Dealers' Relationship, Capital Commitment and Liquidity

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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 the market liquidity (the easiness to trade without negatively impacting the price). There are two important functions of dealers in this market: first, dealers' network serves as an intermediary 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, for most of the time, when a client needs to trade, she still approaches a dealer first. So dealers' network is the most important channel 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. Specifically, if two dealers have separate client bases that tend to trade in a lower correlated direction, and if these dealers strengthen their relationship, each dealer can provide higher liquidity to their clients with the same level of inventory risk, resulting in 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 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 address this issue, 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 theoretical 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 lower (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 insurance companies, on average, trade with only 5 (median) and 11 (mean) dealers throughout their study period, 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.

Based on our model intuition, we propose a hypothesis: dealers have strengthened their trading relations with lower correlated dealers after the crisis (which improves liquidity). If this is the case, combined with the higher cost of committing capital due to post-crisis regulations (which harms liquidity), we can explain why researchers have found ambiguous effects of post-crisis regulations on liquidity in the post-crisis period.

Have dealers strengthened their trading relations with lower correlated partners in the post-crisis period? 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. For example, the Volcker rule, which is part of the Dodd-Frank act and was signed into law in July 2010, aims to discourage dealers from proprietary trading (purchasing financial assets into inventory to bet price moves). However, the market-making activity (providing liquidity by absorbing the temporary order imbalance into inventory) is essentially one kind of proprietary trading (Duffie, (2016)). To distinguish market making from proprietary trading, the rule requires dealers to provide evidence that they are absorbing the order imbalance from the client side when they commit a relatively large amount of capital and also requires dealers to anticipate counterparties' trading demand in advance. These requirements probably motivate dealers to devote more effort to learning these correlations in the post-crisis period. On the other hand, the increased cost of committing capital from these regulations gives a higher incentive for dealers to learn this correlation and optimize their trading relationships accordingly (If a dealer wants to provide a same level of liquidity to satisfy their clients with less capital commitment, then optimizing her trading relations with lower correlated partners is a solution). One support for this hypothesis is that more and more fintech companies had emerged in the bond market advertising that they could provide information about the axe (the desired direction to trade from other parties) after the crisis, a sign of great demand to learn these pieces of 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 dummies 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 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.

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 this dealer trade 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 "TotalDaysThisDealer" 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 'TradedDaysThisDealer' 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

"%TradedDaysThisDealer" by dividing "TradedDaysThisDealer" by "TotalDaysThisDealer". Table 1 summarizes these three variables.

According to Table 1, approximately 75% of the dealers in our sample stay in the market for at least 3150 days. 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.

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

Table 1: **Summary of how actively each dealer trade, TotalDaysThisDealer is the number of days between the quarter this dealer first trade and the quarter this dealer last trade. TradedDaysThisDealer is the number of days this dealer traded at least once, %TradedDaysThisDealer = TotalDaysThisDealer/TradedDaysThisDealer to measure how actively this dealer trade.**

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

Table 2: **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 $Share_{A,B,t} \neq 0$.**

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.

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

Table 3: **Summarize of the correlation of client order imbalance for the dealer pairs for each quarter, where $\rho_{A,B,t}$ is the correlation calculated based on the daily order imbalance from Jun 2002 to the last date of quarter t.**

4 Model

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

At period 1, client a bargains and sell q_A(buy if $q_A < 0$) to dealer A, client b bargains and sell 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 from 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:

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

Dealer B's surplus from interdealer trade:

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

Dealers' bargaining problem:

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

such that:

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

Here, θ represents the bargaining power of dealer A over dealer B.

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:

Gain for client a:

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

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).

Expected surplus for dealer A, given $q_A = q_A^r$

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

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

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

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:

$$E(V(0,0|q_A = q_A^r) = \underbrace{-p_A q_A^r + \int p_d^*(\Phi_0) q_d^*(\Phi_0) f_{\rho_{A,B}}(dq_B|q_A = q_A^r)}_{\text{Expected Proceeds from Interdealer Trade}}$$

$$\underbrace{-\omega_A \sigma_v^2 \int (0 - q_d^*(\Phi_0))^2 f_{\rho_{A,B}}(dq_B|q_A = q_A^r)}_{\text{Expected Cost of Risk Aversion}} - \underbrace{k_A \int (0 - q_d^*(\Phi_0))^2 f_{\rho_{A,B}}(dq_B|q_A = q_A^r)}_{\text{Expected Inventory Cost}} \quad (9)$$

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 maximizing the aggregate surplus

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

such that

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

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:

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

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

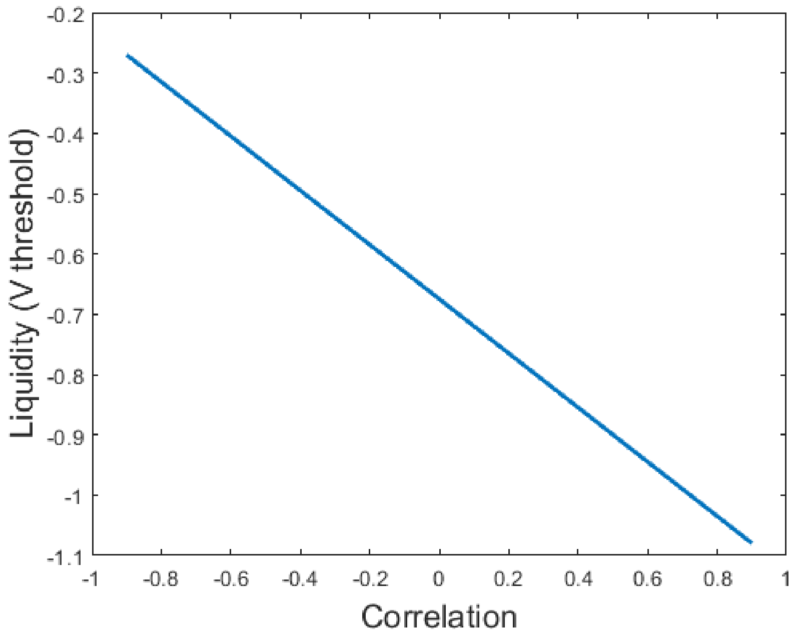

Figure 1: **Liquidity and Correlation of Order Imbalance**

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):

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

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.

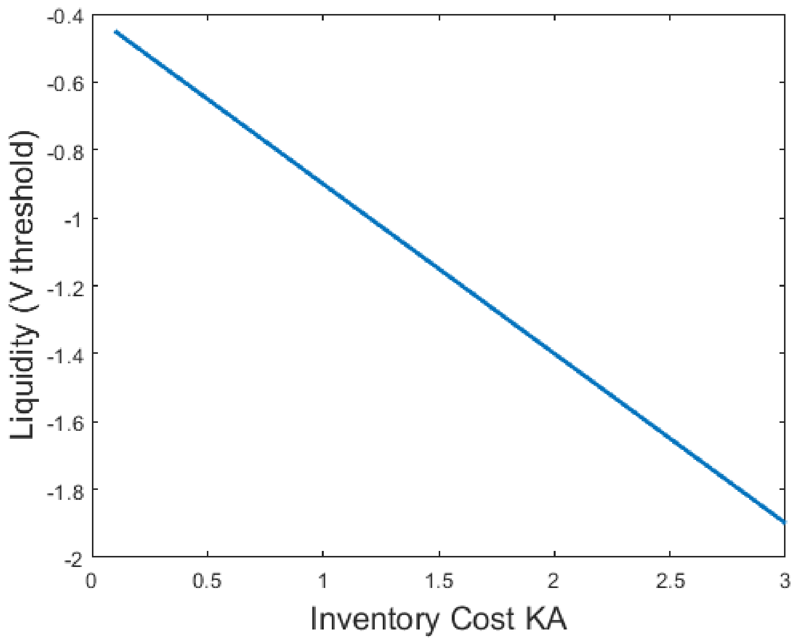

Figure 2: **Liquidity and Inventory Cost**

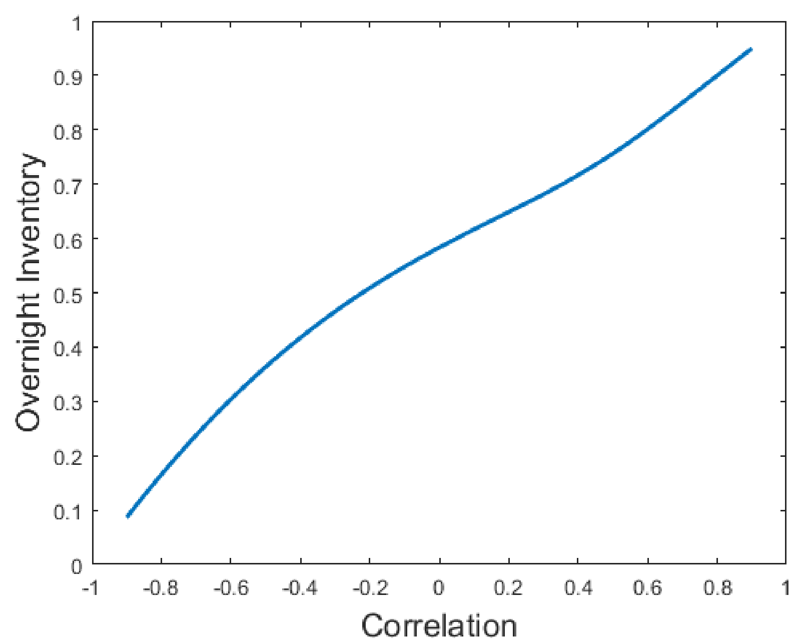

Figure 3: **Capital Commitment (Abs Change of Overnight Inventory) and Correlation of Order Imbalance**

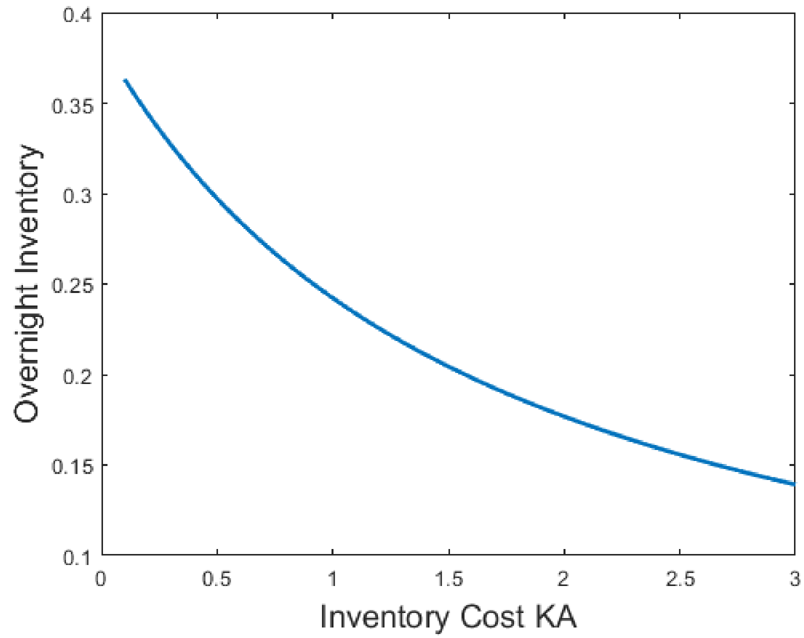

Figure 4: **Capital Commitment (Abs Change of Overnight Inventory) and Inventory Cost**

5 Empirical Regression

To investigate whether it is the case after the crisis. 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 calculate 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 corresponding 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

	(1)	(2)	(2)
γ_1	-0.0014***	-0.0007	0.0011
	(0.0004)	(0.0004)	(0.0007)
γ_2	-0.0022**	-0.0007	-0.0031***
	(0.0009)	(0.0009)	(0.0010)
γ_3	-0.0022	-0.0038***	-0.0030**
	(0.0017)	(0.0011)	(0.0012)
γ_4	-0.0039***	-0.0042***	-0.0057***
	(0.0009)	(0.0010)	(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		

Table 4: **Regression Results: 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.**

imbalance.

We get the data from Trace Academics, which is one of the most comprehensive data set 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 correlation $\rho_{A,B[0,t-1]}$ 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 gamma1 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 control $X_{A,B,q}$ 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 1. To test for robustness, we run seperate regressions by lagging the correlation of order imbalance by 1 quarter, 4 quarters, and 8 quarters, respectively. 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 opposite directions, they would be more inclined to trade with each other in the future. 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.

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.

References

[1] Tobias Adrian, Michael Fleming, Or Shachar, and Erik Vogt. Market liquidity after the financial crisis. *Annual Review of Financial Economics*, 9:43–83, 2017.

[2] Gara Afonso, Anna Kovner, and Antoinette Schoar. Stressed, not frozen: The federal funds market in the financial crisis. *The Journal of Finance*, 66(4):1109–1139, 2011.

[3] Jason Allen and Milena Wittwer. Centralizing over-the-counter markets? 2021.

[4] Ana Babus. The formation of financial networks. 2013.

[5] Ana Babus and Péter Kondor. Trading and information diffusion in over-the-counter markets. *Econometrica*, 86(5):1727–1769, 2018.

[6] Andrea Barbon, Marco Di Maggio, Francesco Franzoni, and Augustin Landier. Brokers and order flow leakage: Evidence from fire sales. *The Journal of Finance*, 74(6):2707–2749, 2019.

[7] Hendrik Bessembinder, Stacey Jacobsen, William Maxwell, and Kumar Venkataraman. Capital commitment and illiquidity in corporate bonds. *The Journal of Finance*, 73(4):1615–1661, 2018.

[8] Hendrik Bessembinder, William Maxwell, and Kumar Venkataraman. Market transparency, liquidity externalities, and institutional trading costs in corporate bonds. *Journal of Financial Economics*, 82(2):251–288, 2006.

[9] Hendrik Bessembinder, Chester Spatt, and Kumar Venkataraman. A survey of the microstructure of fixed-income markets. *Journal of Financial and Quantitative Analysis*, 55(1):1–45, 2020.

[10] Bruno Biais and Richard Green. The microstructure of the bond market in the 20th century. 2007.

[11] Michiel Bijlsma, Jan Boone, and Gijsbert Zwart. Competition for traders and risk. 2012.

[12] Francisco Blasques, Siem Jan Koopman, Andre Lucas, and Julia Schaumburg. Spillover dynamics for systemic risk measurement using spatial financial time series models. *Journal of Econometrics*, 195(2):211–223, 2016.

[13] Yann Bramoullé, Habiba Djebbari, and Bernard Fortin. Identification of peer effects through social networks. *Journal of econometrics*, 150(1):41–55, 2009.

[14] Markus K Brunnermeier. Deciphering the liquidity and credit crunch 2007–2008. *Journal of Economic perspectives*, 23(1):77–100, 2009.

[15] Markus K Brunnermeier and Lasse Heje Pedersen. Market liquidity and funding liquidity. *The review of financial studies*, 22(6):2201–2238, 2009.

[16] Cecilia Caglio, Adam M Copeland, and Antoine Martin. The value of internal sources of funding liquidity: Us broker-dealers and the financial crisis. *FRB of New York Staff Report*, (969), 2021.

[17] Briana Chang and Shengxing Zhang. Endogenous market making and network formation. *Available at SSRN 2600242*, 2021.

[18] Briana Chang and Shengxing Zhang. Risk concentration and interconnectedness in otc markets. Technical report, Working paper, 2021.

[19] Jaewon Choi, Yesol Huh, and Sean Seunghun Shin. Customer liquidity provision: Implications for corporate bond transaction costs. *Management Science*, 2023.

[20] Robert Clark and Jean-François Houde. Collusion with asymmetric retailers: Evidence from a gasoline price-fixing case. *American Economic Journal: Microeconomics*, 5(3):97–123, 2013.

[21] Joao F Cocco, Francisco J Gomes, and Nuno C Martins. Lending relationships in the interbank market. *Journal of Financial Intermediation*, 18(1):24–48, 2009.

[22] John H Cochrane and Monika Piazzesi. Bond risk premia. *American economic review*, 95(1):138–160, 2005.

[23] Jean-Edouard Colliard, Thierry Foucault, and Peter Hoffmann. Inventory management, dealers' connections, and prices in over-the-counter markets. *The Journal of Finance*, 76(5):2199–2247, 2021.

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

[25] Hugues Dastarac. Market making and proprietary trading in the us corporate bond market. *Available at SSRN 3536907*, 2020.

[26] Marco Di Maggio, Amir Kermani, and Zhaogang Song. The value of trading relations in turbulent times. *Journal of Financial Economics*, 124(2):266–284, 2017.

[27] Jens Dick-Nielsen. Liquidity biases in trace. *The Journal of Fixed Income*, 19(2):43–55, 2009.

[28] Jens Dick-Nielsen and Marco Rossi. The cost of immediacy for corporate bonds. *The Review of Financial Studies*, 32(1):1–41, 2019.

[29] Darrell Duffie. *Post-crisis bank regulations and financial market liquidity.* Banca d'Italia, 2017.

[30] Darrell Duffie. Financial regulatory reform after the crisis: An assessment. *Management Science*, 64(10):4835–4857, 2018.

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

[32] Prajit K Dutta and Ananth Madhavan. Competition and collusion in dealer markets. *The journal of finance*, 52(1):245–276, 1997.

[33] David Easley, Soeren Hvidkjaer, and Maureen O'hara. Is information risk a determinant of asset returns? *The journal of finance*, 57(5):2185–2221, 2002.

[34] Maryam Farboodi. Intermediation and voluntary exposure to counterparty risk. 2021.

[35] Peter Feldhütter. The same bond at different prices: identifying search frictions and selling pressures. *The Review of Financial Studies*, 25(4):1155–1206, 2012.

[36] Ingo Fender and Ulf Lewrick. Shifting tides–market liquidity and market-making in fixed income instruments. *BIS Quarterly Review, March*, 2015.

[37] Jean-Sébastien Fontaine and Adrian Walton. Contagion in dealer networks. *Available at SSRN 3617822*, 2020.

[38] Nils Friewald, Florian Nagler, and Christian Wagner. Debt refinancing and equity returns. *The Journal of Finance*, 77(4):2287–2329, 2022.

[39] Pengjie Gao, Paul Schultz, and Zhaogang Song. Liquidity in a market for unique assets: Specified pool and to-be-announced trading in the mortgage-backed securities market. *The Journal of Finance*, 72(3):1119–1170, 2017.

[40] Jonathan Goldberg and Yoshio Nozawa. Liquidity supply in the corporate bond market. *The Journal of Finance*, 76(2):755–796, 2021.

[41] Michael A Goldstein and Edith S Hotchkiss. Providing liquidity in an illiquid market: Dealer behavior in us corporate bonds. *Journal of Financial Economics*, 135(1):16–40, 2020.

[42] Michael A Goldstein, Edith S Hotchkiss, and Erik R Sirri. Transparency and liquidity: A controlled experiment on corporate bonds. *The review of financial studies*, 20(2):235–273, 2007.

[43] Toni Gravelle. The market microstructure of dealership equity and government securities markets: how they differ. *Financial Markets Departments, Bank of Canada*, 1999.

[44] Richard C Green, Burton Hollifield, and Norman Schürhoff. Financial intermediation and the costs of trading in an opaque market. *The Review of Financial Studies*, 20(2):275–314, 2007.

[45] Chao Gu, Guido Menzio, Randall Wright, and Yu Zhu. Market freezes. Technical report, National Bureau of Economic Research, 2021.

[46] Larry Harris, Albert S Kyle, and Erik R Sirri. Statement of the financial economists roundtable, april 2015: The structure of trading in bond markets. *Financial Analysts Journal*, 71(6):5–8, 2015.

[47] Lawrence Harris. Transaction costs, trade throughs, and riskless principal trading in corporate bond markets. *Trade Throughs, and Riskless Principal Trading in Corporate Bond Markets (October 22, 2015)*, 2015.

[48] Joel Hasbrouck and George Sofianos. The trades of market makers: An empirical analysis of nyse specialists. *The Journal of Finance*, 48(5):1565–1593, 1993.

[49] Zhiguo He, Paymon Khorrami, and Zhaogang Song. Commonality in credit spread changes: Dealer inventory and intermediary distress. *The Review of Financial Studies*, 35(10):4630–4673, 2022.

[50] Zhiguo He and Arvind Krishnamurthy. Intermediary asset pricing. *American Economic Review*, 103(2):732–770, 2013.

[51] Stephanie Heck, Dimitris Margaritis, and Aline Muller. Liquidity patterns in the us corporate bond market. In *28th Australasian Finance and Banking Conference*, 2016.

[52] Terrence Hendershott, Roman Kozhan, and Vikas Raman. Short selling and price discovery in corporate bonds. *Journal of Financial and Quantitative Analysis*, 55(1):77–115, 2020.

[53] Terrence Hendershott, Dan Li, Dmitry Livdan, and Norman Schürhoff. Relationship trading in over-the-counter markets. *The Journal of Finance*, 75(2):683–734, 2020.

[54] Terrence Hendershott and Ananth Madhavan. Click or call? auction versus search in the over-the-counter market. *The Journal of Finance*, 70(1):419–447, 2015.

[55] Thomas SY Ho and Hans R Stoll. The dynamics of dealer markets under competition. *The Journal of finance*, 38(4):1053–1074, 1983.

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

[57] Edith S Hotchkiss and Tavy Ronen. The informational efficiency of the corporate bond market: An intraday analysis. *The Review of Financial Studies*, 15(5):1325–1354, 2002.

[58] Plamen Ivanov, Alexei G Orlov, and Michael Schihl. Bond liquidity and dealer inventories: Insights from us and european regulatory data. *Available at SSRN 3529801*, 2022.

[59] Ebehi Iyoha. Estimating productivity in the presence of spillovers: Firm-level evidence from the us production network. Technical report, Working Paper, 2021.

[60] Rainer Jankowitsch, Rainer Pullirsch, and Tanja Veža. The delivery option in credit default swaps. *Journal of Banking & Finance*, 32(7):1269–1285, 2008.

[61] Linas Jurksas, Deimante Teresiene, and Rasa Kanapickiene. Liquidity spill-overs in sovereign bond market: An intra-day study of trade shocks in calm and stressful market conditions. *Economies*, 9(1):35, 2021.

[62] Ralph SJ Koijen and Motohiro Yogo. A demand system approach to asset pricing. *Journal of Political Economy*, 127(4):1475–1515, 2019.

[63] Hayne E Leland. Agency costs, risk management, and capital structure. *The Journal of Finance*, 53(4):1213–1243, 1998.

[64] Benjamin Lester, Guillaume Rocheteau, and Pierre-Olivier Weill. Competing for order flow in otc markets. *Journal of Money, Credit and Banking*, 47(S2):77–126, 2015.

[65] Dan Li and Norman Schürhoff. Dealer networks. *The Journal of Finance*, 74(1):91–144, 2019.

[66] Dong Lou, Hongjun Yan, and Jinfan Zhang. Anticipated and repeated shocks in liquid markets. *The Review of Financial Studies*, 26(8):1891–1912, 2013.

[67] Sriketan Mahanti, Amrut Nashikkar, Marti Subrahmanyam, George Chacko, and Gaurav Mallik. Latent liquidity: A new measure of liquidity, with an application to corporate bonds. *Journal of Financial Economics*, 88(2):272–298, 2008.

[68] Maria Fraga O Martins. Parametric and semiparametric estimation of sample selection models: an empirical application to the female labour force in portugal. *Journal of Applied Econometrics*, 16(1):23–39, 2001.

[69] Amrut Nashikkar, Marti G Subrahmanyam, and Sriketan Mahanti. Liquidity and arbitrage in the market for credit risk. *Journal of Financial and Quantitative Analysis*, 46(3):627–656, 2011.

[70] Maureen O'Hara and Xing Alex Zhou. Anatomy of a liquidity crisis: Corporate bonds in the covid-19 crisis. *Journal of Financial Economics*, 142(1):46–68, 2021.

[71] Maureen O'Hara and Xing Alex Zhou. The electronic evolution of corporate bond dealers. *Journal of Financial Economics*, 140(2):368–390, 2021.

[72] Maureen OâHara, Yihui Wang, and Xing Alex Zhou. The execution quality of corporate bonds. *Journal of Financial Economics*, 130(2):308–326, 2018.

[73] Oliver Randall. Pricing and liquidity in over-the-counter markets. *Available at SSRN 2590351*, 2015.

[74] Ricardo Reis. Debt revenue and the sustainability of public debt. *Journal of Economic Perspectives*, 36(4):103–124, 2022.

[75] Peter C Reiss and Ingrid M Werner. Does risk sharing motivate interdealer trading? *The Journal of Finance*, 53(5):1657–1703, 1998.

[76] Roberto Rigobon. Contagion, spillover, and interdependence. *Economía*, 19(2):69–100, 2019.

[77] Eric S Rosengren et al. Broker-dealer finance and financial stability. In *Keynote Remarks: Conference on the Risks of Wholesale Funding sponsored by the Federal Reserve Banks of Boston and New York*, 2014.

[78] Orphanides A Taylor Rules and A Orphanides. Finance and economics discussion series divisions of research & statistics and monetary affairs federal reserve board. *Washington, DC, January*, 2007.

[79] Paul Schultz. The market for new issues of municipal bonds: The roles of transparency and limited access to retail investors. *Journal of Financial Economics*, 106(3):492–512, 2012.

[80] Paul Schultz. Inventory management by corporate bond dealers. *Available at SSRN 2966919*, 2017.

[81] Karamfil Todorov. The anatomy of bond etf arbitrage. 2021.

[82] Francesco Trebbi and Kairong Xiao. Regulation and market liquidity. *Management Science*, 65(5):1949–1968, 2019.

[83] Chung-Yi Tse and Yujing Xu. Inter-dealer trades in otc markets–who buys and who sells? *Review of Economic Dynamics*, 39:220–257, 2021.

[84] S Viswanathan and James JD Wang. Inter-dealer trading in financial markets. *The Journal of Business*, 77(4):987–1040, 2004.

[85] Karl-Hubert Vogler. Risk allocation and inter-dealer trading. *European Economic Review*, 41(8):1615–1634, 1997.

[86] Chaojun Wang. Core-periphery trading networks. *Available at SSRN 2747117*, 2016.

[87] Jason Wei and Xing Zhou. Informed trading in corporate bonds prior to earnings announcements. *Financial Management*, 45(3):641–674, 2016.

[88] Pierre-Olivier Weill. The search theory of over-the-counter markets. *Annual Review of Economics*, 12:747–773, 2020.