Relationship Trading in OTC Markets*

Terrence Hendershott†
Haas School of Business
University of California, Berkeley
Berkeley, CA 94720

Dan Li‡
Board of Governors of the Federal Reserve System
Washington, DC 20551

Dmitry Livdan§
Haas School of Business
University of California, Berkeley
Berkeley, CA 94720

Norman Schürhoff¶
Faculty of Business and Economics and Swiss Finance Institute
Université de Lausanne
CH-1015 Lausanne, Switzerland

December 20, 2015

*We thank seminar audiences at Carnegie Mellon University, University of Oklahoma, University of Houston, and the 2015 Toulouse Trading and post-trading conference for valuable comments and feedback.

†Tel.: (510) 643-0619; fax: (510) 643-1412.
E-mail addresses: `hender@haas.berkeley.edu` (T. Hendershott), `dan.li@frb.gov` (D. Li), `livdan@haas.berkeley.edu` (D. Livdan), `norman.schuerhoff@unil.ch` (N. Schürhoff).

‡Tel.: (202) 452-2626.

§Tel.: (510) 642-4733; fax: (510) 643-1412.

¶Corresponding author. Tel.: +41 (21) 692-3447; fax: +41 (21) 692-3435. Schürhoff is also a Research Affiliate of the CEPR.

He gratefully acknowledges research support from the Swiss Finance Institute and the Swiss National Science Foundation.

Abstract

Trading in OTC markets is bilateral between dealer and client. Using trade-by-trade data on insurer transactions with corporate bond dealers, we document a tradeoff between order flow concentration and dealer competition for best execution. Consistent with assortative matching, both large and small insurers trade with large dealers offering good execution. Large insurers form more relations than small, leading to better execution by fostering price competition among dealers. Low-quality insurers not establishing trading relations with large dealers receive poor execution from small regional dealers. These findings have implications for the impact of regulation and technological advances on price formation and trading outcomes in bond markets.

JEL Classification: G12, G14, G24

Key words: Corporate bonds, over-the-counter financial market, trading cost, liquidity, decentralization, market quality

There is heightened interest by the regulatory community in the impact of trading frictions on execution costs and liquidity in over-the-counter (OTC) corporate bond markets. The recent financial crisis has led to a prolonged liquidity crisis in corporate bonds that highlighted the old-fashioned nature of bond trading and the crucial role of bond dealers in this process. An influx of market entrants has been attempting to shift trading from the traditional bilateral phone transactions to modern electronic platforms. An important question in the policy and market-design debate is which frictions matter the most for execution costs and liquidity in corporate bonds markets: the (marginal) costs of calling around for best execution or the (fixed) costs of establishing and maintaining long-lasting trading relationships?

In this paper, we provide empirical support for hysteresis in dealer-client relations by showing that trading relations are the most important determinant of good execution terms in OTC markets. Our data comes from the National Association of Insurance Commissioners (NAIC) and the Financial Industry Regulatory Authority (FINRA) that collect audit trail data since the early 2000s. The NAIC data reveal the identities of the traders on both sides, insurers and dealers, for more than 4,300 insurers, including all health, life, and property and casualty insurers between 2001 and 2014.

We use corporate bonds in our study since they trade in a classic OTC market. They are the most important source of public financing for corporations, with a $7.8 trillion market capitalization and more than 20 thousand CUSIPs traded by insurers. There is a large and active OTC secondary market, with more than 400 active broker-dealers. At the same time, the market is illiquid, fragmented, and opaque. No audit trail existed until the early 2000s. Focusing on trading in corporate bonds by insurance companies is interesting for several reasons. Corporate bonds are an important investment vehicle for insurers. They own about 30% of all corporate bonds outstanding and, therefore, they are the major clientele for corporate issuers. At the same time, insurers are long-term buy and hold investors. Their trading is motivated largely by liquidity shocks and, therefore, insurers contribute little to the adverse selection risk associated with informed investors. Finally, insurers exhibit quite different trading needs based on their balance sheet size and type of business, which allows us to study the impact of investor heterogeneity on market outcomes.

We establish several key stylized facts about bilateral trading and price formation in

OTC markets. Consistent with search-based models of OTC trading, insurers' execution costs are dependent on the insurer type, the dealer they trade with, and their relationship networks. Execution costs are higher for smaller insurers, smaller dealers, and smaller networks. These patterns hold on average, but not universally. Insurer, dealer, bond, and time fixed effects explain only about 20-30% of the variation in relative trading costs. Execution costs are mostly relationship specific. Which connections an insurer has and how strong these relations are matter more than the identities of the counterparties. Large insurers receive best execution from any dealer. Large dealers provide modest execution costs to all insurers. Execution costs are highest for small-with-small trades. Low-quality insurers are most likely to enter these suboptimal trading relations. These findings are consistent with both Rolodex-type and random search models of OTC markets.

To disentangle between alternative models of OTC market, we inspect matching patterns between insurers and dealers. Insurers form a few but long-lasting dealer relationships thus pointing towards the presence of frictions in establishing and maintaining these trading relations. About 50% of insurers who trade do it with a single dealer all the time. All insurers buy bonds repeatedly from the same set of dealers to which they sell bonds. Figure 1 gives two examples of dealer-client trading relations over time. Panel A plots buys and sells for an insurer with a single dealer relation and Panel B for an insurer with multiple dealer relations. Such trading behavior is unlikely under the random undirected search for best execution, as several OTC market models posit. Network size reflects a tradeoff between relationship scope and competition. Larger, higher quality, more active insurers possess a larger dealer network while smaller insurers concentrate their trading. There exists an endogenous sorting between insurers and dealers. Large insurers trade with both large and small dealers. By contrast, small insurers trade mostly with large dealers. We see small-to-small matches only for low quality insurers. This evidence is consistent with a Rolodex-type model but not with the off-the-shelf random search model.

[Figure 1 about here]

We contrast our findings against two different models for OTC markets. Both have distinct comparative statics predictions about the dealer-client relationship. We use size of both dealer and client as the dimension along which comparative statics exercise is performed. Our choice is motivated by the high degree of heterogeneity along the size dimension for both dealers and insurers that exist in the data as well as readily available theory predictions. The first model is the competitive random search model where clients repeatedly search among other clients and dealers for best execution but do not enter into long-term relationship with dealers. There exists a large literature utilizing search frictions in OTC markets (Duffie, Garleanu, and Pedersen, 2005, 2007; Weill, 2007; Lagos and Rocheteau, 2007, 2009; Feldhütter, 2011; Neklyudov, 2014) as well as in labor economics and economics of marriages (Acemoglu and Shimer, 1999; Shimer and Smith, 2000; Shi, 2002). The alternative approach is strategic network formation with repeated inner-network interactions, or Rolodex model. In this approach clients strategically build a fixed-size "Rolodex" of dealers and search over it each time a trading need arises. In this model clients trade-off lower search costs, exclusivity, and loyalty[1] and high costs of adding another permanent link to the network, i.e., another phone number in the Rolodex, as well as maintaining this long-term relationship, i.e., re-routing better deals over time, taking either party to dinner or ball game when in town etc.

We use Duffie, Garleanu, and Pedersen (2005) to illustrate the comparative statics implications of the size of both dealer and investor/client on the probability of trade between them and price. In Duffie et al. (2005) a continuum of investors randomly and independently contact each other at some mean rate λ, a parameter that reflects search ability or sophistication. Similarly, dealers contact investors and other dealers at some intensity ρ that reflects dealer availability, i.e. higher ρ means a dealer is more efficient at finding a counterparty. There exists a single asset and both dealers and investors have endogenously determined reservation values for the asset denoted by RV_D and RV_I, respectively. While both inter-dealer and dealer-client markets are competitive, when agents meet they act strategically by bargaining over the terms of trade. In the simplest case of Nash bargaining it yields a price which is an bargaining-power-weighted average of the individual reservation values. The probability of a dealer actually *buying* from a client increases with the trade surplus,

[1] For models of OTC network formation and contracting with externalities see Leitner (2005), Gale and Kariv (2007), Afonso et al. (2011), Condorelli (2011), Babus (2012, Neklyudov and Sambalaibat (2015) and for models of repeat relations, relational contracts, and loyalty please see Levin (2002), Bernhardt et al. (2004), Board (2011), DiMaggio et al. (2015).

$S \equiv RV_D - RV_I$. More sophisticated investors have better access to other investors or to dealers, i.e., higher outside options, and, therefore, their reservation value, RV_I, increases with λ. Likewise, more efficient dealers have higher outside options and, therefore, their reservation value, RV_D, increases with ρ. As a result, the price offered by the dealer increases with both dealer efficiency and investor sophistication, or in other words investor execution costs decline with her sophistication while the probability of a trade increases with dealer efficiency when holding λ fixed and decreases with investor sophistication when holding ρ fixed. We associate investor size and other key characteristics in the data with the degree of its sophistication in the model, i.e., large investors in the data have large λ in the model. Likewise, dealer efficiency in the model is the proxy for their size in the data, i.e., large dealers are more efficient than small ones. Therefore, the probability of trade is relatively high for the following dealer-investor pairwise matching: large-large, large-small, and small-small, with large-small match having the highest probability of trade. The probability of trade is low when small dealer meets large investor. It implies that in the data we should have *positive* assortative size matching where small investors trade with both small and large dealers while large investors trade only with large dealers. Large dealers offer better execution than small dealers with large investors getting the best execution. The worst execution is provided by small dealers to small investors.

While it inherits several features of the Duffie et al. (2005) type models such as more efficient dealers provide better execution, the "Rolodex" type model of the OTC market has different predictions regarding assortative size matching between dealers and investors. In this model investors trade off large fixed costs of adding extra permanent connection with the benefit from the ability to search over the larger pool of permanent connections for better execution. More sophisticated (larger) investors benefit more from larger number of connections then less sophisticated (smaller) investors and as a result build larger Rolodex. Given a choice between more or less efficient dealers the less sophisticated investors pick more efficient dealers on average since they have smaller Rolodex, while more sophisticated investors trade with everyone. As the result, Rolodex model predicts the following dealer-investor pairwise matching: large-large, large-small, and small-large, but not small-small. It implies that in the data we should have *negative* assortative size matching where small investors trade mostly with large dealers while large investors trade with both small and large dealers. Since this model inherits the dealer properties of the random search model, it shares predictions regarding the executions costs with it.

We use empirically observed investor-dealer relationships to learn about the value of trading for both dealers, RV_D, and insurers, RV_I, jointly with the insurer's bargaining power w. We focus on the stationary distribution of relationships and execution costs. This allows us to infer from bilateral average execution costs the sharing rule for how dealers and insurers split the surplus from trading. We use a simple variant of Duffie et al. (2005) to perform this estimation. The key assumption is that each trade is exogenous and motivated exclusively by the insurer's liquidity needs, i.e., the insurer may receive a "positive" or "negative" liquidity shock and then she buys or sells while when the side of the trade is endogenous the insurer compares her private valuation to the offered price. We find that large-large trades result in the highest expected surplus while small-small trades yield the smallest expected surplus. Large insurers have large bargaining power across all dealers, while small dealers have higher bargaining power over small insurers. Surprisingly, larger dealers tend to have low bargaining power when trading with small insurers.

The paper is related to the literature on OTC markets, on search and matching, and on networks in economics and finance. There exists a growing set of papers documenting the microstructure of OTC Markets and its implications for trading, price formation, and liquidity. Edwards, et al. (2005), Bessembinder et al. (2006), Harris and Piwowar (2007), Green, et al. (2007) document the magnitude and determinants of transaction costs and how the introduction of ex-post transparency impacted trading costs for investors in OTC markets. The tradeoffs between phone-based and electronic trading are explored theoretically by Biais (1993) and Yin (2005) and empirically by Hendershott and Madhavan (2015). The role of the interdealer market in price formation and liquidity provision are the focus in Hollifield et al. (2015) and Li and Schürhoff (2015). Recent papers by O'Hara et al. (2015) and Harris (2015) explore what best execution means in OTC markets. The search-and-match literature is vast. Duffie et al. (2005, 2007) provide the seminal treatment of search frictions in OTC financial markets, while Weill (2007), Lagos and Rocheteau (2007, 2009), Feldhütter (2011), Zhu (2012), Babus and Kondor (2013), Neklyudov (2014), Hugonnier et al. (2015), Üslü (2015) explore important generalizations. All of these contributions are framed in the context of random undirected nonstrategic search for best execution. An important alternative are directed search models (Moen, 1997; Lester et al., 2015). They explain assortative matching and show how heterogeneity affects relations and prices in labor, marriage, and other markets (Acemoglu and Shimer, 1999; Shimer and Smith, 2000; Shi, 2002). Strategic network and relationship formation models are closely related. OTC network formation and contracting with externalities are explored in Leitner (2005), Gale and Kariv (2007), Afonso et al. (2013), Gofman (2011), Condorelli and Galeotti (2012), Babus (2012, 2013), Colliard and Demange (2014), Glode and Opp (2014), Chang and Zhang (2015), Neklyudov and Sambalaibat (2015), among others. Repeat relations, relational contracts, and loyalty are explored theoretically by Levin (2002) and Board (2011) and empirically by Bernhardt et al. (2004), Fernando et al. (2012), and DiMaggio et al. (2015).

The remainder is organized as follows. Section 1 describes the data. Section 2 documents our findings. Section 3 concludes.

1 Data

Our primary data are insurance companies' transactions in corporate bonds, obtained from the National Association of Insurance Commissioners (NAIC). Insurance companies are required to report trades of long-term bonds and stocks to NAIC in Schedule D. The form is filed quarterly and it contains in Parts 3 and 4 of Schedule D purchases and sales made during the quarter, except for the last quarter. In the last quarter of each year, insurers file an annual report, in which all transactions during the year are reported.[2] Part 3 of Schedule D reports all long-term bonds and stocks acquired during the year, but not disposed of, while Part 4 of Schedule D reports all long-term bonds and stocks disposed of. In addition, all long-term bonds and stocks acquired during the year and fully disposed of during the current year are reported in a special Part 5 of Schedule D.

The NAIC data provide a wealth of information including the dollar amount of transactions, par value of the transaction, insurer code, date of the transaction, and the counterparty

[2]Many prior studies use this annual report only.

dealer name.[3] But these data are not without limitations. For example, the NAIC data do not provide time stamps of the trades, making it impossible to analyze the potential impact of intraday price movement of the transaction prices of bonds. Given that most bonds do not have multiple trades per day, we think that the impact of intraday price movement is limited to only a small set of bonds that are actively traded.

We compile the information in Parts 3, 4, and 5 of Schedule D to obtain a comprehensive set of corporate bond transactions by all insurance companies regulated by NAIC. Therefore our data does not suffer from the limitation that some third party vendor data suffer from, notably where the transaction value is typically rounded to the nearest $1,000.[4] For the main part of the analysis, we drop trades that happened less than 60 days after issuance and trades less than 90 days to maturity.

Our final sample covers all corporate bond transactions between insurance companies and dealers reported in NAIC from January 2001 to June 2014. After merging the full sample of 7.5 million bond trades with Mergent Fixed Income Security Database (FISD) to obtain the issue and issuer characteristics, we end up with a sample of 506,113 buys and 496,948 sells adding up to the total of 1 million second-market transactions. For the ease of comparisons of prices among different types of traders and for different types of bonds, we apply FISD-based filters largely based on Ellul et al. (2010) for establishing the corporate bond universe with complete data. We exclude a bond if it is exchangeable, preferred, convertible, MTN, foreign currency denominated, puttable or has a sinking fund. We also exclude CDEB (US Corporate Debentures) bonds, CZ (Corporate Zero) bonds, and all government bond (including municipal bonds) based on the reported industry group. Finally, we also drop a bond if any of the following fields is missing: offering date, offering amount, and maturity. We then restrict our sample to bonds with the offering amount greater than $10 million, as issues smaller than this amount are very illiquid and hence are rarely traded.[5] When merged, the data provide detailed information on each transaction of corporate bonds by insurance companies, including the identity of the issue and the issuing

[3]NAIC's counterparty field reports names in text, which can sometimes be mistakenly typed. The bank with the most variation in spelling is DEUTSCHE BANK. We manually clean the field to account for different spellings of broker-dealer names.

[4]See Paul Schultz for this information.

[5]Ellul et al. (2010) have used $50,000 which we find restrictive for our purpose.

firm, the execution date, the transaction price, the par value traded, and the direction of the trade for both parties, e.g., whether the trade was an insurance company/dealer buying from a dealer, or an insurance company/dealer selling to a dealer.

We then supplement this data with data on corporate bond holdings for insurance companies[6] and quarterly bond ratings from Lipper's eMaxx database.[7] Finally, we acquire the insurers' financial information from A.M. Best.[8]

[Table 1 about here]

Table 1 reports descriptive statistics for the corporate bond trades (Panel A), insurers (Panel B), and dealers (Panel C) in our sample that ranges from January 2001 to June 2014. There are 4,324 insurance companies in our sample. We classify all insurance companies into thee groups: (i) Health, containing 617 companies or 14% of the sample; (ii) Life, containing 1,023 companies or 24% of the sample; (iii) P&C containing the majority of the sample at 2,684 or 62%. Health insurance companies account for 166,348 (16.6% of the total) trades worth a total of $85bn (4.7% of the total trading volume). They trade on average with 17 dealers. Life insurance companies account for the majority, both as a level 461,801 and a fraction of the total at 46%, of trades in our sample, as well as the total volume of $1,256bn (69.5% of the total trading volume). They trade on average with 19 dealers. P&C insurance companies come second at 374,912 trades or 37.4% of the total number of trades valued at $467bn (25.8% of the total trading volume). They trade on average with 14 dealers which is slightly below the sample of 16 dealers per insurer.

The top ten insurance companies account for 6.9% of all trades and 15.7% of the total trading volume in our sample, thus implying that these insurers tend to submit large orders and trade reasonably often. As a consequence they tend to use on average 69 dealers which is much higher than the sample average of 16 dealers per insurer. Top 100 insurers account for almost half of the trading volume (46.3%) as well as for 32.8% of the total trading volume.

[6]Specifically we obtain date-specific amount outstanding of corporate bonds held by the insurance companies.

[7]For detailed information on Lipper eMAXX data, refer to Manconi, Massa, and Yasuda (2012) and Becker and Ivashina (2014).

[8]A.M. Best's Financial Strength Ratings (FSR) represent the company's assessment of an insurer's ability to meet its obligations to policyholders.

They use on average 53 dealers, which is also a quite large number. Since top 1,000 insurers use on average 33 dealers we can safely conclude that a large number of smaller insurance companies use on average less than 5 dealers.

Insurance companies trade with 439 broker-dealers while the largest dealer handles 8.6% (16.5% for largest two dealers) of all trades and the top ten dealers handle 66.2% of all trades. The top 100 dealers account for 98% of all trades and 99% of all trading volume in our data.

Insurers trade in a variety of corporate bonds. The average bond issue size in our sample is quite large at $917 million and it is similar across insurer's buys and sells. The average maturity is nine years for insurer buys and eight years for insurer sells. Bonds are on average 2.88 years old with sold bonds being a little older at 3.09 years. Finally, 75% of all bonds are investment grade bonds while only 1% of bonds are unrated bonds with the remainder being high-yield bonds. Privately placed bonds form a small minority of our sample at 8%.

Overall, there exists a large degree of heterogeneity both on the client and dealer sides in our sample. Insurance companies buy and sell large quantities of different corporate bonds and execute these transactions with the number of dealers ranging on average from one to as many as 69. A single dealer may trade with as many as 2,300 insurance companies.

2 Results

This section reports our results. We start with a general description of the trading activity of the insurance companies and then investigate the nature of the dealer-client relationships by casting our analysis in the client-dealer trading network framework. The implications of the dealer-client relationship to execution costs concludes our analysis.

2.1 Insurer and dealer trading activity

We investigate the determinants of both the extensive, i.e., the number of trades, and intensive, i.e., the total dollar volume traded, margins of the insurer's and dealer's trading in a given month and, where applicable, in a given year. Both margins reveal that insurers have heterogenous trading needs and dealers are specializing in satisfying these needs.

We start with the univariate analysis: Panel A of Figure 2 shows the distribution of insurer trades per month. The distributions follow a power law $p(N) \propto N^{-1.2}$. Large number of insurers do not trade in a given month(year) and we have eliminated their fraction from the figure for expositional purposes. The majority of the insurers who do trade monthly do not do it often: Panel A shows that 41% of insurers trade just once per month and 90% of insurers trade three or less times per month. While the mean number of trades per month is just 6, with a median of 3 (conditional on any trade), quite a few insurers are very active and trade more than twice per day and up to 500 times per month. This is consistent with the evidence from Table 1 that while the top 100 insurers constitute just 2.31% of the total sample, they account for as much as 33% of all trades in our sample. The distribution looks quite similar at the annual frequency: 10% of insurers trade just once per year while 1% of the insurers make 25 trades per year or two trades per month. The mean number of trades per year is 16, with a median of 14, with several insurers making more than 1000 trades and up to the maximum of 2,200 trades per year.[9]

[Figure 2 about here]

A natural follow-on question is what characteristics explain heterogeneity in trading needs. Table 2 documents the determinants of the intensive (trading volume in $bn, Column 1) and extensive (number of trades in a month, Column 2) margins of the monthly trading by insurance companies using pooled regressions with time fixed effects. The specification consists of the trade par size, insurer and bond characteristics, as well as the variation in the trade size and bond characteristics across all trades of the insurer during a given month. Insurer's characteristics include its size, cash-to-assets ratio, type, RBC ratio,[10] and rating. Bond characteristics include most of the usual suspects such as size, age, maturity, rating, a private placement dummy, and the trade size. All variables are log-transformed and all regressors are averaged across all trades of the insurer during the period and lagged by one time period.

[9] The picture of the distribution of trades per year is available upon request.

[10] Risk-Based Capital (RBC) is a method of measuring the minimum amount of capital appropriate for a reporting entity to support its overall business operations in consideration of its size and risk profile. RBC limits the amount of risk a company can take and, therefore, it is intended to be a minimum regulatory capital standard. It requires a company with a higher amount of risk to hold a higher amount of capital.

Logarithms of both measures of trade intensity are persistent; the coefficient on the lagged log-volume is 0.52 and the coefficient on the lagged log-number-of-trades is 0.63. Both coefficients are statistically significant at 1% levels. This evidence is consistent with insurance companies rebalancing their holdings over several months.

Insurer trading strongly correlates with insurer size, type, and quality, with bond types and bond varieties and these variables explain 63% of the variation in monthly trading volume and 52% variation in monthly number of trades. A one standard deviation increase in insurer's size increases trading volume by 18%. Larger insurance companies and insurance companies with higher cash-to-assets ratio also trade more often and submit larger orders. Insurers with higher RBC ratio submit larger orders but do not trade more than insurers with low RBC ratio. Both margins of trading increase with the insurer's rating but the size of the regression coefficients is inversely related to the rating quality, i.e. unrated insurers and insurers with the lowest rating (C-F) trade larger quantities and more often then higher rated insurers. Lower rated insurers been hit by the liquidity shocks more often (they may have different clientele) than higher rated insurers may account for this result. Life insurers tend to submit larger orders than P&C insurers.

Both margins of bond turnover increase as bond ratings declines; lower rated bonds are traded more often and in larger quantities. Insurers tend to trade privately placed bonds less since potentially they just own fewer of them than publicly placed bonds. Both margins of bond turnover decline with par size and bond age indicating that the majority of insurers are long-term investors demanding specifically structured cash flows from their bond holdings. Both measures of trade intensity do not depend on bond issue size and remaining life as their regression coefficients are not statistically significant.

Finally, both trading volume and number of trades decline if overall more bond varieties are traded, i.e., trading is concentrated around few bonds with similar characteristics. However, a specific variety can have an opposite effect on the trading intensity. For instance, both measures of trading intensity increase with variation in bond rating and bond life. Once again this finding is consistent with insurers increasing trading intensity when rebalancing their portfolios, i.e. shifting from high-yield to lower yield bond or from younger to older bonds.

[Table 2 about here]

Overall, these analysis highlight large heterogeneity in trading needs across different insurers. Trading needs depend on the variety of bonds in the order, bond specific characteristics, and on the insurer type and quality. A natural follow-up question to which we are now turning our attention is how these characteristics affect the matching between insurers and dealers.

2.2 Properties of insurer-dealer network

Our results from the previous section demonstrate that insurers have highly heterogeneous trading needs which jointly with insurer's characteristics explain the intensity of the insurers' trading. We also observe a large degree of heterogeneity in the insurers' trading intensity; some insurers trade on average twice per day while others trade just once per year. This evidence points in the direction that insurers may have highly heterogeneous demands for both the number of dealers and the range of services offered by them. We are going to unveil the details of the global dealer-insurer network in this section by studying how insurers trade with different dealers, how many dealer links they form over time, and how persistent are these networks.

We will let two opposite theoretical hypotheses of how investors search for best execution in decentralized opaque OTC markets to guide our empirical analysis. The first one is a competitive random search à la Duffie et al. (2005, 2007) where clients repeatedly search among other clients and dealers for the best execution but do not enter into a long-term relationship with dealers. As a result, directed random search for best execution requires time delay in obtaining price quotes but assumes low or nonexistent costs of relationship formation. Direct random search implies exponential distribution for the fraction of insurers with the number of dealers greater than N.

The second one is the strategic "Rolodex" model where clients trade-off lower search costs, exclusivity, and loyalty versus high costs of adding another permanent link, i.e., another phone number in the Rolodex, to the network and maintaining this long-term relationship, i.e., re-rooting better deals over time and others.[11] This model predicts that each client builds a fixed-size Rolodex of dealers and searches over it for the best execution each time a trading need arises thus implying persistence in client-dealer matching over time. It is possible to show that under some realistic assumptions the Rolodex model implies a Power law for the fraction of insurers with the number of dealers greater than N.

We start with examples of the insurer-dealer relationship depicted in Figure 1. They show that some insurers indeed do not trade with a dealer randomly picked from a large pool of corporate bonds dealers. Instead, these insurers buy from the same dealers that they sell bonds to and get engaged into long-run repeat relations with dealers even though theses relations are non-exclusive. We proceed further by documenting how representative are the examples in Figure 1 and which insurer characteristics determine the network size.

Panel B of Figure 2 shows the degree distribution number for insurer-dealer relations by month, i.e., the fraction of insurers trading with the given number of dealers over the entire sample period, using a log-log scale. The plot shows insurers trade with up to 40 (50) dealers every month. The maximum degree is 80 over the entire 2001-14 sample period. Exclusive relations are dominant - almost 50% of insurers trade with a single dealer in a given month. The monthly degree distribution follows approximately a Power law ($\approx .43 \times N^{1.4}$) with exponential tail starting at about 10 dealers.[12] It can be viewed as a hybrid between the Rolodex and competitive random search models. The insurers build Rolodexes with, on average, ten phone numbers in them and they search randomly out side their Rolodexes when they exhaust their permanent contacts without getting a deal.

Table 3 reports the determinants for the size of insurer-dealer network using pooled regressions with time fixed effects. We measure the size of the trading network by the

[11] For models of OTC network formation and contracting with externalities please see Leitner (2005), Gale and Kariv (2007), Afonso et al. (2011), Condorelli (2011), Babus (2012, Neklyudov and Sambalaibat (2015) and for models of repeat relations, relational contracts, and loyalty please see Levin (2002), Bernhardt et al. (2004), Board (2011), DiMaggio et al. (2015).

[12] Erlang distribution is a hybrid between the power law with a shape κ and the exponential with a rate α

$$f(x; \kappa, \lambda) = \frac{\lambda^\kappa x^\kappa e^{-\lambda x}}{(\kappa - 1)!}.$$

The waiting times between κ independent occurrences, with some average rate modeled with a Poisson process, of the event are Erlang distributed. Erlang distribution becomes Gamma distribution when the shape parameter is not integer.

number of different dealers that an insurance company trades with in a given month. We log-transform all dependent variables by $100 * log(1 + x)$. We then average all regressors across all trades of the same insurer during the sample period and lag them by one time period. We perform the estimation on the whole sample (Column 1) and, in order to control for the insurer's size, on sub-samples of small and large insurers. We classify an insurer as small if it falls in the bottom three size quartiles, and we classify an insurer as large if it falls in the top quartile of the size distribution.

[Table 3 about here]

Column 1 indicates that insurer size and type, bond characteristics, and bond varieties matter for the size of the dealer network. Large insurers with more trading needs have more dealers. Insurers with a demand for larger bond variety have larger networks even controlling for their size (Panels 2 and 3). Higher quality insurers, i.e., insurers with higher cash-to-assets ratio or higher ratings, have larger networks but it matters exclusively for smaller insurers as Column 2 indicates. It is potentially due to the fact that it is easier for higher quality insurers to find a dealer through referrals and it is cheaper for a dealer to set up a credit account for higher quality insurers. These factors matter more for small insurers since these insurers face larger adverse selection problem in forming permanent links with dealers. Large insurers trading high-yield (junk) bonds tend to have larger networks. Large insurers trading in unrated bonds, which are potentially offered only by "exclusive" dealers, tend to have smaller networks. An interesting result is that P&C insurers tend to have smaller dealer networks. Overall these findings suggest insurers' network choice is endogenous and dependent on multiple factors. Competition and specialization jointly determine investors' trade choices.

Results from Table 3 also hint on a high degree of persistence in the size of the network as the coefficient on the lagged network size is 0.61 (Column 1). This result is mostly due large insurers, since this coefficient is equal only to 0.29 for small insurers. We explore this further in Table 4 which reports statistics for the frequency with which insurers switch dealers. We compute the likelihood that an insurer uses a certain number of dealers in a given month, Panel A, and year, Panel B, and compare it the corresponding number in the next period.

This yields conditional probabilities for using a network size conditional on the insurer's past behavior:

$$Pr(\text{No. of dealers in } t+1|\text{No. of dealers in } t), \tag{1}$$

where t stands for month or year. The transition probabilities in Table 4 strongly suggest insurers have preferred dealers. Trading relations are persistent from month(year) to month(year). It is especially true for exclusive relations since the probability of staying with the same single dealer each month and year is equal to 0.61. Insurers with more than one dealer are very unlikely to switch to a single dealer as monthly switching probabilities are equal to 0.27 for insurers with 2 to 5 dealers and 0.07 for insurers with 6 to 10 dealers. These probabilities are even lower on the annual frequency. Insurers with largest ($>$ 10 dealers) networks tend to keep their large networks over time, which is especially true for the annual frequency where the probability of staying with a large network is a 'whopping' 0.75.

[Table 4 about here]

Next, we are going to investigate the properties of the insurer's trading network at as granular level as individual insurer-dealer links. We search for the determinants of the insurer-dealer specific sorting and/or matching. One such determinant has stood out through all of our previous results. This determinant is the size of both the insurer and dealer. Therefore we are going to map the trading network pervasive in our sample by sorting all insurers and dealers into their specific size deciles and then plotting the probability of a trade as a function of both dealer and insurer size. In order to guide our intuition behind the outcome of this exercise we once again are going to use the random search and Rolodex models of trade since both models allow for distinct comparative statics predictions about the dealer-client network mapping based on the size of counterparties. We summarize these comparative statics results below.

We start with the competitive random search model in the spirit of Duffie et al. (2005) to illustrate the comparative statics implications of the size of both dealer and investor/client on the probability of trade and the transaction price. In Duffie et al. (2005) type models a continuum of investors randomly and independently contact each other at some mean rate λ, a parameter that reflects search ability or sophistication. Similarly, dealers contact investors and other dealers at some intensity ρ that reflects dealer availability, i.e. higher ρ means a dealer is more efficient at finding a counterparty. There exists a single asset and both dealers and investors have endogenously determined reservation valuations of the asset denoted by RV_D and RV_I, respectively. An investor is characterized by whether he owns the asset or not, and by an intrinsic type that reflects whether he is a holder or a seller which changes randomly over time, i.e., a holder may become a seller and vice versa. While this feature of the model does not affect the comparative statics exercise we discuss here, it implies that the choice of when to buy/sell is exogenous which is important for the structural estimation we perform in Section 3. While both interdealer and dealer-client markets are competitive, when agents meet they act strategically by bargaining over the terms of trade[13] leading to the following price

$$P = wRV_D + (1-w)RV_I, \tag{2}$$

where w is the investor's bargaining power. In addition, the probability of a dealer actually *buying* from a client increases with the trade surplus, $S \equiv RV_D - RV_I$. More sophisticated investors have better access to other investors or to dealers, i.e. higher outside option, and, therefore, their reservation value, RV_I, increases with λ. Likewise, more efficient dealers have higher outside option and, therefore, their reservation value, RV_D, increases with ρ. As a result, the price offered by the dealer increases with both dealer efficiency and investor sophistication, or in other words investor execution costs decline with her sophistication while the probability of a trade increases with dealer efficiency when holding λ fixed and decreases with investor sophistication when holding ρ fixed. We associate investor size in the data with the degree of its sophistication in the model, i.e. large investors in the data have large λ in the model. Likewise, dealer efficiency in the model is the proxy for their size in the data, i.e. large dealers are more efficient than small ones. Therefore, the probability of trade is relatively high for the following dealer-investor pairwise matching: large-large, large-small, and small-small, with large-small match having the highest probability of trade. The probability of trade is low when small dealer meets large investor. It implies that in the data we should have *positive* assortative size matching where small investors trade with

[13]Following Duffie et al. (2005) we are going to use Nash bargaining for the purpose of this exercise.

both small and large dealers while large investors trade only with large dealers. Large dealers offer better execution than small dealers with large investors getting the best execution. The worst execution is provided by small dealers to small investors.

While it inherits several features of the Duffie et al. (2005) type models such as more efficient dealers provide better execution, the "Rolodex" type model of the OTC market has different predictions regarding assortative size matching between dealers and investors. In this model investors trade off large fixed costs of adding extra permanent connection with the benefit from the ability to search over the larger pool of permanent connections for better execution. More sophisticated (larger) investors benefit more from larger number of connections then less sophisticated (smaller) investors and as a result build larger Rolodex. Given a choice between more or less efficient dealers the less sophisticated investors pick more efficient dealers on average since they have smaller Rolodex, while more sophisticated investors trade with everyone. As the result, Rolodex model predicts the following dealer-investor pairwise matching: large-large, large-small, and small-large, but not small-small. It implies that in the data we should have *negative* assortative size matching where small investors trade mostly with large dealers while large investors trade with both small and large dealers. Since this model inherits the dealer properties of the random search model, it shares predictions regarding the executions costs with it.

[Figure 3 about here]

Figure 3 maps the trading networks of each investor and dealer and illustrates where order flow is concentrated. On the horizontal (vertical) axis, we sort insurers (dealers) into deciles by their frequency of trading from low to high.

Panel A depicts the trading activity in terms of the probability that an insurer trades with a dealer of given size over the entire sample period. It reveals that while trading is concentrated between large insurers and large dealers, large dealers trade with everyone including smallest insurers. Large insurers split their orders between large and small dealers. By contrast, small insurers concentrate order flow with very few dealers and mostly with the large dealers. The assortative matching is large-large, small-large, and large-small, but only rarely small-small, thus implying *negative* assortative matching. While this matching is inconsistent with the directed random search model it is in an agreement with the Rolodex model of trade. When combined with the persistence in relations, this result points toward an endogenous concentration of trading with large dealers.

Panel B of Figure 3 shows the corresponding trade concentration for each insurer-dealer decile. Insurers with smaller network, e.g., smaller insurers, have more intense, repeat relations. These insurers are coming back to the same dealer(s) they have traded in the past and they rarely split their orders. These insurers are using a short Rolodex of dealers and are staying within it for every bar few trades. Small insurers have both large and small dealers in their Rolodex, but tend to use large dealers off it whenever they can. Large insurers seem to have only large dealers in the Rolodex since their trades exhibit the highest concentration with large dealers. However, large insurers are not shy to venture away from their Rolodex when a need arise (or when they can get a better deal elsewhere). This is also consistent with the directed random search model where large insurers are more efficient in finding a counterparty. Overall, the insurer-dealer size-based matching provides more support to the Rolodex model of trade than to the random search model of trade.

Table 5 quantifies the results from Figure 3 by reporting in Panel A the fraction of insurers of different size that trade with dealers of different size and in Panel B the fraction of dealers trading with insurers of different size. In this case for the sake of clarity we split insurers and, respectively, dealers into size-based quartiles instead of deciles used in Figure 3.

[Table 5 about here]

Panel A shows that all large and medium insurers trade with large dealers and only 4% of very small insurers and 1% of small insurers do *not* trade with large dealers. Alternatively, these small insurers just could not find a large dealer to take them as a trading partner. 12% of large insurers trade with very small dealers which is by far the largest percentage out of quartiles with the next largest being 4% and coming from the medium insurers. Overall, this panel confirms that large insurers trade with dealers of all sizes while smaller insurers trade mostly with large dealers.

Panel B illustrates how dealers select insurers into their trading networks. All large dealer do not discriminate against size by trading with insurers of all sizes. Only 50% of medium dealers tend to trade with very small insurers, but otherwise very high percentage of medium dealers trade with all other insurers. Small and very small dealers concentrate their trading with medium and large insurers. Very small dealers especially guilty of this matching as only 24% of them trade with small insurers and 18% of them trade with very small insurers, while 61% of very small dealers is trading with large insurers. Finally, 9% of large dealers do not to trade with very small insurers which is consistent with the earlier observation that 4% of very small insurers do not trade with large dealers. Clearly some very small insurers could not find a trading partner amon large dealers. Overall these results confirm the negative size-based assortative matching between insurers and dealers.

Table 6 explores systematically which insurers trade with dealers of a different rank and why, e.g., what bonds they trade and how much variety. Following previous table we have split all dealers into size-based quartiles. The dependent variable is the dealer's rank defined in terms of overall trading activity, ranging from the least active dealer (1) to the most active dealer (439). Estimates are from pooled regressions with day fixed effects and we adjust standard errors for heteroskedasticity and cluster them at the insurer, dealer, bond, and day level.

[Table 6 about here]

Insurer size is matters the most for choosing a trade partner. Larger insurers choose larger dealers within each quartile with the regression coefficient increasing sharply across the quartiles. Insurer size is basically the only variable besides the transaction size and lagged dealer choice which is significant at 1% for very small and small dealer quartiles. Interesting enough, the size of the dealer decreases with the trade size across all quartiles with the magnitude of the regression coefficient increasing across size quartiles. It is possible that it is too costly for smaller dealers to accommodate smaller trades while larger dealers can use economies of scale to minimize these costs and thus are more likely to handle these trades. Bond varieties do not matter for explaining dealer choice for very small and small dealers besides the public-private variety, which could be due to some dealers specializing in privately placed bonds. It is worthwhile to mention that insurers trading in the variety of rated-unrated bonds tend to choose smaller dealers across all quartiles potentially due to smaller dealers once again specializing in unrated bonds. Variety matters though for medium and large dealer quartiles with insurers choosing larger dealers for more variety except the rated-unrated variety in which case insurers choose smaller dealers with the specialization being the potential culprit.

Insurers trading with largest dealers select smaller dealers when requiring very specific bonds indicating that smaller dealers tend to specialize in specific bond types. However, insurers tend to select larger dealers when trading junk bonds. The insurer quality and type matters only when trading with largest dealers, with dealer size increasing with insurer quality. Unrated insurers tend to trade with larger dealers across all quartiles.

In summary, insurer size is extremely important for matching conditional on the dealer size as larger insurers tend to trade with large dealers across all dealer size quartiles. While bond characteristics and varieties matter for overall insurer-dealer matching, they matter the most for medium and large dealers while being almost irrelevant for very small and small dealers. We can conclude that dealer-insurer network is endogenous and strategically chosen by both dealers and insurers. It is most consistent with a hybrid between the Rolodex and directed random search models in which all insurers strategically choose a Rolodex and mostly large insurers go outside their Rolodex when the need arises. We now turn our attention to execution costs implied by this insurer-dealer network.

2.3 Execution costs and investor-dealer relations

Given the endogenous nature of the insurer dealer network it is quite important to understand its implications to prices. Our results from previous section indicate that bond characteristics and varieties matter for the network structure. We have also seen that relation-specific variables proxied in our empirical specification by dealer size and quality and insurer size matter even more. Therefore, we are going to superimpose the trading costs over the network map created in the previous chapter.

To adjust trading costs for bond, time, and bond-time variation, we compare trade prices to Merrill Lynch sell quotes at the time of the transaction. BAML is the largest corporate bond dealer. In addition, we clean buys and sells from residual bond and time fixed effects in most of the regression specifications. Our relative execution cost measure is defined as

$$\text{Execution cost (bp)} = \frac{\text{BAML Quote} - \text{Trade Price}}{\text{BAML Quote}} * (1 - 2 * \mathbf{1}_{Buy}) * 10^4, \tag{3}$$

where $\mathbf{1}_{Buy}$ is an indicator for whether the transaction is by an insurer buying or selling. Since not all bonds quoted and some quotes are stale, we truncate the distribution at 1% and 99%.

Execution costs may depend on the bond being traded, on time, on whether the insurers buys or sells, on the insurer's identity, on the dealer, and on the nature and intensity of the insurer-dealer relation. To capture all these effects, we split execution costs into bond and time specific costs insurer-dealer relation specific costs by estimating the following panel regression:

$$\text{Execution cost}_{it} = \alpha_i + \alpha_t + \beta X_{it} + \epsilon_{it} \tag{4}$$

for bond i at time t. The set of explanatory variables X includes characteristics of the bond or bond fixed effects, time fixed effects, features of the insurer, dealer, and the insurer-dealer relation.

[Tables 7 about here]

Table 7 summarize the estimates. Estimates in both tables are from pooled regressions with day fixed effects and we adjust standard errors for heteroskedasticity and cluster them at the insurer, dealer, bond, and day level. Column 1 of Tables 7 shows that, controlling for bond fixed effects, both dealer and insurer size matters for the execution costs. Large dealers offer quotes on average better than BAML's quotes to insurers of all sizes, but, conditional on the insurer size, smaller dealers offer better quotes as the interaction term between the insurer and dealer sizes indicates. Large insurers pay on average lower execution costs than BAML's costs to dealers of all sizes, but, conditional on the dealer size, smaller insurers pay lower prices as the interaction term between the insurer and dealer sizes indicates.

Column 2 of Tables 7 introduces dealer and insurer characteristics as well as the trade direction (buy or sell) and size conditional on direction into the specification from Column 1. It shows that insurer and dealer size effects on the execution costs change only slightly in magnitude but not in the statistical significance. In addition NYC-located dealers offer better prices to all insurers and more diverse dealers charge, on average, higher prices. On the insurer side, insurers with higher RBC ratio get better prices. Both Life and P&C insurers get, on average, higher prices than Health insurers. The insurer quality does not matter that much for prices as the regression coefficients on variable measuring insurer quality are only marginally significant. Insurers get worse execution when they buy but the execution improves a bit when they buy in larger quantities. On the other hand execution costs climb up when insurers sell in larger quantities. Specification 3 adds individual bond characteristics to the specification 2 while bond fixed effects are removed. Bond characteristics matter for execution costs as insurers pay higher prices for special bonds and lower prices for bonds with larger issue. Insurers get better prices on unrated bonds.

Column 4 adds both network size (number of dealers for a given insurer) and composition (Dealer size *times* Number of dealers) to the specification 2. This kills off the statistical significance of insurer size and its interaction with the dealer size. Large dealers still offer better execution and insurers benefit from the size of their networks as the execution costs decline with network size. However, conditional on network size smaller dealers offer better execution as the interaction term between the dealer size and network size indicates. Finally, the specification in Column 5 adds both network size and composition to the specification 3. All major results from the specification 3 regarding the effects of dealer, insurer, and bond characteristics on the execution costs remain intact while both the insurer size and its interaction with dealer size loose their statistical significance.

In summary, Tables 7 demonstrates that larger dealers offer better execution to all insurers and insurers of any size get better execution if they have larger network. Insurers pay higher prices for exclusivity and sell exclusive bonds back to dealers at lower prices. Insurers get better execution when they sell to a dealer than when they buy from her, but the execution improves(worsens) when the size of the buy(sell) is large.

[Table 8 about here]

Table 8 reports same results as specifications 3 and 5 from Tables 7 when all insurers are first sorted into four size quartiles. Results are reported for small, e.g., bottom three size quartile, and large, e.g., top quartile, insurers. All results from Table 7 remain intact. In this case the size of the network matters more to small insurers as they get a better improvement in execution costs with a lager network size than large insurers get.

Table 9 reports same results as specifications 3 and 5 from Tables 7 when all dealers are first sorted into four size quartiles. Results are reported for small, e.g., bottom three size quartile, and large, e.g., top quartile, dealers. All results from Table 7 remain intact except neither the dealer size nor network size are statistically significant for small dealers.

[Table 9 about here]

We can estimate the bond- and time-specific execution cost component $\widehat{\alpha}_i + \widehat{\alpha}_t$ and the relation-specific costs $\widehat{\beta} X_{it}$ for bond i at time t from (4). Coefficient estimates are obtained from specification (2) in Table 7. Using the predicted execution cost components for each trade, we aggregate each cost component for each insurer-dealer pair by taking averages over time. The maps in Figure 4 depict the deciles of the execution cost distribution. On the horizontal (vertical) axis, we sort insurers (dealers) by their frequency of trading from low to high. We perform the decomposition separately for insurer buys (left) and insurer sells (right).

[Figure 4 about here]

Figure 4 confirms our findings from Tables 7, 8, and 9. Larger dealers offer best execution for everyone and handle most expensive and difficult bonds. Large insurers get best execution from all dealers large and small. Small insurers trading with small dealers get the worst execution.

3 Joint Estimation of Relationships and Execution Costs

In the following, we use the observed investor-dealer relationships to learn about the value of trading for both the dealers and the insurers. We focus on the stationary distribution of relationships and execution costs. This allows us to infer from bilateral average execution costs the sharing rule for how dealers and insurers split the surplus from trading.

A relation between dealer D and insurer I is observed in the data if, when they contact each other, the surplus from trade between the two parties is positive. The respective value functions determine the trade surplus. Upon a contact between dealer D and insurer I, an insurer sale to a dealer occurs if the surplus from the trade is positive:

$$S = RV_D - RV_I \geq 0, \tag{5}$$

where RV_D and RV_I are the reservation values for trading. The conditions for an insurer buy are analogous. The price at which a trade takes place is determined through bilateral Nash bargaining with the insurer bargaining power $w \in [0, 1]$. The resulting price is relation-specific and given by equation (2).

In non-strategic random search models (Duffie et al., 2005/7; Neklyudov, 2014; Hugonnier et al., 2015; Üslü, 2015), the dealer's value of trade, $RV_D = dV_D(X_D, \varepsilon_D)/dPar$, depends on a set of characteristics (X_D, ε_D) that are observable and, respectively, unobservable by the econometrician. The characteristics may include proxies for the dealers' inventory position and risk-taking capacity. The insurer's valuation $RV_I = dV_I(X_I, \varepsilon_I)/dPar$ depends similarly on a set of insurer characteristics X_I and a random error component ε_I. The characteristics may include proxies for the insurer's portfolio holding, trading or liquidity needs, and credit risk. We parameterize the reservation values and bargaining powers by

$$\begin{aligned} RV_I &= X_I'\beta_I + \varepsilon_I, \\ RV_D &= X_D'\beta_D + \varepsilon_D, \\ w &= \Lambda(X_w'\beta_w), \end{aligned} \tag{6}$$

where $\Lambda \in [0, 1]$ is the inverse logit transformation to ensure that the bargaining power parameter is defined over its natural domain, and X_w are covariates of the insurer, dealer, and their relation.

A trading relation between I and D exists if and only if

$$\text{Relation} = 1 \Leftrightarrow \varepsilon_D - \varepsilon_I \geq -(X_D'\beta_D - X_I'\beta_I). \tag{7}$$

The expected observed price is

$$E[P|\text{Relation}=1] = X_I'\beta_I + w(X_D'\beta_D - X_I'\beta_I) + \underbrace{\frac{\gamma}{\sigma}\frac{\phi(\frac{1}{\sigma}(X_D'\beta_D - X_I'\beta_I))}{\Phi(\frac{1}{\sigma}(X_D'\beta_D - X_I'\beta_I))}}_{E[\varepsilon_I + w(\varepsilon_D - \varepsilon_I)|\varepsilon_D - \varepsilon_I \geq -E[S]]}, \tag{8}$$

where the last term follows from assuming joint normality of $(\varepsilon_I, \varepsilon_D)$ with correlation ρ, $\gamma = w\sigma_D^2 - (1-w)\sigma_I^2 + (1-2w)\rho\sigma_I\sigma_D$, $\sigma^2 = Var(\varepsilon_D - \varepsilon_I) = \sigma_I^2 + \sigma_D^2 - 2\rho\sigma_I\sigma_D$, and ϕ (Φ) is the standard normal density (cumulative distribution) function. The transaction occurs if and only if the surplus is positive, which requires adjusting the trade price by the conditional expectation of the unexplained part in reservation values that lead to a positive surplus, i.e., trade. Condition (8) shows the insurers' bargaining power is identified from the regression coefficient of trade prices on the expected trade surplus. In the empirical implementation, we normalize the trade price P by the BAML quote at the time of the trade to obtain a measure of net execution costs, $c = (P_{BAML} - P)/P_{BAML}$, and then average across all trades.

The estimation can be performed in two stages. The first stage estimates a probit regression of trade choices Relation between all insurers and dealers to obtain the determinants of reservation values (β_I and β_D). The second stage performs a nonlinear least-squares regression of (8) to obtain the determinants of insurers' bargaining power (β_w). We treat γ and σ as additional coefficients to be estimated. We estimate the model separately for insurer buys and insurers sells.

[Table 10 and Figure 5 about here]

Table 10 reports the coefficient estimates. Figure 5 plots the predicted trade surplus for each insurer-dealer pair in Panel A and the sharing rule in Panel B. The coefficients in Table 10 show that on insurer sale transactions, in which the dealer buys, larger dealers and larger insurers have lower reservations values.

4 Conclusion

Over-the-counter markets are pervasive across asset classes, yet their functioning is not well documented. This paper uses comprehensive corporate bond trading data for all U.S. insurance companies, one of the largest holders of corporate debt, between 2001 and 2014 to document how trading frictions in over-the-counter financial markets affect who different investors trade with and what execution terms they receive. Our proprietary audit trail data reveals both the relationship network between insurers and dealers and the prices at which bilateral trades occur. We show insurance companies form few long-standing trading relations with corporate bond dealers. About 50% of all insurers do all their buy and sell trading with a single dealer all the time, while larger insurers with more active trading have larger trading networks. Execution costs depend strongly on insurers' trading network and who they are connected to. Larger insurers trade with both large and small dealers which improves price competition among the dealers, while small insurers concentrate their trading mostly with large central dealers. As a result, larger insurers receive the best execution from all dealers, while small insurers face worse terms of trade. The negative size matching is inconsistent with predictions from off-the-shelf random search models but supports models of Rolodex-type search based on relationship-specific investment. Our findings reveal how professional investors use loyalty to mitigate the search and matching frictions that riddle decentralized and opaque trading mechanisms. Any regulation or other market intervention should take these tradeoffs into account.

References

Acemoglu, Daron and Robert Shimer, 1999, "Efficient unemployment insurance,?" *Journal of Political Economy* 107, 893-928.

Afonso, Gara, Anna Kovner, and Antoinette Schoar, 2013 "Trading partners in the interbank lending market," Federal Reserve Bank of New York Staff Report.

Babus, Ana, 2012, "Endogenous Intermediation in Over-the-Counter Markets," Working Paper, Federal Reserve Bank of Chicago.

Babus, Ana, 2013, "The Formation of Financial Networks," Working Paper, Federal Reserve Bank of Chicago.

Babus, Ana and Peter Kondor, 2013, "Trading and Information Diffusion in Over-The-Counter Markets," Working Paper, Federal Reserve Bank of Chicago.

Bernhardt, Dan, Vladimir Dvoracek, Eric Hughson, and Ingrid Werner, 2005, "Why do large orders receive discounts on the London Stock Exchange?" *Review of Financial Studies* 18, 1343-1368.

Bessembinder, Hendrik, William Maxwell, and Kumar Venkataraman, 2006, "Market transparency, liquidity externalities, and institutional trading costs in corporate bonds," *Journal of Financial Economics* 82, 251-288.

Biais, Bruno, 1993, "Price formation and equilibrium liquidity in fragmented and centralized markets," *Journal of Finance* 48, 157-185.

Board, Simon, 2011, "Relational Contracts and the Value of Loyalty," *American Economic Review* 101, 3349?3367.

Chang, Briana and Shengxing Zhang, 2015, "Endogenous market making and network formation," Mimeo.

Colliard, Jean-Edouard and Gabrielle Demange, 2014, "Cash Providers: Asset Dissemination Over Intermediation Chains," Paris School of Economics Working Paper No. 2014-8.

Condorelli, Daniele and Andrea Galeotti, 2012, "Endogenous Trading Networks," Working Paper, University of Essex.

DiMaggio, Marco, Amir Kermani, and Zhaogang Song, 2015, "The Value of Trading Relationships in Turbulent Times ," Mimeo.

Duffie, Darrell, Garleanu, Nicolae, and Lasse Pedersen, 2005, "Over the counter markets," *Econometrica* 73, 1815-1847.

Duffie, Darrell, Garleanu, Nicolae, and Lasse Pedersen, 2007, "Valuation in over the counter markets," *Review of Financial Studies* 20, 1865-1900.

Edwards, Amy, Lawrence Harris, and Michael Piwowar, 2005, "Corporate bond markets transparency and transaction costs," *Journal of Finance* 62, 1421-1451.

Fernando, Chitru, Anthony May, and William Megginson, 2012, "The Value of Investment Banking Relationships: Evidence from the Collapse of Lehman Brothers," *Journal of Finance* 67, 235-270.

Gale, Douglas M., and Shachar Kariv, 2007, "Financial Networks," *American Economic Review* 97, 99-103.

Glode, Vincent and Christian C. Opp, 2014, "Adverse Selection and Intermediation Chains," Working Paper, University of Pennsylvania - The Wharton School.

Gofman, Michael, 2011, "A Network-Based Analysis of Over-the-Counter Markets," Working Paper.

Green, Richard C., Burton Hollifield, and Norman Schürhoff, 2007, "Financial Intermediation and the Costs of Trading in an Opaque Market," *Review of Financial Studies* 20(2), 275-314.

Green, Richard C., Dan Li, and Norman Schürhoff, 2010, "Price Discovery in Illiquid Markets: Do Financial Asset Prices Rise Faster Than They Fall?," *The Journal of Finance* 65(5), 1669-1702

Harris, Larry, 2015, "Transaction Costs, Trade Throughs, and Riskless Principal Trading in Corporate Bond Markets," Mimeo.

Hendershott, Terrence and Ananth Madhavan, 2013, "Click or Call? Auction versus Search in the Over-the-Counter Market," *Journal of Finance*, forthcoming.

Hollifield, Burton, Artem Neklyudov, and Chester Spatt, 2013, "Bid-Ask Spreads and the Pricing of Securitizations: 144a vs. Registered Securitizations," Working Paper, Carnegie Mellon University.

Hotchkiss, Edith S. and Tavy Ronen, 2002, "The Informational Efficiency of the Corporate Bond Market: An Intraday Analysis," *Review of Financial Studies* 15, 1325-1354.

Hugonnier, Julien, Benjamin Lester, and Pierre-Olivier Weill, 2015, "Heterogeneity in Decentralized Asset Markets," Working Paper, Swiss Finance Institute.

Leitner, Yaron, 2005, "Financial Networks: Contagion, Commitment, and Private Sector Bailouts," *Journal of Finance* 60, 2925?2953.

Lester, Benjamin, Guillaume Rocheteau, and Pierre-Olivier Weill, 2015, "Competing for Order Flow in OTC Markets," *Journal of Money, Credit and Banking* 47, 77?126.

Levin, Jonathan, 2002, "Multilateral Contracting and the Employment Relationship," *Quarterly Journal of Economics* 117, 1075?1103.

Moen, Espen R., 1997, "Competitive Search Equilibrium," *Journal of Political Economy* 105, 385-411.

Neklyudov, Artem, 2014, "Bid-Ask Spreads and the Over-the-Counter Interdealer Markets: Core and Peripheral Dealers," Working Paper, Swiss Finance Institute.

Neklyudov, Artem and Batchimeg Sambalaibat, 2015, "Endogenous Specialization and Dealer Networks," Working Paper, Swiss Finance Institute.

O'Hara, Maureen, Yihui Wang, and Xing Zhou, 2015, "The Best Execution of Corporate Bonds," Working paper, Cornell University - Samuel Curtis Johnson Graduate School of Management.

Shimer, Robert and Lones Smith, 2000, "Assortative matching and search," *Econometrica* 68, 343-370.

Shi, Shouyong, 2002, "A Directed Search Model of Inequality with Heterogeneous Skills and Skill-Biased Technology," *Review of Economic Studies* 69, 467-491.

Üslü , Semih, 2015, "Pricing and Liquidity in Decentralized Asset Markets," Working Paper, UCLA.

Yin, Xiangkang, 2005, "A Comparison of Centralized and Fragmented Markets with Costly Search," *Journal of Finance* 60, 1567-1590.

Zhu, Haoxiang, 2012, "Finding a Good Price in Opaque Over-the-Counter Markets." *Review of Financial Studies* 25, 1255-1285.

Appendix

Data description:

The following table summarizes the number of observations affected by each step of the data filters:

Filter	Full sample	Corporates
1. All trades from original filings (includes all markets, all trades since 2001)	19.1	4.5
2. Remove all transactions/events that do not involve a dealer (e.g., paydown, redemption, mature, correction)	6.6	3.1
3. Remove duplicates, aggregate all trades of the same insurance company in the same Cusip on the same day with the same dealer	6.5	3.1
4. Map dealer names to SEC CRD number, drop trades without a name match, drop trades with a dealer that trades less than 10 times in total over the sample period	6.1	2.9
5. Drop if not fixed coupon (based on eMaxx data), drop if outstanding amount information is in neither eMaxx nor FISD	5.3	2.5
6. Drop if trade is on a holiday or weekend	5.2	2.5
7. Drop if counterparty is "various"	4.1	2.1
8. Drop trades less than 90 days to maturity or less than 60 days since issuance (i.e., primary market trade)	2.8	1.5
9. Merge with FISD data, keep only securities that are not exchangeable, preferred, convertible, issued by domestic issuer, taxable muni, missing the offering date, offering amount, or maturity, and offering amount is not less than 100K	1.00	1.00

Table 1: Descriptive statistics

The table reports descriptive statistics for the corporate bond trades (Panel A), insurers (Panel B), and dealers (Panel C) in our sample from 2001 to 2014. Panel A reports the average across all trades over the sample period. Panels B and C report the total over the sample period. In the first and second column, the total is aggregated over the insurers and, respectively, dealers, while in the third column it is the average number of relations.

Panel A: Trades			
	All trades	Insurer buys	Insurer sells
No. of trades (k)	1,003	506	497
Trade par size ($mn)	1.80	1.73	1.87
Bond issue size ($mn)	916.66	921.37	911.87
Bond age (years)	2.88	2.67	3.09
Bond remaining life (years)	8.54	8.94	8.13
Private placement (%/100)	0.08	0.08	0.07
Rating (%/100)			
IG	0.74	0.76	0.72
HY	0.25	0.23	0.28
Unrated	0.01	0.01	0.01

Panel B: Insurers (N= 4,324)			
	Total volume ($bn)	Total no. of trades (k)	Avg. no. of dealers
All insurers	1,808 (100.0%)	1,003 (100.0%)	16 (3.6%)
Top 10 insurers	284 (15.7%)	69 (6.9%)	69 (15.8%)
Top 100 insurers	838 (46.3%)	329 (32.8%)	53 (12.1%)
Top 1,000 insurers	1,656 (91.6%)	834 (83.1%)	33 (7.5%)
Insurer type (N, % of total)			
Health (617, 14%)	85 (4.7%)	166 (16.6%)	17 (3.9%)
Life (1,023, 24%)	1,256 (69.5%)	462 (46.0%)	19 (4.4%)
P&C (2,684, 62%)	467 (25.8%)	375 (37.4%)	14 (3.2%)
Insurer characteristics:		Mean (SD)	
Insurer size		4.97 (0.90)	
Insurer RBC ratio		3.36 (0.35)	
Insurer cash-to-assets		3.49 (10.79)	
Life insurer		0.24 (0.42)	
P&C insurer		0.62 (0.48)	
Insurer rated A-B		0.37 (0.38)	
Insurer rated C-F		0.01 (0.07)	
Insurer unrated		0.53 (0.39)	

Continued

Table 1: Descriptive statistics—Continued

Panel C: Dealers (N= 439)			
	Total volume ($bn)	Total no. of trades (k)	Avg. no. of insurers
All dealers	1,808 (100.0%)	1,003 (100.0%)	155 (3.6%)
Top dealer	168 (9.3%)	86 (8.6%)	2,302 (53.2%)
Top 10 dealers	1,349 (74.6%)	664 (66.2%)	2,396 (55.4%)
Top 100 dealers	1,788 (98.9%)	984 (98.1%)	641 (14.8%)
Dealer characteristics:		Mean (SD)	
Dealer size		1.83 (1.16)	
NYC dealer		0.28 (0.45)	
Primary dealer		0.05 (0.21)	
Dealer leverage		0.13 (0.24)	
Dealer diversity		10.86 (5.02)	
Dealer dispersion		33.28 (21.62)	
Local dealer		0.17 (0.27)	
Dealer distance		0.76 (0.51)	

Table 2: Insurers' trading activity

The table reports the determinants of insurance company trading activity. We measure trading activity by the total dollar volume traded in a given month and, alternatively, by the number of trades over the same time horizon. All dependent variables are log-transformed by 100*log(1+x). All regressors are averaged across all trades of the insurer during the period and lagged by one time period. Estimates are from pooled regressions with time fixed effects. Standard errors are adjusted for heteroskedasticity and clustering at the insurer and time level. Significance levels are indicated by * (10%), ** (5%), *** (1%).

Determinant	(1) Volume ($bn)	(2) No. of trades
Insurer size	20.17***	14.66***
Insurer RBC ratio	2.04***	-0.87
Insurer cash-to-assets	0.09***	0.10***
Life insurer	5.74***	-2.18**
P&C insurer	-0.47	-5.82***
Insurer rated A-B	1.16	2.21***
Insurer rated C-F	5.00**	5.70**
Insurer unrated	6.54***	6.87***
Trade par size	-3.80***	-2.71***
Bond issue size	-0.00***	-0.00
Bond age	-0.44***	-0.63***
Bond remaining life	0.00	0.06**
Bond high-yield rated	5.81***	9.16***
Bond unrated	-4.02**	-4.44***
Bond privately placed	-4.22***	-1.62**
Variation in trade size	5.41***	1.82***
Variation in issue size	0.00	0.00
Variation in bond age	0.17**	0.12
Variation in bond life	0.66***	0.60***
Variation in bond rating	0.35**	0.98***
Variation in rated-unrated	-24.49*	-80.92***
Variation in private-public	8.51***	7.57***
No varieties traded	8.10***	10.32***
Lagged volume	0.52***	
Lagged no. of trades		0.63***
Month fixed effects	Yes	Yes
r2	0.628	0.497
N	165,766	165,766

Table 3: Size of insurers' trading network

The table reports the determinants of the size of insurers' trading network. We measure the size of the trading network by the number of different dealers that an insurance company trades with in a given month. All dependent variables are log-transformed by 100*log(1+x). All regressors are averaged across all trades of the insurer during the period and lagged by one time period. Estimates are from pooled regressions with time fixed effects. Small are insurers in the bottom three size quartiles. Large are insurers in the top quartile of the size distribution. Standard errors are adjusted for heteroskedasticity and clustering at the insurer and time level. Significance levels are indicated by * (10%), ** (5%), *** (1%).

Determinant	(1) All insurers	(2) Small insurers	(3) Large insurers
Insurer size	11.64***	4.54***	9.37***
Insurer RBC ratio	-0.88	-1.00*	-0.26
Insurer cash-to-assets	0.07***	0.03**	0.08***
Life insurer	-0.90	0.48	-2.38**
P&C insurer	-3.94***	-1.58***	-4.12***
Insurer rated A-B	1.43**	2.96***	0.15
Insurer rated C-F	2.86*	4.03***	1.30
Insurer unrated	4.67***	4.04***	2.36**
Trade par size	-2.08***	-0.70***	-1.76***
Bond issue size	-0.00*	-0.00**	-0.00
Bond age	-0.51***	-0.21***	-0.67***
Bond remaining life	0.04*	0.02	0.00
Bond high-yield rated	6.81***	-0.61	7.81***
Bond unrated	-4.18***	-0.96	-5.41**
Bond privately placed	-1.38**	-0.38	-1.46
Variation in trade size	1.21***	0.37	1.12***
Variation in issue size	0.00	-0.00	0.00
Variation in bond age	0.19***	0.26***	0.17**
Variation in bond life	0.48***	0.23***	0.40***
Variation in bond rating	0.63***	0.17	0.61***
Variation in rated-unrated	-50.77***	-14.59	-48.46***
Variation in private-public	6.26***	1.82	4.85***
No varieties traded	4.96***	0.18	6.84***
Lagged no. of dealers	0.61***	0.29***	0.63***
Month fixed effects	Yes	Yes	Yes
r2	0.489	0.092	0.441
N	165,766	64,288	101,478

Table 4: Persistence in insurers' trading network

The table reports the probability that an insurer uses a dealer network with given size next period, conditional on the same insurer using a given network size this period:

$$Pr(\text{No. of dealers in } t+1 | \text{No. of dealers in } t).$$

We compute these dealer switching probabilities for each month (Panel A) and year (Panel B)

Panel A: Monthly switching probabilities

	No. of dealers next month			
No. of dealers this month	1	2-5	6-10	>10
1	0.61	0.35	0.04	0.01
2-5	0.27	0.55	0.15	0.03
6-10	0.07	0.36	0.41	0.15
>10	0.02	0.12	0.34	0.52

Panel B: Annual switching probabilities

	No. of dealers next year			
No. of dealers this year	1	2-5	6-10	>10
1	0.61	0.30	0.06	0.03
2-5	0.20	0.54	0.20	0.06
6-10	0.06	0.31	0.40	0.24
>10	0.01	0.07	0.17	0.75

Table 5: Insurer-dealer trading networks

The table reports the fraction of insurers of different size that trade with dealers of different size. We split insurers and, respectively, dealers into size-based quartiles.

Panel A: Fraction of insurers trading with different dealers

	Insurer size			
Dealer size	Very small	Small	Medium	Large
Large	0.96	0.99	1.00	1.00
Medium	0.11	0.27	0.42	0.70
Small	0.03	0.07	0.14	0.33
Very small	0.02	0.02	0.04	0.12

Panel B: Fraction of dealers trading with different insurers

	Insurer size			
Dealer size	Very small	Small	Medium	Large
Large	0.91	0.99	0.99	1.00
Medium	0.47	0.76	0.86	0.90
Small	0.19	0.50	0.66	0.77
Very small	0.18	0.24	0.32	0.61

Table 6: Who trades more with dealers of different rank?

The table reports the determinants of the insurers' choice to trade with bigger or smaller dealers. The dependent variable is the dealer's rank in terms of overall trading activity, ranging from the least active dealer (1) to the most active dealer (439). Estimates are from pooled regressions with day fixed effects. Standard errors are adjusted for heteroskedasticity and clustering at the insurer, dealer, bond, and day level. Significance levels are indicated by * (10%), ** (5%), *** (1%).

Determinant	(1) Very small dealer	(2) Small dealer	(3) Medium dealer	(4) Large dealer
Insurer size	0.08***	0.31***	1.18***	14.70***
Insurer RBC ratio	0.02	0.09	-0.02	-3.93***
Insurer cash-to-assets	0.00	0.00	0.02***	0.12***
Life insurer	0.00	-0.05	0.23	-1.35
P&C insurer	0.02	-0.09	-0.31	-5.50***
Insurer rated A-B	0.04	0.25**	0.50	2.67***
Insurer rated C-F	0.11	0.04	1.83	3.53
Insurer unrated	0.05	0.40***	0.86**	6.77***
Trade par size	-0.02***	-0.07***	-0.34***	-2.34***
Bond issue size	-0.00	-0.00***	-0.00***	-0.00***
Bond age	-0.00	-0.00	0.01	-0.86***
Bond remaining life	-0.00	0.00	0.02	0.10***
Bond high-yield rated	0.01	0.19*	0.59*	5.24***
Bond unrated	0.05	0.26	0.48	-5.77**
Bond privately placed	-0.06	-0.04	-0.58*	-3.96***
Variation in trade size	0.01	0.03	0.40***	0.34*
Variation in issue size	0.00	-0.00	0.00	0.00***
Variation in bond age	-0.00	0.03*	0.21***	0.90***
Variation in bond life	0.00	0.01	0.02	0.61***
Variation in bond rating	0.02	0.03	0.12**	1.32***
Variation in rated-unrated	-1.58	-2.82	-11.79**	-108.67***
Variation in private-public	0.17**	0.22	1.95***	9.79***
No varieties traded	0.06**	0.06	0.21	-10.29***
Lagged dealer choice	0.08***	0.15***	0.27***	0.28***
Month fixed effects	Yes	Yes	Yes	Yes
r2	0.011	0.039	0.113	0.203
N	165,766	165,766	165,766	165,766

Table 7: Execution costs and investor-dealer relations

The table reports the determinants of execution costs on insurance company trades. Execution costs are expressed in basis points relative to the Merrill Lynch quote at the time of the trade. Estimates are from panel regressions with day fixed effects or, respectively, day and bond fixed effects. Standard errors are adjusted for heteroskedasticity and clustering at the insurer, dealer, bond, and day level. Significance levels are indicated by * (10%), ** (5%), *** (1%).

Determinant	(1)	(2)	(3)	(4)	(5)
Dealer size	-26.47***	-22.58***	-24.17***	-12.03***	-12.66***
Insurer size	-21.97***	-18.85***	-19.52***	-2.18	-1.52
Dealer size × Insurer size	3.68***	3.00***	3.12***	-0.13	-0.28
Insurer no. of dealers				-1.09***	-1.17***
Dealer size × No. dealers				0.20***	0.22***
NYC dealer		-6.25***	-6.51***	-5.68***	-5.92***
Primary dealer		2.64*	2.23	2.37*	1.95
Dealer leverage		-4.58*	-4.71*	-3.96*	-4.02
Dealer diversity		0.34***	0.39***	0.31***	0.35***
Dealer dispersion		0.00	0.02	0.02	0.04
Local dealer		0.27	0.29	0.49	0.52
Dealer distance		-0.09	-0.05	0.16	0.22
Insurer RBC ratio		-4.29***	-4.77***	-4.29***	-4.76***
Insurer cash-to-assets		-0.03*	-0.03*	-0.01	-0.01
Life insurer		5.52***	7.06***	4.91***	6.36***
P&C insurer		2.73***	3.17***	1.84**	2.20**
Insurer rated A-B		-0.62	-0.82	-0.19	-0.39
Insurer rated C-F		12.63*	12.55*	11.40*	11.25
Insurer unrated		0.63	0.63	0.37	0.33
Insurer buy		40.18***	40.65***	39.92***	40.41***
Trade size × Buy		-0.22**	-0.15	-0.32***	-0.27***
Trade size × Sell		0.57***	0.58***	0.48***	0.47***
Bond issue size			-0.00***		-0.00***
Bond age			0.66***		0.64***
Bond remaining life			0.80***		0.81***
Bond HY rated			3.81***		4.30***
Bond unrated			-6.55***		-6.48***
Bond privately placed			3.18***		3.31***
Bond fixed effects	Yes	Yes	No	Yes	No
Day fixed effects	Yes	Yes	Yes	Yes	Yes
r2	0.091	0.151	0.096	0.152	0.098
N	1,004,338	891,138	891,875	891,138	891,875

Table 8: Execution costs and investor-dealer relations—split by insurer size

The table reports the determinants of execution costs on insurance company trades. Execution costs are expressed in basis points relative to the Merrill Lynch quote at the time of the trade. Estimates are from panel regressions with bond and day fixed effects. Small are insurers in the bottom three size quartiles. Large are insurers in the top quartile of the size distribution. Standard errors are adjusted for heteroskedasticity and clustering at the insurer, dealer, bond, and day level. Significance levels are indicated by * (10%), ** (5%), *** (1%).

	(1)	(2)	(3)	(4)
Determinant	Small insurers		Large insurers	
Dealer size	-12.50*	-9.86*	-17.67***	-11.12***
Insurer size	-14.89***	-8.24*	-14.50***	-1.46
Dealer size × Insurer size	0.76	0.39	2.35***	-0.14
Insurer no. of dealers		-1.38***		-0.99***
Dealer size × No. dealers		0.08		0.19***
NYC dealer	-10.34***	-6.79***	-5.06***	-4.88***
Primary dealer	3.51	1.88	2.59**	2.51**
Dealer leverage	1.53	1.97	-5.32**	-4.72**
Dealer diversity	0.71***	0.48***	0.22**	0.22**
Dealer dispersion	0.01	0.02	-0.01	0.01
Local dealer	2.37	2.00	-0.20	0.04
Dealer distance	-0.12	0.12	-0.10	0.10
Insurer RBC ratio	-10.13***	-10.12***	-2.92	-2.83
Insurer cash-to-assets	-0.03	-0.00	-0.01	0.00
Life insurer	9.78***	9.53***	4.11***	3.55***
P&C insurer	6.91***	6.05***	1.73**	1.10
Insurer rated A-B	-2.01	0.29	0.03	0.28
Insurer rated C-F	-0.35	-0.59	17.75*	16.26*
Insurer unrated	-0.04	-0.78	0.55	0.03
Insurer buy	36.95***	35.53***	40.60***	40.50***
Trade size × Buy	-0.70**	-1.34***	-0.26***	-0.34***
Trade size × Sell	0.44	-0.36	0.53***	0.48***
Bond and day fixed effects	Yes	Yes	Yes	Yes
r2	0.298	0.309	0.150	0.151
N	122,477	122,477	766,898	766,898

Table 9: Execution costs and investor-dealer relations—split by dealer size

The table reports the determinants of execution costs on insurance company trades. Execution costs are expressed in basis points relative to the Merrill Lynch quote at the time of the trade. Estimates are from panel regressions with bond and day fixed effects. Small are dealers in the bottom three size quartiles. Large are dealers in the top quartile of the size distribution. Standard errors are adjusted for heteroskedasticity and clustering at the insurer, dealer, bond, and day level. Significance levels are indicated by * (10%), ** (5%), *** (1%).

	(1)	(2)	(3)	(4)
Determinant	Small dealers		Large dealers	
Dealer size	-23.90	-23.10	-19.70***	-9.31**
Insurer size	-21.66***	-13.26	-16.77***	-0.02
Dealer size × Insurer size	4.52	4.71	2.57***	-0.58
Insurer no. of dealers		-0.51		-1.12***
Dealer size × No. dealers		-0.01		0.21***
NYC dealer	-16.19***	-12.52***	-6.04***	-5.57***
Primary dealer	35.70**	41.32**	2.29	2.12
Dealer leverage	23.83	28.74*	-4.08*	-3.56
Dealer diversity	0.35	0.37	0.33***	0.31***
Dealer dispersion	-0.17	-0.15	0.02	0.03
Local dealer	1.89	0.61	0.28	0.51
Dealer distance	-4.08	-3.53	0.01	0.22
Insurer RBC ratio	4.18	7.62	-4.30***	-4.38***
Insurer cash-to-assets	-0.14	-0.11	-0.03*	-0.01
Life insurer	10.29**	8.94**	5.31***	4.76***
P&C insurer	7.27*	5.15	2.62***	1.80**
Insurer rated A-B	7.91	10.12**	-0.63	-0.20
Insurer rated C-F	-8.20	-7.12	12.78*	11.70*
Insurer unrated	12.22**	13.44**	0.51	0.28
Insurer buy	65.44***	63.75***	39.99***	39.77***
Trade size × Buy	-2.00*	-2.50**	-0.20**	-0.31***
Trade size × Sell	4.54***	4.08***	0.56***	0.47***
Bond and day fixed effects	Yes	Yes	Yes	Yes
r2	0.704	0.706	0.149	0.151
N	9,913	9,913	878,022	878,022

Table 10: Insurer-dealer trade surplus and bargaining power determinants

The table reports the determinants of dealers' reservation values RV_D in trading with insurers and, respectively, insurers' reservations values RV_I and of the sharing rule w.

$$
\begin{aligned}
\text{Surplus} \quad S &= (X_D'\beta_D - X_I'\beta_I) * (1 - 2 * \mathbf{1}_{Buy}) + \varepsilon, \\
\text{Price} \quad P &= X_I'\beta_I + \Lambda(X_w'\beta_w)(X_D'\beta_D - X_I'\beta_I) + \frac{\gamma}{\sigma} \frac{\phi(\frac{1}{\sigma}(X_D'\beta_D - X_I'\beta_I))}{\Phi(\frac{1}{\sigma}(X_D'\beta_D - X_I'\beta_I))} * (1 - 2 * \mathbf{1}_{Buy}) + \eta
\end{aligned}
$$

where $\mathbf{1}_{Buy}$ is an indicator for whether the insurer buys or sells, $\Lambda \in [0,1]$ is the inverse logit transformation and X_D, X_I, and X_w are sets of covariates. Estimates are obtained in two stages. The first stage estimates a probit regression to obtain the determinants of reservation values. The second stage estimates a nonlinear least-squares regression to obtain the determinants of insurers' bargaining power. We estimate the model jointly for insurer buys and insurers sells. Standard errors are adjusted for heteroskedasticity and clustering at the insurer and dealer level. Significance levels are indicated by * (10%), ** (5%), *** (1%).

Panel A: Parameter estimates

	Valuations RV		Sharing rule w
Determinant	Dealer (β_D)	Insurer (β_I)	Insurer (β_w)
Dealer size	1.00***		2.42***
NYC dealer	0.07		0.62***
Primary dealer	0.23***		-0.14
Dealer leverage	-0.02		-0.20
Dealer diversity	0.01		-0.03***
Dealer dispersion	-0.00		-0.02***
Local dealer	-0.22**		-0.03
Dealer distance	-0.04		0.05
Insurer size		-0.48***	3.23***
Insurer RBC ratio		0.11***	0.54***
Insurer cash-to-assets		-0.00***	0.00
Life insurer		0.10**	-0.91***
P&C insurer		0.17***	-0.59***
Insurer rated A-B		-0.27***	0.13
Insurer rated C-F		-0.09	-0.29
Insurer unrated		0.01	-0.45***
Dealer size × Insurer size			-0.47***
Insurer buy	0.86***	0.90***	0.20
Constant	-0.54***	6.57***	-15.45***
ln(σ):			γ:
Constant	-0.68***		-0.82***
Insurer buy	0.46***		-0.22
N	3,379,368		108,806

Continued

Table 10: Insurer-dealer trade surplus and bargaining power determinants—Continued

Panel B: Model predictions and counterfactuals						
					Execution cost (bp)	
	$E[RV_D]$	$E[RV_I]$	$E[S]$	w	Predicted	Realized
Insurer buy:						
Relation=0	60.61	34.69	-25.92	0.67	51.30	.
	(19.72)	(13.60)	(9.51)	(0.29)	(9.28)	.
Relation=1	31.56	27.95	-3.62	0.83	37.19	37.17
	(11.17)	(6.22)	(7.56)	(0.16)	(5.76)	(43.90)
All	59.60	34.45	-25.15	0.68	50.81	37.17
	(20.20)	(13.47)	(10.30)	(0.29)	(9.54)	(43.90)
Insurer sell:						
Relation=0	-12.50	4.07	-16.57	0.64	6.14	.
	(12.73)	(8.91)	(6.03)	(0.30)	(5.80)	.
Relation=1	6.48	8.84	-2.36	0.82	-1.95	-1.86
	(6.86)	(4.00)	(4.71)	(0.16)	(3.42)	(48.05)
All	-11.86	4.23	-16.10	0.65	5.87	-1.86
	(13.04)	(8.83)	(6.52)	(0.30)	(5.92)	(48.05)
All:						
Relation=0	24.03	19.37	-21.24	0.66	28.70	.
	(40.15)	(19.14)	(9.23)	(0.30)	(23.87)	.
Relation=1	19.28	18.59	-3.00	0.83	18.02	18.49
	(15.62)	(10.90)	(6.36)	(0.16)	(20.14)	(49.90)
All	23.87	19.34	-20.62	0.66	28.34	18.49
	(39.57)	(18.92)	(9.73)	(0.30)	(23.83)	(49.90)

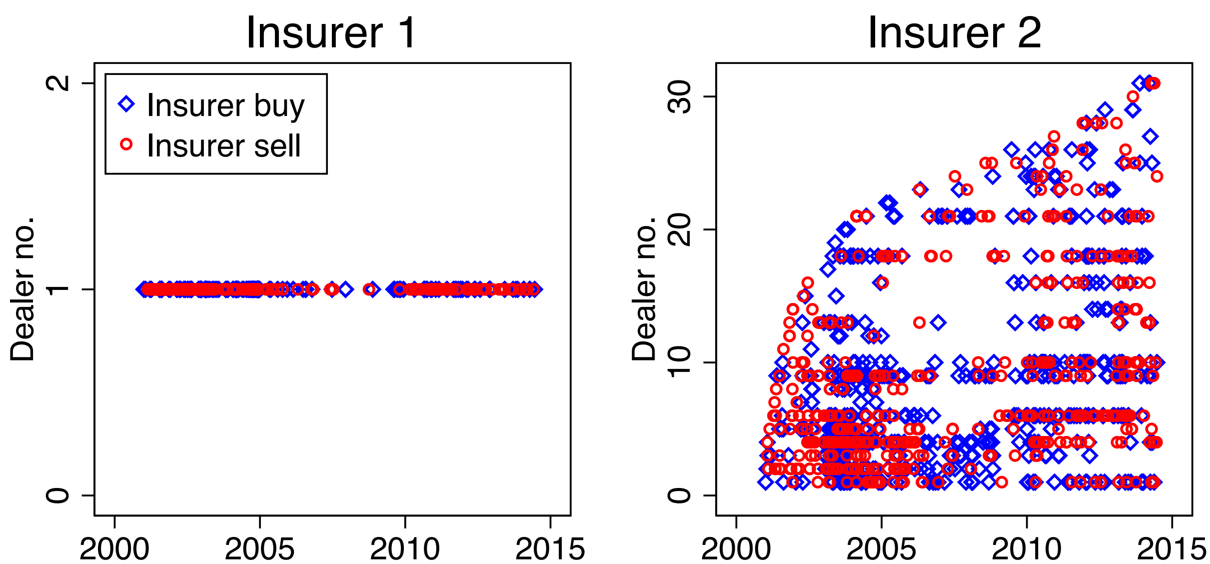
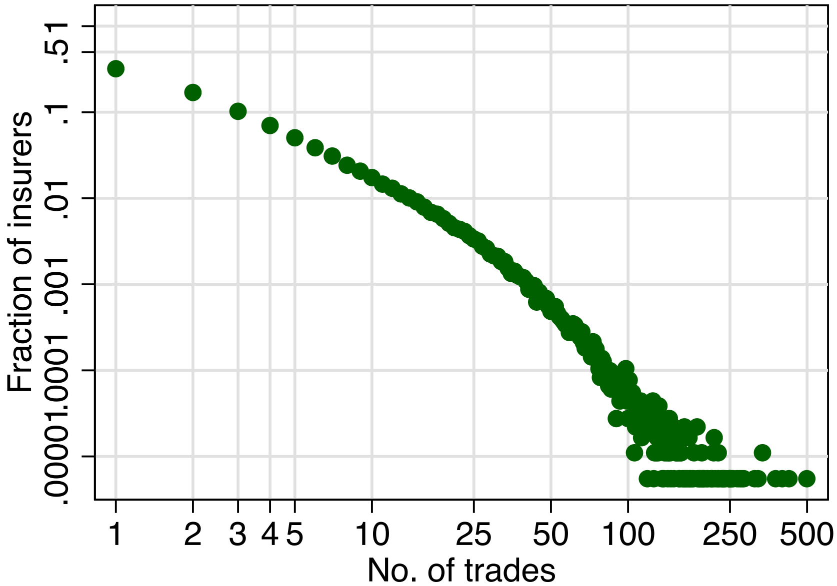


Figure 1: Example of dealer-client trading relations
The figure shows the buy (blue squares) and sell (red circles) trades of two insurance companies with different dealers. We sort the dealers on the vertical axis by the first time they trade with the corresponding insurance company.

Panel A: Distribution of insurer trades



Panel B: Degree distribution for insurer-dealer relations

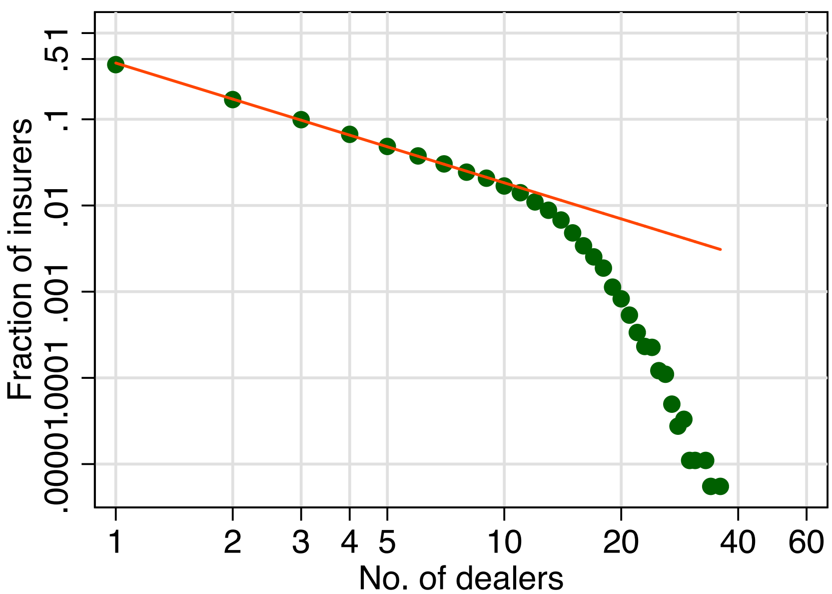
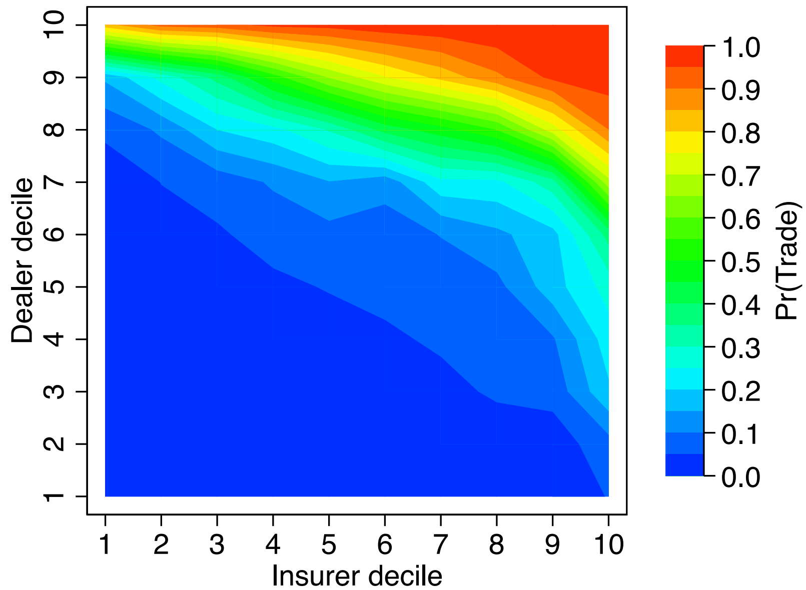


Figure 2: Insurer trading activity and size of insurer-dealer trading networks
The figure shows the distribution of insurer trades per month (Panel A) and the degree distribution for insurer-dealer relations by month (Panel B). We use a log-log scale.

Panel A: Probability that insurer trades with dealer in size bin 1-10



Panel B: Trade concentration when insurer trades with dealer in size bin 1-10

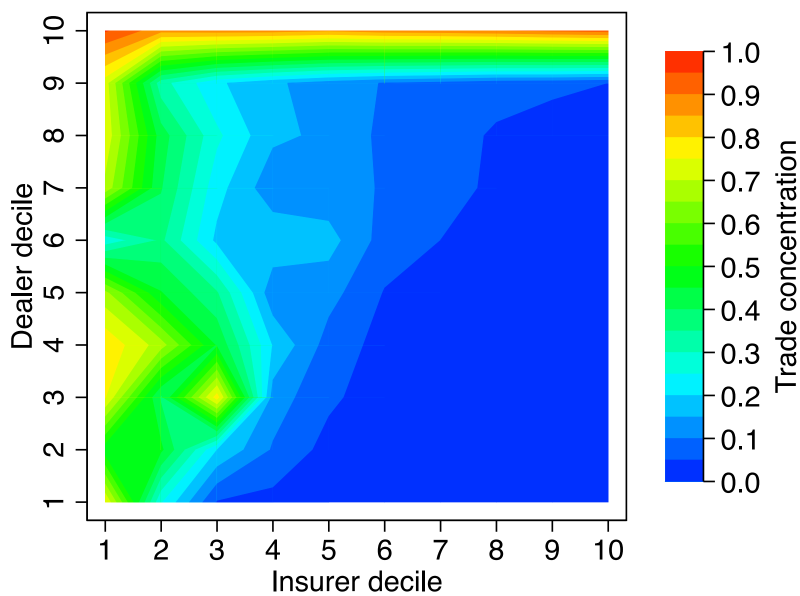


Figure 3: Investor-dealer trading networks and insurers' order flow concentration

The figure illustrates the trading networks of each insurer and, respectively, dealer. Panel A depicts the trading activity in terms of the probability that an insurer trades with a dealer of given size over the entire sample period. Panel B depicts the corresponding trade concentration for each insurer. On the horizontal (vertical) axis, we sort insurers (dealers) from low to high by their frequency of trading over the sample period.

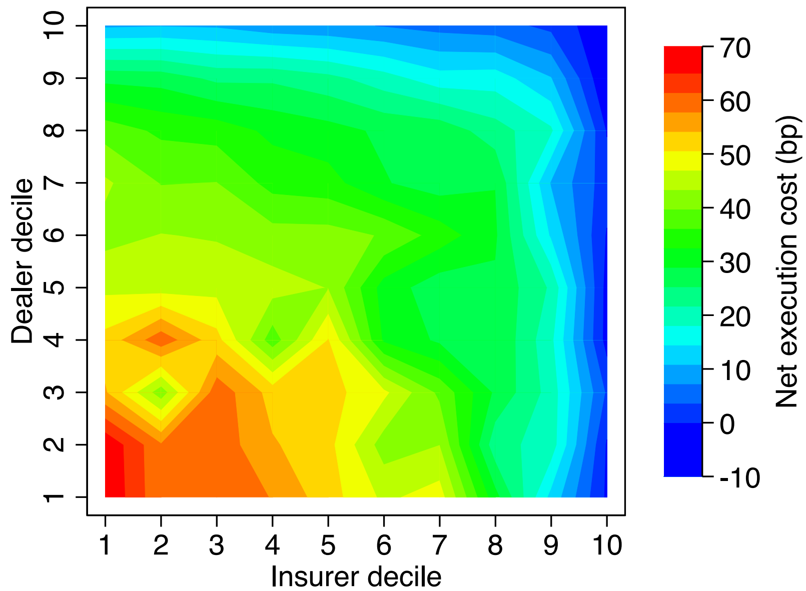
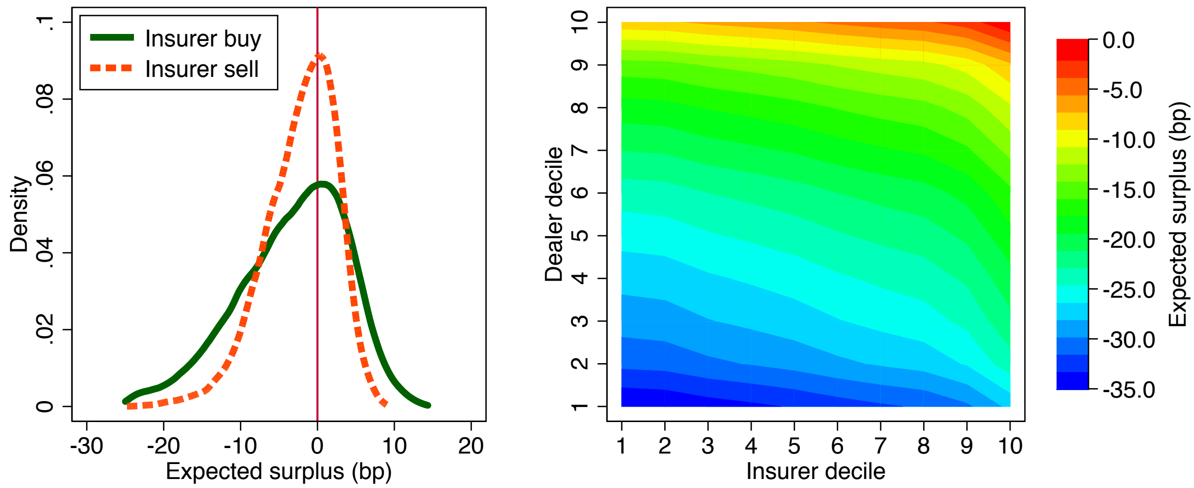


Figure 4: Investor-dealer trading relations and execution costs

The figure illustrates the execution costs specific to the insurer, dealer, and investor-dealer relations. We estimate the relation-specific costs $E[X'_{it}\widehat{\beta}]$ for bond i at time t and the bond- and time-specific costs $\widehat{\alpha}_i + \widehat{\alpha}_t$ from Net execution cost$_{it} = X'_{it}\beta + \alpha_i + \alpha_t + \epsilon_{it}$. Coefficient estimates are obtained from specification (4) in Table 7. Using the predicted execution cost components for each trade, we aggregate each cost component for each insurer-dealer pair by taking averages over time. The map depicts the quantiles of the execution cost distribution. On the horizontal (vertical) axis, we sort insurers (dealers) by their frequency of trading from low to high.

Panel A: Expected surplus by trade type (left) and by dealer and insurer decile (right)



Panel B: Surplus sharing rule by trade type (left) and by dealer and insurer decile (right)

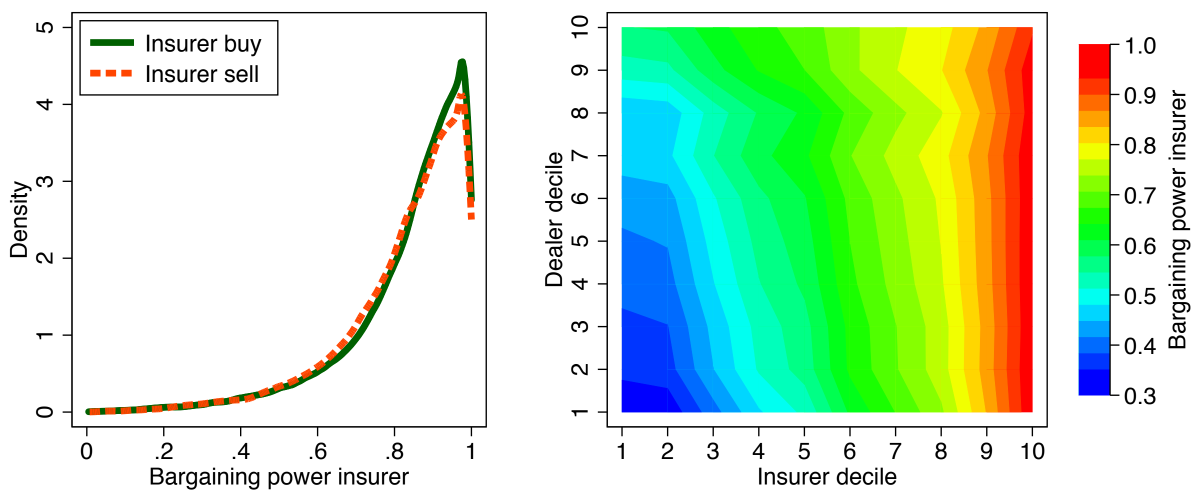


Figure 5: Surplus and sharing rule

The figure illustrates the estimated trade surplus (Panel A) and the surplus sharing rule (Panel B) by trade type (left) and by dealer and insurer decile (right). Coefficient estimates are obtained from Table 10. Using the coefficient estimates, we predict the trade surplus and, respectively, sharing rule and aggregate each variable across trade type and insurer-dealer deciles. On the horizontal (vertical) axis, we sort insurers (dealers) by their frequency of trading from low to high.