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Information Asymmetry in Corporate Bond Markets

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Keywords
corporate bonds, market design, information asymmetry, networks, over-the-counter markets, interdealer networks, intermediation chains

Disciplines
Finance and Financial Management

Information Asymmetry in U.S. Corporate Bond Markets

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1 INTRODUCTION

This research project seeks to empirically support of the theories about the efficiency and structure of over-the counter markets. This paper will examine the distribution of information asymmetry along intermediation chains with the goal of comparing these observations with the results predicted by theories of efficient intermediation, contributing to our understanding about the need for greater regulation in over-the-counter markets.

1.1 Research Question

This paper will explore to what extent the structure of intermediation chains in U.S. corporate bond markets post-TRACE support the hypothesis that an over-the-counter market can still be efficient.

1.2 Hypothesis

In historical transaction data, it is expected that there are intermediation chains composed of agents that gradually vary in the amount of information they have. Furthermore, a significant number of chains with multiple dealers are should appear. This hypothesis relies on the theory proposed in Glode and Opp (2016), which is that intermediation chains can actually lead to more efficient marketplace when there are significant information asymmetries between the ultimate sellers and buyers. Even when a bond is best held by another party, it can be difficult and unlikely for that transaction to happen if the size of the information asymmetry impedes trading. Glode and Opp suggest that intermediation chains can be an efficient solution to this problem when the different agents in the chain have heterogeneous information. As a result, the information asymmetry between two adjacent agents in the intermediation chain is small. It is reasonable for differences in private information to be a major obstacle to efficient trade in the U.S. corporate bond secondary market, especially for sparsely traded or distressed debt.

If there are only short intermediation chains with a few central, well-connected intermediaries, or if all intermediaries are very similarly informed, this may suggest that information asymmetries are not the dominant issue – instead, bargaining frictions or other market imperfections may be a larger issue. It is likely that the relative importance of these different factors fluctuates over time, in different market regimes: given literature showing that dealers tend to rely on long-standing relationships when in periods of heightened uncertainty (Di Maggio, Kermani, and Song, 2016), this suggests that bargaining risks and reputation are at the forefront of traders' minds during these times of crisis. As such, it is expected that the previously described behavior in response to information asymmetry is stronger in times of relative economic stability.

2 LITERATURE REVIEW

The field of over-the-counter market structure research largely focuses on a simple question: is centralization or intermediation more efficient for over-the-counter (OTC) markets? Typically, financial products that tend to have less liquidity and more variation are still traded on OTC markets, instead of a centralized exchange, such as corporate bonds or long-dated options. Given the sheer volume of trading activity that flows through OTC markets every day, as well as the increasing interconnectedness of global financial markets, it is essential to understand whether such a market structure leads to inefficient trade or over-concentration of market power (Morris and Shin, 2012). Historically, OTC markets have been opaque and deal-at-your-own-risk (Glode and Opp, 2016), but there has been a recent push from the SEC and other regulators for increased transparency and oversight (Clayton 2018).

2.1 Theoretical Literature

The theoretical literature is fragmented, but is generally becoming less averse to decentralization. Akerloff (1970), Morris and Shin (2012), and Glode and Opp (2017), all describe models of information asymmetry between dealers and customers; in particular, Glode and Opp argue that under a certain distribution of information, intermediation chains can be as efficient as outside intervention. Li (1998) and Viswanathan and Wang (2004) look at inventory risk as an alternate contributor to the formation and apparent stability of long intermediation chains. They propose a model of interdealer trading where dealers are acutely conscious of inventory risk and seek to minimize it, leading to "hot potato" behavior. However, while models of various dealer behaviors have been proposed, under diverse sets of constraints, there has not been a consensus reached on which of these circumstances actually occur more often in practice, and which may dominate the other.

2.2 Empirical Work

The amount and quality of empirical work has depended heavily on the availability and quality of data for a particular market: for corporate bonds, empirical studies have become more granular in describing intermediation chains and transaction costs after the advent of the Trade Reporting and Compliance Engine (TRACE) in 2002. Now, with the comprehensive transaction-level detail given by TRACE, we are beginning to see researchers conduct more granular studies on the structure and functioning of the corporate bond market. Other OTC markets that have been similarly scrutinized include collateralized mortgage obligations (CMOs), municipal bonds, and asset-backed securities (ABS) (Li and Schürhoff, 2014; Hollifield, Neklyudov, and Spatt, 2017). Many of these markets are treated as analogous, and results from one market often hold for other OTC markets experiencing similar levels of information asymmetry or search frictions.

One line of research involves attempting to measure certain characteristics of OTC markets, like information asymmetry, liquidity, and efficiency. The field agrees on certain characteristics that correspond with larger transaction costs, and these have persisted despite increased recent moves toward greater transparency: dealers tend to quote worse prices if you are offering a small trade size, a retail customer, trading an off-the-run bond, or trading a bond with significant credit risk or complexity (Edwards, Harris, and Piwowar, 2007; Schultz 2001; Goldstein and Hotchkiss, 2017; and O'Hara, Wang, and Zhou, 2018). Jiang and Sun (2015) and Goldstein and Hotchkiss (2017) have also taken steps toward showing that dealer behavior suggests there does exist information asymmetries and inventory risk in corporate bond markets, but their metrics are at a broader market-level and do not fully describe the distribution of information asymmetry or risk amongst dealers in an intermediation chain.

In addition, researchers have examined the structure of the market itself. One clear structure of OTC markets has been described in more recent empirical studies: a core-periphery structure, where some highly interconnected dealers sit in the "core", while less well connected agents are in the periphery and primarily trade through the core rather than directly with each other. Originally coined by Li and Schürhoff (2014) when examining municipal bond markets, other researchers have followed suit in demonstrating its existence in securitization markets like ABS, CMO, and collateralized debt obligations (CDOs) (Hollifield, Neklyudov, and Spatt, 2017). Nonetheless, given the diversity of OTC markets, not every market has been shown to demonstrate this structure, and there has not been a comprehensive empirical study on where and when a core-periphery model applies.

In the area of measuring information asymmetries, much of the existing literature revolves around measuring the aggregate "level" of asymmetry in the marketplace over time, instead of its presence and effects on individual intermediation chains or trades. As mentioned above, there are studies explore how the market structure and efficiency changes around periods of heightened asymmetry: Jiang and Sun (2015) examine changes in asymmetry from news releases; Green, Hollifield, and Schürhoff (2007) examine the increase in asymmetry post-issuance for municipal bonds; Di Maggio, Kermani, and Song (2016) look at changes in trading behavior in the 2008 credit crunch; and Edwards, Harris, and Piwowar (2007) study effects from the introduction of TRACE. There is less literature in the field of OTC markets on estimating levels of information for different agents and its impact on how they trade with each other; however, there are interesting accounting papers, especially in the area of debt covenants and issuance, which attempt to deal with this topic. Ball, Bushman, and Vasvari (2008) explore how issuers of syndicated loans trade with the primary buyers; in particular, how the quality of information disclosed by the financial statements of the borrower affects how that loan issue trades. However, this is concerned with the primary market, which is structured differently from the secondary market.

3 DATA

3.1 Description of Data

The primary dataset is the Trade Reporting and Compliance Engine data, collected by the Financial Industry Regulatory Agency (FINRA) on corporate bond trading. In its raw form, this includes every report of a corporate bond trade, with price, volume, time, whether the reporting party is a dealer or a customer, whether the counterparty is a dealer or a customer, which bond was traded, and other details about the coupon remaining on the bond. In particular, the Academic TRACE dataset is used, which includes a masked identifier of FINRA dealer IDs for each transaction. These analyses use data on all corporate bond transactions in 2008. The data cleaning procedure follows the steps outlined in Dick-Nielsen (2009), which removes cancellations, updates trade reports with corrections, and removes duplicates. Beginning with 9,057,733 trade reports, this procedure yielded 7,060,831 cleaned trade reports.

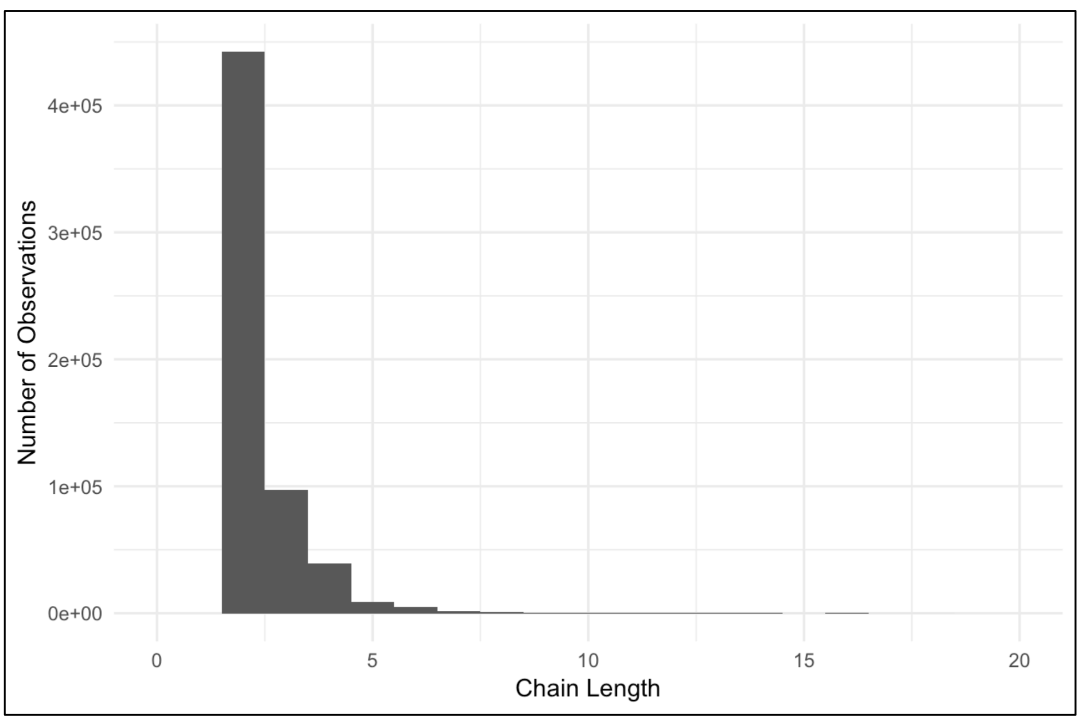
A secondary dataset used is the MERGENT database, which describes each bond issue. Its three broad areas of coverage are information about bond issues (ex. interest rates, convertible terms, unit offerings, covenants), bond issuers (ex. name, SIC code), and bond redemptions (ex. terms of redemption, additional restrictions or options).

3.2 Identification of Intermediation Chains

Intermediation chains were constructed using similar criteria as reported by Li and Schürhoff. The end buyer and seller are customers without FINRA dealer IDs. A chain is initiated when a dealer purchases bonds from a customer, and ends when a dealer sells bonds to a customer. Trades in the chain must have matching CUSIPs and dealer IDs, and two consecutive trades must occur within a time window of 10 days.

Unlike the analyses conducted in Li and Schürhoff (2014) and Goldstein and Hotchkiss, (2017), this algorithm allows for splitting and bundling behavior by the dealers at any step of the intermediation chain, counting these as new chains. For example, if Dealer A buys 500 bonds from a customer, then sells 250 to Dealer B and 250 to Dealer C, who each sell to an end buyer customer, the algorithm identifies both chains (A-B and A-C).

Figure 1. Histogram of Chain Lengths



In total, 586862 such chains were identified in the dataset. They were 2.4 trades long on average, and 26% percent were over 3 trades long. As shown in Figure 1, there is a sharp drop off in the number of chains observed for higher values of chain length, but there is still a substantial number of longer chains. Compared to Li and Schurhoff's observations about the municipal bond market, which had almost no chains longer than 8 dealers long, this suggests that perhaps the U.S. corporate bond market in 2008 had more complexity in intermediation chains. Another possible explanation is that dealers in the middle of long intermediation chains typically bundle and split orders of bonds, so the municipal bond market has similarly long intermediation chains, but they were not identified.

4 INFORMATION PROXY VARIABLES

4.1 Regression

The regression model used was:

$$Degree\ of\ separation = \beta_0 + \beta_1 \cdot (Difference\ in\ Information) + \boldsymbol{\beta_2} \cdot \boldsymbol{X_{chain\ controls}} + \boldsymbol{\beta_3} \cdot \boldsymbol{X_{bond\ controls}} + \boldsymbol{\beta_4} \cdot \boldsymbol{X_{transaction\ controls}} + \varepsilon$$

where β_1 is the coefficient for the difference in information; and β_2, β_3, and β_4 are coefficients for the various controls. The specification of each group of controls is described in section 5.

The response variable *Degree of separation* was selected to describe how far apart two given dealers are on a given intermediation chain. Both absolute and normalized versions of this variable were constructed, with the latter normalized for chain length. The formulas are as follows:

$$Degree\ of\ separation\ (Abs.) = i - j$$

$$Degree\ of\ separation\ (Norm.) = \frac{i - j}{l}$$

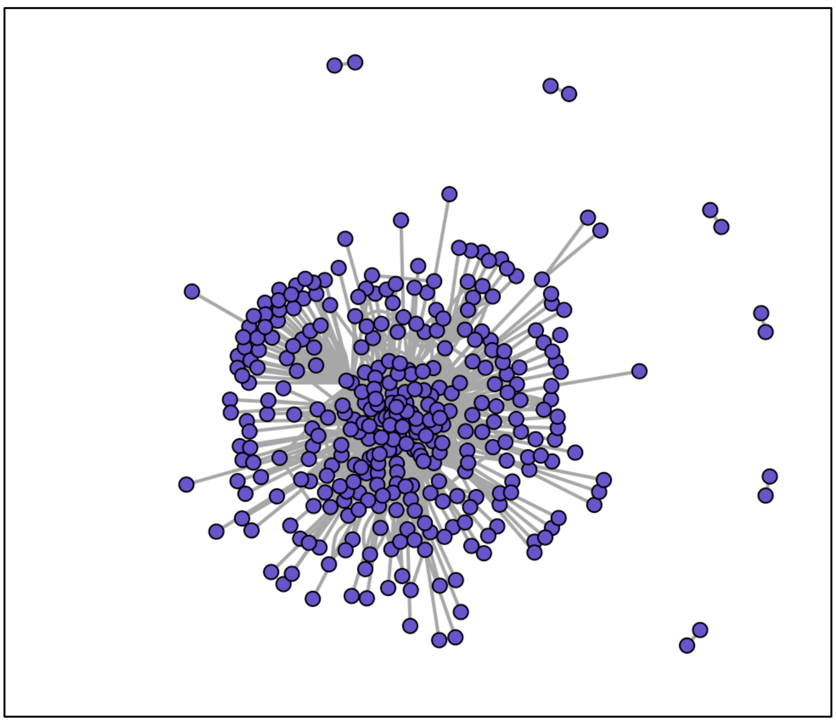
Here, l represents chain length, and i, j are the positions of two dealers, so $i, j < l$, and $i \neq j$.

Thus, this regression imagines that the expected degree of separation of any two dealers on a chain depends on not only on what they are trading, the nature of the overall chain, and characteristics of their respective trades, but also on the magnitude of difference of information that they possess.

4.2 Centrality

A dealer that is well connected within the dealer network would be expected to also be better informed about the private valuations held by its potential counterparties for a given bond. As such, one proxy variable for information held by a dealer is its centrality within the dealer network, as constructed from trades.

Figure 2. Sample of Dealer Network



Taking all the interdealer trades that occurred in 2008, a graph is constructed between the dealers. Figure 2 plots the relationships found in a random sample of the data, and serves as an illustration of the graph structure of this network. The entire interdealer network graph displays characteristics similar to that of the municipal bond interdealer network in Li and Schürhoff (2014). Note that there appears to be a core periphery structure, with a single "core" of exceptionally well connected dealers, and a periphery of less well connected dealers.

Selected measures of centrality from Li and Schurhoff (2014) are used to construct the *Centrality* features: degree, coreness, eigenvector centrality, betweenness, and transitivity. Measures that are not highly dependent on proximity to neighbors are preferred; measures like closeness are not used, as they are too reliant on the "distance" between a dealer and its neighbors by definition and thus may trivially produce a positive correlation when used as an explanatory variable for *Degree of separation*.

For all measures, if both dealers are assigned a high value in that measure of centrality and thus a low difference in centrality, then by construction this does correlate with being closer in given chain. However, this is somewhat mitigated by the fact that these measures of centrality are calculated using all trades, while a given chain can only have trades of one bond issue. Furthermore, if one dealer is assigned a high value and one a low value, or if both are assigned a low value, this does not necessarily force any particular relationship with *Degrees of separation* by construction.

To reduce issues of collinearity, these measures are transformed using principal component analysis (PCA), and the first and second components are used to construct the features used in the regression. The first two components are sufficient to capture 83.9% of the variance in the original set of input variables, which is a reasonable amount of information retained.

Table 1. Principal Component Analysis Rotation

	PCA1	PCA2
Degree (out)	-0.431	-0.010
Degree (in)	-0.434	-0.024
Coreness (out)	-0.413	0.020
Coreness (in)	-0.422	0.010
Eigenvector Centrality	-0.427	-0.021
Betweenness	-0.309	-0.035
Cliquishness	0.033	-0.999

The rotation of a given component in a PCA describes how much each input variable variable is weighted in this component. As such, Table 1 shows that the first component is primarily based on the degree and coreness of a dealer. The degree is a simple measure of the number of dealers a firm is connected to, while the coreness is a measure of the number of subnetworks a given dealer is in. The second component is largely composed of cliquishness, which measures how tightly connected a dealer is to its closest trading partners.

The features Δ *Centrality (PCA1)* and Δ *Centrality (PCA2)* are then defined as:

$$\Delta\, Centrality\ (PCA1) = \left|a_j - a_k\right|$$

$$\Delta\, Centrality\ (PCA2) = \left|b_j - b_k\right|$$

where a_j, a_k are the values of PCA1 for the dealers j and k on some intermediation chain; and similarly for b_j, b_k.

4.3 Rating Class Expertise

Another proxy for information could be the dealer's familiarity with bonds with a similar rating. For example, a dealer may have particularly good experience and thus information about trading junk bonds. This is approximated using the market share of a given dealer measured by percent of trades it is in involved in, out of all trades that occurred in that credit rating. Credit rating is coded as three classes: tier 1 (Aaa – Baa3), tier 2 (Ba1 – B), and tier 3 (Caa1 - C). This feature is called rating class expertise and is defined as:

$$c_{j,r} = \frac{t_{j,r}}{\sum_i t_{i,r}}$$

where $c_{j,r}$ is the level of rating class expertise held by a dealer j in rating class r. The difference in information is defined similarly to the centrality measure, and the formula is as follows.

$$\Delta\, Rating\ Class\ Expertise = \left|c_{j,r} - c_{k,r}\right|$$

5 CONTROLS

5.1 Bond Controls

Characteristics specific to the bond issue and the bond issuer were controlled: the credit rating of the issuer and the industry of the issuer. For a given pair of trades on a chain, these characteristics correspond to the time that the first trade occurs. The credit rating is coded using a 10 tier system that standardizes the rating across rating agencies, and the industry of the issuer is coded using its MERGENT industry code (Appendix A).

5.2 Trade Controls

As the *Degree of separation* measure is defined as the distance between the trade where the first dealer acts as a buyer and the trade where the second dealer acts as a buyer, characteristics pertaining to the pair of trades in question are also controlled. The difference in time, volume, and price between the two trades are control variables.

5.3 Chain Controls

Lastly, the chain that the pair of firms is taken from has characteristics that may influence how far apart they are. We construct features to control for length of chain, total time elapsed from start to finish of chain, time to maturity for the bond issue, and whether the last trade of the chain occurred before the Lehman Brothers bankruptcy.

The feature for time to maturity for the bond issue is defined as an indicator variable that equals 1 if the first trade of the intermediation chain occurred within two months of the bond's maturity date, and 0 otherwise. Trading volumes seem to be elevated during that period of time, as bondholders react to changes in value since they purchased the bond, and consider how they would like to exit. Similarly, the feature related to the Lehman bankruptcy is an indicator variable that equals 1 if the last trade of the intermediation chain occurred after Lehman filed for bankruptcy on September 15, 2008, an event typically considered the beginning of the credit crisis. The onset of the financial crisis would be expected to have a significant impact on bond trades.

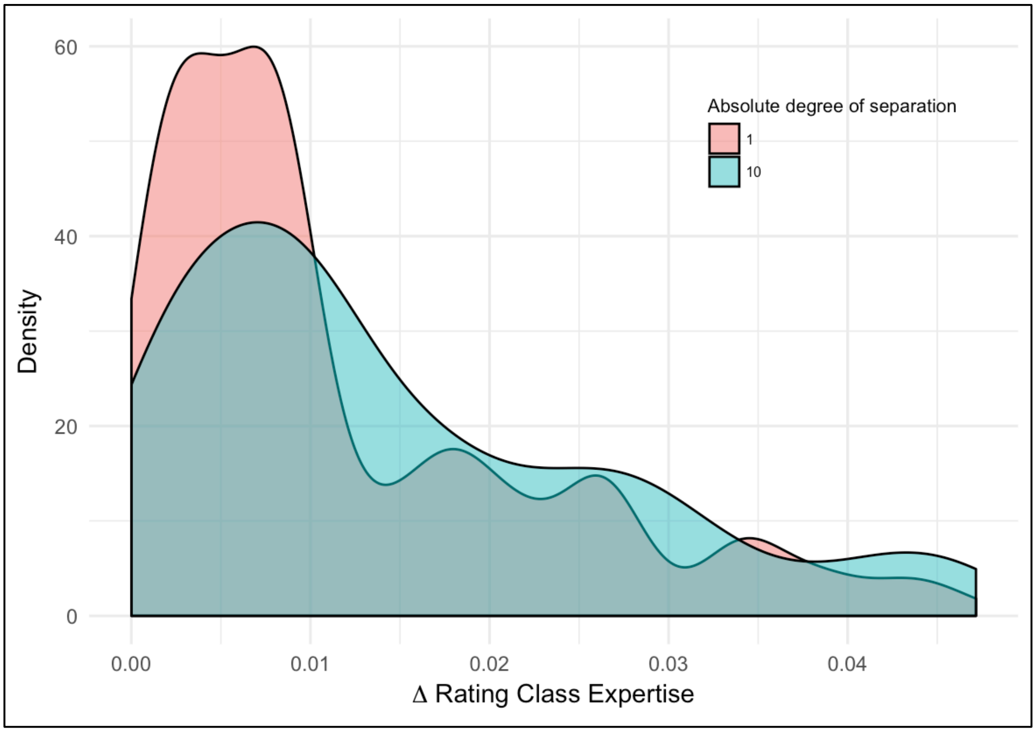
6 RESULTS AND DISCUSSION

6.1 All 2008 U.S. Corporate Bond Data

Using the features and regression described above, the analysis is conducted on all chains that have an identifiable beginning and end customer.

First, the relationship between the information proxy variables and the distance between dealers on a given chain is examined, independent of any controls.

Figure 3. Distribution of Δ *Rating Class Expertise,* Chains of Length 10



As an illustration, Figure 3 is a density plot using data from intermediation chains of length 10. The two overlaid curves compare the shape of the distribution of difference in information for two dealers that are one degree of separation apart, versus the distribution for dealers that are at extreme ends of the chain. The pattern exhibited in Figure 3 holds when looking at any given length of intermediation chain, and for all three information proxy variables: the distribution for difference in information between two dealers that are farther apart on a chain is more right skewed than the corresponding distribution for dealer that are close together on a chain. This corresponds with the expectation that long intermediation chains can reduce issues of information asymmetry by allowing dealers to trade with counterparties that have similar levels of information.

Table 2. Difference in Information and Degree of Separation

	(1) Normalized Degree of Separation	(2)	(3) Absolute Degree of Separation, Baseline
	Baseline w/o Controls	Baseline w/ Controls	
Δ Centrality (PCA1)	9.08×10^{-4} [5.4×10^{-5}]***	1.25×10^{-3} [5.0×10^{-5}]***	6.29×10^{-3} [5.3×10^{-4}]***
Δ Centrality (PCA2)	-6.25×10^{-2} [8.6×10^{-4}]***	-6.67×10^{-2} [7.9×10^{-4}]***	−0.305 [8.4×10^{-3}]***
Δ Rating Expertise	0.785 [0.030]***	0.158 [0.028]***	1.05 [0.30]***
R^2 (Adjusted)	0.00183	0.158	0.556
N (observations)	702584	702584	702584

Significance levels are indicated by *(0.05), **(0.01), and ***(0.001). Standard errors are shown in square brackets. For a full table of coefficients for column (2), see Appendix B.

The coefficient estimates for Δ *Centrality (PCA1)* and Δ *Rating Class Expertise* are positive and significant. This suggests that the correlation is in the direction predicted by Glode and Opp; that is, firms with similar levels of information will also tend to be closer together on a given intermediation chain. The magnitude of the effect of the difference is not straightforwardly interpretable, however, given the varying units of the graph centrality measures from which the PCA component was derived.

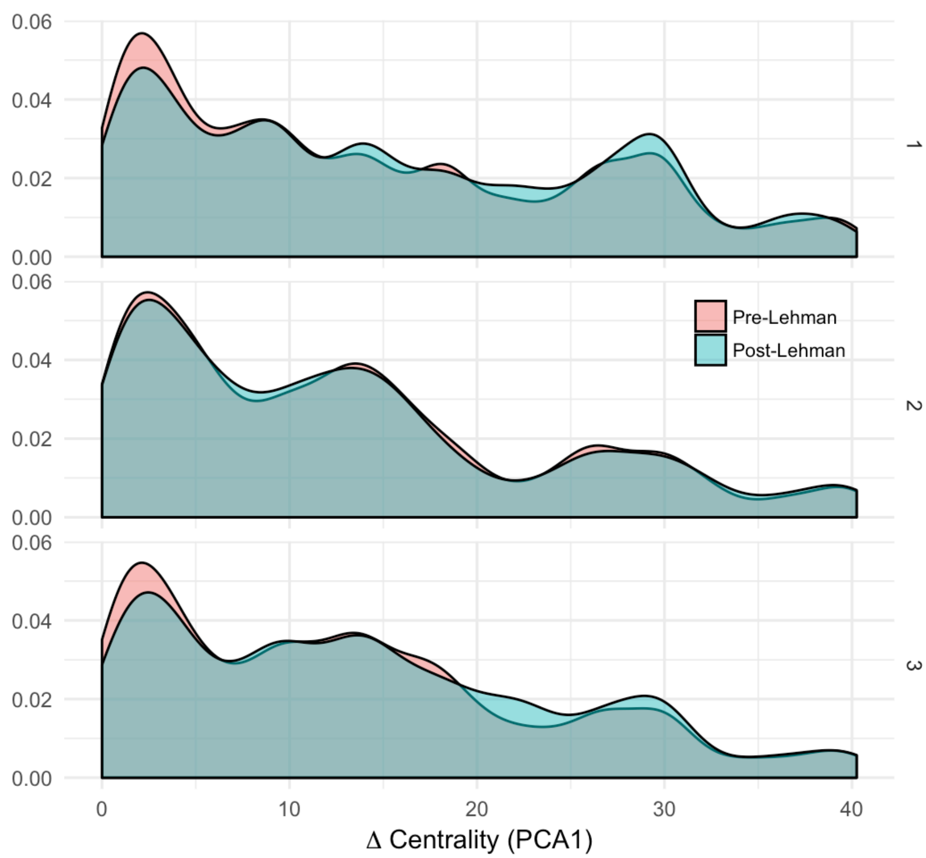
On the other hand, the coefficient estimate for Δ *Centrality (PCA2)* was negative and significant. This is different from what the theory predicts, and one possible explanation is that this is simply not a good measure of information. Δ *Centrality (PCA2)* is almost entirely composed of the cliquishness measure, and this may not be a good proxy for how well informed a dealer is, since it is such a locally constructed metric that depends on how many trades a dealer conducts with the firms closest to it in the network. If two dealers both have low levels of cliquishness, then by definition they are less likely to be close to each other on an intermediation chain. This can be overcome if there is an information effect as posited by Glode and Opp, but perhaps in this particular market, cliquishness does not correspond with being better informed about the private valuations of other people in the market.

6.2 Subset Analyses

Two methods of subsetting are selected for further investigation. The investment grade bond market is compared to the junk bond market, and the pre-Lehman bankruptcy bond market is compared to the post-Lehman bankruptcy bond market.

First, an interesting result about the distribution of the Δ *Centrality (PCA1)* variable across the pre- and post-Lehman bankruptcy subsets is discussed.

Figure 3. Distribution of Δ *Centrality (PCA1)*, Chains of Length 3



Using data from chains of length 3, pane 1 of Figure 3 compares the distribution of Δ *Centrality (PCA1)* for pairs of dealers that are one degree of separation apart on chains that occurred before Lehman, versus pairs of dealers one degree apart on chains that occurred after Lehman. Similarly, pane 2 and 3 compare the distributions for pairs of dealers that are two and three degrees of separation apart, respectively.

It is interesting to note that despite the massive upheaval in global financial markets during the last few months of 2008, these shapes remain remarkably constant, with only slight changes in shape. It seems that the structure of the interdealer market and the relationships between dealers were largely resilient and persistent through this initial phase of the credit crisis.

Now using the same model described in section 4.1 “Regression”, data from each subset is used to obtain estimates of coefficients for each information proxy variable.

Table 3. Difference in Information and Degree of Separation, IG vs. Junk and Before vs. After Lehman

	Normalized Degree of Separation			
	(1) IG	(2) Junk	(3) Before Lehman	(4) After Lehman
Δ Centrality (PCA1)	8.52×10^{-4} $[5.8\times10^{-5}]$***	1.97×10^{-3} $[9.9\times10^{-5}]$***	1.89×10^{-3} $[6.2\times10^{-5}]$***	4.84×10^{-4} $[8.3\times10^{-5}]$***
Δ Centrality (PCA2)	-6.22×10^{-2} $[9.2\times10^{-4}]$***	-7.71×10^{-2} $[1.5\times10^{-3}]$***	-7.34×10^{-2} $[9.9\times10^{-4}]$***	-5.82×10^{-2} $[1.3\times10^{-3}]$***
Δ Rating Expertise	0.210 [0.031]***	0.155 [0.065]*	−0.304 [0.035]***	0.529 [0.046]***
R^2 (Adjusted)	0.147	0.187	0.186	0.154
N (observations)	496725	205859	415708	286876

For a full table that includes coefficient estimates and significance levels of control variables, see Appendix C.

Considering the differences between investment grade bonds versus junk bonds, it is expected that the role played by various types of information would also differ in their corresponding secondary markets. When trading junk bonds, there is more complexity in determining the fundamental value of the company, which is less related to centrality; on the other hand, it can also be more difficult to identify end customers for junk bonds, which would be related to centrality. Since the coefficient estimates for Δ *Centrality (PCA1)* and Δ *Centrality (PCA2)* are similar for both investment grade bonds and junk bonds, this suggests that neither factor overwhelmingly dominates the other in the junk bond market. Furthermore, the coefficient estimate for Δ *Rating Class Expertise* is similar for both investment grade bonds and junk bonds. More specialized investors and intermediaries trade junk bonds, as they are riskier, less conventional holdings, so it is surprising that the importance of expertise is not markedly higher for junk bonds.

Comparing the coefficient estimates for chains that ended before the Lehman bankruptcy versus chains that ended after the Lehman bankruptcy, the results are reasonably for Δ *Centrality (PCA1)* and Δ *Rating Class Expertise*; the signs and significance levels of the coefficient estimates remained the same. However, the coefficient estimate for Δ *Centrality (PCA2)* is positive and significant only after the Lehman bankruptcy. This could be interpreted to mean that during times of higher information asymmetry or panic, the strength of a dealer's connections with those that it is closest to becomes a more important determinant of how much a dealer knows about the market participants' private valuations, which seems like a reasonable possibility.

7 CONCLUSION

We examine the U.S. corporate bond market in 2008 as a representative of an over-the-counter market with significant levels of information asymmetry. Using centrality and expertise in the relevant ratings class as proxies for the amount of information that a dealer has about a bond, we find that dealers that are closer together on a given intermediation chain will also have closer levels of information. These findings support the idea that dealers tend to trade with counterparties that have a similar level of information, so that the disparity between any two dealers on a given chain is less than the overall difference in information across the whole chain. It was found that the relationship between information and dealer location on an intermediation chain is similar across bond ratings, and even remains robust through the Lehman bankruptcy and subsequent crisis. Thus, extending this result by applying Glode and Opp's theory of intermediation chains with a view towards their role in markets with information asymmetries, long intermediation chains can in fact be an efficient way of organizing such markets.

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9 Appendix A: Control Variables for Bond Characteristics

Table A1. Credit Rating Group Codes

Rating Group	Moody's	S&P
1	Aaa	AAA
2	Aa1, Aa2, Aa3	AA, AA-, AA+
3	A1, A2, A3	A+, A, A-
4	Baa1, Baa2, Baa3	BBB+, BBB, BBB-
5	Ba1, Ba2, Ba3	BB+, BB-, BB
6	B1, B2, B3	B+, B-, B
7	Caa1, Caa2, Caa3	CCC+, CCC-, CCC
8	Ca	CC
9	C	D

Note: bonds that were not rated were assigned to Rating Group 10.

Table A2. MERGENT Industry Codes

Industry	
10	Manufacturing
11	Media/Communications
12	Oil & Gas
13	Railroad
14	Retail
15	Service/Leisure
16	Transportation
20	Banking
21	Credit/Financing
22	Financial Services
23	Insurance
24	Real Estate
25	Savings & Loan

Industry	
26	Leasing Utility
30	Electric
31	Gas
32	Telephone
33	Water
40	Foreign Agencies
99	Unassigned

10 Appendix B: Table 2, Column (2) Extended

	Normalized Degree of Separation, Baseline w/ Controls	
Time elapsed between trades	1.93E-07	***
Difference in volume between trades	-5.37E-10	***
Difference in price between trades	4.30E-04	***
Close to maturity	8.62E-03	***
Close to offering	-9.58E-03	***
Industry Code 11	3.26E-03	***
Industry Code 12	1.78E-03	
Industry Code 13	2.11E-02	*
Industry Code 14	-1.50E-04	
Industry Code 15	-5.50E-03	***
Industry Code 16	-7.85E-03	***
Industry Code 20	1.66E-02	***
Industry Code 21	5.99E-03	***
Industry Code 22	2.28E-03	***
Industry Code 23	6.21E-03	***
Industry Code 24	-2.75E-03	
Industry Code 25	-4.39E-03	
Industry Code 26	1.18E-02	
Industry Code 30	1.25E-02	***
Industry Code 31	1.40E-02	***
Industry Code 32	3.30E-03	
Industry Code 33	-1.02E-02	
Industry Code 40	1.91E-02	**
Industry Code 99	1.10E-02	*
Rating Group 2	7.96E-03	***
Rating Group 3	-2.98E-03	***
Rating Group 4	-8.53E-04	***
Rating Group 5	-1.34E-02	
Rating Group 6	-1.28E-02	***
Rating Group 7	-1.11E-02	***
Rating Group 8	-1.03E-02	***
Rating Group 9	-1.45E-02	***
Rating Group 10	-1.96E-03	
Lehman bankruptcy flag	5.70E-03	***

Significance levels are indicated by *(0.05), **(0.01), and ***(0.001).

11 Appendix C: Table 3, Extended

	Normalized Degree of Separation							
	(1) Separation, IG		(2) Junk		(3) Before Lehman		(4) After Lehman	
Time elapsed between trades	1.86E-07	***	2.12E-07	***	1.99E-07	***	1.99E-07	***
Difference in volume between trades	-9.32E-10	***	-1.80E-10	***	-2.19E-10	***	-9.63E-10	***
Difference in price between trades	4.46E-04	***	7.52E-04	***	1.83E-04	*	3.90E-04	***
Close to maturity	2.00E-02	***	5.36E-03	***	1.58E-02	***	6.52E-04	
Close to offering	-1.40E-02	***	1.21E-02	***	1.55E-03		-1.88E-02	***
Industry Code 11	5.16E-03	***	-1.25E-03		2.98E-03	***	6.18E-04	
Industry Code 12	1.40E-03		-2.33E-04		-1.87E-03		4.12E-04	
Industry Code 13	1.24E-02		2.51E-02		1.33E-02		3.90E-02	***
Industry Code 14	-6.72E-04		-1.23E-05		-2.72E-03	*	-7.22E-06	
Industry Code 15	2.90E-03	*	-8.03E-03	***	-1.27E-04		-4.53E-03	**
Industry Code 16	-1.23E-02	***	-4.30E-03		-1.31E-02	***	5.53E-04	
Industry Code 20	1.34E-02	***	2.45E-02	***	6.70E-03	***	1.47E-02	***
Industry Code 21	2.09E-03	*	6.93E-03	***	3.08E-03	***	8.50E-03	***
Industry Code 22	-5.56E-04		1.34E-02	***	1.78E-03	*	3.43E-04	
Industry Code 23	4.32E-03	***	1.15E-02	***	6.04E-03	***	4.12E-03	*
Industry Code 24	-6.78E-03	*	2.68E-03		-6.71E-04		-8.05E-03	*
Industry Code 25	-1.49E-03		-5.12E-03		-8.32E-03		8.70E-03	
Industry Code 26	6.93E-03		7.35E-02		-1.83E-03		5.58E-02	
Industry Code 30	1.37E-02	***	4.69E-03		9.16E-03	***	1.16E-02	***
Industry Code 31	1.91E-02	***	6.39E-03		3.17E-03		1.83E-02	***
Industry Code 32	2.20E-03		6.45E-03		-6.47E-04		3.39E-03	
Industry Code 33	2.19E-02		-2.21E-02		-2.72E-02		5.78E-03	
Industry Code 40	1.51E-02	*	4.85E-02		1.25E-02		1.94E-02	
Industry Code 99			8.44E-03		8.51E-03		5.01E-03	
Rating Group 2	4.59E-03	***			-7.10E-04		1.34E-02	***
Rating Group 3	-4.62E-03	***			-3.36E-03	**	-5.82E-04	
Rating Group 4	-4.07E-03	***			-1.77E-03		-1.14E-03	
Rating Group 5					-4.10E-03	**	-1.35E-02	***
Rating Group 6			1.91E-03		-1.70E-03		-1.65E-02	***
Rating Group 7			5.57E-03	***	4.53E-03	**	-9.68E-03	***
Rating Group 8			1.11E-02	***	-5.03E-03	*	-9.02E-03	***
Rating Group 9			-3.18E-03		-7.25E-03	***	-1.76E-02	***
Rating Group 10			7.14E-03	***	-1.99E-03		-2.95E-03	

Significance levels are indicated by *(0.05), **(0.01), and ***(0.001).