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“Bid-Ask Spreads and the Pricing of Securitizations: 144a vs. Registered Securitizations”

by

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November 15, 2011

Revised December 24, 2013

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Our paper was prepared originally to provide feedback to the Financial Industry Regulatory Authority (FINRA). The data has been provided to us on a confidential basis by FINRA to facilitate analysis of securitization trading under opacity. We thank Allen Carrion, Alié Diagne, Kathleen Hanley, Steve Joachim, Dan Li, Pamela Moulton, Ola Persson, Michael Piwowar, Uday Rajan, Norman Schürhoff and participants at presentations at the EFA meetings, WFA meetings, CKGSB, University of Rochester, NBER Market Microstructure meeting, Federal Reserve Bank of New York, the Board of Governors of the Federal Reserve Bank, 8th Annual Central Bank Workshop on the Microstructure of Financial Markets at the Bank of Canada, Carnegie Mellon University, Tsinghua University and the Securities and Exchange Commission for helpful feedback.

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Abstract

Traditionally, various types of securitizations have traded in opaque markets. During May 2011 the Financial Industry Regulatory Authority (FINRA) began to *collect* transaction data from broker-dealers as an initial step towards increasing transparency and enhancing its understanding of these markets. Securitization markets are highly fragmented and opaque. We study the structure of the dealer network and how that is related to bid-ask spreads. Some dealers are relatively central in the network and trade with many other dealers, while many others are more peripheral. Central dealers receive relatively lower spreads than peripheral dealers. The customer spreads are relatively smaller for central dealers in Rule 144a than in Registered instruments. We also study the structure of the dealer-issuer network and how that is related to bid-ask spreads. Some issuers’ securitizations trade through few active dealers, having lower spreads for such transactions.

Keywords: Securitization; transparency; sophisticated investors; Rule 144a; network analysis

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 broker-dealers, which it regulates.[1] This was an initial step by FINRA to increase the transparency of these markets, as well as more directly a measure to enhance understanding of the markets.

We use the resulting sample of transaction data on securitizations to study dynamics of the transactions prices, spreads, and dealer and issuer network structure in the market for Registered and Rule 144a securitizations. Our empirical findings suggest a number of interesting results about the nature of trading in securitization markets. Fundamentally, there are a large number of securitizations, trading is very fragmented and there is relatively little trading in most individual instruments with many not trading at all in our sample. Some of the absolute spreads in the ABS, CDOs, CMBS and non-agency CMO markets are surprisingly large. The average spread for non-agency CMO instruments is 3.46% of the mid-quote for high-yield and 2.87% for investment grade instruments. The average spread for small-size matches in ABS instruments is 2.07% of the mid-quote for high-yield and 1.40% for investment grade instruments.

For ABS, CMBS and non-agency CMO instruments there is a volume discount with respect to the spread—larger volume matches lead to lower spreads than for smaller volume matches. That larger investors obtain better prices is reminiscent of one of the insights from the pricing of municipal

[1]FINRA's jurisdiction applies to broker-dealers, so under current FINRA rules all broker-dealers have been required to report trades undertaken by them, starting May 16, 2011.

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)).

We study the relationship between bid-ask spreads and a dealer's ability to access and participate in the interdealer market. Our results concerning the connection between the structure of the intermediary network and how it influences the nature of bid-ask spreads are especially informative. Of course, there are some intermediaries who are relatively central in the network and trade with many other dealers, while there are many others who are more tangential. We use network analysis to measure dealers' participation and their relative importance in the interdealer markets. We document a negative relationship between dealers' importance in the interdealer trading network and customer and dealer spreads for most types of securitizations.

More important dealers as measured by their centrality in the interdealer network receive relatively lower spreads. The finding could reflect greater competition by central dealers as they compete for order flow and cost efficiencies of the central dealers. The result is consistent with the equilibrium in a search-and-bargaining model of a decentralized interdealer market in which dealers differ in their trade execution efficiency to proxy for dealer centrality in Neklyudov (2013). In that model, the more connected dealers charge lower spreads because their endogenous reservation values reflect their search efficiency and more connected dealers intermediate trade flows among the less efficient dealers. Babus and Kondor (2013) model information asymmetry in a network model and show that more central dealers charge lower spreads because they are more efficient at information aggregation and thus they are less exposed to adverse selection.

Empirically, we find a more sensitive negative relationship between dealers' importance and bid-ask spreads for Rule 144a instruments than for Registered instruments. In the search-and-bargaining model the result is consistent with customers having higher bargaining power when negotiating with dealers in Rule 144a instruments than with dealers in Registered instruments.

We also study the relationship between issuers and dealers in a dealer-issuer trading network. Many issuers have few active dealers, with the transactions intermediated through those active dealers having lower average spreads.

In studying securitizations we examine data for both Registered instruments, which require detailed disclosures in the issuance process, and Rule 144a instruments, which exempt private resale of restricted instruments to QIBs (Qualified Institutional Buyers) from these disclosure requirements. We consider ABS ("Asset-Backed Securities"), CDOs ("Collateralized Debt (Bond/Loan) Obligations"), CMBS ("Commercial-Mortgage-Backed Securities") and CMO ("Collateralized Mortgage Obligations") instruments due to the presence of Rule 144a instruments and benchmark these against corresponding public (Registered) instruments in the ABS, CMBS and CMO cases.[2]

Preliminary to our statistical analysis we discuss the economics of Rule 144a. First, we emphasize that the use of Rule 144a is a choice by the issuer and that the nature of the choice is one in which the required disclosures are more limited than for Registered securitizations. The Rule 144a instruments experience a corresponding potential reduction in issuance cost and exemption from liability. These Rule 144a instruments are designed for sophisticated investors and the purchase of Rule 144a instruments would reflect self-selection on the part of the buyers, including recognition

[2] Since there are no Rule 144a instruments in the TBA and MBS categories, we have not used these in our benchmark analysis. Similarly, we also have excluded agency CMOs from our analysis, as these do not arise for 144a instruments. We also have limited our treatment of CDOs ("Collateralized Debt Obligations") as these are largely 144a instruments.

of the restrictions on re-trading for the Rule 144a instruments. This suggests relatively less interest ex post in trading the Rule 144a instruments since these are oriented to buy-and-hold investors, which can lead to higher effective spreads because of reduced liquidity. On the other hand, sophisticated investors, such as QIBs, may have enhanced bargaining power with dealers, leading to lower effective spreads. We provide a descriptive analysis of trading and spreads between the Rule 144a and Registered instruments. This does not reflect analysis of the endogenous choice of Rule 144a or Registration. 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 Rule 144a buyers have greater informational sophistication. Indeed, empirically within some asset classes Rule 144a securitizations have higher spreads than Registered securitizations, and within other asset classes Rule 144a securitizations have lower spreads than Registered securitizations. These may reflect in part substantial differences in the composition of Registered and Rule 144a markets.

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

Our sample contains the list of all ABS, CDOs, CMBS and non-agency CMO instruments overseen by FINRA and all trading activity in these instruments between May 16, 2011 and February 29, 2012. These data are a sequence of trade reports, providing the trade identifier, the execution timestamp and settlement date, the side of the reporting party—either the buy side or sell side, the entered volume of the trade measured in dollars of original par balance, and the entered 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. The Appendix provides additional details on the dataset and our data-cleaning procedures.[3]

Table 1 reports the total number of instruments in the population and the number of instruments traded with customers in the sample (these instruments had at least a buy from a customer and a sell to a customer at most 2 weeks apart). The population contains more Rule 144a than Registered ABS and CMBS instruments, and more Registered than Rule 144a CDOs and non-agency CMO instruments. One interpretation is that the selection effects for CDOs and non-agency CMO instruments are different compared to ABS and CMBS instruments. Many instruments traded only once in the sample period.

Across all categories Registered instruments are more likely to have a buy from a customer and a sell to a customer at most two weeks apart compared to Rule 144a instruments. Perhaps the higher frequency of trading in Registered instruments reflects that a larger number of traders can hold and trade Registered instruments than can hold and trade Rule 144a instruments, as well as ex ante selection associated with the difficulty of trading the Rule 144a instruments. It also may reflect that there are fewer disclosure requirements for Rule 144a instruments, so that potential investors have less public information about them and therefore, are reluctant to trade them due to adverse selection risk. We observe similar results within various categories of instruments.

[3] Within our sample period there was an interesting transparency event. About halfway through our sample (five months after the start) FINRA began to disseminate, in conjunction with IDC, daily price index data by collateral type. These informational releases provided the public more detailed information and transparency about valuations for various collateral types and indirectly, greater transparency about spreads and trading costs. This change in informational structure represents just a limited step towards full-blown transparency as it entails considerable aggregation across individual instruments in a category as well as daily rather than transaction level disclosure. We did examine spread differences before and after this informational change, but found only small effects of the transparency event relative to the underlying variability of the spreads.

Table 1 also reports additional summary statistics for ABS, CDOs, CMBS, and non-agency CMO instruments. We report how many instruments are investment grade or high yield,[4] how many instruments have fixed- or floating-rate coupons; indicator variables for the instruments' vintage—with vintage defined as the number of years between the trade execution date and the instrument's issue date; the instruments' average coupon rates, and the instruments' average factors. For many instruments, the principal balance can be reduced through amortization or prepayment; the factor represents the fraction of the original principal outstanding. In Table 2 we report the average number of trades per day, the average number of dealers active in each instrument, the average number of interdealer trades, and the distribution of trade sizes. We classify Retail-size trades as the ones with original par value transacted is less than $100,000. Registered instruments and Rule 144a instruments tend to have similar bond and trading characteristics for the various categories.

It is apparent from the trading frequencies reported in Table 2 that securitized products do not trade very frequently: For example, on average ABS instruments have 0.10 trades per day and CDOs have 0.03 trades per day. Registered instruments tend to have more trades on average than Rule 144a instruments: For example, registered ABS instruments have 0.11 trades per day, and Rule 144a ABS instruments have 0.07 trades per day. The distribution of trades across instruments is quite skewed: There are a few instruments with many trades per day, but most of the instruments in our sample do not trade very often. The trading frequency for CMBS instruments is similar to ABS and slightly larger than the frequency for non-agency CMO instruments.

For the ABS and CDOs instruments, retail-sized trades constitute the smallest fraction of total trades. There are more retail-sized trades in the Registered instruments than in the Rule 144a

[4] We classified unrated instruments as high yield rather than investment grade throughout the paper.

instruments.[5] Retail-sized trades constitute a much larger fraction of the trades in non-agency CMO instruments than in ABS instruments.

On average, there are 6.0 dealers who traded in an average ABS security, with even fewer dealers in other types of instruments. Typically there are more active dealers trading Registered instruments than trading Rule 144a instruments.

We use the collateral type to categorize ABS instruments. We split the CDOs into CDO instruments, CLO instruments and CBO instruments. We use the tranche type to categorize CMBS and CMO instruments. Table 3 reports descriptive statistics for the subcategories.

Figure 1 depicts the kernel density function of the number of distinct customer-dealer and interdealer transactions (conditional on that number being positive) in the entire sample, truncating the plot at the 95th percentile of the distribution. In the top left panel we show ABS instruments , in the bottom left panel we plot CMBS instruments, in the top right panel we plot CDOs, and in the bottom right panel we plot non-agency CMO instruments. These plots and the 95th percentiles illustrate that there are not many trades in individual instruments, with especially limited trading in the Rule l44a instruments. Though we truncate from these plots those instruments with the largest number of trading records to improve the display of this density, we note that these truncated observations are potentially the most important because they correspond to the largest number of trading records and provide the most information for estimating spreads.

Figures 2a through 2d illustrate the nature of trading activity in our sample. In the figures, we provide several examples of Registered and Rule 144a instruments that are highly traded. The left

[5]Only a tiny fraction of the trade in Rule 144a instruments is retail sized (less than $100,000 of original par volume). We would not expect substantial retail activity in these instruments, so the small matches may reflect in part order splitting by larger investors.

panel depicts the interdealer network and the right panel depicts transactional prices. Each node of the network represents a dealer and every edge represents the occurrence of trading behavior between two dealers with the darkness of a link proportional to the volume. There are three subpanels within each panel—the upper subpanel shows buy and sell transactions by volumes during our sample period, the middle subpanel shows the corresponding interdealer trades by volumes and the bottom subpanel shows the corresponding transaction prices (ask, bid and interdealer) during our sample period. The network figures illustrate the heterogeneity in dealers' importance and that important dealers tend to interact with one another.

The limited extent of trading highlighted by the figures illustrates some of the conceptual difficulty in estimating spreads and the importance of using matching methods, especially for less actively traded instruments. The figures illustrate the potential importance of interdealer transactions in reallocating inventory and exposures and matching buy and sell transactions at the aggregate or market level. The bottom subpanels of the plots illustrate the positive nature of the bid-ask spread and that in some situations with relatively active instruments that the bid-ask spreads can nevertheless be quite substantial. The interdealer trades do not always lie between the customer buy and sell trades.

In many situations dealers are potentially buying or selling from existing inventory, but the nature of our data does not provide direct information identifying the initial inventory. Of course, in some cases the matching may be relatively apparent—but in most situations we only have a limited set of matches at a daily level and therefore, we consider broader matching criteria. Indeed, in at least some situations there are considerable imbalances in trading with customers and dealer reliance on trading from pre-existing inventory.

We use the proprietary list of CUSIPs provided by FINRA to data on ratings provided by Moody's for all instruments that have at least a buy from a customer and a sell to a customer at most 2 weeks apart in our sample period from May 16, 2011 to February 29, 2012. Among ABS, CMBS, Rule 144a CDOs and non-agency CMOs there were 20,392 such instruments. 15,216 of these instruments have been rated by Moody's, for other instruments the Moody's ratings were not available (539 instruments were rated "NR", others had missing Moody's ratings). When the Moody's rating is missing, we use the information on whether the instrument is high yield or investment grade provided by FINRA.

Figure 3 summarizes the distribution of the first rating observed within our sample period per security. We observe differences in rating levels for instruments traded in our sample, with relatively frequent high-grade ratings in ABS and CMBS instruments. We examined changes in ratings. Rating upgrades and downgrades crossing the investment grade boundary are relatively infrequent in our sample period. There were more downgrades than upgrades (149 upgrades and 272 downgrades crossing the investment grade boundary); interestingly, CDOs were mostly upgraded in our sample.

3. Bid-Ask Spreads

We use a multi-stage matching technique to disentangle trading activity in each instrument and organize related trades into chains of transactions. Each chain captures the movement of a particular block of volume from a customer to the interdealer network, within the interdealer network, and from the dealer network back to the customer sector. To perform sorting of this nature, we first match related interdealer and customer transactions that have the same volume moving from one party to another in a particular instrument. Second, we look for chains of transactions that may have different volume traded and thus involve volume splits as the security moves from one party to another.[6] Each chain has one buy from customer and one sell to customer, as well as several rounds of intermediation between dealers. A large part of the resulting sample has just one round of dealer intermediation. We are able to disentangle 75% of the total absolute turnover in ABS market, 86% in the CDOs market, 74% in CMBS market, and 80% in non-agency CMO market into complete chains that we use to compute total customer bid-ask spreads.[7] The rest of the turnover in these markets corresponds to: imbalanced trades with no pair of opposite trades with customers: a buy from customer and a sell to customer within a two-week horizon and broken chains that do not link buy from a customer with a sell to customer based on the same dealer mask.

For each chain of transactions we compute the total client bid-ask spread by using a buy price from a customer and a sell price to a customer, ignoring any dealer-to-dealer intermediation rounds in between. We also compute a dealer-specific spread for each inter-dealer transaction in that chain. The total client bid-ask spread for a chain is a weighted sum of dealer-specific spreads corresponding to that chain. We adjust the resulting spreads for accrued interest and factor prepayments.[8]

For each resulting spread observation we have information on how many rounds of intermediation occurred between the two customer transactions and whether the sequence of trades is likely to be prearranged in advance, the time gap between a buy from a customer and a sell to a customer or vice versa, trade volumes, and whether any volume splitting occurred. Few of the resulting spread observations are extreme due to price data entry errors. We remove such observations from the final sample by winsorizing the upper and lower tails of spread distributions within each of the four

[6] We provide additional details on the matching algorithm we use in the Appendix.
[7] We use information on dealer masks to relate different trade reports with each other and construct chains of transactions.
[8] We present detailed discussion of these adjustments in the Appendix.

types of instruments (ABS, CDO, CMBS, and non-agency CMO), two placement types (Registered and Rule 144a, except for CDOs category) and credit quality (investment grade and high yield). In total we modify 2% of extreme observations, controlling for major categories and subtypes.

Table 4 reports mean client bid-ask spreads computed as a percentage of the average bid and ask prices for the ABS, CDO, CMBS and non-agency CMO categories, for Registered and Rule 144a instruments. Dealers may possess potential bargaining advantages with respect to retail-sized trading, thus retail-sized trades may face especially large spreads. For this reason we distinguish spreads among trades of different sizes and adjust for differences in the trade-size composition within different types of instruments. We define a retail-size spread to be the bid-ask spread resulting from two opposite trades both having volume less than $100,000 of par balance. We refer to all other spread observations as non-retail since they result from paired trades of larger volumes.

The first four columns of the table report means and associated standard errors for the spreads for the four different types of instruments: ABS, CDOs, CMBS, and non-agency CMO. The table reports the differences in the average spreads for retail-sized and non-retail-sized trades for the different categories, along with standard errors and the F-test for equality of the average spreads between retail and non-retail sized trades. The top panel of the table reports overall spreads across categories; the second panel reports the spreads for Registered instruments; the third panel reports the spreads for the Rule 144a instruments; and the final panel reports F-tests for differences in spreads between Registered and Rule 144a instruments.

The final four columns of Table 4 report the median—the 50th percentile, and the 10th percentile of the spread distribution for each of the four categories of instruments. Across all categories the mean spread is higher than the median spread, indicating that the spread distributions are skewed to the right—there are some large spreads in all categories. The 10th percentile of the spread distribution for non-retail size transactions is zero or negative for all types of instruments, indicating that dealers sometimes have holding period losses on such transactions.

Perhaps the most striking result reported in Table 4 is the difference in spreads between retail-size and other-size trades. For all categories, retail-size spreads are significantly larger than other-size transactions. In general we confirm the finding from other fixed-income markets that retail-size trades tend to have significantly higher spreads than institutional-size transactions.

We also compare spreads across instrument types. Overall spreads are the largest for non-agency CMO instruments and overall spreads are the smallest for CMBS instruments. Average spreads are higher for Registered instruments than for Rule 144a instruments, with an exception of CMBS instruments—average spreads are lower for Registered CMBS instruments than for Rule 144a CMBS instruments. Perhaps the differences between the relative spreads for Registered and Rule 144a instruments across instrument types reflect selection effects, or that the customers in Rule 144a instruments are more sophisticated than the customers in Registered instruments.

Only sophisticated investors can hold Rule 144a instruments, while both sophisticated and unsophisticated investors can hold Registered instruments. Rule 144a instruments have a smaller pool of potential owners, so that the market for Rule 144a may be more limited. Our finding that many types of Rule 144a instruments have smaller spreads than Registered instruments may reflect that sophisticated investors face lower transactions costs than unsophisticated investors. Registered non-agency CMO instruments have significantly higher average and median spreads than Rule 144a non-agency CMO instruments. Perhaps the lower spread for Rule 144a instruments relative to Registered instruments in these categories reflects that more sophisticated investors are trading the

Rule 144a non-agency CMOs than the Registered non-agency CMOs and more sophisticated investors have greater bargaining power when trading with dealers than less sophisticated investors.

In order to study the importance of the underlying collateral to the spreads, Table 6 reports non-retail spreads for different types of instrument subcategories based on collateral and tranche type. We report the average spreads for overall trade, for Registered and Rule 144a instruments, and by rating. Overall and across all collateral types, Registered ABS instruments have higher average spreads than Rule 144a instruments. Registered ABS instruments of most collateral types have higher average spreads than Rule 144a instruments. Rule 144a CMBS have higher average spreads than Registered CMBS, and Registered non-agency CMO instruments have higher average spreads than Rule 144a non-agency CMO instruments. For all tranche types of non-agency CMO instruments except support tranches and Z-tranches (SUP/Z), Registered CMO instruments have higher average spreads than Rule 144a instruments although there are few Rule 144a SUP/Z instruments.

In most subcategories, High Yield instruments have higher average spreads than Investment Grade instruments. The bottom panel of Table 6 reports p-values of the F-test for the null hypothesis that investment grade and high yield instruments have the same spreads across different collateral types. For the majority of collateral types, the difference between average spreads is statistically significant: High yield instruments have wider average spreads than investment grade instruments in all categories.

Goldstein, Hotchkiss and Sirri (2007) provide estimates of spreads on BBB-rated corporate bonds after the introduction of the TRACE system in 2002. They compute a round-trip spread measure similar in spirit to our measures. Table 6 in their paper reports average spreads for different trade sizes. We can compare our estimated average spreads to the spreads reported by Goldstein, Hotchkiss and Sirri (2007). They report the mean spread in Panel A in Table 6 for different transactions sizes computed using a LIFO method[9] with transactions size measured in the number of $100 face value bonds. The mean spread reported in their Table 6 ranges from $2.37 per $100 of face value for transactions of less than or equal to 10 bonds, to $1.96 per $100 of face for transactions between 21 and 50 bonds, to $0.56 per $100 of face for institutional-size transactions over 1,000 bonds. From Table 4 in our study, our estimates of the retail and non-retail sized spreads are approximately the same order of magnitude as those in the post-transparency corporate bond sample for all categories, except for non-agency CMOs. In our sample, non-agency CMO instruments have larger spreads than in the post transparency sample.

We also compare the non-retail spreads reported in Table 4 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 4 tend to be smaller than the spreads in the corporate bond market for institutional-sized trades. The spreads for Rule 144a instruments in Table 4 tend to be larger than institutional sized trades reported for the corporate bond market; instead the spreads for Rule 144a instruments are similar to spreads for trade sizes of 51-100 bonds in the corporate bond market.

4. Network Analysis

Our sample allows us to recover the interdealer trading network and the dealer-issuer network. We focus on the structure of these networks and the nature of the competition on these markets, the services provided by different intermediaries and the relative importance of different dealers for

[9] Goldstein, Hotchkiss and Sirri (2007) compute spreads matching the trade by dealer while we compute the spread aggregating over all dealers. Our spread measures are computed as a percentage of average trade prices, while their approach is dollars per unit of par. Both calculations should produce similar sized spreads as a first approximation, since the corporate bonds should have been trading close to the order of their par values.

these markets. We describe the cross-sectional differences in trading costs and the division of these costs among participating dealers in different networks.

4.1. Interdealer Networks

In the sample of trade records from May 16, 2011 to February 29, 2012 we observe 679 dealers, of which 664 dealers participated at least once in interdealer trading—370 in ABS, 174 in CDOs, 293 in CMBS, and 556 in CMO—implying that many dealers participate in several markets. On average each dealer participated in 64 interdealer trades in ABS market, 18 interdealer trades in CDOs, 71 interdealer trades in CMBS, and 153 interdealer trades in non-agency CMO, either as a seller or a buyer. Over the sample, an average dealer transacted \$436 million of original balance on interdealer market in ABS, \$335 million in CDOs, \$959 million in CMBS, and \$842 million in CMO.

Dealers are heterogeneous both in terms of their trading with customers and interdealer market participation. Figure 4 presents the Lorenz curves computed using dealers' shares of the original order balance with customers for ABS, CDOs, CMBS and non-agency CMO, and the two placement types. We observe heterogeneity of dealers in terms of total volume traded with customers. A small number of dealers account for a major fraction of customer volume in all markets and for both placement types. There is a noticeable dispersion and skewness in interdealer market participation by different dealers. The order flow is more evenly divided among dealers in Rule 144a markets than in Registered markets.

From May 16, 2011 to February 29, 2012 a median dealer participated in 11 interdealer transactions and transacted in total \$8.9 million, while the 75th percentile of interdealer trade participation by a dealer is 83 transactions in the sample and transacted \$233 million of original balance. Some links between different pairs of dealers are stronger than others, and some dealers have higher levels of importance to the functioning of the interdealer market and act as the key providers of interdealer liquidity.

Figure 5 summarizes the topology of the grand interdealer market for all products. We include links between two dealers when more than 50 trade reports were observed in the overall sample and more than $10 million of current balance in total was transacted during the sample period. Links with more than $100 million transacted are shown as solid lines.

The four broad markets we analyze are significantly interconnected. Individual dealers often participate in different markets at the same time. Some interdealer markets are generally more active than others in terms of number of interdealer trade records with the non-agency CMO market particularly active. For these reasons we measure dealers' activity in different instruments separately, then following Li and Schürhoff (2012) and Milbourn (2003), we perform normalizations of the resulting measures to preserve information on dealers' ranks in the network. For the purpose of our empirical analysis we follow two alternative methodologies. In the first methodology we construct a single aggregate proxy for dealer-specific importance on the interdealer market from a principal component analysis. In the second methodology for each dealer and each submarket we measure coreness and degree centrality, and use the relationship between the two variables to describe dealers' relative position in the network and resulting bargaining power.

We measure the relationship between dealers by their interdealer trade. In our first empirical methodology we compute the following centrality measures for each dealer:

Degree centrality is defined as the number of closest neighboring dealers around a particular dealer in the network.

Eigenvector centrality is computed using eigenvalues of the adjacency matrix (matrix describing links between dealers in the network), for each particular dealer it emphasizes connections with relatively more important dealers of the network.

Betweenness centrality is equal to the total number of shortest trading paths from every single dealer to any potential counterparty that passes through this particular dealer.[10]

Closeness measure is defined as the inverse of the total distance from each particular dealer to any other dealer in the network based on observed trading relationships.

Degree centrality is a local property taking into account only the closest sub-network of a dealer's neighbors, while eigenvector centrality or betweenness centrality account for the global structure, and across different markets (e.g., some dealers are relatively more active in Registered ABS than Rule 144a non-agency CMO). Li and Schürhoff (2012) explore all of these alternative centrality measures in the context of municipal bond trading and demonstrate a significant common component in these measures. We obtain similar results in our sample.

We divide all interdealer trades between May 16, 2011 and February 29, 2012 for the overall sample into seven buckets based on the four types of instruments (ABS, CDOs, CMBS, and non-agency CMO) and two placement types—Registered and Rule 144a. Within each bucket we compute the total volume transacted by all pairs of dealers and compute the four centrality measures described above.

[10] The betweenness centrality measure is a widely used tool in the literature on social networks (Freeman, Linton, "A Set of Measures of Centrality Based upon Betweenness", 1977, Sociometry 40, 35–41).

All of the measures are estimated for each dealer, and the first two of these measures allow us to differently weight the links between dealers based on total volume traded over the particular sample period. We differentiate between buys from and sells to a particular dealer in the interdealer network and so we compute directed networks. We apply the empirical cumulative-density function transformation to each of the six centrality measures obtained, and then extract the first principal component. For each of the seven buckets we have two versions of the dealers' importance—unweighted and weighted by total volume transacted within each market. We perform principal component analysis separately for these two versions to aggregate across different markets. In our empirical analysis we use the measure weighted by total volume transacted, with the correlation between the weighted and unweighted versions equal 0.98. We linearly normalize the resulting variable to a zero-to-one scale. Dealers that did not participate in interdealer trades are assigned zero centrality value. In our analysis of total client bid-ask spreads we use the average dealer centrality variable, which is the average aggregate centrality measure of all dealers that intermediated in a particular chain of matched transactions.

Overall we find evidence for a negative relationship between dealers' interdealer activity measured by aggregate centrality and total client bid-ask spreads. Dealers who participate more actively in the interdealer market have lower inventory risk and may require lower compensation for their services. But these dealers may be generally more visible to other market participants and have a certain degree of market power—in this case we expect these dealers to charge higher compensation through customers' bid-ask spreads. Under the second methodology for each dealer we compute two measures:

Coreness measure 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 a particular dealer participates in 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.

Coreness-Degree Residual is defined as the difference between dealer's degree centrality and dealer's coreness.

A dealer's Degree Centrality is always larger than the dealer's Coreness. Higher Degree Centrality relative to the Coreness means that the dealer is more important as an intermediary between different groups of dealers, because the dealer is bridging different smaller sub-networks. The Coreness-Degree Residual therefore measures the relative importance of a dealer in the sub-network, and is a proxy for the dealer's local bargaining power.

We present graphical illustrations of two different scenarios for dealer's coreness and Coreness-Degree residual in Figure 6. The figure shows sub-networks constructed using the ABS Registered market within the overall network presented in Figure 5, with a relaxed restriction on what constitutes a strong link—we do not require the volume transacted between two parties to be above $10 million in total. On the left panel the dealer with 7 trading partners in the sub-network is shown. The second order neighborhood of that dealer is shown. That dealer's coreness is 2, meaning that the largest sub-network that this dealer participates in has all dealers with at least 2 trading partners in this sub-network.

In the Registered ABS sample of interdealer trades the maximum coreness is 4 and there are a few dealers with coreness of 4. The dealers corresponding to the 4-core sub-network are the set of most important and frequent counterparties for the dealer with 23 partners. This dealer has links to other sub-networks as well and performs the role of a "bridge" across different parts of the interdealer market. There is also another dealer with degree 4, which is the same as its coreness—the weakest node in the 4-core sub-network. The Coreness-Degree residual captures this relative difference in dealer's local positions.

A single centrality measure cannot capture these relative differences in dealers' positions. Two dealers may have similar numbers of trading partners; however, differences in their coreness may result in different bargaining power between the dealers. A dealer with coreness similar to the degree centrality will be the least connected dealer in the main k-core sub-network he belongs to. On the other hand a dealer with coreness much smaller than degree centrality will have the strongest outside options. We perform empirical analysis based on these two measures of dealers' standing in the network and for some of our markets we find their effects having different directions on bid-ask spreads. Figures 7a and 7b plot the dealers' degree vs. dealers' coreness. In general, dealers with higher coreness also have higher degree centrality and those with the highest coreness have the largest variation in degree.

Figures 8a and 8b show the total order flow with customers plotted against interdealer order flow for all participating dealers. We observe that more active dealers in terms of order flow tend to have more customer activity than interdealer activity, while for less active dealers the pattern is reversed. Moreover, many dealers have identical customer and interdealer order flows, indicating that these dealers only transact when they can intermediate between another dealer and a customer. Some other dealers specialize in either only intermediating between a pair of customers or only intermediating between a pair of other dealers.

Dealers with a greater number of counterparties on the interdealer market, measured by the degree centrality, tend to have lower volume imbalances. The top-left panel of Figure 9 shows a scatterplot of different dealers' degree centrality against the interdealer volume imbalance measured as logarithm of the ratio between total volume bought on the interdealer market and total volume sold on the interdealer market. The top-right panel of Figure 9 shows similar results for customer volume imbalances, measured using total volume bought from outside customers and total volume sold to the outside customers. Each dot represents a dealer-market observation, where dealers in different submarkets are always considered as different dealers. These results suggest that more central dealers on the interdealer network are more successful at managing their inventory and are able to match opposite trades efficiently both on the interdealer market and with outside customers.

4.2. Dealer-Issuer Networks

In order to characterize and study the extent of dealer intermediation activity in various instruments, we group instruments that have a common issuer and analyze how dealers' activity is spread across different issuers. We construct the dealer-issuer networks, where dealers and issuers are the nodes of the network, and the substantial extent of trading activity by a particular dealer within one group of instruments is captured as a link between a dealer and an issuer. These networks allow us to study in which products dealers tend to concentrate their intermediation activity among small groups of instruments and whether such concentration is associated with higher transaction costs for customers.

The first six characters of the nine-character CUSIP number uniquely identify the issuer of the instrument. It may be that a single large-scale issuer is comprised of several different legal entities with similar names, which might have slight differences in the way they are coded in the base of the CUSIP number. Thus for the purpose of our analysis we use the first five rather than six characters of the CUSIP number to group together instruments that were originated by a common issuer. Instruments with the same first five characters of the CUSIP number are more likely to have the same economic entity as the issuer, while instruments with different first five characters are more likely to be originated by different economic entities.

In our dealer-issuer networks a dealer is linked to an issuer when the extent of trading activity with customers for this dealer is substantial both in total volume transacted and number of days in the sample these transactions occurred. Within each product type we define an active link between a dealer and an issuer as the one that satisfies the following conditions: First, the total volume transacted by the dealer in instruments of the issuer is above the median volume across all such pairs on the market. Second, the number of days transactions occurred is above 95th percentile across all dealer-issuer pairs in the market. We illustrate the dealer-issuer network topologies for ABS Registered and Rule 144a instruments on Figure 10, and provide descriptive statistics on the dealer-issuer network topologies in Table 5.

Figure 10 demonstrates the heterogeneity of dealers on ABS markets and some common patterns that are typically observed in our dealer-issuer networks. Some dealers provide intermediation services to many more different issuers than other dealers. Some issuers have one single dealer who is actively trading with customers, while other issuers are connected to a few dealers. To control for differences across different instruments, we construct individual topology for each of the product subcategories and separately for Registered and Rule 144a instruments. We report number of nodes in the network of dealers and issuers, and the average and maximum observed number of links in Table 5.

The first column of Table 5 shows the total volume of customer activity for all active dealer-issuer links in the network for each type of instrument, both in dollars and as a percentage of the total overall customer activity that includes both active and infrequent and non-recurring links. In some markets, active links account for a much larger portion of total customer volume; these include Rule 144a credit-card ABS, Registered manufactured housing ABS, both types of SBA ABS, and to a lesser extent Rule 144a P/I CMBS instruments. In all other markets a significant proportion of customer volume is in the inactive part of the market. The second and third columns of Table 5 report the numbers of dealers and issuers that participate in the active part of the market, and the percentages of the total numbers of dealers and issuers on each market. Approximately 10% of dealers and 15% of issuers are in the active part of each market, although these proportions vary across markets.

The last two columns of Table 5 report the maximum and the average number of links per dealer and per issuer. In auto-loans ABS Registered instruments an average active dealer provides active intermediation services to 3 issuers, while there is a most-connected dealer who provides services to 6 issuers. The table demonstrates the heterogeneity of dealers and issuers in Figure 10 for the majority of product types in our sample.

5. Regression Analysis

Table 7 provides the definitions of the right-hand-side variables we use in the regression analysis. The dependent variable is the bid-ask spread, with one observation per pair of matched trades in the sample. We allow the regression slope coefficients to be different across categories of instruments and placement types. We also include fixed effects for each of the six different collateral types of ABS issues, 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 define as subcategories. We combine CBO and CLO in a single category. We cluster standard errors within trade settlement dates, instrument subcategory and placement type.[11]

We also perform analysis of overall categories without differentiating between Registered and Rule 144a security types. We pool together Registered and Rule 144a instruments and obtain overall marginal effects of the aforementioned factors.

Table 8 reports the results from the regressions for the total client spreads. The total client spreads are computed using the complete customer-to-customer chains of matched transactions. 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 the Rule 144a instruments.

The point estimates of the coefficients on 4-6 Year Vintage and >6 Year Vintage are positive for all types of instruments except CDOs: Older maturity instruments tend to have higher spreads, reflecting their lack of trade, and also the possibility that there is more asymmetric information about these instruments. Across all categories of instruments, except the CBO and CLO group, the point estimate on the Investment Grade is negative and economically significant: High yield instruments tend to have higher spreads than Investment Grade instruments.

The point estimate of the coefficient on Security-Specific Match Volume is negative for all categories except the Rule 144a CMBS. A negative coefficient on Security-Specific Volume indicates that instruments with larger trades tend to have small spreads, consistent with more actively-traded instruments having lower transactions costs.

[11] We also experiment by including fixed effects for individual instruments. Our main results are robust to the presence of individual instrument fixed effects.

Deviation of a Particular Match is the transaction size of the matched transaction relative to the average transaction size in that security. The point estimates are negative across all types of instruments, except CDOs where it is positive but not significant. A negative coefficient on Deviation of Particular Match indicates that when the matched trade is larger than typical 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 usual explanation that larger trades carry information so that dealers face higher adverse selection costs on larger trades, as in Babus and Kondor (2013). In many bond markets, smaller trades have larger spreads, with the typical 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. The securitized markets we analyze resemble bond markets with respect to the effects of volume on spreads. The negative relation between match volume and spreads suggests that adverse selection is less important than bargaining effects in determining the spreads in the securitized market.

The effect of Floating Coupon is positive for all ABS instruments, Registered CMBS instruments and Registered CMO instruments: For these categories, instruments with floating coupons tend to have higher spreads. For CDO, CBO/CLO, Rule 144a CMBS, and Rule 144a CMO instruments floating coupon instruments tend to have lower spreads, but not statistically significantly lower. Generally the point estimates on Investment Grade and Floating Coupon imply that instruments with riskier cash flows tend to have higher spreads.

The coefficients on Number of Dealers are of mixed magnitude and sign and economically small and largely statistically insignificant: Perhaps the mixed results on Number of Dealers indicate that the choice of the Number of Dealers in an instrument is endogenous to the size of the spread that the dealers can earn.

The point estimate on the Prearranged Pair of Customer Trades dummy is negative and generally statistically significant. A negative coefficient on the Prearranged Pair of Customer Trades dummy implies that the average spread is lower when the buy from a customer and the sell to a customer in a given intermediation chain occur with less than 15 minutes gap in execution time. We refer to such transactions as prearranged pairs of trades with customers, where dealers were able to locate relatively quickly a customer willing to take the opposite side of the trade. Our results indicate that dealers tend to offer discounts on customer trades when they are able to execute the trade on the opposite side quicker.

In our regression we include two interaction terms: An interaction of Dealer Importance Dummy with the Prearranged Pair of Customer Trades dummy, and an interaction of Dealer Importance Dummy with All Other Trades dummy. The point estimates on both interaction terms are negative and generally statistically significant, and the point estimate on the interaction of Dealer Importance Dummy with All Other Trades dummy is larger in magnitude. These results imply that the average spread is lower if the inventory passes through a dealer who is more active in the inter-dealer network, both for the prearranged trades and all other trades in our sample. The relative benefits for customers to have orders intermediated by central dealers rather than peripheral dealers are greater for trades that are not prearranged and thus are more difficult for dealers to intermediate.

The coefficients for Rule 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 Rule 144a markets. The finding that the negative relationship between dealers' importance and bid-ask spreads is steeper for Rule 144a instruments than for Registered instruments and the average bid-ask spreads in Rule 144a instruments are lower than in Registered instruments. In the search and bargaining model in Neklyudov (2013), these empirical results are consistent with customers having greater bargaining power when negotiating with dealers in Rule 144a instruments than in Registered instruments.

The point estimate on Through Single Active Dealer for the Issuer dummy is negative except for the CDOs category. The point estimate on the Through One of Many Active Dealers for the Issuer dummy is also negative except for CDO instruments and Rule 144a CMBS instruments. These negative coefficients imply that deals that pass an active dealer in a given issuer tend to have lower spreads that for not active dealers. The result holds in either case whether such a dealer is the only one active or one of several active dealers for that particular issuer. In this sense, stronger and more established relationships between a dealer and an issuer are associated with lower costs to customers. Frequent and significant trading by dealers in instruments with a given issuer tends to reduce transaction costs for customers.

Table 9 reports the results from regressions for the dealer spreads. The spreads used in the regression result from decomposing the total client spreads used in Table 8 into individual dealer spreads. For example, the two round chain: Customer to Dealer A, Dealer A to Dealer B and Dealer B to Customer yields two dealer spreads. The first spread is computed from Dealer A's purchase price from the customer and Dealer A's sale price to Dealer B, and the second spread is computed from Dealer B's purchase price from Dealer A and Dealer B's sale price to the customer. If N dealers intermediate a chain between customers, then we compute N dealer spreads.

Overall, we find similar effects of the control variables as in the total client spread regressions reported in Table 8, and we include additional control variables: interactions of Dealer's Coreness with Prearranged Pair of Trades dummy and All Other Trades dummy, Dealer's Degree Residual, and the two customer participation dummies—Buy from Customer and Sell to Dealer, Sell to Customer and Buy from Dealer.

Similar to our result for total customer spreads in Table 8, the point estimate on Prearranged Pair of Trades is negative and is economically and statistically significant for all categories. Our results indicate that dealers tend to offer discounts both to customers and to other dealers when they are able to execute the trade on the opposite side quicker.

The point estimate on the interaction of Dealer's Coreness and Prearranged Pair of Trades dummy in Table 9 is negative for all instruments except for non-agency CMO and CDO instruments. Similarly, the point estimate on the interaction of Dealer's Coreness and All Other Trades dummy is negative, except for non-agency CMO and CDOs (which are positive but not statistically significant). These negative point estimates could reflect greater competition and reduced bargaining power of more central dealers or lower trading costs on the transactions they intermediate. These findings suggest a degree of specialization in the trading of different instruments and the need to look at competition in more subtle ways. Central dealers perform a valuable function by enhancing the linkages in the network and the integration of customer activity.

The point estimate of Dealer's Degree Residual is negative for all instruments except Rule 144a CMBS instruments and Registered non-agency CMO instruments. Holding the size of the interdealer k-core sub-network constant, the higher relative position of a dealer in that sub-network captured by positive Degree Residual results in lower dealer spreads on average. The result is the opposite from the generally positive relationship between dealer's centrality and bid-ask spreads reported by Li and Schürhoff (2012) for municipal bond markets. The finding is consistent with the equilibrium in a search-and-bargaining model of a decentralized interdealer market in which dealers differ in their trade execution efficiency that proxy for dealer centrality in Neklyudov (2013). In that model the more connected dealers charge lower spreads because their endogenous reservation values reflect their search efficiency and consequently, they intermediate trade flows among the less efficient dealers.

The point estimate on Buy from Customer and Sell to Dealer is negative except for Rule 144a CMBS and Rule 144a non-agency CMO instruments, indicating that spreads are lower when the dealer is in the first link of a multi-round intermediation. Perhaps this reflects that dealers need to offer price concessions to sell to another dealer rather than a customer. The point estimate on Buy from Dealer and Sell to Customer is positive across all categories of instruments indicating that spreads are higher when the dealer is in the last link of a multi-round intermediation. It is more valuable to find a customer to sell to and finish the intermediation chain rather than to sell to another dealer and keep the intermediation chain going.

6. Concluding Comments

We utilize data on dealer transactions in securitizations markets to study the nature of dealer networks and how bid-ask spreads vary within the trading network. While trading among instruments is highly fragmented and relatively infrequent, trading is highly concentrated among a relatively small number of dealers. Dealer networks reflect a core-peripheral structure. We document a negative relationship between the importance and 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 in equilibrium as in Neklyudov (2013). The evidence contrasts with the empirical findings in municipal bond markets, where a positive relationship arises between dealers' importance and bid-ask spreads as documented by Li and Schürhoff (2012).

Perhaps this reflects the lack of sophisticated customers in the municipal bond market. Our empirical result that spreads are more sensitive to dealer centrality in Rule 144a markets compared to Registered instruments is consistent with customers having greater bargaining power when negotiating with dealers in Rule 144a instruments than in Registered instruments. This could reflect greater sophistication of the Rule 144a customers relates to the Registered customers.

We document that different issuers of securitizations have a different number of active dealers providing substantial amount of intermediation services to customers throughout our sample period. Customer orders routed through such active dealers tend to be associated with lower bid-ask spreads. Bid-ask spreads tend to be even lower when there is only one active dealer for a given issuer of securitizations.

Our matching techniques allow us to look in more detail at how the total client bid-ask spread gets split among different parties involved in a deal. Longer chains of intermediation result in larger total spreads. Dealer spreads are especially wide on transactions that complete the chain—it is more valuable to find a customer to sell to and finish the intermediation chain rather than to sell to another dealer and keep the intermediation chain going.

We observe a smaller number of active dealers trading in an average Rule 144a instrument than in an average Registered instrument, but at the same time tighter customer bid-ask spreads. We also observe that the order flow is more evenly divided among dealers in Rule 144a instruments and that customers in Rule 144a markets face smaller bid-ask spreads when trading with more central dealers. These findings emphasize that the extent of competition differs between Registered and Rule 144a instruments.

It is important to understand the microeconomic aspects of the trading process, especially in light of the dramatic disclosure differences between Registered and Rule 144a instruments. Rule 144a securitizations have less disclosure requirements than Registered securitizations, but they could represent higher quality assets, that are held only by sophisticated investors with access to additional sources of information.

Our study points to a variety of additional directions for study. Empirical findings that emerge from the data have natural potential to inform the theory of over-the-counter markets and provide grounds for validation of different theoretical models. The nature of the data allows one to identify different counterparties and construct trading networks, offering a natural environment to perform network analysis. Network analysis has the potential to enhance our understanding of intermediation patterns for dealer markets and concentrations of risk more broadly, including systemic risks.

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APPENDIX: Data Cleaning

For the purpose of this study we have trading activity data ranging from May 16, 2011 to February 29, 2012 in several classes of securitized products: ABS, CDOs, CMBS, CMO, MBS and TBA, as well as the database with issue characteristics for all issues subject to FINRA reporting requirement.[12] We limit our attention to ABS, CMBS and non-agency CMO securitizations because these classes have both Registered as well as Rule 144a placed instruments in our sample. We also present our results for CDO, CBO and CLO Rule 144a instruments separately to allow for comparisons across asset classes. In our analysis we use Moody's ratings for instruments that have at least two opposite trades with customers. For other instruments we were able to utilize the investment grade data for these instruments provided by FINRA. Moody's ratings were collected for all instruments that satisfy our minimal-trading requirement: There are at least two opposite transactions with customers at most 2 weeks apart in our sample period from May 16, 2011 to February 29, 2012. We used the proprietary list of CUSIPs provided by FINRA to locate Moody's ratings for these instruments on the corporate website.

We perform several rounds of cleaning before we obtain a workable sample of trades: 1) Adjust for trade corrections and removed cancelled trades; 2) address double-reporting issue for interdealer trades—both dealers were typically reporting the same trade from opposite sides; 3) match trading reports with issue-specific characteristics from the database provided by FINRA; 4) clean the data from the issues with insufficient trading activity to perform our analysis; 5) compute bid-ask spreads using an iterative cascading matching technique discussed below; 6) adjust resulting spreads for coupon and factor payments; 7) perform cleaning for outliers. Below we discuss each of these rounds of data cleaning in greater detail.

[12] Among others the characteristics included: maturity date, coupons with update dates, type of coupon (fixed or floating), factors with update dates, type of placement (Registered or Rule 144a), description of the issue.

For some trade records, traders entered incorrect trade information or canceled previous transactions. Traders corrected the records by entering additional reports marked as “Corrected Trades”, “Trade Cancels” or “Cancels”, and “Historical Reversals” (if correction was reported not on the say trading day). In the first round of cleaning we remove all trade records that were subsequently corrected to keep only the effective transaction records, we remove all records that were cancelled and do not count them in our subsequent analyses, and we disregard all corrections when no initial trade record is reliably identified by entered volume, entered price, trade execution date and counterparty masks.

According to the FINRA reporting rule, each interdealer trade must be reported by both sides to the transaction, effectively leading to double reporting in our sample, with a few exceptions. Customer transactions and so-called “locked-in trades”[13] are always reported once. In order to cope with the double-reporting problem we implement an iterative pair-matching procedure. We look at pairs of identical transactions reported from different sides by the same counterparties. The counterparties often reported slightly different trade execution timestamps, so that we have to be careful distinguishing the second report for a particular transaction from other trading activity unrelated to it. The pair-matching procedure consists of one hundred iterative rounds of search for very similar entries in terms of entered volume, price, execution timestamps, settlement date, counterparty masks. In each round we flag trade reports that are sufficiently similar to constitute candidates for a double-entry of the same trade. Anytime we find several alternative candidate trades, we pick the ones closest in time according to the reported execution timestamp. Anytime 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 unique matching reports, which were subsequently

[13] Locked-in trades are defined in the layouts for trading data files provided by FINRA.

removed from the sample.[14] The result of this cleaning constitutes our working sample of transactions.

We match each transaction report to the issue-specific characteristics and description from the database provided by FINRA. The database for ABS, CDOs, CMBS and non-agency CMO instruments consists of eleven time-stamped files corresponding to May 15, May 31, June 30, July 31, August 31, September 31, October 31, November 30, December 31, January 31, 2012, and February 29, 2012. Using these files we are able to reconstruct the time-series of coupon rates and prepayment factors, as well as product collateral or underlying pool types, maturity, original balance, type of placement (Registered or Rule 144a), type of coupon (fixed or floating). In the few cases when the instrument-specific characteristics (such as the product category or the type of placement) are different in different files for the same issue identifier—we take the data from the latest files available for this issue, having in mind potential data entry issues. In the very rare cases when instruments with the same CUSIP code have different symbol IDs we treat those as different instruments.

It is worth noting that most of securitizations in our sample traded very thinly. For example, only 2,807 out of 12,663 ABS instruments, 1,222 out of 7,543 CDOs instruments, 2,967 out of 13,720 CMBS instruments, and 13,396 out of 78,350 non-agency CMO instruments did have at least two opposite trades with customers at most two weeks apart in time. Table 1 presents more detailed information. We could compute client spreads for these instruments only.

[14] These numbers apply to ABS, CDO, CMBS, and non-agency CMO only.

Then we perform several steps of matching seemingly related transaction into chains. We use the complete trading sample from May 16, 2011 to February 29, 2012 to look for chains. The implementation of our matching technique consists of three rounds.

In the first round we match related interdealer and customer transactions that have the same volume and each pair in a chain is no further than one month apart. For example, when we see among other trading activity three transactions in the same instrument of $1 million original balance that form a potential chain: Customer to dealer A, dealer A to dealer B, dealer B to customer, we perform two checks: 1) For each link of the potential chain there are no other alternative candidates resulting in a different branch of a chain that are closer in time based on the execution timestamp; 2) each link in the chain is no further than 1 month apart based on execution timestamp. If both conditions are satisfied, we take this chain out of the dataset and proceed with search for other chains iteratively. Different links of a single chain can be tangled in other trading activity in a given instrument, so in order to find candidates and establish links we sort our dataset by execution timestamp within each separate instrument and look for each trade record we look for candidate matches 15 record forward and 15 records backward. Note that we do not impose any timing sequence within a chain—buy from customers can follow as well as precede the sell to customer, and all seemingly related interdealer trades may happen at any point in time that satisfies the one-month maximum link span. We find most of our chains with a step size smaller than 15, so this step size limit does not constrain our results in a noticeable way. In order to search for all chains with no splits of volume we perform the aforementioned algorithm iteratively 100 times, which completely exhausts all candidate links that fall in the non-split category. The result of the first round is a set of 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 find 10,871 non-split chains in ABS (1.2 links on average, 5 links maximum), 1,959 chains in CDOs (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 transaction volume to split when moving through a chain. For example, when we see among other trading activity three transactions in the same instrument forming a potential chain but having 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 same two checks as in the first round for the candidate links and in case these checks are satisfied we split the chain in three pieces: 1) $0.5 million customer to dealer A; 2) $1.5 million dealer A to dealer B; 3) $0.5 million customer to dealer A, $0.5 million dealer A to dealer B, $0.5 million dealer B to customer. The last piece corresponds to a valid two-links chain we take out from the sample, while the first two pieces are returned back for further iterations of search-for-chains. This splitting is designed to treat the trading patterns when different chains branch into sub-chains or merge together and potentially have common links. Similarly to the first round we search for candidate links 15 records forward and backward each in a sorted trade sample, and perform 100 rounds. This way we find 8,719 additional chains in ABS (1.51 links on average, 9 links maximum), 794 chains in CDOs (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).

In the second round the 15 step size constraint binds for instruments with heavy trading activity and many trade records happening within a trading day. The second round ensures that we link most of the related interdealer links to trades with customers when they are less than 15 trade records away from each other. After the second round we drop all interdealer trades that have not yet been used to form a chain with any client transactions and perform LIFO matching of the opposite client transactions. This constitutes our third and final round of matching process. We keep track of all interdealer links established in prior rounds that were attached to these transactions. This way we find 3,396 additional chains in ABS (1.86 links on average, 11 links maximum), 406 chains in CDOs (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 a sample of chains both involving splits of volume and non-split chains. We have in total 23,036 chains in ABS (1.41 links on average, 11 links maximum), 3,198 chains in CDOs (1.25 links on average, 10 links maximum), 26,124 chains in CMBS (1.35 links on average, 19 links maximum), and 84,788 chains in non-agency CMO (1.76 links on average, 10 links maximum). On average we find relatively longer chains in non-agency CMO market. In our regression analysis we refer to the number of links in a chain as number of rounds in the deal.

The complete chains we find constitute 75% of the total absolute turnover in the ABS market, 86% in the CDOs market, 74% in the CMBS market, and 80% in the non-agency CMO market. We also include broken chains in which dealer codes do not match.

Within each chain of related transaction we adjust prices for coupon and factor payments that happened between the settlement time of a particular trade and the settlement time of the logical beginning of the chain (a buy from customer, not necessary the first trade to happen within a chain by execution time). For each chain of transactions having two opposite trades with customers, 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 (capital committed). The quotes observed in our dataset are clean prices per unit of current balance, thus we adjust our bid-ask spread measures for accrued interest and factor prepayments. We use the following approach to perform these adjustments:

Firstly, the direct way to compute bid-ask spread having two quotes on the opposite sides of an intermediating trade and the full information on factor and coupon payments in between is the following. Here we consider the case when settlement date effective for the ask quote occurs after the settlement date effective for the bid quote, however the formulas generalize to allow for opposite cases (below T stands for number of calendar days in between and c is the annual dollar coupon amount per $100 of original balance):

$$Spread = 100 \times \frac{(P_{ask} \times factor_{ask} - P_{bid} \times factor_{bid} + adj)}{\left({(P_{ask} \times factor_{ask} + P_{bid} \times factor_{bid} + adj)}\big/_{2} \right)}, where:$$

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

We use the following fair-pricing condition to simplify the above formula:

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

Assuming the above condition holds, the bid-ask spread calculation simplifies to:

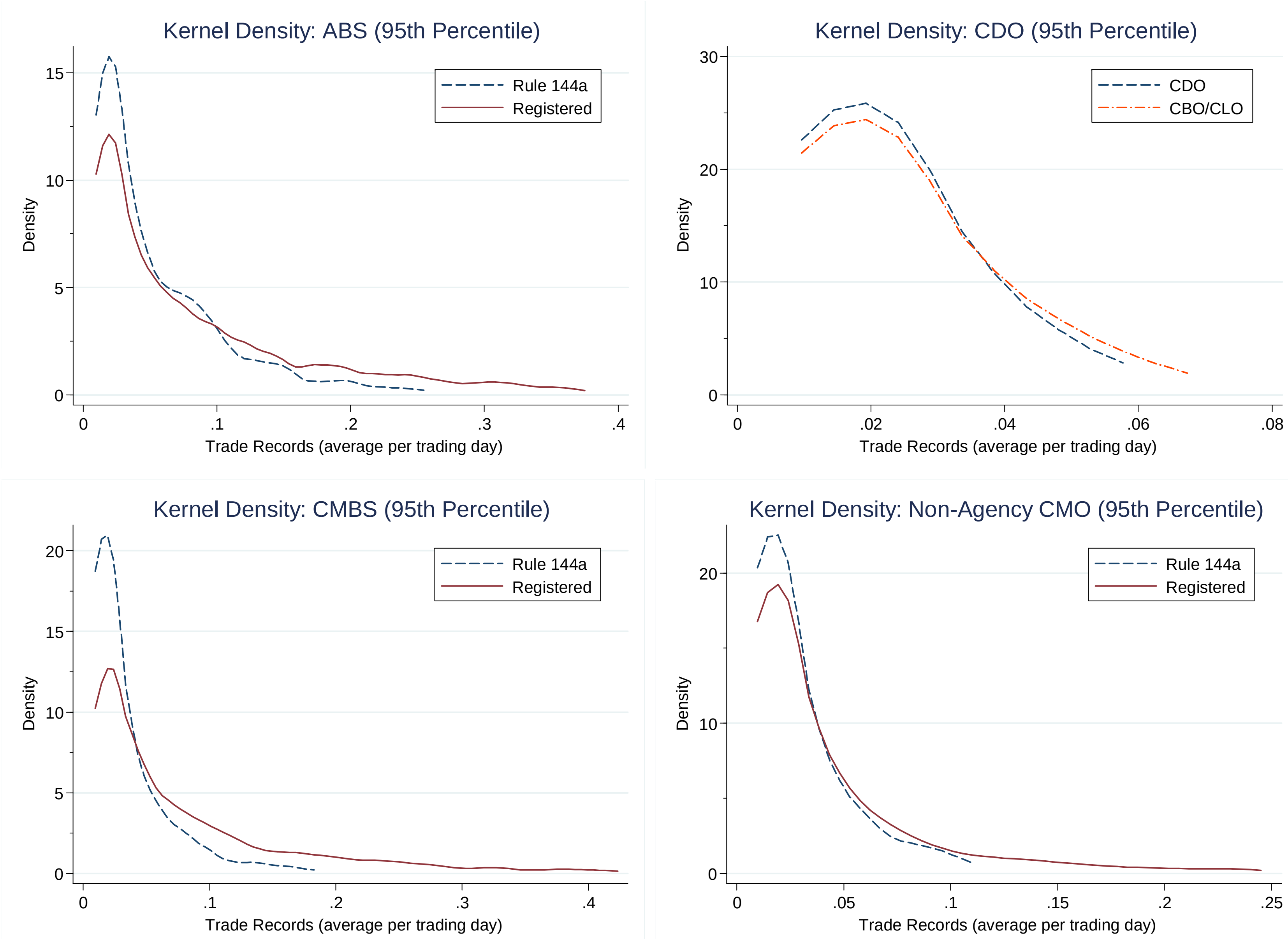
$$Spread = 100 \times \frac{\left(P_{ask} - P_{bid} + c \times \frac{T}{365}\right)}{\left(P_{ask} + P_{bid} + c \times \frac{T}{365}\right)\big/_{2}}$$

We performed both the direct spread computation and the simplified computation and did not find significant difference in terms of spread distributions. This can be explained by the fair-pricing condition outlined being a relatively good approximation for those matches that involve factor payments in between the two settlement dates. All results that follow correspond to the simplified approach.

The obtained spread observations contain outliers. In order to address this issue we winsorize 1% off each tail of the distribution of total client spreads within each subtype of instrument based on its overall type (ABS, CDOs, CMBS, non-agency CMO) and collateral sub-type, its placement type -- Registered or Rule 144a, and its investment rating. The distribution characteristics of resulting total client bid-ask spreads are presented in Table 4 for the overall sample from May 16, 2011 to February 29, 2012.

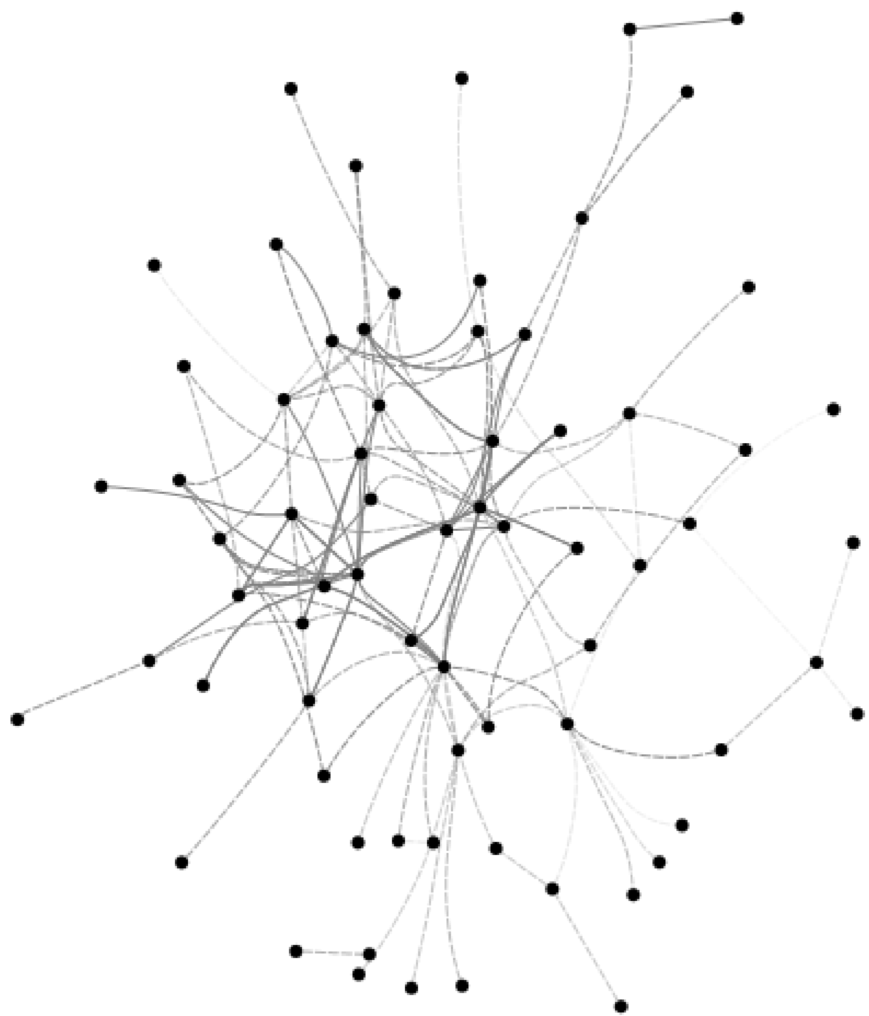
In our analysis we use information on trade sizes measured in dollars of original par underlying pairs of trades we use to construct each spread observation. We use three buckets for trade sizes: Retail trades (R), amounting to less than $100,000 original par, medium trades (M) between $100,000 and $1,000,000 original par, and institutional trades (I) amounting to more than $1,000,000 original par. Table 2 reports proportions of trade reports falling within the retail-size bucket. In our analysis we focus on non-retail chains when both original buy from customer and sell to customer volumes were greater than $100,000 original par (when a chain of transactions involves a split, we take into consideration the volume.

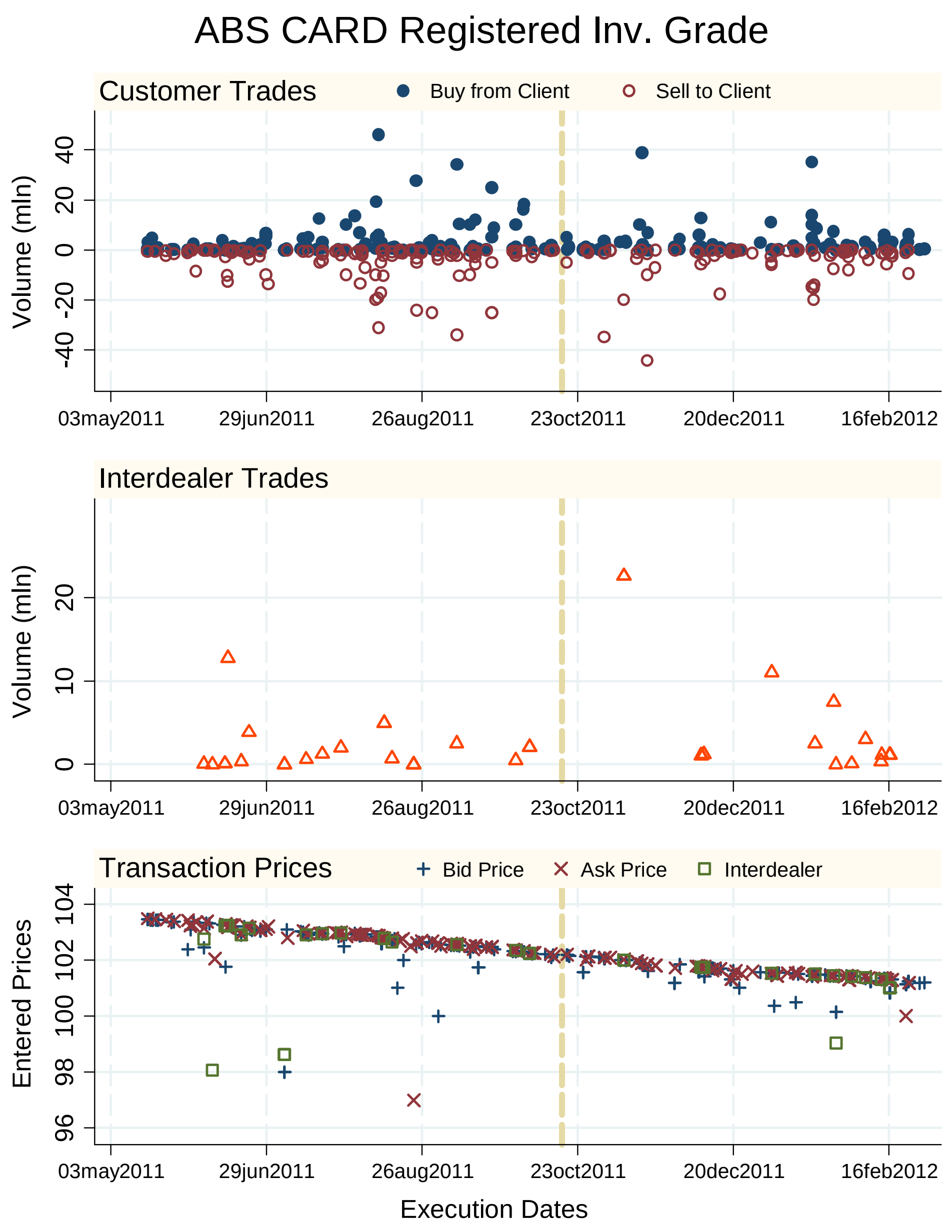
Figure 1: Distribution of Number of Trading Records per Day



Legend: Number of trade records includes both trades with customers and interdealer trades after appropriate record cleaning (discussed in the Data section). The graphs show estimated distributions of the lower 95th percentile within each group 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.

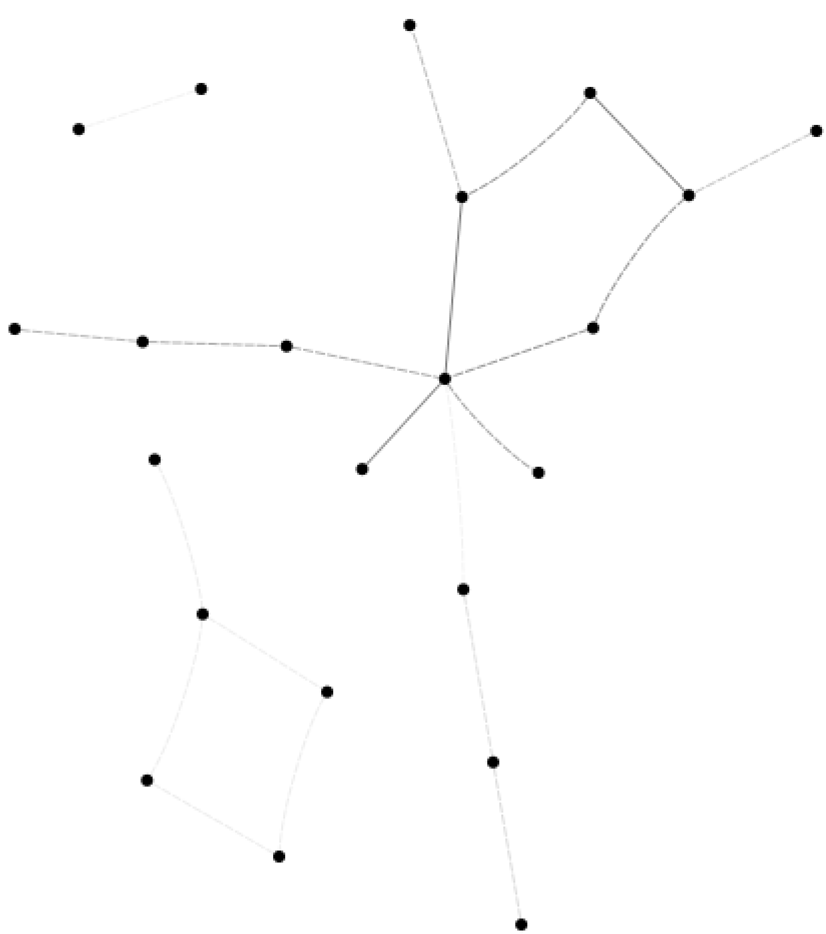
Figure 2a: Examples of Trading Patterns and Interdealer Networks

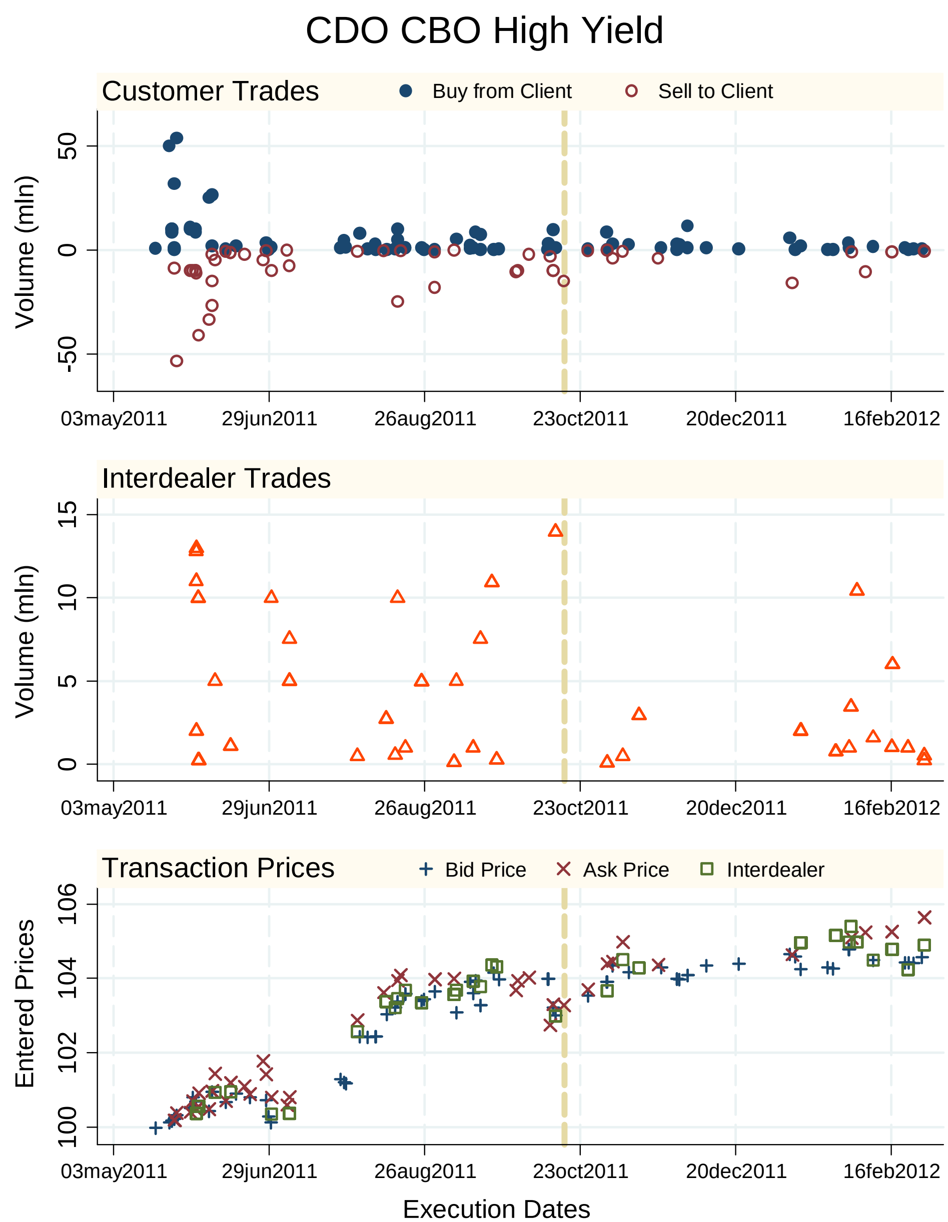




Legend: Every node of the network is a dealer, every edge represents occurrence of trading between two dealers (the darkness of a link is proportional to the volume, links with total volume less than \$10M are shown as dashed). Total number of reports includes both customer and interdealer trades. Buys from customers are shown as having positive volumes traded and sells to customers are shown as having negative volume. Bold vertical line corresponds to the IDC Index release date (October 17, 2011).

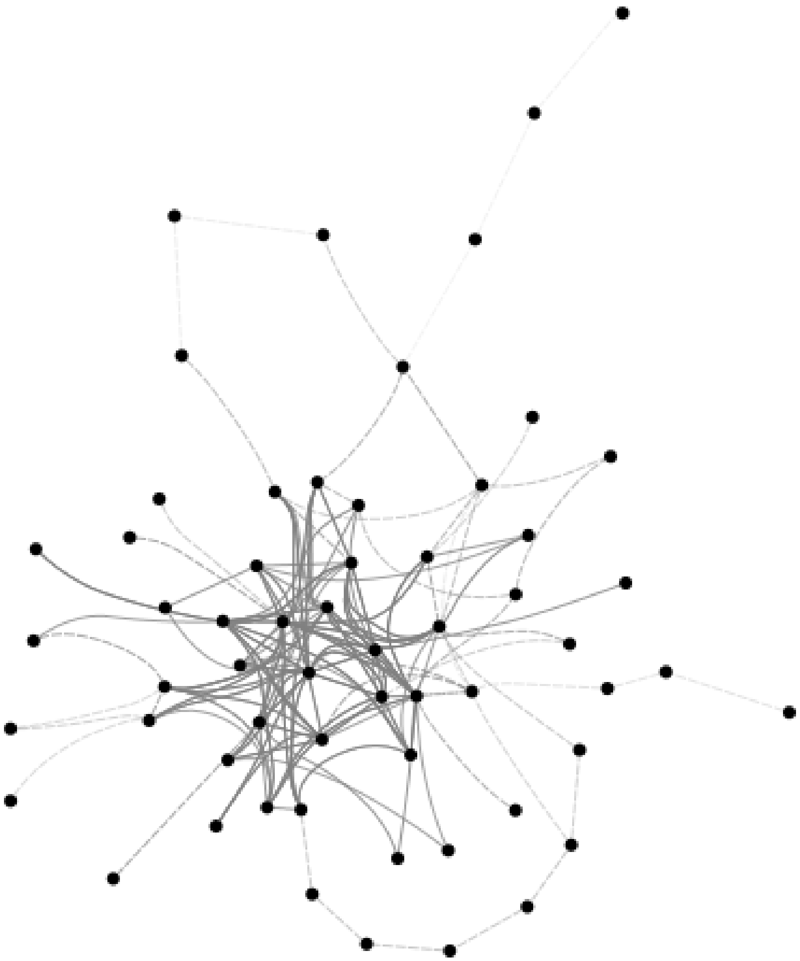
Figure 2b: Examples of Trading Patterns and Interdealer Networks

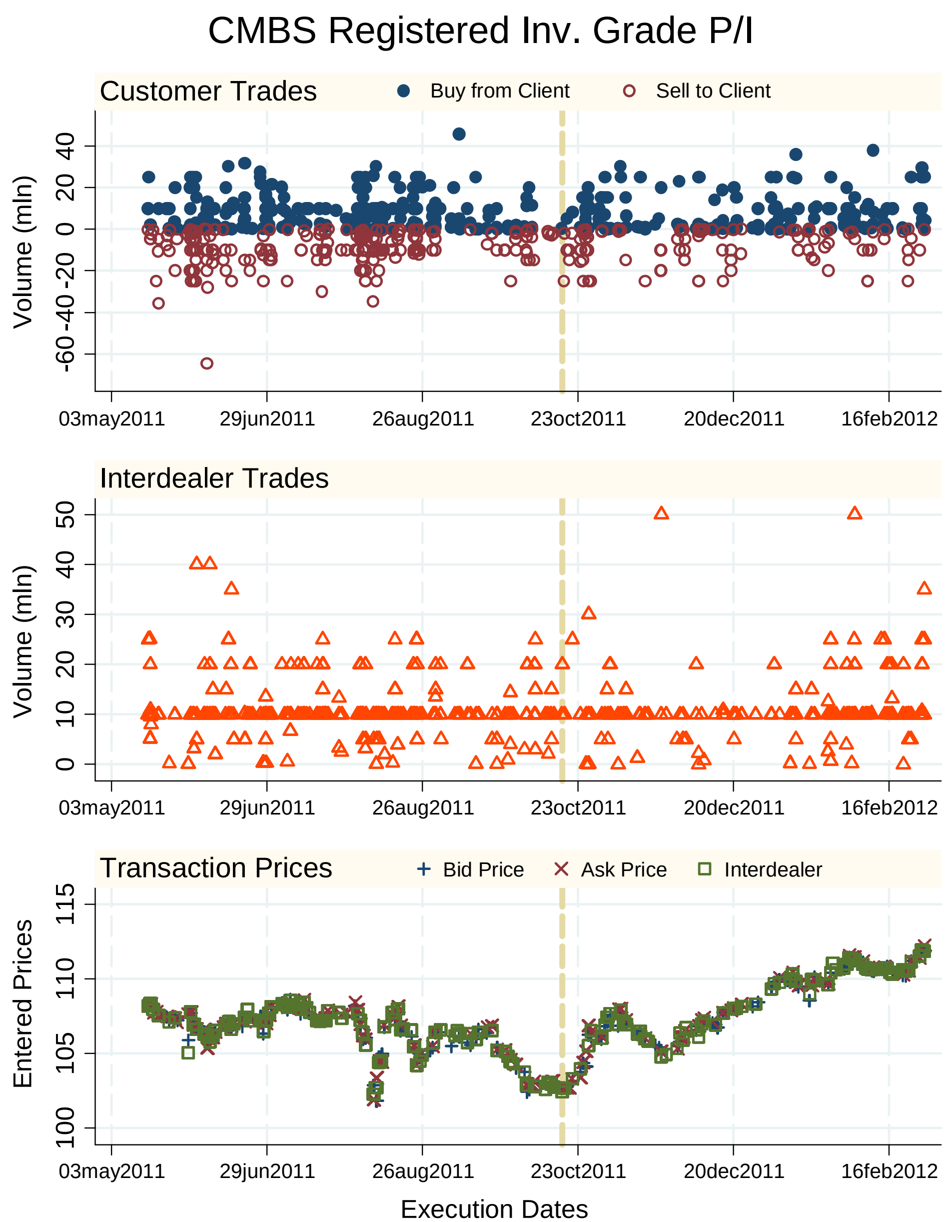




Legend: Every node of the network is a dealer, every edge represents occurrence of trading between two dealers (the opacity of a link is proportional to the volume, links with total volume less than $10M are shown as dashed). Total number of reports includes both customer and interdealer trades. Buys from customers are shown as having positive volumes traded and sells to customers are shown as having negative volume. Gray vertical line corresponds to the IDC Index release date (October 17, 2011).

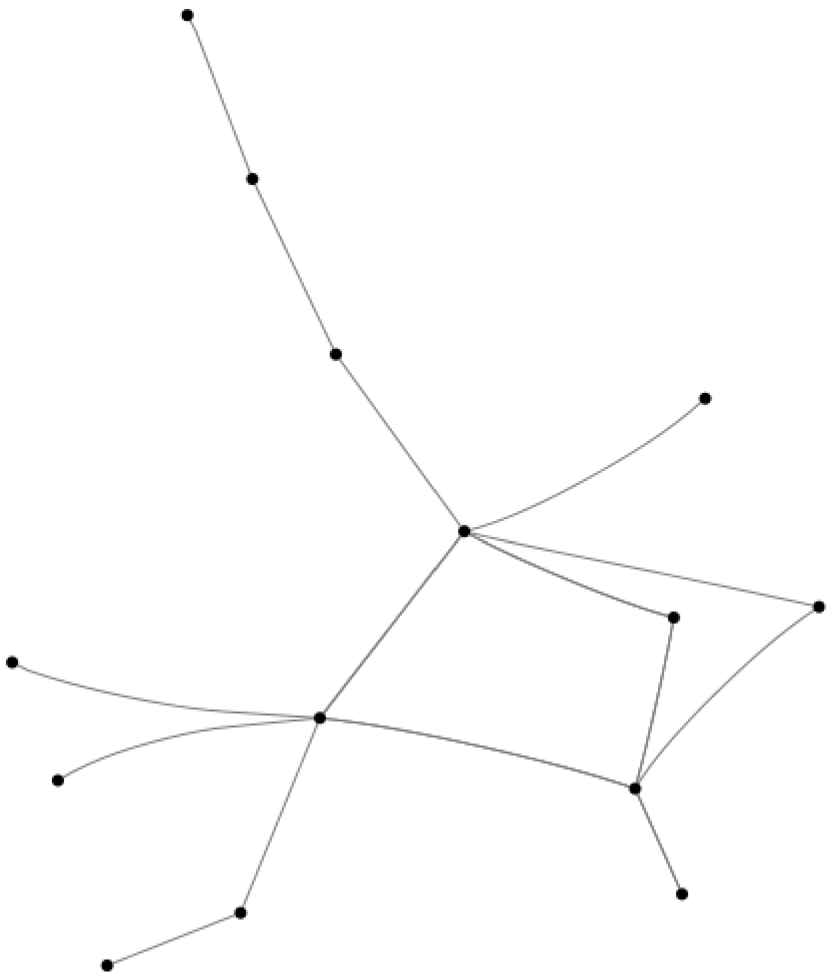
Figure 2c: Examples of Trading Patterns and Interdealer Networks

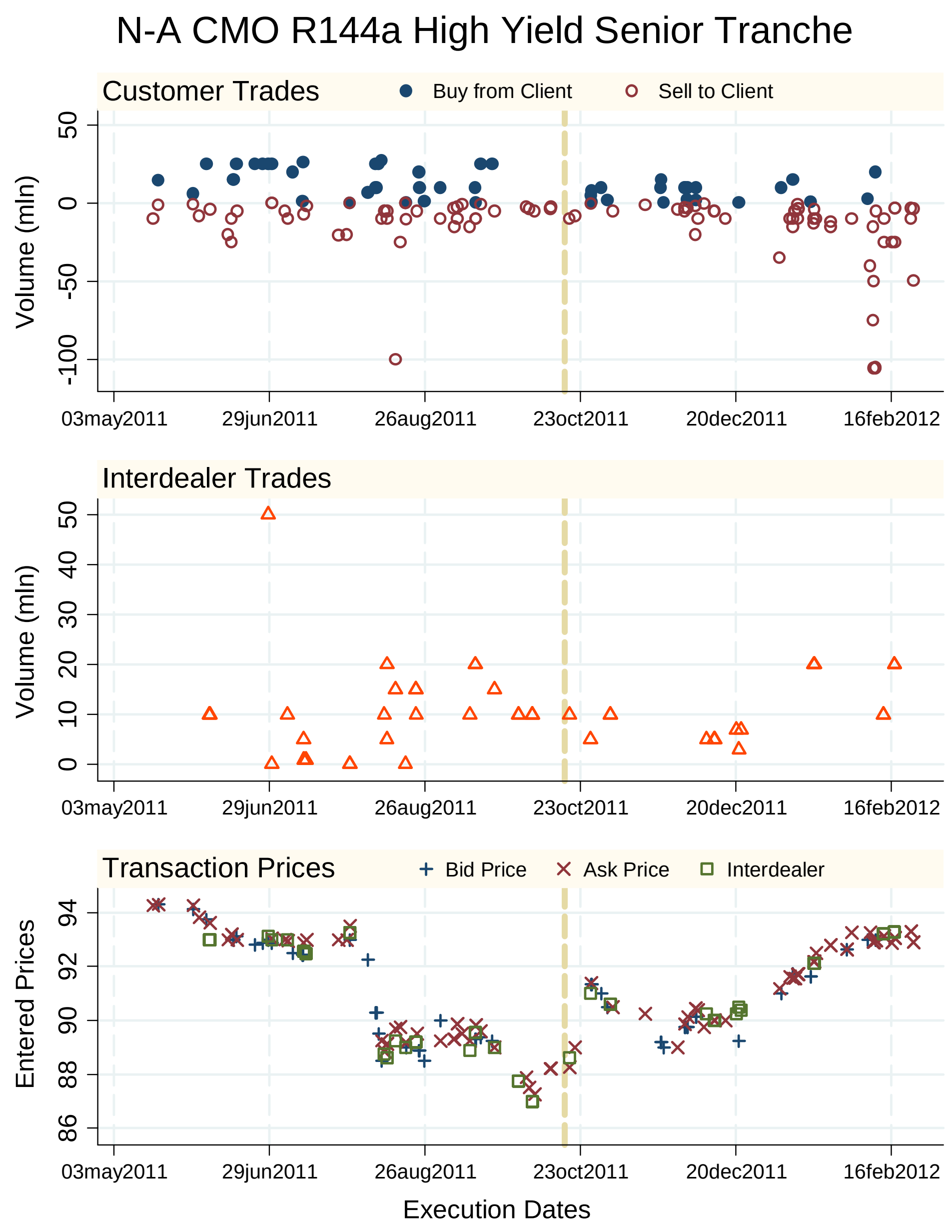




Legend: Every node of the network is a dealer, every edge represents occurrence of trading between two dealers (the opacity of a link is proportional to the volume, links with total volume less than \$10M are shown as dashed). Total number of reports includes both customer and interdealer trades. Buys from customers are shown as having positive volumes traded and sells to customers are shown as having negative volume. Bold vertical line corresponds to the IDC Index release date (October 17, 2011).

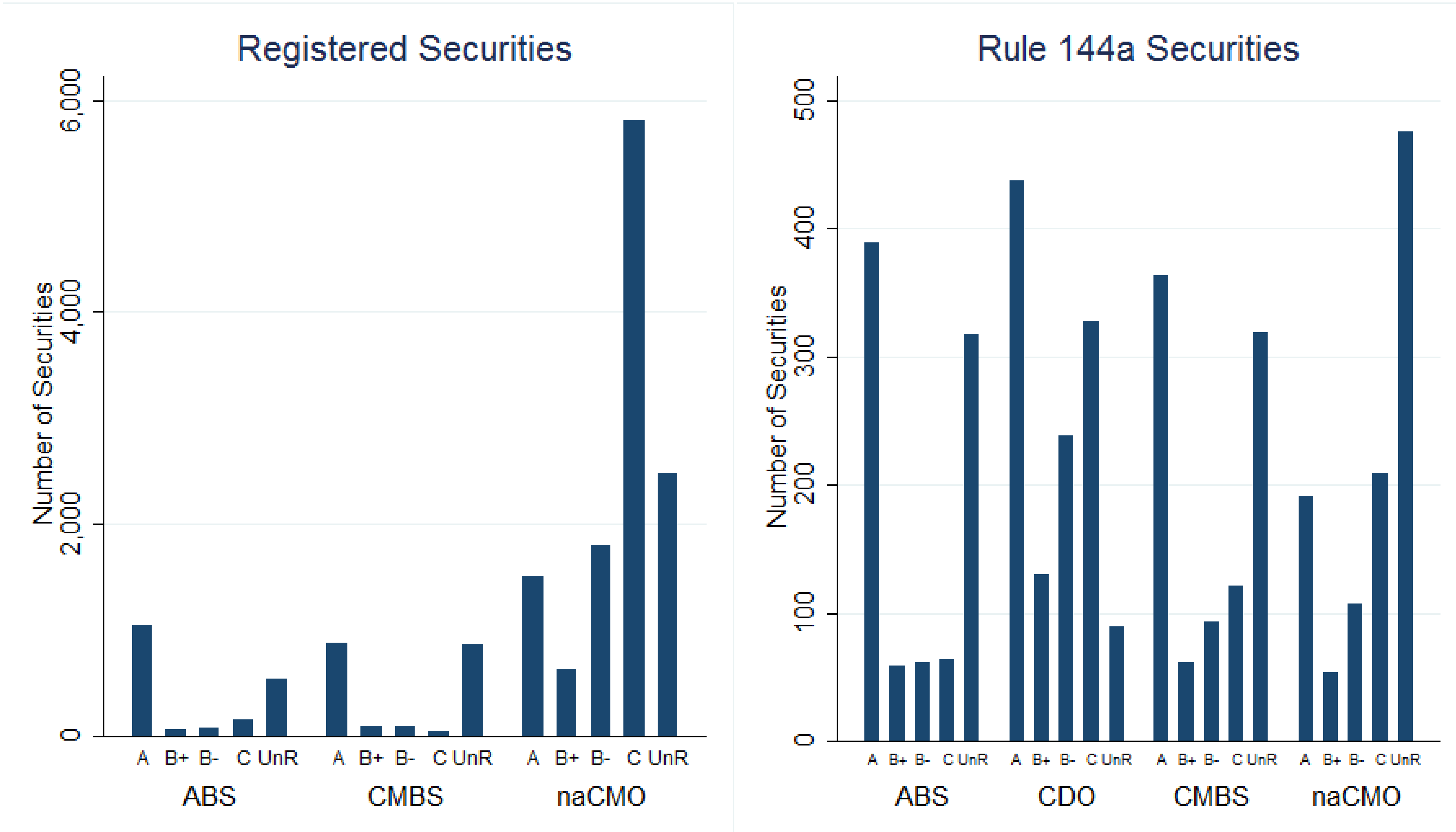
Figure 2d: Examples of Trading Patterns and Interdealer Networks





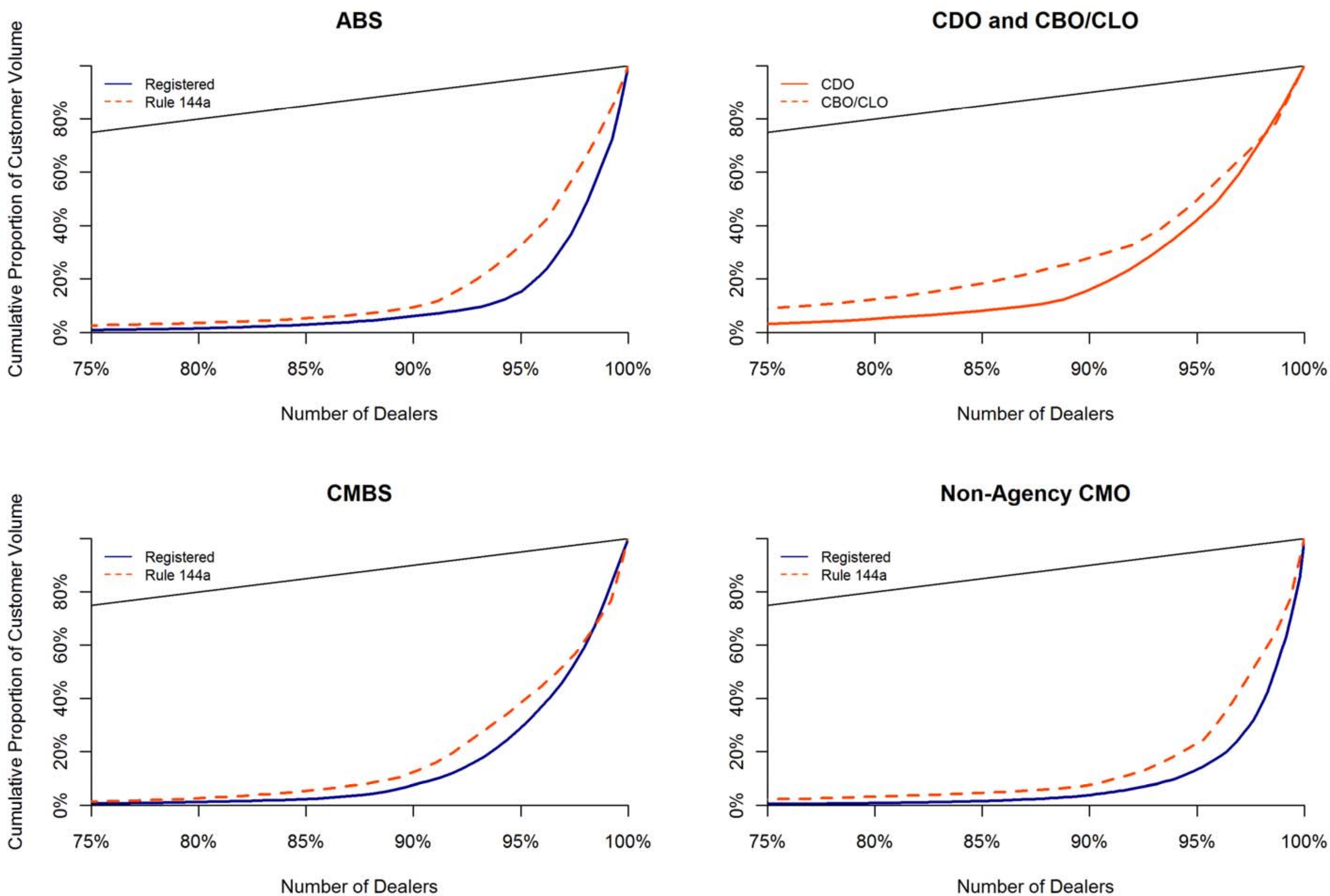
Legend: Every node of the network is a dealer, every edge represents occurrence of trading between two dealers (the opacity of a link is proportional to the volume, links with total volume less than $10M are shown as dashed). Total number of reports includes both customer and interdealer trades. Buys from customers are shown as having positive volumes traded and sells to customers are shown as having negative volume. Bold vertical line corresponds to the IDC Index release date (October 17, 2011).

Figure 3: Distribution of Moody's Ratings in the Sample



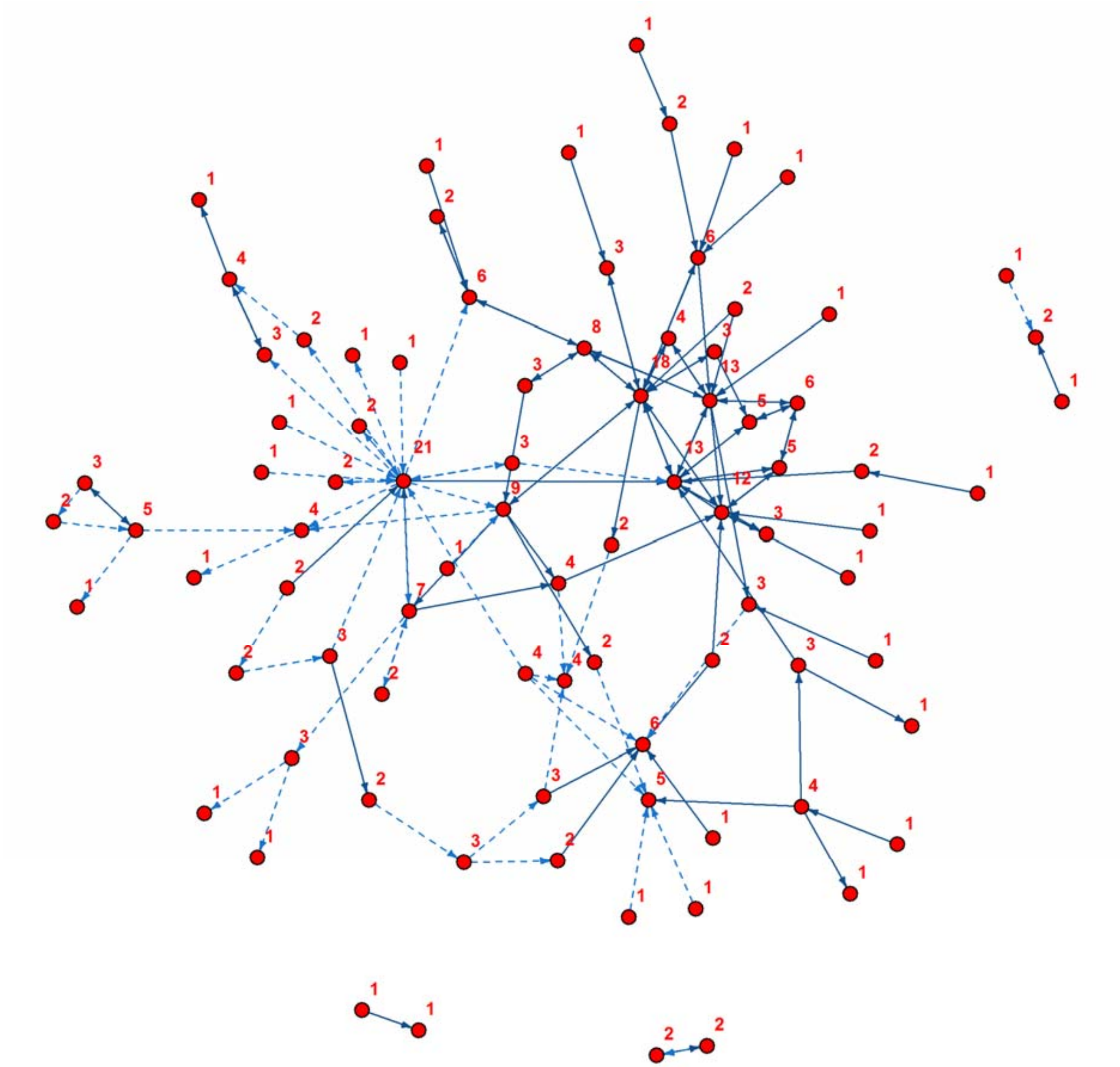
Legend: The bars show the distribution of the first Moody's rating effective in the sample period from May 16, 2011 to February 29, 2012. A category includes Aaa, Aa1, Aa2, Aa3, A1, A2, A3. B+ category includes Baa1, Baa2, and Baa3. B- category includes Ba1, Ba2, Ba3, B1, B2, B3. C category includes Caa1, Caa2, Caa3, Ca, C. "UnR" category includes instruments rated NR, instruments for which rating is withdrawn, or instruments not found on Moody's website.

Figure 4: Dealers' Shares in Original Balance with Customers (Lorenz Curves by Market)



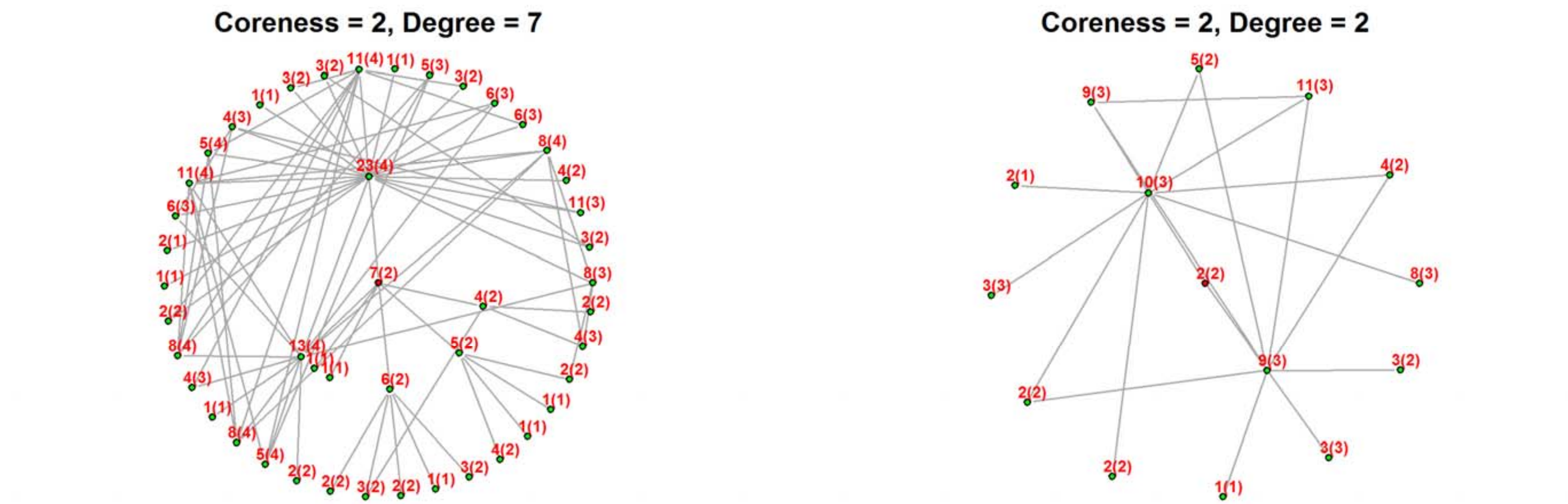
Legend: The 25% of dealers with largest volumes of original balance traded with customers are shown for each market. Numbers of Dealers in brackets correspond to dash Lorenz curves. All customer trades in the sample period from May 16, 2011 to February 29, 2012 are used to construct Lorenz curves.

Figure 5: The Most Active Links of the Interdealer Network



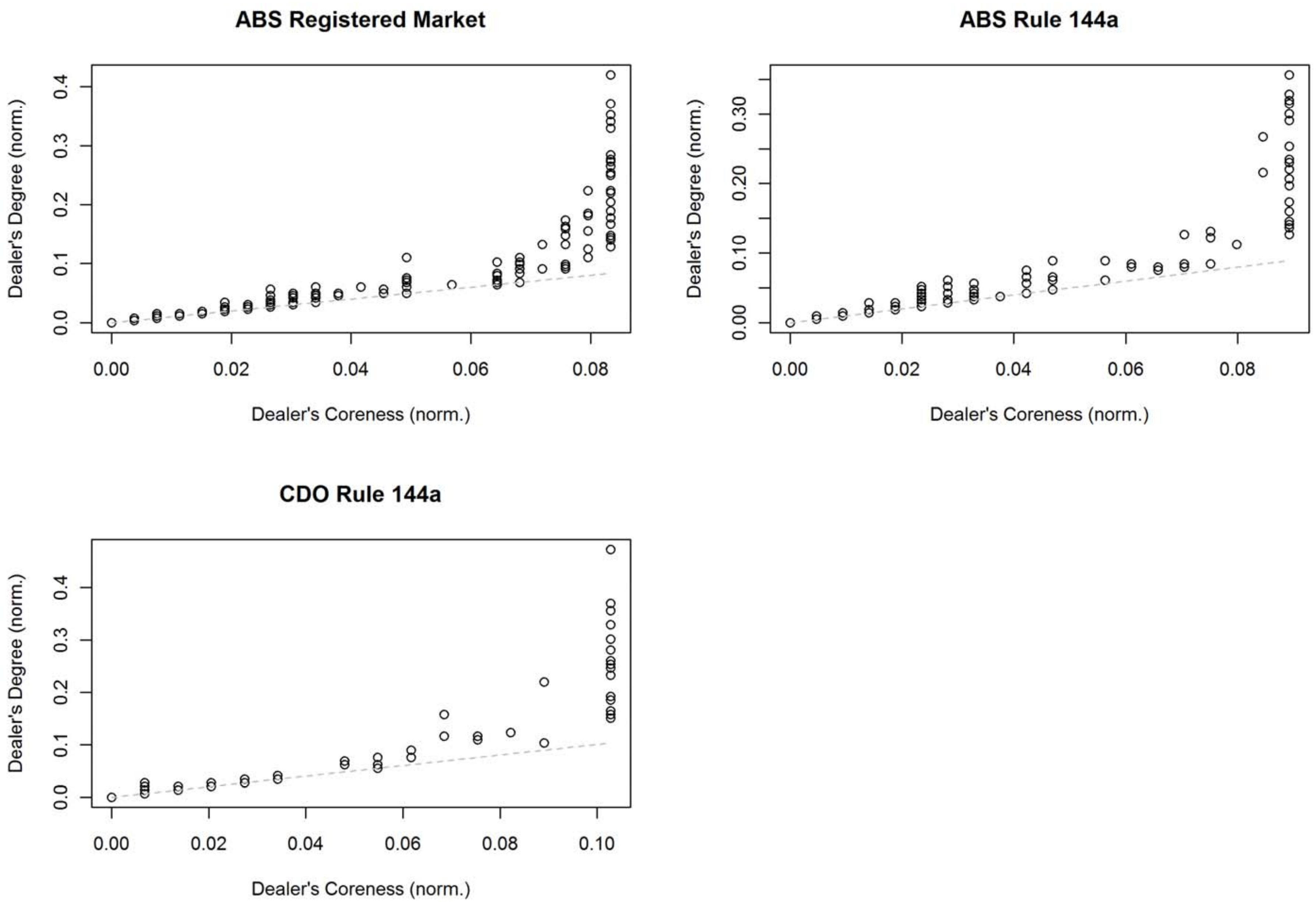
Legend: Each node represents a dealer; each arrow represents the direction of order flow from one dealer to the other. Dealers are labeled by the number of trading partners (both buy and sell directed orders) in the sample from May 16, 2011 to February 29, 2012. Only trading relationships (links) with at least 50 trade reports and at least $10 million of original balance transacted are shown in the graph; links with more than $100 million transacted are shown as solid lines.

Figure 6: Examples of Dealers Coreness and Degree Centrality



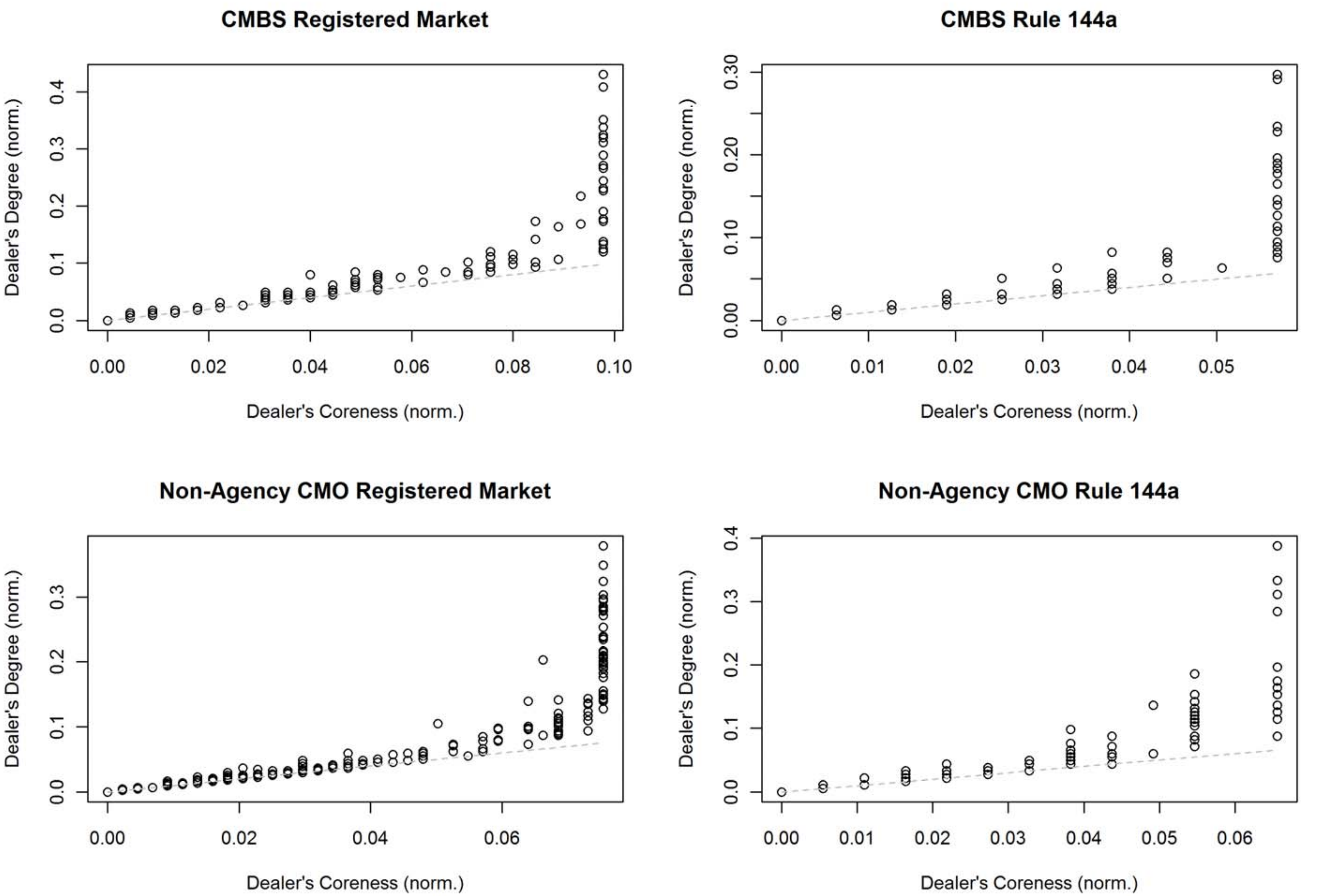
Legend: Degree centrality (undirected) shown for each dealer and coreness shown in brackets. The local neighborhoods up to the second degree (neighbors of neighbors) are presented for two combinations of degree and coreness of dealer in the middle (root). These neighborhoods correspond to the graph of interdealer market in Figure 6 with restriction on the volume of original balance transacted removed (each link restricted only to at least 50 transactions).

Figure 7a: Non-Retail Dealers' Degree and Coreness



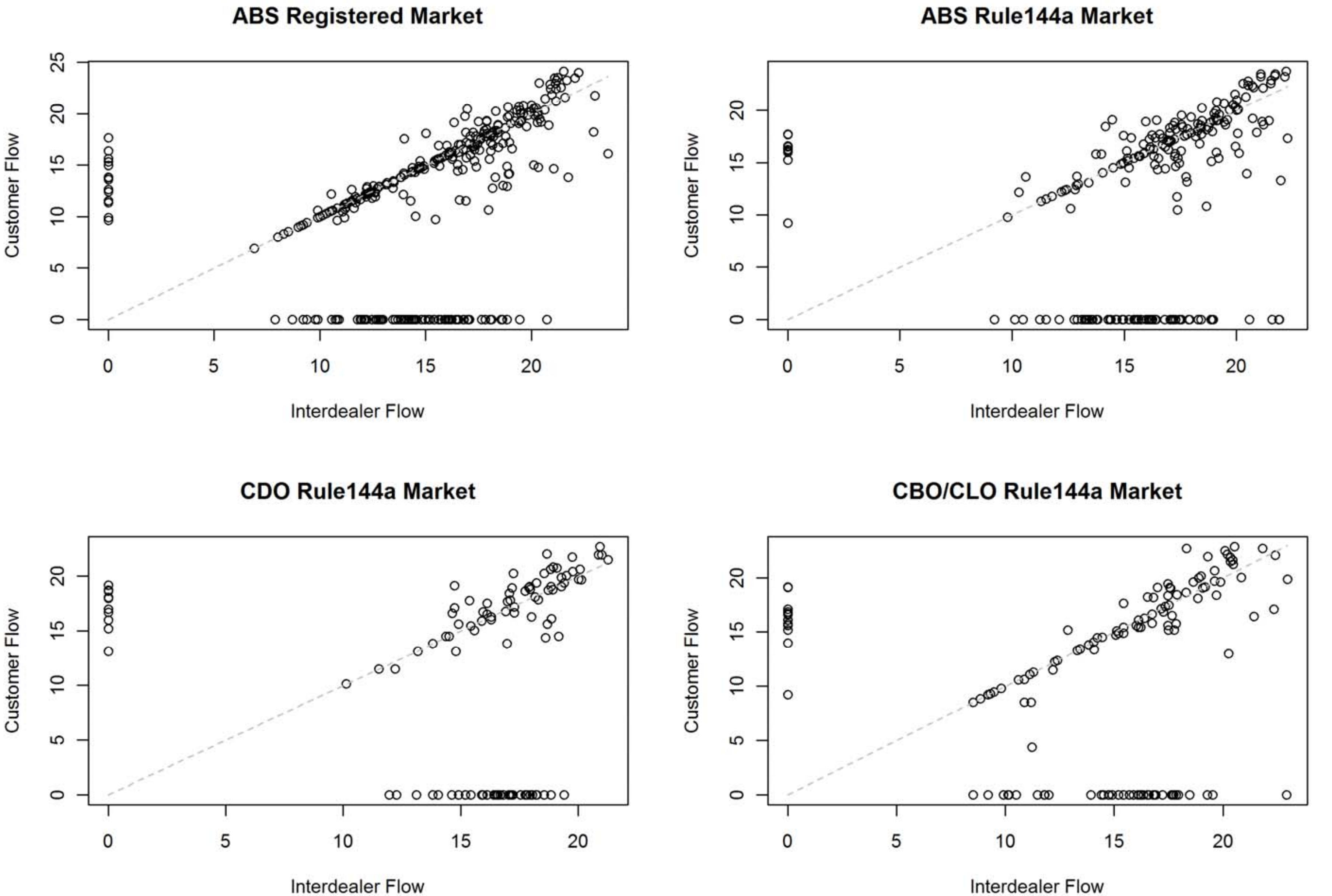
Legend: Each dot is a dealer with particular degree centrality and coreness in a given class of instruments. Degree centrality is the number of trading partners of a dealer in the sample. Dealer's coreness is the number of trading partners in the k-core sub-network that includes that dealer (k-core is the largest sub-network where all dealers have at least k number of trading partners). Higher dealer's degree relative to his coreness means higher importance of this dealer as an intermediary between different groups of other dealers.

Figure 7b: Non-Retail Dealers' Degree and Coreness



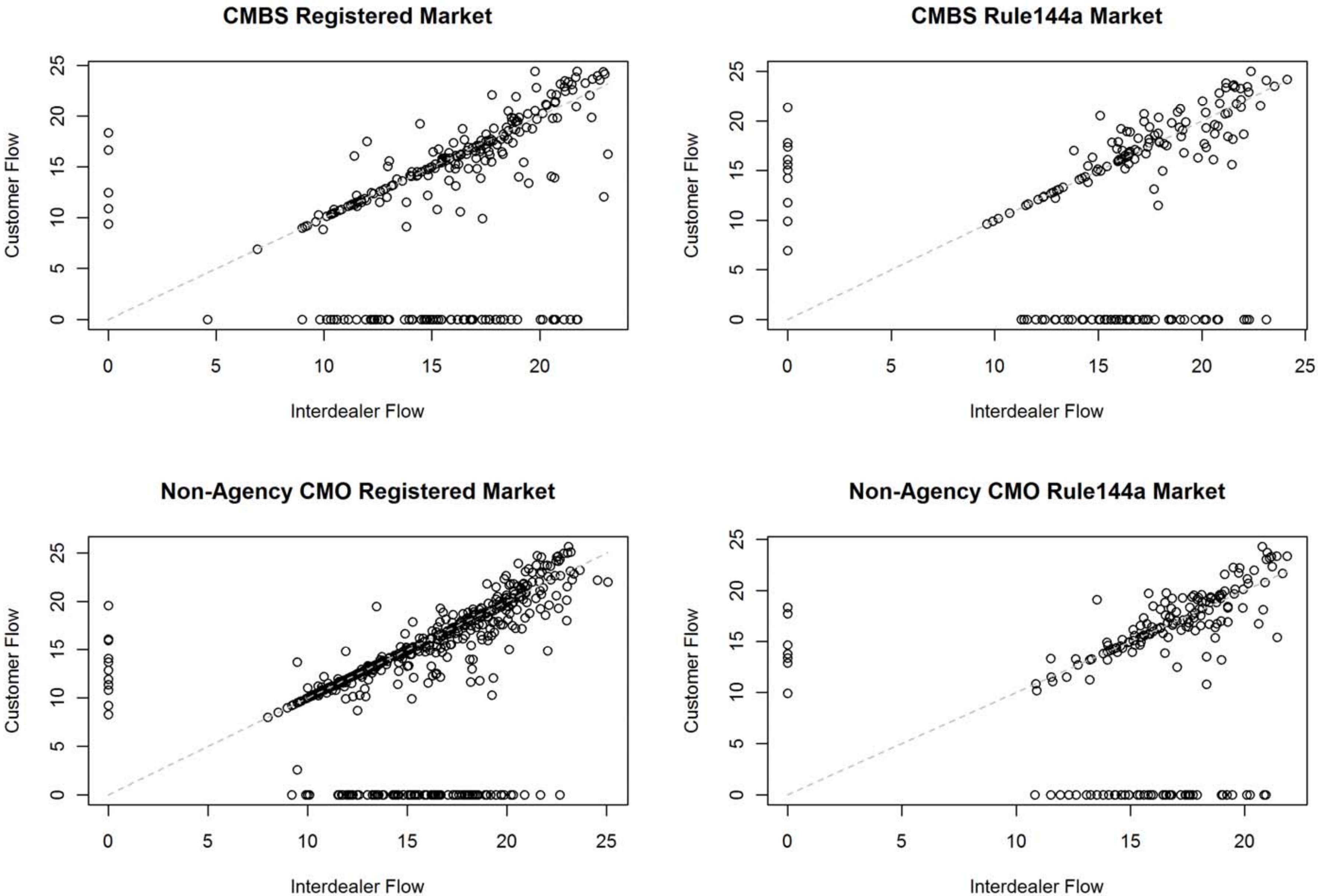
Legend: Each dot is a dealer with particular degree centrality and coreness in a given class of instruments. Degree centrality is the number of trading partners of a dealer in the sample. Dealer's coreness is the number of trading partners in the k-core sub-network that includes that dealer (k-core is the largest sub-network where all dealers have at least k number of trading partners). Higher dealer's degree relative to his coreness means higher importance of this dealer as an intermediary between different groups of other dealers.

Figure 8a: Dealers' Customer and Interdealer Flows for ABS and CDO Instruments



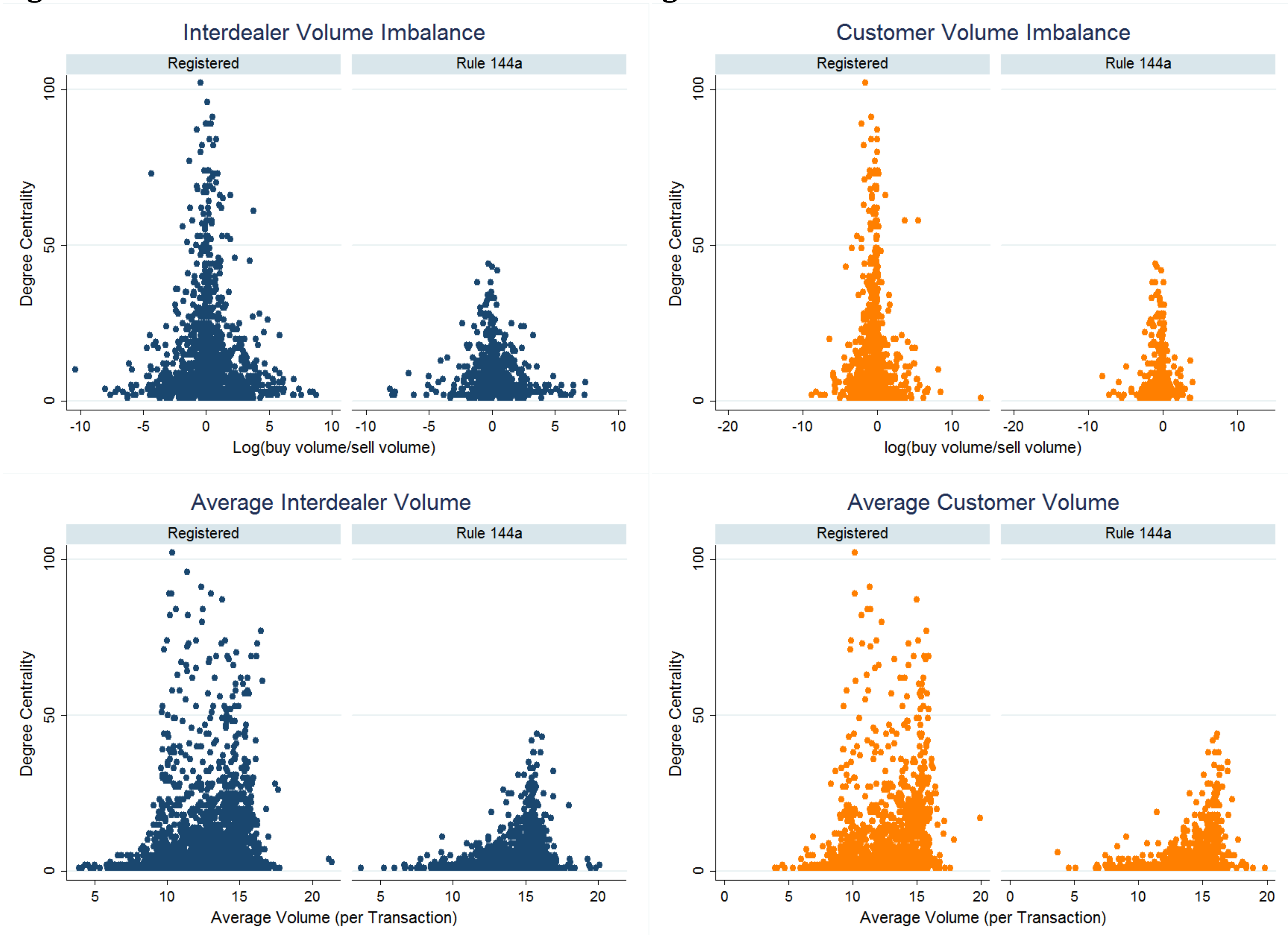
Legend: Each dot is a dealer; the coordinates are logarithm of total interdealer and customer order flow over the sample period from May 16, 2011 to February 29, 2012. Interdealer order flows are shown against order flows with customers for each dealer by category and instrument placement type.

Figure 8b: Dealers' Customer and Interdealer Flows for CMBS and Non-Agency CMOs



Legend: Each dot is a dealer; the coordinates are logarithm of total interdealer and customer order flow over the sample period from May 16, 2011 to February 29, 2012. Interdealer order flows are shown against order flows with customers for each dealer by category and instrument placement type.

Figure 9: Dealers' Volume Imbalance and Average Size of Transaction



Legend: Each dot represents a dealer on one of the submarket based on the instrument type, collateral type, and placement type. The degree centrality is the number of counterparties for each dealer within a particular submarket.

Figure 10: The Most Active Links of the Dealer-Issuer Network

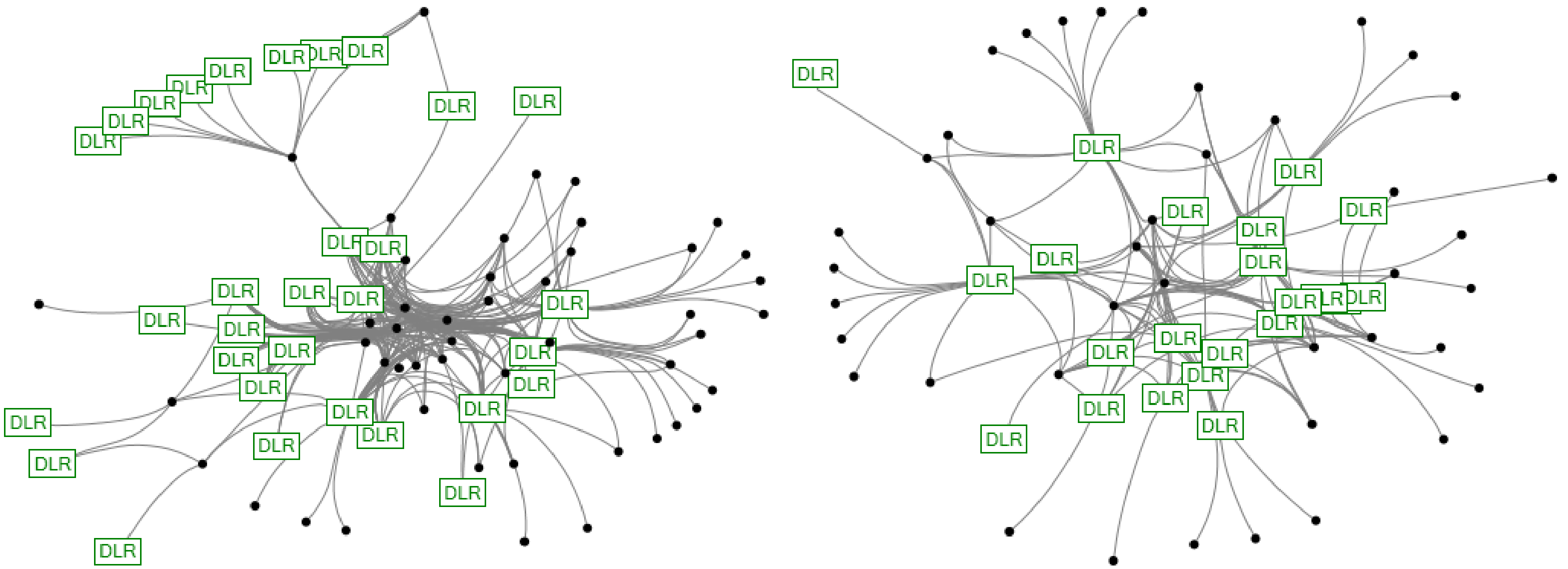


Illustration: ABS Registered **Illustration: ABS Rule 144a**

Legend: Within each product category we define an active link between a dealer and an issuer as the one that satisfies the following: the total volume transacted by the dealer in instruments of the issuer is above the median volume across all such pairs on the market and the number of days such transactions occurred is above 95th percentile across all such pairs on the market. We plot active links for ABS Registered and Rule 144a markets for illustration, each dot represents an issuer, and each DLR sign represents a dealer.

Table 1: Descriptive Instrument Characteristics

	ABS	CDO	CMBS	CMOs
Population	12,661	7,543	13,720	78,350
Registered	4,567	55	5,765	61,687
Rule 144a	8,094	7,488	7,955	16,663
Traded	2,807	1,222	2,967	13,396
Registered	1,905	---	1,997	12,355
Inv. Grade	1,231	---	928	2,024
High Yield	674	---	1,069	10,331
Floaters:	47%		36%	70%
Rule 144a	902	1,222	970	1,041
Inv. Grade	291	655	411	110
High Yield	611	567	559	931
Floaters:	70%	97%	66%	84%
Maturity	2023	2025	2039	2035
Registered	2021	---	2040	2035
Rule 144a	2025	2025	2036	2035
Vintage<4y	38%	9%	34%	10%
Registered	38%	---	31%	8%
Rule 144a	38%	9%	39%	29%
Coupon	3.09	1.81	4.54	8.74
Registered	3.08	---	4.91	9.05
Rule 144a	3.11	1.81	3.76	2.98
Factor	54.67	87.76	85.12	52.63
Registered	61.11	---	85.65	53.71
Rule 144a	41.06	87.76	84.05	39.76

Legend: Descriptive statistics are omitted for the unclassified instruments (other category). 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. For each instrument we take average of each characteristic within each instrument group. Vintage percentages represent relative percentage of instruments with less than 4 years in between first Moody's rating date and the trade execution date.

Table 2: Descriptive Trading Characteristics

	ABS	CDO	CMBS	CMOs
Trades / Day	0.10	0.03	0.09	0.07
Registered	0.11	---	0.12	0.07
Inv. Grade	0.12	---	0.15	0.07
High Yield	0.09	---	0.09	0.07
Rule 144a	0.07	0.03	0.05	0.04
Inv. Grade	0.12	0.03	0.07	0.04
High Yield	0.05	0.02	0.03	0.04
N. Dealers	6.0	2.4	5.6	3.9
Registered	6.7	---	6.8	4.0
Rule 144a	4.5	2.4	3.1	2.7
Interdealer	13%	9%	10%	14%
Registered	14%	---	11%	14%
Rule 144a	12%	9%	7%	9%
Retail-Size	14%	2%	12%	55%
Registered	17%	---	14%	57%
Inv. Grade	13%	---	13%	59%
High Yield	27%	---	16%	56%
Rule 144a	3%	2%	4%	5%
Inv. Grade	3%	1%	4%	1%
High Yield	2%	4%	2%	6%

Legend: We define traded instruments as having at least two opposite trades with customers at most two weeks apart in the sample period. For each instrument we take average of each characteristic within each instrument group. Retail-Size Trades represent proportion of trades with less than $100,000 of original par volume.

Table 3: Descriptive Instrument Characteristics by Subcategories

Category:	**ABS**						**CDOs**			**CMBS**		**Non-Agency CMO**					
	Auto	Card	ManH	SBA	Stud	Other	CBO	CLO	Other	IO/PO	P/I	IO/PO	PAC/TN	SEQ/PT	SUP/Z	Oth.SR	Other
Population	1,193	410	661	350	1,223	8,824	392	2,993	4,158	1,421	12,299	8,798	4,520	29,366	1,456	15,998	18,212
Registered	750	356	616	329	957	1,559	44	3	8	628	5,137	7,906	4,487	24,505	1,280	13,432	10,077
Rule 144a	443	54	45	21	266	7,265	348	2,990	4,150	793	7,162	892	33	4,861	176	2,566	8,135
Traded	645	261	213	237	417	1,034	45	749	428	249	2,718	326	839	7,129	300	3,687	1,115
Registered	466	243	206	227	328	435	---	---	---	94	1,903	304	832	6,712	295	3,534	678
Inv. Grade	330	213	66	227	301	94	---	---	---	42	886	34	108	1,137	23	681	41
High Yield	136	30	140	---	27	341	---	---	---	52	1,017	270	724	5,575	272	2,853	637
Floaters:	9%	77%	10%	0%	100%	72%	---	---	---	100%	33%	79%	23%	77%	30%	66%	90%
Rule 144a	179	18	7	10	89	599	45	749	428	155	815	22	7	417	5	153	437
Inv. Grade	115	12	4	10	78	72	21	529	105	104	307	3	2	86	---	19	---
High Yield	64	6	3	---	11	527	24	220	323	51	508	19	5	331	5	134	437
Floaters:	16%	67%	28%	10%	99%	84%	80%	99%	93%	100%	60%	73%	43%	78%	40%	70%	97%
Trades / Day	0.13	0.22	0.03	0.09	0.07	0.07	0.06	0.03	0.03	0.03	0.10	0.03	0.08	0.05	0.13	0.10	0.04
Registered	0.14	0.19	0.03	0.09	0.07	0.10	---	---	---	0.03	0.12	0.03	0.08	0.05	0.13	0.11	0.04
Inv. Grade	0.14	0.20	0.03	0.09	0.07	0.12	---	---	---	0.02	0.16	0.04	0.05	0.06	0.12	0.10	0.04
High Yield	0.14	0.14	0.03	---	0.05	0.10	---	---	---	0.03	0.09	0.03	0.08	0.05	0.13	0.11	0.04
Rule 144a	0.11	0.50	0.03	0.14	0.08	0.05	0.06	0.03	0.03	0.03	0.05	0.04	0.05	0.03	0.02	0.05	0.03
Inv. Grade	0.12	0.56	0.02	0.14	0.08	0.08	0.08	0.02	0.04	0.03	0.08	0.02	0.06	0.03	---	0.05	---
High Yield	0.10	0.38	0.04	---	0.07	0.04	0.04	0.03	0.02	0.04	0.03	0.05	0.04	0.03	0.02	0.05	0.03

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.

Table 4: Mean Client Spreads by Transaction Sizes

	Overall Bid-Ask Spreads				Spread Percentiles				
	ABS	CDOs	CMBS	N-A CMO		ABS	CDOs	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	1.625	2.647	1.760	4.247	50th	0.943	1.527	0.607	3.604
	(0.045)	(0.914)	(0.057)	(0.019)	10th	0.001	-0.794	-0.078	1.572
Obs.	*2,664*	*26*	*2,750*	*40,328*					
Non-Retail	0.304	0.811	0.245	2.069	50th	0.057	0.158	0.110	0.882
	(0.008)	(0.055)	(0.011)	(0.025)	10th	-0.024	0.000	-0.609	0.000
Obs.	*16,135*	*2,092*	*17,978*	*27,719*					
Diff. F-test p-value:	*0.000*	*0.040*	*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	1.655	---	1.712	4.250	50th	0.962	---	0.626	3.604
	(0.046)		(0.054)	(0.019)	10th	0.004		-0.077	1.590
Obs.	*2,558*		*2,616*	*40,229*					
Non-Retail	0.302	---	0.200	2.188	50th	0.058	---	0.104	0.995
	(0.008)		(0.010)	(0.027)	10th	-0.014		-0.607	0.000
Obs.	*12,045*		*14,944*	*25,315*					
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	0.895	2.647	2.700	2.986	50th	0.155	1.527	0.410	2.273
	(0.207)	(0.914)	(0.466)	(0.348)	10th	-0.002	-0.794	-0.100	0.000
Obs.	*106*	*26*	*134*	*99*					
Non-Retail	0.310	0.811	0.469	0.815	50th	0.052	0.158	0.145	0.193
	(0.022)	(0.055)	(0.040)	(0.043)	10th	-0.085	0.000	-0.612	0.000
Obs.	*4,090*	*2,092*	*3,034*	*2404*					
Diff. F-test p-value:	*0.005*	*0.040*	*0.000*	*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 either side of transactions 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 5: The Most Active Links of the Dealer-Issuer Network

	ABS						CDOs			CMBS		Non-Agency CMO					
	Auto	Card	ManH	SBA	Stud	Other	CBO	CLO	CDO	IO/PO	Other	IO/PO	PACTN	SEQPT	SUP/Z	Oth.SR	Other
Volume through Active Links (in billions of dollars of par)																	
Registered	23.6	19.3	4.6	6.9	15.1	4.3	---	---	---	13.7	96.6	60.1	1.2	135.	0.1B	62.1B	4.4B
as % of total volume	*37.2%*	*37.3%*	*54.3%*	*62.0%*	*41.0%*	*12.6%*	---	---	---	*14.4%*	*36.2%*	*30.5%*	*5.8%*	*27.3%*	*3.6%*	*25.6%*	*18.6%*
Rule 144a	5.4	5.9	0.1	5.1	3.1	30.3	6.0	13.4	1.3	51.3	31.1	7.4	---	14.4	0.1B	8.1B	27.8B
as % of total volume	*20.8%*	*54.0%*	*33.5%*	*82.7%*	*25.0%*	*29.4%*	*17.7%*	*25.5%*	*28.3%*	*20.6%*	*46.3%*	*25.1%*	---	*37.7%*	*24.1%*	*41.3%*	*39.7%*
Number of Active Dealers																	
Registered	12	11	8	5	13	23	---	---	---	11	17	13	12	44	13	39	28
as % of total dealers	*11.8%*	*11.5%*	*8.0%*	*8.3%*	*13.1%*	*11.7%*	---	---	---	*28.9%*	*8.8%*	*11.8%*	*5.7%*	*12.3%*	*6.1%*	*10.6%*	*15.7%*
Rule 144a	9	4	1	2	5	19	15	12	5	8	15	4	---	20	1	9	14
as % of total dealers	*13.4%*	*10.3%*	*9.1%*	*7.4%*	*7.6%*	*14.5%*	*20.0%*	*17.4%*	*8.6%*	*16.0%*	*13.2%*	*11.1%*	---	*18.5%*	*8.3%*	*12.0%*	*14.4%*
Number of Active Issuers																	
Registered	20	7	7	1	7	31	---	---	---	9	40	28	40	102	17	67	31
as % of total issuers	*30.3%*	*31.8%*	*31.8%*	*50.0%*	*15.6%*	*7.5%*	---	---	---	*14.5%*	*35.4%*	*17.6%*	*23.3%*	*23.8%*	*25.0%*	*26.8%*	*10.5%*
Rule 144a	7	1	1	2	6	52	45	67	3	15	30	5	---	37	2	12	38
as % of total issuers	*13.7%*	*14.3%*	*12.5%*	*66.7%*	*25.0%*	*10.1%*	*14.9%*	*22.8%*	*7.1%*	*16.5%*	*16.0%*	*17.2%*	---	*21.4%*	*15.4%*	*21.4%*	*9.7%*
Issuers per Active Dealer \ Dealers per Active Issuer																	
Registered																	
Mean	6\3	2\4	2\2	1\5	2\5	3\2	---	---	---	1\2	10\4	3\1	5/2	8/3	3/3	6/3	2/2
Maximum	*16\12*	*6\7*	*5\7*	*1\5*	*6\9*	*10\11*	---	---	---	*4\4*	*25\13*	*16\4*	*38/8*	*50/28*	*12/8*	*46/33*	*13/8*
Rule 144a																	
Mean	3\4	1\4	1\1	1\1	2\2	4\2	2\3	5\2	9\2	2\1	5\2	1\1	---	3/1	2/1	2/1	4/2
Max	*6\8*	*1\4*	*1\1*	*1\1*	*4\4*	*16\5*	*2\4*	*19\6*	*27\7*	*10\2*	*15\7*	*2\1*	---	*9/4*	*2/1*	*5/3*	*11/7*

Legend: Within each product category we look for active links between dealers and issuers that correspond to relatively large volumes transacted (the total volume transacted by the dealer in instruments of the issuer is above the median volume across all such pairs on the market) and persistent in time (the number of days such transactions occurred is above 95^{th} percentile across all such pairs on the market). We report maximum and average numbers of issuers for each dealer and dealers for each issuer in the table.

Table 6: Total Client Non-Retail Bid-Ask Spreads

	ABS						CDOs			CMBS		Non-Agency CMO					
	Auto	Card	ManH	SBA	Stud	Other	CBO	CLO	CDO	IO/PO	Other	IOPO	PACTN	SEQPT	SUPZ	Oth.SR	Other
All	0.075	0.062	1.224	0.713	0.467	0.558	0.251	0.358	1.772	0.351	0.243	3.130	2.760	2.075	2.679	1.857	1.919
	(0.003)	(0.006)	(0.129)	(0.014)	(0.038)	(0.027)	(0.055)	(0.051)	(0.134)	(0.114)	(0.011)	(0.196)	(0.060)	(0.041)	(0.175)	(0.028)	(0.103)
Reg.	0.072	0.078	1.294	0.714	0.511	0.553	---	---	---	0.156	0.200	3.346	2.768	2.137	2.675	1.942	2.853
	(0.003)	(0.007)	(0.124)	(0.014)	(0.050)	(0.026)	---	---	---	(0.248)	(0.010)	(0.214)	(0.060)	(0.043)	(0.179)	(0.029)	(0.165)
	4001	3143	268	1522	1127	1984	---	---	---	116	14828	466	1939	13198	267	8130	1315
R 144a	0.087	-0.011	-0.211	0.668	0.342	0.563	0.251	0.358	1.772	0.478	0.468	1.110	1.006	1.174	2.849	0.479	0.591
	(0.008)	(0.009)	(1.115)	(0.075)	(0.034)	(0.049)	(0.055)	(0.051)	(0.134)	(0.097)	(0.043)	(0.216)	(0.495)	(0.062)	(0.698)	(0.115)	(0.061)
	1193	659	13	56	392	1777	155	1256	681	179	2855	50	9	914	6	500	925
Diff.	*0.083*	*0.000*	*0.165*	*0.543*	*0.005*	*0.859*	---	---	---	*0.227*	*0.000*	*0.000*	*0.000*	*0.000*	*0.794*	*0.000*	*0.000*
Inv. Grade	0.072	0.057	0.960	0.713	0.443	0.344	0.220	0.352	0.598	0.464	0.159	3.783	1.777	1.707	1.436	1.632	0.498
	(0.003)	(0.006)	(0.160)	(0.014)	(0.033)	(0.025)	(0.032)	(0.042)	(0.101)	(0.127)	(0.011)	(0.580)	(0.165)	(0.051)	(0.587)	(0.062)	(0.054)
Reg.	0.068	0.072	0.985	0.714	0.468	0.323	---	---	---	0.407	0.156	4.345	1.811	1.771	1.436	1.693	1.109
	(0.003)	(0.007)	(0.169)	(0.014)	(0.043)	(0.022)	---	---	---	(0.331)	(0.011)	(0.641)	(0.168)	(0.054)	(0.587)	(0.065)	(0.115)
	3287	2982	111	1522	1063	981	---	---	---	37	9512	38	160	2671	8	1286	248
R 144a	0.088	-0.012	0.560	0.668	0.367	0.378	0.220	0.352	0.598	0.482	0.171	0.737	0.387	0.888	---	0.630	0.056
	(0.010)	(0.009)	(0.221)	(0.075)	(0.037)	(0.055)	(0.032)	(0.042)	(0.101)	(0.131)	(0.034)	(0.509)	(0.219)	(0.114)	---	(0.183)	(0.021)
	885	645	7	56	342	594	131	881	266	117	1780	7	4	209	---	78	343
Diff.	*0.052*	*0.000*	*0.114*	*0.543*	*0.072*	*0.362*	---	---	---	*0.832*	*0.678*	*0.000*	*0.000*	*0.000*	---	*0.000*	*0.000*
High Yield	0.088	0.179	1.415	---	0.766	0.712	0.420	0.374	2.525	0.228	0.393	3.067	2.851	2.169	2.717	1.900	2.429
	(0.008)	(0.030)	(0.190)	---	(0.301)	(0.042)	(0.315)	(0.137)	(0.202)	(0.194)	(0.023)	(0.208)	(0.063)	(0.050)	(0.179)	(0.031)	(0.136)
Reg.	0.090	0.189	1.512	---	1.226	0.778	---	---	---	0.038	0.278	3.258	2.854	2.230	2.713	1.989	3.259
	(0.009)	(0.031)	(0.172)	---	(0.527)	(0.046)	---	---	---	(0.329)	(0.020)	(0.225)	(0.063)	(0.053)	(0.183)	(0.032)	(0.199)
	714	161	157	---	64	1003	---	---	---	79	5316	428	1779	10527	259	6844	1067
R 144a	0.085	0.063	-1.111	---	0.176	0.657	0.420	0.374	2.525	0.470	0.960	1.171	1.501	1.259	2.849	0.451	0.907
	(0.015)	(0.090)	(2.468)	---	(0.078)	(0.068)	(0.315)	(0.137)	(0.202)	(0.135)	(0.096)	(0.238)	(0.845)	(0.073)	(0.698)	(0.132)	(0.094)
	308	14	6	---	50	1183	24	375	415	62	1075	43	5	705	6	422	582
Diff.	*0.764*	*0.174*	*0.250*	---	*0.052*	*0.138*	---	---	---	*0.228*	*0.000*	*0.000*	*0.075*	*0.000*	---	*0.000*	*0.000*
IG-HY	*0.059*	*0.000*	*0.067*	---	*0.286*	*0.000*	*0.523*	*0.881*	*0.000*	*0.309*	*0.000*	*0.242*	*0.000*	*0.000*	*0.028*	*0.000*	*0.000*
Reg.	*0.025*	*0.000*	*0.030*	---	*0.149*	*0.000*	---	---	---	*0.430*	*0.000*	*0.107*	*0.000*	*0.000*	*0.029*	*0.000*	*0.000*
R144a	*0.847*	*0.384*	*0.511*	---	*0.027*	*0.001*	*0.523*	*0.881*	*0.000*	*0.947*	*0.000*	*0.423*	*0.248*	*0.006*	---	*0.425*	*0.000*

Legend: Total client bid-ask spreads are computed using buy from a customer and sell to a customer at most two weeks apart in the sample. The sample is from May 16, 2011 to February 29, 2012. Bid-ask spreads are winsorized within each product sub-type, placement type and investment grade. Standard errors are shown in parentheses.

Table 7: Definitions of Control Variables used in Regressions

	Name of the variable	Description
Vintage	*4-6 Years Vintage Dummy*	Medium vintage dummy variable equals to one when the time elapsed since the issuance date of the security is from four to six years. The issuance date is the first coupon or first Moody's rating date.
	> 6 Years Vintage Dummy	Old vintage dummy variable equals to one when the time elapsed since the issuance date of the security is greater than six years.
Security Type	*Investment Grade Dummy*	Investment grade dummy variable equals to one when the credit rating of the security is at or above BBB level based either on Moody's rating or rating in the FINRA reference bond dataset.
	Floating Coupon Dummy	Floating coupon dummy variable equals to one when the coupon rate of the security changed at least once over the sample period, or when security is flagged as floating rate type.
	Number of Trades in Sample	The logarithm of the total number of trading records observed for this security during the overall sample period.
	Number of Dealers	The total number of different dealers observed during the sample period trading in the security either with customers or on the interdealer market.
Volume	*Security Specific Match Volume*	The average security-specific log volume variable is equal to the average trade log volume standardized by the collateral type of the security.
	Deviation of Particular Match	The match-specific log volume deviation variable is equal to the difference between the match-specific log volume and average security-specific log volume, which is standardized by the collateral type of the security.
Centrality	*Dealers' Importance Dummy*	The dummy is based on the interdealer market centrality measure: it equals to one when both dealers in the given match were top-20% most connected dealers in the market for this type of collateral.
	Dealer's Coreness	The coreness of the dealer, normalized within each type of the collateral: captures the dealer's overall importance on the interdealer market for the given type of collateral.
	Dealer's Degree Residual	The difference between the degree centrality and the coreness of the dealer, normalized within each collateral type: captures relative importance of the dealer among primary counterparties.
Match Type	*Prearranged Pair Of Trades*	The prearranged trade dummy equals to one when the time between executions of the two opposite trades is less than 15 minutes.
	Buy from Customer Sell to Dealer	Dummy variable equals to one if the dealer spread is computed using two trades, one of which is a buy from a customer, while the other is a sell to another dealer.
	Buy from Dealer Sell to Customer	Dummy variable equals to one if the dealer spread is computed using two trades, one of which is a buy from another dealer, while the other is a sell to a customer.
	Through Single Active Dealer For the Issuer	Dummy variable equals to one if the matched trades are intermediated by a single active dealer for the issuer of these products.
	Through One of Many Active Dealers For the Issuer	Dummy variable equals to one if the matched trades are intermediated by one active dealer out of several for the issuer of these products

Table 8: Regression for Non-Retail Total Client Spreads

	ABS			**CDOs**		**CMBS**			**Non-Agency CMO**		
Variables:	Overall	Reg.	R144a	CDO	CBO/L	Overall	Reg.	R144a	Overall	Reg.	R144a
4-6 Years Vintage	0.155	0.076	0.397	-0.419	0.085	0.320	0.199	0.565	0.776	0.341	0.573
Dummy	(0.043)	(0.029)	(0.176)	(0.855)	(0.170)	(0.057)	(0.047)	(0.157)	(0.155)	(0.185)	(0.172)
> 6 Years Vintage	0.141	0.129	0.151	-0.511	0.243	0.123	0.017	0.476	0.738	0.268	0.404
Dummy	(0.043)	(0.030)	(0.151)	(0.838)	(0.161)	(0.053)	(0.040)	(0.252)	(0.145)	(0.183)	(0.207)
Investment Grade	-0.197	-0.212	-0.172	-1.654	0.020	-0.190	-0.085	-0.518	-0.670	-0.541	-0.529
Dummy	(0.039)	(0.038)	(0.094)	(0.278)	(0.161)	(0.043)	(0.032)	(0.136)	(0.102)	(0.109)	(0.101)
Floating Coupon	0.079	0.087	0.105	-0.745	-0.244	0.127	0.099	-0.087	0.162	0.300	-0.193
Dummy	(0.022)	(0.024)	(0.062)	(0.697)	(0.213)	(0.034)	(0.031)	(0.130)	(0.092)	(0.098)	(0.164)
Number of	-0.069	-0.036	-0.121	-0.462	-0.084	-0.139	-0.106	-0.234	0.336	0.205	-0.030
Trades in Sample	(0.020)	(0.020)	(0.059)	(0.312)	(0.104)	(0.037)	(0.026)	(0.110)	(0.066)	(0.066)	(0.091)
Number of	0.003	-0.002	0.012	0.040	0.008	-0.002	-0.002	0.001	-0.106	-0.096	-0.013
Dealers	(0.003)	(0.003)	(0.012)	(0.084)	(0.033)	(0.007)	(0.005)	(0.025)	(0.017)	(0.017)	(0.017)
Security Specific	-0.149	-0.151	-0.185	-0.426	-0.093	-0.038	-0.019	0.029	-0.697	-1.108	-0.078
Match Volume	(0.031)	(0.027)	(0.072)	(0.194)	(0.075)	(0.051)	(0.035)	(0.124)	(0.068)	(0.079)	(0.107)
Deviation of	-0.056	-0.059	-0.049	0.046	0.027	-0.097	-0.105	-0.033	-0.503	-0.676	-0.449
Particular Match	(0.011)	(0.010)	(0.026)	(0.208)	(0.090)	(0.015)	(0.017)	(0.047)	(0.064)	(0.068)	(0.255)
Prearranged Pair of	-0.174	-0.111	-0.356	-1.973	-0.323	-0.371	-0.330	-1.157	-1.503	-1.458	-0.757
Customer Trades	(0.071)	(0.080)	(0.162)	(1.069)	(0.415)	(0.100)	(0.072)	(0.485)	(0.169)	(0.176)	(0.277)
Dealers' Importance	-0.241	-0.238	-0.237	0.330	-0.509	-0.196	-0.124	-0.303	-0.400	-0.262	-0.435
&Prearranged Trade	(0.068)	(0.077)	(0.136)	(0.544)	(0.235)	(0.069)	(0.045)	(0.216)	(0.084)	(0.087)	(0.166)
Dealers' Importance	-0.292	-0.268	-0.382	-1.690	-0.882	-0.570	-0.494	-1.290	-0.987	-0.782	-0.816
&All Other Trades	(0.033)	(0.033)	(0.111)	(1.041)	(0.362)	(0.074)	(0.060)	(0.391)	(0.181)	(0.190)	(0.239)
Through Single Active	-0.221	-0.130	-0.254	0.664	0.076	-0.005	-0.021	-0.036	-0.658	-0.323	-0.798
Dealer For the Issuer	(0.104)	(0.035)	(0.235)	(0.518)	(0.155)	(0.061)	(0.076)	(0.175)	(0.206)	(0.167)	(0.338)
Through One of Many	-0.024	-0.023	-0.035	0.121	-0.201	-0.018	-0.038	0.218	-0.284	-0.324	-0.180
Active Dealers For the Issuer	(0.018)	(0.018)	(0.051)	(0.385)	(0.119)	(0.027)	(0.025)	(0.140)	(0.105)	(0.109)	(0.108)

Subcategory Fixed Effects: Yes. Number of observations: 63924. R-squared: 0.280

Legend: The regression includes fixed-effects 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 9: Regression for Non-Retail Dealer Spreads

Variables:	ABS Overall	ABS Reg.	ABS R144a	CDOs CDO	CDOs CBO/L	CMBS Overall	CMBS Reg.	CMBS R144a	Non-Agency CMO Overall	Non-Agency CMO Reg.	Non-Agency CMO R144a
4-6 Years Vintage Dummy	0.145 (0.031)	0.066 (0.023)	0.436 (0.117)	-0.985 (0.910)	0.222 (0.113)	0.315 (0.044)	0.206 (0.034)	0.572 (0.121)	0.709 (0.069)	0.486 (0.075)	0.679 (0.138)
> 6 Years Vintage Dummy	0.107 (0.034)	0.092 (0.019)	0.165 (0.117)	-1.245 (0.878)	0.209 (0.113)	0.100 (0.045)	0.002 (0.030)	0.403 (0.201)	0.604 (0.077)	0.360 (0.083)	0.380 (0.136)
Investment Grade Dummy	-0.165 (0.031)	-0.177 (0.030)	-0.125 (0.078)	-1.439 (0.243)	-0.187 (0.106)	-0.177 (0.032)	-0.082 (0.023)	-0.524 (0.113)	-0.539 (0.050)	-0.462 (0.049)	-0.437 (0.093)
Floating Coupon Dummy	0.063 (0.018)	0.058 (0.018)	0.074 (0.043)	-0.177 (0.556)	-0.179 (0.187)	0.179 (0.022)	0.138 (0.020)	-0.020 (0.105)	0.202 (0.045)	0.270 (0.047)	-0.140 (0.118)
Number of Trades in Sample	-0.059 (0.014)	-0.024 (0.014)	-0.142 (0.045)	-0.687 (0.267)	-0.120 (0.070)	-0.119 (0.025)	-0.106 (0.018)	-0.170 (0.090)	0.113 (0.030)	0.042 (0.028)	-0.099 (0.072)
Number of Dealers	0.001 (0.002)	-0.005 (0.002)	0.016 (0.009)	0.066 (0.079)	0.004 (0.026)	-0.004 (0.005)	-0.001 (0.003)	-0.010 (0.017)	-0.054 (0.006)	-0.050 (0.006)	-0.008 (0.018)
Security Specific Match Volume	-0.111 (0.021)	-0.117 (0.017)	-0.116 (0.054)	-0.314 (0.159)	-0.117 (0.047)	0.012 (0.034)	0.024 (0.024)	0.054 (0.081)	-0.337 (0.036)	-0.532 (0.038)	-0.075 (0.090)
Deviation of Particular Match	-0.033 (0.008)	-0.041 (0.007)	-0.009 (0.019)	0.195 (0.191)	0.060 (0.068)	-0.092 (0.013)	-0.093 (0.013)	-0.050 (0.041)	-0.286 (0.037)	-0.361 (0.040)	-0.273 (0.154)
Prearranged Pair Of Trades	-0.118 (0.020)	-0.080 (0.015)	-0.233 (0.062)	-0.513 (0.283)	-0.130 (0.086)	-0.088 (0.025)	-0.040 (0.019)	-0.384 (0.108)	-0.539 (0.050)	-0.538 (0.053)	-0.428 (0.093)
Dealer's Coreness &Prearranged Trade	-0.046 (0.015)	-0.024 (0.013)	-0.091 (0.040)	0.282 (0.229)	-0.157 (0.063)	-0.046 (0.021)	-0.033 (0.016)	-0.068 (0.062)	0.013 (0.041)	0.015 (0.045)	0.026 (0.064)
Dealer's Coreness &All Other Trades	-0.070 (0.022)	-0.071 (0.024)	-0.054 (0.052)	0.116 (0.299)	0.003 (0.097)	-0.052 (0.035)	-0.010 (0.019)	-0.231 (0.144)	0.244 (0.048)	0.247 (0.053)	0.093 (0.088)
Dealer's Degree Residual	-0.036 (0.009)	-0.024 (0.009)	-0.069 (0.027)	-0.551 (0.180)	-0.064 (0.034)	-0.010 (0.015)	-0.023 (0.011)	0.061 (0.065)	-0.006 (0.041)	0.034 (0.041)	-0.302 (0.062)
Buy from Customer Sell to Dealer	-0.031 (0.028)	-0.030 (0.031)	-0.038 (0.059)	-0.087 (0.471)	-0.194 (0.113)	-0.055 (0.035)	-0.081 (0.029)	0.178 (0.181)	-0.152 (0.059)	-0.192 (0.063)	0.096 (0.154)
Buy from Dealer Sell to Customer	0.045 (0.018)	0.037 (0.018)	0.076 (0.051)	0.429 (0.440)	0.060 (0.124)	0.174 (0.030)	0.126 (0.025)	0.598 (0.162)	0.374 (0.063)	0.353 (0.068)	0.057 (0.097)

Subcategory Fixed Effects: Yes. Number of observations: 78910. R-squared: 0.297

Legend: The regression includes fixed-effects 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.