The value of trading relations in turbulent times[*]

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ABSTRACT

This paper investigates how dealers' trading relations shape their trading behavior in the corporate bond market. Dealers charge lower spreads to dealers with whom they have the strongest ties and more so during periods of market turmoil. Systemically important dealers exploit their connections at the expense of peripheral dealers as well as clients, charging higher markups than to other core dealers. Also, intermediation chains lengthened by 20% following the collapse of a flagship dealer in 2008 and even more for institutions strongly connected to this dealer. Finally, dealers drastically reduced their inventory during the crisis.

Keywords: Corporate bond, Dealer network, Intermediation chain, Over-the-counter financial market, Trading relationship

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1. Introduction

The global financial crisis of 2008-2009 highlights the key role of the intertwined nature of financial markets in shaping the transmission of risk and the buildup of fragility throughout the system. At the same time, the growing importance of off-exchange trading, with many securities traded in opaque over-the-counter markets [corporate bonds, mortgage-backed securities, credit default swaps (CDSs), etc.], has been blamed for the persistent illiquidity of these markets. Even the new regulatory frameworks adopted in the aftermath of the crisis, from the proposal that clearinghouses serve as central counterparties to the definition of systemically important financial institutions, have incorporated these views. Yet exactly what role is played by financial system interconnectedness and the ways in which large financial institutions can affect OTC market liquidity remain at best imperfectly understood.

This paper investigates dealers' trading behavior and pricing strategy in the corporate bond market to shed new light on the role of the network of existing relations among dealers in shaping the transmission of risk and influencing market liquidity. The corporate bond market is one of the world's largest and most important sources of capital for firms, with outstanding debt as of 2016 of about $8 trillion.[1] Daily trading volume in the US averages $20 billion, virtually all between broker-dealers and large institutions in a decentralized OTC market.[2] Hence, this market is ideal for studying how the network of dealer relationships shapes trading behavior and liquidity provision and for investigating how dealers responded during the crisis.[3]

We start by showing that the inter-dealer corporate bond market has a definite, persistent core-periphery network structure. In other words, only a few highly interconnected dealers, the

[1] Based on data from the Securities Industry and Financial Markets Association (SIFMA). See http://sifma.org/research/statistics.aspx.

[2] In the last few years, investors have been attracted to fixed income securities, and bond issuers have taken advantage of the low interest rate environment. For instance, the Financial Industry Regulatory Authority (FINRA) reports that in 2012 issuers borrowed a record $1.54 trillion, up 29% from 2011, owing chiefly to a shift in retail portfolio composition from equities to fixed income instruments.

[3] Our empirical findings are informed and guided by the burgeoning theoretical literature on networks and off-exchange markets. Following the seminal articles of Allen and Gale (2000) and Freixas, Parigi, and Rochet (2000), a growing body of work has considered financial networks as a possible mechanism for shock propagation and amplification. For instance, Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) characterize the extent of contagion when financial institutions are linked via unsecured debt contracts, and Elliott, Golub, and Jackson (2015) study cascading failures in a model of equity cross-holdings. In a similar vein, Stanton, Walden, and Wallace (2014) develop a network model in which heterogeneous financial norms and systemic vulnerabilities are endogenous and test its implications with data on financial intermediaries' securitization network.

core dealers, intermediate most of the transactions with other dealers and with clients (retail investors, insurance companies, mutual and hedge funds, etc.), and many sparsely connected ones transact less frequently, i.e., the peripheral dealers.[4] Given this structure, we analyze how dealers' markups and trading behavior differ according to their counterparties' position in the network and how their previous relations with counterparties affect trading outcomes.[5] When dealers trade with clients instead of other dealers, they profit significantly more. On average, similar bonds in the same industry traded by the same dealer go at a significantly higher price to non-dealer clients, an extra markup of about 50 basis points. We also show that more central dealers pay lower spreads while charging significantly higher spreads to their counterparties.[6]

We also find significantly lower spreads between dealers with stronger prior relations, as proxied by the fraction of bonds exchanged between two counterparties in the previous quarter. Here, the results do not depend on differences in the type, volume, or quality of the transactions of more or less connected dealers, because these characteristics are controlled for. The magnitude of the effects, moreover, is economically significant. The difference in the terms of trade between the bottom and the top decile of relation strength comes to about 20 basis points. And the results hold even in the most conservative specification, in which we control for seller- and buyer-month fixed effects, to offset time-varying shocks at the dealer level that could affect trading behavior. Overall, our findings constitute evidence that existing trading relations, which most of the theoretical literature abstracts from, are crucial in determining trading behavior, at least on a par with network centrality.

Now we can answer the main questions we want to pose. Does the importance of these prior relations vary over time? And do dealers tend to provide liquidity to their counterparties in

[4] This network structure has been the subject of recent theoretical studies on the risks created by highly interconnected institutions [see, for instance, Babus (2016), Farboodi (2014), and Atkeson, Eisfeldt, and Weill (2015)].

[5] Our main dependent variable is the difference between the price at which a dealer sells a bond and his previous buying price. We call this the spread, profit margin or markup. We provide results for two different measures. The more conservative approach considers only trades in which the dealer buys a bond and then sells it within an hour. However, we also provide consistent evidence in which the benchmark buy price is the average at which other dealers buy the same bond during the same week.

[6] Given these results, our paper is related to empirical studies on OTC market transaction costs and price discovery, such as Bessembinder, Maxwell, and Venkataraman (2006), Schultz (2001), Edwards, Harris, and Piwowar (2007), Green, Hollifield, and Schürhoff (2007b), and Green, Li, and Schürhoff (2010). In other related works, Biais (1993) and Hendershott and Madhavan (2015) consider the comparative advantages of bilateral and electronic trading. Our focus is on how relations shape dealers' liquidity provision during periods of uncertainty.

times of market turmoil? We capture periods of financial market stress in two ways. One is a simple volatility index [Chicago Board Options Exchange Volatility Index (VIX) or Merrill Lynch Option Volatility Estimate (MOVE) Index]. The second splits the full sample into three subperiods: January 2005–December 2006, January 2007–August 2008, and September 2008–July 2009. The first period represents normal times, the second corresponds to the run-up to crisis, and the third is the peak of the crisis following the default of Lehman Brothers. We find that having stronger relations and being a more central dealer are all the more important during periods of high uncertainty. During periods of stress, dealers provide less liquidity to clients and peripheral dealers (than to other core dealers), charging them significantly higher markups. In other words, at times of market turmoil, dealers tend to rely even more heavily on their central position in the network, as more connected institutions can impose higher spreads and purchase at significantly lower prices. The results are further confirmed when we split the sample over time. Markups charged are significantly larger for the more central dealers during the run-up and even more so at the peak of the crisis. In contrast, dealers did provide liquidity to the other institutions with which they had the strongest relations. In fact, existing trading relations drive a significant portion of the variation in spreads during the peak of the crisis. This implies that, in turmoil, dealers rely more heavily on their closest counterparties, as is suggested by Glode and Opp (2016). Our results carry important implications for the theoretical models of trading in OTC markets. Essentially, the common random-matching framework, which ignores bilateral trading relations, de facto, by assuming that traders interact only in anonymous spot transactions, misses an important feature of off-exchange markets.

Also, we examine how dealers' trading behavior reacted to the collapse of a flagship dealer that defaulted in September 2008. We code this dealer as Dealer D.[7] After the failure of Dealer D, the intermediation chains between buyers and sellers lengthened significantly. Because longer chains are associated with higher spreads, they also have adverse effects on the clients who are seeking liquidity. Furthermore, we test whether dealers tend to lean against the wind, i.e., accumulating bond inventories during periods of turmoil. We compute dealers' inventories in the weeks before and after Dealer D's collapse, excluding new issuance and maturing bonds, and find that they shrank significantly more for the bonds that clients were selling more vigorously. In fact, dealers decreased their holdings of the bonds that other market participants

[7] Under an agreement with the FINRA, we are not allowed to disclose dealer identities.

were selling most intensely by at least 20%. This is strongly suggestive that one of the main factors in the increase in intermediation costs and market illiquidity was dealers' inability (or unwillingness) to expand inventories. As further evidence of this channel, we show that inventories shrank most for the bonds in whose regard the intermediation chain lengthened the most. These results can inform the debate on dealers' role during the crisis and how significantly they aggravated the market disruption.

Finally, if these existing trading relations are readily replaceable among dealers, then the failure of Dealer D should not have an impact on its counterparties. Instead, we find that the dealers most closely connected with Dealer D reduced their markups significantly after September 2008. One possible explanatory factor could be a difference in the composition of the bonds traded after the collapse. Alternatively, the results could be driven by endogenous matching between more fragile counterparties. In reality, however, we show that these results persist over time and are not driven by these factors. Comparing the same bond traded by the same counterparties in the same week, the only difference is sellers' relative exposure to Dealer D. This suggests that, having lost their main counterparty, dealers had to form new trading relations, but that these were significantly less profitable.

Overall, our findings contribute to improving understanding of the role of financial system interconnectedness, which has become a theme of policy debate. In the words of Donald L. Kohn, the former vice chairman of the Federal Reserve Board: "Supervisors need to enhance their understanding of the direct and indirect relationships among markets and market participants, and the associated impact on the system. Supervisors must also be even more keenly aware of the manner in which those relationships ... can change over time and how those relationships behave in times of stress."[8] These results shed new light on the way in which these prior relations can sometimes act as a buffer in periods of distress. They also show that they accentuate systemic fragility, as connections with vulnerable dealers could affect trading outcomes even for sound dealers.

For the most part, the literature on the role of the network is theoretical, but exceptions exist, such as Li and Schürhoff (2014), Hollifield, Neklyudov, and Spatt (2012), Choi and Shachar (2013), Afonso, Kovner, and Schoar (2013), Hendershott, Livdan, and Schürhoff

[8] See Kohn (2008).

(2016), and Di Maggio, Franzoni, Kermani and Sommavilla (2016).[9] Li and Schürhoff (2014) show that the municipal bond market has a persistent core-periphery structure, with a trade-off between execution costs (lower in the periphery) and speed (faster in the core). A similar network structure is uncovered by Hollifield, Neklyudov, and Spatt (2012) in the securitization market. Choi and Shachar (2013) inquire into the misalignment between corporate bond and CDS spreads during the financial crisis. Afonso, Kovner, and Schoar (2013) study the overnight interbank market, finding that borrowers that have more concentrated lenders could pay higher rates and that banks get lower interest rates from their most important lenders.[10] Finally, Hendershott, Livdan, and Schürhoff (2016) use data on insurers' transactions with corporate bond dealers to show a trade-off between order flow concentration and dealer competition for best execution, whereas Di Maggio, Franzoni, Kermani and Sommavilla (2016) uncover the role of the brokers network for the information diffusion in the stock market. We complement these existing studies by highlighting the time-varying importance of the relations between dealers and the role played by the network in the propagation of shocks such as Dealer D's collapse.[11]

Further, cooperation and reputation have been shown to affect liquidity costs in exchange markets by Battalio, Ellul, and Jennings (2007), who find an increase in liquidity costs in the trading days surrounding a stock's relocation to the floor of the exchange, while Pagano and Röell (1992) and Benveniste, Marcus, and Wilhelm (1992) demonstrate that reputation attenuate the repercussions of information asymmetries in trading and liquidity provision.[12] We complement this strand of the literature with our evidence that existing relations are at least as important as bargaining power in explaining dealers' behavior.

The remainder of the paper is organized as follows. Section 2 gives the data sources and summary statistics, and Section 3 develops, in relation to the theoretical literature, the empirical hypotheses that we test and outlines our empirical strategy. Section 4 demonstrates the clear

[9] See the presidential address by Green (2007) and the references therein as additional studies related to ours.

[10] Another related work is Ang, Shtauber, and Tetlock (2013), which compares the characteristics of OTC and listed stocks, showing that OTC stocks exhibit an illiquidity premium several times higher and even more for stocks held predominantly by retail investors and investors that do not disclose financial information.

[11] A related work is Gabrieli and Georg (2014), which studies liquidity reallocation in the European interbank market and shows a significant change in the network structure around the bankruptcy of Lehman Brothers.

[12] Also related are Henderson and Tookes (2012) on repeated interactions between placement agents (investment banks) and investors in the initial pricing of convertible bonds and Cocco, Gomes, and Martins (2009), with evidence from the interbank market that banks provide liquidity to one another at times of financial stress.

core-periphery structure of the corporate bond market, which shapes trading behavior. Section 5 describes the main results on the importance of the trading relations at times of market turmoil and presents evidence on how the failure of Dealer D affected its trading partners and how the shock was propagated. Section 6 examines the changes in dealers' inventories to test if they provided liquidity during bad times. Section 7 conclude and the Online Appendix presents further robustness checks.

2. Data and summary statistics

We collect information on transactions of corporate bonds from an enhanced version of the Trade Reporting and Compliance Engine (TRACE). For each trade the dealer reports the date, the terms, and the counterparty identifier. The enhanced TRACE data provided by the Financial Industry Regulatory Authority (FINRA) (not publicly available) have several advantages. We can observe whether the trade is between two dealers or with a customer. And we can distinguish buyers and sellers. Thus, we can trace the chains of intermediation; that is, we can see whether a dealer who has gotten a buy order from a client has then gone to another dealer or another client to acquire the bond demanded. For our analysis, the most important feature of this proprietary data set is that we can observe the identity of the dealers, which allows us to construct a panel of dealer-specific variables and to measure the existing trading relations between various dealers and Dealer D and study how Dealer D's collapse affected trading in the network.

Table 1 presents the summary statistics. Panel A refers to the bonds and the trades we observe. Columns 1 and 2 are for the entire data set; Columns 3 and 4 for our most restrictive sample, i.e., trades concluded within an hour of their initiation. Columns 5 and 6 report the statistics for a less restrictive sample, for which we compute the markup as the difference between the ask price and the average price at which other dealers have bought the same bond during the week. We use this broader sample in the Online Appendix to perform robustness checks. Our data run from 2005 to 2011, covering more than 56 thousand bonds traded and 52 million transactions. Due to computing limitations, our main analysis and the samples in Columns 3-6 relate to a 10% random sample of the entire TRACE database, reducing the sample from 52 million to about five million trades.[13] Our principal measure of the spread, which refers

[13] The random sample consists of trades whose last Committee on Uniform Security Identification Procedures (CUSIP) digit is 0. As Table 1 shows, the sample so reduced looks very similar to the full sample.

to buy and sell transactions that occur within one hour of each other, further restricts the sample to some 700,000 trades.

Most of these bonds, about 85% of all the bonds, are investment grade, and 15% are high yield or unrated. The average issue volume is $21 million (85% of the issues are smaller than $100 million); maturity, ten years; and rating, BBB+. No significant difference exists in the distribution of bond characteristics between the full sample and our main sample.

Panel B reports the statistics on the main variables. These include dealers' spread, i.e. the difference between the price at which they buy a bond (from another dealer or a client) and their resale price. The spread averages between 40 and 60 basis points. Our main measure of network centrality is the eigenvector centrality. This takes account of all direct and indirect trading partners and is computed by assigning scores to all dealers in the network. Connections to more connected dealers increase the score more than similar connections to less connected dealers. In other words, what counts is not only the number of connections, but also with whom they are connected. However, our qualitative results are robust to alternative measures of centrality, such as the degree of centrality, betweenness and closeness. We also report statistics on the number of transactions between core dealers (about 30% of total trades), between peripheral dealers (25%), and between a core and a peripheral dealer (the remaining 45%).

3. Empirical framework

Our paper is informed by recent theoretical work on trading in OTC markets, starting with the seminal work of Duffie, Garleanu, and Pedersen (2005, 2007) on the asset pricing implications of OTC trading. Our empirical investigation of the dealers' trading strategy in the OTC corporate bond market could prove valuable to this literature by showing what types of strategic interaction are the result of the relations formed among dealers and how these relations affect asset prices and dealers' response to shocks.

We develop and test four main hypotheses inspired by recent developments in this strand of the literature.

Hypothesis I. *Bilateral inter-dealer existing relations significantly affect markups*.

Formally, we estimate the specification

$$Spread_{i,j,k,t} = \beta_1 Fraction\ Selling\ to\ Counterparty_{i,j} + \beta_2 Fraction\ Buying\ from\ Counterparty_{i,j} + \Gamma X_{i,j,k} + \lambda_t + \varphi_k + \theta_i + \varepsilon_{i,j,k,t},$$

where $Spread_{i,j,k,t}$ is the difference between the price at which dealer i sold bond k to counterparty j at time t and the price at which he had bought it.[14] The main independent variables considered are the fraction sold by dealer i to dealer j and the fraction of bonds purchased by dealer i from dealer j in the previous quarter. To make sure we are comparing similar transactions, the vector X includes as controls the log of trade size, the bond's rating, and the fraction of bond k held in inventory by seller i, normalized by the volume outstanding, which proxies for the seller's market share of this market segment. We also control for week (λ_t), CUSIP (Committee on Uniform Security Identification Procedures) (φ_k) and seller (θ_i) fixed effects. To capture possible industry-level shocks, in the most conservative specification, we include industry month fixed effects. This ensures that our results are not driven by purchases of bonds in some particular industry, say energy, that is hit by a common shock, say, oil price changes. Throughout, in computing standard errors we take the most conservative approach, double-clustering them at both the CUSIP and the week level. This procedure allows for arbitrary correlation across time and across bonds.[15]

If β_1 and β_2 are negative, this suggests that counterparties benefit from repeated transactions, as their stronger ties tend to predict lower markups. This possibility is of special interest in that to date the theoretical literature has generally adopted a random-matching framework, which ignores bilateral trading relations, de facto, by assuming that traders interact only in anonymous spot transactions. Our results could motivate new theoretical work to accommodate this important feature of the data.

We can also test if the price discrimination proposed in Hypothesis I becomes even more pronounced at times of market turmoil.

[14] We compute the spread in two different ways. We refer only to trades concluded within an hour of their initiation, meaning that we observe both the purchase and the sale by the same dealer i in the same hour. This narrows the field to transactions in which the spread precisely measures the dealer markup. However, the bonds in these transactions could have special characteristics, such as a particularly high degree of liquidity. To address this concern, in robustness checks (in the Online Appendix) we also consider transactions in which the dealer sells directly from his inventory, in which we do not necessarily observe the previous purchase price. We overcome this limitation by using the average price of the bond bought by other dealers in the same week, as a proxy of its actual value. The two measures yield similar results.

[15] Single clustering on either of these two dimensions produces smaller standard errors (results available upon request).

Hypothesis II. *Dealers exploit their position in the network more forcefully in times of market turmoil.*

Formally, we test whether, during spike periods of the CBOE Volatility Index, dealers take greater advantage of their position in the network to trade at better terms than in normal times.[16] If confirmed, this hypothesis would relate to Carlin, Lobo, and Viswanathan (2007), who describe an equilibrium in which traders cooperate most of the time through repeated interactions, providing liquidity to one another. However, cooperation breaks down when the stakes are high, leading to predatory trading and episodic illiquidity.

We can also test whether dealers performed their expected role of liquidity providers during the crisis. Weill (2007) has examined the conditions under which dealers could provide liquidity by "leaning against the wind", i.e., accumulating bond inventories in bad times. Debate is ongoing about whether dealers coped successfully with the increased selling pressure at the height of the crisis, because, as Mitchell and Pulvino (2012) show, the deleveraging of other institutions, such as highly leveraged hedge funds, after the Lehman Brothers default significantly increased the demand for liquidity in the corporate bond market. And adverse shocks can induce dealers, too, to unload their bond positions in periods of distress.

Hypothesis III. *During financial disruptions, market-makers provide liquidity by absorbing external selling pressure.*

To test this hypothesis, we use transaction data to construct a measure that captures dealers' inventory, sorting bonds into three bins depending on the intensity of clients' selling pressure, defined as the amount sold by clients to dealers normalized by the amount outstanding. We then estimate the specification

$$\begin{aligned} Inventory_{i,t} = {} & \beta_1 TopTercile \times Post + \beta_2 MidTercile \times Post + Post + \\ & TopTercile + MidTercile + \theta_i + \lambda_t + \varepsilon_{i,t}, \end{aligned}$$

where we have three observations for dealer i's inventory in each week, one for each tercile. We interact our main independent variable with $Post$, a dummy equal to one after the collapse of Dealer D, and the omitted category is the identifier for the bonds in the lowest tercile of selling pressure (defined as the amount sold by clients to dealers normalized by the amount

[16] We also find very similar results using the MOVE Index.

outstanding). To be sure that the inventory variations captured are due to the intensified demand for liquidity and not to some general trend, we estimate this specification in a narrow window around Dealer D's default and only for investment-grade bonds. If β_1 and β_2 are negative, this strongly suggests that dealers ran down their inventories especially for the bonds that their clients were selling most intensely, by reselling them immediately. In other words, dealers' unwinding of corporate bond positions could have exerted heavy selling pressure precisely during the period when many market participants were selling and demanding liquidity.[17]

Finally, the data also allow us to trace the trades that involve several layers of intermediation. Glode and Opp (2016) argue that, given asymmetric information, trading an asset through several heterogeneously informed intermediaries can reduce adverse selection between counterparties and so preserve the trade efficiency.[18] This result suggests Hypothesis IV.

Hypothesis IV. *The length of the trading chain increases with adverse selection in the market.*

We can test this hypothesis by examining the length of the trading chain during periods of market turmoil, when adverse selection should be more pronounced, for instance, by comparing lengths before and after the collapse of Dealer D.

4. Trading network of the corporate bond market

Before testing our main hypotheses, let us analyze the type of network that came into being in the corporate bond market and its persistency. Fig. 1 shows the cumulative distribution of all trades as a function of the seller's centrality measure. The top 50 dealers account for some 80% of all transactions, suggesting a definite core-periphery structure in the interdealer market. This is confirmed by Fig. 2, which plots the intermediation network using transaction data. Each red circle represents a dealer, the center of the network is occupied by clients, and the links connecting participants are more intense as the volume of the transactions increases. The

[17] If dealers do not lean against the wind but instead sell during periods of market turmoil, bond prices drop significantly. This is one possible reason for the large negative basis of non-AAA bonds during the financial crisis.

[18] The recent literature has also suggested a few other reasons for the emergence of intermediation chains. Afonso and Lagos (2015) focus on heterogeneity of banks' reserves, Atkeson, Eisfeldt, and Weill (2015) consider the banks' exposure to aggregate default risk, and Hugonnier, Lester, and Weill (2014) and Shen, Wei, and Yan (2015) show how search costs and heterogeneous asset valuations can lead traders with intermediate valuation to act as intermediaries.

network consists of a few top dealers at the core, carrying out a high volume of trades among themselves and with clients, and a larger number of peripheral dealers making fewer trades.[19]

Accordingly, we begin by differentiating three types of market participants: core dealers, peripheral dealers, and clients. The first question is whether core dealers are able to charge other participants higher prices for the assets they sell.[20] Columns 1-5 of Table 2, Panel A report on the entire sample of transactions, with the relevant coefficient being the indicator variable *Client Buyer*. Column 1, controlling only for week fixed effects to absorb changes in the average cost of intermediation, shows that on average dealers charge clients 50 basis points more than they charge other dealers. In Columns 2 and 3, we control for transaction volume, rating, dealer's market share, and the bond fixed effect (CUSIP). The results are similar. In Column 4, we also include seller fixed effects, and the results remain unaffected. In Column 5, we saturate the model with industry-month fixed effects, so that we exploit variation only for the bonds in the same industry traded in the same month. Again, the results are unaffected. In Column 6, we restrict the sample to investment-grade bonds; in column 7, to non-investment-grade bonds. The data show that dealers charge similar prices for the two grades. Columns 8 and 9, instead, show that both core and peripheral dealers charge their clients about 50 basis points more than they do other dealers, even controlling for week and bond fixed effects. That is, clients' transaction costs appear to be about the same regardless of whether their counterparty is a core or a peripheral dealer. Panel B shows the same regression estimates, but now the markup is related to transaction size. We find that markups decline with the size of the trade, suggesting that for small trades the client does not search for the best deal, and for larger transactions there is more competition among dealers, resulting in reductions in the spread of as much as 60 basis points.

So far, we have compared transactions among dealers with those between dealers and clients. However, Fig. 3 and 4 show that, even among interdealer transactions, there is significant heterogeneity. The trades with the lowest spreads are those between core dealers and peripheral-to-core dealer transactions. Core-peripheral dealer and core-client transactions show significantly higher spreads, which increase significantly during the crisis that began in the first quarter of

[19] In unreported results, we find that this structure is also highly persistent, with the probability of switching from the core to the periphery, or vice versa, being negligible.

[20] Theoretical support for this hypothesis is provided by Babus and Kondor (2013) and Farboodi (2014). Babus and Kondor (2013) show that more central dealers can learn faster from the prices of the transactions they execute, increasing their trading gains. Similarly, in the context of an endogenous network formation model, Farboodi (2014) shows that core dealers charge higher average prices to the peripheral dealers than to other core dealers.

2008. So, we explore these findings further by analyzing interdealer transactions (Table 3). The comparison group is inter-core-dealer transactions, i.e., trades in which both seller and buyer have a network centrality measure in the top 30.[21] Column 1 shows a clear ranking among different types of trades as far as the spread is concerned. Core-core transactions are the cheapest, periphery-core trades are slightly more costly, periphery-periphery are about 20 basis points more expensive than core-core, and core-periphery transactions are the most expensive by almost 30 basis points. Columns 2-4 show that these results remain both statistically and economically significant even when we include controls. Columns 5 and 6 show that core dealers charge the peripheral dealers about 10 basis points more for non-investment-grade than for investment grade bond trades. However, no significant difference is evident by bond rating when peripheral sellers are dealing with core buyers. It would thus appear that the core dealers can profit more from riskier investments when they transact with marginal dealers than with other core dealers. Transactions between peripheral dealers show a similar pattern, with non-investment-grade bond trades exhibiting higher margins. These results are consistent with the findings of Green, Hollifield, and Schürhoff (2007a), Green (2007), and Li and Schürhoff (2014) for other off-exchange markets.

In short, these results establish a very significant relation between a dealer's position in the network and the profits captured in trades with clients or other dealers. Our measure of network centrality could be proxying for the dealer's bargaining power, one of the main parameters common to the theoretical literature on OTC trading. However, we can now show that the prior bilateral relations among dealers, which are usually left unmodeled, are at least as important as bargaining power in predicting spreads.

5. Main results

We start by analyzing how existing bilateral trading relations among dealers affect spreads, especially in times of market turmoil. We then investigate how the network reacts when a core dealer defaults.

[21] The results are qualitatively the same if the sample is narrowed to the top 20 or broadened to the top 40 dealers.

5.1. Trading relations

To this point, we have considered only position in the network, core versus periphery, as a factor potentially affecting profit margins. We now turn to a more in-depth analysis of the role of prior bilateral relations in the OTC corporate bond market. We compute the fraction of sales that seller *s* had with buyer *b* in the previous quarter, normalized by S's total sales (*Fraction Sales*$_{s,b}$/*Total Sales*$_{s}$), which we label *Fraction Selling to Counterparty*. We also compute the fraction of trades in which buyer *b* bought bonds from seller *s*, normalized by *b*'s total purchases in the previous quarter (*Fraction Purchases*$_{s,b}$/*Total Purchases*$_{b}$), designated *Fraction Buying from Counterparty*.

Table 4 reports the estimation results from our formal test of Hypothesis I. Column 1 shows the effect of *Fraction Selling to Counterparty* and *Fraction Buying from Counterparty* on seller's spread controlling for week fixed effects, the volume of the trade, market share, and the bond's rating. On average a higher fraction of past sales to the buyer predicts significantly lower profit margins. Similarly, a higher fraction of purchases by the buyer from the same seller, compared with his total purchases, predicts significantly lower profit margins. The data also confirm that in general higher transaction volume corresponds to lower profit margins and lower-rated bonds are associated with higher profit margins.

Column 2 confirms these results by controlling for the bond fixed effects. The coefficient is similar and both economically and statistically significant. In other words, comparing the same bond traded between two different pairs of counterparties in the same week, those with the stronger past tie have lower spreads. Column 3 adds industry-month fixed effects, to make sure that the result is not driven by unobserved heterogeneity in the type of bonds traded by some counterparties and not others. The results are economically significant. A difference exists in the markup of about 20 basis points between the bottom and the top decile of relation strength. The results hold even in our most conservative specification, in which we control for seller- and buyer-month fixed effects, which neutralize any time-varying shocks at the dealer level that could affect trading behavior.

Thus, the results show the importance of the existing relationships between counterparties. Column 4 focuses on the positions of the seller and buyer in the network, controlling for week and bond fixed effects. In this way, we test whether or not the importance of bilateral relations is subsumed by relative centrality in the network. We find that a more central buyer can get a lower price from his counterparties than a more peripheral one, while the results for the seller are weaker, both statistically and economically. Although this shows that dealer centrality is important in explaining markups (central sellers buy at lower prices), it also shows that network centrality does not explain the importance of prior bilateral relations away.

Columns 5 and 6 demonstrate that the importance of existing bilateral relations remains even including seller- and buyer-month fixed effects, thus controlling for time-varying heterogeneity at the dealer level. Overall, evidence shows that existing trading relations play a major role in shaping trading behavior, at least as important as the dealer's degree of network centrality.

5.2. Dealer network and trading relations in times of market turmoil

Now we are in a position to address one of our main questions: When are these prior relations most valuable? And, do dealers demand higher spreads during periods of high uncertainty, especially from the counterparties that are most dependent on them? In answering, we exploit the time series dimension of our data to test Hypothesis II. Our data set covers the financial crisis, so we can investigate dealers' trading behavior as a function of their existing relations during the crisis.

Table 5 shows the results. We take two different approaches. First, we interact our measures of prior trading relations and of network centrality with the volatility index (VIX). Second, we split the sample into three periods to capture the different phases of the crisis. We begin, in Columns 1-2, by interacting the intensity of the relation between seller and buyer with the volatility index controlling for week and bond fixed effects. If the two parties have a strong tie, the incidence of the trading relation on the spreads becomes even more pronounced in periods of intense uncertainty. Holding the bond constant is particularly important, because changes in the spreads could be due to a change in the composition of the bonds traded at the peak of the crisis, as dealers could be reducing inventories by getting rid of their riskier holdings. Comparing the same bond, traded in the same week among different counterparties, we find that dealers who had previously done a significant fraction of their corporate bond business with the same counterparties were able to strike a better deal and that profit margins were lower in correspondence with spikes in market uncertainty. In terms of magnitude, a one standard deviation increase in the VIX reduces margins by 35 basis points. At the worst of the crisis, the VIX increased by about three standard deviations, which makes these results economically significant. The results are very similar when we control for industry-month fixed effects. That is, in times of market distress, dealers tended to be liquidity providers for their closest counterparties.

Did dealers also serve as liquidity providers for market participants in general? Columns 4-6 address this issue by testing whether the degree of network centrality becomes more important during periods of market turmoil. Interacting our centrality measure for buyer and seller with the volatility index, we find that more central sellers profit even more from their position during periods of stress and central buyers, too, have greater bargaining power, concluding transactions at lower prices. This means that a core dealer can capture even higher rents by trading with peripheral dealers in bad times, but peripheral dealers cannot do the same when selling to a core dealer. Thus, the gap between core and peripheral dealers is accentuated in crisis periods, as only the former can take advantage of their position. This supports the thesis that in bad times dealers provide liquidity selectively to their closest counterparties only, while exploiting their centrality with other market participants.

As a complementary strategy, in Panel B of Table 5 we split the sample into three subperiods: January 2005–December 2006, January 2007–August 2008, and September 2008–July 2009. The first period represents normal times; the second, the run-up to the financial crisis; and the third, the crisis peak after the failure of Lehman Brothers. Comparing the results in the three columns, relative to other traders, central sellers and buyers capture a significantly larger fraction of the trading profits during the crisis than in normal times, even controlling for week and bond fixed effects. The difference is significant statistically as well as economically. Sellers charge six times more during the crisis than during the run-up, and buyers get discounts four times larger. Buyers in the top decile of centrality purchase at spreads 50 basis points narrower than those charged to buyers in the bottom decile, and the markups of the most central sellers are 40 basis points higher.

The comparison further confirms that the role of existing relations was even more important than in normal times. At the height of the crisis, the presence of a repeated seller or buyer relation with a given counterparty led to lower margins than in normal times. Unlike the centrality measure, whose coefficient increases monotonically as the market turmoil intensifies, the bilateral relations have the same impact on spread in Columns 1 and 2. Their importance increases significantly only at the peak of the crisis (Column 3). The economic effect, too, is important. The gap between the markups of dealers in the top and in the bottom decile of our measure of relation is about 40 basis points between the precrisis and crisis period. Thus, this analysis confirms the time-varying role of bilateral relations in turbulent times and their importance, on a par with the network centrality.

Fig. 3 suggests that all spreads increase significantly around the Lehman Brothers' collapse, but with considerable heterogeneity across transactions among the different types of market participant. This heterogeneity could be due to a variety of factors, such as a change in the pool of bonds traded by different counterparties or shocks to specific dealers. We address this issue formally in Table 6, splitting the transactions between dealer types as in Table 3 and interacting the main indicator variables with the VIX (Columns 1-4). We also split the sample into our three periods (Columns 5-7). Core dealers are able to extract even higher rents from peripheral dealers in periods of high volatility, but peripheral dealers are not able to do the same when selling to core dealers. Transactions at the periphery tend to exhibit higher profit margins in turbulent times. Comparing Column 3 with Column 4, core dealers profit even more at times of greater uncertainty in trading with peripheral dealers when the bond is non–investment grade. The results are robust to controls for trade characteristics interacted with the VIX, as well as week-, bond- and industry-month fixed effects. When transactions are compared over time (Columns 5-7) the results are very similar, with core dealers profiting about three times more from peripheral dealers at the peak of the crisis.

These results highlight the main finding of this section: Existing relations are good predictors of profit margins, and they become even more important under market turmoil. This contrasts with the theoretical literature on OTC markets, which, with the exceptions of Seppi (1990) and Glode and Opp (2016), generally posits that interactions between buyers and sellers are anonymous and price dispersion is not affected by the parties' transaction history.[22] A further original feature of our study is the discovery that the importance of existing relations is

[22] The models proposed by Seppi (1990) and Glode and Opp (2016) highlight how the identity of the counterparty could significantly shape the trading process.

time-varying. In addition, relation-based trading behavior benefits core dealers at the expense of peripheral dealers.

5.3. Default of a core dealer

Having established that prior trading relations and network centrality shape dealers' rent shares and liquidity provision and that their importance is heightened in crisis, we now investigate the impact on a dealer's behavior of losing a major trading partner. The question is whether these relations are easily substitutable. If there are no frictions, i.e., if dealers can readily locate new counterparties and new relations can be easily formed, losing a tie with a specific dealer should not affect profitability or transaction costs. We test this hypothesis formally using the information on dealer identities contained in our regulatory data. We want to see how the network reacts to the shock of Dealer D's default and how this affected the dealers that had prior relations with Dealer D.

Table 7 reports the regressions that relate the strength of the relation with Dealer D with other dealers' profit margins after the collapse. For each dealer we compute the fraction of all bonds sold to Dealer D as the average for the year 2007. This is to make sure we capture a stable relation with Dealer D, instead of deleveraging on the eve of the bankruptcy. We consider the fractions of securities both bought from and sold to Dealer D, but in fact the two are very closely correlated. Formally, we estimate the regression

$$\begin{aligned} Spread_{i,j,k,t} = {} & \beta_1 Fraction\ of\ Purchase\ Transactions_{i,D} \times Post + \\ & \beta_2 Fraction\ of\ Purchase\ Transactions_{i,D} + \\ & \Gamma X_{i,j,k} + \lambda_t + \varepsilon_{i,j,k,t}, \end{aligned}$$

where i and j denote the two counterparties, k indexes the bond, and t is the week. $Fraction\ of\ Purchase\ Transactions_{i,D}$ proxies the intensity of the relation between dealer i and Dealer D in the pre-period. $Post$ is a dummy equal to one in the period after the default. We include several controls in the vector $X_{i,j,k}$ to capture heterogeneity across dealers and bonds, and all specifications include week fixed effects. The relevant coefficient is β_1 on the interaction between the intensity of the pre-default trading relation with Dealer D and the indicator for the postdefault period. Column 1, controlling for week and CUSIP fixed effects, shows that the dealers that were buying the most from Dealer D suffered a significant decline in profit margins.

The effect is both statistically and economically significant. A one standard deviation increase in the fraction of assets bought from Dealer D narrows the spread by an average of 14 basis points.

This result is robust to the inclusion of trade characteristics (volume and bond rating) and of our measure of the strength of the relation (Column 2). Columns 3 and 4 further test the sensitivity of the result by including, in turn, the seller and the buyer fixed effects to control for possible unobserved heterogeneity across dealers more or less closely connected to Dealer D. Column 5 is our most restrictive specification, controlling also for seller- and buyer-month fixed effects. This means that, comparing transactions in the same period, in the same bond, and by similar dealers, the dealers that were relying more heavily on Dealer D suffered the most with its collapse.

Columns 6-10 complement these results by studying how the dealers that were selling more of their assets to Dealer D responded. As before, the main coefficient is the interaction between the dummy *Post* (equal to one after the default) and the average fraction of assets sold to Dealer D in 2007. As above, we find that dealers more exposed to Dealer D experienced a significant reduction in profit margins after the default. However, statistical significance is reduced. It is significant at the 10% level only when seller- and buyer-month fixed effects are included (Column 10). Presumably, this is because the fractions of sale and purchase transactions are very closely correlated.

6. Dealers' inventories in bad times

As is discussed in Section 3, theoretical work considers whether and how dealers could be able to lean against the wind by expanding inventories at times of distress [see, for instance, Weill (2007)]. We test Hypothesis III by addressing the following question: Were the dealers able to absorb the selling pressure of other market participants? We can employ transaction data to compute dealers' inventory around the collapse of Dealer D.[23] One problem with calculating inventories from trade data is that we do not observe the primary market, so our measure necessarily excludes newly issued bonds. To avoid bias in our computation, we use a very narrow time window around the failure and exclude both new issues and those maturing within

[23] To make sure our results are not driven by smaller broker-dealers, we focus on the top one hundred by transaction volume. We also ran the same analysis with the top 30 only, with highly similar results.

that time. Moreover, the primary market was significantly less active during our period than ordinarily, so our measure can be considered a good proxy for the dealers' actual inventory in this brief period.

We start by plotting, in Fig. 5, the dealers' inventory of bonds characterized by differential selling pressure, defined as the volume sold by clients to dealers normalized by the amount outstanding. If the dealers are providing liquidity by fulfilling sell orders without immediately unloading the bonds to avoid further price declines, then an expansion of inventories of the bonds subject to the most intense selling pressure should be evident. Instead, around the peak of the crisis, dealers reduced their inventories most sharply precisely for these bonds.

Table 8 formally tests and quantifies this proposition, dividing bonds into terciles of selling pressure. The regressions are normalized by dividing the inventory for each dealer for each tercile by the standard deviation of inventory for that dealer and tercile. Columns 1 and 2 are for a three-month window around the failure of Dealer D, and Column 3 restricts the sample to a four-week window. The first two columns show that dealers reduced their inventory of bonds in the top two terciles of selling pressure significantly, by 25%–30% of one standard deviation. The result holds also for the shorter window in Column 3, which shows a reduction of 20% of one standard deviation for the bonds in the top tercile. These results strongly suggest that, in the midst of the market turmoil, dealers did not readily provide liquidity to clients. We can now seek to determine whether their behavior also increased transaction costs. One possible source of such an increase is a lengthening of the intermediation chain owing to dealers' inability to increase their inventories.

The prevalence of transactions among intermediaries along intermediation chains has been recently highlighted by Li and Schürhoff (2014) for the municipal bond market, Hollifield, Neklyudov, and Spatt (2012) for securitized products, and Weller (2014) for metals futures. However, no study exists of the way in which these intermediation chains respond to shocks. One possible reason that spreads have widened following the default of Dealer D is the lengthening of the chains, as in Hypothesis IV. To test this hypothesis, Fig. 6 plots the estimated week fixed effects for a regression whose dependent variable is trading chain length. After the failure of Dealer D, intermediation chains between seller and buyer lengthened significantly. This suggests that, with the disappearance of a major counterparty, dealers had to form new trading relations, and as Table 7 shows, these were significantly less profitable than their predecessors. We can also confirm this result in Table 9 by estimating a regression of chain length over the *Post* indicator (equal to one after the bankruptcy). Even controlling for bond- and industry-month fixed effects and other trade characteristics, we find that on average the intermediation chain becomes significantly longer and that the effect appears to be more pronounced when the seller is core instead of peripheral.

This increase in the intermediation length matters because it could increase the overall intermediation cost. Table 10 shows how the spread is allocated among intermediaries along the chain. We find that being closer to the client yields higher profits. Moreover, because the average spread is about 60 basis points, and the intermediaries other than the one closest to the client charge about 20–30 basis points less than the average spread, we have that intermediation costs increases with the length of the chain.

Is there a relation between the change in length shown in Table 9 and the change in dealers' inventory? On this question, Fig. 7 plots our measure of inventory for bonds that underwent changes in average intermediation chain length above and below the median. By this measure, inventory shrinks most markedly for the bonds whose chains lengthened, suggesting that dealers were not providing liquidity, because they were diminishing their inventories, making it harder to accommodate clients' order requests and thus requiring a longer intermediation chain.

Formally, Table 11 reports the results of the regression

$$Inventory_{i,j,t} = \beta_1 Above\ Median_{i,D} \times Post + \beta_2 Above\ Median_{i,D} + Post + \theta_i + \lambda_t + \varepsilon_{i,j,t},$$

where i is the dealer, j is the bond and t is the week. $AboveMedian_{i,D}$ equals one for the bonds whose intermediation chain lengthened by more than the median. $Post$ equals one after the Dealer D's default. We control for dealers (θ_i) and time fixed effects (λ_t). Because we cannot observe the issuance of new bonds, our measure of inventory excludes them. Given the especially turbulent period covered, however, we are convinced that this does not significantly affect our estimates. However, to alleviate such concerns, in Columns 1 and 2 we take a three-month window around the default; in Column 3, a more restrictive four-week window. To simplify interpretation, we normalize our measure of inventory by dividing the inventory for each dealer above and below the median by the standard deviation in that dealer's inventory. In the most restrictive specification, we find a reduction of 20% of inventory for the bonds whose intermediation chain lengthened. This result does not appear to be driven by differences across dealers or by common shocks to the bond market, as we control for dealer and time fixed effects. The evidence is that intermediation costs increased because dealers were deleveraging and holding smaller inventories at the peak of the crisis.

Overall, our results offer new insights into dealers' behavior during one of the most severe episodes of financial market turmoil in recent times. Instead of providing price support by absorbing the excess supply from other market participants, dealers tried to unload these bonds immediately. And by reducing inventories they also made the market more illiquid, as the average length of the intermediation chain increased significantly, which means higher transaction costs for clients.

7. Concluding remarks

The recent crisis has spotlighted the issue of how governments should handle complex financial institutions that are too connected to fail. Theoretical contributions have shown how connections between financial institutions, stemming both from correlation in asset holdings and from an intricate system of cross-liabilities, could trigger a cascade of bank failures. However, little, if any, evidence exists on the role played by existing bilateral relations among financial institutions.

This paper focuses on a crucial over-the-counter market, that is, corporate bonds, and inquires into the way in which the network of relations between dealers shapes trading behavior and liquidity provision in normal times and in periods of turmoil. We start by showing the clear core-periphery structure of the market, in which a few highly interconnected dealers intermediate most of the trades with other dealers and with clients and many sparsely connected ones trade less frequently. This structure is highly stable over time. Next we show that the dealers' bilateral relations and their degree of network centrality are reliable predictors of their transaction costs, the more central dealers taking advantage of their connections to get better deals. More important, during periods of distress, dealers tend to provide liquidity to the counterparties with whom they have the strongest ties. But core dealers exploit their connections at the expense of peripheral dealers and of clients, increasing the spreads they charge to them. In the same vein, the value of being highly connected and systemically important increases when uncertainty is high.

In contrast to most of the empirical studies of the corporate bond market, we are able to learn the identity of each dealer and to see how the network responded to a large shock such as the failure of Dealer D. We find that Dealer D's main counterparties had to narrow their spreads after September 2008, by comparison with other, similar dealers trading the same bonds in the same period.

To conclude, our results shed new light on the way in which prior bilateral relations between financial institutions sometimes serve as a buffer in times of stress but also reveal that they heighten the fragility of the system, insofar as connection to more fragile dealers can worsen trading outcomes even for healthy dealers.

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Table 1

Summary statistics

This table reports descriptive statistics for the main variables employed in our analysis. In the Panel A, we present the main bond characteristics: the number of bonds, trades, the bonds' credit quality, issue size, and maturity, as provided by a confidential version of the Trade Reporting and Compliance Engine (TRACE) for the period 2005–2011. Columns 1 and 2 report the statistics for the full data sample. Due to computing limitations, we focus on a random 10% sample [the draw is based on the last digit of the Committee on Uniform Security Identification Procedures (CUSIP) being equal to zero. Columns 3 to 6 report the summary statistics for the main estimation sample, which restricts attention to buy and sell transactions observed within an hour from each other, and for the sample used in the robustness checks in the Online Appendix. Panel B provides summary statistics for these characteristics and for the transactions, such as the bilateral relations, the profit margins, and the sellers' centrality measure for the main results.

Panel A

	Full sample		Estimation sample		Appendix estimation	
	Bonds	Trades	Bonds	Trades	Bonds	Trades
	(1)	(2)	(3)	(4)	(5)	(6)
Number of bonds and trades	56,707	52,151,496	4,540	773,200	4,636	5,296,107
Credit quality distribution (percent)						
Superior (AA and UP)	10.0	9.5	10.24	8.90	10.42	8.95
Other investment grade (BBB-A)	68.6	79.7	74.82	79.18	73.47	81.24
High-yield (below BBB)	5.3	7.3	5.62	8.29	5.65	6.97
Not rated	16.2	3.5	9.32	3.63	10.46	2.84
Issue size distribution (percent)						
Small (< $100 million)	85.9	61.4	86.04	68.23	86.48	64.70
Medium ($100 million– $500 million)	3.8	24.4	3.94	17.77	3.77	21.54
Large (> $500 million)	0.0	0.14	0.02	0.14	0.02	0.17
Missing offering data	10.3	14.1	10.00	13.86	9.73	13.59
Maturity distribution (percent)						
Under 2 years	7.0	0.3	6.34	0.68	7.25	0.41
2–5 years	20.8	6.8	19.6	6.73	20.0	6.54
5–20 years	59.9	76.4	60.0	76.84	59.10	79.91
20+ years	12.0	15.8	13.74	15.01	13.33	12.53
Missing maturity data	0.3	0.6	0.31	0.74	0.32	0.61

Panel B:

	N	Mean	Standard Deviation	1st percentile	10th percentile	50th percentile	90th percentile	99th percentile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Statistics for Table 3								
Average Spread	773,200	0.621	1.427	-1.152	0	0.239	1.976	4.455
Counterparty Buyer	773,200	0.422	0.494	0	0	0	1	1
Network Centrality	730,225	52.16	94.28	1	2	25	107	554
Log(Transaction Volume)	722,914	8.397	2.015	4.630	6.225	7.832	11.58	13.30
Market Share	773,200	0.00553	0.0329	1.33e-06	1.00e-05	0.000233	0.00708	0.102
Rating	773,200	8.555	4.918	0	3	8	16	22
Investment Grade	773,200	0.730	0.444	0	0	1	1	1
Statistics for Tables 4–7								
Average Spread	446,854	0.393	1.515	-1.832	0	0.102	1.132	4.999
Fraction Selling to Counterparty	417,640	0.112	0.161	7.79e-05	0.00184	0.0426	0.319	0.727
Fraction Buying from Counterparty	417,639	0.135	0.203	8.64e-05	0.00233	0.0523	0.386	1
Network Centrality Seller	421,221	0.102	0.0397	0.00231	0.0483	0.102	0.151	0.170
Network Centrality Buyer	420,139	0.101	0.0463	0.00104	0.0235	0.113	0.152	0.172
Core-Periphery	446,854	0.185	0.388	0	0	0	1	1
Periphery-Core	446,854	0.244	0.430	0	0	0	1	1
Periphery-Periphery	446,854	0.256	0.437	0	0	0	1	1
Log(Transaction Volume)	424,872	8.466	2.051	4.626	6.223	7.869	11.63	13.21
Market Share	446,854	0.00358	0.0229	1.14e-06	1.00e-05	0.000233	0.00541	0.0554
Rating	446,854	8.984	5.074	0	3	8	17	22
Statistics for Table 8								
Average Spread	30,687	0.596	2.549	-7.514	0	0.183	2.064	9.482
Fraction of Sale Transactions with Dealer D	30,687	0.0174	0.0269	0	0.000368	0.00337	0.0678	0.0929
Fraction of Purchase Transactions with Dealer D	30,687	0.0219	0.0279	0	0.000535	0.00995	0.0740	0.104
Fraction Selling to Counterparty	29,582	0.0936	0.129	6.58e-05	0.00194	0.0378	0.256	0.611
Fraction Buying from Counterparty	29,582	0.134	0.218	0.000133	0.00255	0.0522	0.242	1
Log(Transaction Volume)	29,394	8.105	1.891	4.508	6.109	7.749	11.16	12.73
Market Share	446,854	0.00358	0.0229	1.14e-06	1.00e-05	0.000233	0.00541	0.0554
Rating	30,687	8.096	5.386	1	2	6	16	22

Table 2
Spreads: clients versus dealers

This table reports the coefficient estimates relating the spread (difference between sell and buy price) with the type of counterparty. The sample contains bond transactions for the period 2005–2011 as reported in an enhanced version of the Trade Reporting and Compliance Engine (TRACE). *Client Buyer* is a dummy equal to one if the buyer is a client. *Log(Transaction Volume)* is the size of the transaction. *Rating* captures the numerical equivalent of the bond rating, with higher number capturing riskier bonds. *Market Share* is the fraction of bond i held in inventory by seller s in the previous quarter normalized by the bond outstanding. Columns 6 and 7 divide the sample between investment–grade and non-investment–grade bonds, and Columns 8 and 9 differentiate between sellers in the core or in the periphery. Column 5 shows the most conservative specification in which we control for week, bond, seller, and industry×month fixed effects. Panel B reports the results for different samples based on the size of the transaction. Robust standard errors double–clustered at both the Committee on Uniform Security Identificatioin Procedures (CUSIP) and the week level are reported in parentheses. Asterisks denote significance levels (*** = 1%, ** = 5%, * = 10%).

Panel A

						Investment grade bonds	Non-investment grade bonds	Core dealers	Periphery dealers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Client buyer	0.524***	0.585***	0.529***	0.563***	0.564***	0.549***	0.464***	0.500***	0.536***
	(0.0309)	(0.0287)	(0.0237)	(0.0217)	(0.0218)	(0.0305)	(0.0242)	(0.0319)	(0.0221)
Log (Transaction Volume)		-0.113***	-0.0768***	-0.0843***	-0.0838***	-0.0683***	-0.0978***	-0.0602***	-0.0919***
		(0.00533)	(0.00408)	(0.00445)	(0.00442)	(0.00373)	(0.00882)	(0.00515)	(0.00446)
Rating			0.0108**	0.0102*	0.0117**	0.00156	0.00831	0.0215***	0.00375
			(0.00538)	(0.00523)	(0.00524)	(0.00880)	(0.00781)	(0.00637)	(0.00677)
Market Share			0.718**	0.738**	0.719**	0.572**	3.182*	0.391	0.825***
			(0.277)	(0.285)	(0.282)	(0.262)	(1.826)	(0.446)	(0.174)
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CUSIP fixed effects			Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seller fixed effects				Yes	Yes				
Industry × month fixed effects					Yes				
Number of observations	773,200	722,914	722,609	722,466	722,466	523,613	198,952	370,727	351,478
R-squared	0.044	0.077	0.158	0.202	0.203	0.242	0.078	0.159	0.181

Panel B:

	Transaction size below median	Transaction size between 50th and 75th	Transaction size between 75th and 90th	Transaction size above 90th
	(1)	(2)	(3)	(4)
Client buyer	0.658***	0.558***	0.202***	0.0850***
	(0.0317)	(0.0267)	(0.0135)	(0.0147)
Log (Transaction Volume)	-0.0515***	-0.0874***	-0.0801***	-0.0146
	(0.00844)	(0.00765)	(0.00922)	(0.0177)
Rating	0.00710	0.0200**	0.0337***	0.0269***
	(0.00668)	(0.00842)	(0.00818)	(0.00554)
Market Share	0.854***	0.681*	0.0679	1.135
	(0.290)	(0.398)	(0.468)	(1.720)
Week fixed effects	Yes	Yes	Yes	Yes
CUSIP fixed effects	Yes	Yes	Yes	Yes
Number of observations	361,106	180,390	107,992	72,039
R-squared	0.216	0.149	0.069	0.056

Table 3

Spreads and network structure

This table reports the coefficient estimates relating the spreads with the type of counterparty. The sample contains bond transactions for the period 2005–2011 as reported in an enhanced version of the Trade Reporting and Compliance Engine (TRACE). *Core-Periphery* is a dummy equal to one if the seller is a core dealer and the buyer is a peripheral dealer. *Periphery-Periphery* identifies transactions between dealers in the periphery, and *Periphery-Core* is a dummy equal to one for transactions in which the seller is in the periphery and the buyer is in the core. The comparison group contains interdealer transactions between core dealers. *Log (Transaction Volume)* is the size of the transaction. *Rating* captures the numerical equivalent of the bond rating, with higher number capturing riskier bonds. *Market Share* is the fraction of bond i held in inventory by seller s in the previous quarter normalized by the bond outstanding. Column 4 shows the most conservative specification in which we control for week, bond, and industry×month fixed effects. Columns 5 and 6 divide the sample between investment-grade and non-investment-grade bonds. Robust standard errors double-clustered at both the Committee on Uniform Security Identification Procedures (CUSIP) and the week level are reported in parentheses. Asterisks denote significance levels (*** = 1%, ** = 5%, and * = 10%).

	All bonds				Investment-grade bonds	Non-investment-grade bonds
	(1)	(2)	(3)	(4)		
Core-Periphery	0.281***	0.298***	0.260***	0.261***	0.243***	0.317***
	(0.0174)	(0.0174)	(0.0160)	(0.0162)	(0.0169)	(0.0332)
Periphery-Periphery	0.196***	0.231***	0.145***	0.148***	0.115***	0.207***
	(0.0169)	(0.0159)	(0.0137)	(0.0137)	(0.0148)	(0.0293)
Periphery-Core	0.0602***	0.141***	0.0905***	0.0898***	0.0811***	0.118***
	(0.0138)	(0.0159)	(0.0143)	(0.0143)	(0.0180)	(0.0230)
Log (Transaction Volume)		-0.0746***	-0.0502***	-0.0499***	-0.0426***	-0.0753***
		(0.00456)	(0.00407)	(0.00410)	(0.00323)	(0.0113)
Rating		0.0160***	0.0220***	0.0227***	0.0129*	0.0165*
		(0.00207)	(0.00612)	(0.00635)	(0.00678)	(0.00890)
Market Share		1.123***	0.876**	0.871**	0.445***	8.942
		(0.312)	(0.342)	(0.342)	(0.157)	(5.454)
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
CUSIP fixed effects			Yes	Yes	Yes	Yes
Industry × month fixed effects				Yes		
Number of observations	446,854	424,872	424,561	424,561	295,843	128,662
R-squared	0.016	0.026	0.062	0.063	0.077	0.065

Table 4
Spreads and bilateral relationships

This table reports the coefficient estimates relating the spreads with the existing of bilateral relations between seller and buyer and to their network centrality. The sample contains bond transactions for the period 2005–2011 as reported in an enhanced version of the Trade Reporting and Compliance Engine (TRACE). *Fraction Selling to Counterparty* is the fraction of sales of this seller to this buyer computed in the previous quarter, *Fraction Buying from Counterparty* the fraction of purchases of this buyer to this seller. *Log (Transaction Volume)* is the size of the transaction. *Rating* captures the numerical equivalent of the bond rating, with higher number capturing riskier bonds. *Market Share* is the fraction of bond i held in inventory by seller s in the previous quarter normalized by the bond outstanding. The centrality measures are computed using the eigenvector centrality measure in the previous quarter. Column 6 shows the most conservative specification, which includes seller×month, buyer×month, and industry×month fixed effects in addition to week and bond fixed effects. Robust standard errors double clustered at both the Committee on Uniform Security Identification Procedures (CUSIP) and the week level are reported in parenthesws. Asterisks denote significance levels (*** = 1%, ** = 5%, and * = 10%).

	(1)	(2)	(3)	(4)	(5)	(6)
Fraction Selling to Counterparty	-0.697***	-0.727***	-0.725***	-0.514***	-0.332***	-0.333***
	(0.0424)	(0.0389)	(0.0390)	(0.0310)	(0.0746)	(0.0748)
Fraction Buying from Counterparty	-0.472***	-0.447***	-0.442***	-0.713***	-0.658***	-0.654***
	(0.0277)	(0.0234)	(0.0231)	(0.0333)	(0.0883)	(0.0967)
Log(Transaction Volume)	-0.0812***	-0.0581***	-0.0578***	-0.0601***	-0.0534***	-0.0532***
	(0.00509)	(0.00449)	(0.00452)	(0.00445)	(0.00514)	(0.00542)
Rating	0.0153***	0.0180***	0.0185***	0.0204***	0.0258***	0.0261***
	(0.00210)	(0.00571)	(0.00598)	(0.00597)	(0.00433)	(0.00477)
Market Share	1.543***	0.910**	0.903**	0.958**	0.630	0.622
	(0.278)	(0.354)	(0.353)	(0.375)	(0.391)	(0.408)
Seller Network Centrality				0.272		
				(0.196)		
Buyer Network Centrality				-2.031***		
				(0.167)		
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
CUSIP fixed effects		Yes	Yes	Yes	Yes	Yes
Industry × month fixed effects			Yes			Yes
Seller × month fixed effects					Yes	Yes
Buyer × month fixed effects					Yes	Yes
Number of observations	397,419	397,102	397,102	375,889	366,748	366,748
R-squared	0.033	0.069	0.070	0.072	0.285	0.286

Table 5

Spreads in turbulent times

This table reports the coefficient estimates relating the spread with the existing of bilateral relations between seller and buyer and to their network centrality. The sample contains bond transactions for the period 2005–2011 as reported in an enhanced version of the Trade Reporting and Compliance Engine (TRACE). *Fraction Selling to Counterparty* is the fraction of sales of this seller to this buyer computed in the previous quarter, *Fraction Buying from Counterparty* the fraction of purchases of this buyer to this seller. *VIX* is the volatility index as provided by the Chicago Board Options Exchange (CBOE). We also control for the bond rating, the market share, and the log of the transaction size interacted with the volatility index. The centrality measures are computed using the eigenvector centrality measure in the previous quarter. Panel B reports the coefficient estimates relating the spread with the existing of bilateral relations between seller and buyer and to their network centrality for three time periods: January 2005–December 2006 (Column 1), January 2007–August 2008 (Column 2) and September 2008–July 2009 (Column 3). Robust standard errors double clustered at both the Committee on Uniform Security Identification Procedures (CUSIP) and the week level are reported in

Panel A:

	(1)	(2)	(3)	(4)	(5)	(6)
Fraction Selling to Counterparty × *VIX*	-0.435***	-0.431***	-0.442***	-0.237***	-0.219***	-0.228***
	(0.0402)	(0.0392)	(0.0399)	(0.0386)	(0.0390)	(0.0391)
Fraction Buying from Counterparty × *VIX*	-0.0542**	-0.0406*	-0.0376*	-0.210***	-0.216***	-0.215***
	(0.0230)	(0.0226)	(0.0222)	(0.0330)	(0.0326)	(0.0324)
Seller Network Centrality × *VIX*				1.078***	1.262***	1.253***
				(0.212)	(0.211)	(0.214)
Buyer Network Centrality × *VIX*				-1.085***	-1.222***	-1.250***
				(0.183)	(0.176)	(0.181)
Fraction Selling to Counterparty	-0.743***	-0.763***	-0.761***	-0.513***	-0.555***	-0.551***
	(0.0380)	(0.0344)	(0.0347)	(0.0359)	(0.0313)	(0.0312)
Fraction Buying from Counterparty	-0.466***	-0.442***	-0.439***	-0.762***	-0.692***	-0.690***
	(0.0263)	(0.0220)	(0.0217)	(0.0328)	(0.0294)	(0.0291)
Seller Network Centrality				-0.248	0.267	0.279*
				(0.180)	(0.169)	(0.168)
Buyer Network Centrality				-2.435***	-1.981***	-1.993***
				(0.164)	(0.136)	(0.136)
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls × VIX	Yes	Yes	Yes	Yes	Yes	Yes
CUSIP fixed effects		Yes	Yes		Yes	Yes
Industry × month fixed effects			Yes			Yes
Number of observations	397,389	397,072	397,072	376,171	375,859	375,859
R-squared	0.035	0.071	0.072	0.041	0.075	0.077

Panel B:

	January, 2005–December, 2006	*January, 2007–August, 2008*	*September, 2008–July, 2009*
	(1)	(2)	(3)
Fraction Selling to Counterparty	-0.428***	-0.387***	-1.211***
	(0.0572)	(0.0434)	(0.112)
Fraction Buying from Counterparty	-0.397***	-0.517***	-1.176***
	(0.0302)	(0.0388)	(0.0897)
Seller Network Centrality	0.411	0.588**	3.383***
	(0.259)	(0.255)	(0.648)
Buyer Network Centrality	-0.953***	-1.407***	-4.138***
	(0.179)	(0.192)	(0.505)
Week fixed effects	Yes	Yes	Yes
CUSIP fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Number of observations	75,898	59,522	70,347
R-squared	0.083	0.090	0.132

Table 6
Network structure and turbulent times

This table reports the coefficient estimates relating the spreads with the type of counterparty. The sample in Columns 1–4 contains bond transactions for the period 2005–2011 as reported in an enhanced version of the Trade Reporting and Compliance Engine (TRACE). *Core-Periphery* is a dummy equal to one if the seller is a core dealer and the buyer is a peripheral dealer, *Periphery-Periphery* identifies transactions between dealers in the periphery, and *Periphery-Core* is a dummy equal to one for transactions in which the seller is in the periphery and the buyer is in the core. The comparison group contains interdealer transactions between core dealers. *VIX* is the volatility index as provided by the Chicago Board Options Exchange (CBOE). We also control for the log of the transaction size, the bond rating, and the market share interacted with the volatility index. Columns 5-7 reports the coefficient estimates relating the spread with the type of counterparty for three distinct time periods: January 2005–December 2006 (Column 5), January 2007–August 2008 (Column 6) and September 2008–July 2009 (Column 7). Robust standard errors double clustered at both the Committee on Uniform Security Identification Procedures (CUSIP) and the week level are reported in parentheses. Asterisks denote significance levels (*** = 1%, ** = 5%, and * = 10%).

	All bonds	All bonds	Investment grade bonds	Non-investment grade bonds	January 2005–December 2006	January 2007–August 2008	September 2008–July 2009
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Core-Periphery × *VIX*	0.145***	0.146***	0.143***	0.203***			
	(0.0193)	(0.0201)	(0.0204)	(0.0427)			
Periphery-Core × *VIX*	-0.0281	-0.0305*	-0.0581***	0.0439			
	(0.0179)	(0.0180)	(0.0218)	(0.0311)			
Periphery-Periphery × *VIX*	0.0373**	0.0373**	0.0406**	0.0591*			
	(0.0173)	(0.0174)	(0.0196)	(0.0348)			
Core-Periphery	0.247***	0.248***	0.211***	0.373***	0.0710***	0.169***	0.464***
	(0.0140)	(0.0142)	(0.0125)	(0.0368)	(0.0174)	(0.0216)	(0.0484)
Periphery-Periphery	0.0802***	0.0793***	0.0729***	0.129***	-0.00613	-0.0118	-0.0175
	(0.0152)	(0.0152)	(0.0179)	(0.0272)	(0.0226)	(0.0189)	(0.0572)
Periphery-Core	0.143***	0.146***	0.109***	0.228***	0.0633***	0.0520**	0.136**
	(0.0143)	(0.0143)	(0.0144)	(0.0346)	(0.0206)	(0.0207)	(0.0555)
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CUSIP fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls x volatility index	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × month fixed effects		Yes					
Number of observations	424,529	424,529	295,815	128,658	81,966	62,125	75,119
R-squared	0.064	0.065	0.080	0.067	0.082	0.088	0.115

Table 7
Spreads and dealer D's collapse

This table reports the coefficient estimates relating the spread with the existing of bilateral relations between seller and Dealer D. The sample period is the third and fourth quarter of 2008. *Fraction of Purchase Transactions with Dealer D* is the fraction of bonds purchased by seller i from Dealer D averaged over 2007. *Post* is a dummy equal to one after the Dealer D default. We control for the log of the size of the transaction, the bond rating, and the fraction of bond i held in inventory by seller s in the previous quarter normalized by the bond outstanding. All columns include both week and bond fixed effects. Seller and buyer fixed effects are sequentially included in Columns 3 and 4. Column 5 is the most conservative specification which includes seller×month and buyer×month fixed effects. *Fraction of Sale Transactions with Dealer D* is the fraction of sales of this seller to this buyer in 2007 and its interaction with *Post* is included in Columns 6-10. Robust standard errors double clustered at both the Committee on Uniform Security Identification Procedures (CUSIP) and the week level are reported in parentheses. Asterisks denote significance levels (*** = 1%, ** = 5%, and * = 10%).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Fraction of Purchase Transactions with Dealer D × Post	-4.790***	-5.151***	-4.008***	-4.320***	-3.208	-6.528*	-5.355*	-8.145***	-8.104**	-21.93***
	(1.089)	(1.204)	(1.030)	(1.058)	(3.096)	(3.492)	(3.009)	(2.800)	(2.910)	(5.161)
Fraction of Purchase Transactions with Dealer D	0.706	-1.214				-4.200**	-6.226***			
	(1.054)	(1.113)				(1.914)	(1.984)			
Fraction Selling to Counterparty		-2.343***	-1.003***	0.00630	0.0778		-2.305***	-0.988***	0.0386	0.116
		(0.237)	(0.256)	(0.425)	(0.509)		(0.237)	(0.256)	(0.0347)	(0.506)
Fraction Buying from Counterparty		-0.464***	-0.546***	-1.067**	-1.496***		-0.485***	-0.546***	-1.081***	-1.509***
		(0.0873)	(0.0664)	(0.385)	(0.446)		(0.0867)	(0.0664)	(0.387)	(0.447)
Fraction of Sale Transactions with Dealer D						6.619***	6.599***			
						(1.759)	(1.749)			
Fraction of Sale Transactions with Dealer D × Post						1.899	0.166	4.847	4.442	21.82**
						(3.682)	(2.914)	(2.995)	(3.199)	(8.009)
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CUSIP fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seller fixed effect			Yes	Yes	Yes			Yes	Yes	Yes
Buyer fixed effect				Yes	Yes				Yes	Yes
Seller × month fixed effects					Yes					Yes
Buyer × month fixed effects					Yes					Yes
Number of observations	29,145	28,074	28,027	27,903	27,396	29,145	28,074	28,027	27,903	27,396
R-squared	0.143	0.157	0.246	0.291	0.371	0.144	0.158	0.247	0.291	0.371

Table 8

Changes in dealers' inventories

This table investigates how the dealers' inventory changes around the collapse of Dealer D for bonds that experience different degrees of selling pressure by clients, which is defined as the amount sold by clients to dealers normalized by the amount outstanding. The sample period in Columns 1 and 2 is a three-month window around Dealer D's collapse, and in Column 3 it is a one-month before and after this event. The dependent variable is the dealer's inventory normalized by the standard deviation of the inventory for each dealer. *Post* is a dummy equal to one after the Dealer D default. *Top Tercile Selling Pressure* is a dummy variable equal to one for the bonds that experience the highest selling pressure by the clients. *Middle Tercile Selling Pressure* is a dummy variable equal to one for the bonds that experience an intermediate selling pressure by the clients. The omitted category is the indicator for the bonds in the bottom tercile. All specifications include dealer and week fixed effects. Robust standard errors clustered at the dealer level are in parentheses. Asterisks denote significance levels (*** = 1%, ** = 5%, and * = 10%).

	Dealer's Inventory		
	(1)	(2)	(3)
Top Tercile Selling Pressure × *Post*	-0.269**	-0.302***	-0.205*
	(0.104)	(0.105)	(0.116)
Middle Tercile Selling Pressure × *Post*	-0.248**	-0.251**	-0.0331
	(0.0968)	(0.0983)	(0.101)
Top Tercile Selling Pressure	-0.0952	-0.160**	-0.148
	(0.0692)	(0.0730)	(0.114)
Middle Tercile Selling Pressure	0.0326	0.000412	0.0673
	(0.0609)	(0.0624)	(0.106)
Post	-0.174*	-0.714***	0.122
	(0.0907)	(0.182)	(0.123)
Time period around Dealer D's collapse	+/- 3 months	+/- 3 months	+/- 4 weeks
Dealer and week fixed effects	No	Yes	Yes
Number of observations	6,711	6,711	1,937
R-squared	0.033	0.257	0.317

Table 9
Trading chains after Dealer D's collapse

default. The sample period is the third and fourth quarter of 2008. *Post* is a dummy equal to one after the Dealer D default. *Log(Transaction Volume)* is the size of the transaction. *Rating* captures the numerical equivalent of the bond rating, with higher number capturing riskier bonds. *Market Share* is the fraction of bond *i* held in inventory by seller *s* in the previous quarter normalized by the bond outstanding. All columns include both bond and week fixed effects. Column 2 also includes i+ndustry×month fixed effects. Column 3 focuses on transactions in which the seller is in the core (top 30 dealers), and Column 4 focuses on transactions in which the seller is in the periphery. Robust standard errors double-clustered at both the Committee on Uniform Security Identification Procedures (CUSIP) and the week level are reported in parentheses. Asterisks denote significance levels (*** = 1%, ** = 5%, and * = 10%).

	All bonds (1)	All bonds (2)	Seller is in the core (3)	Seller is in the periphery (4)
Post	0.0280***	0.0277**	0.0541***	0.0153
	(0.00937)	(0.0101)	(0.0109)	(0.0220)
Log (Transaction Volume)	-0.0341***	-0.0342***	-0.0404***	-0.00849
	(0.00469)	(0.00460)	(0.00749)	(0.0104)
Rating	-0.00515	-0.00524	0.00274	-0.0213
	(0.0103)	(0.0101)	(0.0100)	(0.0170)
Market Share	0.561	0.570	-0.526	0.600
	(0.522)	(0.518)	(0.713)	(0.800)
Seller Network Centrality	-4.118***	-4.124***	2.076***	-1.397
	(0.334)	(0.333)	(0.617)	(0.868)
CUSIP fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Industry × month fixed effects		Yes		
Number of observations	125,527	125,527	69,099	56,102
R-squared	0.193	0.193	0.150	0.275

Table 10
Spreads over trading chains

This table investigates how the spread charged over the intermediation chain depending on the position of the dealer in the chain. The first position is always captured by the buyer, who is the client. The benchmark is then the spread charged by the intermediary in the second position. The sample period is the third and fourth quarter of 2008. Transaction controls are the size of the transaction, the numerical equivalent of the bond rating, the market share, and the type of transaction, i.e., if it is a core-core, core-periphery, or periphery-core transaction. Robust standard errors double clustered at both the Committee on Uniform Security Identification Procedures (CUSIP) and the week level are reported in parentheses. Asterisks denote significance levels (*** = 1%, ** = 5%, and * = 10%).

	(1)	(2)	(3)	(4)	(5)
Third Intermediary in the Chain	-0.271***	-0.264***	-0.310***	-0.262***	-0.149***
	(0.0307)	(0.0291)	(0.0297)	(0.0285)	(0.0218)
Fourth Intermediary in the Chain	-0.326***	-0.323***	-0.307***	-0.240***	-0.167***
	(0.0387)	(0.0385)	(0.0402)	(0.0350)	(0.0298)
Fifth Intermediary in the Chain	-0.383***	-0.377***	-0.313***	-0.231***	-0.181***
	(0.0632)	(0.0629)	(0.0587)	(0.0596)	(0.0643)
Week fixed effects	Yes	Yes	Yes	Yes	Yes
CUSIP fixed effects			Yes	Yes	Yes
Transaction controls				Yes	Yes
Seller fixed effects					Yes
Number of observations	112,401	112,401	111,997	106,155	106,039
R-squared	0.044	0.047	0.139	0.139	0.197

Table 11

Dealers' inventory and change in trading chains

This table investigates how the dealers' inventory changes around the collapse of Dealer D for bonds for which the change in trading chain is above or below the median change. The sample period in Columns 1 and 2 is a three-month window around Dealer D's collapse, while in Column 3 it is a one-month before and after this event. The dependent variable is the dealer's inventory normalized by the standard deviation of the inventory for each dealer. *Post* is a dummy equal to one after the Dealer D default. All specifications include dealer and week fixed effects. Robust standard errors clustered at the dealer level are in parenthesss. Asterisks denote significance levels (*** = 1%, ** = 5%, and * = 10%).

	Dealer's Inventory		
	(1)	(2)	(3)
Above Median Change Chain Length × *Post*	-0.291***	-0.297***	-0.226**
	(0.0718)	(0.0757)	(0.0709)
Above Median Change Chain Length	0.0219	0.00262	0.106
	(0.0530)	(0.0558)	(0.0963)
Post	-0.182**	-0.526***	0.180**
	(0.0847)	(0.0857)	(0.0604)
Time period around Lehman Brothers default	+/- 3 months	+/- 3 months	+/- 4 weeks
Dealer and week fixed effects	No	Yes	Yes
Number of observations	6,731	6,731	1,939
R-squared	0.027	0.261	0.335

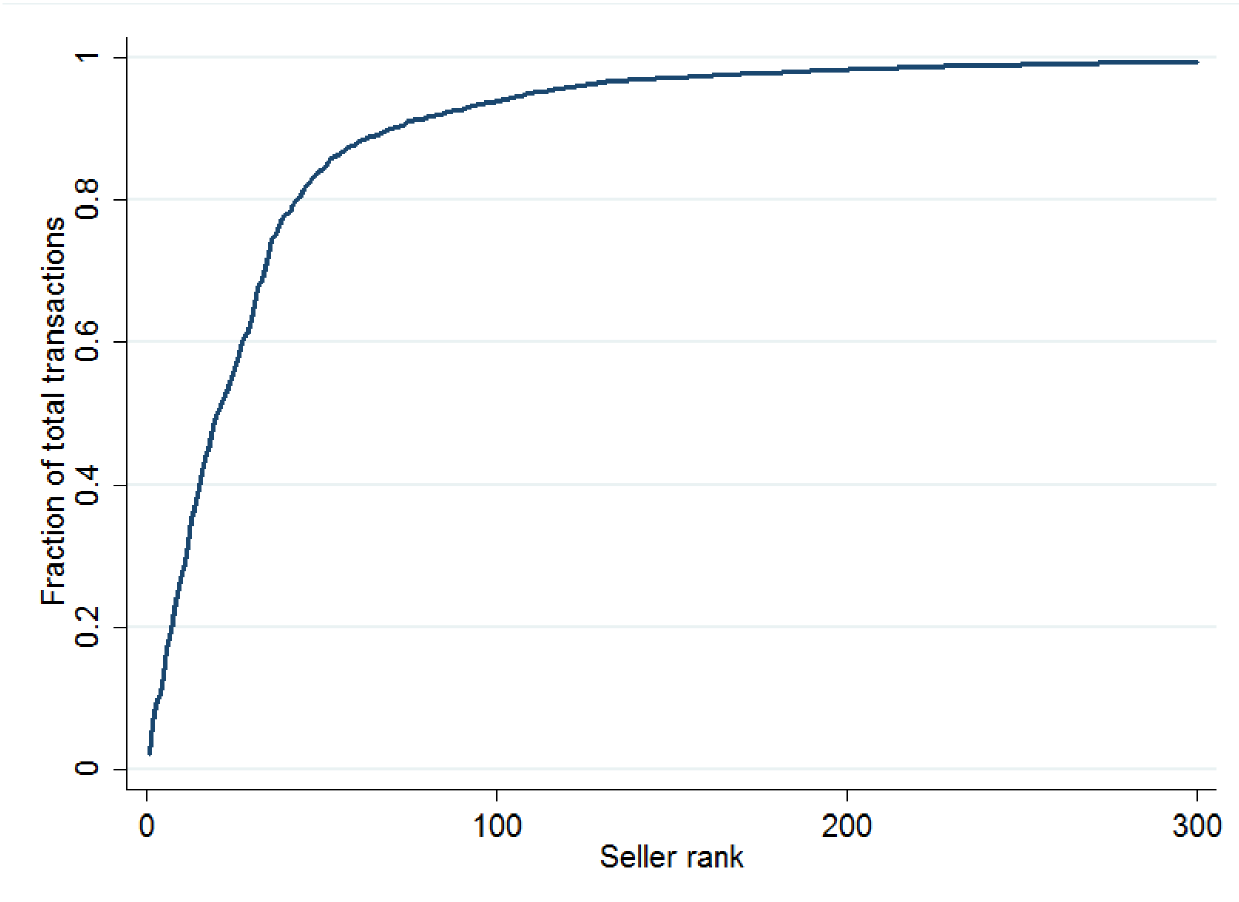

Figure 1. Fraction of total transactions by seller rank, January 2005-May 2011. This figure plots the cumulative distribution of seller's network centrality for all transactions, both among dealers and with clients.

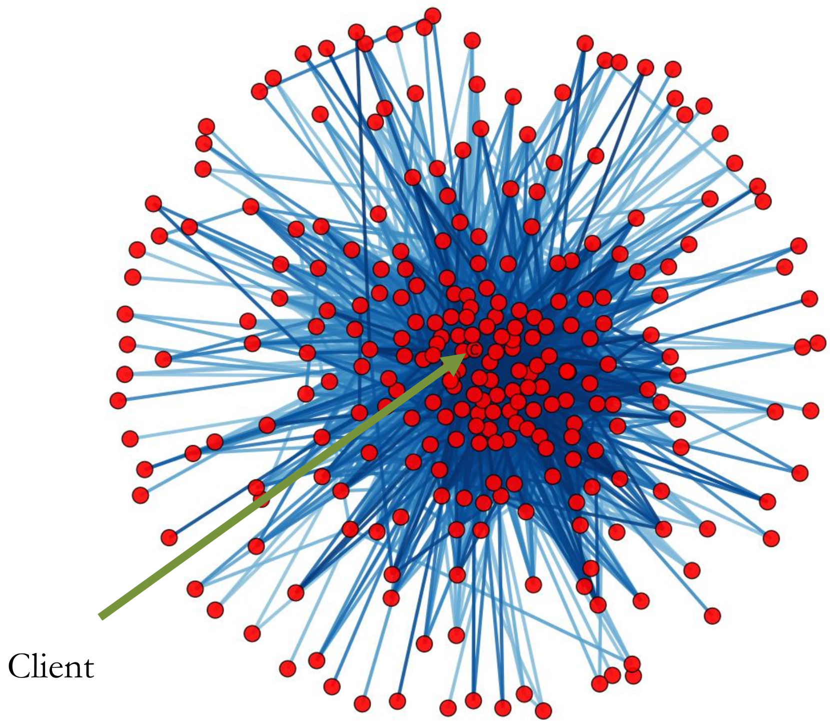

Figure 2. The network. This figure plots the core-periphery network structure in which each link is a transaction, and the transactions with clients are at the center. Darker lines indicate a higher number of transactions between the two nodes.

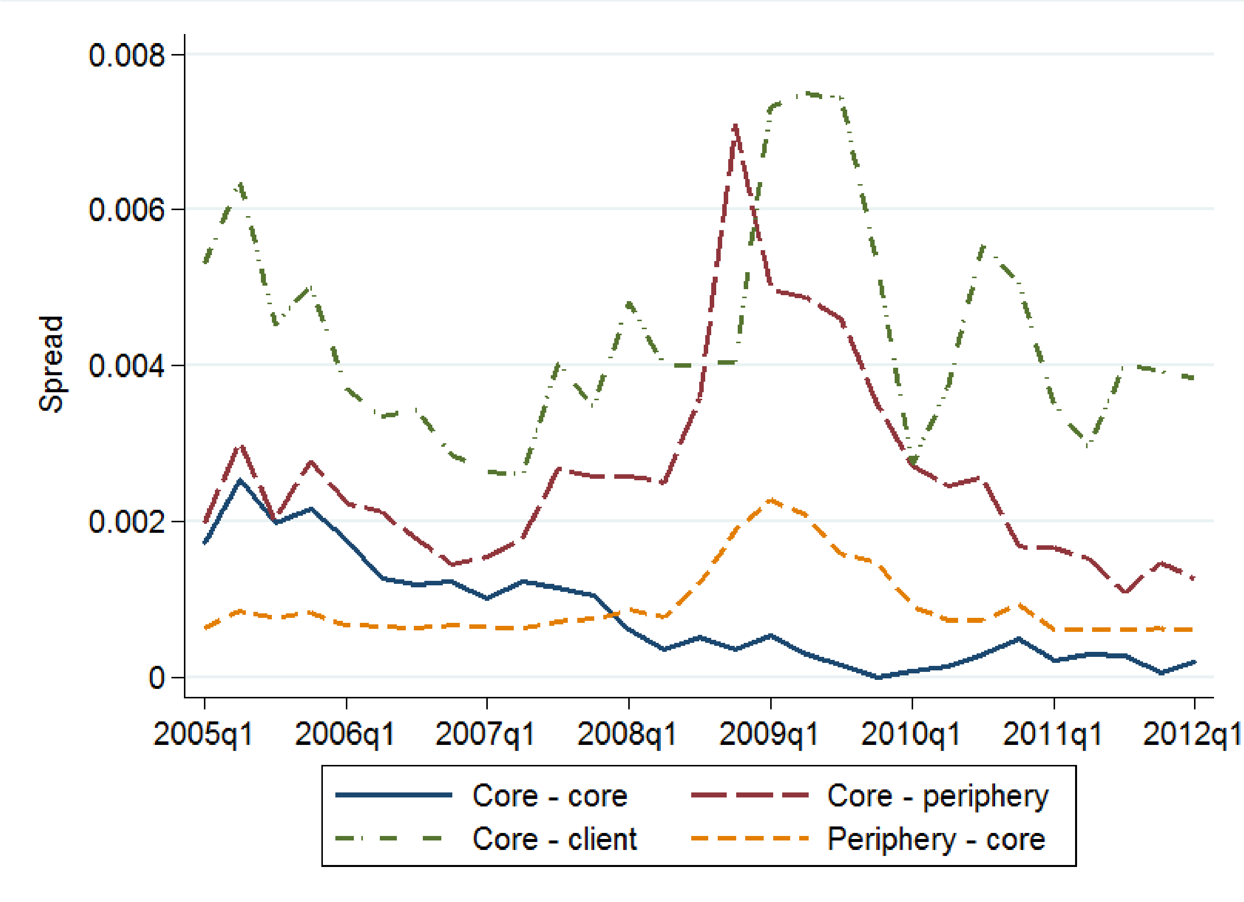

Figure 3. Spreads: median by pair type. This figure plots the profit margins over time, for transactions among different types of counterparties.

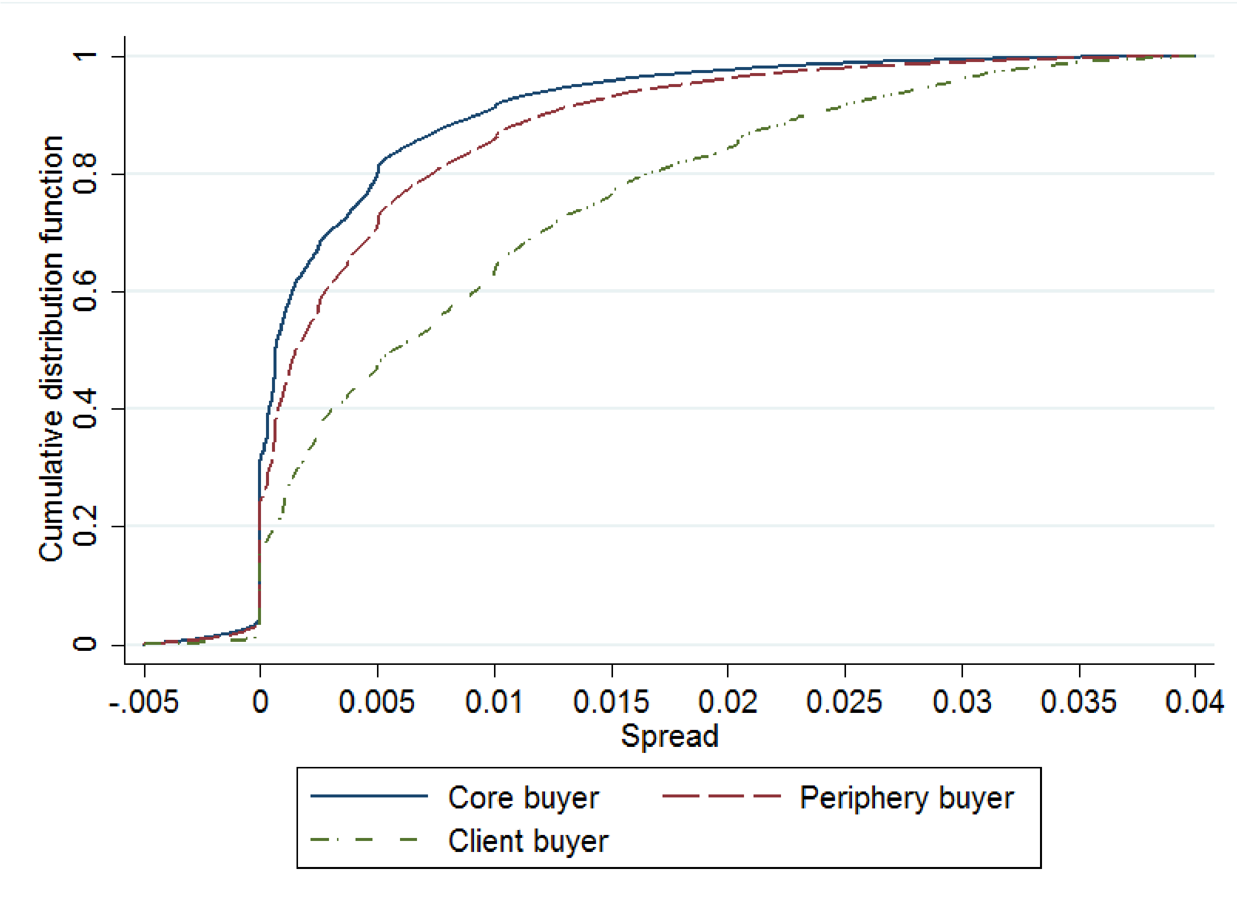

Figure 4. Spreads: cumulative distribution by buyer's type, 2005-2011. This figure plots the cumulative distribution of the profit margins for the different types of counterparties.

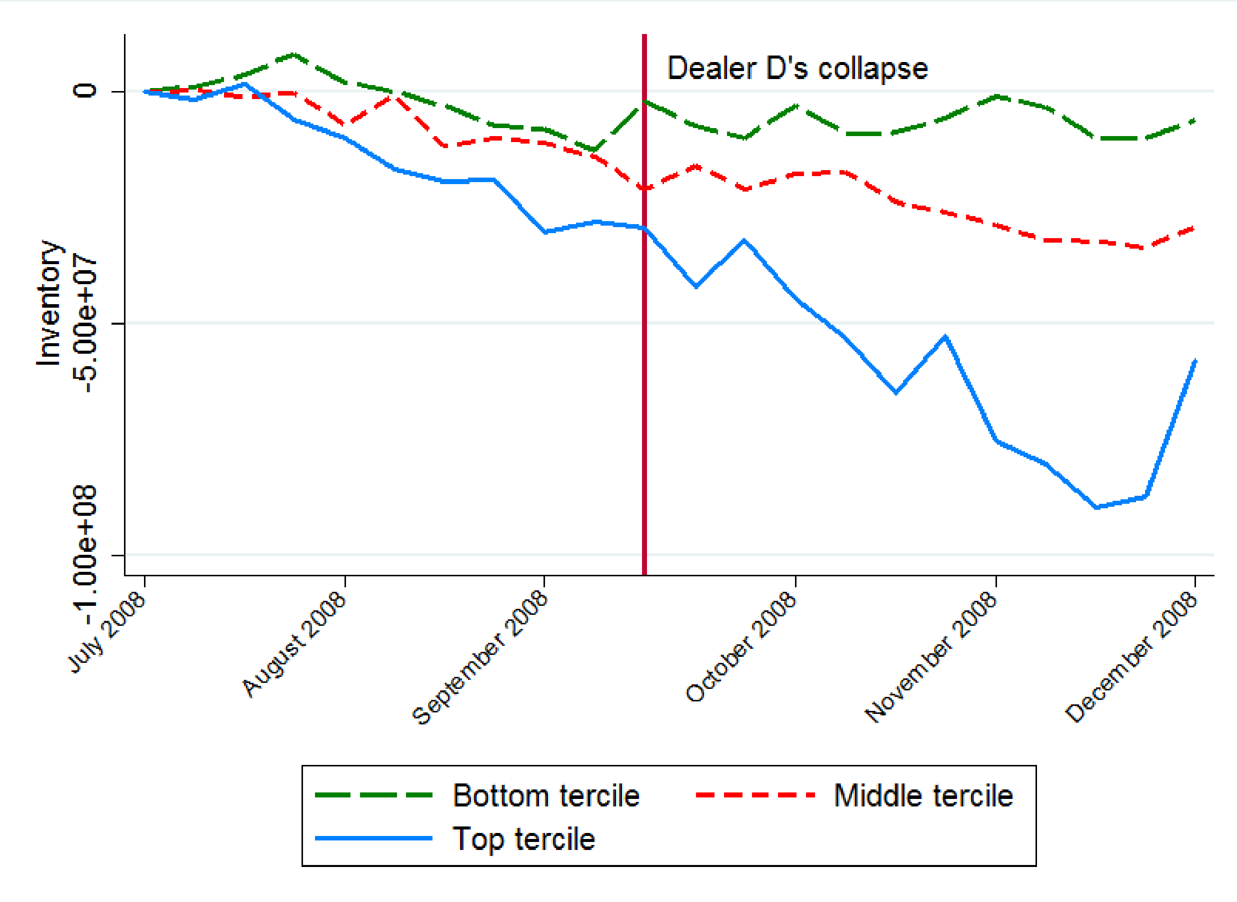

Figure 5. Core dealers' inventory by clients' selling pressure. This figure plots the dealers' inventory for bonds that experienced different selling pressure from the clients, which is defined as the amount sold by clients to dealers normalized by the amount outstanding.

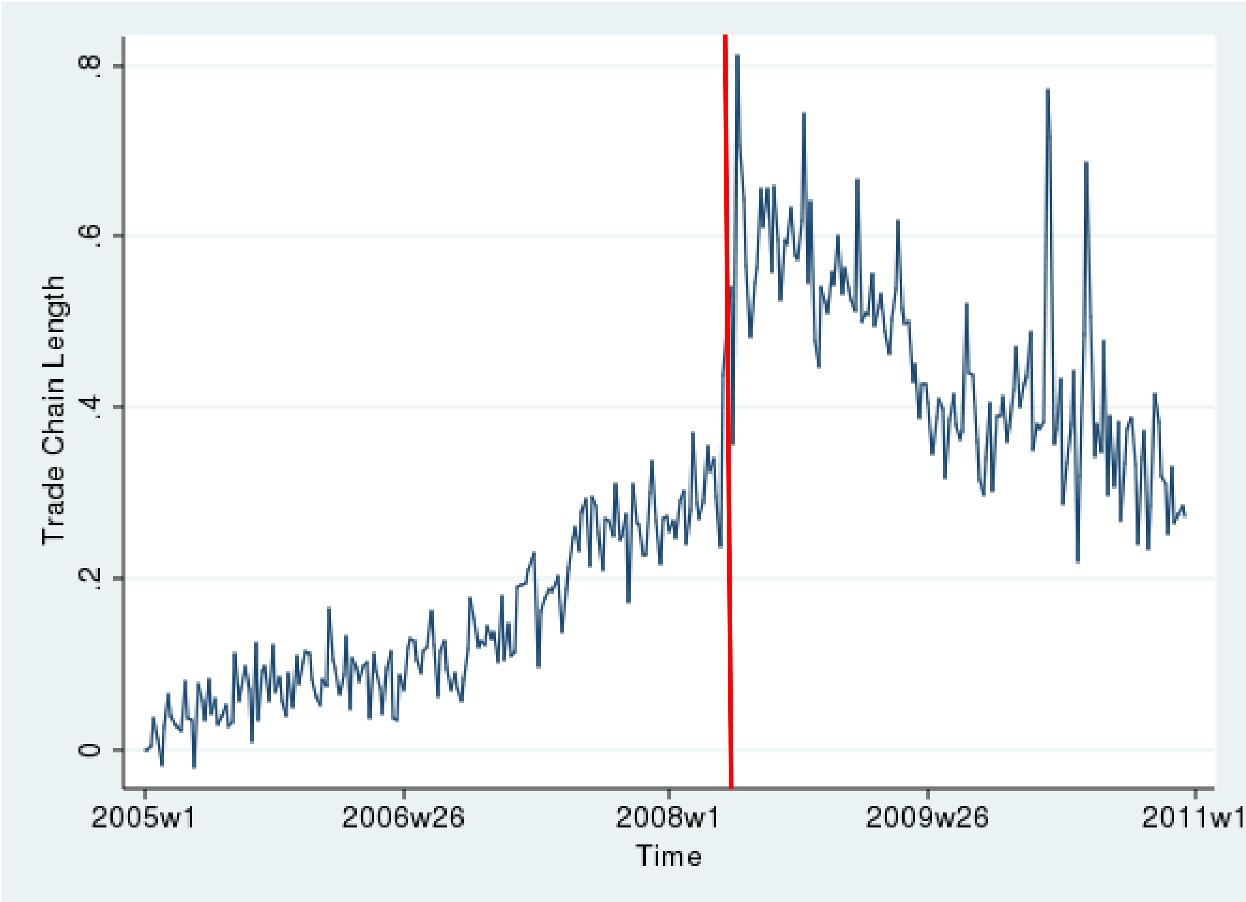

Figure 6. Trade chain length over time. This figure plots the average trading chain length over time normalized to the first week in 2005. The vertical line indicates the default of Dealer D.

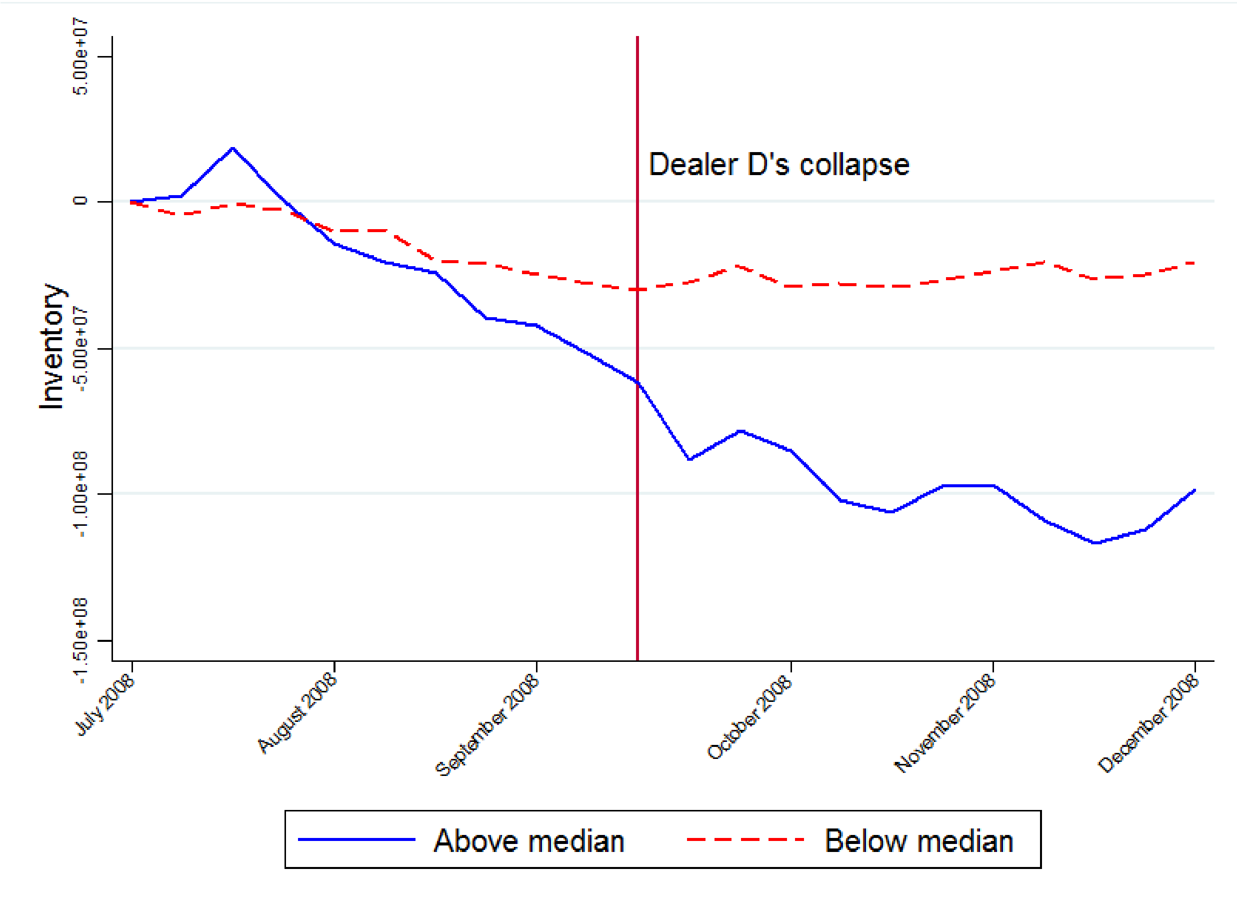

Figure 7. Core dealers' inventory by change in chain length. This figure plots the dealers' inventory, normalized to July 2008, i.e. three months before Dealer D's default. The blue solid (red dashed) line shows the inventory for bonds that experienced a change in the length of the intermediation chain above (below) median, as computed by comparing the length of the chain before and after the Dealer D's default.