Dealer Networks and the Cost of Immediacy*

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Abstract

We show that uninformed corporate bond index trackers pay lower transaction costs when they request immediacy from dealers with central network positions. This centrality discount supports recent network models in which core dealers have a comparative advantage in carrying inventory. We show that core dealers provide more immediacy and revert deviations from their desired inventory faster. When dealers trade with other dealers, we find a centrality premium consistent with core dealers deriving market power from their network position. We rule out alternative explanations based on adverse selection and customer clienteles.

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1 Introduction

The dealer network in many over-the-counter (OTC) markets exhibits a core-periphery structure. Core dealers are highly interconnected and account for most of the trading activity relative to peripheral dealers who are less connected. Identifying how network structure affects transaction costs is important for understanding price formation and liquidity provision in OTC markets. The theoretical literature suggests numerous channels through which network position and transaction costs interact.[1] Likewise, the empirical literature finds conflicting evidence showing the existence of both a centrality discount and a centrality premium.[2] Li and Schürhoff (2019) and Hasbrouck and Levich (2020) find a premium in markets for municipal bonds and foreign exchange, whereas Hollifield et al. (2017) find a discount for securitized debt. For corporate bonds, Di Maggio et al. (2017) and Hollifield et al. (2020) find a premium, whereas Goldstein and Hotchkiss (2020) find a discount. A significant empirical challenge is to identify the channels that determine the centrality spread.

In this paper, we exploit a unique trading environment in the US corporate bond market to isolate the inventory management channel. This channel describes that dealers with wider trading networks are better able to manage inventory risk (see e.g., Huang and Wei (2017), Üslü (2019), and Colliard et al. (2020)). We consider exclusions from the Bloomberg Barclays US Corporate Bond Index because index trackers have a strong desire to sell bonds exiting the index to minimize tracking error. The urgency to trade close to the exclusion date requires index trackers to demand immediacy from dealers. Because dealers use their inventory to provide immediacy, we can isolate the effect of inventory risk while ruling out alternative explanations based on adverse selection and customer clienteles. Mechanical index rules make exclusions information-free events and the need for execution speed implies that dealers possess essentially all bargaining power vis-á-vis index trackers when negotiating the price. We focus on index exclusions for identification but find similar results for the entire

[1] See e.g., Huang and Wei (2017), Babus and Kondor (2018), Sambalaibat (2018), Wang (2018), Li and Song (2019), Neklyudov (2019), Üslü (2019), Colliard et al. (2020), Hugonnier et al. (2020), Li and Song (2020), and Shen et al. (2020).

[2] Centrality discount or premium denotes if the centrality spread (i.e., the difference in transaction costs between core and peripheral dealers) is negative or positive.

corporate bond market suggesting that the inventory management channel also dominates outside index exclusions.

We document a centrality discount when index trackers (the sellers) request immediacy from dealers (the buyers) close to the exclusion date and when dealers sell off their newly acquired inventory to customers after exclusion. The economic magnitude is sizeable with a one standard deviation change in dealer centrality corresponding to 5–13% of the mean and 11–37% of the median bid-ask spread. This centrality discount for customer–dealer trades supports the inventory management channel because core dealers have a comparative advantage in carrying inventory and therefore charge lower transaction costs. Our analysis of the dealer-specific speed of inventory adjustment shows that core dealers unwind their newly acquired inventory substantially faster than peripheral dealers do. Dealers can unwind inventory by trading with customers or with other dealers. When dealers trade index-excluded bonds with each other, we find an interdealer centrality premium. This finding suggests that core dealers derive market power from their network position and therefore trade at more favorable interdealer prices. Since core dealers can unwind inventory at more favorable interdealer prices, they can offer better prices (i.e., lower transaction costs) to their customers.

The inventory management channel affects the centrality spread for those trades only where dealers use their inventory. In a prearranged trade, the dealer acts as a broker by matching buyers and sellers without taking any inventory risk. We follow Friewald and Nagler (2019) and use prearranged trades as a proxy for aversion to inventory risk. We find that peripheral dealers on average prearrange 5–11% of their trading volume compared to 2–5% for core dealers. Core dealers are therefore more willing to use their inventory to provide immediacy consistent with the inventory management channel. When dealers prearrange trades between customers, the centrality spread is statistically insignificant from zero consistent with dealers not taking any inventory risk. When dealers use the interdealer network in a prearranged trade, we find a centrality discount. This finding reflects that prearranging dealers with central network positions trade at more favorable interdealer prices and pass on some of this benefit to customers.

Our results support recent models of trading in OTC markets with network frictions and inventory risk (Huang and Wei (2017), Üslü (2019), and Colliard et al. (2020)). In these models, dealers use the interdealer network to unwind inventory. Core dealers are better connected and therefore have a comparative advantage in managing inventory. Huang and Wei (2017) assume that dealers compete on offering the best price to win a customer order before distributing their inventories through bilateral trading with directly connected dealers. The core-periphery structure creates market power for dealers because how much they trade affect interdealer prices. Core dealers trade at more favorable interdealer prices because they can divide their trades between a higher number of directly connected dealers. In turn, core dealers outbid peripheral dealers to win the customer order when their relative inventory is not too high. As core dealer inventories increase, they trade more in the interdealer market and move interdealer prices against them. Eventually, the higher inventory level outweighs the connection advantage and a peripheral dealer wins the customer order. Importantly, a winning core dealer offers better prices (i.e. higher bid or lower ask) to the customer than a winning peripheral dealer does. The inventory management channel therefore predicts a customer–dealer centrality discount and an interdealer centrality premium originating from the asymmetry in dealer connections and market power in the interdealer market.[3]

Colliard et al. (2020) develop a model in which core dealers share inventory risk efficiently between each other while peripheral dealers have heterogeneous connections to the core and face bargaining frictions. Better connected peripheral dealers gain market power from their network position relative to less connected peripheral dealers. Interdealer trades may therefore reflect a centrality premium while customer–dealer trades typically reflect a centrality discount consistent with our results. In the search-and-bargaining model by Üslü (2019), the faster execution speed of core dealers gives a comparative advantage in carrying inventory. Core dealers are therefore less averse to inventory risk and charge lower transaction costs to customers. Faster execution speed, however, also enables core dealers to extract more surplus when bargaining with (slower) peripheral dealers. This speed premium predicts that interdealer transaction costs increase with dealer centrality consistent with our results. The

[3] In the internet appendix, we derive the centrality spread in the Huang and Wei (2017) model.

model features either a centrality premium or a discount depending on whether the inventory management channel or the speed premium dominates, but in any case, faster execution speed enables core dealers to dominate the trading relationship.

Our focus on index exclusions rules out a number of alternative explanations for the centrality spread. First, adverse selection models such as Babus and Kondor (2018) predict a centrality discount because core dealers observe more order flow and therefore face less adverse selection. Adverse selection cannot explain our centrality spread because mechanical index rules, not information, dictate the decision to trade. Second, search-based models with customer clienteles predict either a centrality premium or a discount for customer–dealer trades. Li and Schürhoff (2019) show that a centrality premium arises when customers have weak outside options, need fast execution speed, and dealers have sufficiently high bargaining power. Hollifield et al. (2017) also model a customer clientele segmented on the need for fast execution speed but they assume that fast-preference customers have stronger outside options unlike Li and Schürhoff (2019). Their model predicts a centrality discount because core dealers offering fast execution speed attract customers with stronger outside options. Customer clienteles are unlikely to explain our findings because we estimate the centrality spread within a specific customer clientele (index trackers). Finally, we also construct proxies motivated by these alternative explanations and show that they do not explain our results.

Our results also help reconcile the mixed empirical evidence on the centrality spread in the corporate bond market. Di Maggio et al. (2017) find a centrality premium for interdealer trades but no significant centrality spread for customer–dealer trades. Their centrality spread is derived from trades executed within at most 1 hour of each other. Since these trades carry little inventory risk, their results cannot directly identify the effect of inventory risk management. Hollifield et al. (2020) find a centrality premium using spreads computed when a dealer buys from a customer and sells to either a customer or to another dealer.[4] Goldstein and Hotchkiss (2020) find a centrality discount without conditioning on counterparty type (dealer versus customer). Our findings of a centrality discount for customer–dealer trades and

[4]In Table A1 in the internet appendix, we use round-trip intermediation chains from Feldhütter and Poulsen (2018) to show the implications of using spreads as opposed to prices when estimating the centrality spread.

a centrality premium for interdealer trades suggest that the sample used by Goldstein and Hotchkiss (2020) is likely tilted more towards customer–dealer trades than interdealer trades.[5] Finally, Di Maggio et al. (2017), Hollifield et al. (2020), and Goldstein and Hotchkiss (2020) consider the cross-section of all trades where it is not clear a priori, which channel dominates in determining the centrality spread. In contrast, we identify information-free trades where dealers provide immediacy and use their network position to manage inventory risk. By doing so, we can uniquely identify inventory risk as a dominating channel for determining transaction costs in a network structure.

2 Corporate Bond Index Tracking

We follow Dick-Nielsen and Rossi (2019) and consider monthly exclusions from the Bloomberg Barclays US Corporate Bond Index (previously called the Lehman corporate bond Index and the Barclay Capital corporate bond Index) from July 2002 to November 2013. The index includes all US investment grade corporate bonds with more than one year to maturity in addition to several other requirements.[6] Index-eligible bonds account for a large fraction of the US corporate bond market. The index is rebalanced at 3PM EST on the last trading day of each month. Importantly, the rules for bonds entering or exiting the index are fully transparent and available to all market participants. Bonds enter the index for two main reasons: (1) they are newly issued and satisfy the index requirements or (2) they are upgraded from speculative to investment grade. Bonds exit the index for three main reasons: (1) the remaining time to maturity drops below one year, (2) they are downgraded from investment grade to speculative grade, or (3) they are called by the issuer. We follow Dick-Nielsen and Rossi (2019) and focus on maturity exclusions and downgrade exclusions.[7]

[5]This observation is also consistent with the way the centrality spread is calculated in Goldstein and Hotchkiss (2020). They compute spreads based on dealer round trips involving both customer–dealer and interdealer trades. We can infer from Table 4 in their paper that out of all dealer round trips 29% are interdealer round trips while the remaining 71% involve at least one customer trade.

[6]The most recent index requirements are described at https://data.bloomberglp.com/professional/sites/10/2017-08-08-Factsheet-US-Corporate1.pdf

[7]Dick-Nielsen and Rossi (2019) report that there is little price pressure for bond inclusions due to the sampling strategy followed by index trackers. There are only 392 exclusions due to bonds being called by the issuer in our sample period.

Unlike equity index trackers that hold a fraction of each stock in the index, bond index trackers instead follow a sampling strategy. They invest only in a fraction of index-eligible bonds to match their portfolio on duration, cash flows, quality, and callability to that of the index. Bond index trackers' objective is to minimize the tracking error between their portfolio and the index. They compete on having a low tracking error because it resolves the agency problem between outside investors and index trackers by showing the commitment to track the index. This objective creates a strong motive to trade as close as possible to index rebalancing. Dick-Nielsen and Rossi (2019) show that index trackers could in principle reduce transaction costs by trading away from the exclusion date but they would do so at the expense of increasing tracking error risk.

3 Data

We use bond transactions data from Academic TRACE distributed by FINRA and clean the data according to Dick-Nielsen and Poulsen (2019). The data contain all transactions in US corporate bonds with anonymized dealer identifiers for each transaction. This feature allows us to trace out the dealer network structure and track how individual dealer inventories change over time. We follow Dick-Nielsen and Rossi (2019) and use trades with a par value of at least $100,000 when computing prices[8] but keep all trades when computing network variables and dealer inventories. We obtain bond characteristics from Mergent Fixed Income Securities Database (FISD).

[INSERT TABLE 1]

Table 1 presents summary statistics for our sample of index exclusions from July 2002 to November 2013 and for a sample of all corporate bonds. We use the latter sample of all non-convertible corporate bonds that are not rule 144A to characterize the dealer network structure in Section 4. These bonds resemble the universe of index-eligible bonds. Panel A

[8]We show in the internet appendix that our results are robust to including all trade sizes.

in Table 1 shows that most bond exclusions have transactions in TRACE.[9] The third column reports the number of excluded bonds that dealers buy from customers at exclusion (event days -2, -1, and 0 where event day 0 is the exclusion date). This number is lower than the total number of exclusions because index trackers follow a sampling strategy instead of holding all index-eligible bonds. The last column contains the number of excluded bonds that dealers sell to customers after exclusion (event days 1 to 30). In Panel B of Table 1, we present bond characteristics for each sample.[10]

4 Dealer Network

In this section, we analyze the dealer network structure and show that it is core dealers mostly that provide immediacy to index trackers when the index is rebalanced.

4.1 Core-periphery structure

We use interdealer transactions from our sample of all corporate bonds to characterize the dealer network structure. Our main measure of dealer centrality is the eigenvector centrality score which is also used by for example Hollifield et al. (2017), Li and Schürhoff (2019), and Goldstein and Hotchkiss (2020).[11] At the end of each month, we compute dealer-level eigenvector centrality scores which reflect both direct and indirect trading partners. This centrality measure assigns higher scores to dealers with more trading partners and also to dealers with more connected trading partners. The eigenvector centrality score is bounded between zero and one with the most central dealer attaining a score of one.

[INSERT FIGURE 1]

Figure 1 confirms the finding by Di Maggio et al. (2017) that the dealer network in the

[9]We have a slightly higher number of bond exclusions with transactions in TRACE than the sample used by Dick-Nielsen and Rossi (2019) because we use a different procedure to clean the Academic TRACE data (see Dick-Nielsen and Poulsen (2019) for details).

[10]The number of downgrade exclusions in Panel A exceeds the number of bonds in Panel B because some bonds are downgraded to speculative grade more than once.

[11]We show in the internet appendix that our results remain almost the same when we instead use the degree centrality measure.

corporate bond market has a definite core-periphery structure with few highly connected dealers and a larger number of peripheral dealers. Panel A shows the distribution of eigenvector centrality scores over the entire sample period. Panel B visualizes the network structure in a single month where each circle denotes a broker-dealer firm and the size and shade of each circle is proportional to the centrality score.

4.2 Immediacy-providing dealers

We now focus on those dealers that provide immediacy to selling index trackers close to the exclusion date. Panel C in Table 1 reports the distribution of eigenvector centrality scores for all dealers in the corporate bond market and for those dealers that buy excluded bonds from index trackers. There are 3,499 unique dealers that transact at least once in the interdealer market during our sample period. The mean and median eigenvector centrality score of 0.08 and 0.02 confirm that the distribution is highly skewed towards zero meaning that most dealers are peripheral. Dealers that provide immediacy for index-excluded bonds have substantially higher mean and median centrality measures. The mean is 0.49 and 0.44 for maturity and downgrade exclusions respectively while the median is 0.49 and 0.43. Hence, it is core dealers mostly that provide immediacy for index-excluded bonds.

[INSERT FIGURE 2]

Figure 2 shows the cumulative fraction of immediacy provision as a function of dealer centrality rank (lower rank means more central dealer). We measure immediacy provision by the total volume dealers buy from customers and the total inventory acquired by dealers on the exclusion date and over the two preceding trading days. Immediacy provision is clearly concentrated among a handful of dealers. For example, the 50 most central dealers (illustrated by the dashed line) collectively account for 62–67% of immediacy provision. For downgrade exclusions, the 50 most central dealers' share of immediacy provision is 67–70%. These findings are consistent with Li and Schürhoff (2019) who show that impatient customers with strong liquidity needs trade mostly with core dealers in the municipal bond market.

[INSERT FIGURE 3]

In Figure 3, we consider how the number of immediacy-providing dealers varies over time. Panel A shows that the number of dealers varies more for downgrade exclusions than for maturity exclusions consistent with downgrades being clustered over time. Panel B presents the fraction of core dealers to total dealers that provide immediacy. At the end of each month, we rank dealers according to their eigenvector centrality and define the top 5 percentile as core and the rest as peripheral dealers. For maturity exclusions, core and peripheral dealers are fairly equally represented, whereas downgrade exclusions are typically dominated by core dealers. As we show in the next section, core dealers have a comparative advantage in carrying inventory making them better suited to provide immediacy for risky downgraded bonds.

5 Volume and Inventory Dynamics

We now study trading volume and inventory dynamics for index-excluded bonds around the exclusion date.

5.1 Volume dynamics around index exclusions

First, we examine the evolution of average daily trading volume for customer–dealer trades and interdealer trades separately for maturity and downgrade exclusions. The event window is 100 trading days before and after the exclusion date, which is event day 0. We aggregate trading volume across all bonds excluded during a given month and then average it across each event day in the event window.

[INSERT FIGURE 4 and TABLE 2]

Figure 4 shows a similar pattern in the average daily trading volume of index-excluded bonds for both customer–dealer and interdealer trades. Trading volume begins to surge in the days immediately leading up to the exclusion date and peaks on the exclusion date. In the days immediately after exclusion, there is a marked reduction in average transacted volume. For example, the average trading volume for maturity-excluded bonds 10 days before and after the exclusion date is only 24% to 21% of that at the exclusion date for customer–dealer trades and 62% to 59 % for interdealer trades. Similarly, the average trading volume for downgrade-excluded bonds is only 34% to 26% for customer–dealer trades and 69% to 53% for interdealer trades. Overall, the volume dynamics reveal a significant surge in customer trading volume in the days leading up to the exclusion date. The interdealer volume shows a spike for maturity exclusions, whereas the pattern is less pronounced for downgrades.

5.2 Inventory dynamics around index exclusions

We now examine the inventory dynamics of core and peripheral dealers. The inventories are cumulative, aggregated over all dealers according to dealer type, and with a chosen benchmark of $0 50 trading days before the exclusion date. The daily change in inventory is the total volume in dealer buys minus the sales. Figure 5 and Table 3 present the evolution of average cumulative inventories of index-excluded bonds over the period starting 50 trading days prior to the exclusion date and ending 100 trading days after the exclusion date. Core dealers provide substantially more immediacy than peripheral dealers do and both have a significant inventory buildup leading up to the exclusion date. For maturity exclusions, the inventory buildup starts 3 days before the exclusion date. For downgrade exclusions, the inventory buildup starts earlier partly because dealers also buy bonds on the actual downgrade date which is typically before the exclusion date.[12] Nonetheless, the inventory buildup is considerably larger from 2 days before the exclusion date.

[INSERT FIGURE 5 AND TABLE 3]

For maturity exclusions, core dealers provide three times more immediacy than peripheral dealers do when measured on the exclusion date. Both core and peripheral dealers unwind the entire stock of newly acquired inventory over roughly the same time interval. This finding implies that core dealers reduce their inventory about three times faster than peripheral dealers do. For downgrade exclusions, core dealers provide around twice the amount of immediacy

[12] Dick-Nielsen and Rossi (2019) show that the inventory buildup is far less on the downgrade date than on the exclusion date.

offered by peripheral dealers. The downgraded bonds are more risky and stay longer on dealer balance sheets than maturity-excluded bonds do. Even 100 trading days after the exclusion date, dealers are left with a substantial amount of downgraded bonds in inventory. Nevertheless, we again find that core dealers reduce their inventory considerably faster than peripheral dealers do. For example, while it takes about 26 trading days for core dealers to unwind half of their inventory balance, peripheral dealers are not able to achieve the same even after 100 trading days. Our findings reveal that core dealers have a comparative advantage in carrying inventory regarding the speed of inventory adjustment. We test this statement formally in the next section.

5.3 Speed of inventory adjustment

Our approach for estimating the speed of inventory adjustment builds on Madhavan and Smidt (1993). For each dealer in each month, we first estimate the inventory adjustment speed using the regression equation:

$$I_t - I_{t-1} = \beta(I_{t-1} - I^*) + \epsilon_t$$

where I_t is the cumulative dealer inventory across all excluded bonds on event day t, I^* is the dealer's desired level of inventory, and $\beta \in$ [-1,0] captures the sensitivity of dealer inventory to deviations from the desired inventory level. A more negative value of β corresponds to a higher speed of inventory adjustment. Given the significance of the exclusion event, we follow Dick-Nielsen and Rossi (2019) and estimate the desired level of inventory using the specification:

$$I^* = \alpha_0 + \alpha_1 I_{[t>-3]}$$

where α_0 represents the desired level of inventory before the exclusion event and α_1 represents the change in desired inventory after exclusion (the indicator variable $I_{[t>-3]}$ takes a value of one after event day -3). Finally, we examine the relation between the speed of inventory adjustment and dealer centrality by estimating the regression:

$$\beta_{im} = \alpha + \theta Centrality_{im} + \delta_m + \epsilon_{im} \tag{1}$$

where β_{im} is the speed of inventory adjustment for dealer i in month m, $Centrality_{im}$ is the eigenvector centrality score based on all interdealer transactions during the month, and δ_m denotes month fixed effects. We exclude dealers with non-positive cumulative inventory buildup over event days -2 to 0. Assuming that the excluded bonds are close substitutes, then these dealers did not use their inventory to provide immediacy.

[INSERT TABLE 4]

Panel A in Table 4 reports the regression results for maturity and downgrade exclusions with and without month fixed effects. The coefficient estimates on centrality are negative in all regressions meaning that the speed of inventory adjustment increases with centrality. For maturity exclusions, the increase in average inventory adjustment speed from a one standard deviation increase in centrality corresponds to 18% of the mean $(-0.12 * 0.25 / -0.16)$ and 25% of the median $(-0.12 * 0.25 / -0.11)$. The estimate is almost the same when we include month fixed effects. For downgrade exclusions, the increase in average inventory adjustment speed from a one standard deviation increase in centrality corresponds to 9% of the mean $(-0.05 * 0.25 / -0.14)$ and 13% of the median $(-0.05 * 0.25 / -0.09)$. When we include month fixed effects in the last column, the coefficient on centrality remains negative but becomes statistically insignificant.

To better understand the economic magnitude of these results, we sort dealers into quartiles according to their eigenvector centrality score and compute the average inventory half-life within each quartile using the formula $-ln(2)/ln(\beta + 1)$. Panel B shows that as we move from the first (peripheral) to the fourth (core) centrality quartile, the inventory half-life decreases by about 2.25 trading days for maturity exclusions and about 1.50 trading days for downgrade exclusions. These are economically sizeable differences showing that core dealer unwind their inventory faster than peripheral dealers do.

6 The Centrality Spread

In this section, we examine the centrality spread between core and peripheral dealers. We document a customer–dealer centrality discount and an interdealer centrality premium when dealers use their inventories to provide immediacy. Finally, we examine prearranged trades in which the prearranging dealer avoids inventory risk.

6.1 Customer–dealer trades

We estimate the centrality spread by comparing transaction prices of the same bond at the same time across dealers when they trade with customers. We study buy and sell transactions separately for maturity exclusions, downgrade exclusions, and for our sample of all corporate bonds. Specifically, we estimate the regression:

$$Price_{ijt} = \alpha + \beta_1 Centrality_{it} + \beta_2 Log(Volume_{ijt}) + \delta_{jt} + \epsilon_{ijt} \tag{2}$$

where $Price_{ijt}$ is the daily volume-weighted average dealer buy or sell price measured in basis points for dealer i, bond j, and day t. For index exclusions, we follow Dick-Nielsen and Rossi (2019) and calculate the dealer buy price over event days -2, -1, and 0. Event day 0 is the exclusion date. We compute the dealer sell price on each event day $t \in \{1, ..., 30\}$ after the exclusion date. In our sample of all corporate bonds, the dealer buy and sell prices are computed on each trading day. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. When dealers sell to customers after the exclusion date, we use centrality scores from the month of exclusion. We lag the centrality measure by one month in the sample of all corporate bonds. $Volume_{ijt}$ is the cumulative volume of the transactions used to compute the volume-weighted dealer-bond specific price. All regressions include bond-times-day fixed effects δ_{jt} such that we compare prices for the same bond at the same time across dealers. This estimation requires at least two dealer-bond specific observations in the same month. We winsorize prices at the 1st and 99th percentiles and cluster standard errors by bond issuer and trading day. To focus on trades where dealers use their inventory to provide immediacy, we exclude transactions where a dealer buys from a customer and sells the same bond with the same volume to another customer within 60 seconds.

[INSERT TABLE 5]

Table 5 presents the coefficient estimates of equation (2). For maturity exclusions, the coefficient estimate on centrality is positive when dealers buy bonds from index trackers close to the exclusion date. When dealers sell off their newly acquired inventory after the exclusion date, the coefficient estimate on centrality is negative. The fact that dealers with a more central network position buy at higher prices and sell at lower prices on average is synonymous with lower bid-ask spreads and hence a centrality discount.[13] A one standard deviation increase in centrality increases the average dealer buy price by 1.2 bps ($4.704 * 0.25$) and decreases the average dealer sell price by 2.6 bps ($-9.282 * 0.28$). These magnitudes correspond to 6–13% of the average and 25–37% of the median bid-ask spread.[14]

For downgrade exclusions, the coefficient estimate on centrality is positive but statistically insignificant when dealers buy from index trackers. The lack of statistical significance is due to the financial crisis period during which transaction prices are especially volatile for downgraded bonds. When we exclude observations from this period, the coefficient on centrality is 27.208 with a t-statistic of 2.20 (see Table A2 in the internet appendix). The coefficient estimate on centrality is negative as dealers unwind their inventory after the exclusion date. A one standard deviation increase in centrality increases the average dealer buy price by 11 bps ($45.952 * 0.24$) and decreases the average dealer sell price by 5.16 bps ($-20.354 * 0.25$). These magnitudes correspond to 5–11% of the average and 11–24% of the median bid-ask spread.[15]

Our finding of a centrality discount for index-excluded bonds supports the inventory man-

[13]The results are robust to using an indicator variable for core dealers instead of using continuous centrality measures.

[14]The average bid-ask spreads is 20 bps and the median is 7 bps for maturity-excluded bonds. We compute the bid-ask spread for each bond on each event day $t = \{-2, ..., 30\}$ as the difference between the daily volume-weighted average dealer sell and buy price (across all dealers) divided by the mid price.

[15]The average bid-ask spread is 102.7 bps and the median is 45.2 bps for downgrade exclusions.

agement channel. Because dealers use their inventory to provide immediacy to selling index trackers, the price dispersion across dealers reflects compensation for inventory risk. As we would expect, the magnitude of the centrality discount is larger for downgrade exclusions because these bonds are more risky and have longer inventory duration than maturity exclusions. In the Internet Appendix, we show that the Huang and Wei (2017) model has a customer–dealer centrality discount. Core dealers derive market power from their network position and can therefore unwind inventory at more favorable prices in the interdealer market. This comparative advantage in managing inventory enables core dealers to offer higher bid prices to index trackers when competing with peripheral dealers to win the sell orders.

The last two columns in Table 5 show that we also find a centrality discount in the sample of all corporate bonds. While the channel is not uniquely identified outside index exclusions, an interpretation of this result is that the inventory management channel dominates other determinants of the centrality spread. Finally, in all regressions the coefficient estimate on volume is positive when dealers buy and negative when dealers sell meaning that transaction costs decrease with the amount of immediacy provided.

Because index trackers sample the index they hold only some of the excluded bonds. The results in Table 5 may therefore give too much weight to bonds for which index trackers do not seek immediacy. We therefore also estimate the regression in equation (2) separately for two groups of bonds based on how much immediacy dealers provide. For each bond exclusion, we use transactions on event days -2, -1, and 0 to compute the bond-specific aggregate volume dealers buy from customers and the aggregate inventory buildup of all dealers. One may also expect index trackers to demand more immediacy in those months where many bonds exit the index. We therefore use the number of exclusions to proxy for immediacy. Finally, we use the median of each measure to divide our sample into a high or low immediacy group.

[INSERT TABLE 6]

Table 6 shows that the centrality discount is typically more pronounced among those bonds where dealers provide above median immediacy. In most cases, we also find that the magnitude of the centrality discount is larger for high-immediacy bonds than for low-immediacy bonds. These findings also support the inventory management channel because the effect of inventory risk should be more pronounced for those bonds where dealers provide more immediacy by using their inventory.

6.2 Interdealer trades

Dealers can unwind inventory by trading with customers or with other dealers. Schultz (2017) shows that dealers use interdealer trades mostly to manage their inventory risk. We therefore now turn to investigate the centrality spread when dealers trade with each other in the interdealer market. Specifically, we estimate the following regression separately for maturity exclusions, downgrade exclusions, and for our sample of all corporate bonds:

$$Price_{jt} = \alpha + \beta_1 Buyer\ centrality_t + \beta_2 Seller\ centrality_t + \beta_3 Log(Volume_{jt}) + \delta_{jt} + \epsilon_{jt} \quad (3)$$

where $Price_{jt}$ is the daily volume-weighted average transaction price measured in basis points between the buying and selling dealer for bond j on day t. For index exclusions, we compute the interdealer price on each event day $t \in \{-2, ..., 30\}$ where event day 0 is the exclusion date.[16] In our sample of all corporate bonds, the interdealer prices are computed on each trading day. $Buyer\ centrality_t$ and $Seller\ centrality_t$ denote the eigenvector centrality scores of the buying and selling dealer based on all interdealer transactions during the exclusion month. We lag the centrality measure by one month in the sample of all corporate bonds. $Volume_{jt}$ is the cumulative volume of the transactions used to compute the interdealer price. All regressions include bond-times-day fixed effects δ_{jt} such that we compare prices for the same bond at the same time across dealer pairs. We winsorize prices at the 1st and 99th percentiles and cluster standard errors by bond issuer and trading day.

[INSERT TABLE 7]

Table 7 shows negative coefficients on buyer centrality and positive coefficients on seller centrality in all regressions. The fact that dealers with more central network positions buy

[16] The results are qualitatively similar when considering the period before and after exclusion separately.

at lower prices and sell at higher prices on average is synonymous with core dealers charging higher bid-ask spreads. Our finding of a centrality premium in the interdealer market is consistent with Di Maggio et al. (2017) who document an interdealer centrality premium across all corporate bonds. By using information-free trades around index exclusions, we can rule out that the interdealer centrality spread reflects adverse selection for these trades. Since dealers use their inventories to provide immediacy for index-excluded bonds, the interdealer centrality spread reflects compensation for inventory risk and interdealer frictions. On the one hand, core dealers' comparative advantage in carrying inventory allow them to charge lower transaction costs to peripheral dealers. On the other hand, core dealers derive market power from their comparative advantage and may therefore charge higher transaction costs to peripheral dealers. Our finding of an interdealer centrality premium suggests that market power dominates in interdealer trades consistent with the Huang and Wei (2017) model in the Internet Appendix.

6.3 Prearranged trades

The inventory management channel affects the centrality spread for those trades only where dealers use their inventories. When a seller contacts a dealer, the dealer may offer immediate execution and take the bonds into inventory (usually called a principal trade) or ask the seller to wait until a matching counterparty can be found (prearranged trade). In the latter case, the dealer assumes no inventory risk and acts as a broker between the seller and buyer. We therefore use prearranged trades as a proxy for aversion to inventory risk and to analyze the centrality spread for a set of trades unaffected by the inventory management channel.

We define a prearranged trade as one in which the same dealer buys and sells the same bond with the same volume within 60 seconds (similar to e.g., Bessembinder et al. (2018), Dick-Nielsen and Rossi (2019), and Schultz (2017)). We consider only trade sizes of at least $100,000 and use a filter similar to Choi and Huh (2019) to delete trades between dealers and their non-FINRA affiliates.[17] For index exclusions, we identify prearranged trades on

[17]When FINRA-registered dealers transfer bonds to their non-FINRA affiliates for bookkeeping purposes, the trades are registered in TRACE as customer–dealer trades before November 2015. Affiliate trades are not

event days -2, -1, and 0 in each month. In the sample of all corporate bonds, we identify prearranged trades on all trading days. We divide prearranged trades into four groups based on counterparty type: (1) the dealer buys from a customer and sells to a customer (CDC), (2) the dealer buys from a dealer and sells to a dealer (DDD), (3) the dealer buys from a customer and sells to a dealer (CDD), and (4) the dealer buys from a dealer and sells to a customer (DDC).

[INSERT TABLE 8]

First, we use the fraction of prearranged trades as a proxy for aversion to inventory risk similar to Friewald and Nagler (2019). For index-excluded bonds, we compute the average ratio of CDC and CDD prearranged volume to the total volume dealers buy from customers using transactions on event days -2, -1, and 0 in each month. We then compute the average ratio across months. For comparison, we also compute the average monthly fraction of prearranged volume for our sample of all corporate bonds using transactions during the entire month. Panel A in Table 8 shows that peripheral dealers use substantially more prearranged trades than core dealers do. For maturity exclusions, peripheral dealers on average prearrange 5% of their trading volume compared to less than 2% for core dealers. For downgrade exclusions, the fractions are 11% for peripheral dealers and 5% for core dealers. The last column shows that in the sample of all corporate bonds, the ratio for peripheral dealers is also almost twice the ratio of core dealers. These findings suggest that peripheral dealers are more averse to inventory risk than core dealers.[18] Core dealers are therefore more willing to use their inventory to provide immediacy consistent with the inventory management channel.

Panel B in Table 8 shows that downgrade exclusions have the highest average spreads

actual risk transfers between dealers and customers and should therefore be deleted (see e.g., Bessembinder et al. (2018), Choi and Huh (2019), and An (2020)). We use an algorithm similar to Choi and Huh (2019) to identify and delete affiliated trades. Specifically, we identify two offsetting trades by the same dealer in the same bond with the same volume and the same price executed within 60 seconds of each other where at least one counterparty is a customer. Because the dealer buys and sells at the same price, all these paired trades have zero spread. We delete all zero-spread trades offset within the same second and all zero-spread trades offset within 60 seconds when the trade size is $1 million and above. We also delete zero-spread trades by dealers whose fraction of zero-spread trades exceeds 95% of their prearranged trades (involving at least one customer) in terms of trade count or volume over the entire sample period.

[18] Li and Schürhoff (2019) also find that peripheral dealers use more prearranged trades than core dealers in the municipal bonds market.

followed by the sample of all corporate bond and maturity exclusions. The average trade size is typically larger for index exclusions than for the all corporate bond sample reflecting that trades around exclusions are those of large institutional index trackers. Across all three samples, average centrality scores are similar for each type of prearranged trade. We report the average centrality score for each dealer in the prearranged trade. For DDD prearranged trades, the selling dealer has a higher centrality score than the buying dealer on average. For CDD prearranged trades, the prearranging dealer has a lower centrality score than the buying dealer on average. In untabulated results, we find that the prearranging dealer sells the bond to a dealer with a higher centrality score in 82–84% of the cases. For DDC prearranged trades, the selling dealer has a higher centrality score than the prearranging dealer. In 71–84% of the cases, the prearranging dealer buys the bond from a dealer with a higher centrality score. These findings also suggest that peripheral dealers are more averse to inventory risk. When a customer wants to buy or sell, a peripheral dealer avoids inventory risk by prearranging the trade with a core dealer.

Next, we compute the markup from the prearranging dealer's point of view as the sell price minus the buy price divided by the mid price and winsorize markups at the 1st and 99th percentiles. We analyze the centrality spread for prearranged trades by estimating the following regression separately for maturity exclusions, downgrade exclusions, and for our sample of all corporate bonds:

$$Markup_{ijt} = \alpha + \beta Centrality_{it} + \gamma Log(Trade\ size_{ijt}) + Controls_{jt} + FE + \epsilon_{ijt} \quad (4)$$

where $Markup_{ijt}$ is measured in basis points for the prearranging dealer i for bond j on day t. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. We include the centrality score for each dealer in the prearranged trade. We lag the centrality measure(s) by one month in the sample of all corporate bonds. The sample sizes are relatively small for index exclusions and we therefore use bond controls (coupon rate, bond rating, time to maturity, bond age, and issue size) together with month fixed effects. In the all corporate bond sample, we include bond-times-day fixed effects δ_{jt}

such that we compare spreads for the same bond at the same time across dealers.[19] We cluster standard errors by bond issuer and month for index exclusions and by bond issuer and trading day in the all corporate bond sample.

[INSERT TABLE 9]

Table 9 shows that the coefficient estimates on centrality are statistically insignificant from zero for CDC prearranged trades. Since the dealer assumes no inventory risk in these trades, the inventory management channel predicts that the centrality spread should be zero. The centrality spread for CDC prearranged trades is the cleanest test of this prediction because a single dealer is involved in each trade only. For the other types of prearranged trades, the centrality spread may reflect interdealer frictions because the prearranging dealer buys from and/or sells to another dealer. The significant coefficient estimates on seller centrality and buyer centrality show that counterparty network positions affect the markup.

For DDD, CDD, and DDC prearranged trades, the negative coefficient estimates on prearranging dealer centrality imply a centrality discount. This centrality discount neither reflects inventory risk nor adverse selection because the prearranging dealer does not take ownership of the bond and is therefore not concerned about the risk of trading with potentially informed counterparties. In CDD and DDC prearranged trades, the customer likely demands liquidity. For index exclusions, index trackers are clearly demanding liquidity in CDD trades and the prearranging dealer in turn demands liquidity from another dealer. Since dealers face an interdealer centrality premium, a prearranging dealer with a higher centrality score trades on better terms in the interdealer market (i.e., buy at lower prices and sell at higher prices). The fact that core dealers earn lower average markups when they prearrange trades with other dealers suggest that they pass on some of this benefit to their customers. Finally, the coefficient estimate on trade size is mostly negative consistent with findings by e.g., Schultz (2001), Chakravarty and Sarkar (2003), Edwards et al. (2007), and Feldhütter (2012).

[19] We obtain qualitatively similar results for the all corporate bond sample when using bond-times-week fixed effects to increase the sample size.

7 Alternative explanations

Using trades around index exclusions isolate the inventory management channel and rule out several alternative explanations. In addition, the inclusion of bond-times-day fixed effects in our regressions absorb potential variation that otherwise may be linked to several other channels. We now show that our results from Table 5 remain unchanged when we consider proxies at the dealer-month level motivated by alternative explanations of the centrality spread.

[INSERT TABLE 10]

7.1 Adverse selection

Babus and Kondor (2018) develop a network model in which market participants have private information. The model shows that core dealers are less exposed to adverse selection because they observe more order flow. This feature allows core dealers to charge lower spreads than peripheral dealers resulting in a centrality discount. Adverse selection is unlikely to explain our centrality spread because mechanical index rules, not information, dictate the decision to trade by index trackers. While maturity exclusions are entirely information-free, Dick-Nielsen and Rossi (2019) note that if prices incorporate information slowly then the cost of immediacy for downgrade exclusions could potentially reflect new information released on the downgrade date (i.e., before the exclusion date). The inclusion of bond-times-day fixed effects in our regressions absorb all time-varying bond and issuer specific information but dealers may still have different capacities to obtain new information. We therefore use transactions on event days -2, -1, and 0 to compute the dealer-level fraction of total order flow across all excluded bonds in each month. Table 10 shows that our results remain unchanged when we include this proxy for adverse selection.

7.2 Customer clienteles

Search-based models with customer clienteles predict either a centrality premium or a discount. Li and Schürhoff (2019) show that a centrality premium arises for customer–dealer trades when customers have weak outside options, need fast execution speed, and dealers have sufficiently high bargaining power. In contrast, we document a centrality discount for index-excluded bonds where index trackers have weak outside options, need fast execution speed, and dealers have essentially all bargaining power. Hollifield et al. (2017) also model a customer clientele segmented on the need for fast execution speed but they assume that fast-preference customers have stronger outside options unlike Li and Schürhoff (2019). Customers with weak outside options are indifferent about trading with either core or peripheral dealers. Customers with strong outside options trade only with core dealers offering sufficiently fast execution speed. The average transaction cost is therefore lower at core dealers because their customers on average have stronger outside options. Our focus on index exclusions entail a low degree of customer heterogeneity because we estimate the centrality spread within a specific customer clientele (index trackers).

To explore the possibility that some dealers may trade more frequently with index trackers having stronger bargaining positions, we consider two proxies of customer bargaining power. First, because bargaining power is split between the dealer and the index tracker, we use the dealer's bargaining power as an inverse proxy for customer bargaining power. Similar to Dick-Nielsen and Rossi (2019) and Friewald and Nagler (2019), we use dealer market share to proxy for dealer bargaining power. For each dealer in each month, we compute the share of total dealer buy volume from customers across excluded bonds on days -2, -1, and 0. Second, we also use block trades to proxy for customer bargaining power similar to Friewald and Nagler (2019). For each dealer in each month, we compute the number of block trades defined as dealer buys from customers with a trade size of at least 5 million USD on days -2, -1, and 0 across excluded bonds. Table 10 shows that our results remain unchanged when we include these proxies for customer bargaining power.

Trade size is often used to proxy for customer sophistication (see e.g., Feldhütter (2012)). If core dealers trade more with sophisticated institutional customers on average, then we should expect a positive relationship between trade size and centrality. We therefore estimate the regression:

$$Log(Trade\ size_{ijt}) = \alpha + \beta_1 Centrality_{it} + \delta_{jt} + \epsilon_{ijt} \quad (5)$$

where $Trade\ size_{ijt}$ is for dealer i, bond j, and day t. For index exclusions, we use transactions where dealers buy from customers on event days -2, -1, and 0 and transactions where dealers sell to customers on event days $t \in \{1, ..., 30\}$. In our sample of all corporate bonds, we use customer–dealer trades on all trading days. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. We lag the centrality measure by one month in the sample of all corporate bonds. All regressions include bond-times-day fixed effects δ_{jt} and we cluster standard errors by bond issuer and trading day. We consider trade sizes of at least $100,000.

[INSERT TABLE 11]

Table 11 shows negative coefficient estimates on centrality for maturity exclusions when dealers trade with customers. Core dealers provide more immediacy than peripheral dealers do but this finding means that core dealers on average trade in smaller sizes with customers for institutional-sized transactions. The coefficient estimate is insignificant for downgrade exclusions when dealers buy from index trackers at exclusion but positive when dealers sell to customers after exclusion. In the all corporate bond sample, we also find negative coefficient estimates on centrality. Taken together, these findings suggest that the customer–dealer centrality discount is not driven by customer sophistication proxied by trade size. Search-based models with customer clienteles therefore cannot explain our results.

8 Conclusion

In this paper, we use bond index exclusions to study the relationship between dealer network position and transaction costs. We document a centrality discount for customer–dealer trades and a centrality premium for interdealer trades. Using trades around index exclusions identify the relationship between the centrality spread and inventory risk while ruling out alternative explanations based on adverse selection and customer clienteles. Our results support recent models of trading in OTC markets with network frictions and inventory risk (see e.g., Huang and Wei (2017), Üslü (2019), and Colliard et al. (2020)).

We show that core dealers have a comparative advantage in carrying inventory. Core dealers provide more immediacy, unwind their newly acquired inventory faster, and use less prearranged trades than peripheral dealers do. This inventory management channel is consistent with the centrality discount for customer–dealer trades. When dealers trade with each other, we find an interdealer centrality premium consistent with dealers deriving market power from their network position. Finally, we exploit that dealers can avoid inventory risk by prearranging trades. When dealers prearrange trades between selling and buying customers, we find an insignificant centrality spread consistent with dealers taking zero inventory risk. When dealers use the interdealer network in a prearranged trade, we find a centrality discount reflecting that core dealers trade at more favorable interdealer prices.

Our results extend not only to index-excluded bonds but also to the entire corporate bond market. While the inventory management channel is not uniquely identified outside index exclusions, an interpretation of our results is that the same channel dominates outside index exclusions as results are more or less identical. Because the use of inventories for market-making is a fundamental feature of OTC markets, our findings are also important for understanding the centrality spread in other markets.

Table 1: Summary statistics

This table presents summary statistics for our sample of monthly exclusions from the Bloomberg Barclays US Corporate Bond Index over the period July 2002 to November 2013. We focus on two exclusion reasons. The bond's maturity can become less than 1 year during the month. The bond can be downgraded from investment grade to speculative grade during the month. In both cases, the bond is excluded at the end of the month. Panel A shows the number of excluded bonds with transactions in TRACE, the number of bonds bought (sold) by dealers (customers) at exclusion (event days -2, -1, and 0 where event day 0 is the exclusion date), and the number of bonds sold (bought) by dealers (customers) after exclusion (event days 1 to 30). Panel B reports the number of unique bonds together with average bond characteristics. Coupon is measured in percent, issue size is in millions of USD, and initial maturity is measured in years. We also show summary statistics for our sample of all corporate bonds which are non-convertible corporate bonds that are not rule 144A. Panel C presents the eigenvector centrality distribution across dealers. At the end of each month, we use interdealer transactions from our sample of all corporate bonds to computer dealer-level eigenvector centrality scores. We then show the distribution across those dealers that buy excluded bonds from customers at exclusion (event days -2 to 0) and also for all dealers featured in our sample of all corporate bonds.

Panel A: Index exclusions

	Number of exclusions	Exclusions in TRACE	Dealer buys at exclusion	Dealer sells after exclusion
Maturity exclusions	3,102	3,069	2,840	2,978
Downgrade exclusions	1,070	1,054	935	969

Panel B: Bond characteristics

	Bonds	Coupon	Issue size	Initial maturity
Maturity exclusions	3,102	5.70	624.25	6.80
Downgrade exclusions	1,026	6.80	593.97	14.42
All corporate bonds	59,190	4.75	190.69	9.17

Panel C: Dealer centrality

	Dealers	Mean	SD	P5	P50	P95
Maturity exclusions	476	0.49	0.27	0.02	0.49	0.94
Downgrade exclusions	452	0.44	0.27	0.02	0.43	0.93
All corporate bonds	3,499	0.08	0.16	0.00	0.02	0.45

Table 2: Trading activity around index exclusions

This table shows the average daily trading volume measured in millions of USD around index exclusions for customer–dealer and interdealer trades. Event day 0 is the exclusion date and event time is measured in trading days. We aggregate trading volume across all bonds excluded in a given month and then average across all months.

	Customer–dealer				**Interdealer**			
	Maturity		Downgrade		Maturity		Downgrade	
Event day	Volume	Fraction	Volume	Fraction	Volume	Fraction	Volume	Fraction
-100	29.9	0.14	31.6	0.16	13.6	0.40	15.5	0.47
-50	36.6	0.17	38.4	0.19	15.2	0.45	20.3	0.61
-40	32.6	0.15	25.6	0.13	13.3	0.39	12.4	0.37
-30	38.3	0.18	28.3	0.14	18.4	0.54	11.7	0.35
-20	45.7	0.21	38.4	0.19	11.3	0.33	12.3	0.37
-10	50.6	0.24	68.8	0.34	21.1	0.62	23.1	0.69
-9	44.6	0.21	61.6	0.30	14.9	0.44	21.6	0.65
-8	52.6	0.25	68.7	0.34	16.6	0.49	25.3	0.76
-7	50.2	0.23	74.6	0.37	16.8	0.49	29.6	0.89
-6	55.4	0.26	59.7	0.29	16.1	0.47	21.5	0.65
-5	58.8	0.27	59.1	0.29	20.0	0.59	19.6	0.59
-4	74.9	0.35	70.4	0.35	17.8	0.52	24.6	0.74
-3	165.9	0.77	83.7	0.41	27.0	0.79	24.6	0.74
-2	163.7	0.76	112.3	0.55	37.0	1.09	24.9	0.75
-1	118.6	0.55	110.6	0.54	29.6	0.87	28.7	0.86
0	214.5	1.00	203.5	1.00	34.1	1.00	33.3	1.00
1	89.2	0.42	83.7	0.41	30.2	0.89	26.8	0.80
2	76.8	0.36	84.8	0.42	29.5	0.87	30.6	0.92
3	72.8	0.34	67.0	0.33	28.0	0.82	29.8	0.90
4	64.9	0.30	61.4	0.30	23.8	0.70	25.8	0.78
5	61.8	0.29	61.5	0.30	22.2	0.65	20.0	0.60
6	60.0	0.28	50.9	0.25	21.2	0.62	19.7	0.59
7	52.2	0.24	49.2	0.24	20.8	0.61	19.6	0.59
8	55.2	0.26	47.6	0.23	22.1	0.65	21.9	0.66
9	53.5	0.25	37.1	0.18	21.7	0.64	12.4	0.37
10	45.8	0.21	52.1	0.26	20.1	0.59	17.6	0.53
20	36.5	0.17	42.2	0.21	11.0	0.32	15.1	0.45
30	37.6	0.18	34.2	0.17	13.6	0.40	13.2	0.40
40	38.0	0.18	38.4	0.19	11.2	0.33	16.4	0.49
50	37.9	0.18	40.2	0.20	11.7	0.34	14.8	0.45
100	35.0	0.16	34.8	0.17	9.4	0.28	20.5	0.62

Table 3: Cumulative dealer inventory around index exclusions

This table shows the average cumulative dealer inventory measured in millions of USD around index exclusions by dealer type. Event day 0 is the exclusion date and event time is measured in trading days. At the end of each month, we rank dealers based on eigenvector centrality score and define the top 5 percentile as core and the rest as peripheral dealers. For each event day in a given month, we first compute the aggregate daily inventory change as the difference between the aggregate dealer buying and selling volume across all excluded bonds. Next, we set the inventory level at the beginning of event day -50 to $0 and cumulate the daily inventory change over time. Finally, we compute the average aggregate cumulative inventory across all months by dealer type.

	Maturity exclusions				**Downgrade exclusions**			
	Core		Peripheral		Core		Peripheral	
Event day	Inventory	Fraction	Inventory	Fraction	Inventory	Fraction	Inventory	Fraction
-50	0.2	0.00	1.2	0.03	-1.7	-0.02	-0.1	-0.00
-40	4.4	0.03	2.3	0.05	-1.1	-0.01	1.9	0.06
-30	1.4	0.01	-0.7	-0.02	-1.4	-0.02	0.5	0.02
-20	18.8	0.14	4.8	0.11	-1.3	-0.02	-0.4	-0.01
-10	7.7	0.06	4.5	0.10	16.8	0.21	6.8	0.21
-9	4.3	0.03	3.4	0.08	19.3	0.25	8.3	0.25
-8	3.7	0.03	3.1	0.07	19.5	0.25	10.0	0.31
-7	1.5	0.01	0.6	0.01	22.1	0.28	10.8	0.33
-6	2.8	0.02	-0.4	-0.01	22.8	0.29	12.3	0.38
-5	4.1	0.03	-2.1	-0.05	22.0	0.28	13.8	0.42
-4	12.5	0.09	0.6	0.01	25.7	0.33	15.5	0.48
-3	56.4	0.42	12.4	0.28	29.3	0.37	16.8	0.51
-2	74.0	0.55	19.4	0.43	38.5	0.49	18.9	0.58
-1	80.0	0.59	23.4	0.53	46.8	0.60	24.1	0.74
0	135.0	1.00	44.5	1.00	78.5	1.00	32.7	1.00
1	126.1	0.93	43.5	0.98	72.4	0.92	30.4	0.93
2	114.5	0.85	39.0	0.88	69.7	0.89	28.5	0.87
3	100.5	0.74	33.9	0.76	66.3	0.85	29.3	0.90
4	89.6	0.66	30.8	0.69	64.9	0.83	27.1	0.83
5	80.7	0.60	28.5	0.64	62.5	0.80	26.8	0.82
6	74.6	0.55	25.3	0.57	60.6	0.77	25.6	0.78
7	65.6	0.49	22.7	0.51	57.9	0.74	26.2	0.80
8	58.8	0.44	20.1	0.45	57.7	0.74	25.7	0.79
9	54.3	0.40	15.7	0.35	59.5	0.76	26.7	0.82
10	51.4	0.38	14.0	0.31	63.2	0.81	27.8	0.85
20	20.9	0.15	3.5	0.08	49.9	0.64	20.9	0.64
30	-5.5	-0.04	-0.8	-0.02	36.4	0.46	20.0	0.61
40	-27.6	-0.20	-6.0	-0.14	34.3	0.44	22.1	0.68
50	-41.1	-0.30	-11.4	-0.26	22.8	0.29	21.1	0.65
100	-73.8	-0.55	-16.2	-0.36	25.5	0.33	17.4	0.53

Table 4: Speed of inventory adjustment

Panel A presents coefficient estimates from the regression:

$$\beta_{im} = \alpha + \theta Centrality_{im} + \delta_m + \epsilon_{im}$$

where β_{im} is the estimated speed of inventory adjustment for dealer i in month m. $Centrality_{im}$ is the eigenvector centrality score based on all interdealer transactions during the month. The second and fourth column include month fixed effects δ_m. For each month, we estimate the speed of inventory adjustment for every dealer with a positive cumulative inventory buildup of excluded bonds over event days -2 to 0 using the regression:

$$I_t - I_{t-1} = \beta(I_{t-1} - \alpha_0 - \alpha_1 I_{[t>-3]})$$

where I_t is the cumulative inventory (across all excluded bonds) for a given dealer on event day t, α_0 represents the desired level of inventory before the exclusion event [$t \in \{-50, \cdots, -3\}$], and α_1 represents the change in desired level of inventory after the exclusion event [$t \in \{-2, \cdots, 100\}$]. Event day 0 is the exclusion date. We use robust standard errors and report t-statistics in parenthesis with the convention *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. Panel B shows the average speed of inventory adjustment and inventory half-life for dealer quartiles based on eigenvector centrality scores. The average speed is converted into its respective half-life quantity using the formula $-\ln(2)/\ln(1+\beta)$.

Panel A: Inventory adjustment speed

	Maturity exclusions		Downgrade exclusions	
Centrality	-0.12***	-0.11***	-0.05***	-0.02
	(-12.11)	(-10.94)	(-3.30)	(-1.05)
Constant	-0.09***		-0.11***	
	(-16.23)		(-11.93)	
Month FE	No	Yes	No	Yes
Adj. R^2	0.04	0.06	0.01	0.04
Dealers	210	210	197	197
Months	137	137	101	96
Observations	3,134	3,134	1,151	1,146

Panel B: Inventory half-life

Quartile	Speed	Half-life	Speed	Half-life
1	-0.11	5.89	-0.11	5.77
2	-0.15	4.31	-0.13	5.10
3	-0.19	3.30	-0.15	4.13
4	-0.17	3.68	-0.15	4.38

Table 5: Centrality spread for customer–dealer trades

This table presents coefficient estimates from the regression:

$$Price_{ijt} = \alpha + \beta_1 Centrality_{it} + \beta_2 Log(Volume_{ijt}) + \delta_{jt} + \epsilon_{ijt}$$

where $Price_{ijt}$ is the daily volume-weighted dealer buy or sell price measured in basis points for dealer i, bond j, and day t. All prices are from the dealer's perspective. For index exclusions, we calculate the dealer buy price over event days -2, -1, and 0. Event day 0 is the exclusion date. We compute the dealer sell price on each event day $t \in \{1, ..., 30\}$ after the exclusion date. In the sample of all corporate bonds, we compute dealer-bond specific volume-weighted buy and sell prices on each trading day. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. We lag the centrality measure by one month in the sample of all corporate bonds. $Volume_{ijt}$ is the cumulative volume of the transactions used to compute the volume-weighted dealer-bond specific price. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to November 2013. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions		Downgrade exclusions		All corporate bonds	
	Buy from customer	Sell to customer	Buy from customer	Sell to customer	Buy from customer	Sell to customer
Centrality	4.704**	-9.282***	45.952	-20.354***	11.149***	-20.130***
	(2.53)	(-7.37)	(0.97)	(-3.81)	(15.72)	(-22.36)
Log(Volume)	3.943***	-3.442***	17.828***	-23.337***	7.173***	-12.242***
	(13.97)	(-10.82)	(5.05)	(-8.92)	(17.90)	(-27.01)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.991	0.991	0.983	0.992	0.997	0.996
Issuers (clusters)	715	685	256	261	3,951	4,026
Days (clusters)	137	2,537	103	1,320	2,849	2,851
Dealers	240	575	263	524	1,632	1,799
Bonds	2,173	2,184	715	675	21,281	25,565
Observations	7,962	26,391	4,036	15,631	2,542,764	3,370,986

Table 6: Centrality spread and immediacy provision

This table presents coefficient estimates on eigenvector centrality from the regression:

$$Price_{ijt} = \alpha + \beta_1 Centrality_{it} + \beta_2 Log(Volume_{ijt}) + \delta_{jt} + \epsilon_{ijt}$$

where $Price_{ijt}$ is the daily volume-weighted dealer buy or sell price measured in basis points for dealer i, bond j, and day t. All prices are from the dealer's perspective. For index exclusions, we calculate the dealer buy price over event days -2, -1, and 0. Event day 0 is the exclusion date. We compute the dealer sell price on each event day $t \in \{1, ..., 30\}$ after the exclusion date. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. $Volume_{ijt}$ is the cumulative volume of the transactions used to compute the volume-weighted dealer-bond specific price. All regressions include bond-times-day fixed effects δ_{jt}. We estimate the regression separately for two groups of bonds based on how much immediacy dealers provide. For each bond-exclusion, we use transactions on days -2, -1, and 0 to compute (1) the aggregate volume dealers buy from customers of the specific bond and (2) the aggregate inventory buildup in the specific bond. We also compute the number of exclusions each month. We then divide our sample into a high and low immediacy group based on the median of each of these bond-level measures over the entire sample period. The sample period is from July 2002 to November 2013. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions		Downgrade exclusions	
	Buy from customer	Sell to customer	Buy from customer	Sell to customer
High immediacy				
Dealer buy volume	5.043**	-8.260***	41.378	-21.851***
	(2.30)	(-6.53)	(1.08)	(-3.87)
Inventory buildup	7.317***	-8.813***	45.451	-20.084***
	(3.29)	(-6.19)	(0.98)	(-3.53)
Number of exclusions	4.004***	-9.002***	43.304	-22.378***
	(3.22)	(-5.00)	(0.84)	(-4.17)
Low immediacy				
Dealer buy volume	3.731	-13.422***	73.585	-12.079
	(1.46)	(-4.23)	(0.69)	(-0.90)
Inventory buildup	-0.679	-10.304***	47.105	-19.729**
	(-0.20)	(-4.21)	(0.91)	(-2.37)
Number of exclusions	5.903	-9.671***	76.917	7.789
	(1.27)	(-5.10)	(1.62)	(0.51)

Table 7: Centrality spread for interdealer trades

This table presents coefficient estimates from the regression:

$$Price_{jt} = \alpha + \beta_1 Buyer\ centrality_t + \beta_2 Seller\ centrality_t + \beta_3 Log(Volume_{jt}) + \delta_{jt} + \epsilon_{jt}$$

where $Price_{jt}$ is the daily volume-weighted interdealer price measured in basis points between the buying and selling dealer for bond j on day t. For index exclusions, we calculate the interdealer price on each event day $t \in \{-2, ..., 30\}$ where event day 0 is the exclusion date. In the sample of all corporate bonds, we compute interdealer prices on each trading day. $Buyer\ centrality_t$ and $Seller\ centrality_t$ denote the eigenvector centrality scores of the buying and selling dealer based on all interdealer transactions during the exclusion month. We lag the centrality measure by one month in the sample of all corporate bonds. $Volume_{jt}$ is the cumulative volume of the transactions used to compute the volume-weighted price. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to November 2013. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions	Downgrade exclusions	All corporate bonds
Buyer centrality	-8.218***	-22.323***	-9.900***
	(-8.62)	(-3.98)	(-12.36)
Seller centrality	13.447***	19.495***	9.943***
	(10.58)	(4.17)	(15.82)
Log(Volume)	-1.217**	2.442	-2.117***
	(-2.51)	(0.99)	(-8.54)
Bond×day FE	Yes	Yes	Yes
Adj. R^2	0.994	0.998	0.998
Issuers (clusters)	741	276	4,260
Days (clusters)	2,634	1,662	2,851
Buying dealers	851	788	2,303
Selling dealers	710	734	2,196
Bonds	2,323	777	35,346
Observations	37,992	37,757	6,301,315

Table 8: Prearranged trades

This table presents summary statistics for prearranged trades defined as trades where a dealer buys and sells the same bond with the same volume within 60 seconds. We divide prearranged trades into four groups based on counterparty type (C denotes customer and D denotes dealer) and the naming convention reflects how a bond travels from the seller through the prearranging dealer to the buyer. For index exclusions, we identify prearranged trades on event days -2, -1, and 0 where event day 0 is the exclusion date. In the sample of all corporate bonds, we identify prearranged trades on all trading days. Panel A shows the average ratio of CDC and CDD prearranged volume to the total volume dealers buy from customers. At the end of each month, we identify dealers with eigenvector centrality scores above the 95th percentile as core dealers and the rest as peripheral dealers. We lag the centrality measure by one month in the sample of all corporate bonds. The ratios are time-series averages across months. Panel B shows sample averages of markups measured in basis points from the prearranging dealer's point of view, trade sizes measured in $millions, and eigenvector centrality scores of the selling dealer, the prearranging dealer, and the buying dealer. The sample period is from July 2002 to November 2013.

Panel A: Prearranged volume out of total volume (%)

	Maturity exclusions	Downgrade exclusions	All corporate bonds
Peripheral	5.02	11.30	9.04
Core	1.81	4.91	4.60

Panel B: Summary statistics

	CDC			DDD		
	Maturity	Downgrade	All bonds	Maturity	Downgrade	All bonds
Markup	12.30	132.29	37.01	2.93	13.83	7.63
Trade size	3.56	4.13	2.43	1.32	0.81	0.99
Seller centrality				0.65	0.60	0.58
Prearranging centrality	0.49	0.44	0.44	0.61	0.51	0.52
Buyer centrality				0.38	0.54	0.47
Observations	183	343	298,719	443	536	731,623

	CDD			DDC		
	Maturity	Downgrade	All bonds	Maturity	Downgrade	All bonds
Markup	14.96	49.28	33.37	21.72	88.34	55.66
Trade size	1.52	0.57	0.54	1.03	0.76	0.58
Seller centrality				0.71	0.69	0.70
Prearranging centrality	0.38	0.38	0.35	0.40	0.43	0.39
Buyer centrality	0.70	0.68	0.70			
Observations	270	243	330,934	884	360	702,459

Table 9: Centrality spread for prearranged trades

This table presents coefficient estimates from the regression:

$$Markup_{ijt} = \alpha + \beta Centrality_{it} + \gamma Log(Trade\ size_{ijt}) + Controls_{jt} + FE + \epsilon_{ijt}$$

where $Markup_{ijt}$ is measured in basis points for the prearranging dealer i, bond j on day t. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month for each dealer in the prearranged trade. We lag the centrality measure(s) by one month in the sample of all corporate bonds. For index exclusions, we use prearranged trades on event days [-2, 0] and include month fixed effects together with bond controls: coupon rate, rating, time to maturity, age, and issue size. In the sample of all corporate bonds, we use prearranged trades on all trading days and include bond-times-day fixed effects. Standard errors are clustered by bond issuer and time with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	CDC			DDD		
	Maturity	Downgrade	All bonds	Maturity	Downgrade	All bonds
Seller centrality				-0.970	-7.582	1.779***
				(-0.77)	(-1.09)	(4.58)
Prearranging centrality	-5.082	-44.059	2.133	-7.692***	-16.856**	-5.402***
	(-0.94)	(-1.15)	(1.10)	(-3.17)	(-2.09)	(-4.46)
Buyer centrality				2.906**	2.007	3.240***
				(2.24)	(0.60)	(6.80)
Log(Trade size)	-2.037*	-23.624	-1.535***	-0.129	-0.982	-0.039
	(-1.87)	(-1.24)	(-3.31)	(-0.49)	(-0.55)	(-0.25)
Adj. R^2	0.200	0.230	0.601	0.354	0.359	0.421
Issuers (clusters)	114	98	2,702	173	82	2,737
Months/days (clusters)	47	41	2,780	73	44	2,834
Dealers	59	61	448	68	80	686
Bonds	139	176	6,495	285	179	11,602
Observations	150	321	48,245	414	524	294,779

	CDD			DDC		
	Maturity	Downgrade	All bonds	Maturity	Downgrade	All bonds
Seller centrality				3.575	45.591**	12.989***
				(0.75)	(2.64)	(8.49)
Prearranging centrality	-21.326***	-78.307**	-28.409***	-17.939***	13.211	-35.726***
	(-3.95)	(-2.79)	(-14.08)	(-3.93)	(0.52)	(-21.84)
Buyer centrality	-6.003	-0.068	-2.550*			
	(-0.55)	(-0.00)	(-1.68)			
Log(Trade size)	-4.188***	2.350	-5.814***	-3.909***	-12.998	-12.514***
	(-2.87)	(0.25)	(-13.59)	(-5.14)	(-1.50)	(-26.14)
Adj. R^2	0.143	0.140	0.451	0.154	0.227	0.544
Issuers (clusters)	111	45	1,496	279	59	2,212
Months/days (clusters)	66	22	2,698	108	40	2,828
Dealers	94	92	998	179	118	1,355
Bonds	185	111	5,420	490	144	10,815
Observations	231	225	53,984	870	343	230,485

Controls, month FE	Yes	Yes	No	Yes	Yes	No
Bond×day FE	No	No	Yes	No	No	Yes

Table 10: Alternative explanations for the centrality spread

This table presents coefficient estimates from the regression:

$$Price_{ijt} = \alpha + \beta_1 Centrality_{it} + \beta_2 Log(Volume_{ijt}) + \beta_3 Proxy_{it} + \delta_{jt} + \epsilon_{ijt}$$

where $Price_{ijt}$ is the daily volume-weighted dealer buy or sell price measured in basis points for dealer i, bond j, and day t. All prices are from the dealer's perspective. For index exclusions, we calculate the dealer buy price over event days -2, -1, and 0. Event day 0 is the exclusion date. We compute the dealer sell price on each event day $t \in \{1, ..., 30\}$ after the exclusion date. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. $Volume_{ijt}$ is the cumulative volume of the transactions used to compute the volume-weighted dealer-bond specific price. $Proxy_{it}$ is either (1) the dealer's share of total order flow, (2) the dealer's share of total dealer buy volume from customers, or (3) the number of block trades (trade size of at least 5 million) for each dealer out of all dealer buys from customers. All proxies are computed at the dealer-month level across all excluded bonds (maturity and downgrade exclusions separately) using trades on event days -2, -1, and 0. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to November 2013. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Buy from customer			Sell to customer		
Panel A: Maturity exclusions						
Centrality	4.743**	4.787**	4.839**	-8.664***	-8.600***	-8.874***
	(2.56)	(2.57)	(2.59)	(-7.02)	(-6.97)	(-7.15)
Log(Volume)	3.992***	4.032***	3.816***	-3.250***	-3.243***	-3.192***
	(13.90)	(13.65)	(13.52)	(-10.36)	(-10.24)	(-10.22)
Order flow	-2.383			-18.274***		
	(-0.65)			(-5.61)		
Dealer market share		-3.507			-17.584***	
		(-0.85)			(-4.81)	
Block trades			1.803			-8.832***
			(1.28)			(-8.24)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.991	0.991	0.991	0.991	0.991	0.991
Observations	7,962	7,962	7,962	26,391	26,391	26,391
Panel B: Downgrade exclusions						
Centrality	46.690	46.635	46.083	-20.698***	-20.341***	-20.059***
	(0.99)	(0.99)	(0.98)	(-3.67)	(-3.64)	(-3.81)
Log(Volume)	18.880***	18.859***	17.600***	-23.495***	-23.330***	-22.753***
	(5.75)	(5.92)	(5.46)	(-8.01)	(-8.00)	(-6.86)
Order flow	-34.944			8.314		
	(-0.95)			(0.27)		
Dealer market share		-30.044			-0.346	
		(-0.82)			(-0.01)	
Block trades			3.090			-10.378
			(0.18)			(-0.48)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.983	0.983	0.983	0.992	0.992	0.992
Observations	4,036	4,036	4,036	15,631	15,631	15,631

Table 11: Trade size and dealer centrality

This table presents coefficient estimates from the regression:

$$Log(Trade\ size_{ijt}) = \alpha + \beta_1 Centrality_{it} + \delta_{jt} + \epsilon_{ijt}$$

where $Trade\ size_{ijt}$ is for dealer i, bond j, and day t. For index exclusions, we use transactions on event days -2, -1, and 0. Event day 0 is the exclusion date. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. We lag the centrality measure by one month in the sample of all corporate bonds. All regressions include bond-times-day fixed effects δ_{jt}. We exclude trade sizes below $\$100,000$. The sample period is from July 2002 to November 2013. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions		Downgrade exclusions		All corporate bonds	
	Buy from customer	Sell to customer	Buy from customer	Sell to customer	Buy from customer	Sell to customer
Centrality	-0.351***	-0.221***	0.043	0.249***	-0.053**	-0.067**
	(-3.79)	(-4.97)	(0.27)	(3.00)	(-2.04)	(-2.53)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	-0.027	0.134	0.098	0.296	0.311	0.353
Issuers (clusters)	761	868	290	327	4,373	4,391
Days (clusters)	137	137	107	106	2,867	2,863
Dealers	249	659	271	577	1,654	1,819
Bonds	2,367	2,858	792	872	26,679	30,165
Observations	12,011	56,196	7,885	28,907	3,847,323	5,054,495

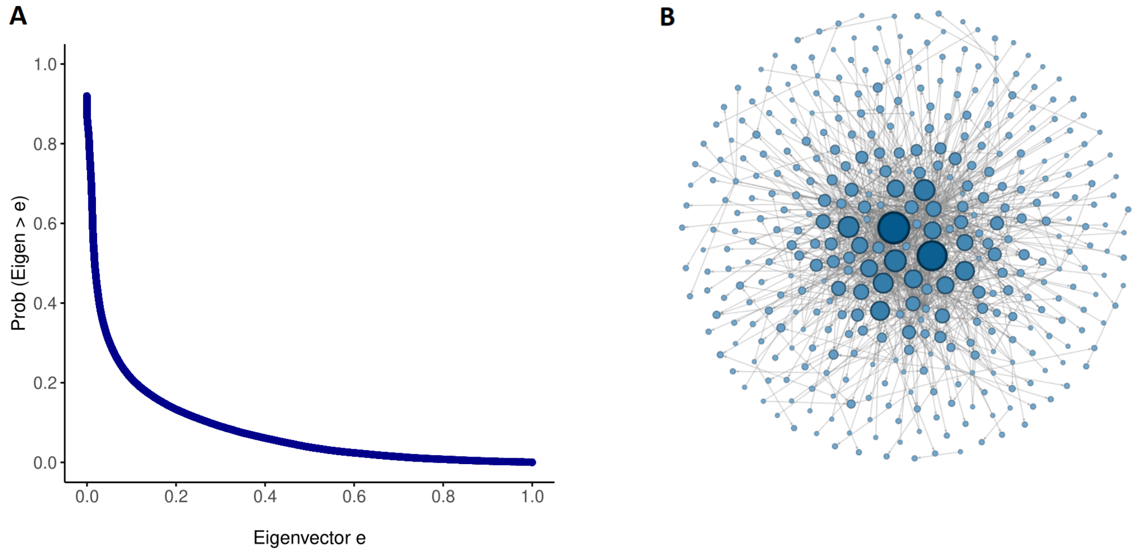

Figure 1: Network structure

These figures show the core-periphery network structure in the corporate bond market. Panel A presents the inverse distribution function for eigenvector centrality scores. Panel B illustrates the dealer network in a single month where each circle represents a broker-dealer firm, and the size and shade of each circle is proportional to the centrality score.

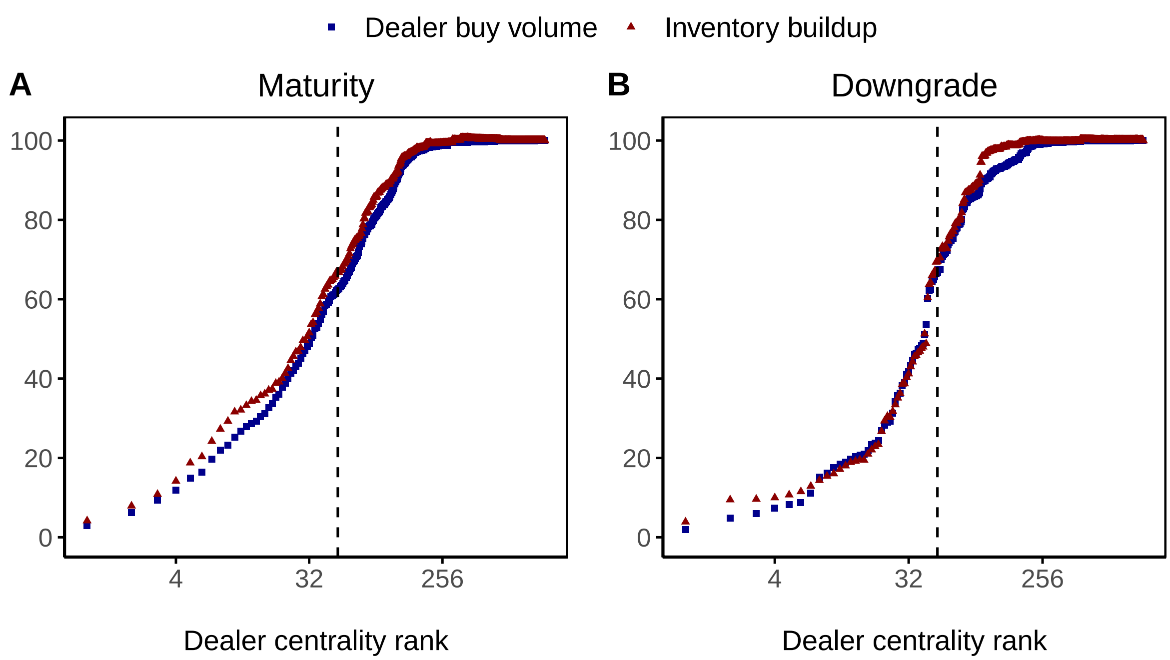

Figure 2: Immediacy provision and dealer centrality

This figure shows the cumulative fraction in percent of immediacy provision for index-excluded bonds as a function of dealer centrality rank (lower rank means more central dealer). We use two measures of immediacy. Dealer buy volume is the cumulative volume dealers buy from customers over event days -2 to 0 where 0 is the exclusion date. Inventory buildup is the cumulative inventory buildup over event days -2 to 0. The dashed vertical line corresponds to the centrality rank of 50. The x-axis in both panels is shown on a logarithmic scale with a base of 2.

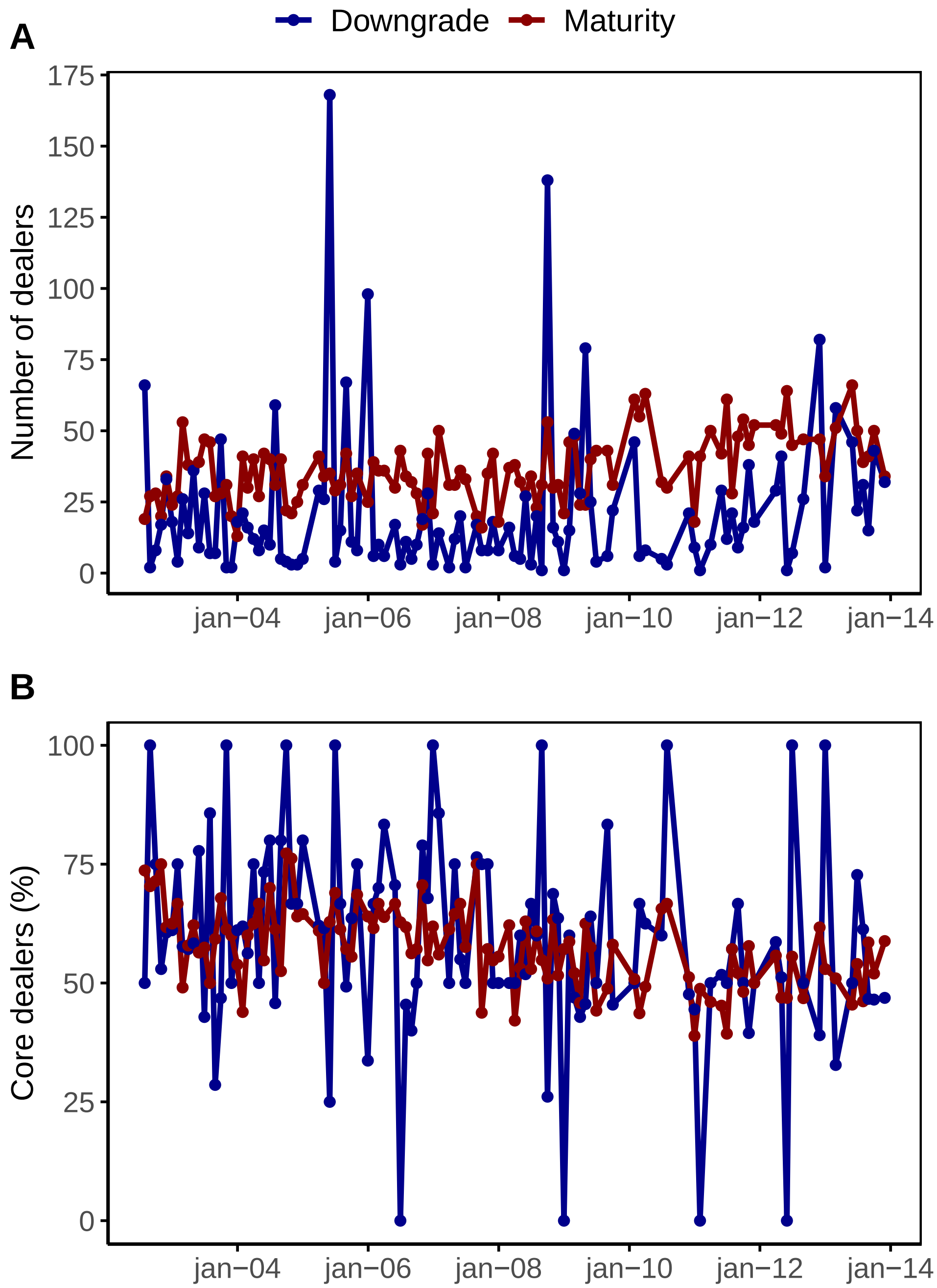

Figure 3: Immediacy-providing dealers

This figure presents information on immediacy-providing dealers defined as dealers that buy excluded bonds from index trackers at exclusion (event days -2 to 0). Panel A shows the number of immediacy-providing dealers in each month by exclusion reason. Panel B shows the fraction of core dealers in each month.

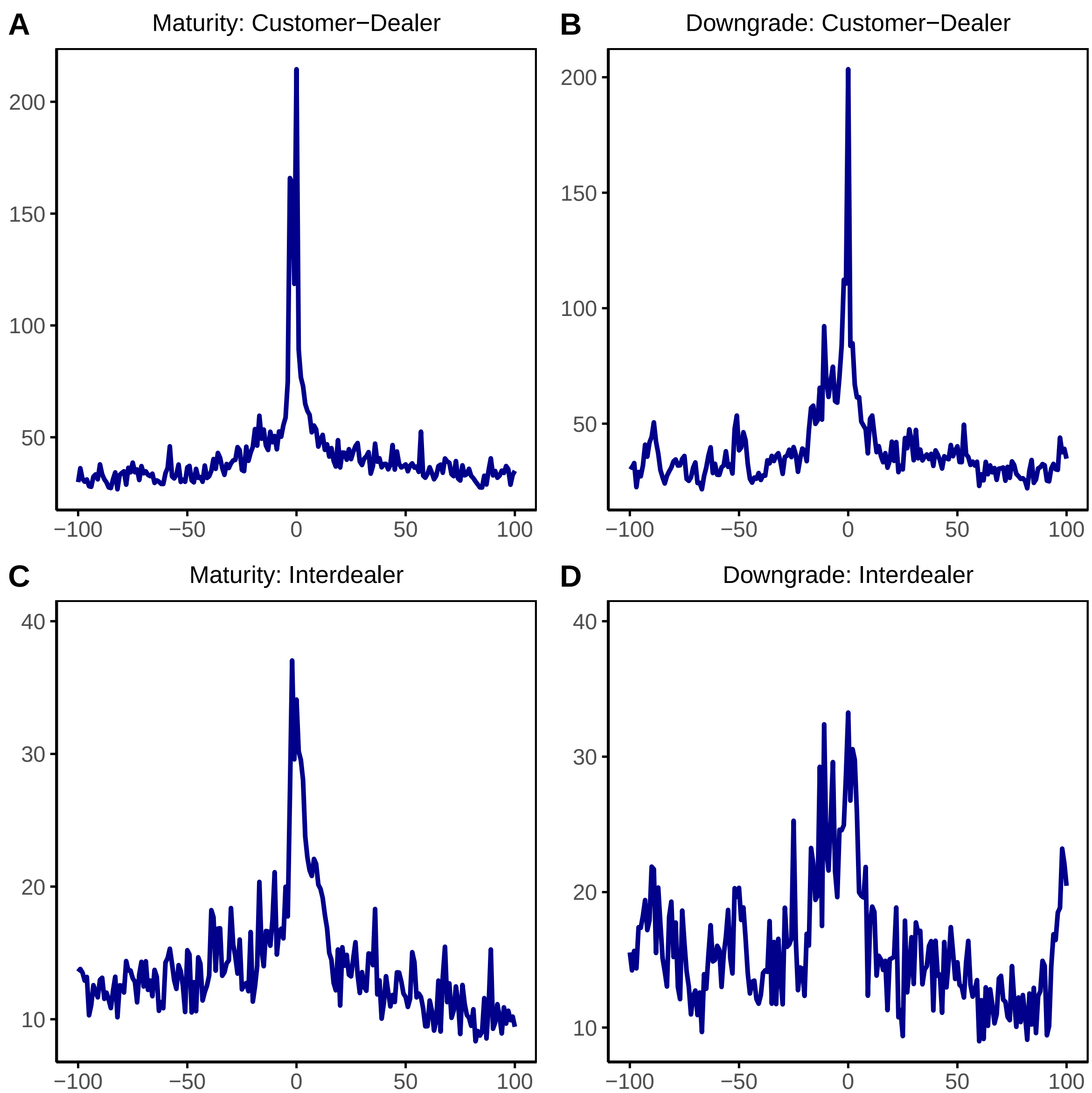

Figure 4: Trading activity around exclusions

This figure shows the average daily trading volume measured in millions of USD around index exclusions. Event day 0 is the exclusion date and event time is measured in trading days. We aggregate trading volume across all bonds excluded in a given month and then average across all months. Panels A–B present customer–dealer volume and Panels C–D present interdealer volume.

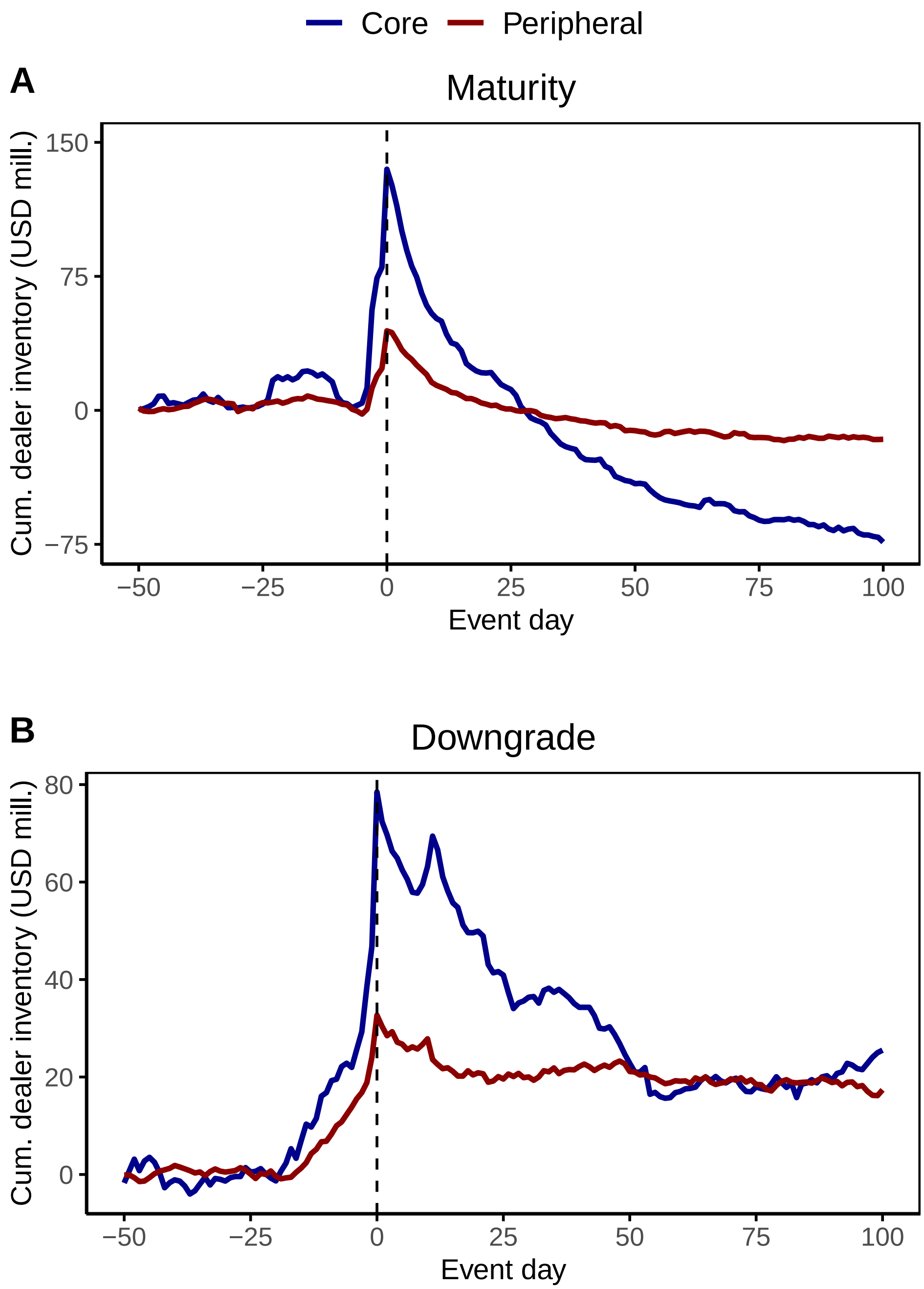

Figure 5: Cumulative dealer inventory around exclusions

This figure shows the average cumulative dealer inventory measured in millions of USD around index exclusions by dealer type. Event day 0 is the exclusion date and event time is measured in trading days. At the end of each month, we rank dealers based on eigenvector centrality score and define the top 5 percentile as core and the rest as peripheral dealers. For each event day in a given month, we first compute the aggregate daily inventory change as the difference between the aggregate dealer buying and selling volume across all excluded bonds. Next, we set the inventory at the beginning of event day -50 to $0 and cumulate the daily inventory change over time. Finally, we compute the average aggregate cumulate inventory across all months by dealer type.

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Internet Appendix:

Dealer Networks and the Cost of Immediacy

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Internet Appendix A

Huang and Wei (2017) Model

In this internet appendix, we derive the centrality spread in the Huang and Wei (2017) model. We first present the structure of the model before solving for equilibrium prices and quantities in the interdealer and customer-dealer markets. The model has an interdealer centrality premium and a customer-dealer centrality discount consistent with our empirical findings. Dealer market power results in an interdealer centrality premium and competition between dealers in the dealer-customer market generates a centrality discount.

A.1 Network Structure and Timing

We focus on a star network where a single (core) dealer is connected with $N \geq 2$ (peripheral) dealers. The total number of dealers is therefore $N + 1$ and we refer to the core dealer as dealer 0. Peripheral dealers cannot trade directly with each other so all interdealer trades go through the core dealer. There is one risk-free asset with zero interest rate and one risky asset with payoff $\tilde{v} \sim N(\bar{v}, \sigma^2)$. Dealers are risk averse and have exponential utility with risk-aversion coefficient γ. Dealer $i \in \{0, 1, ..., N\}$ has an initial endowment of w_i units of the risk-free asset and x_i units of the risky asset. Each dealer trades strategically by taking into account all other dealers' optimal trading strategies. The model has three dates:

- **Date 0: Bidding game.** The customer submits an order for z units of the risky asset where $z > 0$ denotes a customer sell order (the dealer buys) and $z < 0$ is a customer buy order (the dealer sells). Dealers compete on offering the best price to win the customer order. In case multiple dealers offer the same best price then the customer randomly selects one of these dealers to trade with.

- **Date 1: Network trading game.** Dealers trade simultaneously with all directly connected trading partners in the interdealer network to distribute and smooth their inventories due to risk aversion.

- **Date 2: Payoffs.** The payoff of the risky asset $\tilde{v}$ is realized and agents are paid off.

Huang and Wei (2017) solve the model for the subgame perfect Nash equilibrium using backward induction starting on date 1.

A.2 Network Trading Game Equilibrium

To derive the linear equilibrium in the interdealer market, Huang and Wei (2017) follows Kyle (1989), Vives (2011), and Babus and Kondor (2018) in assuming exogenous liquidity supply. This assumption is required for the existence of a linear equilibrium and can be interpreted as outside arbitrageurs trading against the dealers when prices are attractive. In particular, for each bilateral interdealer connection there is a downward sloping liquidity supply $\beta(p_i - \bar{v})$ where $\beta < 0$ and p_i is the interdealer price between the core dealer and peripheral dealer i. This exogenous liquidity supply can be interpreted as limited arbitrage: risk-neutral arbitrageurs buy the risky asset when $p_i < \bar{v}$, sell when $p_i > \bar{v}$, and the maximum number of units they can trade is proportional to $p_i - \bar{v}$.

At date 1 before interdealer trading begins, dealer i owns w_i' units of the risk-free asset and x_i' of the risky asset. If dealer i won the customer's order at date 0 then she has $w_i' = w_i - P^* z$ and $x_i' = x_i + z$ where P^* is the winning price in the customer transaction on date 0. In each interdealer connection, the core dealer buys or sells Q_i units of the risky asset while peripheral dealer i buys or sells q_i units. Excess demand from this interdealer connection is absorbed by the exogenous liquidity supply. The market clearing condition is therefore $Q_i + q_i + \beta(p_i - \bar{v}) = 0$. Proposition 5 in Huang and Wei (2017) shows that the equilibrium interdealer prices and quantities between the core dealer and each peripheral dealer $i \in \{1, ..., N\}$ are

$$\begin{aligned} p_i &= \bar{v} - \frac{\gamma\sigma^2}{2}\left(\frac{c}{c+\beta}x_i' + \theta X'\right) \\ Q_i &= -\frac{\gamma\sigma^2(c+\beta)}{2}\left(\frac{c}{c+\beta}x_i' - \theta X'\right) \\ q_i &= \frac{\gamma\sigma^2 c}{2}\left(\frac{c+2\beta}{c+\beta}x_i' - \theta X'\right) \end{aligned} \tag{A.1}$$

where

$$
\begin{aligned}
X' &\equiv x'_0 - \frac{b}{2}\sum_{i=1}^{N} x'_i \\
\theta &\equiv \frac{2}{2 - N\gamma\sigma^2(c+\beta)} \\
b &\equiv \gamma\sigma^2 c
\end{aligned}
$$

Proposition 3 in Huang and Wei (2017) states that there is a unique linear equilibrium where $c \in \left(-\frac{1}{\gamma\sigma^2}, 0\right)$ is part of the solution. One can interpret the coefficient c as the core dealer's willingness to share and distribute the peripheral dealers' inventories. The core dealer is less willing to perform inventory risk sharing (c is closer to zero) when the exogenous liquidity supply is low, dealers are more risk averse, and when the asset is more risky. From equation (A.1) it is clear that $\frac{\partial Q_i}{\partial x'_i} > 0$ and that $\frac{\partial q_i}{\partial x'_i} < 0$ because $c < 0$ and $\beta < 0$. These signed derivatives reflect the core dealer's role of performing inventory risk sharing in the interdealer network. The core dealer buys more from peripheral dealer i when this peripheral dealer has a greater demand for selling inventory.

Interdealer centrality premium

To analyze how interdealer prices vary, we sort peripheral dealers increasingly by their date 1 inventories

$$
x'_1 < x'_2 < \cdots < x'_s < x'_{s+1} < \cdots < x'_N
$$

where the inventories of peripheral dealers s and $s+1$ are such that $q_s > 0$ and $q_{s+1} < 0$. Peripheral dealers $i \in \{s+1, ..., N\}$ with high inventory levels sell to the core dealer. In turn, the core dealer sells to peripheral dealers $i \in \{1, ..., s\}$ and thereby performs inventory risk sharing throughout the interdealer network. We determine the sign of the interdealer centrality spread by comparing buy and sell prices between the core and peripheral dealers respectively. Because the interdealer price p_i from equation (A.1) decreases with x'_i we have that $p_s > p_{s+1}$.

The ordering of peripheral dealers' inventories implies that the core dealer sells to peripheral dealers at prices of at least p_s. When peripheral dealers sell to the core dealer they do so at prices of at most p_{s+1}. The fact that $p_s > p_{s+1}$ shows that the core dealer sells at higher prices than peripheral dealers do in the interdealer market. Since each transaction involves both a buyer and a seller, it is also clear that the core dealer buys at lower interdealer prices than peripheral dealers do. The model therefore has an interdealer centrality premium because of dealer market power originating from bilateral trading in the network. Since the core dealer has a connection advantage in the interdealer market, she trades at more favorable interdealer prices than peripheral dealers do.

A.3 Bidding Game Equilibrium

The bidding game at date 0 has two possible equilibria: either the core dealer or one of the peripheral dealers wins the customer's order. We assume the customer submits a sell order (i.e., $z > 0$) to reflect the trading direction of index trackers at exclusion. The case of a buy order can be analyzed in the same way with the maximum bid price replaced by the minimum ask price. Huang and Wei (2017) use reservation prices Ψ_{ij} associated with dealer j ($j \neq i$) winning the customer order to characterize the bidding game equilibrium. Conditional on dealer j winning the customer's order then Ψ_{ij} is the maximum bid price that dealer i is willing to pay in order to outbid dealer j and thereby win the customer's order. In particular, Ψ_{ij} is defined from dealer i's utility function u_i

$$u_i(w_i - \Psi_{ij} z, \boldsymbol{x} + z\boldsymbol{e}_i) = u_i(w_i, \boldsymbol{x} + z\boldsymbol{e}_j)$$

where $\boldsymbol{x} \equiv (x_0, ..., x_N)^T$ is a vector of initial inventories and $\boldsymbol{e}_k$ is an $N+1$-dimensional vector of zeros except for the k^{th} element which is equal to one. Proposition 6 in Huang and

Wei (2017) shows that the reservation prices are given by

$$
\begin{aligned}
\Psi_{0i} &= \bar{v} + \psi_z z + \psi_x x_i + \psi_X X \\
\Psi_{i0} &= \bar{v} + \psi'_z z + \psi'_x x_i + \psi'_X X \\
\Psi_{ij} &= \bar{v} + \psi''_z z + \psi''_x x_i + \psi''_X X
\end{aligned} \tag{A.2}
$$

where $X \equiv x_0 - \frac{b}{2}\sum_{i=1}^{N} x_i$ and the coefficients are

$$
\begin{aligned}
\psi_z &= \frac{1}{2}\psi_x + \frac{1}{2}\left(1 - \frac{b}{2}\psi_X\right) \\
\psi_x &= \frac{b^2}{2(c+\beta)} \\
\psi_X &= -\frac{1}{2}\gamma\sigma^2\theta(2+b)
\end{aligned}
$$

and

$$
\begin{aligned}
\psi'_z &= \frac{1}{2}\psi'_x + \frac{1}{2}\left(1 - \frac{b}{2}\psi'_X\right) \\
\psi'_x &= \left[-\gamma\sigma^2 - \frac{\gamma\sigma^2}{4}b(2+b)\left(\frac{c+2\beta}{c+\beta} + \left(1+\frac{b}{2}\right)\theta\right)\frac{c+2\beta}{c+\beta}\right] \\
\psi'_X &= \left[\frac{\gamma\sigma^2}{4}b(2+b)\left(\frac{c+2\beta}{c+\beta} + \left(1+\frac{b}{2}\right)\theta\right)\theta\right]
\end{aligned}
$$

and

$$
\begin{aligned}
\psi''_z &= \frac{1}{2}\psi''_x - \frac{1}{2}b\psi''_X \\
\psi''_x &= -\gamma\sigma^2 - \frac{\gamma\sigma^2}{4}b(2+b)\left(\frac{c+2\beta}{c+\beta}\right)^2 \\
\psi''_X &= \frac{\gamma\sigma^2}{4}b(2+b)\frac{c+2\beta}{c+\beta}\theta
\end{aligned}
$$

All these coefficients $\psi_z, \psi'_z, \psi''_z, \psi_x, \psi'_x, \psi''_x, \psi_X, \psi'_X, \psi''_X$ are negative. This feature implies that the reservation prices can be ranked based on peripheral dealers' inventories. Huang and Wei (2017) use this feature to determine the bidding game equilibrium in their Proposition

7: when sorting peripheral dealers increasingly by their initial inventories x_i, the core dealer wins the customer's sell order if and only if

$$x_0 \leq \frac{\psi_z - \psi'_z}{\psi'_X - \psi_X} z + \frac{\psi_x - \psi'_x}{\psi'_X - \psi_X} x_1 + \frac{b}{2} \sum_{i=1}^{N} x_i \tag{A.3}$$

This condition highlights the key trade-off in the model. The core dealer has a comparative advantage in inventory management because she can trade directly with all peripheral dealers. For a given order size z, this connection advantage implies that the core dealer wins the customer's sell order as long as her inventory is not too much higher than peripheral inventories. As the core dealer's inventory level increases, it will eventually outweigh the connection advantage and allow a peripheral dealer to win the customer's order. We compare prices from these two possible outcomes to derive the centrality spread in the customer-dealer market.

Customer-dealer centrality discount

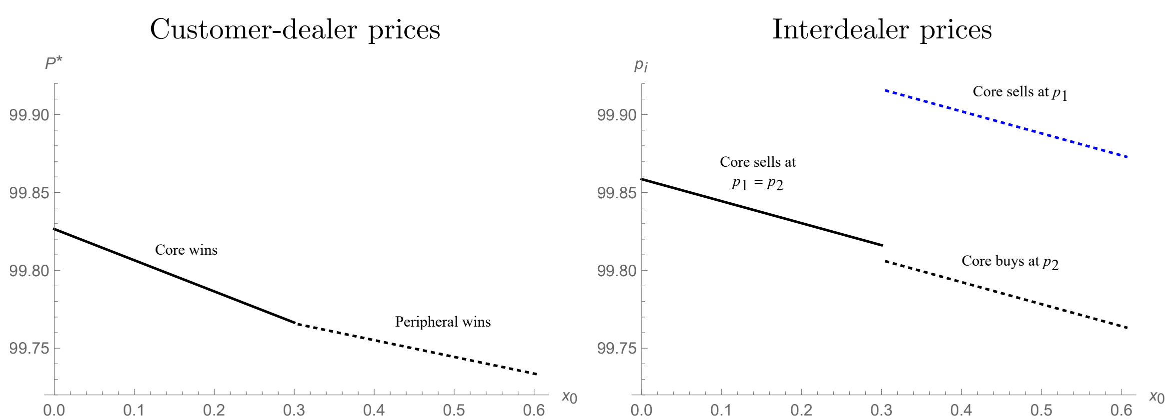
The condition in equation (A.3) implies that the equilibrium dealer-customer price P^* is a piece-wise linear function of $X \equiv x_0 - \frac{b}{2} \sum_{i=1}^{N} x_i$

$$P^*(X) = \begin{cases} \Psi_{0i} = \bar{v} + \psi_z z + \psi_x x_i + \psi_X X, & \text{when } X \leq \dfrac{\psi_z - \psi'_z}{\psi'_X - \psi_X} z + \dfrac{\psi_x - \psi'_x}{\psi'_X - \psi_X} x_1 \\ \Psi_{i0} = \bar{v} + \psi'_z z + \psi'_x x_i + \psi'_X X, & \text{when } X > \dfrac{\psi_z - \psi'_z}{\psi'_X - \psi_X} z + \dfrac{\psi_x - \psi'_x}{\psi'_X - \psi_X} x_1 \end{cases} \tag{A.4}$$

The difference between the two reservation prices $\Psi_{0i} - \Psi_{i0}$ is zero when $X = \frac{\psi_z - \psi'_z}{\psi'_X - \psi_X} z + \frac{\psi_x - \psi'_x}{\psi'_X - \psi_X} x_1$, so $P^*(X)$ is a continuous function of X. The equilibrium dealer-customer price decreases with X because $\psi_X < 0$ and $\psi'_X < 0$. When the core dealer wins the customer's sell order, she therefore buys at a higher price $P^*(X) = \Psi_{0i}$ than when a peripheral dealer wins the order and $P^*(X) = \Psi_{i0}$. The model therefore has a customer-dealer centrality discount because dealers compete for the customer order. The core dealer's connection advantage in the interdealer market implies that the customer receives a better price when the core dealer wins the order.

A.4 Numerical example

To illustrate the features of the model, we consider a customer sell order $z = 1$ and set $N = 2$, $\bar{v}$=100, $\sigma = 0.25$, $\gamma = 10$, $\beta = -1$. We assume peripheral initial inventories are zero $x_1 = x_2 = 0$. Equation (A.3) specifies that the core dealer wins the customer's sell order when $x_0 \leq 0.31$. In this case, the core dealer subsequently sells part of the order to the peripheral dealers in the interdealer market. When $x_0 > 0.31$, the two peripheral dealers post the same bid price and the customer randomly trades with one of them. Assuming peripheral dealer 2 wins the customer's order, she then sells part of the order at price p_2 to the core dealer who in turn sells to peripheral dealer 1 at price p_1. The figures below show the equilibrium customer-dealer and interdealer prices as a function of the initial core inventory x_0.



The solid (dashed) line denotes the equilibrium in which the core (peripheral) dealer wins the customer's order. The figure on the left shows that the core dealer buys at higher prices from the customer than peripheral dealers do. This result implies a customer-dealer centrality discount. The figure on the right shows interdealer prices. When the core dealer wins the customer order, she sells part of it to each of the peripheral dealers at the same price $p_1 = p_2$. The prices are identical because peripheral inventories are the same $x_1' = x_2' = 0$. When peripheral dealer 2 wins the customer order, the peripheral inventories are $x_2' = z > 0$ and $x_1' = 0$. This difference in inventories implies that $p_1 > p_2$. The price at which peripheral dealer 2 sells to the core dealer (dashed black line) is below the price at which the core dealer sells to (1) peripheral dealer 1 in the same equilibrium (dashed blue line) and (2) both peripheral dealers in the other equilibrium (solid black line). The core dealer therefore sells at higher interdealer prices than peripheral dealers do. Conversely, the same figure shows that the core dealer buys at lower interdealer prices than peripheral dealers do. These results imply an interdealer centrality premium.

Internet Appendix B

Additional Tables

Table A1: Round-trip intermediation chains

This table presents results for round-trip intermediation chains using the sample from Feldhütter and Poulsen (2018). This sample resembles our sample of all corporate bonds. We estimate the regression:

$$Y_{ijt} = \alpha + \beta_1 Centrality_{it} + \beta_2 Log(Volume_{ijt}) + \delta_{jt} + \epsilon_{ijt}$$

where Y_{ijt} is either the daily volume-weighted spread, dealer buy price, or dealer sell price measured in basis points for dealer i, bond j, and day t. All prices are from the dealer's perspective. $Centrality_{it}$ is the eigenvector centrality score of the dealer buying from the customer based on all interdealer transactions during the exclusion month. We lag the centrality measure by one month. $Volume_{ijt}$ is the cumulative volume of the transactions used to compute the dealer-bond specific dependent variable. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to November 2013. Panel A shows a centrality premium when we analyze spreads. The spread is the log difference between either the first and last leg in the chain (both are customer trades), or the first and second leg in the chain (the second leg can be either a customer or an interdealer trade). Panel B shows a centrality discount using the dealer buy price from customers as dependent variable. The third and fourth column, however, show a centrality premium when we use dealer sell prices that are part of round-trip chains. In the last column, we find a centrality discount when using all dealer sell prices (also those that are not part of a round-trip chain). Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Panel A: Spreads

	Last minus first chain leg	Second minus first chain leg
Centrality	4.60***	22.17***
	(2.84)	(14.34)
Log(Volume)	-12.30***	-6.44***
	(-12.58)	(-9.78)
Bond×day FE	Yes	Yes
Adj. R^2	0.090	0.020
Issuers (clusters)	2,304	2,429
Days (clusters)	2,852	2,859
Dealers	1,130	1,411
Bonds	10,639	11,893
Observations	589,130	830,871

Panel B: Prices

	Dealer buys from customer		Dealer sells to		
	All trades	Completed chains	Customer/dealer in 2nd chain leg	Customer in final chain leg	Customer all trades
Centrality	4.81***	3.64***	28.07***	6.02***	-18.91***
	(6.77)	(5.05)	(15.02)	(3.59)	(-20.04)
Log(Volume)	5.88***	4.30***	-2.40***	-9.21***	-11.22***
	(17.22)	(11.51)	(-4.47)	(-14.59)	(-25.06)
Bond×day FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	1.000	1.000	0.980	0.980	1.000
Issuers (clusters)	2,662	2,304	2,429	2,304	2,800
Days (clusters)	2,863	2,852	2,859	2,852	2,850
Dealers	1,514	1,130	1,411	1,130	1,701
Bonds	13,698	10,639	11,893	10,639	15,752
Observations	1,788,143	589,130	830,871	589,130	2,578,851

Table A2: Centrality spread for customer-dealer trades (exclude crisis period)

This table presents coefficient estimates from the regression:

$$Price_{ijt} = \alpha + \beta_1 Centrality_{it} + \beta_2 Log(Volume_{ijt}) + \delta_{jt} + \epsilon_{ijt}$$

where $Price_{ijt}$ is the daily volume-weighted dealer buy or sell price measured in basis points for dealer i, bond j, and day t. All prices are from the dealer's perspective. For index exclusions, we calculate the dealer buy price over event days -2, -1, and 0. Event day 0 is the exclusion date. We compute the dealer sell price on each event day $t \in \{1, ..., 30\}$ after the exclusion date. In the sample of all corporate bonds, we compute dealer-bond specific volume-weighted buy and sell prices on each trading day. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. We lag the centrality measure by one month in the sample of all corporate bonds. $Volume_{ijt}$ is the cumulative volume of the transactions used to compute the volume-weighted dealer-bond specific price. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to November 2013 excluding the crisis period 2007Q3–2009Q4. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions		Downgrade exclusions		All corporate bonds	
	Buy from customer	Sell to customer	Buy from customer	Sell to customer	Buy from customer	Sell to customer
Centrality	5.418***	-8.514***	27.208**	-21.277***	11.955***	-20.032***
	(2.96)	(-6.58)	(2.20)	(-3.77)	(15.32)	(-20.63)
Log(Volume)	3.766***	-2.247***	12.374***	-22.352***	6.452***	-11.146***
	(14.41)	(-8.68)	(4.05)	(-10.10)	(17.29)	(-19.38)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.992	0.994	0.995	0.995	0.997	0.996
Issuers (clusters)	676	638	191	191	3,917	3,987
Days (clusters)	107	1,991	82	1,042	2,221	2,222
Dealers	218	499	214	496	1,568	1,722
Bonds	1,828	1,790	495	486	20,478	24,638
Observations	6,798	20,562	2,820	13,303	2,095,587	2,675,587

Table A3: Centrality spread for customer-dealer trades (degree centrality)

This table presents coefficient estimates from the regression:

$$Price_{ijt} = \alpha + \beta_1 Degree\ centrality_{it} + \beta_2 Log(Volume_{ijt}) + \delta_{jt} + \epsilon_{ijt}$$

where $Price_{ijt}$ is the daily volume-weighted dealer buy or sell price measured in basis points for dealer i, bond j, and day t. All prices are from the dealer's perspective. For index exclusions, we calculate the dealer buy price over event days -2, -1, and 0. Event day 0 is the exclusion date. We compute the dealer sell price on each event day $t \in \{1, ..., 30\}$ after the exclusion date. In the sample of all corporate bonds, we compute dealer-bond specific volume-weighted buy and sell prices on each trading day. $Degree\ centrality_{it}$ is the degree centrality based on all inter-dealer transactions during the exclusion month. We lag the centrality measure by one month in the sample of all corporate bonds. $Volume_{ijt}$ is the cumulative volume of the transactions used to compute the volume-weighted dealer-bond specific price. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to November 2013. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions		Downgrade exclusions		All corporate bonds	
	Buy from customer	Sell to customer	Buy from customer	Sell to customer	Buy from customer	Sell to customer
Degree centrality	0.008**	-0.021***	0.096	-0.061***	0.025***	-0.045***
	(2.61)	(-9.17)	(0.93)	(-4.91)	(18.62)	(-26.33)
Log(Volume)	3.926***	-3.408***	17.745***	-23.090***	7.149***	-12.162***
	(14.01)	(-10.91)	(5.06)	(-8.91)	(17.88)	(-27.10)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.991	0.991	0.983	0.992	0.997	0.996
Issuers (clusters)	715	685	256	261	3,951	4,026
Days (clusters)	137	2,537	103	1,320	2,849	2,851
Dealers	240	575	263	524	1,632	1,799
Bonds	2,173	2,184	715	675	21,281	25,565
Observations	7,962	26,391	4,036	15,631	2,542,764	3,370,986

Table A4: Centrality spread for customer-dealer trades (all trade sizes)

This table presents coefficient estimates from the regression:

$$Price_{ijt} = \alpha + \beta_1 Centrality_{it} + \beta_2 Log(Volume_{ijt}) + \delta_{jt} + \epsilon_{ijt}$$

where $Price_{ijt}$ is the daily volume-weighted dealer buy or sell price measured in basis points for dealer i, bond j, and day t. All prices are from the dealer's perspective. For index exclusions, we calculate the dealer buy price over event days -2, -1, and 0. Event day 0 is the exclusion date. We compute the dealer sell price on each event day $t \in \{1, ..., 30\}$ after the exclusion date. In the sample of all corporate bonds, we compute dealer-bond specific volume-weighted buy and sell prices on each trading day. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. We lag the centrality measure by one month in the sample of all corporate bonds. $Volume_{ijt}$ is the cumulative volume of the transactions used to compute the volume-weighted dealer-bond specific price. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to November 2013. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions		Downgrade exclusions		All corporate bonds	
	Buy from customer	Sell to customer	Buy from customer	Sell to customer	Buy from customer	Sell to customer
Centrality	21.963***	-11.813***	31.405	-11.067	31.707***	-16.593***
	(8.20)	(-8.51)	(0.86)	(-1.61)	(36.45)	(-12.75)
Log(Volume)	9.091***	-1.677***	21.854***	-20.641***	13.961***	-13.058***
	(20.62)	(-8.22)	(5.62)	(-15.38)	(25.60)	(-36.08)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.972	0.980	0.982	0.991	0.996	0.992
Issuers (clusters)	768	799	273	286	4,150	4,201
Days (clusters)	137	2,816	103	1,770	2,859	2,860
Dealers	462	933	441	966	2,163	2,211
Bonds	2,428	2,597	765	769	31,817	39,663
Observations	12,806	77,239	6,244	45,748	8,888,875	11,314,151

Table A5: Centrality spread for interdealer trades (excluding the crisis)

This table presents coefficient estimates from the regression:

$$Price_{jt} = \alpha + \beta_1 Buyer\ centrality_t + \beta_2 Seller\ centrality_t + \beta_3 Log(Volume_{jt}) + \delta_{jt} + \epsilon_{jt}$$

where $Price_{jt}$ is the daily volume-weighted interdealer price measured in basis points between the buying and selling dealer for bond j on day t. For index exclusions, we calculate the interdealer price on each event day $t \in \{-2, ..., 30\}$ where event day 0 is the exclusion date. In the sample of all corporate bonds, we compute interdealer prices on each trading day. $Buyer\ centrality_t$ and $Seller\ centrality_t$ denote the eigenvector centrality scores of the buying and selling dealer based on all interdealer transactions during the exclusion month. We lag the centrality measure by one month in the sample of all corporate bonds. $Volume_{jt}$ is the cumulative volume of the transactions used to compute the volume-weighted price. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to November 2013. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions	Downgrade exclusions	All corporate bonds
Buyer centrality	-4.370***	-20.747***	-6.839***
	(-4.37)	(-4.02)	(-9.08)
Seller centrality	6.843***	16.263***	6.142***
	(5.37)	(5.65)	(11.84)
Log(Volume)	0.226	-0.957	-1.534***
	(0.57)	(-0.73)	(-6.88)
Bond×day FE	Yes	Yes	Yes
Adj. R^2	0.995	0.998	0.998
Issuers (clusters)	682	200	4,229
Days (clusters)	2,054	1,303	2,221
Buying dealers	731	755	2,229
Selling dealers	637	688	2,123
Bonds	1,895	543	33,733
Observations	28,147	31,938	5,144,144

Table A6: Centrality spread for interdealer trades (degree centrality)

This table presents coefficient estimates from the regression:

$$Price_{jt} = \alpha + \beta_1 Buyer\ centrality_t + \beta_2 Seller\ centrality_t + \beta_3 Log(Volume_{jt}) + \delta_{jt} + \epsilon_{jt}$$

where $Price_{jt}$ is the daily volume-weighted interdealer price measured in basis points between the buying and selling dealer for bond j on day t. For index exclusions, we calculate the interdealer price on each event day $t \in \{-2, ..., 30\}$ where event day 0 is the exclusion date. In the sample of all corporate bonds, we compute interdealer prices on each trading day. $Buyer\ centrality_t$ and $Seller\ centrality_t$ denote the degree centrality scores of the buying and selling dealer based on all interdealer transactions during the exclusion month. We lag the centrality measure by one month in the sample of all corporate bonds. $Volume_{jt}$ is the cumulative volume of the transactions used to compute the volume-weighted price. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to November 2013. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions	Downgrade exclusions	All corporate bonds
Buyer centrality	-0.014***	-0.037***	-0.014***
	(-8.55)	(-3.71)	(-10.87)
Seller centrality	0.020***	0.028***	0.016***
	(10.21)	(4.27)	(16.57)
Log(Volume)	-1.251**	2.372	-2.081***
	(-2.58)	(0.99)	(-8.39)
Bond×day FE	Yes	Yes	Yes
Adj. R^2	0.994	0.998	0.998
Issuers (clusters)	741	276	4260
Days (clusters)	2,634	1,662	2,851
Buying dealers	851	788	2,303
Selling dealers	710	734	2,196
Bonds	2,323	777	35,346
Observations	37,992	37,757	6,301,315

Table A7: Centrality spread for interdealer trades (all trade sizes)

This table presents coefficient estimates from the regression:

$$Price_{jt} = \alpha + \beta_1 Buyer\ centrality_t + \beta_2 Seller\ centrality_t + \beta_3 Log(Volume_{jt}) + \delta_{jt} + \epsilon_{jt}$$

where $Price_{jt}$ is the daily volume-weighted interdealer price measured in basis points between the buying and selling dealer for bond j on day t. For index exclusions, we calculate the interdealer price on each event day $t \in \{-2, ..., 30\}$ where event day 0 is the exclusion date. In the sample of all corporate bonds, we compute interdealer prices on each trading day. $Buyer\ centrality_t$ and $Seller\ centrality_t$ denote the eigenvector centrality scores of the buying and selling dealer based on all interdealer transactions during the exclusion month. We lag the centrality measure by one month in the sample of all corporate bonds. $Volume_{jt}$ is the cumulative volume of the transactions used to compute the volume-weighted price. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to November 2013. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions	Downgrade exclusions	All corporate bonds
Buyer centrality	-18.444***	-56.301***	-29.718***
	(-10.20)	(-9.29)	(-19.53)
Seller centrality	38.068***	55.793***	45.824***
	(17.05)	(8.58)	(30.53)
Log(Volume)	3.258***	3.921**	3.271***
	(11.91)	(2.30)	(10.67)
Bond×day FE	Yes	Yes	Yes
Adj. R^2	0.979	0.996	0.997
Issuers (clusters)	842	304	4443
Days (clusters)	2,842	2,026	2,857
Buying dealers	1191	1204	2694
Selling dealers	1201	1115	2643
Bonds	2,719	842	47,753
Observations	166,753	101,254	23,204,193

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