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Bid-Ask Spreads, Trading Networks and the Pricing of Securitizations: 144a vs. Registered Securitizations

by

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Abstract

During May 2011 the Financial Industry Regulatory Authority began to collect transaction data from broker-dealers as a step towards enhancing its understanding of these markets. We use transaction data to document the importance of dealer network structure for market quality. Some dealers are relatively central in the network and trade with many dealers, while others are peripheral. Central dealers receive relatively lower and less dispersed spreads than peripheral dealers. We develop a model in which central and peripheral dealers trade with different customer clienteles and argue that the presence of relatively sophisticated customers in the securitization markets explains these facts.

Keywords: Securitization; sophisticated investors; Rule 144a; network analysis; price discovery; clienteles

1. Introduction

Relatively little is known about the pricing of securitizations, because these have traded traditionally in opaque markets. The importance of the shadow banking system, in general, and securitization, in particular, has been recognized strongly in the aftermath of the financial crisis. In May 2011 the Financial Industry Regulatory Authority (FINRA) used its regulatory authority to begin to collect transaction data on securitizations from all broker-dealers, which it regulates. FINRA undertook this as an initial step to enhance understanding of the markets and to increase transparency. A second step occurred five months later when FINRA began to disseminate daily price index data by collateral type. These steps followed FINRA's efforts to increase the transparency of the corporate bond markets more than a decade ago, and parallel efforts by the Municipal Securities Rule-making Board to increase transparency in the municipal bond markets.

In studying securitizations we examine the import of the interdealer network structure for intermediation, bid-ask spreads, information flows, and market quality. We document the core-periphery nature of interdealer trading. We also study the effects of varying customer clienteles on the dealer markets by examining the contrast between Registered instruments, which require detailed disclosures in the issuance process, and Rule 144a instruments, which exempt private resale of restricted instruments to Qualified Institutional Buyers (QIBs) from these disclosure requirements. We focus our analysis upon Asset-Backed Securities (ABS), Collateralized Debt Obligations (CDO), Commercial-Mortgage-Backed Securities (CMBS) and Collateralized Mortgage Obligations (CMO) instruments due to the mix of trading of 144a instruments. We benchmark 144a instruments against corresponding Registered instruments.[1]

[1]Since there are no 144a instruments in the TBA, MBS and agency CMO categories, we do not use these in our benchmark analysis. We include the CDO category, even though these are largely 144a instruments, so we cannot construct a Registered benchmark within this category.

We provide a descriptive analysis of the bid-ask spreads and the trading networks of 144a and Registered instruments. In the interdealer market some dealers are relatively central and trade with many dealers, while others are more peripheral. We emphasize that the dealers' centrality in interdealer markets is an important determinant of the terms of trade for customers; the resulting bid-ask spreads vary depending on a dealer's position in the network. We document a negative relationship between a dealer's centrality and the bid-ask spreads for most types of securitizations, which we refer to as the centrality discount.

We develop a model with heterogeneous customers to study the determinants of pricing by central and peripheral dealers and use the model to interpret our findings. Customers differ in their outside options and choose dealers based on trade execution speed and offered price. We view customers with weak outside options as unsophisticated traders and customers with strong outside options as sophisticated traders. Peripheral dealers provide slower trade execution than central dealers. Because peripheral dealers provide slower trade execution they cannot offer favorable enough pricing to attract customers with strong outside options. Both peripheral and central dealers can offer favorable enough pricing to attract customers with weak outside options. Spreads are higher with central dealers when there are few customers with strong outside options, and spreads are lower with central dealers when there are many customers with strong outside options. We provide conditions under which the peripheral dealers' distribution of bid-ask spreads is more dispersed than the central dealers' distribution. Interpreting our empirical findings of a centrality discount and a higher dispersion of bid-ask spreads with peripheral dealers through the lens of our model, we argue that customers are heterogeneous with many of them relatively sophisticated.

We provide empirical evidence for the theoretical literature on the economics of interdealer networks in over-the-counter markets. Hugonnier, Lester and Weill (2014) develop a search model and show how the core-periphery nature of interdealer trading and intermediation chains arise endogenously when traders have heterogeneous private values. Shen, Wei and Yan (2015) show how trading costs and trading speeds affect intermediation chains in search markets and Neklyudov (2013) shows how intermediation chains arise endogenously when traders have heterogeneous trading speeds. Glode and Opp (2013) and Viswanathan and Wang (2004) study how intermediation chains arise in the presence of information asymmetry. We document the nature of intermediation chains in the markets for securitizations.

Babus and Kondor (2014) introduce information asymmetry in a network model of over-the-counter markets. In equilibrium, relatively central dealers charge lower spreads because they can aggregate additional information by trading with more counterparties and so are less exposed to adverse selection. The network model predicts that in the presence of information asymmetries trades with central dealers should carry greater informational content than trades with peripheral dealers. We use price-impact regressions and vector autoregressions to study the price discovery process in the network, finding mixed evidence that trades with central dealers carry greater informational content than trades with peripheral dealers.

Amihud and Mendelson (1980) highlight the impact of a monopoly dealer's pricing decision on the dynamics of the order arrival process. Ho and Stoll (1983) study competing risk-averse dealers in which bid-ask spreads depend on the assets' return volatility, dealers' risk aversion, and trade sizes. More central dealers may be less exposed to inventory and liquidity risks endogenously—Neklyudov (2013) shows that in equilibrium dealers with higher levels of trade execution efficiency receive lower spreads because the reservation values of those dealers are less exposed to idiosyncratic liquidity shocks. In our model, the various dealers face distinct price elasticities of their order flow, leading to different bid-ask spreads across the dealer network.

We offer a number of other empirical results about the nature of trading in securitization markets. Fundamentally, there are a large number of securitizations, trading is very fragmented with relatively few transactions in most individual instruments, and many instruments even not trading at all in our sample. Some of the bid-ask spreads in the ABS, CDO, CMBS and Non-Agency CMO markets are surprisingly large—for example, the average spread for Non-Agency CMO instruments is 3.36% of the mid-quote. For ABS, CMBS and Non-Agency CMO instruments there is a volume discount with respect to the bid-ask spread—larger volume trades result in lower spreads than smaller volume trades. That larger trades obtain better prices is reminiscent of a core insight from pricing municipal bonds (Green, Hollifield, and Schürhoff (2007) and Harris and Piwowar (2006)) and corporate bonds (Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2007) and Goldstein, Hotchkiss, and Sirri (2007)). Atanasov and Merrick (2012) document volume discounts and that institutional investors enjoy better overall liquidity in specified-pool MBS and TBA markets.

Our sample contains both Registered and Rule 144a instruments. The use of 144a is a choice by the issuer and the nature of the choice is one in which the required disclosures are more limited than for Registered securitizations. Rule 144a instruments experience a corresponding potential reduction in issuance cost and exemption from liability. Rule 144a instruments are designed for sophisticated investors and the purchase of 144a instruments would reflect self-selection on the part of the buyers, including recognition of the restrictions on re-trading for 144a instruments. This suggests relatively less interest afterwards in trading 144a instruments since these are oriented to buy-and-hold investors, which can lead to higher effective spreads and reduced liquidity. But sophisticated investors such as QIBs may have enhanced bargaining power with dealers, leading to lower effective spreads. Rule 144a instruments can have larger spreads than Registered offerings due to the more limited initial publicly available information or can have smaller spreads, if either these instruments are of higher quality or if the 144a buyers have greater sophistication. Indeed, empirically within some asset classes 144a securitizations have higher spreads than Registered securitizations and within other asset classes 144a securitizations have lower spreads than Registered securitizations.

We describe the markets for Registered and 144a securitization trading and describe our data in Section 2. We present our analysis of interdealer trading networks in Section 3. We provide a theoretical interpretation of the centrality discount and supporting empirical evidence in Section 4. We examine price discovery in the network in Section 5. We conclude in Section 6.

2. The Market for Registered and 144a Securitizations and Our Data

Our sample contains all trading activity in ABS, CDO, CMBS and Non-Agency CMO instruments overseen by FINRA between May 16, 2011 and February 29, 2012. These data are a sequence of trade reports that provide the trade identifier, the execution timestamp and settlement date, the side of the reporting party—either the buy side or sell side, the trade volume of the trade measured in dollars of original par balance, and the trade price measured in dollars per $100 par. The trade report allows us to determine if the trade is between a dealer and an outside customer, or between two dealers. We use the collateral type to categorize ABS instruments, we split the CDO category into Collateralized Bond Obligations (CBO), Collateralized Loan Obligations (CLO), and all other CDO instruments, and we use the tranche type to categorize CMBS and CMO instruments. We provide details on our data-cleaning procedures in the Appendix A.

The population of instruments is the comprehensive list of securitizations in the FINRA database that consists of all private-label and agency securitizations outstanding. Table 1 reports the total number of instruments in the population and the number of instruments that have at least one buy from a customer and one sell to a customer less than two weeks apart. In Table 1 we report how many instruments are investment grade or high yield;[2] how many instruments have fixed- or floating-rate coupons; the average number of trades per day; the average vintage in years; and the average number of dealers who were active in each instrument.

It is apparent from the trading frequencies reported in Table 1 that securitized products do not trade frequently: For example, on average ABS instruments have 0.10 trades per day and CDO instruments have 0.03 trades per day. Registered instruments are more likely to trade in our sample and tend to have more trades on average than 144a instruments, which often are purchased by QIBs as buy-and-hold investments. As an example, on average Registered ABS instruments have 0.11 trades per day, and 144a ABS instruments have 0.07 trades per day. Perhaps the higher frequency of trading in Registered instruments reflects that a larger number of investors can hold and trade Registered instruments than 144a instruments. The higher frequency of trading may also reflect the greater disclosure requirements for Registered instruments so that potential investors have more public information about these instruments and are more willing to trade them.

Figure 1 depicts the kernel density function for the number of customer and interdealer transactions. To improve the display of the densities, we truncate the plot at the 95th percentile of each distribution. Though we truncate from these plots those instruments with the largest number of trading records, these truncated instruments are potentially the most important for our subsequent empirical analysis because they provide the largest number of bid-ask spread observations.

Figure 2 illustrates the nature of trading activity in two of the most actively traded instruments in our sample. The upper subpanel in each panel shows the customer buy and sell volumes during our

[2] We classify unrated instruments as high yield rather than investment grade instruments.

sample period, the middle subpanel shows the interdealer trade volumes and the bottom subpanel shows the trade prices. The figures illustrate the potential importance of interdealer trades in reallocating inventory and exposures and matching customer buy and sell trades. The bottom subpanels of the plots illustrate that bid-ask spreads are quite substantial, even for actively traded instruments, and that the interdealer trade prices do not always lie between the customer buy and sell trade prices.

We compute the realized proportional bid-ask spreads, which we refer to as total client bid-ask spreads, using a matching technique. For intermediation chains with multiple dealers we also compute dealer-specific bid-ask spreads for each participating dealer. The total client bid-ask spread is a weighted sum of dealer-specific spreads in a chain. We adjust the resulting spreads for accrued interest and factor prepayments.[3]

Dealers may possess bargaining advantages with respect to retail-sized trades. Following FINRA, we define a retail-size trade as a trade of less than \$100,000 of current balance volume. Bid-ask spreads resulting from two opposite retail-size trades are retail-size bid-ask spreads, while all other are non-retail bid-ask spreads.

Table 2 reports summary statistics of the total client bid-ask spreads for the ABS, CDO, CMBS and Non-Agency CMO categories, and for Registered and 144a instruments. The first four columns of the table report means and associated standard errors. The table reports the differences in average retail-size bid-ask spreads and average non-retail bid-ask spreads for each of the four categories of instruments, along with standard errors and the p-values from an F-test for their equality. The final

[3]Few of the resulting spread observations are extreme, potentially reflecting pricing data errors. We address such observations by Winsorizing the upper 1% and lower 1% tails of the spread distributions within each of the four types of instruments, each of the two placement types and the two types of credit quality.

four columns of Table 2 report the 50th and the 10th percentile of the bid-ask spread distribution for each of the four categories of instruments.

Across most categories the spread distributions are skewed to the right—there are some large spreads in all categories so the mean spread is higher than the median spread. The 10th percentile of the retail-size bid-ask spread distribution is zero or negative for most types of instruments; dealers can have as high as a 10% chance of realizing a holding period loss on retail-size trades. The difference in spreads between retail-size trades and all other trades reported in Table 2 is striking. For all categories, retail-size bid-ask spreads are larger than other spreads. Such large retail-size spreads may indicate that dealers exercise greater bargaining power when they intermediate retail-size customer trades. Babus and Kondor (2014) provide an alternative explanation for why retail-size trades have higher spreads. In their model, dealers with fewer trading partners execute smaller trades and post larger bid-ask spreads because they are exposed to larger adverse selection. In Section 5 we study the adverse selection hypothesis, finding mixed empirical evidence that trades with dealers with fewer trading partners carry lower informational content.

We also compare spreads across instrument types. Overall average spreads are the largest for Non-Agency CMO instruments. Many types of 144a instruments have smaller spreads than Registered instruments, which may reflect that sophisticated investors face lower transactions costs and have greater bargaining power than unsophisticated investors.

Our findings on relative bid-ask spread sizes are consistent with other studies of securitizations based on the data from FINRA. Bessembinder, Maxwell, and Venkataraman (2013) provide similar sized trading cost estimates using a regression-based trading cost model for ABS and MBS instruments, with a focus on quantifying the effects of a potential transparency regime change. Friewald, Jankowitsch, and Subrahmanyam (2014) analyze liquidity of the markets for structured products and also demonstrate that transaction cost measures that are based on less detailed information are good proxies for measures that use more detailed dealer-specific information. We compare the non-retail spreads reported in Table 2 with the spreads for corporate bonds reported by Goldstein, Hotchkiss, and Sirri (2007) in their Table 6. For ABS instruments, the spreads for Registered instruments reported in our Table 2 tend to be smaller than the spreads in the corporate bond market for institutional-sized trades. The spreads for 144a instruments in Table 2 tend to be larger than for institutional-sized trades reported for the corporate bond market; instead for trade sizes of 51-100 bonds, the spreads in the corporate bond market are similar to the spreads for 144a instruments in our sample.

On October 18, 2011, about halfway through our sample, FINRA began to disseminate daily price index data for various collateral types of structured products. These informational releases provided the public more detailed information about valuations for various collateral types and indirectly, greater transparency about spreads and trading costs. We did examine spread differences before and after this transparency event, but found only small effects of the event relative to the underlying variability of the spreads.

3. The Trading Networks in Securitizations

We use network analysis to document the structure of the relationships among dealers. By forming relationships dealers can reduce trading frictions, such as search, opacity and informational frictions created by the nontransparent environment. Empirically, we relate the structure of the interdealer trading network and dealers' positions in the network to their trading behavior.

Our data allows us to identify individual dealers and their trades during the sample period. From May 16, 2011 to February 29, 2012 we observe 667 dealers who participated at least once in interdealer trading. Of those dealers, 370 participated in ABS, 225 in CDO, 293 in CMBS, and 556 in Non-Agency CMO markets. Over the sample, an average dealer transacted $436 million of original balance on the interdealer market in ABS, $335 million in CDO, $959 million in CMBS, and $842 million in Non-Agency CMO instruments. The four broad markets we analyze are significantly interconnected and the same dealers often participate in different markets.

Dealers are remarkably heterogeneous in terms of their trading activity. Figure 3 presents the Lorenz curves computed using dealers' shares of the customer volumes for ABS, CDO, CMBS and Non-Agency CMO instruments and for Registered and 144a instruments. A small number of dealers account for a major fraction of customer volume in all markets.

We use the timing of interdealer trades to identify which dealers have trading relationships. Our identification strategy assumes that fast interdealer transactions are more likely to happen when dealers have an underlying trading relationship with each other in the interdealer trading network.

Definition 3.1: A *prearranged trade* is a buy trade and a sell trade of the same size executed by the same dealer within 15 minutes.

For example, when dealer A buys a given volume of a security from a customer and within 15 minutes resells the same volume to dealer B, we conclude that dealers A and B have a pre-established trading relationship. Otherwise, it would have been difficult for dealer A to find a trading opportunity with dealer B so quickly. Using our identification assumption, we keep only those pairs of interdealer trades that are part of at least one prearranged trade in constructing the dealer network and computing the network measures, however our empirical results are robust to using all interdealer trades in computing the network measures.

3.1. Describing the Intermediation Chains

We use a matching technique to identify intermediation chains in our sample. Each chain captures the movement of a block of volume between a customer-seller and a dealer, between dealers in the interdealer network, and between a dealer and a customer-buyer. We call a chain complete when we are able to track the movement of a block between the customer-seller and the customer-buyer. Some chains are incomplete—those that involve a dealer who holds the volume in inventory for longer than two weeks. For each intermediation chain we know how many rounds of intermediation occurred between the two customer trades, the time elapsed between each round, trade volumes and prices at each round, and whether any volume splitting occurred from one round to another. Many intermediation chains we identify have no interdealer trades, so that the same dealer buys from a customer and sells to another customer. We match 75% of the total absolute turnover in ABS market, 86% in the CDO market, 74% in CMBS market, and 80% in Non-Agency CMO market into complete chains we use to compute total customer bid-ask spreads.

The sequential nature of trading and the interdealer chains have gathered attention in the literature on interdealer trading. Viswanathan and Wang (2004) emphasize the superiority of sequential trading to achieve price efficiency in an environment in which customer trades are followed by interdealer trades. Glode and Opp (2013) demonstrate theoretically how multi-round intermediation chains with informed intermediaries can reduce adverse selection costs. When dealers are relatively less informed about bond fundamentals than customers, Viswanathan and Wang (2004) show that sequential trading may lead to a small number of trading rounds and trade breakdowns. Hugonnier, Lester and Weill (2014) demonstrate how intermediation chains arise endogenously when agents have heterogeneous private values for the asset. In their model agents with relatively low private values are likely to meet and sell the asset to agents with slightly higher private values, who in turn resell the asset to other agents with even higher private values in a sequence of trades, giving rise to an intermediation chain.

Table 3 reports lengths of the intermediation chains in our sample. There are somewhat shorter intermediation chains in 144a instruments than in Registered instruments. In the Glode and Opp (2013) model this implies lower adverse selection in 144a markets compared to Registered markets. In the Viswanathan and Wang (2004) model this is consistent with dealers being less informed than customers in 144a markets.

3.2. Describing the Network Structures

Figure 4 depicts the interdealer network. The network has 667 dealers, each represented by circles of different size, where the size is proportional to the number of the dealer's counterparties in the interdealer market. Relationships between pairs of counterparties are shown as lines. The figure shows the core-peripheral structure of the underlying interdealer network. To study the interdealer network structure we define a dealer's interdealer neighborhood and the following network centrality measures. Different centrality measures capture different aspects of a dealer's relative position in the interdealer network.

Definition 3.2: A dealer's *Interdealer Neighborhood* is the set of dealers with whom the dealer has pre-established trading relationships in the interdealer market.

To describe the network structures we use Degree Centrality, Second-order Degree Centrality and Coreness:

- *Degree Centrality* is the number of dealers in the interdealer neighborhood of a given dealer.
- *Second-order Degree Centrality* is the number of dealers in the interdealer neighborhoods of those dealers, who themselves are in the interdealer neighborhood of a given dealer.

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

Adamic, Brunetti, Harris, and Kirilenko (2012) study trading networks in E-mini S&P 500 futures contracts and use Degree Centrality to study the interactions of network metrics with transaction prices, volume and liquidity measures. Li and Schürhoff (2014) explore several centrality measures including our measures in a sample of municipal bond trades and document a significant common component in these measures.[4]

Panel A of Figure 5 plots the dealer's Degree Centrality against the dealer's Second-order Degree Centrality. When a dealer becomes more central in the network he typically connects to more and more peripheral dealers and the Second-order Degree Centrality increases at a slower rate. Panel B of Figure 5 plots the dealers' Degree Centrality against the Dealers' Coreness. In general, dealers with higher Coreness also have higher Degree Centrality with the relation convex. When the gap between dealer's Degree Centrality and Dealer's Coreness is large, the dealer acts as a bridge between less connected interdealer neighborhoods. When Dealer's Degree Centrality and Dealer's Coreness are close to each other, the dealer does not act as a bridge and this may affect bargaining.

Panel A of Figure 6 shows the fraction of Prearranged Trades for central and peripheral dealers. Panel B of Figure 6 shows average time in inventory for non-prearranged trades, calculated as the average difference in execution times for a buy trade and a sell trade of the same size executed by the same dealer within a longer time window than 15 minutes. For most types of trades the average

[4] Li and Schürhoff (2014) construct a single aggregate proxy for a dealer's position in the interdealer market from a principal component analysis of all centrality measures, which is then normalized following Milbourn (2003). Our results are robust to the use of these measures.

time in inventory is larger for central dealers—central dealers are willing to take on more inventory risk than peripheral dealers.

Central dealers in the interdealer market tend to hold inventories longer and are less likely to prearrange trades with their counterparties. When we use a single Degree Centrality measure for all categories of instruments rather than computing Degree Centrality for each category separately, the fractions of prearranged trades become comparable between central and peripheral dealers.

3.3. Bid-Ask Spreads and the Network Structures

To study further the effect of dealer centrality on the quality of the intermediation services that dealers offer to their counterparties, we plot the average dealer-specific spreads and compare average spreads for central dealers with those for peripheral dealers. Panel A of Figure 7 shows average dealer spreads for Prearranged Trades only. Panel B of Figure 7 shows average dealer spreads for all other non-prearranged trades. The findings suggest that central dealers provide cheaper intermediation services to their counterparties. In all markets, dealer spreads tend to be higher for peripheral dealers, with these differences more pronounced for 144a instruments than for Registered instruments.

We use regressions to study the relation between bid-ask spreads and dealer network characteristics. Table 4 provides the definitions of the right-hand-side variables we use in the regressions. The dependent variable is the bid-ask spread, with one observation per pair of matched trades in the sample. 30% of intermediation chains in Registered instruments and 42% of intermediation chains in 144a instruments occur within a relatively short time interval, taking less than 15 minutes, while 38% and 32%, respectively take longer than a day.[5] Across all instruments the average execution

[5] We impose a 14-day upper bound for the order execution time. The upper bound is almost never binding.

time conditional on the order lasting longer than a day is 3.5 days. We control for possible valuation changes between the execution times by including contemporaneous changes in several market-wide control variables in our regressions: the Baa credit spread, the Treasury term structure slope, the TED spread, and the aggregate mortgage rate obtained from the St. Louis Federal Reserve Economic Data.

We allow the regression slope coefficients to be different across categories of instruments and Registered and 144a placement types. We include fixed effects for each of the six different collateral types of ABS instruments, for CDO, CBO, and CLO instruments, CMBS interest-only or principal-only (IO/PO) and all other CMBS instruments (P/I), and six different types of CMO tranches separately, which we refer to as subcategories. We combine CBO and CLO into a single subcategory. We cluster standard errors within trade settlement dates, instrument subcategory and placement type.[6] We also perform regression analysis for overall categories without differentiating between Registered and 144a placement types. We report the slope coefficient estimates in Tables 5 and 6, and the estimates of constant fixed effects and the additional control variables in Table 7.

Table 5 reports the results from the regressions for the total customer non-retail spreads. In each group of columns, we report the point estimates of the coefficients with standard errors in parentheses below. We report the estimates for the overall category, estimates for Registered instruments within the category, and estimates for 144a instruments.

Generally, older instruments and instruments with riskier cash flows tend to have higher spreads, and instruments with more participating dealers tend to have lower spreads. The regression also documents volume discounts. The point estimate of the coefficient on Security-Specific Match

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

Volume is negative for all categories, indicating that instruments with larger trades tend to have small spreads. Deviation of a Particular Match is the trade size of the matched trade relative to the average trade size in that security. The point estimates are negative across all types of instruments, except for CBO and CLO where the point estimate is positive, but not statistically significant. A negative coefficient on Deviation of Particular Match indicates that when the matched trade is larger than average for that instrument, the match will have a lower spread reflecting a volume discount.

In typical equity markets, larger trades tend to have larger spreads, with the standard explanation being that larger trades carry more information so that dealers face higher adverse selection costs on larger trades. In many bond markets, smaller trades have larger spreads, with the standard explanation being that smaller trades tend to proxy for less sophisticated customers so that dealers have greater bargaining power in smaller trades and so are able to earn higher spreads on smaller trades. Lester, Rocheteau and Weill (2015) show that such a volume discount arises in a competitive search model of over-the-counter trading. The securitized markets we analyze resemble typical bond markets with respect to the effects of volume on spreads.

The point estimate on Dealers' Importance Dummy is negative and statistically significant for all instruments. The average spread is lower if the inventory passes through a dealer who is more central in the interdealer network. Central dealers perform a valuable function by enhancing the linkages in the network and the integration of customer activity. The coefficients for 144a instruments are often lower than the coefficients for Registered instruments: The relative benefits for customers to have orders intermediated by central dealers are larger in 144a markets. In Section 4 we develop a model where central and peripheral dealers trade with different customer clienteles and argue that the presence of relatively sophisticated customers in the securitization markets explains why spreads are relatively lower with central dealers than with peripheral dealers. The model predicts that the centrality discount is stronger in markets for 144a instruments when there are more sophisticated customers in the 144a markets. Neklyudov (2013) shows that these empirical results are also consistent with customers having greater bargaining power when negotiating with dealers in 144a instruments than in Registered instruments.

The regression includes the interaction between the Match Volume and Dealers' Importance. The volume discount is somewhat weaker for central dealers than for peripheral dealers.

3.4. Bid-Ask Spreads and Characteristics of the Intermediation Chains

Several dealers may contribute their share to the total bid-ask spread and the intermediation cost for customers. When a customer contacts a dealer to sell a block of volume, the exact path of this block within the interdealer network and the length of the intermediation chain are uncertain. To study how individual dealer's contributions affect the costs of the intermediation service, we decompose the total client spreads used in Table 5 into dealer-specific bid-ask spreads and repeat the regression analysis with additional controls for the characteristics of the intermediation chain.

Table 6 reports the results from the regressions for the dealer-specific bid-ask spreads. We include the same controls for instrument characteristics as in Table 5, but do not report them in Table 6, as our findings are generally the same for these control variables in the client spread and dealer spread regressions.

The point estimates on Deviation of Match Volume are negative for both Central and Peripheral dealers; the volume discounts documented above are robust at the dealer spread level. The point estimates on the Prearranged Pair of Trades are generally negative for both Central and Peripheral dealers—dealers tend to offer discounts both to customers and to other dealers when they are able to execute quicker the trade on the opposite side.

The point estimates on Dealers' Importance Dummy are negative and statistically significant for all categories of instruments, except CMBS. The point estimates on Dealers' Coreness is generally positive and statistically significant across categories: Individual dealers have market power when they bridge smaller interdealer neighborhoods in the interdealer network. The sum of the coefficients on Dealers' Importance Dummy, Dealers' Second-Order Neighbors and Dealer's Coreness is negative—the dealers' market power we identify with Dealers' Coreness is dominated by the centrality discount. We confirm the centrality discount for each individual dealer participating in an intermediation chain.

The point estimate on Buy from Customer is generally negative for Peripheral dealers, indicating that spreads are lower when a peripheral dealer participates in the first link of a multi-round intermediation chain. This reflects that peripheral dealers tend to offer price concessions in order to sell to another dealer rather than a customer. The point estimate on Sell to Customer is positive for Peripheral dealers, indicating that spreads are higher when a peripheral dealer participates in the last link of a multi-round intermediation chain. For the peripheral dealers, it is more valuable to find a customer to sell to and complete the intermediation chain rather than to sell to another dealer and keep the intermediation chain going. The point estimates on the same dummies for central dealers are more often of mixed sign and economic significance, suggesting that central dealers are less affected by the aforementioned need to make price concessions. When a peripheral dealer receives a bond in an intermediation chain from another dealer, he sells it to a customer 72% of the time on average. When a central dealer receives a bond in an intermediation chain from another dealer, he sells it to a customer 80% of the time on average. This suggests that customers willing to buy the securitization are more of a scarce resource among peripheral dealers than among central dealers.

We use the regression estimates to compare average bid-ask spreads of a representative instrument within each category. The average spread is obtained from the point estimates of the fixed effects from the regressions in Tables 5 and 6. The coefficients reported in Table 7 correspond to the effect of Registered or 144a placement type on bid-ask spreads, after controlling for the variables listed in Table 4 and the additional market-wide control variables. There is a lower bid-ask spread for a representative ABS and Non-Agency CMO instrument when it is placed as a 144a rather than a Registered instrument. We observe the opposite pattern for an average CMBS instrument. Overall, most of the spread estimated reported in Table 2 are robust to controlling for cross-sectional composition effects across Registered and 144a markets.

To summarize, we document a centrality discount—both total client bid-ask spreads and dealer spreads tend to be lower when more central dealers intermediate trades. The centrality discount in the market for securitizations contrasts with the centrality premium reported by Li and Schürhoff (2014) for municipal bond markets. The model we develop in Section 4 explains why spreads are relatively lower with central dealers than with peripheral dealers in the securitization markets, while spreads are relatively higher with central dealers than with peripheral dealers in municipal bond markets.

4. A Model of Spread Determination for Central and Peripheral Dealers

We develop a model in which heterogeneous customers choose to transact with heterogeneous dealers differing in their trade execution speeds, and provide conditions for a centrality discount or a centrality premium to arise. Central dealers use their network connections to execute customer trades faster than do peripheral dealers. Heterogeneous buyers[7] endogenously trade with central and peripheral dealers and the centrality discount arises when central and peripheral dealers have different trade execution technologies and serve sufficiently different types of buyers.

Risk neutral buyers discount cash flows at rate $0 < r < 1$. Once a buyer acquires the asset he receives a flow of dividends of 1 per unit of time so has holding value for the asset of

$$V_h = 1/r \,. \tag{1}$$

Each buyer has reservation utility level $u \geq 0$, drawn independently from a uniform distribution on the interval $[0, U]$. Buyers with low reservation utility have weak outside options and buyers with high reservation utility have strong outside options. An increase in U implies that there are more buyers with strong outside options. We interpret such buyers as the more sophisticated buyers; an increase in U increases the number of sophisticated buyers in the market.

Dealers' differ in their exogenous trade execution speeds. We denote the dealers' execution speed by λ_j for $j \in \{c, p\}$, where c denotes a central dealer and p denotes a peripheral dealer, with $\lambda_c > \lambda_p$. Dealers value the asset at $L < V_h = 1/r$, so that there are gains from trade with buyers. The lowest price a dealer would sell the asset to a buyer is L.

Dealers observe buyers' outside options u. A dealer with execution speed λ_j makes a take-it-or-leave-it offer of price $P_j(u)$ to a buyer with outside option u. A buyer accepts the offer when the buyer's utility from trading is at least u. A buyer's value function of choosing dealer j with execution speed λ_j who offers a price $P_j(u)$ is

$$V_0(u; P_j(u)) = e^{-r\,dt}\big(\lambda_j\, dt\, \big(V_h - P_j(u)\big) + \big(1 - \lambda_j\, dt\big)V_0(u; P_j(u))\big), \tag{2}$$

[7] We focus on buyers, although a similar argument applies to sellers. A centrality discount would imply that the average bid price for sellers offered by central dealers is higher than the bid price offered by peripheral dealers.

with solution

$$V_0(u; P_j(u)) = \frac{\lambda_j}{r+\lambda_j}\left(\frac{1}{r} - P_j(u)\right). \tag{3}$$

Because dealers make take-it-or-leave-it offers, buyers only trade with dealers offering prices that satisfy

$$V_0(u; P_j(u)) = u, \tag{4}$$

or

$$P_j(u) = \frac{1}{r} - \left(1 + {}^{r}/_{\lambda_j}\right)u. \tag{5}$$

A dealer with trade execution speed λ_j will only offer the price $P_j(u)$ when $P_j(u) \geq L$, otherwise the trade would not happen between the dealer with trade execution speed λ_j and the buyer with outside option u.

To describe the equilibrium define u_p as the maximum value of u such that a trade would happen between a buyer with outside option u and a peripheral dealer with trade execution speed λ_p

$$u_p = \frac{1-rL}{r(1+r/\lambda_p)}. \tag{6}$$

Similarly define u_c as the maximum value of u such that a trade would happen between a buyer with outside option u and a central dealer with trade execution speed λ_c

$$u_c = \frac{1-rL}{r(1+r/\lambda_c)} > u_p. \tag{7}$$

The equilibrium decision rule for a buyer with outside option u is

$$\begin{array}{ll} \text{Trade with dealer } j \text{ at } P_j(u), & \text{if } u \leq u_j\,, \\ \text{Do not trade with dealer } j, & \text{if } u > u_j\,. \end{array} \tag{8}$$

Figure 8 shows the decision rules for buyers. Buyers with weak outside options $u \le u_p$ can trade with both central dealers and peripheral dealers, and are indifferent between them. Buyers with stronger outside options $u_p < u \le u_c$ trade only with central dealers. Buyers with high outside options $u > u_c$ do not trade. When buyers are indifferent between trading with either central or peripheral dealers, they choose peripheral dealers with probability π, and when buyers are indifferent between trading or not, they always choose to trade.

Proposition 4.1 describes the average prices and price dispersion for central and peripheral dealers in terms of the model parameters. We define price dispersion as the cross-sectional standard deviation of transaction prices.

Proposition 4.1:

1) *When $U < u_p$ the average ask prices are higher and the price dispersion is lower for trades with central dealers than for trades with peripheral dealers.*
2) *When $u_p < U \le u_c$ the average ask prices can be higher or lower and the price dispersion can be higher or lower for trades with central dealers than for trades with peripheral dealers.*
3) *When $u_p < u_c < U$, the average ask prices are lower for trades with central dealers than for trades with peripheral dealers. If $u_c \ge 2u_p$ the price dispersion is lower for trades with central dealers than for trades with peripheral dealers for any values of π. Otherwise if $u_c < 2u_p$ the price dispersion is higher for trades with central dealers than for trades with peripheral dealers when π is low enough.*

Proof: See Appendix B.

Recall that with higher U there are more buyers with strong outside options and we interpret this as more sophisticated buyers in the market. Proposition 4.1 states that markets with fewer sophisticated buyers and less buyer heterogeneity should exhibit a centrality premium and markets with more sophisticated buyers should exhibit a centrality discount. That there is a centrality discount in the markets for securitizations is consistent with the presence of sophisticated customers.

Proposition 4.1 also states that if $u_c \geq 2u_p$ the price dispersion is lower for trades with central dealers than for trades with peripheral dealers. In Appendix B we show that the condition $u_c \geq 2u_p$ holds when central dealers and peripheral dealers differ enough in their trade execution speed and buyers discount cash flows by enough. When $u_c \geq 2u_p$ the trade volume with central dealers is at least as high as with peripheral dealers.

We use quantile regressions of customer bid-ask spreads on dealers' centrality measure to study price dispersions. The first two rows of Table 8 report unconditional standard deviations of the distribution of customer bid-ask spreads for the central dealers and peripheral dealers. The standard deviation of spreads for central dealers is lower than for peripheral dealers. We use quantile regressions that control for instrument characteristics and market-wide control variables to check the robustness of relative dispersions of bid-ask spreads between central and peripheral dealers. The last three rows of Table 8 report the coefficients on Dealers' Importance Dummy in a quantile regression of the spreads where we control for instrument characteristics and market-wide control variables described in Section 3.3. The coefficients on Dealers' Importance Dummy are negative with the largest negative effect observed for the 90th percentile of bid-ask spreads and the weakest negative effect for the 10th percentile of bid-ask spreads. The estimates imply that after controlling instrument characteristics and market-wide movements the distribution of bid-ask spreads is less dispersed at the center of the dealer network compared to the periphery.

Our finding of the price discount and lower price dispersion at the center of the dealer network is also consistent with the equilibrium in a search-and-bargaining model in Neklyudov (2013), where more connected dealers charge lower spreads because their endogenous reservation values reflect their search efficiency, while customers cannot strategically choose which dealers to trade with.

5. Price Discovery in the Network

Our empirical finding that more central dealers charge lower bid-ask spreads on average than peripheral dealers is also consistent with the model in Babus and Kondor (2014), in which more central dealers charge lower bid-ask spreads due to lower exposure to adverse selection risk, and also with Malamud and Rostek (2014), who study price discrimination patterns by dealers in a decentralized core-peripheral dealership structure where different dealers receive random endowment shocks and may have heterogeneous preferences for holding the asset.

We use price-impact regressions and VAR models to test the informational hypothesis from the Babus and Kondor (2014) model and to document the nature of the price discovery process in the securitization trading networks.

Our version of the price impact regression is motivated by the analysis of corporate bond markets in Bessembinder, Maxwell, and Venkataraman (2006), but modified to study the effect of dealers' centrality and handle those securitized products that do not trade very frequently in our sample. We estimate the price impact regression separately for the subsamples of trades with central dealers and trades with peripheral dealers for the full set of instruments

$$\Delta p_t = A_0 + \omega \Delta X_t + \lambda d_t^* + \beta \Delta d_t + u_t, \qquad d_t^* = E[d_{t+1}] = \varphi d_t. \tag{9}$$

Here d_t denotes the trade direction equal to +1 for a buy from customer, -1 for a sell to customer, and 0 for an interdealer trade, Δd_t denotes the change in the trade direction for a given instrument, d_t^* denotes the unexpected portion of the trade and is estimated using an AR(1) process with coefficient φ, and X_t denotes changes in the market-wide control variables. The β coefficient reflects the bid-ask spread component due to inventory risk borne by dealers or order processing costs. The λ coefficient reflects the bid-ask spread component due to asymmetric information—more informed dealers and customers convey their private information through the unexpected changes in the direction of trades.

To handle those securitized products that do not trade very frequently in our sample, we constrain the coefficient of the order flow AR(1) process and the price impact coefficients to be the same for all instruments within each category. The top panel of Table 9 reports the price impact coefficients estimated for the different categories of instruments. The price impact of the order volume for central dealers in the first row and for peripheral dealers in the third row of Table 9 provide estimates of the inventory holding costs and order processing costs that are not associated with adverse selection. Most of these estimated coefficients are negative, reflecting the volume discounts observed in these markets. The price impact of the unexpected order volume for central dealers in the second row and for the peripheral dealers in the fourth row of Table 9 provide estimates of the adverse selection costs. We do not observe significant effects of the unexpected order flow on the price changes, and we do not find significant differences in these coefficients for the central and peripheral dealers. Our estimates imply that adverse selection is not important for dealers' pricing; nor do we find differences in the informational content of trades with central and peripheral dealers.

We also estimate the price impact regressions for a subsample of the most-traded instruments to ensure that the composition effects do not drive our findings. We construct this subsample by taking the five instruments with the highest number of total client bid-ask spread observations within each category of instruments and separately for Registered and 144a placement types. The bottom panel of Table 9 reports our estimates. We find similar patterns for the subsample of the most-traded instruments as we do for the full sample.

As a further robustness check for each instrument in the subsample we estimate a separate VAR model with 2 lags, based on Hasbrouck (2007). We consider customer trades and interdealer trades, let t be the event time when a trade occurs, and let Δp_t be the dollar trade price change between trades at t and $t-1$. Define q_t as a vector consisting of three variables, a variable equal to +1 when a central dealer[8] buys from a customer, -1 when a central dealer sells to a customer, and zero otherwise; a similar variable for customer trades with a peripheral dealer; and a dummy variable equal to one for an interdealer trade, and zero otherwise. Let $y_t = (q_t \quad \Delta p_t)^T$. The VAR specification is

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + u_t, \qquad E[u_t] = 0, E[u_t u_t'] = \Sigma. \tag{10}$$

We use the estimates of the coefficients to compute the informational attributions of order flow and price changes as in Hasbrouck (2007, chapter 9) to proxy for information content, where price changes are ordered last in the VAR ordering. Panel A of Figure 9 plots the proportion of the variance of permanent price changes from the innovations in customer volume equal to the combined effect of the first two variables in q_t on the vertical axis against the proportion from the innovation in trade prices on the horizontal axis. For all instruments volume accounts for a much

[8] We use the Dealer Importance Dummy defined in Table 4 to classify dealers as central and peripheral in this section.

smaller fraction of permanent price changes than price innovations do.[9] We interpret this as evidence that there is limited trade-related information in the markets we study.

In order to compare central and peripheral dealers in terms of their contribution to price discovery, Panel B of Figure 9 plots the proportions of the variance of permanent price changes from customer trades with peripheral dealers on the vertical axis and with central dealers on the horizontal axes. These proportions are normalized by dividing by the total variance attributed to volume variables in q_t to subtract the price-related information effects. We find mixed evidence for the informational hypothesis from Babus and Kondor (2014), reflecting the lack of information asymmetries in these markets. Overall, customer volume has limited impact on the price discovery process with volume explaining on average only 7% of the permanent price changes. We find mixed evidence that customer trades intermediated by central dealers contribute more to the price discovery process—for many instruments customer trades with peripheral dealers are more informative about permanent price changes.

6. Concluding Comments

We utilize data on customer and dealer trades in securitization markets to study the nature of dealer networks and how bid-ask spreads vary within the trading network. Interdealer networks have a core-peripheral structure in the market for securitizations, similar to the municipal bond markets (see Li and Schürhoff (2014)). We document a negative relationship between interconnectedness of dealers and their bid-ask spreads.

Theoretical work studying over-the-counter markets predicts that customers that trade with more interconnected dealers with higher trade execution efficiency face lower bid-ask spreads on average

[9] Our results are robust to alternative specifications of the volume variable, as well as alternative orderings within the volume vector q_t.

in equilibrium, as in Babus and Kondor (2014), Malamud and Rostek (2013), Neklyudov (2013). We estimate price impact regressions modified to study the effect of dealers' centrality and handle those securitized products that do not trade very frequently in our sample. As a further robustness check for each instrument in the subsample we also estimate a separate VAR model. Overall, we find mixed evidence that customer trades intermediated by central dealers contribute more to the price discovery process—for many instruments customer trades with peripheral dealers are more informative about permanent price changes.

Our evidence contrasts with the empirical findings in municipal bond markets, where a positive relationship arises between dealers' centrality and bid-ask spreads and prices are more efficient when the trades are intermediated by central dealers, as documented by Li and Schürhoff (2014). We present a model where enough customer and dealer heterogeneity can result in a centrality discount. The difference across markets may reflect the presence of more sophisticated traders in the securitization markets than in the municipal bond markets.

Our paper points to a variety of additional directions for study. Empirical findings inform the theory of over-the-counter markets and offer a basis for exploring different theoretical models. It is important to understand the microeconomic aspects of the trading process in the presence of the dramatic disclosure differences between Registered and 144a instruments. Customer bid-ask spreads are tighter in 144a instruments, even though there are fewer active dealers in an average 144a instrument and 144a instruments have less disclosure requirements. The structure of our data allows us to identify different counterparties and construct trading networks, offering a natural environment to perform network analysis. Network analysis can enhance our understanding of intermediation patterns for dealer markets and concentrations of risk more broadly, including systemic risks.

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APPENDIX A: Data Construction

Our sample contains trading activity data ranging from May 16, 2011 to February 29, 2012 in several categories of securitized products: ABS, CDO, CMBS, CMO, MBS and TBA, and security characteristics for all securities subject to the FINRA reporting requirements. We limit our attention to ABS, CMBS, CDO and Non-Agency CMO securitizations because these classes have 144a instruments in our sample. We used the proprietary list of CUSIPs provided by FINRA to obtain Moody's ratings for these instruments on the Moody's corporate website. For those instruments not rated by Moody's in our sample, FINRA provides information whether the instruments are investment grade or high yield. We classify unrated instruments as high yield rather than investment grade instruments.

We perform several rounds of data cleaning to obtain our sample of trades. For some trade records traders entered incorrect trade information or canceled previous trades. For those cases we have reports marked as "Corrected Trades", "Trade Cancels" or "Cancels", and "Historical Reversals" if the correction was reported on a different trading day. In the first round of cleaning we search for all trade records that were subsequently corrected and trades that were cancelled by entered volume, entered price, trade execution date and counterparty codes, and update them accordingly. We do not count cancelled trades in our subsequent analyses.

The FINRA reporting rule is that each interdealer trade must be reported by both sides to the trade, leading to double reporting in our sample, with a few exceptions. Customer trades and locked-in trades are reported once, and in our data we observe whether the trade is a customer trade or a locked-in trade. To address the double reporting of trades we implement an iterative matching procedure. We look for pairs of identical trades reported by different sides to the trade. The matching procedure consists of one hundred iterative rounds of search for similar entries in terms of entered volume, price, execution timestamps, settlement date, and counterparty codes. In each round we flag trade reports that are sufficiently similar. When we find several alternative pairs of similar trades, we pick the ones that are closest in execution times. When we cannot identify a match based on the above criteria, we assume there was no second report for the trade. For 84.77% of all trade reports we were able to identify the unique match. The result of this cleaning procedure constitutes our sample of trades.

We use the bond-reference data provided by FINRA and construct the time-series of coupon rates and prepayment factors, the type of collateral, maturity, original balance, type of placement (Registered or 144a), and coupon type (fixed or floating) for each instrument. We identify instruments by the CUSIP code and symbol ID. In the few cases when instruments have the same CUSIP code and different symbol IDs we treat those as different instruments.

We perform several rounds of matching to sort trades into intermediation chains. In the first round we match related interdealer and customer trades that have the same volume and are no further than one month apart. For example, when we observe three trades of $1 million original balance in an instrument that form a potential chain: Customer to dealer A, dealer A to dealer B, dealer B to customer, we perform two checks: For each link of the chain there are no alternative links that reduce the total execution time of the chain, and each two links in the chain are no further than two weeks apart according to the execution timestamp. We do not impose any sequence in terms of which trade is executed first in the chain—a buy from customers can be executed earlier or later than a sell to customer in a chain, as well as all interdealer trades in a chain. Almost all our chains are shorter than 15 links; so to stop our iterative algorithm we impose the maximum length of a chain to be 15 links.

In the first round we obtain chains of various lengths: C-D-C (1 link), C-D-D-C (2 links), etc., with the same volume moving through the chain. We call these non-split chains. We find 10,871 non-split chains in ABS (1.2 links on average, 5 links maximum), 1,959 chains in CDO (1.08 links on average, 6 links maximum), 11,298 chains in CMBS (1.15 links on average, 9 links maximum), and 30,179 chains in Non-Agency CMO (1.32 links on average, 7 links maximum).

In the second round we allow trade volume to be split when moving through a chain. For example, when we see three trades in the same instrument that have different trade volumes: $1 million customer to dealer A, $2 million dealer A to dealer B, $0.5 million dealer B to customer, we perform the two checks as in the first round and then split the chain in three pieces: 1) $0.5 million from a customer to dealer A; 2) $1.5 million from dealer A to dealer B; 3) $0.5 million from a customer to dealer A, $0.5 million from dealer A to dealer B, $0.5 million from dealer B to a customer. We find 8,719 additional chains in ABS (1.51 links on average, 9 links maximum), 794 chains in CDO (1.43 links on average, 10 links maximum), 10,111 chains in CMBS (1.38 links on average, 15 links maximum), and 41,135 chains in Non-Agency CMO (1.9 links on average, 9 links maximum).

After the second round we perform the LIFO matching based on the last-in-first-out inventory accounting principle for the remaining customer trades. This constitutes our third and final round of matching process. We find 3,396 additional chains in ABS (1.86 links on average, 11 links maximum), 406 chains in CDO (1.72 links on average, 7 links maximum), 4,621 chains in CMBS (1.8 links on average, 19 links maximum), and 13,192 chains in Non-Agency CMO (2.3 links on average, 10 links maximum).

After the three rounds we have the total number of 23,036 chains in ABS, each with 1.41 links on average and 11 links maximum; 3,198 chains in CDO with 1.25 links on average and 10 links maximum; 26,124 chains in CMBS with 1.35 links on average and 19 links maximum; and 84,788 chains in Non-Agency CMO with 1.76 links on average and 10 links maximum. We find relatively longer chains in the Non-Agency CMO instruments. The complete chains we find constitute 75% of the total absolute turnover in the ABS market, 86% in the CDO market, 74% in the CMBS market, and 80% in the Non-Agency CMO market.

We adjust prices for coupon and factor payments that happened between the settlement time of a trade and the settlement time of a buy from customer (the beginning of the chain), as well as for accrued interest. For each chain we compute two types of bid-ask spread measures: total client bid-ask spread and dealer-specific spread—both measured per \$100 of current value.

We compute bid-ask spread using the two prices and the information on factor and coupon payments as follows. Consider the case when the settlement date of the ask trade occurs after the settlement date of the bid trade. Let T be the number of calendar days in between and let c be the annual dollar coupon amount per \$100 of original balance:

$$Spread = 100 \times \frac{(P_{ask}\, factor_{ask} - P_{bid}\, factor_{bid} + adj)}{(P_{ask}\, factor_{ask} + P_{bid}\, factor_{bid} + adj)/_2}\ , \tag{A1}$$

where $adj = c\ \frac{T}{360}\ factor_{bid} + factor\ prepayment.$

The fair-pricing condition is:

$$\frac{factor\ prepayment}{P_{ask}} = factor_{bid} - factor_{ask}. \tag{A2}$$

When the fair-pricing condition (A2) holds, the bid-ask spread equation (A1) simplifies to:

$$Spread = 100 \times \frac{\left(P_{ask} - P_{bid} + c\,\frac{T}{365}\right)}{\left(P_{ask} + P_{bid} + c\,\frac{T}{365}\right)/_2}. \tag{A3}$$

Both formulas result in similar spread distributions. The fair-pricing condition is thus a relatively good approximation for those matches that involve factor payments in between the two settlement dates. Few spread observations are outliers so we winsorize 1% of the upper and lower tails of the distribution of total client spreads within each collateral type, placement type, and credit rating.

APPENDIX B: Proof of Proposition 4.1

Case 1: Consider the case when $U \le u_p$. In this case all buyers are indifferent between central and peripheral dealers. The transaction price with peripheral dealers is uniformly distributed on the interval

$$\left[\frac{1}{r} - \left(1 + {}^{r}/_{\lambda_p}\right) U,\ \frac{1}{r}\right], \tag{B1}$$

and the transaction price with central dealers is uniformly distributed on the interval

$$\left[\frac{1}{r} - \left(1 + {}^{r}/_{\lambda_c}\right) U,\ \frac{1}{r}\right]. \tag{B2}$$

Since $\lambda_c > \lambda_p$, average ask prices are higher on average and price dispersion is lower for trades with central dealers than for trades with peripheral dealers.

Case 2: Consider the case when $u_p < U \le u_c$. In this case the buyers with reservation utility $u_p < u \le U$ do not trade with the peripheral dealers, but always trade with the central dealers. The buyers with reservation utility $u \le u_p$ trade with the peripheral dealers with probability π and trade with the central dealers with probability $1 - \pi$. The transaction price with peripheral dealers is uniformly distributed on the interval

$$\left[L,\ \frac{1}{r}\right], \tag{B3}$$

and the transaction price with central dealers is a mixture of two uniform distributions with the weight $\frac{U-u_p}{(1-\pi)u_p+U-u_p}$ on a uniform distribution on the interval

$$\left[\frac{1}{r} - \left(1 + {}^{r}/_{\lambda_c}\right) U,\ \frac{1}{r} - \left(1 + {}^{r}/_{\lambda_c}\right) u_p\right], \tag{B4}$$

and the weight $\frac{(1-\pi)u_p}{(1-\pi)u_p+U-u_p}$ on a uniform distribution on the interval

$$\left[\frac{1}{r} - \left(1 + {}^{r}/_{\lambda_c}\right) u_p,\ \frac{1}{r}\right]. \tag{B5}$$

Since $U \leq u_c$ we have $\frac{1}{r} - \left(1 + {}^{r}/_{\lambda_c}\right) U \geq L$, so transaction prices have wider range of possible values among the peripheral dealers than among the central dealers. The average prices are higher on average among peripheral dealers when

$$\frac{1}{2}\left(\frac{1}{r} - \left(1 + {}^{r}/_{\lambda_c}\right) u_p\right) - \frac{U-u_p}{(1-\pi)u_p+U-u_p}\left(\frac{1}{2}\left(1 + {}^{r}/_{\lambda_c}\right) U\right) \leq \frac{1}{2} L\,. \tag{B6}$$

When $U = u_c$ inequality (B6) always holds. When $U = u_p$ inequality (B6) never holds. The left-hand side of the inequality is monotonically decreasing in U, so we conclude that average ask prices can be higher or lower for trades with central dealers than for trades with peripheral dealers.

Case 3: Consider the case when $u_p < u_c < U$. The transaction price with peripheral dealers is uniformly distributed on the interval

$$\left[L,\ \frac{1}{r}\right], \tag{B7}$$

and the transaction price with central dealers is a mixture of two distributions with the weight $\frac{u_c-u_p}{(1-\pi)u_p+u_c-u_p}$ on a uniform distribution on the interval

$$\left[L,\ \frac{1}{r} - \left(1 + {}^{r}/_{\lambda_c}\right) u_p\right], \tag{B8}$$

and the weight $\frac{(1-\pi)u_p}{(1-\pi)u_p+u_c-u_p}$ on a uniform distribution on the interval

$$\left[\frac{1}{r} - \left(1 + {}^{r}/_{\lambda_c}\right) u_p,\ \frac{1}{r}\right]. \tag{B9}$$

The average prices are higher on average among peripheral dealers when

$$\frac{1}{2}\left(\frac{1}{r} - \left(1 + {}^{r}/_{\lambda_c}\right) u_p\right) - \frac{u_c-u_p}{(1-\pi)u_p+u_c-u_p}\left(\frac{1}{2}\left(\frac{1}{r} - L\right)\right) \leq \frac{1}{2} L\,. \tag{B10}$$

The left-hand side of inequality (B10) is monotonically increasing is π, and for $\pi = 0$ (B10) holds as an equality. Thus for any $0 < \pi < 1$ we have a strict inequality and the average ask prices are lower for trades with central dealers than for trades with peripheral dealers.

We use the distribution for the transaction price with central dealers in equations (B8) and (B9) to compute the price dispersion as a function of π. The price dispersion for trades with central dealers is a quadratic function of π, which is maximized when:

$$\pi^* = \frac{\lambda_c(r+\lambda_p)(r(2\,\lambda_p-\lambda_c)+\lambda_c\,\lambda_p)}{\lambda_p(r+\lambda_c)(r(2\,\lambda_c-\lambda_p)+\lambda_c\,\lambda_p)}. \tag{B11}$$

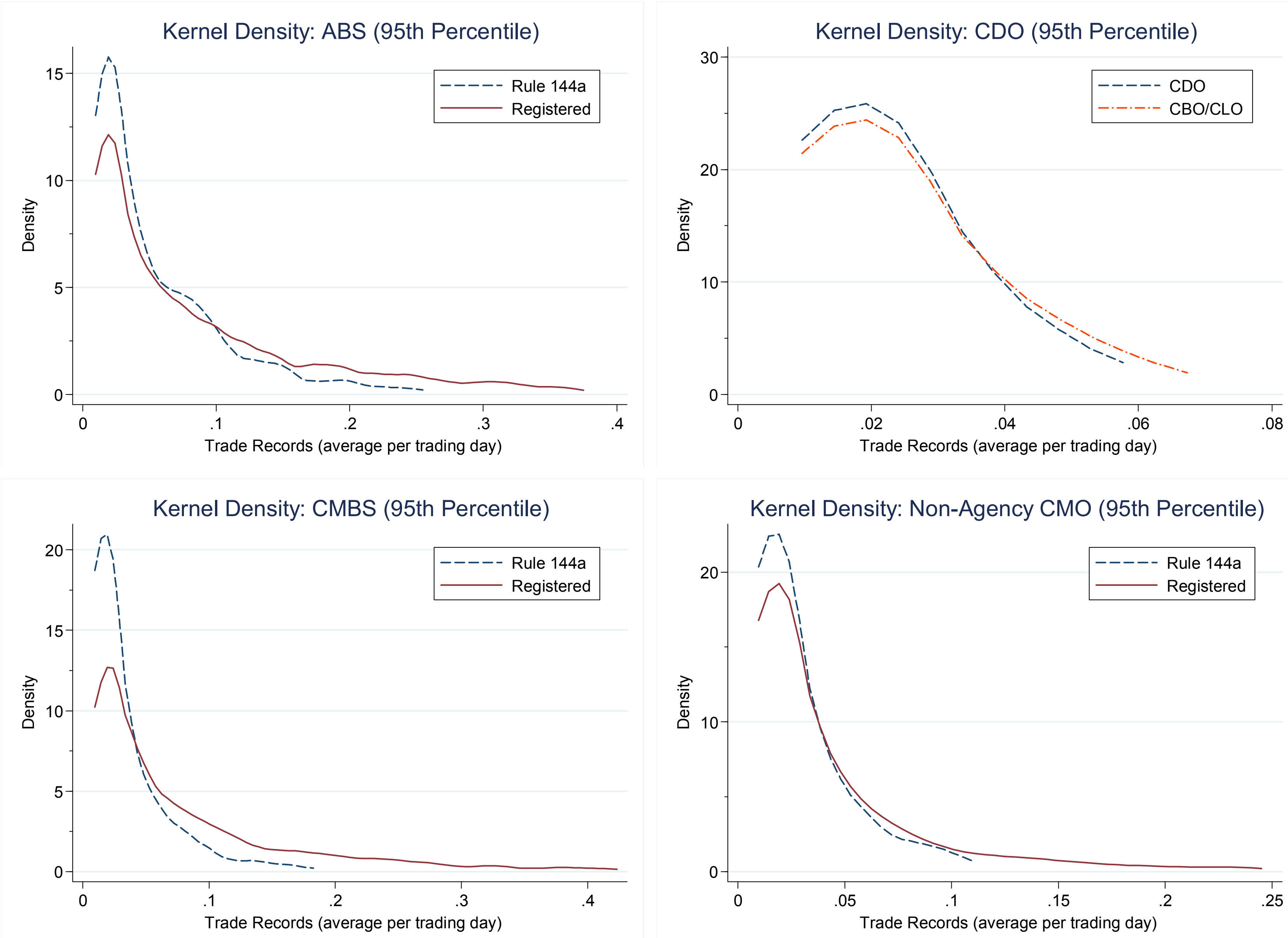
When $\pi = 0$ then the price dispersions for trades with central dealers than for trades with peripheral dealers are equal. When

$$\lambda_c > 2\,\lambda_p \text{ and } r \geq \lambda_c\lambda_p/(\lambda_c - 2\,\lambda_p), \tag{B12}$$

then $\pi^* \leq 0$, and the derivative of the price dispersion for trades with central dealers with respect to π is negative. Therefore the price dispersion is lower for trades with central dealers than for trades with peripheral dealers for any values of π. When inequalities (B12) do not hold, the derivative of the price dispersion for trades with central dealers with respect to π is positive at $\pi = 0$, so the price dispersion will be higher for trades with central dealers than for trades with peripheral dealers when π is low enough.

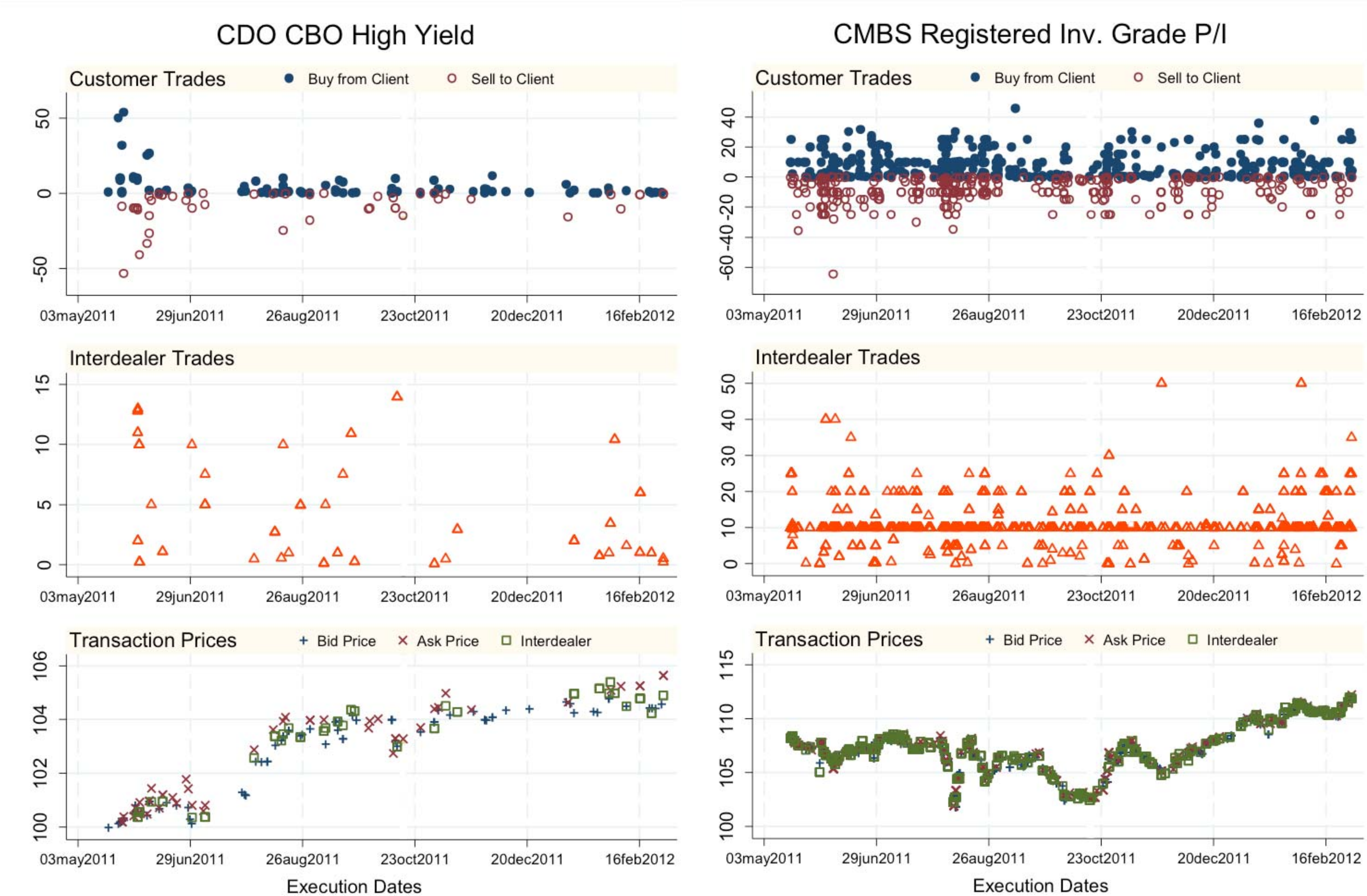
QED.

Figure 1: Distribution of Number of Trading Records per Day



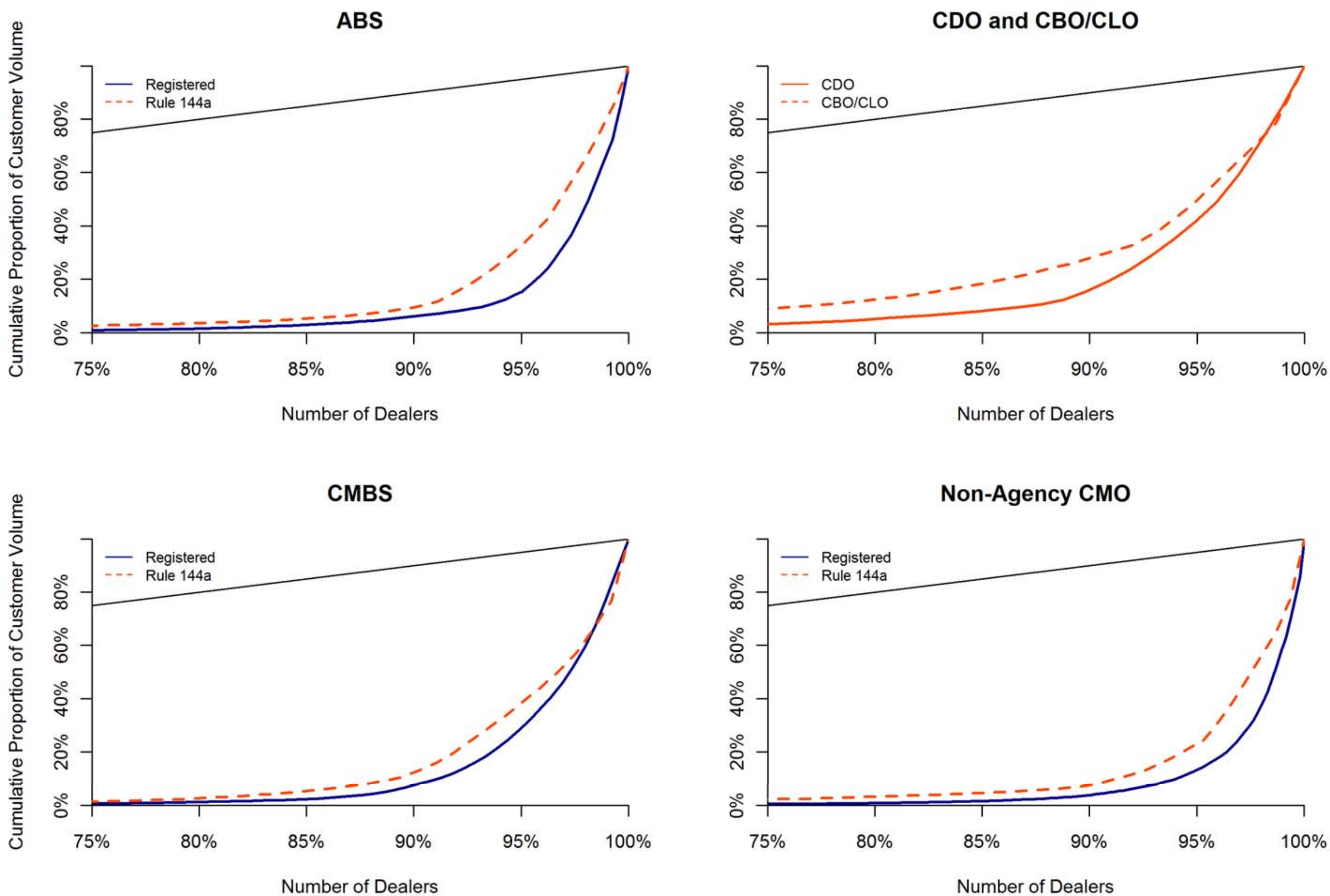
Legend: Number of trade records includes both trades with customers and interdealer trades. The graphs show estimated distributions of the lower 95th percentile within each category of instruments. The distribution is estimated using Epanechnikov kernel density with 1/100 bandwidth. The sample period is from May 16, 2011 to February 29, 2012.

Figure 2: Examples of Trading Patterns



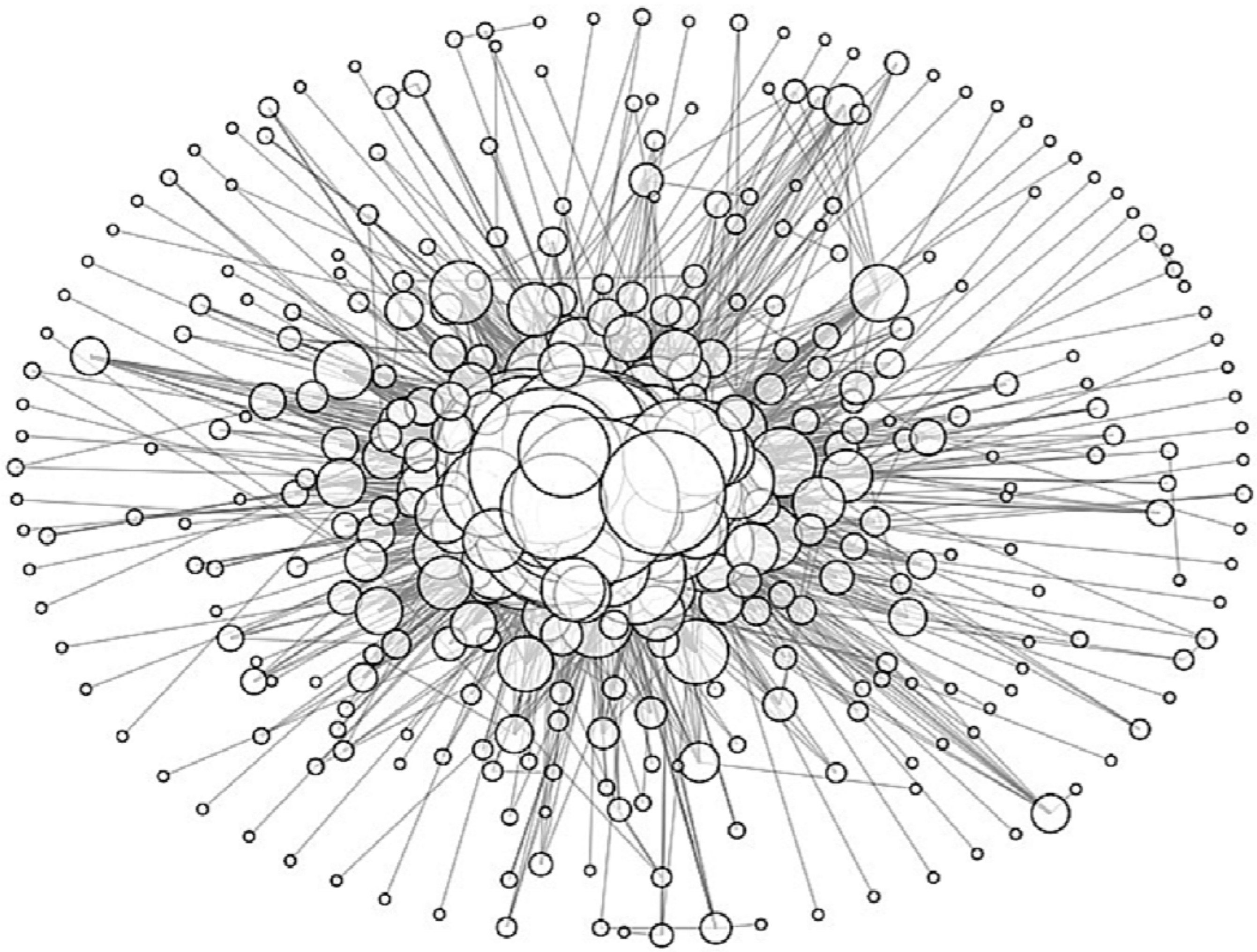
Legend: the top panel shows the logarithm of trade volumes in original par balance, where buys from customers are shown as having positive volumes traded and sells to customers are shown as having negative volume. The middle panel shows the logarithm of interdealer trade volumes, and the bottom panel shows realized transaction prices.

Figure 3: Dealers' Shares of Customer Volume



Legend: All customer trades in the sample period from May 16, 2011 to February 29, 2012 are used to construct Lorenz curves. The 25% of dealers with largest volumes of original balance traded with customers are shown for each market.

Figure 4: The Interdealer Network



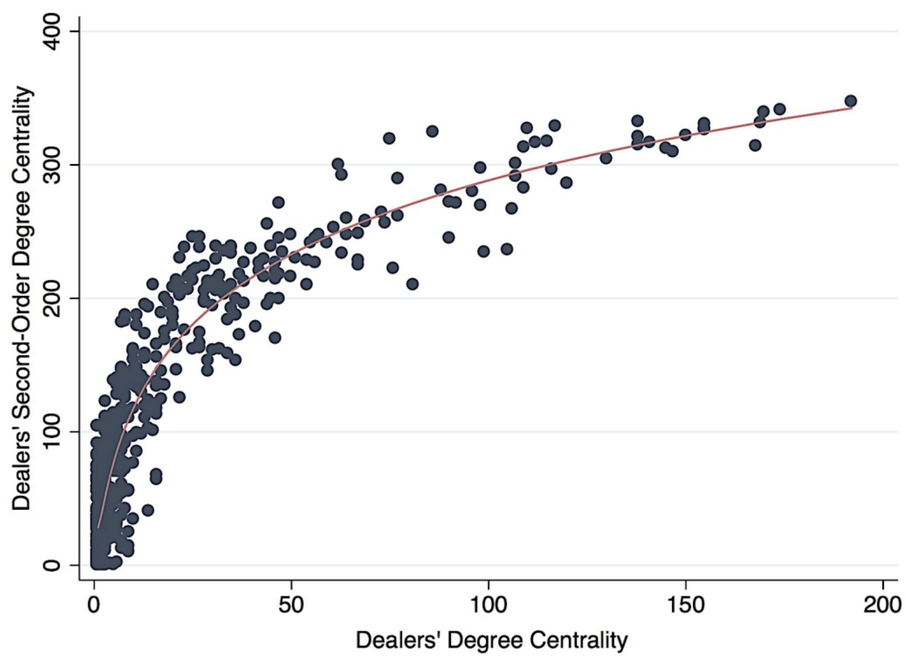
Total Number of Dealers: 667

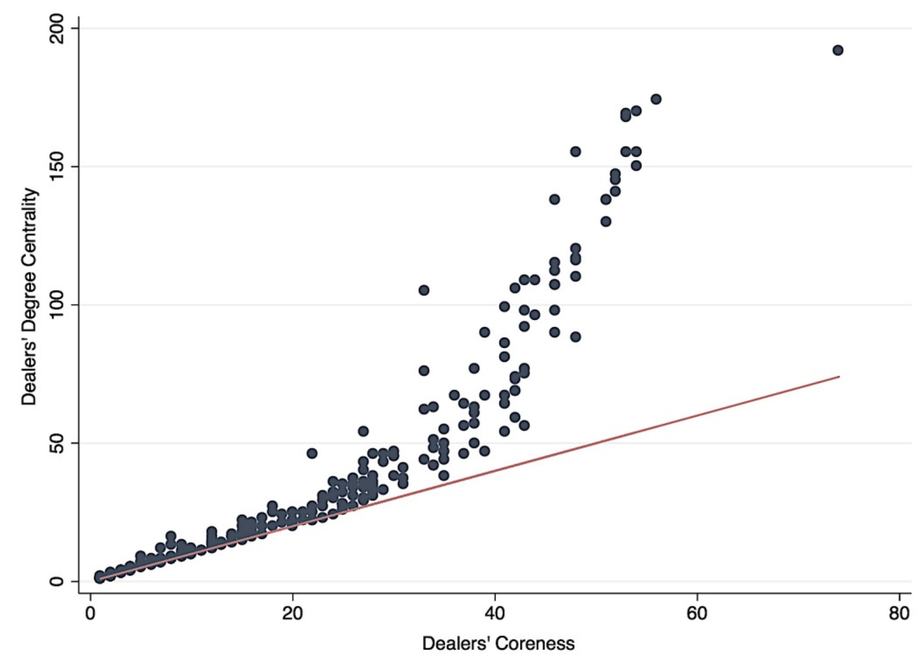
Legend: The figure shows the interdealer network. Each circle represents a dealer, the size of the circle is proportional to the Degree Centrality—number of connections the dealer has on the interdealer market, depicted as lines connecting the circles.

Figure 5: Dealers' Network 2nd Order Degree and Coreness

Panel A: Dealers' Degree and Second-Order Degree Centrality

Panel B: Dealers' Degree Centrality and Coreness

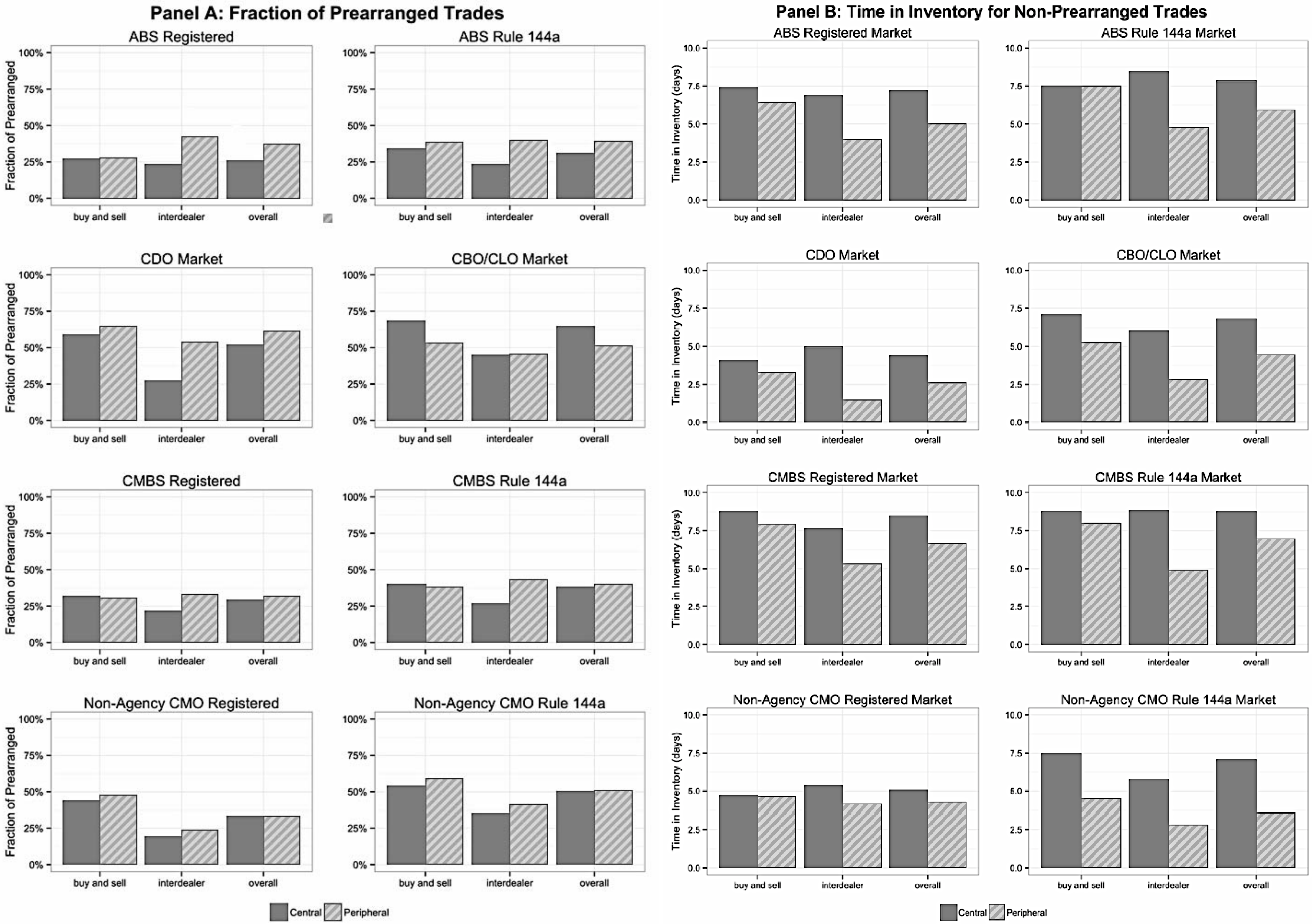




Total Number of Dealers: 667

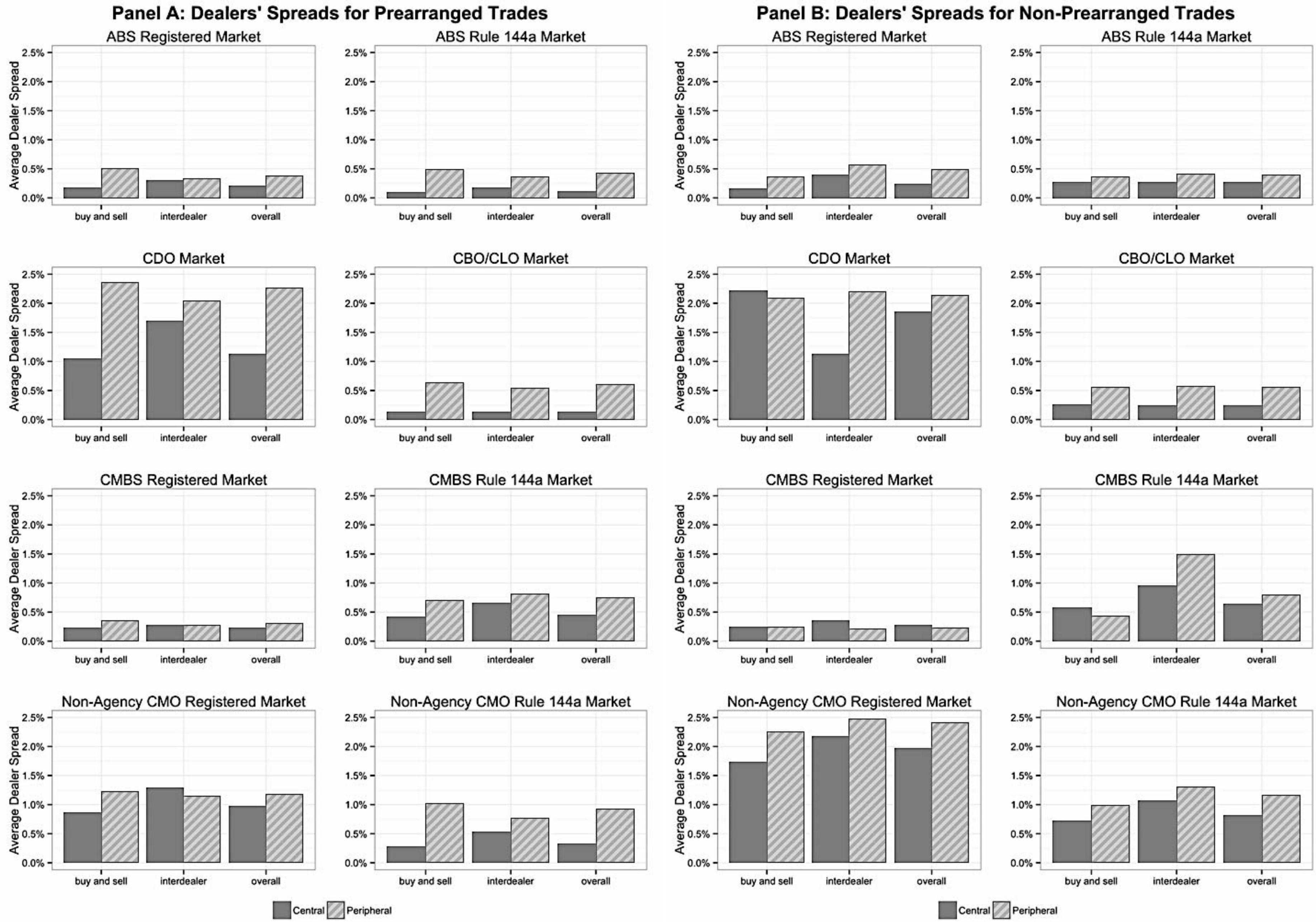
Legend: Degree Centrality is the number of trading partners of a dealer in the sample. Dealer's Coreness is the number of trading partners in the *k*-core sub-network that includes that dealer (*k*-core is the largest sub-network where all dealers have at least *k* number of trading partners). In Panel A Degree Centrality is shown for each dealer against the number of second order neighbors of each dealer. In Panel B each dot is a dealer with particular Degree Centrality and Coreness.

Figure 6: Prearranged Trades and Time in Inventory for Central and Peripheral Dealers



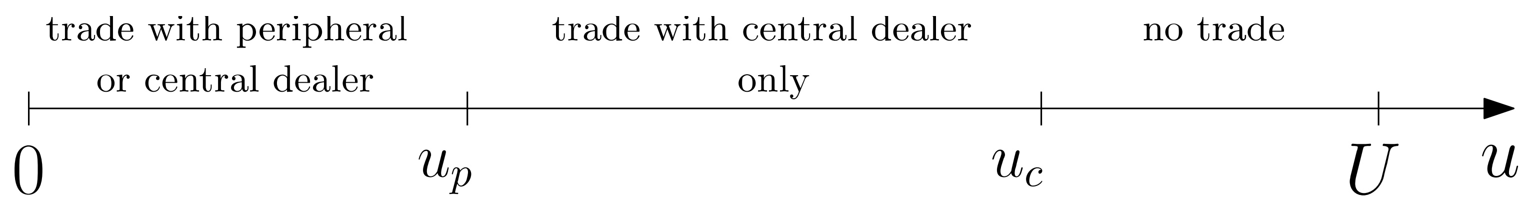
Legend: Panel A plots prearranged trades defined as pairs of trades of the same size and opposite signs, a buy trade and a sell trade, that are executed by the same dealer within 15 minutes against the types of matches, where "buy and sell" is a dealer buying from a customer and then selling to a customer. Panel B plots the time in inventory calculated as the difference between execution times for a pair of trades of opposite signs, against the types of matches.

Figure 7: Average Spreads for Central and Peripheral Dealers



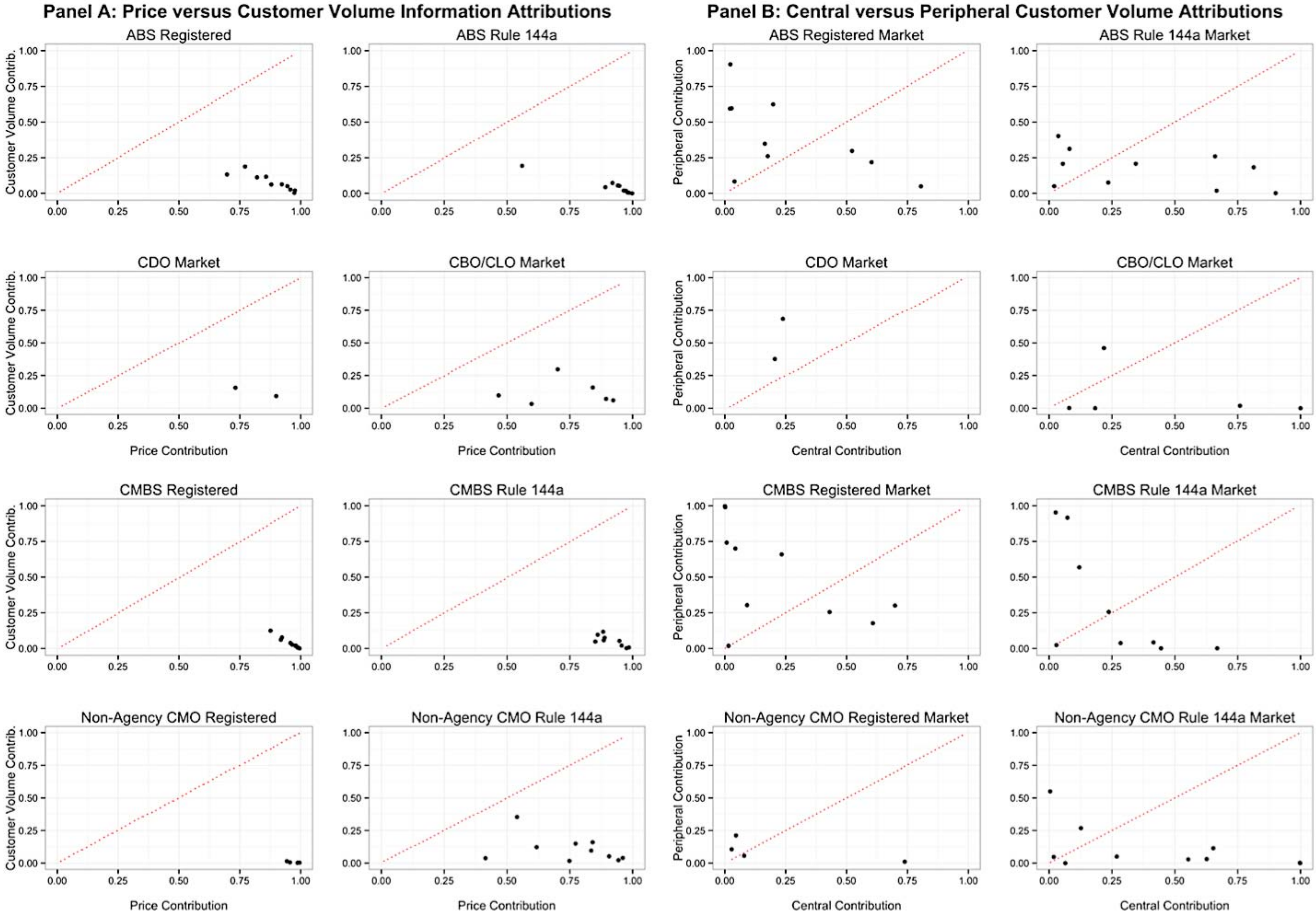
Legend: Panel A plots average dealer spreads for prearranged trades defined as pairs of trades of the same size and opposite signs, a buy trade and a sell trade, that are executed by the same dealer within 15 minutes against the types of matches, where "buy and sell" is a dealer buying from a customer and then selling to a customer. Panel B plots average dealer spreads for all other trades against their types.

Figure 8: The Equilibrium Decision Rules



Legend: The figure provides the graphical description of the equilibrium decision rules of the buyers. The plot shows the decision rules for buyers as a function of the realized reservation utility $\boldsymbol{u}$.

Figure 9: Contributions to Price Discovery for Central and Peripheral Dealers



<u>Legend:</u> The figure plots the informational attributions computed using the VAR model in equation (10). Panel A reports information attributed to price innovations against the information attributed to customer volume innovations. Panel B reports information attributed to customer trades by central against peripheral dealers. The sample of trades in 62 most frequently traded instruments is used for the time period from May 16, 2011 to February 29, 2012.

Table 1: Descriptive Statistics for Instruments

Category:	**ABS**							**CDO**			**CMBS**			**Non-Agency CMO**						
	All	Auto	Card	ManH	SBA	Stud	Other	All	CDO	CBO/L	All	IO/PO	P/I	All	IO/PO	PAC/TN	SEQ/PT	SUP/Z	Oth.SR	Other
Population	12,661	1,193	410	661	350	1,223	8,824	4,158	392	2,993	13,720	1,421	12,299	78,350	8,798	4,520	29,366	1,456	15,998	18,212
Registered	4,567	750	356	616	329	957	1,559	8	44	3	5,765	628	5,137	61,687	7,906	4,487	24,505	1,280	13,432	10,077
Rule 144a	8,094	443	54	45	21	266	7,265	4,150	348	2,990	7,955	793	7,162	16,663	892	33	4,861	176	2,566	8,135
Traded	2,807	645	261	213	237	417	1,034	1,222	428	794	2,967	249	2,718	13,396	326	839	7,129	300	3,687	1,115
Inv. Grade:	54%	69%	86%	33%	100%	91%	16%	54%	25%	69%	45%	59%	44%	16%	11%	13%	17%	8%	19%	4%
Floaters:	54%	11%	76%	10%	0%	100%	79%	96%	94%	98%	46%	100%	41%	71%	78%	24%	77%	31%	66%	93%
Rule 144a	902	179	18	7	10	89	599	1,222	428	794	970	155	815	1,041	22	7	417	5	153	437
Inv. Grade:	32%	64%	67%	57%	100%	88%	12%	54%	25%	69%	42%	67%	38%	11%	14%	29%	21%	0%	12%	0%
Floaters:	70%	16%	67%	29%	10%	99%	84%	96%	94%	98%	66%	100%	60%	84%	73%	43%	78%	40%	71%	97%
Trades / Day	0.10	0.13	0.21	0.03	0.09	0.07	0.07	0.03	0.03	0.03	0.09	0.03	0.10	0.07	0.03	0.08	0.05	0.13	0.10	0.04
Registered	0.11	0.14	0.19	0.03	0.09	0.07	0.10	---	---	---	0.12	0.03	0.12	0.07	0.03	0.08	0.05	0.13	0.11	0.04
Rule 144a	0.07	0.11	0.50	0.03	0.14	0.08	0.05	0.03	0.03	0.03	0.05	0.03	0.05	0.04	0.04	0.05	0.03	0.02	0.05	0.03
Vintage	4.8	1.5	4.6	11.9	6.5	5.8	4.5	5.8	6.2	5.5	4.7	4.1	4.7	5.7	5.2	6.1	5.7	6.5	5.7	5.5
Registered	5.3	1.6	4.8	12.2	6.4	5.8	5.2	---	---	---	4.8	4.1	4.8	5.9	5.3	6.1	5.8	6.6	5.8	6.1
Rule 144a	3.7	1.4	3.1	4.5	9.2	5.8	4.1	5.8	6.2	5.5	4.4	4.2	4.5	3.9	3.6	6.3	3.8	2.7	3.8	4.1
N of Dealers	5.0	7.3	8.3	2.5	4.5	4.4	3.6	2.0	2.0	2.0	4.7	2.1	5.0	3.0	1.8	2.6	2.8	5.3	3.6	2.1
Registered	5.6	7.8	8.3	2.5	4.5	4.4	4.9	---	---	---	5.7	1.9	5.9	3.0	1.7	2.6	2.8	5.3	3.7	2.2
Rule 144a	3.6	6.0	8.1	1.7	4.2	4.5	2.6	2.0	2.0	2.0	2.7	2.2	2.8	2.3	2.7	2.4	2.4	1.6	2.8	2.0

Legend: The population of instruments is all issues in the FINRA database up to February 29, 2012. We define traded instruments as having at least two opposite trades with customers at most two weeks apart over the relevant sample period. The sample period is from May 16, 2011 to February 29, 2012 (208 trading days).

Table 2: Mean Client Spreads by Trade Sizes

	Customer Bid-Ask Spreads				Customer Spread Percentiles				
	ABS	**CDO**	**CMBS**	**N-A CMO**		**ABS**	**CDO**	**CMBS**	**N-A CMO**
Overall	0.491	0.833	0.446	3.360	50th	0.077	0.161	0.141	2.997
	(0.010)	(0.056)	(0.013)	(0.016)	10th	-0.019	0.000	-0.556	0.126
Retail	1.185	2.668	1.644	3.978	50th	0.503	1.575	0.530	3.419
	(0.046)	(0.870)	(0.058)	(0.018)	10th	0.004	0.000	0.030	1.047
Non-Retail	0.416	0.810	0.322	2.787	50th	0.063	0.158	0.121	2.105
	(0.010)	(0.055)	(0.012)	(0.024)	10th	-0.025	0.000	-0.621	0.032
Diff. *F*-test *p*-value:	0.000	0.030	0.000	0.000					
Registered	0.539	---	0.425	3.454	50th	0.085	---	0.140	3.065
	(0.011)		(0.013)	(0.016)	10th	-0.009	---	-0.549	0.152
Retail	1.235	---	1.671	3.986	50th	0.559	---	0.538	3.422
	(0.048)		(0.059)	(0.018)	10th	0.005	---	0.030	1.083
Non-Retail	0.446	---	0.276	2.927	50th	0.066	---	0.115	2.372
	(0.011)		(0.012)	(0.026)	10th	-0.015	---	-0.625	0.066
Diff. *F*-test *p*-value:	0.000	---	0.000	0.000					
Rule 144a	0.325	0.833	0.563	0.901	50th	0.055	0.161	0.152	0.200
	(0.022)	(0.056)	(0.044)	(0.044)	10th	-0.084	0.000	-0.594	0.000
Retail	0.508	2.668	0.858	2.113	50th	0.154	1.575	0.229	0.562
	(0.136)	(0.870)	(0.218)	(0.259)	10th	0.000	0.000	0.031	0.000
Non-Retail	0.319	0.810	0.557	0.830	50th	0.051	0.158	0.151	0.192
	(0.023)	(0.055)	(0.045)	(0.044)	10th	-0.090	0.000	-0.606	0.000
Diff. *F*-test *p*-value:	0.168	0.030	0.174	0.000					
Reg.-Rule Difference *F*-test *p*-value:	0.000	---	0.003	0.000					

Legend: A retail trade corresponds to less than $100,000 of original par traded on both sides of trade with customers in each matched pair. *p*-values correspond to the null hypothesis that spreads are equal to zero. The sample is from May 16, 2011 to February 29, 2012. Standard errors are shown in parentheses. The median and the 10th percentile spreads are reported in the final four columns.

Table 3: The Interdealer Chain Lengths for Non-Retail Client Spreads

	ABS						CDO			CMBS		Non-Agency CMO					
The chain length	Auto	Card	ManH	SBA	Stud	Other	CDO	CBO	CLO	IO/PO	Other	IO/PO	PAC/TN	SEQ/PT	SUP/Z	Oth.SR	Other
Registered																	
Total # Matches	4,223	3,324	299	1,536	1,167	2,466				116	15,822	483	4,026	17,511	582	15,197	1,753
and total $ volume	*13.0B*	*17.1B*	*1.4B*	*3.4B*	*11.2B*	*7.5B*				*14.5B*	*70.1B*	*53.2B*	*6.9B*	*144.0B*	*0.8B*	*72.0B*	*5.0B*
1 dealer	3,052	2,168	240	826	729	1,400				83	10,716	332	1,612	11,093	198	8,146	780
% of matched volume	*85%*	*86%*	*95%*	*51%*	*84%*	*81%*				*80%*	*80%*	*91%*	*89%*	*92%*	*88%*	*88%*	*79%*
2 dealers	543	330	30	419	110	261				4	883	38	801	2184	144	2522	331
	9%	*6%*	*3%*	*26%*	*6%*	*4%*				*0%*	*3%*	*1%*	*5%*	*4%*	*7%*	*6%*	*11%*
3 dealers	105	85	4	146	61	146				2	509	39	832	1274	125	1071	310
	1%	*1%*	*0%*	*11%*	*2%*	*1%*				*2%*	*2%*	*1%*	*3%*	*1%*	*1%*	*1%*	*2%*
4 and more	18	18	9	20	19	60				4	162	22	62	438	57	589	38
	0%	*0%*	*0%*	*2%*	*0%*	*0%*				*4%*	*0%*	*0%*	*0%*	*0%*	*1%*	*0%*	*1%*
Average Length	1.22	1.22	1.23	1.55	1.32	1.40				1.22	1.21	1.44	1.81	1.41	2.10	1.54	1.74
Excl. Prearranged	*1.26*	*1.26*	*1.48*	*1.62*	*1.42*	*1.53*				*1.31*	*1.28*	*1.89*	*1.93*	*1.62*	*2.26*	*1.66*	*2.10*
Total Number of	3,718	2,601	283	1,411	919	1,867				93	12,270	431	3,307	14,989	524	12,328	1,459
Complete Matches	*96%*	*94%*	*99%*	*90%*	*92%*	*87%*				*85%*	*85%*	*94%*	*97%*	*97%*	*96%*	*95%*	*93%*
Rule 144a																	
Total # Matches	1,199	660	13	56	398	1,813	683	163	1,256	179	2,937	50	15	923	7	509	952
and total $ volume	*4.5B*	*3.7B*	*0.0B*	*0.2B*	*3.8B*	*21.8B*	*9.7B*	*1.0B*	*14.5B*	*21.7B*	*16.3B*	*6.0B*	*0.0B*	*9.9B*	*0.1B*	*5.6B*	*10.9B*
1 dealer	739	296	10	27	290	1,382	555	129	1,106	139	2,180	30	12	724	5	399	752
% of matched volume	*73%*	*52%*	*99%*	*49%*	*91%*	*90%*	*83%*	*90%*	*89%*	*83%*	*83%*	*52%*	*65%*	*85%*	*95%*	*86%*	*92%*
2 dealers	129	33	3	9	36	95	39	4	22	5	146	7	1	101	1	45	58
	12%	*4%*	*1%*	*8%*	*3%*	*2%*	*9%*	*2%*	*1%*	*0%*	*3%*	*18%*	*17%*	*3%*	*0%*	*4%*	*2%*
3 dealers	35	56	0	2	9	37	6	1	13	2	35	3	0	19	1	13	15
	1%	*8%*	*0%*	*2%*	*1%*	*1%*	*1%*	*0%*	*0%*	*0%*	*1%*	*17%*	*0%*	*1%*	*5%*	*1%*	*0%*
4 and more	9	12	0	1	7	11	0	1	3	0	17	0	1	5	0	0	3
	0%	*1%*	*0%*	*1%*	*0%*	*0%*	*0%*	*0%*	*0%*	*0%*	*0%*	*0%*	*10%*	*0%*	*0%*	*0%*	*0%*
Average Length	1.25	1.51	1.23	1.41	1.23	1.14	1.09	1.07	1.05	1.06	1.11	1.33	1.29	1.18	1.43	1.16	1.12
Excl. Prearranged	*1.31*	*1.54*	*1.00*	*1.37*	*1.32*	*1.22*	*1.17*	*1.10*	*1.10*	*1.06*	*1.16*	*1.35*	*1.33*	*1.30*	*1.50*	*1.24*	*1.25*
Total Number of	912	397	13	39	342	1,525	600	135	1,144	146	2,378	40	14	849	7	457	828
Complete Matches	*86%*	*65%*	*100%*	*60%*	*95%*	*93%*	*93%*	*93%*	*91%*	*83%*	*86%*	*87%*	*92%*	*89%*	*100%*	*91%*	*95%*

Legend: To show the lengths of trade chains we use the subset of complete client-to-client matches with matching dealer codes within the chain. For each such chain we report the number of participating dealers. All other matches include chains where dealer codes do not match.

Table 4: Definitions of Control Variables used in Regressions

	Variable Name	Description
Vintage	*4-6 Years Vintage Dummy*	Dummy variable equal to one when the time elapsed between the issuance date of the security and the trade date is between four and six years. The issuance date is the first coupon date or the first Moody's rating date.
	> 6 Years Vintage Dummy	Dummy variable equal to one when the time elapsed between the issuance date of the security and the trade date is greater than six years. The issuance date is the first coupon date or the first Moody's rating date.
Security Type	*Investment Grade Dummy*	Dummy variable equal to one when the credit rating of the security is above BBB level based either on Moody's rating or the credit rating provided by the FINRA reference bond dataset.
	Floating Coupon Dummy	Dummy variable equal to one when the security is flagged as a floating rate coupon type in the FINRA reference bond dataset.
	Number of Trades in Sample	The number of trading records for the security during the sample period including trades with customers and interdealer trades.
	Number of Dealers	The number of dealers participating either in interdealer or customer trading in the security during the sample period.
Volume	*Security Specific Average Match Volume*	The average log volume per trade for the security.
	Deviation of Match Volume from Average	The difference between the average log volume per trade for the security and the volume of a given trade.
Centrality	*Dealer Specific Importance Measure*	The number of dealers in the interdealer neighborhood of a given dealer (Definition 3.2).
	Dealers' Importance Dummy	Dummy variable equal to one when the number of dealers in the interdealer neighborhood of a given dealer (see Definition 3.2) is above the median number across all dealers for a given instrument category.
	Dealers' Coreness	The number of trade counterparties in the *k*-core sub-network that includes that dealer, where the *k*-core is the largest sub-network with all dealers having at least *k* trade counterparties.
	Dealers' Second-Order Neighbors	The number of trade counterparties a dealer's trade counterparties had during the sample period in the interdealer market.
Match Type	*Prearranged Pair of Trades*	Dummy variable equal to one when the time between the dealer's buy transaction and the dealer's matched sell transaction is less than 15 minutes.
	Number of Rounds	The number of links in the interdealer intermediation chain.
	Buy from Customer Dummy	Dummy variable equal to one when a dealer buys from a customer and sells to another dealer.
	Sell to Customer Dummy	Dummy variable equal to one when a dealer buys from another dealer and sells to a customer.

Table 5: Regression for Non-Retail Total Client Spreads

	ABS			CDO		CMBS			Non-Agency CMO		
	Overall	Reg.	R144a	CDO	CBO/L	Overall	Reg.	R144a	Overall	Reg.	R144a
Average Customer Spread:	*0.416*	*0.446*	*0.319*	*1.775*	*0.345*	*0.322*	*0.276*	*0.557*	*2.787*	*2.927*	*0.830*
4-6 Years Vintage Dummy	0.209	0.134	0.462	-0.929	-0.006	0.245	0.020	0.921	0.809	0.632	0.573
	(0.042)	(0.036)	(0.161)	(0.832)	(0.148)	(0.059)	(0.044)	(0.183)	(0.270)	(0.365)	(0.199)
> 6 Years Vintage Dummy	0.137	0.123	0.163	-0.985	0.182	0.103	-0.106	0.690	0.380	0.181	0.372
	(0.045)	(0.035)	(0.151)	(0.829)	(0.137)	(0.049)	(0.043)	(0.246)	(0.238)	(0.328)	(0.221)
Investment Grade Dummy	-0.198	-0.215	-0.125	-1.704	0.031	-0.355	-0.202	-0.645	-0.589	-0.542	-0.467
	(0.042)	(0.040)	(0.096)	(0.279)	(0.150)	(0.046)	(0.034)	(0.148)	(0.197)	(0.239)	(0.105)
Floating Coupon Dummy	0.106	0.100	0.084	-0.740	-0.317	0.167	0.073	0.036	0.626	0.677	-0.065
	(0.026)	(0.033)	(0.057)	(0.642)	(0.228)	(0.039)	(0.033)	(0.136)	(0.269)	(0.284)	(0.191)
Number of Trades in Sample	0.072	0.111	-0.005	-0.472	-0.013	0.019	-0.008	0.450	0.200	0.180	-0.018
	(0.017)	(0.026)	(0.049)	(0.321)	(0.130)	(0.018)	(0.018)	(0.187)	(0.105)	(0.108)	(0.072)
Number of Dealers	-0.121	-0.184	-0.049	0.325	-0.064	-0.190	-0.106	-0.697	-0.320	-0.323	-0.058
	(0.025)	(0.031)	(0.059)	(0.362)	(0.122)	(0.032)	(0.019)	(0.218)	(0.069)	(0.077)	(0.063)
Security Specific Average Match Volume	-0.280	-0.312	-0.131	-0.289	-0.082	-0.247	-0.228	-0.261	-1.538	-1.579	-0.076
	(0.026)	(0.030)	(0.049)	(0.149)	(0.063)	(0.044)	(0.034)	(0.162)	(0.136)	(0.145)	(0.114)
Deviation of Match Volume from Average	-0.163	-0.198	-0.049	-0.064	0.017	-0.173	-0.184	-0.129	-0.262	-0.256	-0.302
	(0.014)	(0.017)	(0.023)	(0.084)	(0.048)	(0.017)	(0.017)	(0.048)	(0.032)	(0.031)	(0.124)
Dealer Specific Importance Measure	-0.123	-0.108	-0.159	-0.516	-0.264	-0.140	-0.120	-0.210	-0.431	-0.431	-0.323
	(0.015)	(0.016)	(0.031)	(0.182)	(0.052)	(0.020)	(0.014)	(0.083)	(0.207)	(0.227)	(0.066)
*Interaction Term (Match Volume * Importance)*	0.098	0.109	0.063	0.007	0.004	0.115	0.116	0.106	0.039	0.050	-0.138
	(0.015)	(0.015)	(0.036)	(0.115)	(0.069)	(0.026)	(0.018)	(0.125)	(0.056)	(0.058)	(0.119)

Subcategory Fixed Effects: Yes. Additional Control Variables: Yes. Number of observations: 72529. R-squared: 0.394

Legend: The regression includes fixed-effects for each of the subcategories and placement types (Registered or Rule 144a) and additional control variables (changes from bid to ask trade): Moody's Baa credit spread, Slope of the Treasury Term Structure, TED Spread and Mortgage rate. Standard errors are reported in parentheses. Standard errors are clustered within trade settlement dates, instrument subcategory and placement type. The average non-retail client bid-ask spreads are shown in the first row for reference.

Table 6: Regression for Non-Retail Dealer Spreads Components

	ABS			CDO		CMBS			Non-Agency CMO		
	Overall	Reg.	R144a	CDO	CBO/L	Overall	Reg.	R144a	Overall	Reg.	R144a
Deviation of Match Volume if Central	-0.046 (0.009)	-0.060 (0.009)	-0.007 (0.022)	0.160 (0.105)	-0.016 (0.021)	-0.105 (0.012)	-0.113 (0.012)	-0.045 (0.037)	-0.200 (0.030)	-0.197 (0.029)	-0.304 (0.141)
Deviation of Match Volume if Peripheral	-0.079 (0.011)	-0.099 (0.011)	-0.017 (0.027)	-0.040 (0.135)	0.099 (0.052)	-0.075 (0.019)	-0.063 (0.011)	-0.113 (0.085)	-0.054 (0.019)	-0.055 (0.020)	-0.052 (0.042)
Dealers' Importance Dummy	-0.055 (0.025)	-0.068 (0.022)	-0.011 (0.075)	-0.190 (0.680)	-0.132 (0.155)	0.060 (0.035)	0.072 (0.029)	-0.147 (0.176)	-0.447 (0.096)	-0.373 (0.100)	-0.419 (0.193)
Dealers' Second-Order Neighbors	-0.073 (0.027)	-0.043 (0.032)	-0.142 (0.056)	-0.448 (0.592)	-0.209 (0.115)	-0.047 (0.037)	-0.024 (0.022)	-0.196 (0.200)	-0.006 (0.118)	0.020 (0.128)	-0.311 (0.116)
Dealers' Coreness	0.045 (0.028)	0.021 (0.031)	0.104 (0.062)	0.583 (0.512)	0.149 (0.113)	0.006 (0.030)	-0.022 (0.021)	0.188 (0.179)	0.177 (0.076)	0.151 (0.083)	0.436 (0.132)
Prearranged Pair of Trades if Central	-0.124 (0.031)	-0.071 (0.020)	-0.254 (0.104)	-1.032 (0.377)	-0.339 (0.105)	-0.117 (0.029)	-0.086 (0.024)	-0.396 (0.133)	-0.684 (0.074)	-0.665 (0.079)	-0.482 (0.143)
Prearranged Pair of Trades if Peripheral	-0.174 (0.031)	-0.195 (0.035)	-0.111 (0.074)	0.030 (0.454)	-0.044 (0.113)	-0.018 (0.041)	-0.002 (0.022)	-0.386 (0.222)	-0.681 (0.084)	-0.674 (0.086)	-0.214 (0.130)
Number of Rounds Central Dealer	-0.003 (0.015)	-0.030 (0.017)	0.055 (0.033)	0.328 (0.338)	0.010 (0.111)	0.074 (0.020)	0.055 (0.020)	-0.008 (0.090)	-0.035 (0.032)	-0.023 (0.033)	0.027 (0.100)
Number of Rounds Peripheral Dealer	-0.040 (0.011)	-0.054 (0.014)	-0.020 (0.018)	0.176 (0.295)	-0.035 (0.047)	0.040 (0.015)	0.014 (0.013)	0.043 (0.067)	-0.060 (0.036)	-0.063 (0.037)	-0.035 (0.046)
Central Dealer Buy from Customer	0.047 (0.057)	0.111 (0.067)	-0.133 (0.105)	-0.773 (0.979)	-0.237 (0.258)	-0.064 (0.062)	-0.053 (0.050)	0.220 (0.382)	0.113 (0.128)	0.029 (0.138)	0.327 (0.377)
Peripheral Dealer Buy from Customer	-0.020 (0.031)	-0.028 (0.032)	0.016 (0.084)	-0.466 (0.838)	-0.203 (0.161)	-0.171 (0.051)	-0.196 (0.037)	0.143 (0.294)	-0.439 (0.080)	-0.493 (0.085)	0.127 (0.199)
Central Dealer Sell to Customer	0.156 (0.038)	0.189 (0.047)	0.050 (0.066)	-0.766 (0.905)	-0.134 (0.231)	0.125 (0.045)	0.122 (0.042)	0.686 (0.297)	0.255 (0.084)	0.169 (0.089)	-0.082 (0.228)
Peripheral Dealer Sell to Customer	0.152 (0.038)	0.157 (0.042)	0.174 (0.092)	0.351 (0.783)	0.025 (0.157)	0.212 (0.071)	0.125 (0.043)	0.830 (0.423)	0.424 (0.083)	0.401 (0.088)	0.195 (0.156)

Subcategory Fixed Effects: Yes. Additional Control Variables: Yes. Number of observations: 86595. R-squared: 0.398

Legend: The regression includes fixed-effects for each of the subcategories and placement types (Registered or Rule 144a) and additional control variables (changes as well as levels): Moody's Baa credit spread, Slope of the Treasury Term Structure, TED Spread and Mortgage rate. Standard errors are reported in parentheses. Standard errors are clustered within trade settlement dates, instrument subcategory and placement type.

Table 7: Fixed-Effect Coefficients and Control Variables

Fixed-Effects (Non-Retail Total Client Spreads)

ABS				**CDO**		**CMBS**				**Non-Agency CMO**			
	Overall	Reg.	R144a		R144a		Overall	Reg.	R144a		Overall	Reg.	R144a
Auto	0.254	0.310	0.117	*CDO*	4.044	*IO/PO*	0.823	0.697	0.941	*IO/PO*	3.857	4.213	1.266
	(0.037)	(0.038)	(0.086)		(1.033)		(0.224)	(0.417)	(0.313)		(0.430)	(0.506)	(0.656)
Card	0.286	0.377	0.169	*CBO*	0.585	*Other*	0.331	0.386	0.530	*PAC/TN*	1.849	2.079	0.887
	(0.049)	(0.051)	(0.099)		(0.254)		(0.040)	(0.043)	(0.118)		(0.304)	(0.392)	(0.557)
ManH	1.208	1.320	-0.790	*CLO*	0.592					*SEQ/PT*	2.160	2.409	1.010
	(0.202)	(0.201)	(1.393)		(0.268)						(0.227)	(0.303)	(0.128)
SBA	0.704	0.765	0.574							*SUP/Z*	2.376	2.580	2.827
	(0.053)	(0.050)	(0.159)								(0.407)	(0.480)	(1.005)
Stud	0.629	0.798	0.212							*Oth.SR*	1.686	1.944	0.357
	(0.074)	(0.095)	(0.143)								(0.281)	(0.374)	(0.281)
Other	0.613	0.646	0.392							*Other*	1.951	2.500	0.774
	(0.055)	(0.045)	(0.125)								(0.548)	(0.843)	(0.222)

Control Coefficients

	ABS			**CDO**		**CMBS**			**Non-Agency CMO**		
	Overall	Reg.	R144a	CDO	CBO/L	Overall	Reg.	R144a	Overall	Reg.	R144a
Baa Credit Spread Changes	0.031	0.032	0.032	0.593	0.036	0.279	0.281	0.305	-0.948	-0.990	0.038
	(0.014)	(0.017)	(0.021)	(0.229)	(0.088)	(0.057)	(0.056)	(0.081)	(0.664)	(0.691)	(0.060)
Term Structure Slope Changes	0.022	0.031	-0.010	-0.332	-0.015	-0.039	-0.068	0.139	-0.201	-0.199	-0.040
	(0.016)	(0.018)	(0.029)	(0.172)	(0.064)	(0.045)	(0.044)	(0.084)	(0.126)	(0.131)	(0.095)
Liquidity TED Spread Changes	0.020	0.019	0.018	-0.026	0.230	0.051	0.046	0.030	0.442	0.447	0.108
	(0.016)	(0.021)	(0.025)	(0.131)	(0.111)	(0.040)	(0.041)	(0.093)	(0.175)	(0.179)	(0.072)
Mortgage Rate Changes	0.002	-0.013	0.058	0.594	-0.118	0.160	0.153	0.204	0.560	0.570	0.158
	(0.014)	(0.017)	(0.031)	(0.255)	(0.091)	(0.060)	(0.060)	(0.094)	(0.233)	(0.241)	(0.104)

Legend: The table shows fixed-effects coefficients from the non-retail total client spread regression presented in Table 5 for each of the subcategories and placement types (Registered or Rule 144a). Standard errors are reported in parentheses. Standard errors are clustered within trade settlement dates, instrument subcategory and placement type.

Table 8: Client Spreads Quantile Regressions

	ABS			CDO		CMBS			Non-Agency CMO		
Customer Spreads:	Overall	Reg.	R144a	CDO	CBO/L	Overall	Reg.	R144a	Overall	Reg.	R144a
St.Dev. Central	0.793	0.724	0.982	2.617	0.874	1.129	1.016	1.569	2.639	2.641	1.396
St.Dev. Peripheral	1.240	1.214	1.302	3.510	1.748	1.588	1.363	2.412	3.200	3.252	1.952
Quantile Regressions											
90% Quantile	-0.454	-0.483	-0.233	-2.478	-0.916	-0.318	-0.299	-0.473	-0.809	-0.724	-0.968
	(0.032)	(0.036)	(0.101)	(0.673)	(0.211)	(0.046)	(0.045)	(0.210)	(0.073)	(0.082)	(0.206)
50% Quantile	-0.073	-0.100	-0.038	-0.505	-0.146	-0.058	-0.057	-0.077	-0.071	-0.033	-0.213
	(0.006)	(0.009)	(0.008)	(0.158)	(0.021)	(0.007)	(0.007)	(0.025)	(0.021)	(0.021)	(0.036)
10% Quantile	-0.032	-0.030	-0.004	-0.356	0.006	0.020	0.013	-0.032	0.076	0.106	-0.021
	(0.005)	(0.005)	(0.026)	(0.188)	(0.139)	(0.037)	(0.037)	(0.104)	(0.019)	(0.024)	(0.030)

Coefficients on Dealer's Importance Dummy shown. Additional Control Variables: Yes.

Legend: The quantile regression includes additional control variables (changes from bid to ask trade): Moody's Baa credit spread, Slope of the Treasury Term Structure, TED Spread and Mortgage rate. Standard errors are reported in parentheses.

Table 9: Price Impact Regressions

Most-Traded Instruments:

	ABS			CDO		CMBS			Non-Agency CMO		
Variable: Δp_t	Overall	Reg.	R144a	CDO	CBO/L	Overall	Reg.	R144a	Overall	Reg.	R144a
Central Dealer Δq_t	-0.036 (0.016)	-0.068 (0.027)	-0.004 (0.015)	0.016 (0.089)	0.020 (0.059)	-0.061 (0.026)	-0.087 (0.032)	0.022 (0.022)	-0.285 (0.048)	-1.551 (0.196)	-0.004 (0.007)
Central Dealer Δq_t^* *Trade Innovation*	0.033 (0.023)	0.107 (0.041)	-0.035 (0.021)	-0.087 (0.127)	0.024 (0.100)	-0.006 (0.037)	0.001 (0.046)	-0.036 (0.032)	0.047 (0.068)	0.331 (0.237)	-0.022 (0.011)
Peripheral Dealer Δq_t	-0.117 (0.022)	-0.152 (0.036)	-0.067 (0.023)	-0.094 (0.092)	-0.161 (0.093)	-0.109 (0.034)	-0.142 (0.045)	-0.035 (0.026)	-0.464 (0.035)	-1.012 (0.054)	-0.028 (0.029)
Peripheral Dealer Δq_t^* *Trade Innovation*	-0.018 (0.031)	-0.041 (0.052)	0.000 (0.033)	0.226 (0.141)	0.232 (0.148)	0.060 (0.051)	0.062 (0.066)	0.042 (0.041)	0.041 (0.057)	0.129 (0.090)	-0.020 (0.047)

All Instruments:

	ABS			CDO		CMBS			Non-Agency CMO		
Variable: Δp_t	Overall	Reg.	R144a	CDO	CBO/L	Overall	Reg.	R144a	Overall	Reg.	R144a
Central Dealer Δq_t	-0.047 (0.040)	-0.058 (0.042)	-0.010 (0.103)	-0.083 (0.048)	-0.102 (0.036)	-0.034 (0.007)	-0.030 (0.007)	-0.059 (0.017)	-0.430 (0.009)	-0.470 (0.010)	-0.021 (0.028)
Central Dealer Δq_t^* *Trade Innovation*	0.053 (0.066)	0.093 (0.070)	-0.064 (0.163)	-0.057 (0.086)	0.085 (0.072)	-0.011 (0.011)	-0.023 (0.012)	0.056 (0.029)	0.106 (0.015)	0.122 (0.016)	-0.097 (0.051)
Peripheral Dealer Δq_t	-0.142 (0.009)	-0.149 (0.010)	-0.119 (0.019)	-0.366 (0.088)	-0.144 (0.045)	-0.108 (0.008)	-0.112 (0.008)	-0.085 (0.022)	-0.622 (0.009)	-0.657 (0.009)	-0.180 (0.031)
Peripheral Dealer Δq_t^* *Trade Innovation*	0.042 (0.014)	0.052 (0.016)	0.013 (0.029)	-0.010 (0.155)	-0.040 (0.079)	0.055 (0.013)	0.055 (0.014)	0.050 (0.035)	0.085 (0.015)	0.082 (0.015)	0.126 (0.053)

Legend: Trade indicator is defined as +1 for customer buy trades (an +2 for trades above \$100,000 current balance), -1 for customer sell trades (and -2 for trades above \$100,000 current balance), 0 for interdealer trades. In the regression Δq_t is the change in the value of the trade indicator from the last trade that occurred for this instrument ID when trades are sorted by the execution timestamp. Trade innovation is computed as the residual in the AR(1) estimation within each category of instruments.