control market.

Upon the completion of the matching process, we proceed with a difference-in-differences regression analysis involving both the treatment group and the synthetic control markets. This analytical method empowers us to ascertain the impact of the event on the advertising rates within the markets that were influenced by the newspaper swap.

Our findings indicate a significant increase in the mean advertising rate within the markets affected by the swap event. This increase is observed not only in the mean advertising rate for all newspapers but also in the mean advertising rate for newspapers owned by Postmedia or Metroland, both of which experience substantial surges. On average, post-event, the rate difference between the treated and untreated markets increased by \$0.41 per line. For newspapers owned by either Postmedia or Metroland, this difference increased by \$0.62 post-event. This implies a challenging environment for companies aiming to advertise within the markets impacted by these events. The loss of access to lower-rate options indicates that these companies are encountering a less favorable landscape for their advertising endeavors following the swap. However, our findings suggest that the surge in rates originates from the two companies shutting down lower-rated newspapers. Both Postmedia and Metroland are actively shutting down lower rated newspapers acquired from the swap. Given that most community newspapers are free, a lower-rated newspaper is likely cost-benefit inefficient. We find no evidence, however, of a significant competitive effect on the advertising side due to these events. There is no evidence indicating that these events allowed the consistently existing newspapers operated by the two companies to charge higher rates in these affected local markets.

The remainder of the paper is organized as follows: Section 3 provides literature review. Section 3 provides background information on the event, data specifics and descriptive statistics. Section 4 summarizes market structure and advertising rate series. Section

5 outlines the empirical framework, and Section 6 presents the results and includes a robustness check. Section 7 concludes.

4.2 Literature Review

Many studies examine the newspaper industry with majority focus on daily newspapers. Extensive literature studies the two-sided market feature in the newspaper industry. Evan (2002) points out that in a two-sided market feature, focusing on one side can lead to misleading interpretations of market power. Chandra and Collard-Wexler (2009) corroborate this opinion with an empirical study of a merger in the Canadian newspaper industry. They show that neither subscription prices nor advertising rates necessarily increase after newspapers merge, as opposed to a product with one-sided customers. Two-sided market structures also exhibit network feedback loops. Rysman (2004) finds that there are positive network effects in the Yellow Pages, in which readers value advertisements and advertisers value readerships, thus, more readers lead to more advertisements, and vice versa. This poses challenges for modeling the equilibrium. Filistrucchi and Klein (2013) introduce a two-sided market model with heterogeneous consumers, taking network effects into consideration. Filling the gaps in theoretical literature often relies on oversimplification to achieve a unique equilibrium, such as assuming firms set prices only on one side or restricting one side's network effect to zero. Filistrucchi, Klein, and Michielsen (2012) study the merger effects in a hypothetical merger in the Dutch newspaper industry, considering heterogeneous products on both sides and accounting for network effects.

Apart from the feedback loops between the two side, another reason newspapers often exhibit counterintuitive post merger price series is that they frequently subsidize one side from another. Rochet and Tirole (2003) corroborate the incentive for publishers to subsidize one market side from another, stating that publishers might set copy prices below the cost to attract readers. Pattabhiramaiah (2014) concludes that as advertising revenue decreases, newspapers are less willing to subsidize readers compared to the past, leading to an increase in the subscription price for newspapers in general. Argentesi et al. (2007) develop a structural model to study competition in both the readers' and advertisers' segments of Italian newspapers. They find that newspapers have more market power on the readers' side than on the advertisers' side.

Newspaper markets exhibit strong evidence of economies of scale. Dertouzos and Trautman (1990) find significant economies of scale in the circulation and content of newspapers. Rosse (1967) identifies economies of scale in both the readership and advertiser sides. Reasons for these economies of scale include readers not necessarily disliking advertisements, as suggested by Kaiser and Song (2009), and newspapers with larger scales potentially offering better quality, thus attracting more readers Berry and Waldfogel (2010). The newspaper industry also shows high concentration. Dertouzos and Trautman (1990) reveal that only 1% of the newspaper industry faces competition in the same city. Fan (2013) emphasizes that product characteristics significantly influence consumer welfare, noting that mergers in the daily newspaper sector cause shifts in these characteristics. Overlooking these shifts and focusing solely on price might lead to skewed welfare estimations. examines the influence of cross ownership and chain ownership, along with competition between local newspapers and broadcasters, on newspaper advertising rates. While there has been ample analysis on market structures in daily newspapers, the ownership structure in community newspapers remains under researched.

The number of newspapers has seen a significant decline in recent decades, especially with the rise of internet platforms. Kroft and Pope (2014) demonstrate that websites, such as Craigslist, directly reduce advertisement in print newspapers.

Our paper relates closely to these studies with regarde to the erosion of advertising revenue, consolidation, and post merger price series. We observe that the Canadian community newspaper industry has a high concentration, with Postmedia and Metroland accounting for around 50% of publications. In line with previous literature, chain newspapers (those owned by Postmedia and Metroland in this context) have markedly higher rates than those owned by smaller companies. Additionally, our research supports the observation that newspapers are on the decline. We note that Postmedia and Metroland have been shutting down newspapers with lower rates. As most community newspapers are free, closing community newspapers becomes a strategy to halt reader subsidies.

However, most of the research listed above centers on daily newspapers and magazines. Notably, there exists a research gap concerning community newspapers. Even though daily newspapers receive extensive scrutiny, community newspapers, which mainly serve local communities and circulate weekly, have not been as thoroughly examined. Community newspapers often distribute issues at no cost, relying heavily on advertising for revenue. This model mirrors the Yellow Pages. Rysman (2004) explores the Yellow Pages market structure, highlighting how increased advertising directly enhances readership and the reverse. Still, Yellow Pages studies can not fill the research gap on community newspapers. While both rely on advertising revenue, their target readers differ: Yellow Pages readers usually look for advertisements, while community newspaper readers seek both news content and ads. Our research seeks to bridge this gap, illuminating the price series of community newspapers and potentially offering insights to simliar prodcuts such as Yellow Pages. By studying how community newspapers navigate competition from internet platforms, we aim to provide insights into challenges of simliar free printed product such as Yellow Pages might also encounter.

4.3 Data and Background

We collect newspaper ownership, circulation, and circulation area data from News Media Canada covering the period from 2013 to 2019. The News Media Canada dataset includes information about circulation areas, operating companies, circulations, and distribution days for each newspaper. Using the circulation area of each newspaper, we determine representative latitude and longitude coordinates corresponding to their locations. Subsequently, we identify the census subdivisions that encompass these points and define the census subdivision in which a newspaper circulates as its market. Through analyzing this dataset, we are able to determine the census subdivisions affected by the newspaper swap in 2017 and identify the newspapers operating within those markets. We consider the census subdivision an appropriate market definition for community newspapers, as they primarily provide news relevant to the local municipality, including government initiatives, fundraising events, and political activities. The term "census subdivision" is synonymous with "municipality" and accurately reflects the scope of coverage provided by these newspapers. In aggregate, there are 214 markets, out of which 33 experienced a swap in 2017.

It is important to note that the dataset provided by News Media Canada, while comprehensive, may be subject to noise and incompleteness. This is because newspapers have the choice to subscribe to membership with News Media Canada and voluntarily report their circulation statistics. Consequently, not all community newspapers across Canada are captured in this dataset. Furthermore, if a newspaper appeared in the dataset previously but is absent in the current year, it does not necessarily imply that the newspaper has ceased publication. It could be due to the newspaper suspending its membership or choosing not to report statistics to the association. However, our discussions with the data provider indicate that most influential newspapers opt to subscribe to News Media Canada, as it is the leading association for community newspapers. Membership offers valuable benefits such as low-cost webinars for editorial, marketing, and advertising departments, sales training, auditing, and representation of members' interests in various public affairs issues. These services and resources are valuable to community newspapers and can potentially yield cost-cutting benefits. Consequently, we believe that this dataset adequately captures market features and can provide answers to our research questions.

We gather the rate data from Adoreach, the dataset containing the line rate for each community newspaper in Ontario. Most of the newspapers from Adoreach can be merged with the dataset collected from News Media Canada. Some newspapers are in the rate dataset but not in the News Media Canada dataset, and vice versa—certain newspapers in the News Media Canada dataset do not appear in the Adoreach dataset. To enhance completeness, we create an outer join of the two datasets so that any newspaper appearing in one of the datasets will be included in the analysis. Furthermore, given the fact that the majority of newspapers, especially the more influential ones and those well-known to the public, reside in both datasets, we believe that both datasets can capture a comprehensive view of the characteristics we are interested in investigating in this paper.

Figure 1 visualizes the number of newspapers involved in the analysis from 2013 to 2019. During this period, there are approximately 200 to 300 community newspapers in Ontario. The ownership of these newspapers is relatively concentrated. For most of the years, more than 50% of the newspapers are owned by Postmedia and Metroland, underscoring the significant roles these two companies play in communicating local news. The substantial closures by these two companies can lead to a significant loss of local news sources and platforms for companies to advertise their local businesses.

In 2017, Postmedia and Metroland (owned by Torstar) engaged in an ownership exchange involving more than 40 local community newspapers without monetary transactions, as both companies asserted that the newspapers held similar values. Subsequent to the exchange, many of the newly acquired newspapers were slated for closure. Postmedia intended to retain only two out of the 24 newly acquired newspapers, while the rest were set to be shut down. Similarly, Metroland also revealed its plan to close a majority of the newly acquired newspapers, opting to keep only 4 out of the 15 newly acquired newspapers operational.

4.4 Market Structure and Advertising Rate

Can this action potentially lead to a reduction in competition by withdrawing from areas where the other company primarily operated its business? What is the pre- and post-market structure in these swap-affected local areas? To address these questions, we

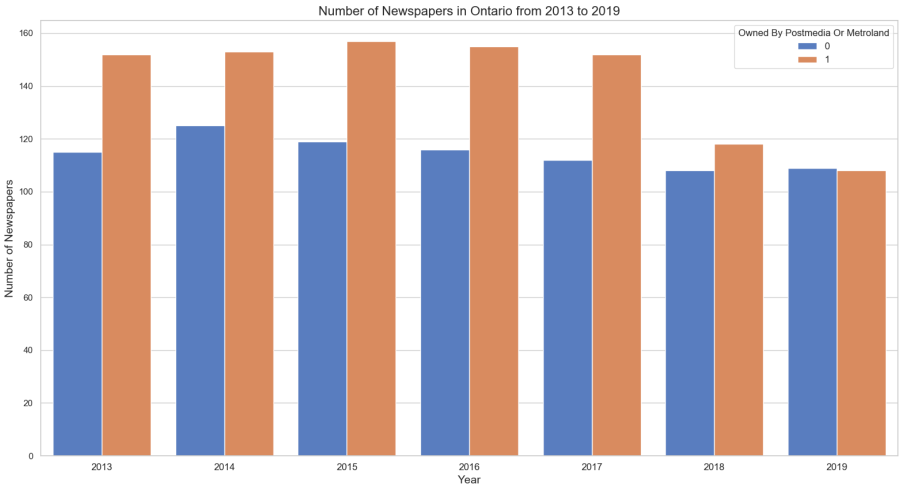

Figure 4.1: Number of Newspapers In Ontario

conduct an examination for each impacted census subdivision to determine if Metroland or Postmedia are avoiding competition. This involves counting the newspapers owned by Metroland, Postmedia, and other entities before and after the ownership swap within these markets. Our assessment of newspaper presence is based on observations, recognizing that the available data might not encompass all newspapers operating within a market. Therefore, Table 1 should be interpreted with caution.

For instance, based on the tabulation results of the data presented in Table 1, it appears that Postmedia does not possess any newspapers in the Ottawa census subdivision, both before and after the swap. However, news reports regarding the swap event suggest that Postmedia does indeed own some newspapers in Ottawa, even though they are not included in the dataset. "In addition, Postmedia will acquire the free commuter newspapers, Metro Ottawa and Metro Winnipeg. Postmedia already owns other newspapers in both of those cities, and plans to shut down Metro in each of them." (CBC News, 2017)

However, the data clearly indicates a significant shift in market structures that gives rise to suspicions of anti-competitive behavior by the two companies. In numerous census subdivisions, prior to the swap, both companies were operating at least one newspaper. Surprisingly, after the swap, a considerable number of markets were left with only one of the two companies (Postmedia or Metroland) operating newspapers. Out of the 33 markets affected by the swap, 21 had newspapers from both Postmedia and Metroland, and some had newspapers operated by other companies too. However, post-swap, one of either Postmedia or Metroland withdrew from these 21 markets. In some of these areas, companies other than Postmedia or Metroland continued their newspaper operations. Furthermore, among these 21 markets, 12 had 2 or more companies (comprising entities beyond Postmedia and Metroland) operating newspapers. After the swap, only one of Postmedia or Metroland continued its operations in these 12 markets, eliminating any other company's presence and establishing a monopoly for the remaining company (since our data does not guarantee to include all community newspapers, this interpretation should be kept with caution). This pattern suggests potential strategic actions taken by the companies to reduce competition and raises concerns about increased market concentration.

It is important to note that Table 1 enumerates all newspapers in the markets influenced by the swap (at least one newspaper operated in each of these markets). This includes both newspapers that were swapped and those that were not. Most of the community newspapers closed right after the swap. For these newspapers, the data reflects only their immediate closure and not any change in ownership. However, these closures affect the market structure. There are many markets that have one newspaper owned by Metroland and one newspaper owned by Postmedia. After these newspapers are swapped and closed, only one newspaper owned either by Metroland or Postmedia remains in the market.

Markets sometimes show distinct trends in ownership changes. Take, for example, the situation in South Huron before 2017. At that time, Metroland owned two newspapers: the Exeter Times Advocate Weekender and the Exeter Times Advocate. After 2017, these two newspapers were acquired by Postmedia, which chose to continue their operation after the swap. Intuitively, we expect to see in each of the markets, the two companies avoid contact. However, post-2017, the ownership of these two newspapers shifted to Postmedia, which decided to sustain their operation post-acquisition.

Intuitively, we expect to see in the swap-affected markets, Postmedia and Metroland would strive to avoid direct competition. However, while our market definition based on census subdivisions is generally effective, it is not perfect. The strategic vision of companies' CEOs might extend beyond these designated subdivisions. For instance, in the case of South Huron, if its geographic location is proximate to other areas where Postmedia has a presence, Postmedia might have an incentive to consolidate its foothold by acquiring all newspapers in South Huron. However, defining markets based on census subdivisions still reflect a tendency to avoid contact within the same market, as suggested by the previously discussed statistics.

Table 2 provides a tabulation of the total 39 community newspapers that were involved in the swap during the events. This includes details about ownership before the swap, whether a newspaper was shut down immediately after the swap, and the census subdivisions where a newspaper was operating. Most of the newspapers were shut down immediately, left only 6 newspapers remain operation. Postmedia acquired 24 newspapers from Metroland and subsequently shut down 22 of these acquired newspapers. On the other hand, Metroland acquired 15 newspapers from Postmedia and closed 11 of the acquired newspapers. Both companies shut down a substantial number of newspapers, with the majority of closures originating from Postmedia.

Figure 1 presents the Series of rates of community newspapers classified into various groups. These groups encompass newspapers owned by Postmedia or Metroland that are operating in the event-affected market but not swapped, newspapers that were swapped and subsequently closed, newspapers that were swapped and continue to operate after the event, newspapers owned by Postmedia or Metroland and operating in unaffected markets, and newspapers owned by other companies. Among the 39 community newspapers, rate data is available for 31 newspapers. Furthermore, we have closely observed rate trends for two newspapers that continued operations after the swap, both originating from the

Metroland to Postmedia transition. This suggests that interpreting rate series for the group in which newspapers were swapped and maintained operations post-event should be approached with thoughtful consideration.

Nonetheless, it is reassuring to note that the majority of the swapped newspapers do have accompanying rate data. This ensures that the figure effectively captures rate patterns across different groups.

An intriguing observation is that newspapers which underwent swapping and subsequent shutdown exhibit lower rates, in contrast to the newspapers owned by Postmedia or Metroland that operate in event-affected markets, showing the highest average rate. Newspapers owned by other companies and newspapers owned by Postmedia or Metroland that operate in unaffected markets have rate patterns that fall in the middle of the groups. The two newspapers that remained operational after being swapped from Metroland to Postmedia also exhibit significantly lower rates compared to the other groups. However, there are no noticeable signs of a significant increase in rates for these newspapers after the swap took effect post-2017. Instead, it is apparent that these newspapers, with notably lower rates, were either swapped or closed.

Figure 2 and 3 depict the separate rate series of newspapers owned by Metroland and Postmedia, each further divided into various categories. Both companies are involved in swapping or shutting down newspapers with lower advertising rates. The distinction lies in the fact that, for Metroland, newspapers operating in affected markets but not swapped exhibit a similar average rate compared to newspapers operating in unaffected markets. Conversely, in the case of Postmedia, newspapers operating in affected markets but not swapped show a higher rate compared to newspapers operating in unaffected markets.

	Before Swap			After Swap		
CSDs	Others	M	P	Others	M	P
Alnwick/Haldimand	0	0	1	0	0	0
Barrie	1	1	1	1	1	0
Belleville	1	1	1	1	0	1
Bradford West Gwillimbury	0	1	1	0	1	0
Brantford	0	1	1	0	0	1
Brockville	1	1	0	1	0	0
Cobourg	0	1	1	0	1	0
Collingwood	0	1	1	0	1	0
Cramahe	0	1	1	0	1	0
Fort Erie	0	1	1	0	1	0
Innisfil	0	1	1	0	1	0
Kingston	1	1	1	1	0	1
London	3	1	1	4	0	1
Meaford	1	1	0	1	0	0
Niagara-on-the-Lake	0	1	1	0	1	0
Norfolk County	2	1	1	2	0	1
Orillia	1	1	1	1	1	0
Ottawa	5	8	0	9	0	0
Pelham	2	1	2	2	2	0
Peterborough	1	1	1	1	2	0
Port Colborne	0	1	1	0	1	0
Port Hope	0	1	1	0	1	0
Quinte West	2	1	1	2	0	1
South Frontenac	0	1	1	0	0	1
South Huron	0	2	0	0	0	2
Southwold	0	1	0	0	0	0
St. Catharines	1	0	1	1	1	0
St. Marys	1	2	0	1	0	0
St. Thomas	0	1	0	0	0	0
Stirling-Rawdon	0	1	0	0	0	0
Stratford	0	1	1	0	0	1
Thorold	0	0	1	0	0	0
Welland	1	0	1	1	1	0
Sum of Each Column	24	38	26	29	17	10

Table 4.1: Market Structure: Number of Newspapers Owned by Metroland, Postmedia, and Other Companies Before and After the Swap for Each Census Subdivision Affected by the Newspaper Swap

Newspaper	CSDs	Closure	Previous Owner
Kingston Heritage	Kingston	YES	M
Nepean Barrhaven News	Ottawa	YES	M
Norfolk News	Norfolk County	YES	M
Orleans News	Ottawa	YES	M
Ottawa East News	Ottawa	YES	M
Ottawa South News	Ottawa	YES	M
Ottawa West News	Ottawa	YES	M
Meaford Express	Meaford	YES	M
Our London	London	YES	M
St. Marys Journal Argus	St. Marys	YES	M
St. Marys Journal Argus Weekender	St. Marys	YES	M
St. thomas Elgin Weekly News	Southwold and St. Thomas	YES	M
Stirling Central Hastings News	Stirling-Rawdon	YES	M
Stittsville News	Ottawa	YES	M
Stratford Gazette	Stratford	YES	M
Quinte West News	Quinte West	YES	M
Kanata Kourier Standard	Ottawa	YES	M
West Carleton Review	Ottawa	YES	M
Frontenac Gazette	South Frontenac	YES	M
Belleville News	Belleville	YES	M
St. lawrence News	Brockville	YES	M
Exeter Times Advocate	South Huron	NO	M
Exeter Times Advocate Weekender	South Huron	NO	M
Brantford Brant News	Brantford	YES	M
Fonthill Pelham News	Pelham	YES	P
Collingwood Enterprise Bulletin	Collingwood	YES	P
Fort Erie Times	Fort Erie	YES	P
In Port News	Port Colborne	YES	P
Bradford West Gwillimbury Times	Bradford West Gwillimbury	YES	P
Thorold Niagara News	Thorold	YES	P
Welland Tribune	Welland	NO	P
St. Catharines Standard	St. Catharines	NO	P
Peterborough Examiner	Peterborough	NO	P
Orillia Packet and Times	Orillia	YES	P
Niagara Falls Review	Pelham	NO	P
Innisfil Examiner	Innisfil	YES	P
Niagara Advance	Niagara-on-the-Lake	YES	P
Barrie Examiner	Barrie	YES	P
Northumberland Today	Cramahe, Port Hope, Alnwick/Haldimand and Cobourg	YES	P

Table 4.2: Newspapers Swapped in 2017, Closure Status of Operating Market, and Ownership Before Swap, Where M Represents Metroland and P Represents Postmedia.

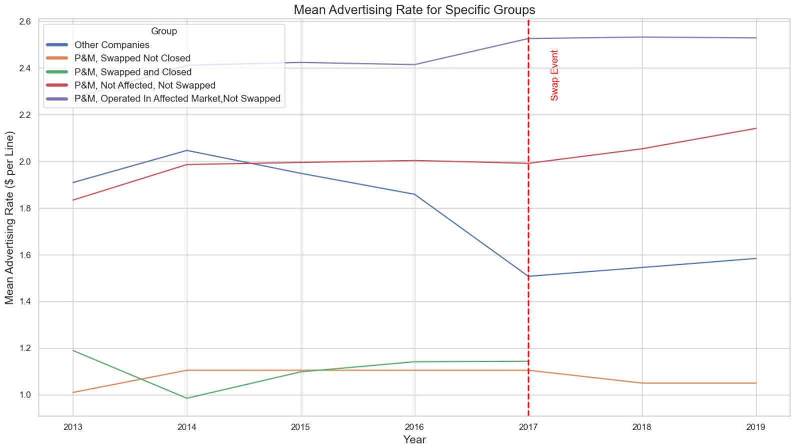

Figure 4.2: Rate Series for Different Specific Group

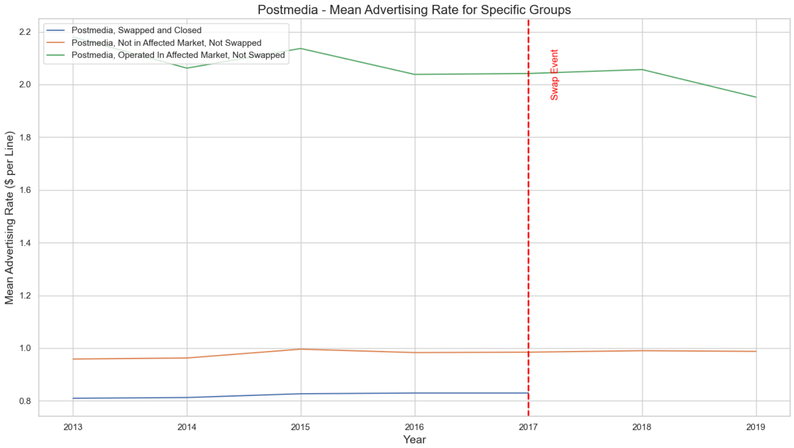

Figure 4.3: Rate Series for Postmedia

4.5 Matching and Construction of Control Markets

Whether this shift in market structure is reflected in the rates charged by newspapers in these swapped markets is our first main objective. To investigate this, we employ a matching strategy to identify the treatment effect on the rate environment in markets where at least one newspaper was swapped.

The objective of our approach is to estimate the average treatment effect on the mean advertising rate for the markets that have been influenced by the swap event for market i and year t.

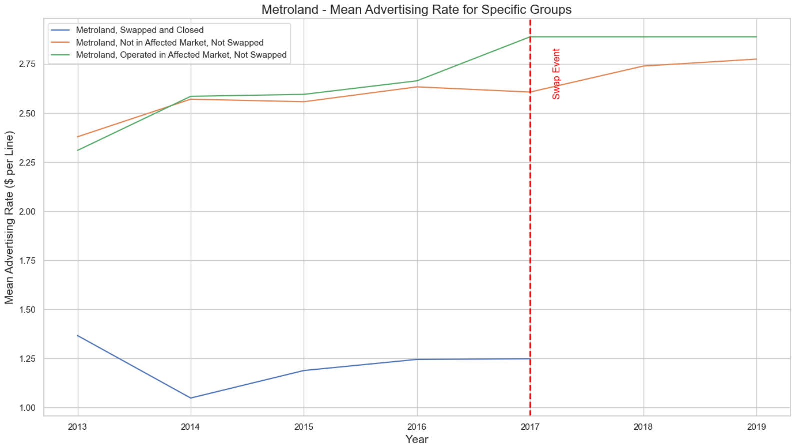

Figure 4.4: Rate Series for Metroland

$$ATT = E\{r_{it}^1 | d_{it} = 1\} - E\{r_{it}^0 | d_{it} = 1\}$$

The indicator d_{it} takes a value of 1 if market i experienced any newspaper swaps during the event. r_{it}^1 represents the observed average advertising rate after the swap. On the other hand, r_{it}^0 denotes the unobserved counterfactual average advertising rate that would have prevailed had the markets not been affected by the swap event.

Before the 2017 swap and cessation of operations across dozens of newspapers by the two companies, it is likely that the CEOs had already internally negotiated and settled on the decision. This might have led newspapers, particularly those owned by Postmedia and Metroland in the affected markets, to adjust their rates. Consequently, the average rate for these markets could have changed, potentially creating anticipation effects.

To minimize bias and exclude control markets that fail to meet the common time trend assumptions, we employ a probit regression to calculate a propensity score. This score is based on demographic and market structure variables, predicting the likelihood of a market being chosen for a newspaper swap. We incorporate demographic variables from Fan (2013) that might influence newspaper outcomes. With the propensity scores available, we match each treatment market with control markets based on score proximity. Instead of pairing a single market for each treatment, we match n control markets (unaffected by the swap) to each treatment market, based on the closest propensity scores. A synthetic control market is then constructed by averaging the characteristics of these n matched control markets.

To determine the value of n, we use a balance test discussed in Smith and Todd (2005). We start with $n = 1$ and conduct repeated balance tests to gauge the reduction in bias for market characteristics after each match. We choose the value for n to achieve the maximum bias reduction in market characteristics. Additionally, we match the control markets with replacement, allowing a given control market to be paired with more than one treatment market. This scenario ensures each treatment market is matched with a high-quality candidate, reducing the bias in market characteristics. However, this approach also decreases the number of distinct markets matched to calculate the counterfactual mean in market characteristics, leading to an increase in variance. Dehejia and Wahba (DW) (1999, 2002) show that matching without replacement can lead to poor matches because many treatment members are paired with members having significantly different propensity scores. Matching without replacement also has a drawback in that the match result depends on the order in which each treatment member is matched.

4.5.1 Propensity Score Outcomes

Of the 214 markets analyzed, 33 underwent a newspaper swap in 2017, with 29 of these experiencing newspaper closures from either Postmedia or Metroland. We assigned a value of 1 to markets impacted by the swap and 0 to those that were not affected, focusing our analysis at the market level. To ensure comprehensiveness, we executed an outer join between the rate data sourced from Adoreach and the information from News Media Canada. Although most newspapers were present in both datasets, a significant number of newspapers did not have available rate data. Given that our objective is to compare the rates, it is vital for the markets to have newspapers with available rate data. Conducting an analysis on markets without any newspapers providing rate data is unfeasible. To address this challenge, we initially tallied the number of newspapers in each market, taking into account even those without available rate data. We subsequently exclude any newspapers that do not have rate data available for at least one year. It is worth noting that some newspapers have rate data for certain years but not for all. This could be due to reasons such as the newspapers' closure or their decisions not to report rates to Adoreach. Nevertheless, these newspapers with partial data are still included in our further study when computing the mean rate of each market. For example, if newspaper A has rate data available for 2013 and 2019, but not for 2014, 2015, 2016, 2017, or 2018 (this could be because newspaper A in market K chose not to report the rate to Adoreach from 2014 to 2018, but decided to report the rate for 2013 and 2019), then newspaper A is included in the mean rate calculation of market K for years where data is available but excluded for the years where rate is unavailable.

We run the regression for the propensity score to determine whether a market would be chosen to undergo a newspaper swap, focusing on the observations from 2017. This is because the event occurs exclusively in that year, and most of the market characteristics, such as demographic variables, are time-invariant. Some markets only have newspapers with missing rate data for certain years, resulting in specific market-year observations without details. Although the probit regression does not mandate a market to possess rate data, the outcome of the regression is a key factor in determining the control groups. Therefore, it is crucial for markets forming the potential control group to offer a majority of the rates from 2013 to 2019. To address this issue, in the regression, we exclude markets that, as of 2017, only have newspapers missing rate data for every year from 2013 to 2019. For instance, if a market have 2 newspapers in 2017 and neither of them has rate data availibe for any years between 2013 and 2019. We will exclude that market from the probit regression. However, if these two newspapers do not have rate data for 2017 but possess rate data for at least one year outside of 2017, this market will still be included in the probit regression. This is because we aim to compare the rates between swap-affected markets and control markets over the years from 2013 to 2019. We do not want to omit a market simply because it lacks rate data for 2017 if it has data from other years.However, markets that, as of 2017, solely contain newspapers with missing rate data spanning the entire period from 2013 to 2019 tend to lack rate data for most, if not all, of those years. It is essential to exclude these markets from the probit regression to avoid skewing the results in the subsequent rate analysis. By excluding these market, we retain 190 out of total 214 markets and 31 out of 33 swap-affected markets in the regression. As a result, there is not significant loss of information.

Our regression findings reveal that the average age within a market is a significant predictor of the likelihood of a newspaper swap. Specifically, both Postmedia and Metroland seem to favor swapping newspapers in areas with a predominantly older demographic. A plausible explanation could be the predilection of older individuals towards community newspapers, making it more cost-effective for businesses to tailor strategies in such locales. Including additional variables in the regression can enhance its explanatory power. However, this may lead to the exclusion of certain markets if data for those variables is absent. To choose the most effective variables, we incorporate demographic variables based on the selection presented as controls in Fan (2013). We use these to estimate propensity scores, which in turn help select control markets, reinforcing the common time trend assumption. In subsequent analysis, the common time trend tests show these variables uphold the common time trend assumption necessary for DID analysis.

Other variables are not potent predictors for the probability of a market to be affected in the swap event. Nevertheless, this does not mean there is no potential influence. We further our study with a balance test to see how the matching process influenced the differences in market characteristics. If a variable doe not help in predicting a market's treatment, we would expect negligible changes in bias after matching, though the bias can still decrease by chance.

	Prob (Treat=1)
Intercept	-29.1604 (21.3834)
Age	5.5666** (2.5434)
Education	-0.4351 (0.4453)
Income	0.0338 (1.2155)
# of Newspapers	-0.0787 (0.7640)
Population	0.7881 (0.5474)
Population Growth	0.5755 (0.3528)
N	190
Pseudo R2	0.08

Table 4.3: Probit Regressions for the Possibility of a Market Being Affected by a Swap: Any observations with missing values are dropped to run the regression. All variables are log-transformed. For example, if the population of a market is 1000, then Population = log(1000 + 10). Other variables are transformed in a similar manner. We add 10 before the log transform because some variables, like the population growth rate, can be negative. Treatment markets are defined as swap-affected markets.

Variable	Treated	UnTreated	Matched	Bias (Untreated)	Bias (Matched)	Reduction
Pop	10.2784	9.5938	10.1725	6.6601%	1.0306%	84.5256%
Pop Growth	2.5966	2.4695	2.5902	4.8953%	0.2466%	94.9628%
Age	3.984	3.9745	3.9903	0.2393%	-0.1577%	34.0742%
Income	10.4275	10.4493	10.4182	-0.2088%	0.0888%	57.4609%
Education	8.2323	7.4565	8.1327	9.4231%	1.209%	87.1698%
# of Papers	2.5317	2.475	2.4873	2.2409%	1.7552%	21.6716%

Table 4.4: Balance Test Results and Bias Reduction: Bias Calculation as Percentage Difference (Mean Value of Treated Minus Mean Value of All Untreated Markets, Divided by the Mean Value of Treated Markets). Treatment markets are defined as swap-affected markets.

4.5.2 Balance Test and Bias Reduction

For each treatment market, we select a set of n markets that have the most similar propensity scores and calculate the average characteristics of these matched markets. Starting with $n = 1$, we adjust and test until we determine which n provides the greatest reduction in bias. Through our testing, we discover that when n is set to 4, the difference between the treatment market and the matched control means is minimized.

Table 3 presents the balance test results, revealing a notable reduction in bias across all variables. Given that all variables are log-smoothed, the magnitude of the bias in all unmatched markets is relatively small, so the magnitude of bias reduction applying matching methods for the matched control markets compared with the bias in all unmatched markets is more interesting. The population growth variable stands out with a remarkable 94% reduction in bias. The population variable sees a bias reduction of over 84%. Age, Income, and Education show reductions in bias of 34%, 57%, and 87%, respectively. These results from the balance test indicate that our matching approach effectively aligns markets with similar characteristics.

This result suggests that markets which experienced newspaper swaps had significantly different characteristics endogenous to the decision of whether a market would undergo a swap. Consequently, the full sample of unaffected markets might not serve as an appropriate control group.

4.5.3 Difference in Difference Regression

We conduct a difference-in-differences regression to analyze the impact of the treatment market and associated synthetic control markets. The regression equation is as follows:

$$Rate_{it} = \alpha + \beta_1 Treated + \beta_3 Post + \beta_2 TreatedPost + \epsilon_{it}$$

Here, *Rate* represents the dependent variable for market i in year t. *Post* is a dummy variable equal to 1 if $t > 2017$, indicating the post-treatment period. *Treated* is a dummy variable equal to 1 for treated markets. The interaction term *TreatedPost* captures the combined effect of being a treated market in the post-treatment period. We do not include fixed effects because all demographic variables are time-invariant. Moreover, since all treatments occur in 2017, including year fixed effects leads to collinearity with the *Post* dummy, so we do not include time fixed effects either. However, when we conduct a robust analysis with market and time fixed effects and drop demographic variables, the treatment effect remains significant.

The coefficient of *TreatedPost* represents the treatment effect we aim to investigate. To determine the source of variation, we perform three regressions. In Regression (1), we calculate the mean rate of each market year using all newspapers in the dataset. In Regression (2), we calculate the mean rate of each market year using newspapers owned either by Postmedia or Metroland. Finally, in Regression (3), we calculate the mean rate of each market year using newspapers both owned by Postmedia or Metroland and operated at least one year on or before 2017 and at least one year after 2017. The mean rate is calculated annually for all eligible newspapers in the market based on the criteria specified for each regression.

The goal of the first regression is to determine how the rate environment changed after the swap. The results indicate that the average advertising rate increased and stayed high following the newspaper swap in 2017 within these impacted markets. Consequently, companies seeking to advertise in these areas now face significantly higher rates. It is important to note that companies interested in advertising in community newspapers are likely targeting local businesses and projects. Therefore, policymakers in regional areas should be aware of the potential negative effects on businesses due to the increased rate environment post the 2017 swap.

Regression (2) examines the rate series for newspapers run by Postmedia and Metroland. It appears that the average rate of products in these affected markets rises significantly. Given the dominant market concentration in the community newspaper industry across Canada, the increase in average rates for newspapers owned by Postmedia and Metroland likely contributes substantially to this elevated rate environment in the affected markets.

There are potential reasons for the increased average advertising rate. One is that Postmedia or Metroland might be discontinuing newspapers with lower rates. The absence of these low-rate newspapers could raise the average advertising rate for newspapers they own in these markets. Another possibility is that Postmedia or Metroland have swapped and closed several newspapers, which might grant remaining newspapers more market power, allowing these papers to charge higher rates, leading to an elevated average rate.

To differentiate between these scenarios, Regression (3) considers the rate of continuously operating newspapers owned by Postmedia or Metroland. If newspaper swaps and closures empower other ongoing newspapers to charge more, we should see a positive coefficient on TreatedPost, especially for those owned by Postmedia or Metroland. This would suggest these companies use swaps and closures to benefit their existing newspapers. However, regression results contradict this. The coefficient for Regression (3) is not statistically significant. Hence, no evidence that supports the theory that the closure of newspapers leads to remaining newspapers gaining market power and charging higher rates. Instead, it seems Postmedia or Metroland are discontinuing lower-rate newspapers, and these closures do not confer more market power to the other newspapers in these affected markets.

Considering that most community newspapers are free, those with lower rates might be less cost-effective, prompting Postmedia or Metroland to discontinue these cheaper options. While this may be a viable business decision, it could adversely impact companies that are financially limited, restricting their ability to invest in advertising in these local markets, because they have less lower price options after 2017.

Most of the market characteristic variables are consistent across the four regressions. A higher average age contributes to a lower mean rate in the market, possibly because older people have a lower inclination to consume, pushing down the rates newspapers can charge. A market with a higher number of newspapers leads to a lower rate, consistent with the idea that competition puts downward pressure on the rates newspapers can charge. Interestingly, higher incomes are associated with lower rates in the market, given that most community newspapers post advertisements for products on sale. An entity with a higher income may be less likely to be attracted to the advertisements in community newspapers. The focus of this research is to identify the Treatment Effect. Future studies exploring how market characteristics affect rate series will be interesting.

4.6 Robustness Checks

4.6.1 Fixed Time and Market Effects and Common Time Trend Test

Given that demographic variables remain consistent over time, and considering that the newspaper swap event took place in 2017, incorporating both market and year fixed effects will result in the demographic variables, $Treated$ and $Post$ being omitted. Nonethelss, excluding market and year fixed effects could yield inconsistent coefficients if there are unobserved market or year factors that correlate with “TreatedPost”. To ensure robustness, we conduct regressions without the demographic variables, $Treated$ and $Post$ variables, controlling for both market and year fixed effects. This helps verify the reliability of the $TreatedPost$ coefficient.

Table 5 presents the regression results. We observe that the ’TreatedPost’ variable remains highly statistically significant in Regression 1 and Regression 2, aligning with

	All	**P&M**	**P&M Cross**
Intercept	40.9397*** (8.8359)	37.5023*** (10.8245)	21.3530* (11.7164)
Treated	-0.0074 (0.0701)	-0.4026*** (0.0846)	0.3729*** (0.0956)
TreatedPost	0.4100*** (0.1408)	0.6177*** (0.1748)	-0.0661 (0.1671)
Post	0.0710 (0.0891)	0.0349 (0.1076)	0.0183 (0.0979)
Pop	-1.4259*** (0.2068)	-1.4597*** (0.2513)	-2.6153*** (0.2630)
Pop Growth	-0.3726*** (0.1287)	0.0804 (0.1568)	-0.0729 (0.1753)
Age	-3.5617*** (0.9563)	-0.6109 (1.1802)	1.6954 (1.2563)
Income	-1.7795*** (0.5460)	-2.5857*** (0.6634)	-1.8046*** (0.6926)
Education	1.6807*** (0.1621)	1.7520*** (0.1962)	2.7297*** (0.2021)
# of Newspapers	-1.8685*** (0.4108)	-2.2381*** (0.4968)	-1.0209 (0.6726)
R-squared	0.5252	0.5006	0.6087
N	407	398	336

Table 4.5: Difference-in-Differences Regression Analysis: Dependent Variables Represent the Mean Rate of Each Market Year Calculated using Different Subsets of Newspaper: Regression (1) Utilizes All Newspapers in the Dataset. Regression (2) Utilizes Newspapers Owned by Postmedia or Metroland. Regression (3) Utilizes Newspapers Owned by Postmedia or Metroland and Operated Both Before and After the Swap Event. Each treatment market is matched with n optimal control markets based on propensity scores, where n is chosen to minimize biases in characteristics. For each treatment market, a synthetic control market is constructed by averaging the characteristics of the n matched control markets. Regression analyses are conducted on the treatment markets and their corresponding synthetic control markets. Treatment markets are defined as swap-affected markets.

Mean Rate	**Mean Rate**	**P&M Mean Rate**	**P&M Mean Rate Cross**
TreatedPost	0.2774*** (0.0482)	0.3811*** (0.0576)	-0.0203 (0.0344)
Within R-squared	0.0891	0.1170	0.0012
N	407	398	336

Table 4.6: Regression with Market and Yearly Fixed Effects: Regression (1) Utilizes All Newspapers in the Dataset. Regression (2) Utilizes Newspapers Owned by Postmedia or Metroland. Regression (3) Utilizes Newspapers Owned by Postmedia or Metroland and Operated Both Before and After the Swap Event. Treatment markets are defined as swap-affected markets.

the findings from Table 4. However, the coefficient in Regression 3, where the mean rate is calculated based on newspapers owned by Postmedia or Metroland, is statistically insignificant. This furthur suggests no significant evidence of a competitive effect. Instead, our findings align with the hypothesis that Postmedia and Metroland swapped and then closed newspapers which charged lower rates. The removal of these lower-rated newspapers subsequently elevated the mean rate in the markets affected by the swaps.

One of the critical assumptions for identifying the treatment effect in a difference-in-differences regression is that treated and control markets follow common time trends. Given that the CEOs of both companies formed a decision to strategically swap several newspapers before its actual execution, it is conceivable that the rates of the newspapers owned by Postmedia or Metroland changed prior to the event. To investigate whether the treatment markets and control markets adhered to a similar time trend before the event, we conducted the following regression to test the common time trend assumption:

$$\begin{aligned} Rate_{it} = \beta_1 Treated * Year_{2015} + \beta_2 Treated * Year_{2016} + \beta_3 Treated * Year_{2017} \\ + \beta_4 TreatedPost + u_i + \eta t + \epsilon_{it} \qquad (5) \end{aligned}$$

The regression is similar to the one with market and year fixed effects. The key difference

	Mean Rate	**P&M Mean Rate**	**P&M Mean Rate Cross**
TreatedPost	0.2498*** (0.0561)	0.3573*** (0.0666)	-0.0047 (0.0416)
Treated*Year2015	-0.0122 (0.0630)	-0.0232 (0.0729)	0.0473 (0.0507)
Treated*Year2016	-0.0331 (0.0635)	-0.0341 (0.0731)	0.0272 (0.0505)
Treated*Year2017	-0.0918 (0.0635)	-0.0610 (0.0731)	0.0025 (0.0505)
R-squared	0.0951	0.1190	0.0050
N	407	398	336

Table 4.7: Common Time Trend Test: Regression (1) Utilizes All Newspapers in the Dataset. Regression (2) Utilizes Newspapers Owned by Postmedia or Metroland. Regression (3) Utilizes Newspapers Owned by Postmedia or Metroland and Operated Both Before and After the Swap Event. Treatment markets are defined as swap-affected markets.

is the addition of an interaction between *Treated* and the Year dummy, spanning three years before the post-swap period. By controlling for each year's fixed effect, the coefficients β_1, β_2, and β_3 capture the difference in the time trend in rates starting from three years before the post-swap period. Table 6 presents the results. As evident, the coefficients are not statistically different from zero. This suggests that there is no significant anticipation effect prior to the event's occurrence.

4.6.2 Treatment Markets Defined as Markets with Closure

Of the 31 swapped-affected markets included in the analysis, 29 experienced newspaper closure from either Postmedia or Metroland. To test robustness, we categorize these 29 markets as treatment markets and use swap-unaffected markets as control groups to replicate the aforementioned analysis. The rate series are simliar to the previous analysis. There is a slight loss of significance for *TreatedPost* in the DiD regression according to Table 9. However, when controlling for time and market fixed effects, *TreatedPost* is significant at the 0.01 level.

Variable	**Treated**	**UnTreated**	**Matched**	**Bias (Untreated)**	**Bias (Matched)**	**Reduction**
Pop	10.2795	9.5938	10.3617	6.6704%	-0.7991%	88.0207%
Pop Growth	2.6033	2.4695	2.5786	5.1393%	0.949%	81.5347%
Age	3.9828	3.9745	3.981	0.2089%	0.046%	77.99%
Income	10.4319	10.4493	10.4259	-0.1663%	0.0579%	65.1898%
Education	8.2414	7.4565	8.3393	9.5235%	-1.1877%	87.5291%
# of Papers	2.5322	2.475	2.5049	2.2589%	1.077%	52.3227%

Table 4.8: Balance Test Results and Bias Reduction: Bias Calculation as Percentage Difference (Mean Value of Treated Minus Mean Value of All Untreated Markets, Divided by the Mean Value of Treated Markets). Treatment markets are defined as swap-affected markets with at least one swapped newspaper closed.

4.7 Conclusion

In recent decades, the newspaper industry has grappled with significant challenges due to market contraction, a result of the rise of the internet and digital news platforms. This shift has garnered considerable attention from both the industry and academic circles. However, the majority of research in this field has focused on daily newspapers. The study of community newspapers and the decline of local news remains largely overlooked by scholars, despite growing concerns about the profound impact of losing local news sources. In 2017, Postmedia and Metroland exchanged ownership of several community newspapers, subsequently closing many of them. Following the swap, a number of markets, previously served by both companies, were left with a single newspaper under the operation of just one of the firms. This sparked concerns regarding consolidation and the potential avoidance of competition, as well as disppearing of local news. On the other hand, the company contends that their objective is to concentrate on areas where their primary business is located, subsequently closing down newspapers in regions that are not their main focus. They believe this approach helps achieve cost savings, particularly given the ongoing challenges in the newspaper industry. To ascertain which of the two factors plays a pivotal role, we sourced data from News Media Canada and AdoReach. We applied matching strategies to minimize potential biases between the treatment and control groups. Following this, we undertook a difference-in-differences analysis using matched control

	All	**P&M**	**P&M Cross**
Intercept	79.5553*** (9.7452)	90.6046*** (13.8671)	89.8537*** (16.5342)
Treated	-0.1141 (0.0870)	-0.5900*** (0.1224)	0.1800 (0.1544)
TreatedPost	0.4316** (0.1773)	0.5793** (0.2589)	-0.1084 (0.2815)
Post	0.1012 (0.1120)	0.0716 (0.1610)	0.0515 (0.1678)
Population	-2.1364*** (0.2354)	-2.3093*** (0.3286)	-3.3941*** (0.3803)
Population Growth	-0.6544*** (0.1406)	-0.4325** (0.2026)	-0.6861*** (0.2468)
Age	-7.2341*** (1.0727)	-6.0315*** (1.5785)	-5.2102*** (1.8867)
Income	-3.9622*** (0.5860)	-5.2874*** (0.8316)	-5.4426*** (0.9562)
Education	2.2928*** (0.1872)	2.5939*** (0.2603)	3.5449*** (0.2987)
# of Newspapers	-1.1528*** (0.4235)	-2.2689*** (0.5953)	-1.0374 (0.8504)
R-squared	0.5966	0.5439	0.5603
N	379	361	293

Table 4.9: Difference-in-Differences Regression Analysis: Dependent Variables Represent the Mean Rate of Each Market Year Calculated Using Different Subsets of Newspapers: Regression (1) Utilizes All Newspapers in the Dataset. Regression (2) Utilizes Newspapers Owned by Postmedia or Metroland. Regression (3) Utilizes Newspapers Owned by Postmedia or Metroland and Operated Both Before and After the Swap Event. Each treatment market is matched with n optimal control markets based on propensity scores, where n is chosen to minimize biases in characteristics. For each treatment market, a synthetic control market is constructed by averaging the characteristics of the n matched control markets. Regression analyses are conducted on the treatment markets and their corresponding synthetic control markets. Treatment markets are defined as swap-affected markets with at least one swapped newspaper closed.

Mean Rate	**Mean Rate**	**P&M Mean Rate**	**P&M Mean Rate Cross**
TreatedPost	0.2610*** (0.0625)	0.4133*** (0.0705)	-0.0529 (0.0515)
Within R-squared	0.0524	0.1030	0.0043
N	379	361	293

Table 4.10: Regression with Market and Yearly Fixed Effects: Regression (1) Utilizes All Newspapers in the Dataset. Regression (2) Utilizes Newspapers Owned by Postmedia or Metroland. Regression (3) Utilizes Newspapers Owned by Postmedia or Metroland and Operated Both Before and After the Swap Event. Treatment markets are defined as swap-affected markets with at least one swapped newspaper closed.

	Mean Rate	**P&M Mean Rate**	**P&M Mean Rate Cross**
TreatedPost	0.2261*** (0.0725)	0.3944*** (0.0811)	-0.0480 (0.0624)
Treated*Year2015	-0.0075 (0.0807)	0.0002 (0.0873)	0.0434 (0.0760)
Treated*Year2016	-0.0323 (0.0813)	-0.0153 (0.0877)	0.0203 (0.0758)
Treated*Year2017	-0.1330 (0.0813)	-0.0782 (0.0877)	-0.0391 (0.0758)
R-squared	0.0611	0.1058	0.0084
N	379	361	293

Table 4.11: Common Time Trend Test: Regression (1) Utilizes All Newspapers in the Dataset. Regression (2) Utilizes Newspapers Owned by Postmedia or Metroland. Regression (3) Utilizes Newspapers Owned by Postmedia or Metroland and Operated Both Before and After the Swap Event. Treatment markets are defined as swap-affected markets with at least one swapped newspaper closed.

groups to determine the effect on rates after the newspaper swap.

Our regression results suggest that the mean advertising rate in the affected markets surged significantly post-swap. This increase, however, can be attributed to the closure of lower-rated newspapers by Postmedia and Metroland, inadvertently raising the average advertising rate in these swap-impacted markets. While an exploration of the market structure reveals evidence of potential competition avoidance, the rates of newspapers owned by Postmedia and Metroland that survived in the swap-affected regions did not increase significantly. These findings support the idea that Postmedia and Metroland are primarily cutting operating costs by discontinuing newspapers with lower rates. There is no clear evidence suggesting that competitive series significantly affected the advertising rates of newspapers owned by the two firms.

It is important to underscore that advertising rates in the impacted markets remained elevated following the swap events. This trend poses challenges for existing companies, limiting their access to more economical advertising options. While there is no evidence to suggest that Postmedia and Metroland executed newspaper swaps with the intent of boosting rates for their other ongoing newspapers in these markets, the disappearance of certain publications, particularly those offering lower rates, is a cause for concern. The repercussions extend beyond the simple reduction of news sources. It could also potentially restrict essential advertising avenues for local businesses and government entities.

Chapter 5

Conclusion

This thesis encompasses two essays that delve into liquidity and dealer trading behaviors in the U.S. corporate bond market, accompanied by a third essay that focuses on the consolidation of the Canadian community newspaper market. The first essay scrutinizes the influence of post-crisis regulations, designed to mitigate inventory risk for dealers, on their trading practices. Challenging the predominant academic view that these regulations adversely affect liquidity, the essay introduces one possible overlooked channel. It posits that such regulations might compel dealers to refine their trading partnerships, consequently boosting market liquidity while curbing inventory costs. Employing a straightforward model, the essay elucidates that dealers can enhance liquidity and diminish inventory risk by fortifying trading connections with partners whose client bases exhibit lower correlation with their own, leading to enhanced welfare and greater market efficiency. The theoretical predictions of the model were empirically tested using the TRACE Academic dataset. A notable structural shift was detected through regression analysis following the implementation of the Dodd-Frank Act, a key post-crisis regulation. The analysis confirmed that dealers have indeed intensified trading relationships with partners having less correlated client bases, indicating the regulations' effectiveness in urging dealers to optimize trading partnerships for higher liquidity at reduced inventory risk. The validity of these regression findings was reinforced by controlling for variables such as time-fixed effects and common characteristics between dealer pairs, ensuring the robustness of the results.

The second essay delves into the centrality premium in the U.S. corporate bond market, using a structural model to dissect the trade-off between increased search efforts for high-value clients and the costs of holding inventory. Estimating the model with the TRACE Academic dataset clarifies that central dealers, due to their extensive networks, actively seek out and engage clients who place higher valuations on bonds. The estimation result shows that core dealers not only sell at higher prices on average but also retain bonds longer than their peripheral counterparts, and they are inclined to purchase bonds at higher rates. Nonetheless, the propensity of core dealers to sell at higher prices is more pronounced than their willingness to buy at elevated prices, leading to a wider spread between buying and selling prices and, consequently, a centrality premium relative to peripheral dealers.

In the final essay, I analyze the consolidation within the Canadian community newspaper market, focusing on the 2017 exchange of dozens of newspapers between Postmedia and Metroland. This event sparked concerns among industry professionals regarding the potential for increased market concentration and anti-competitive behavior. To investigate these concerns, I implemented a difference-in-differences regression analysis. Additionally, matching methods were employed to mitigate endogeneity issues. The findings reveal no evidence of anti-competitive behavior. The observed increase in average advertising rates in the markets impacted by this event was linked to the closure of lower-rated newspapers. This decision was driven by both companies' strategies to reduce costs, leading to their reluctance to maintain free newspapers that offered lower advertising rates.

The thesis presents essays that have substantial implications for policy. The first essay offers a counterintuitive perspective on post-crisis regulations. Contrary to the prevalent academic critique that views such regulations as excessively restrictive and detrimental to market liquidity, the essay posits that these regulations may, in reality, bolster liquidity and diminish risk. This assertion calls into question the commonly held assumptions regarding the effects of inventory regulations on dealer operations. The second essay shifts focus to the corporate bond market, suggesting that the observed centrality premium may stem from the efforts of core dealers. It posits that these dealers invest substantial effort in identifying clients with a greater propensity to trade. This finding underscores the crucial function that these dealers serve in sustaining market liquidity. In the third essay, the focus turns to the community newspaper market, which is shown to be profoundly affected by the advent of the internet and technological innovation. The prevalent strategy among major industry players to shut down newspapers as a cost-saving measure highlights a concerning trend. This trend signals the potential necessity for governmental involvement, possibly through subsidies, to preserve the community newspaper sector.

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