

The Value of Trading Relationships in Turbulent Times*

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Abstract

This paper investigates how the network of relationships between dealers shapes their trading behavior in the corporate bond market. We show that dealers tend to provide liquidity during periods of distress to the counterparties with whom they have the strongest tie. However, highly connected and systemically important dealers exploit their connections at the expense of peripheral dealers as well as of their clients, charging them higher prices than to other core dealers, especially during high-uncertainty periods. We then exploit the flagship collapse of a large dealer in 2008 as a shock to the network of relationships among dealers. We show that institutions with stronger ties to this dealer are forced to route their trades through longer intermediation chains to contact new counterparties, which charge them significantly higher prices. Moreover, we provide evidence suggesting that dealers did not *lean against the wind*; in contrast they drastically reduced their inventory. These results inform the debate on the risks related to the interconnectedness of the financial system by showing how it might be a source of market fragility and illiquidity.

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1 Introduction

The global financial crisis of 2008 has highlighted the key role played by the intertwined nature of the 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 financial securities (corporate bonds, mortgage-backed securities, credit default swaps, etc.) traded in opaque OTC markets, has been blamed for some of the persistent illiquidity of these markets. Even the new regulatory frameworks adopted in the aftermath of the crisis, from the proposal for a central counterparty clearing house (CCP) to the definition of systemically important financial institutions, have incorporated these views. Yet the exact role played by the interconnectedness of the financial system, as well as how large financial institutions might affect OTC market liquidity, remain at best imperfectly understood.

This paper investigates dealers' trading behavior and their pricing strategy in the corporate bond market to shed new light on the role played by the network of relationships among dealers in shaping the transmission of risk and its effect on market liquidity. The corporate bond market is the world's largest and most important source of capital for firms, with the size of the outstanding debt being about \$8 trillion. Moreover, nearly all of the \$20 billion average daily trading volume in the U.S. bond market takes place between broker-dealers and large institutions in a decentralized, over-the-counter (OTC) market.¹ Hence, it provides a perfect setting to analyze how the network of relationships between dealers shapes their trading behavior and liquidity provision, and to investigate how these responded during the crisis.

We start by showing that the corporate bond dealer network has a clear and persistent core-periphery structure. In other words, there are few highly interconnected dealers that intermediate most of the transactions with other dealers and with clients (e.g., retail in-

¹In the last few years, investors have been attracted to fixed income securities, and corporate bond issuers have taken advantage of the low interest rate environment. For instance, FINRA reports that in 2012 issuers borrowed a record \$1.54 trillion, up 29% from 2011, mainly thanks to retail investors shifting their portfolio composition from equities to fixed income instruments.

vestors, insurance companies, mutual and hedge funds, etc.) and many sparsely connected ones transacting less frequently.² Given this structure, we analyze how the spreads and the dealers' trading behavior differ when they trade with counterparties holding a different position in the network, and how their previous relationships with such counterparties affect trading outcomes. The first result is that when dealers trade with clients rather than with dealers they profit significantly more. These results are robust to week, bond as well as seller fixed effects. This means that the same bond, traded in the same week by the same dealer sells at a significantly higher price to clients, about 50 basis points, than to other dealers. We also find that, consistent with the search literature (Duffie et al. (2005) and Duffie et al. (2007)), these markups decline with the size of the transaction, while the dealers' market share in that bond issuance strongly predicts higher spreads.

Having shown the pricing behavior between dealers and clients, we turn to the inter-dealer transactions. We show that more central dealers are able to pay lower spreads but charge significantly higher spreads to their counterparties. However, spreads are significantly lower among dealers with stronger trading relationships, as proxied by the fraction of bonds exchanged among these two counterparties in the previous quarter. These results are not driven by differences in the type, volume or quality of the transactions that dealers who are more or less connected engage in, as we control for these characteristics in our analysis. Overall, these results provide evidence that existing trading relationships and the dealers' connections play a crucial role in shaping their trading behavior.

Now we can answer the main question of the paper: does the importance of these relationships vary over time? Do dealers tend to provide liquidity to their counterparties in turbulent times? We capture periods of stress in financial markets in two ways. We use the volatility index (VIX or MOVE), but also split the sample into the period from January 2005 to August 2008 and the one from September 2008 until May 2009 to capture the peak of the

²As we shall discuss in the later sections, this network structure has been the subject of recent theoretical studies on the risks resulting from having highly interconnected institutions (see for instance Babus (2014), Farboodi (2014a) and Atkeson et al. (2013)).

financial crisis after Lehman’s collapse. We find that having stronger relationships and being a more central dealer play an even more important role during high-uncertainty periods. Specifically, during periods of stress, dealers provide less liquidity to clients and periphery dealers (compared to other core dealers), which results in them paying significantly higher spreads. Similarly, dealers tend to rely even more on their central position in the network during turbulent periods, as more connected institutions are able to charge higher spreads and face significantly lower transaction costs. The results are confirmed when we split the sample over time, with transaction costs being between two and three times lower, during the peak of the crisis, among dealers having stronger ties or for the ones exhibiting a higher degree of interconnectedness.

We complement the previous findings by examining how these relationships might also shape the transmission of financial shocks among financial institutions. Taking advantage of a proprietary dataset provided by the Financial Industry Regulatory Authority (FINRA), we compute for each dealer how much it was transacting in the year preceding the recent financial crisis with a flagship dealer who collapsed in September 2008. We code this dealer as Dealer D.³ First, we show that after Dealer’s D collapse, the length of the intermediation chains between the buyer and the seller significantly increased. This suggests that having lost their main counterparty, new trading relationships had to be formed, although these were significantly less profitable than before. Since longer chains are associated with higher spreads, this also has adverse effects on the clients searching for liquidity.

Moreover, we can test whether dealers tend to *lean against the wind* during periods of turmoil. We employ transactions data to compute the inventory of the dealer in the weeks surrounding the Dealer D’s collapse excluding new issuances and maturing bonds. We can show that the dealers’ inventory declined significantly more for the bonds for which the intermediation chain length increased the most. This is highly suggestive that one of the main factors contributing to the increase in intermediation costs and illiquidity of the market

³We are not allowed to disclose dealer identities according to the agreement with the FINRA.

was the dealers' inability or unwillingness to increase their inventory during that period. To provide further evidence of this channel, we also show that dealers' inventory decline the most for the bonds that clients were selling more vigorously.

Finally, if these trading relationships are easily substitutable among dealers, the collapse of Dealer D should not impact its counterparties. Instead, we find that the dealers more connected with Dealer D tend to significantly reduce their spreads after September 2008. One potential factor which might explain these results is a difference in the composition of the bonds traded after Dealer's D collapse. Alternatively, endogenous matching between more fragile counterparties might drive these results as well. However, we show that these results persist over time and are not driven by these factors, as we compare the same bond traded by the same counterparties in the same week, with the only difference being the relative exposure of the sellers to Dealer D.

Our results contribute to improving our understanding of the role of the interconnect- edness of the financial system, which has been the topic of a recent policy debate. In the words of Donald 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"⁴ These results shed new light on the way in which these relationships might sometime serve as a buffer in periods of distress, but also on how they increase the fragility of the system, as being connected to more fragile dealers might adversely affect trading outcomes for healthy dealers as well.

1.1 Related Literature

Since the seminal works of [Allen and Gale \(2000\)](#) and [Freixas et al. \(2000\)](#), a growing liter- ature has focused on the role of financial networks as a shock propagation and amplification

⁴Senate testimony on June 5, 2008.

mechanism. For instance, [Acemoglu et al. \(2015\)](#) characterize the extent of contagion when financial institutions are linked via unsecured debt contracts, whereas [Elliott et al. \(2014\)](#) study cascading failures in a model of equity shares cross-holdings.⁵ [Babus \(2014\)](#) and [Farboodi \(2014a\)](#), instead, study intermediation by endogenizing the network structure. In a similar vein, [Stanton et al. \(2014\)](#) provides a network model where heterogeneous financial norms and systemic vulnerabilities arise endogenously and test its implications with data on the mortgage-origination and securitization network of financial intermediaries.⁶

However, most of the existing literature highlighting the role of the network is theoretical in nature. Recent exceptions include [Li and Schürhoff \(2012\)](#), [Choi and Shachar \(2013\)](#) and [Afonso et al. \(2013\)](#). [Li and Schürhoff \(2012\)](#) investigate the municipal bond market, showing that it has a persistent core-periphery structure with about 30 highly interconnected dealers at the center and a few hundred sparsely connected peripheral broker firms. Their main focus is on the trade-off between execution costs (lower in the periphery) and speed (higher in the core), but they also show that the introduction of post-trade transparency in 2005 benefitted investors by eroding the markups of central dealers. [Choi and Shachar \(2013\)](#) show that, in contrast to what commonly is thought, the misalignment between corporate bond and credit default swap (CDS) spreads during the financial crisis was not due to dealers shedding off their inventory right when liquidity was scarce. [Afonso et al. \(2013\)](#), instead, study the overnight interbank lending market using data from the Fedwire Funds Service, highlighting the role of relationships among banks. Specifically, the paper shows that the more frequently banks borrow, the less concentrated are their trading patterns; moreover, borrowing banks that have more concentrated lenders may pay higher interest rates in the interbank market, and banks get lower interest rates from their most important lenders.⁷

⁵Other related contributions include [Leitner \(2005\)](#), [Atkeson et al. \(2013\)](#), [Zawadowski \(2013\)](#), [Cabrales et al. \(2014\)](#), [Amini et al. \(2014\)](#), [Caballero and Simsek \(2013\)](#), [Lester et al. \(2014\)](#), [Glasserman and Young \(2015\)](#) and [Colliard and Demange \(2014\)](#). For a survey of the earlier literature on financial networks, see [Allen and Babus \(2009\)](#).

⁶Our work is also related to few recent papers that study trading over networks, such as [Condorelli and Galeotti \(2012\)](#), [Choi et al. \(2014\)](#) and [Manea \(2014\)](#).

⁷Also related is the recent work of [Ang et al. \(2013\)](#) which compares the characteristics of stocks traded in

We complement these existing studies by highlighting the time-varying importance of the relationships between dealers and the role played by the network in the propagation of shocks such as Dealer D's collapse.

Our paper is also informed by the results provided by theoretical work on trading in OTC markets. For instance, there have been several papers studying the asset pricing implications of trading over-the-counter (Duffie et al. (2005) and Duffie et al. (2007)); others have examined under which conditions dealers might behave as liquidity providers by "leaning against the wind" (Weill (2007)), or when even well-capitalized dealers may not find it privately optimal to accumulate inventories, which requires a government intervention in the interdealer market (Lagos et al. (2011)). Empirical papers that study transactions cost and price discovery in OTC markets include Bessembinder et al. (2006), Edwards et al. (2007), Green et al. (2007), and Green et al. (2010). Biais (1993) and Hendershott and Madhavan (2014) consider the trade-off between bilateral and electronic trading. Our focus, instead, is first on the role of the relationships during uncertain times in shaping the role of the dealers as liquidity providers and the propagation of shocks through the network.

Our paper belongs to the recent literature that focuses on the emergence of intermediation chains in over-the-counter markets. For instance, Glode and Opp (2014) argue that, in the presence of asymmetric information, trading an asset through several heterogeneously informed intermediaries can reduce the extent of adverse selection between counterparties, and hence preserve the efficiency of trade. Few other reasons have recently been proposed in the literature for the emergence of intermediation chains: Afonso and Lagos (2014) focuses on heterogeneity in banks reserves, Atkeson et al. (2014) on the banks' exposure to aggregate default risk, while Hugonnier et al. (2014) and Shen et al. (2015) show how search costs and heterogeneous asset valuations might lead traders with intermediate valuation to act as intermediaries. By empirically investigating the dealers' trading strategy in the OTC

OTC markets with those traded on listed markets and show that the former exhibit an illiquidity premium several times higher, and even larger among stocks held predominantly by retail investors and those not disclosing financial information.

corporate bond market, our paper might also prove valuable to this literature by showing what type of strategic interactions are the result of the relationships that get formed among dealers, and how these relationships affect both the asset prices and the dealers' responses to shocks.

More recently, [Babus and Kondor \(2013\)](#) provide a model where dealers possess private information and can engage in many bilateral transactions at the same time to study trading and information diffusion in OTC markets. The model has several empirical implications that are consistent with our results, for instance, more central dealers intermediate larger quantities and intermediate more. Moreover, by learning more from all the prices they observe, they are able to earn more profit per trade.

The remainder of the paper is organized as follows. Section 2 provides details on the data sources and summary statistics. Section 3 argues that the corporate bond market is characterized by a clear core-periphery structure which shapes the dealers' trading behavior. Section 4 describes the main results on the importance of the trading relationships especially during turbulent times. Section 4.3 presents evidence on the effects that the failure of Dealer D had on its trading partners and how the shock propagated in this market. Section 5 concludes.

2 Data and Summary Statistics

We collect information on the universe of corporate bonds and transactions from an enhanced version of the Trade Reporting and Compliance Engine (TRACE). For each transaction, the dealer has to report all the relevant information, from the date at which the transaction takes place to the terms of the transaction and the identifier for its counterparty to the regulator. Specifically, one main advantage of employing the enhanced TRACE data is that we can observe whether a trade is carried out between two dealers, or between a customer and a dealer. Moreover, we can distinguish between buyers and sellers. As a result, we

can trace out the intermediation chains, e.g., if a dealer who receives a purchase request by a client has reached out to a different dealer or client to acquire the bond demanded. Furthermore, the most important feature of this proprietary dataset for our analysis is the identifying information on dealers that allows us to not only construct a panel of dealer-specific variables but also to measure the trading relationships between various dealers and Dealer D and study how the Dealer D's collapse affected the trading over the network.

Panel A of Table 1 presents the summary statistics. Our data covers the period starting in 2005 up to 2013, with more than 56 thousand bonds traded and more than 52 million transactions. Most of these bonds and transactions, about 85 percent of the whole bonds, are concentrated in the investment grade segment, while about 15 percent are high-yield or not rated. The average size of the bond issuance is about 21 million, with 85 percent being smaller than 100 million, with a maturity of 10 years and a rating of BBB+.

Panel B presents some statistics on the trading behavior in this market. Specifically, the median holding period is 37 days, confirming that these bonds are not all frequently traded. However, the median number of trades for each bond is one hundred. We can also compute the dealers' spread, namely, the difference between the price at which they purchase a bond from other dealers or from clients and the price at which they are able to resell it. On average, the spread is about 20 basis points. In order to have a meaningful calculation, we restrict attention to transactions that are concluded within an hour from the time of the initiation of the trade. We ignore, instead, the transactions for which the dealer sells directly from his inventory, as we cannot precisely know the price at which the dealer bought that security.

As a main measure of network centrality we use the eigenvector centrality. It takes all direct and indirect trading partners into account and is computed by assigning scores to all dealers in the network based on the principle that connections to more-connected dealers increase more the score of the dealer than similar connections to less-connected dealers. In other words, it is not only how many connections that matters, but *who* they are connected

to that matters. However, all of our results are robust to using other measures of centrality, such as degree centrality, betweenness, closeness, and cliquishness.

3 The Trading Network of Corporate Bonds

In spite of the growing network and OTC literature, very little is known about the interdealer network, the relationships that emerge between market participants and their effects on rent sharing and trading behavior in off-exchange markets. To better understand the role of the network structure on the trading behavior of the different market participants, we start by analyzing the type of network that emerged in this market, and how persistent it is over time.

Figure 1 shows the cumulative distribution of all transactions as a function of the sellers' centrality measure. It clearly shows that about 80 percent of all transactions are made by the top 50 dealers, which suggests that the interdealer market exhibits a core-periphery structure. Figure 2 uses the transaction data between dealers and clients and inter-dealers to plot the intermediation network in the corporate bond market taking the average of the transactions occurred over our sample period. Each red circle represents a dealer, the center of the network is occupied by clients, while the links connecting the market participants are more intense as the volume of the bilateral transactions increases. It confirms that the network is composed by the top 20-30 dealers in the core, transacting a high volume of trades among themselves and with the clients, and the rest of the dealers in the periphery with fewer transactions.

Being an average over our sample period, Figure 2 already suggests that the network structure is an important characteristics of this market. However, it might be that dealers switch between the core and the periphery over time. Thus, we test if this network structure is persistent by computing the dealers' transition probabilities to experience an increase or a decrease in their centrality ranking. Table 2 tests this hypothesis by dividing dealers in

different bins based on their centrality measure, starting with the top 10 and finishing with very peripheral dealers (>200), and computing for each month the probability to switch between bins in the subsequent month. The table shows that the network is very persistent; in fact the top 10 dealers have about 90 percent probability to remain in the top 10 and at most can switch to the next bin, with a ranking between 11 and 20, with almost 10 percent probability. This means that the same dealers always intermediate the highest number of transactions and interact the most both with other dealers and with clients. This finding is symmetric, in the sense that peripheral dealers are significantly more likely to stay in the same position in the next month than significantly increasing their ranking. The last two columns also show the probability to move up or down in the ranking.

In sum, the structure of the network exhibits a very active interdealer market between few top dealers, and several other dealers that intermediate fewer transactions and tend to transact with other dealers rather than directly with the clients. Then, we can meaningfully start our analysis by differentiating between three types of market participants: core dealers, periphery dealers and clients. The first question we can address is if more central dealers are able to charge other market participants more for the assets they sell. Theoretical support for this hypothesis is provided by [Babus and Kondor \(2013\)](#) which shows that being a more central dealer allows to learn faster from the prices of all the transactions executed, which increases the gains from trade that these core dealers are able to capture.

Panel A of Table 3 formally tests this hypothesis. Columns (1)-(4) consider the whole sample of transactions, where the coefficient of interest is the one on the indicator variable "*Client Counterparty*". Column (1) only controls for week fixed effects in order to absorb shocks and find that dealers charge on average 52 basis points to clients compared to other dealers. In Column (2) we control for the "*Log(Transaction Volume)*", which shows that larger transactions are cheaper, and the coefficient on our main variable is still statistically significant and even slightly larger. Since these results might be driven by heterogeneity in the assets traded by the different market participants, in column (3) we control for the bond

(CUSIP) fixed effect and find similar results. Moreover, we also show that lower-rated bonds (the ones with higher values for the variable “*Rating*”) are more profitable, and that when the dealer has a larger market share for this bond, computed as the share of the bond that the dealer has in its inventory, he is able to sell it at higher prices. In column (4) we also include seller fixed effects, and the results remain unaffected. This means that considering the same seller and the same bond, sold to a client rather than to another dealer in the same week, the client is charged on average 50 basis points more.

In other words, these results provide evidence that the dealers profit more from their interactions with clients than with other dealers. This might be for different reasons. For instance, being a dealer allows them to acquire private information about the securities they intermediate and to take advantage of this private information in their interactions with the less informed clients. If the main driver is private information, then we should observe heterogeneous effects across bonds of different quality, with non-investment grade bonds being more profitable to dealers than investment grade bonds when transacting with clients. Hence, in Columns (5) and (6) we restrict to the sample of investment grade and non-investment grade bonds, respectively. We find that dealers charge similar price for both types of bonds. It seems that for non-investment grade the profit margins are about 10 basis points lower than these for investment grade. Hence, these results do not seem to suggest that the higher profit margins are mainly driven by the presence of private information.

An alternative rationale behind these results might be that being a core dealer increases bargaining power, so we should expect these dealers are able to profit even more from transacting with their clients than periphery dealers. To investigate if there exists such heterogeneity among dealers, in Column (7) we restrict attention to transactions in which the seller is a core dealer, while in Column (8) we consider the trades in which the seller is a periphery dealer. The main coefficients show that both core and periphery dealers charge their clients about 50 basis points more than when transacting with other dealers, even controlling for week and bond fixed effects. This seems to suggest that the client faces similar transaction

costs when dealing with both core and peripheral dealers. Panel B shows the regression estimates but based on the size of the transaction. Consistent with the search literature (Duffie et al. (2005) and Duffie et al. (2007)), these markups decline with the size of the transaction, suggesting that for small transactions the buyer does not search for the best deal, while for larger transactions, there is more competition among dealers, which result in lower spread.

Up to this point we have compared transaction among dealers with those between dealers and clients. However, we in Figure 3 and 4 we show that there exists significant heterogeneity also among interdealer transactions. Figure 3 and 4 visualizes the spread for the four different types of transactions: core-core, core-client, core-periphery and periphery-core for our sample period 2005-2013. Two main things are worth noting. First, there has been a significant increase in profit margins starting in the second quarter of 2008 with a subsequent decline after 2009. Second, there exists an important heterogeneity between different types of transactions. Specifically, inter-core dealers transactions and periphery-to-core transactions are the ones with the lowest spreads. Core-periphery as well as core-client transactions have significantly higher spreads, at least 20 basis points higher, and experience a significant increase during the recent crisis starting in the first quarter of 2008.

Thus, we further explore these findings by analyzing interdealer transactions in Table 4. The comparison group is composed by inter-core transactions, that is, transactions where both the seller and the buyer exhibit values for network centrality measure in the top 30. Column (1) shows a clear ranking among different types of transactions for what concern the spreads. Specifically, core-core transactions are the cheapest, then periphery-core are slightly more expensive, then periphery-periphery are about 20 basis points more expensive than inter-core transactions, while the most expensive are core-periphery transactions. These results remain both statistically and economically significant even when we control for the volume of the transaction and the bond ratings (Column 2), as well as when we include bond fixed effects (Column 3).

Columns (4) and (5) investigate if there are significant differences between investment grade and non-investment grade securities. Interestingly, for transactions involving non-investment grade bonds the core dealers charge the periphery about 13 basis points more than for investment grade transactions. Instead, there are no significant differences across bonds of different quality when looking at periphery sellers transacting with buyers in the core. This suggests that the core dealers are indeed able to 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 transactions exhibiting higher margins than investment-grade ones.

In sum, the previous results establish a very significant relationship between the dealers' position in the network and the profits that the dealers can capture transacting with clients or with other dealers.

4 Main Results

In this section we present the main results of the paper. We start by analyzing the role of bilateral trading relationships among dealers in affecting the spreads, especially in turbulent times. We then turn to investigating how the network reacts when a core dealer defaults.

4.1 Trading Relationships

Up to now we have considered only the position in the network, core versus periphery, as a potential factor affecting the profit margins. We now turn to a more in-depth analysis of the role of bilateral relationships in this market. We compute the fraction of sale transactions that the seller s had with the buyer b in the previous quarter, normalized by the total sales of s , that is, $\text{Fraction Sales}_{s,b} / \text{Total Sales}_s$ which we label "*Fraction Selling to Counterparty*". We also compute the fraction of transactions in which the buyer b bought corporate bonds from the seller s , normalized by the total purchases made by the dealer b in the previous

quarter, namely $\text{Fraction Purchases}_{s,b}/\text{Total Purchases}_b$ which we label the "*Fraction Buying from Counterparty*".

Table 5 reports the estimation results. Column (1) shows the results for the effect of $\text{Fraction Sales}_{s,b}/\text{Total Sales}_s$ and $\text{Fraction Purchases}_{s,b}/\text{Total Purchases}_b$ on the seller's spreads controlling for the week fixed effects, the volume of the transaction and the bond rating. It shows that on average a higher fraction of sales to the buyer in the past predicts a significantly lower profit margins. Similarly, a higher fraction of purchases made by the buyer from the same seller, compared to his total purchase transactions, predicts significantly lower profit margins. We can also confirm the result that in general a higher transaction volume is related to a lower profit margin, whereas lower-rated bonds are associated with higher profit margins.

In Column (2) we confirm the previous results by controlling for the bond fixed effects and find a very similar economic and statistically significant coefficient. In other words, comparing the same bond traded by two different pairs of counterparties in the same week, the ones that have had a stronger tie in the past exhibit lower spreads. This shows that this result is not driven by unobserved heterogeneity in the type of bonds that are exchanged by some counterparties and not by others.

While the previous results shows the importance of the existing relationships between counterparties, Columns (3) and (4) focus on the seller's and buyer's position in the network controlling in turn for week and bond fixed effects. This allows us to test for the hypothesis that the prices at which trading happens are influenced by the possibility that dealers can take advantage of their connection in the network to have access to more profitable trading opportunities. For instance, more central dealers should face lower transaction costs, as they can intermediate a higher number of transactions, capture higher rents due to larger bargaining power and being able to have access to larger inventories. We indeed find that a more central buyer is able to obtain a lower price from his counterparties than a more peripheral one. The results for the seller are weaker, both statistically and economically,

in fact, only when controlling for the bond fixed effect we find that more central sellers are able to capture a higher profit margin than more peripheral sellers. These results complement the previous ones in Table 4 in showing that there exists an important heterogeneity across different dealers depending on their position in the network and the strength of their connections. In other words, existing relationships between dealers do matter.

4.2 Dealer Network and Trading Relationships in Turbulent Times

Now we can address one of the main question of the paper: *when* are these relationships more valuable? Do dealers tend to demand higher spreads during periods of high-uncertainty, especially from the ones that are more dependent on them? To answer these questions, we can now exploit the time series dimension of our data. Specifically, our dataset covers the financial crisis, then we can investigate the dealers' trading behavior as a function of their relationships during that time.

Table 6 shows the estimates. We follow two different approaches: first, we interact our measures of trading relationships and of the network centrality with the volatility index (VIX); second, we split the sample in the period before and after the Lehman Brothers' default. We begin our analysis in Columns (1) and (2) by interacting the intensity of the relationship between seller and buyer with the volatility index controlling for week and bond fixed effects. Interestingly, we find that if the two parties have a strong tie, the incidence of the existing trading relationships on the spreads becomes even more important in high uncertainty periods. Holding fix the bond is particularly important over this period, because changes in the spreads might be due to a change in the composition of bonds traded during the peak of the crisis, e.g. dealers might reduce their inventory by selling their riskier holdings. Specifically, comparing the same bond, traded in the same week among different counterparties, we find that those who have sold or purchased a significant fraction of their corporate bonds to or from the same counterparties, are able to strike a better deal, with profit margins being lower when market uncertainty spikes. In terms of magnitude, a one

standard deviation increase in the VIX, reduces the margins by 35 basis points. During the hike of the crisis, the VIX increased by about three standard deviations, which makes these results even more economically significant.

Can the dealers take advantage of their position in times of crisis? In Columns (3) and (4) we specifically test if the dealers' network centrality becomes more important during high-uncertainty periods. To test this hypothesis, we interact the centrality measure for the buyer and seller with the volatility index. We find that more central sellers profit even more from their position during high-uncertainty periods, similarly, central buyers have a higher bargaining power during volatile times as they can conclude transactions at lower prices. This means that a core dealer is able to capture even higher rents by trading with peripheral dealers in bad times, while peripheral dealers are not able to do the same when selling to a core dealer. Hence, the gap between core and periphery dealers becomes even more important during turbulent times, as the former can take advantage of their position.

As an alternative strategy, we divide the sample in the period preceding the peak of the crisis, from January 2005 until May 2008, and in the most turbulent times as identified by the period in which the VIX is above its long-run average of 25. Column (5) focuses on normal times, whereas Column (6) investigates the role of relationships and network centrality in the crisis period from September 2008 to May 2009. Comparing the results in the two columns we can confirm the results above that central seller and buyer capture a significantly higher fraction of the gains from trade during the crisis than during normal times, even controlling for week and bond fixed effects. The difference is both statistically and economically significant, with the seller charging eight times more in a crisis than in normal times, and buyer obtaining discounts four times larger in a crisis than in normal times.

Furthermore, the comparison between the two columns also confirms that the existing relationships played an even more important role in the crisis than in normal times. In fact, during the acme of the crisis, having had a repeated seller or buyer relationship to a

particular counterparty led to lower margins than during normal times. The magnitude is also important as the discount seems to be at least double during the 2008-2009 period than before the crisis.

These results raise a natural question: do all market participants benefit from lower transaction costs during periods of high uncertainty? Figure 1 already suggests that all spreads increase significantly around the Lehman Brothers' bankruptcy, but there is substantial heterogeneity across transactions among the different types of market participants. However, this heterogeneity might be due to several factors, such as a change in the pool of bonds traded by different counterparties, or shocks that hit some specific dealers. Thus, we formally address this question in Table 7 by splitting the transactions between different types of dealers as in Table 4, and by interacting the main indicator variables with the VIX indicator (Columns (1)-(3)). We also split the sample across the two different periods (Columns (4) and (5)). Interestingly, we find that core dealers are able to extract even higher rents from peripheral dealers in periods of high-VIX, while peripheral dealers are not able to do the same when selling to core dealers, and transactions at the periphery tend to exhibit higher profit margins in turbulent times. Comparing Column (2) with Column (3) we show that core dealers profit even more during periods of high uncertainty by dealing with peripheral dealers, when the bond is non-investment grade. Results are robust to the inclusion of controls for the transaction characteristics, as well as week and bond fixed effects, and are very similar when we compare transactions over time in Columns (4) and (5), with core dealers profiting about three times more from peripheral dealers during the acme of the crisis than during normal times.

We augment these results by examining if the transaction costs faced by client changes over time. Table 8 investigates the relationship between dealers' profit margins when dealing with the clients as a function of the size of the transaction. Column (1) shows that on average there is no significant variation of the client's transaction costs when the VIX changes. However, in Columns (2) and (3) we split the sample between transactions with size below

median and transactions in the top quantile. We find that while smaller transactions are counter-cyclical, as the margins significantly decrease with the volatility index, larger transactions exhibit significantly larger margins during periods of high uncertainty. This suggests that for larger transactions, the dealers make their clients pay higher transactions costs in turbulent times.

The results using the VIX as a measure of uncertainty and the comparison between different subsamples highlight the main result of this section: relationships are important as they can predict profit margins, and these become even more crucial during turbulent times. This is in contrast to the theoretical literature on OTC markets where the interactions between buyers and sellers are completely anonymous and there is no possibility for the price dispersion to be driven by the previous parties' transaction history. Moreover, novel to the existing literature, we have unveiled a time-varying importance of these relationships and how they benefit core dealers at the expense of peripheral ones as well as of the clients.

4.3 Default of a Core Dealer

Having established that trading relationships and the network centrality shape the rent sharing and liquidity provision among dealers and play an even more important role during the crisis, we can now turn to the study of how disruptly losing an important trading counterparty affects the dealers' trading behavior. That is, are these relationships easily substitutable? In absence of frictions, if dealers can easily search for counterparties or relationships can be quickly formed, losing a specific tie with another dealer should not affect their profitability or transaction costs. We can formally test this hypothesis by employing the information on dealer identities contained in the regulatory data we use. In particular, we study how the network reacts to the shock of Dealer D's default and how this shock affected dealers who had an ongoing relationship with Dealer D before its collapse.

Table 9 shows the estimates that relate the strength of the relationship with Dealer D with the profit margins captured by other dealers after the collapse. We compute the fraction

of all the bonds sold to Dealer D before its collapse and took the average for the year 2007, that is, several months before the default. This is to make sure to capture the persistent relationship that Dealer D had with other dealers, rather than the deleveraging that might have happened right before filing for bankruptcy. We consider both the fraction of securities bought from and sold to Dealer D, but the two are very correlated with each other. Formally, we estimate the following regressions:

$$Spread_{i,j,\eta,t} = \beta_1 Fraction\ of\ Transactions_{i,D} \times Post + \beta_2 Fraction\ of\ Transactions_{i,D} + \Gamma X_{i,j,\eta} + \lambda_t + \varepsilon_{i,j,\eta}$$

where i and j denotes the two counterparties, while η indexes the bond and t the week. "*Fraction of Transactions_{i,D}*" proxies the intensity of the relationship between dealer i and Dealer D. "*Post*" is a dummy equal to one after the Dealer D's default. We include several controls in the vector $X_{i,j,\eta}$ to capture heterogeneity across dealers and across bonds, and all specifications include week fixed effects. The main coefficient of interest is β_1 on the interaction between the intensity of the trading relationship pre-default with Dealer D and the indicator for the post-bankruptcy period. Column (1) controls for week and CUSIP fixed effects and finds that the dealers that were buying the most from Dealer D experience a significant reduction in their profit margin. This effect is both statistically and economically significant as a one standard deviation increase in the fraction of asset bought from Dealer D decreases the spread by 14 basis points on average.

This result is robust to the inclusion of characteristics of the transaction such as its volume and the rating of the bond, as well as to the inclusion of our measure of the strength of the bilateral relationships (Column 2). Moreover, in Columns (3) and (4) we further test the sensitivity of this result by including in turn the seller and the buyer fixed effects, which take into account potential unobserved heterogeneity across dealers more or less connected to Dealer D. This means that comparing transactions during the same week, for the same

bond, by similar dealers, we find that those that were relying more intensely on Dealer D suffer the most after its bankruptcy.

Columns (5) to (8) complement the previous results by studying how dealers that were selling a higher fraction of their assets to Dealer D respond to its bankruptcy. As before, the main coefficient of interest is the interaction between the dummy Post equal to one after the default of Dealer D which captures the average fraction of assets sold to Dealer D in 2007. Consistent with previous results we find that dealers more exposed to Dealer D experience a significant reduction in their profit margins in the aftermath of Dealer D's default, even when we control for week and bond fixed effects (Column 1), for the two proxies for the strength of the relationship between seller and buyer (Column 2) and for seller and buyer fixed effects (Column 3 and 4). However, since the fraction of sale transactions is very correlated with the fraction of purchase transactions, only the latter is statistically significant once interacted with the Post indicator.

4.4 Leaning against the Wind

Many papers document the importance of transactions among intermediaries along intermediation chains. For instance, according to a 2013 report by the Bank of International Settlements, in foreign exchange markets inter-dealer transaction volume averages \$2.1 trillion per day. For metals futures contracts, [Weller \(2014\)](#) shows that a median number of 2 intermediaries are involved in round-trip transactions and up to 10% of transactions involve 5 or more intermediaries. In municipal bond markets, [Li and Schürhoff \(2012\)](#) show that 13% of intermediated trades involve a chain of 2 intermediaries and an additional 10% involve 3 or more intermediaries. [Hollifield et al. \(2012\)](#) find evidence of intermediation chains for many securitized products: intermediated trades of non-agency collateralized mortgage obligations involve 1.76 dealers on average and in some instances the chain includes up to 10 dealers.

However, there is no evidence on how these intermediation chains respond to shocks.

Specifically, one potential reason why spreads might significantly increase after Dealer D's default is due to the increase in the length of the intermediation chains. To test this hypothesis, Figure 5 plots the estimated week fixed effects for a regression whose dependent variable is the trading chain length. We show that after Dealer's D collapse, the length of the intermediation chains between the buyer and the seller significantly increased. This suggests that having lost their main counterparty, new trading relationships has to be formed, and as Table 9 has shown these are significantly less profitable than previous relationships. We can also confirm this result by estimating a regression of the intermediation length over the Post indicator which is equal to 1 after the collapse of Dealer D. We find that even controlling for bond fixed effects and other characteristics of the transaction, we find that on average the chain of intermediation becomes about 20% longer. We do not find any significant difference among investment and non investment bonds, however, the effect seems more pronounced when the seller is in the core than when he belongs to the periphery.

This increase in the intermediation length matters because it leads to an increase in the intermediation costs. Table 11 shows how the spread is allocated among intermediaries along the chain. Consistent with [Farboodi \(2014b\)](#), we find that being closer to the client leads to higher profits. Moreover, since the average spread is about 60 bps, and the intermediaries other than the closest to the client charge about 20-30 bps less, we have that intermediation costs increases with the length of the chain.

We can further examine what are the reasons behind this increase in the intermediation length by employing transaction data to compute the inventory of the dealers around the collapse of Dealer D. To avoid any bias in our computation, we focus on a narrow time window around this event and exclude the issuance of new bonds and those maturing within the time window. Existing theories analyze if and how dealers might be able to lean against the wind by building inventory in periods of distress (see for instance [Weill \(2007\)](#)). Figure 6 plots our measure of inventory for bonds that have experienced a change in the average intermediation chain length above and below the median. Interestingly, we find that inventory declines the

most for the bonds for which the intermediation chain became longer. This seems to suggest that dealers are not leaning against the wind, because they hold less inventory which makes it harder for them to accommodate clients' order requests.

Finally, we corroborate this evidence by plotting in Figure 7 the dealers' inventory for bonds that experienced different selling pressure from the clients. This is defined as the amount sold by clients to dealers normalized by the amount outstanding. The idea is that if the dealers are leaning against the wind by fulfilling clients' selling orders without immediately reselling the bonds to avoid a further price decline, we should observe the dealers' inventory increasing for the bonds that are sold more intensely by the clients. In contrast to this hypothesis, we find that dealers' inventory drops more significantly and more rapidly for the bonds that are experiencing a higher selling pressure from their clients.

5 Concluding Remarks

The current crisis has brought the question of how governments should handle complex financial institutions that are "too connected to fail" under the spotlight. Several theoretical contributions have shown how connections between financial institutions stemming both from correlation in their assets holdings and from an intricate system of cross-liabilities might generate a cascade of bank failures. However, the evidence on the role played by bilateral relationships among financial institutions is at best scarce.

This paper focuses on a crucial over-the-counter market, the one for corporate bonds, and investigates how the network of relationships between dealers shapes both their trading behavior and their liquidity provision in normal times and in periods of distress. We start by showing that the market exhibits a clear core-periphery structure, where few highly interconnected dealers intermediate most of the transactions with other dealers and clients and many sparsely connected ones transacting less frequently, which is very stable over time. Then, we show that the dealers' bilateral relationships and their network centrality strongly

predict the transaction costs they face in the market, with more central dealers being able to take advantage of their connections to strike better deals. What is more important is that dealers tend to provide liquidity during periods of distress to the counterparties with whom they have the strongest tie. However, core dealers exploit their connections at the expense of peripheral ones as well as of the clients, because they tend to increase the transaction costs faced by peripheral dealers and by the clients during turbulent times. Similarly, being a highly connected and systemically important dealer becomes more valuable during periods of high uncertainty.

In contrast to most of the empirical literature on the corporate bond market, we are able to identify the identity of each dealer. This allows us to examine how the network responded to a large shock such as the failure of Dealer D. We show that Dealer D's main counterparties, had to reduce the spreads after September 2008, compared to similar dealers trading the same bonds over the same period.

In sum, these results shed new light on how bilateral relationships between financial institutions might sometime serve as a buffer in periods of distress, but also on how they increase the fragility of the system, as being connected to more fragile dealers might adversely affect trading outcomes for healthy dealers as well.

6 Appendix

In this appendix we provide more details on how we compute the spread measure employed in the baseline regressions.

There are several cases. First, consider the case in which the first order for a specific CUSIP by a dealer is a buy order. The buy price is then the price of that first order. As the dealer buys more of the bond at different prices, the buy price changes to a weighted price, with weights being the total number of shares at each price. Note, if some shares are sold before a new buy order, then the weight on the old price is the number of shares remaining on the dealer's inventory. We use the same logic to calculate the buy time. The hold time is just the sell time minus the last calculated weighted buy time as long as the dealer still holds shares of that bond after the sale.

If the first order for a specific CUSIP by a dealer is a sell order, then we compute the weighted sell price and the hold time following a similar logic to the one discussed above. The sell time is calculated the same as well.

Second, consider the case in which the dealer reaches a balance of 0 shares at some later point for a specific CUSIP. The buy price is then the price of the first order after they reached a balance of 0. As the dealer buys more of the bond at different prices, the buy price changes to a weighted price, with weights being the total shares at each price. Note, if shares are sold before a new buy, then the weight on the old price is the number of shares remaining. We use the same logic to calculate the buy time. The hold time is just the sell time minus the last calculated weighted buy time as long as the dealer still holds shares of that bond after the sale (they don't sell more than they own). Similarly for a sell order.

Lastly, consider the case in which the dealer starts with a negative balance for a specific CUSIP, but in 1 order purchases more than the negative balance and ends up with a positive balance. The buy price is then the price of the one order that caused their balance to change from negative to positive. As the dealer buys more of the bond at different prices, the buy price changes to a weighted price, with weights being the total shares at each price. Note,

if shares are sold before a new buy, then the weight on the old price is the number of shares remaining. We use the same logic to calculate the buy time. The hold time is just the sell time minus the last calculated weighted buy time. We no longer restrict the calculation based on the balance after the transaction. Similarly, if the dealer starts with a positive balance but in 1 order, sells more than their balance so they end up with a negative balance, we can calculate the (weighted) sell price and sell time. The hold time is just the buy time minus the last calculated weighted sell time.

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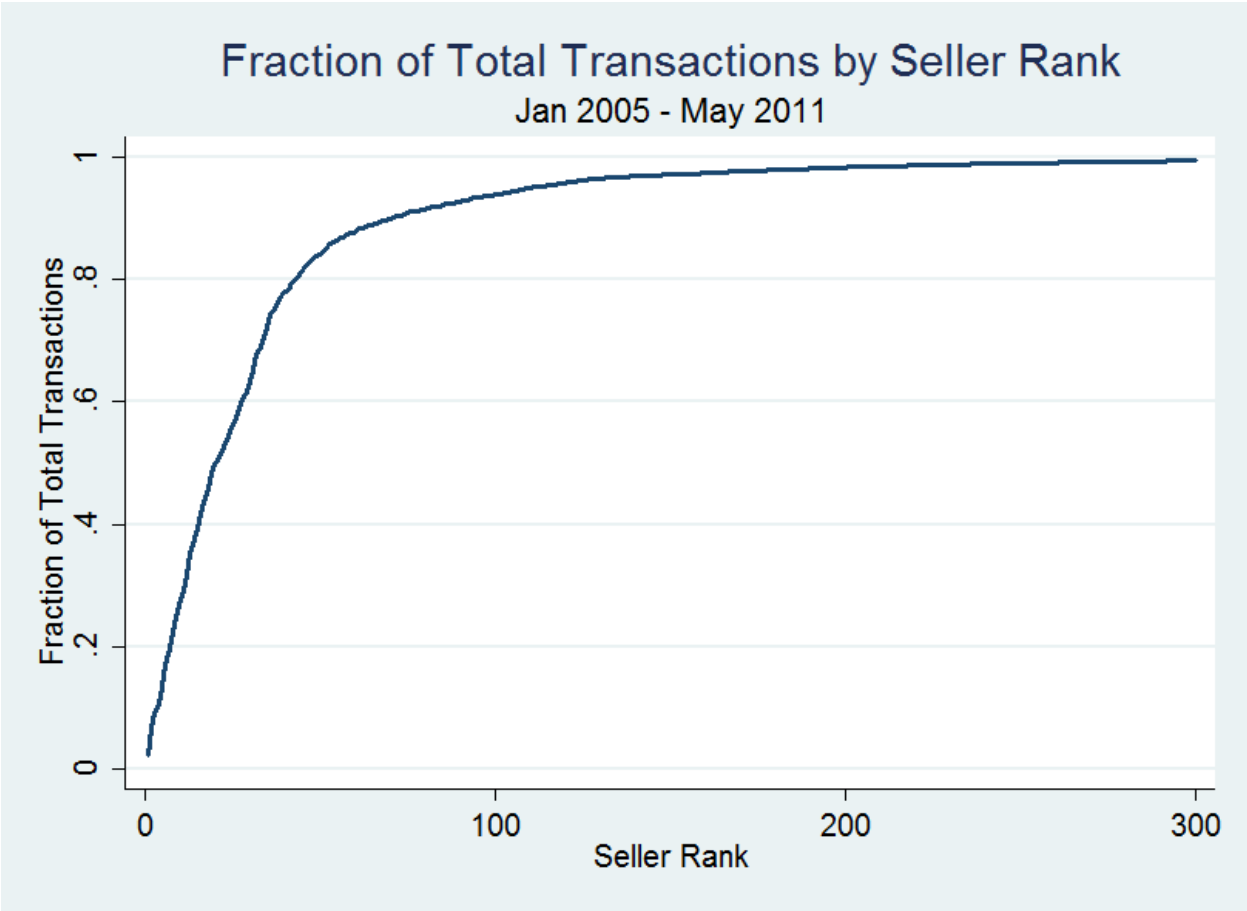


Figure 1

This figure plots the cumulative distribution of seller's network centrality for all transactions, both among dealers and with clients.

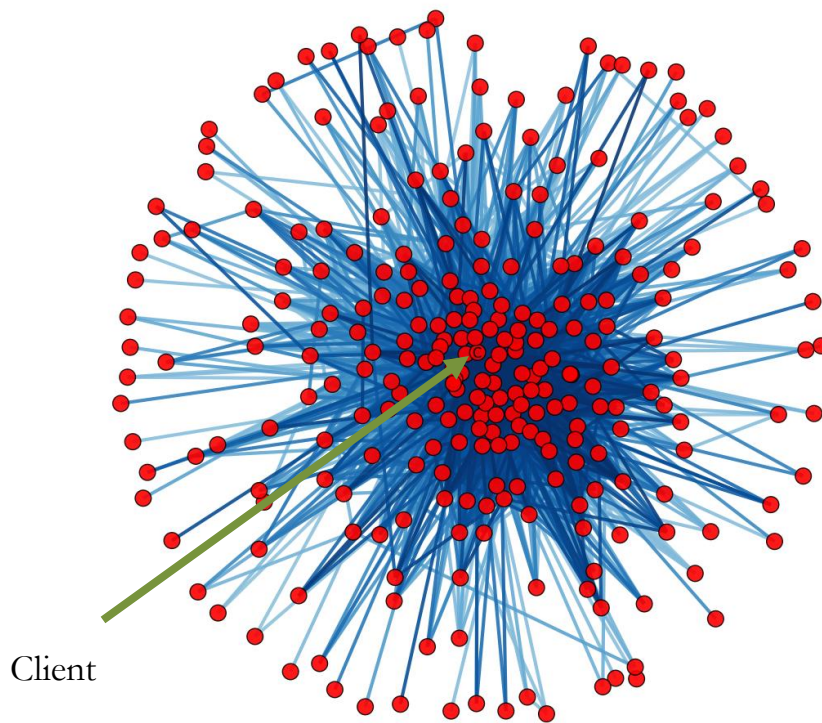


Figure 2

This figure plots the core-periphery network structure where each link is a transaction, and at the center there are the transactions with clients.

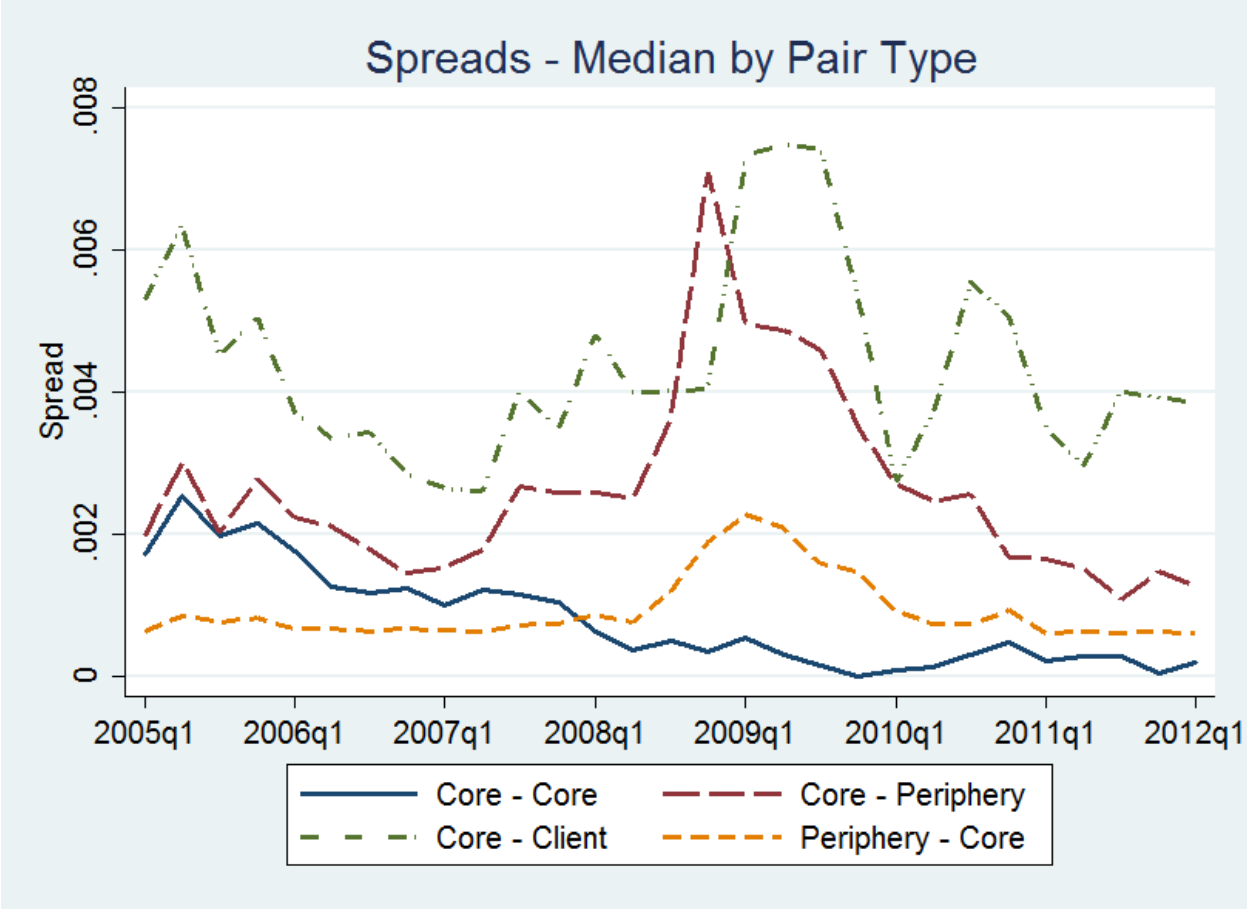


Figure 3

This figure plots the profit margins over time, for transactions among different types of counterparties.

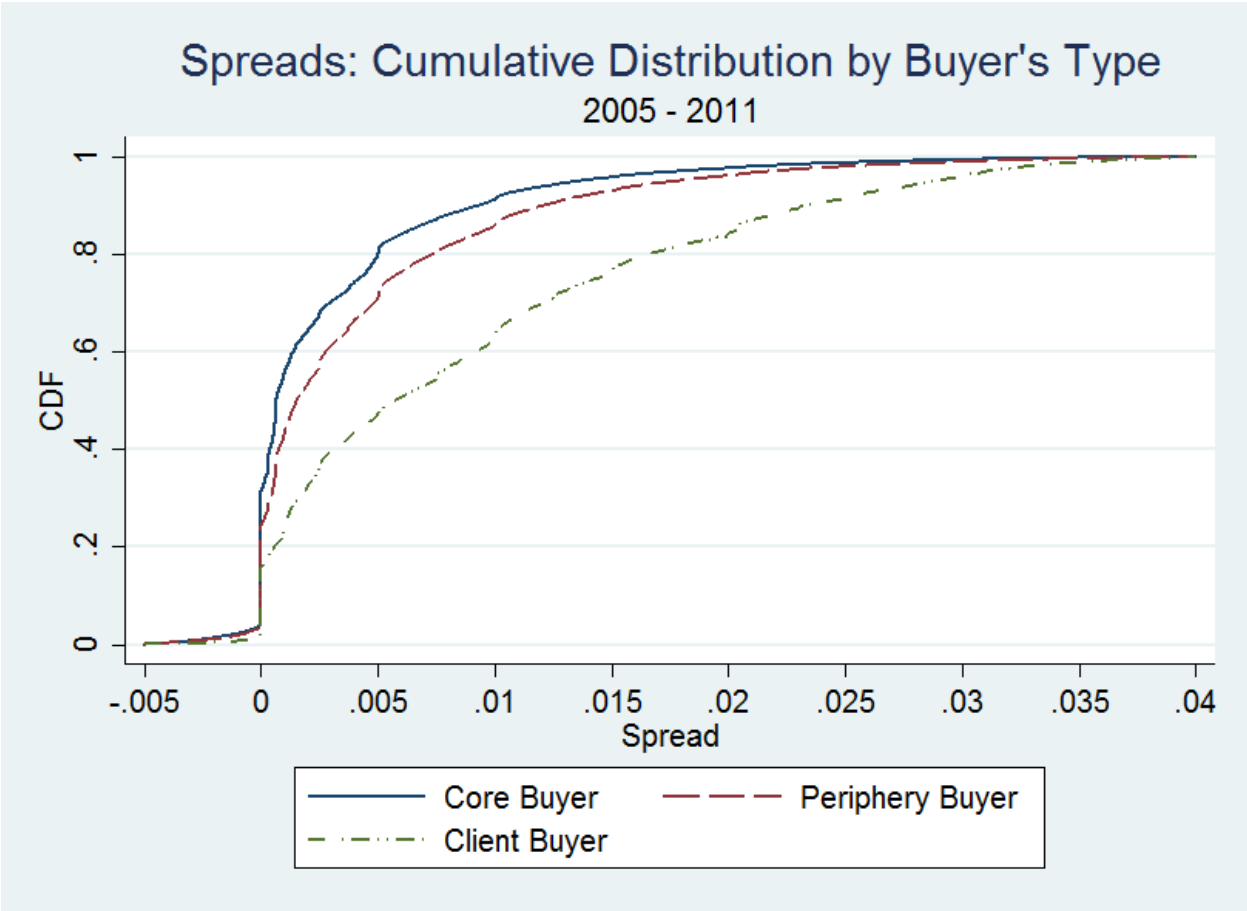


Figure 4

This figure plots the cumulative distribution of the profit margins for the different types of counterparties.

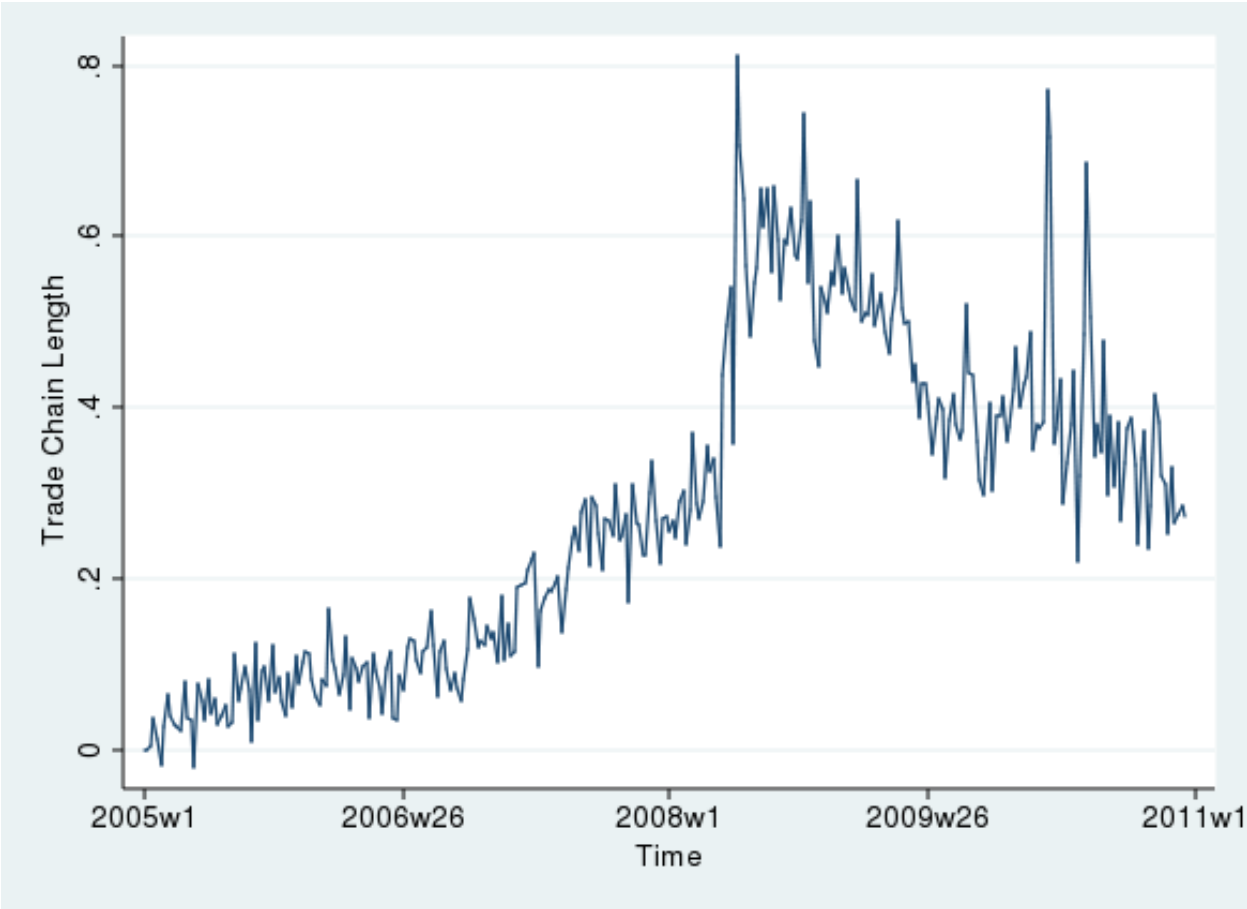


Figure 5

This figure plots the average trading chain length over time.

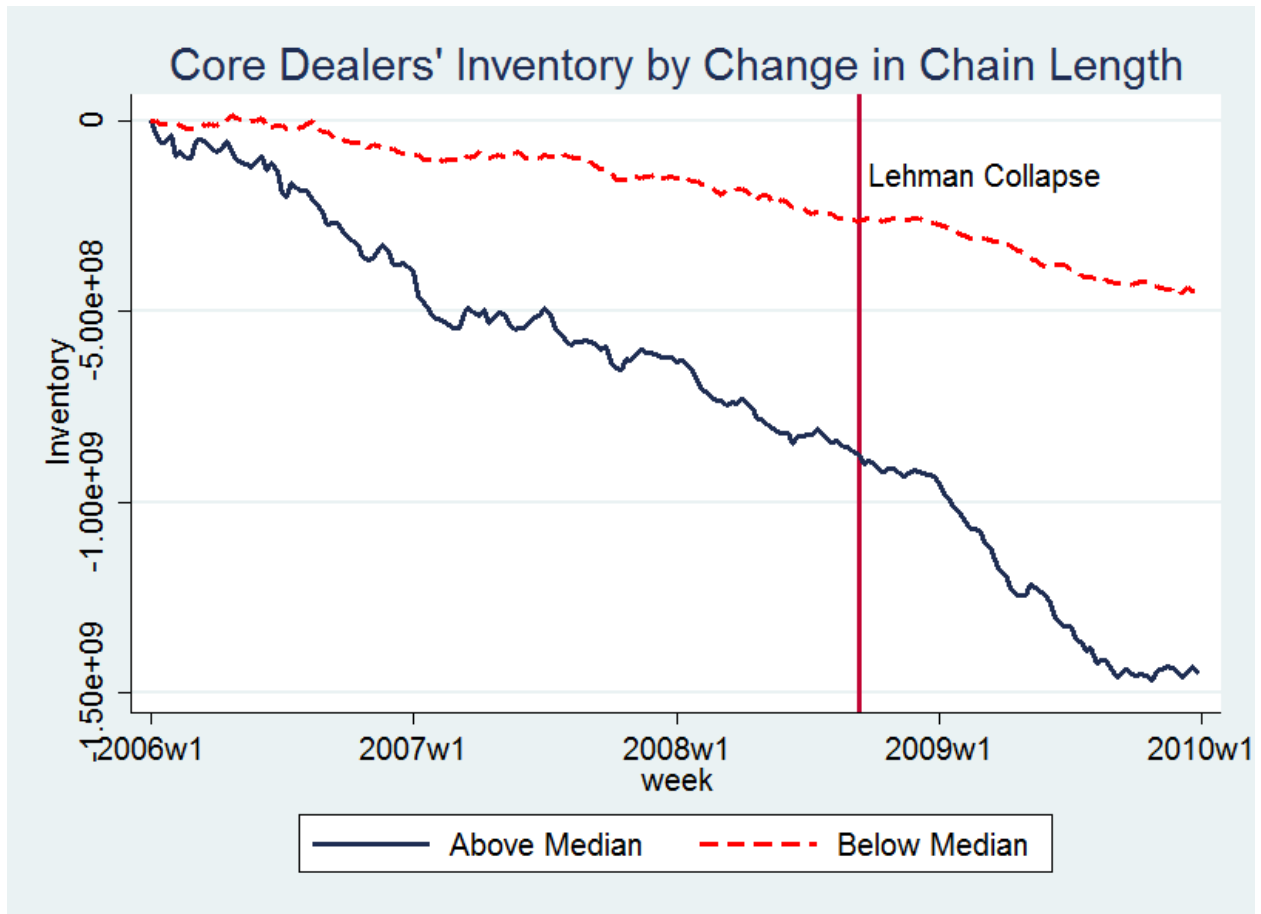


Figure 6

This figure plots the dealers' inventory for bonds that experienced a change in the length of the intermediation chain above and below median.

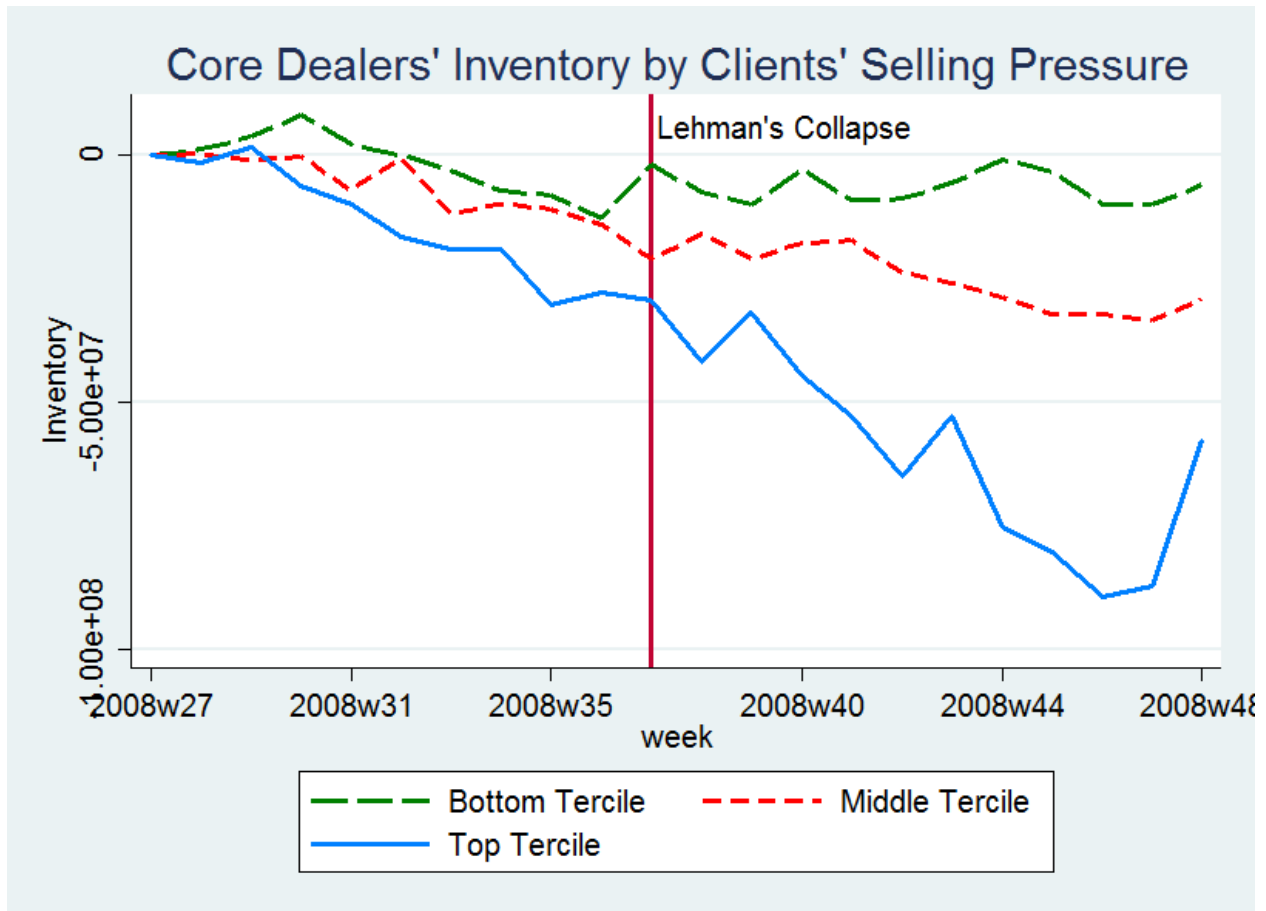


Figure 7

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.

Table 1
Summary Statistics

The 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 and the number of trade, the bonds' credit quality, issue size and maturity, as provided by a confidential version of TRACE for the period 2005-2011. Panel B provides summary statistics for these characteristics and for the transactions, such as the holding time, the volume, the profit margins and the seller's centrality measure.

Panel A

	Bonds	Trades			
Number of Bonds and Trades	56,707	52,151,496			
Credit Quality Distribution (%)					
Superior (AA and UP)	9.7%	8.8%			
Other Investment Grade (BBB-A)	74.5%	81.5%			
High-Yield (below BBB)	5.4%	7.3%			
Not Rated	10.4%	2.4%			
Issue Size Distribution (%)					
Small (< \$100 Million)	85.9%	61.4%			
Medium (\$100 - \$500 Million)	3.8%	24.4%			
Large (> \$500 Million)	0.0%	0.14%			
Missing Offering Data	10.3%	14.1%			
Age Distribution (%)					
Under 2 years	51.30%	35.6%			
2-5 years	31.61%	35.3%			
5+ years	17.08%	29.1%			
Maturity Distribution (%)					
Under 2 years	7.0%	0.3%			
2-5 years	20.8%	6.8%			
5-20 years	59.9%	76.4%			
20+ years	12.0%	15.8%			
Missing Maturity Data	0.3%	0.6%			
	Mean	Median	Min	Max	Std Dev
By Bonds					
Rating	BBB+	A-	D	AAA	
Size	\$21.0 M	\$2.5 M	\$400	\$798 M	\$41.2 M
Age	2.9	1.9	0	78.5	3.3
Maturity	9.6	7.5	0.5	100.2	8.6
By Trade					
Rating	BBB	BBB+	D	AAA	
Size	\$93.1 M	\$59.9 M	\$400	\$798 M	\$97.3 M
Age	3.9	3.1	0	82.0	3.5
Maturity	11.8	10	0.5	100.2	8.8

Panel B

	Mean	Median	Min	Max	Std Dev
By Bonds					
Volume of Trade	1,785.5	90	0.2	250,000	7,258.3
Holding Period (days)	59.8	37.2	0	1,454.4	69.8
Average Spread	0.0189	0.0068	-0.7143	99	0.6269
Centrality Measure	44.6	39.4	1	844.9	30.8
Number of Trades	920	109	1	138,271	3,527
Market Concentration	54.3%	54.4%	0%	100%	22.8%
By Trade					
Volume of Trade	401	25	0.24	619,550	1,777
Holding Period (days)	107	16.8	0	3,447	214
Average Profit Margin	0.1056	0.0055	-0.9999	2926.928	0.6
Centrality Measure - Rank	41.7	21	1	1,152	64.4

Table 2
Transition Probabilities

This table shows the transition probabilities to change centrality ranking between two subsequent quarters.

		Rank quarter t+1						Pr(Up)	Pr(Down)
		Top 10	11-20	21-50	51-100	101-200	> 200		
Rank quarter t	Top 10	90.00%	9.31%	0.69%	0.00%	0.00%	0.00%	0%	10%
	11-20	9.31%	75.52%	14.14%	0.34%	0.34%	0.34%	9%	15%
	21-50	0.12%	5.06%	84.12%	9.67%	0.46%	0.58%	5%	11%
	51-100	0.07%	0.00%	6.29%	83.13%	9.68%	0.83%	6%	11%
	101-200	0.00%	0.00%	0.00%	4.82%	81.83%	13.35%	5%	13%
	> 200	0.00%	0.00%	0.00%	0.06%	1.57%	98.37%	2%	0%

Table 3
Spreads: Clients vs Dealers

This table reports the coefficient estimates relating the spreads with the type of counterparty. The sample includes bond transactions for the period 2005-2009 as reported in an enhanced version of TRACE. "Client Counterparty" is a dummy equal to one if the counterparty 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 sold by seller s in the previous quarter. Columns (5) and (6) divide the sample between investment grade and non-investment grade bonds, whereas Columns (7) and (8) differentiate between sellers in the core or in the periphery. Panel B reports the results for different samples based on the size of the transaction. Robust standard errors clustered at the CUSIP level in parenthesis. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>All Bonds</i>				<i>Investment Grade Bonds</i>	<i>Non- Investment Grade Bonds</i>	<i>Core Dealers</i>	<i>Periphery Dealers</i>
Client Counterparty	0.00526*** (0.000296)	0.00587*** (0.000276)	0.00531*** (0.000233)	0.00564*** (0.000212)	0.00550*** (0.000297)	0.00468*** (0.000235)	0.00520*** (0.000300)	0.00514*** (0.000218)
Log(Transaction Volume)		-0.00112*** (4.89e-05)	-0.000761*** (3.26e-05)	-0.000836*** (3.31e-05)	-0.000678*** (3.25e-05)	-0.000971*** (7.48e-05)	-0.000569*** (4.44e-05)	-0.000997*** (3.68e-05)
Rating			0.000101** (5.08e-05)	9.46e-05* (4.87e-05)	2.36e-05 (6.68e-05)	8.29e-05 (7.06e-05)	0.000192*** (6.16e-05)	2.78e-05 (6.67e-05)
Market Share			0.00698*** (0.00248)	0.00705*** (0.00258)	0.00564** (0.00235)	0.0307* (0.0176)	0.00464 (0.00359)	0.00896*** (0.00191)
Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CUSIP Fixed Effects			Yes	Yes	Yes	Yes	Yes	Yes
Seller Fixed Effects				Yes				
Observations	789,985	738,659	738,659	738,659	536,387	202,272	419,044	319,615
R-squared	0.044	0.078	0.157	0.201	0.243	0.078	0.162	0.182

Panel B

	(1)	(2)	(3)	(4)
	<i>Transaction Size Below Median</i>	<i>Transaction Size between 50th and 75th</i>	<i>Transaction Size between 75th and 90th</i>	<i>Transaction Size Above 90th</i>
Client Counterparty	0.00656*** (0.000301)	0.00542*** (0.000262)	0.00185*** (0.000121)	0.000887*** (0.000145)
Log(Transaction Volume)	-0.000493*** (7.72e-05)	-0.000956*** (7.51e-05)	-0.000779*** (9.63e-05)	-0.000151 (0.000183)
Rating	5.99e-05 (6.28e-05)	0.000216*** (7.88e-05)	0.000309*** (7.20e-05)	0.000262*** (5.13e-05)
Market Share	0.00832*** (0.00261)	0.00620* (0.00348)	-0.00336 (0.00527)	0.0111 (0.0161)
Week Fixed Effects	Yes	Yes	Yes	Yes
CUSIP Fixed Effects	Yes	Yes	Yes	Yes
Observations	381,317	185,563	103,149	68,630
R-squared	0.216	0.140	0.071	0.060

Table 4
Spreads and Network Structure

This table reports the coefficient estimates relating the spreads with the type of counterparty. The sample includes bond transactions for the period 2005-2009 as reported in an enhanced version of TRACE. "Core-Periphery" is a dummy equal to one if the seller is a core dealer and the buyer is a peripheral dealer, while "Periphery-Periphery" identifies transactions between dealers in the periphery, and "Periphery-Core" is a dummy equal to one for transactions where the seller is in the periphery and the buyer is in the core. The comparison group are 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. Columns (4) and (5) divide the sample between investment grade and non-investment grade bonds. Robust standard errors clustered at the CUSIP level in parenthesis. Asterisks denote significance levels (**=1%, ***=5%, *=10%).

	(1)	(2)	(3)	(4)	(5)
		<i>All Bonds</i>		<i>Investment Grade Bonds</i>	<i>Non-Investment Grade Bonds</i>
Core-Periphery	0.00253*** (0.000124)	0.00270*** (0.000128)	0.00234*** (0.000118)	0.00201*** (0.000110)	0.00339*** (0.000314)
Periphery-Periphery	0.00191*** (0.000143)	0.00236*** (0.000144)	0.00153*** (0.000129)	0.00116*** (0.000134)	0.00224*** (0.000276)
Periphery-Core	0.000725*** (0.000120)	0.00159*** (0.000154)	0.00106*** (0.000132)	0.00107*** (0.000163)	0.00121*** (0.000232)
Log(Transaction Volume)		-0.000761*** (3.96e-05)	-0.000503*** (3.39e-05)	-0.000438*** (2.89e-05)	-0.000651*** (8.23e-05)
Rating		0.000150*** (1.88e-05)	0.000209*** (5.69e-05)	0.000129*** (5.80e-05)	0.000171** (7.61e-05)
Week Fixed Effects	Yes	Yes	Yes	Yes	Yes
CUSIP Fixed Effects			Yes	Yes	Yes
Observations	456,868	434,390	434,390	303,659	130,731
R-squared	0.015	0.026	0.061	0.076	0.064

Table 5
Spreads and Bilateral Relationships

This table reports the coefficient estimates relating the spreads with the existing of bilateral relationships between seller and buyer and to their network centrality. The sample includes bond transactions for the period 2005-2009 as reported in an enhanced version of TRACE. "Fraction Selling to Counterparty" is the fraction of sales of this seller to this buyer computed in the previous quarter. Similarly for the "Fraction Buying from Counterparty". "Log(Transaction Volume)" is the size of the transaction. "Rating" captures the numerical equivalent of the bond rating, with higher number capturing riskier bonds. The centrality measures are computed using the eigenvector centrality measure in the previous quarter. Robust standard errors clustered at the CUSIP level in parenthesis. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	(1)	(2)	(3)	(4)
Fraction Selling to Counterparty	-0.00672*** (0.000270)	-0.00700*** (0.000240)	-0.00360*** (0.000294)	-0.00426*** (0.000253)
Fraction Buying from Counterparty	-0.00464*** (0.000232)	-0.00447*** (0.000187)	-0.00774*** (0.000270)	-0.00717*** (0.000254)
Log(Transaction Volume)	-0.000797*** (4.26e-05)	-0.000573*** (3.52e-05)	-0.000798*** (4.22e-05)	-0.000577*** (3.58e-05)
Rating	0.000139*** (1.92e-05)	0.000164*** (5.40e-05)	0.000135*** (1.85e-05)	0.000178*** (5.43e-05)
Seller Network Centrality			-0.00256 (0.00159)	0.00267* (0.00146)
Buyer Network Centrality			-0.0261*** (0.00152)	-0.0213*** (0.00130)
Week Fixed Effects	Yes	Yes	Yes	Yes
CUSIP Fixed Effects		Yes		Yes
Observations	423,251	423,251	423,203	423,203
R-squared	0.032	0.069	0.036	0.071

Table 6
Spreads in Turbulent Times

This table reports the coefficient estimates relating the spreads with the existing of bilateral relationships between seller and buyer and to their network centrality. The sample includes bond transactions for the period 2005-2009 as reported in an enhanced version of TRACE. "Fraction Selling to Counterparty" is the fraction of sales of this seller to this buyer computed in the previous quarter. Similarly for the "Fraction Buying from Counterparty". VIX is the volatility index as provided by CBOE. We also control for the bond rating and the transaction size interacted with the VIX. The centrality measures are computed using the eigenvector centrality measure in the previous quarter. In Panel B we restrict attention to two subsamples, the period preceding the acme of the crisis from January 2005 to August 2008, and the period between September 2008 until May 2009, where the VIX was above its long-run average of 30. Robust standard errors clustered at the CUSIP level in parenthesis. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	(1)	(2)	(3)	(4)
Fraction Selling to Counterparty × VIX	-0.00364*** (0.000282)	-0.00358*** (0.000286)	-0.00160*** (0.000310)	-0.00137*** (0.000327)
Fraction Buying from Counterparty × VIX	-0.000509*** (0.000181)	-0.000347** (0.000173)	-0.00214*** (0.000294)	-0.00217*** (0.000291)
Seller Network Centrality × VIX			0.00928*** (0.00167)	0.0110*** (0.00169)
Buyer Network Centrality × VIX			-0.0102*** (0.00179)	-0.0117*** (0.00175)
Fraction Selling to Counterparty	-0.00716*** (0.000286)	-0.00735*** (0.000260)	-0.00401*** (0.000301)	-0.00461*** (0.000262)
Fraction Buying from Counterparty	-0.00456*** (0.000227)	-0.00440*** (0.000181)	-0.00751*** (0.000277)	-0.00690*** (0.000258)
Seller Network Centrality			-0.00344** (0.00158)	0.00190 (0.00146)
Buyer Network Centrality			-0.0254*** (0.00153)	-0.0204*** (0.00129)
Week Fixed Effects	Yes	Yes	Yes	Yes
CUSIP Fixed Effects		Yes		Yes
Observations	423,220	423,220	423,172	423,172
R-squared	0.034	0.071	0.039	0.074

Panel B

	(1)	(2)
	<i>Jan05-Aug08</i>	<i>Sep08-May09</i>
Fraction Selling to Counterparty	-0.00368*** (0.000321)	-0.00939*** (0.00130)
Fraction Buying from Counterparty	-0.00507*** (0.000238)	-0.0116*** (0.000906)
Seller Network Centrality	0.00576*** (0.00177)	0.0316*** (0.00587)
Buyer Network Centrality	-0.0139*** (0.00122)	-0.0439*** (0.00489)
Week Fixed Effects	Yes	Yes
CUSIP Fixed Effects	Yes	Yes
Observations	140,498	57,101
R-squared	0.076	0.160

Table 7
Network Structure and Turbulent Times

This table reports the coefficient estimates relating the spreads with the type of counterparty. The sample includes bond transactions for the period 2005-2009 as reported in an enhanced version of TRACE. "Core-Periphery" is a dummy equal to one if the seller is a core dealer and the buyer is a peripheral dealer, while "Periphery-Periphery" identifies transactions between dealers in the periphery, and "Periphery-Core" is a dummy equal to one for transactions where the seller is in the periphery and the buyer is in the core. The comparison group are interdealer transactions between core dealers. VIX is the volatility index as provided by CBOE. We also control for the transaction size, the bond rating and the market share interacted with the VIX. In Panel B we restrict attention to two subsamples, the period preceding the acme of the crisis from January 2005 to August 2008, and the period between September 2008 until May 2009, where the VIX was above its long-run average of 30. Robust standard errors clustered at the CUSIP level in parenthesis. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	(1)	(2)	(3)
	<i>All Bonds</i>	<i>Investment Grade Bonds</i>	<i>Non-Investment Grade Bonds</i>
Core-Periphery \times VIX	0.000921*** (0.000173)	0.000885*** (0.000174)	0.00169*** (0.000396)
Periphery-Core \times VIX	-0.000171 (0.000170)	-0.000337* (0.000195)	0.000367 (0.000322)
Periphery-Periphery \times VIX	0.000477*** (0.000182)	0.000409** (0.000188)	0.00104*** (0.000396)
Log(Transaction Volume) \times VIX	-0.000153*** (3.49e-05)	-8.63e-05*** (3.05e-05)	-0.000401*** (9.35e-05)
Rating \times VIX	1.26e-05 (1.82e-05)	1.68e-05 (3.06e-05)	0.000161*** (5.07e-05)
Market Share \times VIX	0.0132** (0.00554)	0.0123*** (0.00328)	0.0157 (0.0552)
Core-Periphery	0.00227*** (0.000120)	0.00185*** (0.000102)	0.00383*** (0.000350)
Periphery-Core	0.000980*** (0.000142)	0.001000*** (0.000169)	0.00136*** (0.000260)
Periphery-Periphery	0.00154*** (0.000136)	0.00111*** (0.000131)	0.00258*** (0.000330)
Log(Transaction Volume)	-0.000517*** (3.60e-05)	-0.000436*** (2.96e-05)	-0.000834*** (0.000109)
Rating	0.000195*** (5.66e-05)	0.000124** (5.62e-05)	8.47e-05 (8.07e-05)
Market Share	0.0101*** (0.00319)	0.00601*** (0.00181)	0.0897* (0.0511)
Week Fixed Effects	Yes	Yes	Yes
CUSIP Fixed Effects	Yes	Yes	Yes
Observations	434,358	303,631	130,727
R-squared	0.062	0.078	0.066

Panel B

	(1)	(2)
	<i>Jan05-Aug08</i>	<i>Sep08-May09</i>
Core-Periphery	0.00137*** (0.000131)	0.00332*** (0.000441)
Periphery-Core	3.80e-05 (0.000154)	-0.000556 (0.000564)
Periphery-Periphery	0.000660*** (0.000155)	0.00123** (0.000563)
Log(Transaction Volume)	-0.000780*** (5.26e-05)	-0.000888*** (0.000143)
Rating	0.000113* (6.12e-05)	0.000514* (0.000284)
Market Share	0.0253 (0.0159)	0.0463* (0.0251)
Week Fixed Effects	Yes	Yes
CUSIP Fixed Effects	Yes	Yes
Observations	144,496	58,666
R-squared	0.071	0.144

Table 8
Spreads: Client vs Dealers in Turbulent Times

This table reports the coefficient estimates relating the spread with the type of counterparty. The sample includes bond transactions for the period 2005-2009 as reported in an enhanced version of TRACE. "Client Counterparty" is a dummy equal to one if the counterparty is a client. VIX is the volatility index as provided by CBOE. We also control for the bond rating and the transaction size interacted with the VIX. Columns (5) and (6) divide the sample between investment grade and non-investment grade bonds, whereas Columns (7) and (8) differentiate between sellers in the core or in the periphery. Panel B reports the results for different samples based on the size of the transaction. Robust standard errors clustered at the CUSIP level in parenthesis. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	(2)	(1)	(3)
	All Bonds	Transaction Size Below Median	Transaction Size Above 75th
Client Counterparty × VIX	-0.000159 (0.000117)	-0.000721*** (0.000147)	0.000537*** (0.000133)
Week Fixed Effects	Yes	Yes	Yes
CUSIP Fixed Effects	Yes	Yes	Yes
Observations	738,606	381,283	171,774
R-squared	0.158	0.217	0.056

Table 9
Spreads and Dealer D's Collapse

This table reports the coefficient estimates relating the spreads with the existing of bilateral relationships 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 this seller from Dealer D as computed in the previous quarter. "Post" is a dummy equal to one after the Dealer D' default. "Fraction Selling to Counterparty" is the fraction of sales of this seller to this buyer computed in the previous quarter. Similarly for the "Fraction of Sale Transactions with Dealer D" and for the "Fraction Buying from Counterparty". "Log(Transaction Volume)" is the size of the transaction. "Rating" captures the numerical equivalent of the bond rating, with higher number capturing riskier bonds. Robust standard errors clustered at the CUSIP level in parenthesis. Asterisks denote significance levels (***)=1%, (**)=5%, (*)=10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fraction of Purchase Transactions with Dealer D × Post	-0.0484*** (0.0123)	-0.0567*** (0.0129)	-0.0433*** (0.0109)	-0.0441*** (0.0113)	-0.0655* (0.0389)	-0.0665** (0.0334)	-0.0824** (0.0329)	-0.0765** (0.0327)
Fraction of Purchase Transactions with Dealer D	0.00779 (0.0115)	-0.00688 (0.0120)	3.160*** (0.784)		-0.0421** (0.0205)	-0.0539*** (0.0203)		
Fraction Selling to Counterparty		-0.0212*** (0.00202)	-0.00922*** (0.00234)	0.00251 (0.00376)		-0.0208*** (0.00201)	-0.00916*** (0.00234)	0.00261 (0.00375)
Fraction Buying from Counterparty		-0.00440*** (0.000754)	-0.00554*** (0.000664)	-0.0138*** (0.00301)		-0.00466*** (0.000735)	-0.00552*** (0.000664)	-0.0138*** (0.00301)
Log(Transaction Volume)	-0.00113*** (0.000203)	-0.00129*** (0.000214)	-0.00139*** (0.000214)	-0.00131*** (0.000216)	-0.00123*** (0.000207)	-0.00138*** (0.000218)	-0.00139*** (0.000214)	-0.00131*** (0.000216)
Rating	0.00114** (0.000469)	0.00109** (0.000473)	0.000881** (0.000384)	0.000781** (0.000345)	0.00114** (0.000466)	0.00109** (0.000471)	0.000893** (0.000385)	0.000791** (0.000345)
Fraction of Sale Transactions with Dealer D					0.0673*** (0.0208)	0.0624*** (0.0206)		
Fraction of Sale Transactions with Dealer D × Post					0.0185 (0.0401)	0.0104 (0.0324)	0.0460 (0.0346)	0.0382 (0.0344)
Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CUSIP Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seller Fixed Effect			Yes	Yes			Yes	Yes
Buyer Fixed Effect				Yes				Yes
Observations	29,398	28,855	28,855	28,855	29,398	28,855	28,855	28,855
R-squared	0.148	0.163	0.254	0.299	0.149	0.164	0.254	0.299

Table 10
Trading Chains after Dealer D's Collapse

This table reports the coefficient estimates relating the length of the trading chain with Dealer D's default. The sample period is 2005-2011. "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 sold by seller s in the previous quarter. The centrality measures are computed using the eigenvector centrality measure in the previous quarter. Robust standard errors clustered at the CUSIP level in parenthesis. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	<i>All Bonds</i>	<i>All Bonds</i>	<i>All Bonds</i>	<i>Investment Grade Bonds</i>	<i>Non-Investment Grade Bonds</i>	<i>Seller is in the Core</i>	<i>Seller is in the Periphery</i>
Post	0.285*** (0.00548)	0.189*** (0.00560)	0.189*** (0.00604)	0.194*** (0.00665)	0.187*** (0.0148)	0.205*** (0.00848)	0.165*** (0.00846)
Log(Transaction Volume)			-0.0360*** (0.00179)	-0.0338*** (0.00201)	-0.0430*** (0.00400)	-0.0451*** (0.00246)	-0.00800*** (0.00271)
Rating			-0.00846** (0.00337)	-0.0315*** (0.00645)	0.0111 (0.00686)	-0.00763* (0.00457)	-0.0176*** (0.00507)
Market Share			-0.138 (0.161)	-0.843*** (0.217)	0.665*** (0.246)	-1.420*** (0.266)	0.311 (0.239)
Seller Network Centrality			-3.410*** (0.0646)	-3.559*** (0.0707)	-2.789*** (0.161)	2.035*** (0.220)	-1.445*** (0.157)
CUSIP Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,164	143,164	125,818	108,553	17,265	69,406	56,412
R-squared	0.019	0.176	0.193	0.195	0.176	0.169	0.275

Table 11
Trading Chains after Dealer D's Collapse

This table investigates how the spreads charged over the intermediation chain change 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 2005-2011. "Post" is a dummy equal to one after the Dealer D' default. Transaction controls include the size of the transaction, as well as the numerical equivalent of the bond rating, with higher number capturing riskier bonds. Robust standard errors clustered at the CUSIP level in parenthesis. Asterisks denote significance levels (**=1%, ***=5%, *=10%).

	(1)	(2)	(3)	(4)	(5)
Third Intermediary in the Chain	-0.263*** (0.0123)	-0.255*** (0.0123)	-0.302*** (0.0122)	-0.255*** (0.0126)	-0.145*** (0.0131)
Fourth Intermediary in the Chain	-0.317*** (0.0217)	-0.313*** (0.0217)	-0.297*** (0.0214)	-0.231*** (0.0221)	-0.160*** (0.0216)
Fifth Intermediary in the Chain	-0.368*** (0.0365)	-0.362*** (0.0364)	-0.293*** (0.0359)	-0.215*** (0.0367)	-0.167*** (0.0359)
Transaction Controls				Yes	Yes
CUSIP Fixed Effects	No	No	Yes	Yes	Yes
Seller Fixed Effects	No	No	No	No	Yes
Observations	115,079	115,079	115,079	109,098	109,098
R-squared	0.034	0.037	0.132	0.133	0.195