Information Flows in Trading Networks

Stefan Huber[a], Edward M. Watts[b], and Christina Zhu[c]

[a]Rice University
[b]Yale School of Management
[c]The Wharton School, University of Pennsylvania

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Abstract

We study the informational value of trading networks in over-the-counter (OTC) markets. Using detailed transaction-level data from the corporate bond market, we show that investors with larger dealer trading networks make superior trading decisions before changes in credit fundamentals and yield better risk-adjusted performance. Our evidence indicates that an important mechanism for this result is that dealers reward their trading clients with private information. Consistent with this mechanism, we show that investors make superior trading decisions when they have trading relationships with dealers likely to have novel information. In addition, investors with trading relationships with deal-affiliated dealers transact more profitably before important merger and acquisition (M&A) deals are publicly announced. Collectively, our evidence highlights the importance of trading relationships for investors' private information acquisition.

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Email addresses: Stefan Huber (`sjhuber@rice.edu`); Edward Watts (`edward.watts@yale.edu`); Christina Zhu (`chrzhu@wharton.upenn.edu`).

1. Introduction

Over-the-counter (OTC) markets are characterized by significant fragmentation, and absent a centralized exchange, investors rely heavily on dealers to facilitate trade. As a result, investors dedicate substantial resources to developing and maintaining their dealer network (i.e., "trading network"). Although growing empirical evidence highlights the importance of trading networks for investors to obtain liquidity and competitive pricing, significantly less is known about the auxiliary benefits that dealers provide to investors to maintain and strengthen these relationships.

In this paper, we explore one such benefit that trading networks can provide to investors—private information. Prior work on the economics of networks highlights how economic agents can improve their outcomes by acquiring information through their network (e.g., Conley and Udry, 2010; Bertrand, Luttmer, and Mullainathan, 2000). A growing literature in finance also highlights the importance of social networks for information dissemination in various other financial markets settings (e.g., Hirshleifer, 2020; Kuchler and Stroebel, 2021). Hence, information sharing is one potentially important auxiliary benefit that investors obtain from their relationships with dealers in OTC markets.

Using detailed, deanonymized data from the OTC corporate bond market, we trace investors' entire dealer networks. Leveraging these novel data, we provide evidence that investors with larger dealer networks trade more profitably ahead of adverse credit-relevant events, leading to improved investment performance. Additional analyses trace investors' trading decisions directly to individual connections in their dealer network, helping to rule out alternative explanations for this outperformance by focusing on instances where the dealers are the most likely sources of private information.[1] Collectively, our evidence is consistent with dealers rewarding investors with private information for their trading flow.

To explore these issues, we leverage detailed transaction data reported by an important type of investor, insurance companies. Insurance companies are one of the largest investor types in corporate bonds, which are traded primarily in OTC markets. Each quarter, insurance companies are required to report data on all their financial market transactions to the National Association of Insurance Commissioners (NAIC), including the identity of the dealer with whom each trade is executed. Using these data, which include approximately 2 million secondary market transactions across 1,577 insurers from 2009 through 2022, we study the impact of insurers' dealer networks on their investment decision-making.

We begin by investigating the relation between insurers' trading networks and the performance of their trades. Specifically, we explore the relation between the size of the insurer's trading network and the informativeness of the insurer's trading decisions with respect to future credit rating downgrades. This provides a powerful setting to detect informed trading by insurers because credit ratings not only impact the value of their bond holdings (e.g., Hand, Holthausen, and Leftwich, 1992; Cornaggia, Cornaggia, and Israelsen, 2018; Bonsall, Gillette, Pundrich, and So, 2024) but also determine their risk-based capital requirements (i.e., see Appendix B).

We show that the trading decisions of well-connected insurers are indicative about future credit rating downgrades over various time horizons. Specifically, as insurers' network size

[1] These analyses help to address the concerns that more active traders with larger dealer networks are sophisticated in other ways (i.e., larger research teams with more resources), which would lead to improved decision-making. For instance, this may be because they have alternative sources of information outside dealer networks or are more effective at processing publicly available information (e.g., Blankespoor, DeHaan, and Marinovic, 2020). These concerns are not unique to our study, as work on trading networks is inherently descriptive given the endogenous nature of their development.

increases, their sell transactions, relative to their buy transactions, are significantly more positively related to future downgrades. These findings are also robust to the inclusion of insurer and bond fixed effects, alleviating many potential alternative explanations.

We also show these results are particularly prevalent among the most significant adverse credit-related events. Specifically, we find that better-connected insurers exhibit improved trading ahead of downgrades to non-investment grade status and bond defaults. Those events have the most severe consequences for bonds' valuations and insurers' risk-based capital charges and, therefore, are those that insurers have strong incentives to avoid.

We supplement the above results with portfolio analyses to provide evidence of the aggregate impact of the improved decision-making we document. Using monthly bond return data, we construct a long-short portfolio based on the bonds that are strongly bought and sold by well-connected insurers. The monthly risk-adjusted abnormal returns of this portfolio is approximately 6.5 basis points (t-statistic = 3.4). Next, comparing the excess risk-adjusted performance of this high-connections portfolio to a similarly constructed portfolio from low-connections investors yields monthly risk-adjusted abnormal high-low returns of approximately 7.0 basis points (t-statistic = 3.2), or approximately 0.84% annually. This outperformance is economically meaningful when considering the average monthly bond return in our sample is just 38 basis points.

Collectively, our primary findings highlight that investors with larger dealer networks appear significantly more informed than investors with smaller networks. Because we cannot observe the specific interactions between insurers and dealers, an important question is whether investors are sourcing this information from the dealer firms themselves or whether larger networks are associated with improved information acquisition abilities from other sources. We provide several sets of analyses to establish that the dealer networks themselves are the sources of some of these information advantages, and to provide insights into the incentives of dealers to provide this information to insurers.

First, we explore cross-sectional variation across dealers to show that insurers' investment decision-making only improves with the size of dealer networks when those dealers are likely to have information. Specifically, we leverage the fact that many dealers operate as stand-alone trading desks without either investment banking or research divisions. As these dealers are significantly less likely to have novel information, we would expect network connections to these dealers to be significantly less important to investors for information acquisition purposes. Consistent with this interpretation, we find that the sell transactions of insurers who are well-connected to dealers with M&A advisory and research divisions are relatively (compared to buy transactions) more predictive of future adverse credit events, whereas this predictive ability is not present for the sell transactions of insurers who are well-connected to dealers without M&A advisory and research divisions.

Second, we study transactions ahead of M&A deal announcements. These announcements offer a powerful setting where non-public information is likely privy to specific dealers, i.e., those who have an investment banking arm that is advising that M&A deal. We find that trading clients of those deal-affiliated dealers exhibit improved decision-making in the 30 trading days before these deals are publicly announced. Specifically, when an insurer is connected to a deal-affiliated dealer, the insurer is more likely to avoid losses from bonds of target companies' bonds that experience negative returns or a credit rating downgrade after the event. We also find this relationship strengthens with the number of potential sources of this information, in that the association increases in the insurer's number of deal-affiliated trading connections.

Finally, we provide evidence of dealers' incentives to provide private information to insurers. To do so, we further leverage the M&A setting which allows us to observe the strength of the relationships between dealers and their trading clients in terms of order flow. We find that the more important the trading flow of an insurer is to a dealer, the more likely that the insurer will trade profitably ahead of M&A announcements with which the dealer is affiliated. As M&A transactions are relatively rare, we also provide more generalizable evidence on these issues in the context of credit ratings downgrades. Collectively, our findings are consistent with dealers rewarding their trading clients with information for their order flow, similar to what has been found for traditional research channels in equities markets (e.g., Irvine, 2000; Frankel, Kothari, and Weber, 2006; Green, Jame, Markov, and Subasi, 2014).

Our central contribution is to provide evidence of the informational value of dealer networks. The amount of private information flowing from dealers to their trading clients in these networks is largely unknown, given the networks themselves are typically unobservable. We use novel data to overcome this challenge, thus adding to a growing body of empirical literature in accounting, economics, and finance that has explored the importance of networks in improving decision-making and outcomes in several settings.[2] Within the context of equity markets, Di Maggio, Franzoni, Kermani, and Sommavilla (2019) and Barbon, Di Maggio, Franzoni, and Landier (2019) show that brokerage firms leak informed order flow information to their best clients. Our study complements this prior literature by showing that OTC

[2] For instance, extant literature explores the various informational benefits of director networks (e.g., Larcker, So, and Wang, 2013; Akbas, Meschke, and Wintoki, 2016), analyst networks (e.g., Martens and Sextroh, 2021; Huang, Lin, and Zang, 2022), equity investor networks (e.g., Ozsoylev, Walden, Yavuz, and Bildik, 2014; Ahern, 2017; Caskey, Minnis, and Nagar, 2024), and political networks (e.g., Christensen, Mikhail, Walther, and Wellman, 2017; Stephan, Walther, and Wellman, 2021).

bond market connections allow investors to acquire valuable private information about firms' credit-related performance.[3] In doing so, we also add to the broader literature on information acquisition and privately informed trade and, in particular, the comparatively limited literature which investigates these issues in the context of fixed income markets (e.g., De Franco, Vasvari, Vyas, and Wittenberg-Moerman, 2014; Even-Tov, 2017; De Franco, Shohfi, Xu, and Zhu, 2023; Hagenberg, 2024).

Our paper also relates to the extensive literature that establishes the importance of dealers for trade intermediation in OTC markets (e.g., Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018; Bessembinder, Spatt, and Venkataraman, 2020; Huber, Kim, and Watts, 2024). Prior studies have established the importance of trading networks for the ability of both investors (e.g., O' Hara, Wang, and Zhou, 2018; Choi, Huh, and Shin, 2024) and dealers (e.g., Di Maggio, Kermani, and Song, 2017; Schultz and Song, 2019) to obtain liquidity and price execution. We have significantly less empirical evidence on other functions of trading networks for investors, despite prior studies' acknowledgment that they may exist. For instance, Hendershott, Li, Livdan, and Schürhoff (2020) highlight non-trade-related benefits to explain why some corporate bond investors choose to have a *larger* dealer network despite appearing to obtain *worse* liquidity by doing so. We offer an important explanation for this observed equilibrium behavior by highlighting the role of dealer networks in investors' information acquisition.

The remainder of the paper proceeds as follows. The next section provides an overview

[3] Our findings are also related to, yet fundamentally different from, prior research that documents that informed investors split their trades to transact with more counterparties to conceal their informed trading in some markets (e.g., Kondor and Pintér, 2022). Given the relative illiquidity of corporate bond markets, trade splitting is exceedingly rare. In untabulated results, we find that in the overwhelming majority of trades and value of trades (more than 95% of each), the insurer transacts with only one dealer counterparty in that bond over the course of a month.

of the institutional setting and theoretical motivation for our predictions. Section 3 describes the data used in the study and presents descriptive statistics. Section 4 discusses the empirical strategy and provides the main results of the paper on network size and insurer trading performance. Section 5 presents evidence of the mechanism for our results. Section 6 concludes.

2. Motivation and Institutional Details

At approximately $10.8 trillion in principal amount outstanding, the U.S. corporate bond market is one of the world's largest and most economically important markets. The market continues to grow and serves as the chief source of new capital for many firms, with a primary issuance market averaging around $1.5 trillion each year.[4] It also serves as a primary investment vehicle for many investors of critical importance in the economy, with pension funds and insurance companies as some of the primary holders.

Trading occurs in a largely decentralized marketplace characterized by fragmentation and limited price and quote transparency. To place a trade, investors need to search for a dealer willing to transact in a security. Therefore, this type of market is characterized by high search frictions in which dealer networks play a role (e.g., see Bessembinder et al., 2020 for a review). Dealers hold inventory, bearing significant inventory-holding risk, which is one reason trading relationships with investors are useful to dealers. Prices are agreed upon through bilateral negotiations, often over the phone or via Bloomberg. Although each individual security is illiquid, significant trading transaction volume occurs in aggregate,

[4] All numbers in this section are calculated by the Securities Industry and Financial Markets Association (SIFMA) during Q1 of 2024. See `https://tinyurl.com/33d7cn2z`.

with approximately \$56.1 billion in daily trading volume.[5]

Given the heavy involvement of dealers in these markets, investors often form close relationships with dealers through which they transact. In practice, institutional investors are typically assigned a dedicated salesperson who manages the relationship on behalf of the dealer and acts as a liaison between the investor and other parts of the trading desk. The salesperson facilitates investors' interactions with traders, research analysts, or the syndicate desk for primary bond issues. Many of these relationships last for long periods of time, often following investment professionals and salespersons as they move firms.

Prior studies have explored the importance of these relationships as they relate to liquidity and execution costs. For instance, using similar data to ours, empirical studies find that dealers provide better liquidity to more active traders (O' Hara et al., 2018). Hendershott et al. (2020) show that execution costs are non-monotone in investors' dealer network size, initially declining and then increasing. This non-monotone relation is consistent with investors trading off lower transaction costs of repeat business with the same dealer, which favors a smaller network, with a preference for a larger network for other reasons. These reasons include benefits of these relationships that are unrelated to execution costs. For instance, by trading with multiple counterparties, investors gain access to different dealer inventories of bonds in primary market allocations and secondary market transactions. Consistent with this particular benefit, Nikolova, Wang, and Wu (2020) find that underwriters reward their clients with preferential treatment in primary market allocations.

We focus on another crucial benefit investors can obtain from their dealer networks:

[5] In the last several years, algorithmic execution has become more prominent, particularly for non-institutional trade sizes (e.g., Hendershott and Madhavan, 2015; O'Hara and Zhou, 2021).

information. Through their trading relationships, investors can gain access to a range of value-relevant information about the securities they trade. This includes formal channels, such as investment research, which have been the subject of prior research.[6] In many cases, this access will be through less formal channels. For example, investors may have one-off conversations with desk analysts, receive market commentary disseminated via Bloomberg chats, or even obtain pricing information on related securities. At the extreme, the type of information they obtain may also include rumors or information about non-public upcoming credit-related events, such as rating changes or M&A deals.

Based on the above, we predict that investors with larger observed dealer networks display information advantages over those with smaller ones. Each trading connection gives investors an incremental opportunity to obtain information from different dealers who may have novel information. As a result, we expect to observe improved investment decision-making by investors who, in equilibrium, are able to maintain larger dealer networks. Moreover, we also expect these advantages to be particularly prevalent for dealers' best trading clients, as the primary channel through which this result occurs is rewarding order flow with private information.

[6] Although formal sell-side debt analyst reports exist, not every firm provides them. Moreover, they typically only cover a small subset of bonds outstanding. Prior studies focusing on these reports include: Johnston, Markov, and Ramnath (2009); De Franco, Vasvari, and Wittenberg-Moerman (2009); De Franco et al. (2014); Gurun, Johnston, and Markov (2016); Gillette (2023).

3. Data

3.1. Transaction and Dealer Trading Network Data

We develop our dealer trading network data based on comprehensive transaction-level data on insurance companies' transactions in corporate bonds. Although trading networks are typically unobservable in other settings, an advantage of our setting is that U.S.-based insurance companies are required to file a quarterly and annual Schedule D with the National Association of Insurance Commissioners (NAIC). This schedule includes detailed information on each transaction, including the transaction date, the direction of the trade, the quantity traded, and the price paid. Important for our analysis, it provides the identities of the insurance company and the dealer with whom each trade is completed.[7]

We obtain annual Schedule D data for all acquisitions and disposals of corporate bonds by all U.S. insurance companies (e.g., health, life/fraternal, and property and casualty insurance companies) from 2009 to 2022 from S&P Capital IQ's Insurance Investment Transactions database.[8] S&P Global aggregates these Schedule D filings into a structured format for investors and other S&P clients, and performs cleaning and data quality assessment. We follow O' Hara et al. (2018) and implement several further cleaning and filtering steps. Specifically, we retain transactions only for bonds whose face value is standard (i.e., $1,000), issuance amounts of $1 million or greater, and those with characteristics data on Mergent FISD (e.g., only U.S. bonds). We also follow the steps outlined in O' Hara et al. (2018) to

[7]These records are comprehensive and highly accurate. The signature of an insurance company officer (e.g., president or comptroller) is required, and inaccuracies or fraudulent reports can lead to statutory fines or criminal charges.

[8]The sample period begins in 2009, when S&P Global began cleaning and aggregating these data from Schedule D filings (e.g., Hagenberg, 2024).

correct potential data errors related to reported prices.

We implement several additional cleaning techniques. To focus on secondary market transactions, we drop those trades occurring in the 60 days after issuance and those related to non-secondary market transactions, such as bond redemptions, maturities, and primary market issuances (e.g., Hendershott et al., 2020). Importantly, we also clean and standardize the dealer names. The filings contain self-reported counterparty names, which can include typos and different variants of reported names for the same dealer. We clean dealer names using a combination of manual cleaning, standardizing common abbreviations and suffixes, and fuzzy matching. We further consolidate all insurer trading data at the Ultimate Parent level.[9]

The resulting dataset consists of approximately 2.0 million transactions across 1,577 insurers and 370 dealers. The detailed nature of the transaction-level data allows us to construct measures of the dealer networks we study. Specifically, we construct the dealer network of each insurer, which allows us to measure both the number of separate counterparties as well as the total volume transacted between counterparties in our dataset.

Figure 1 shows three example insurers' dealer networks in 2018. It depicts the dealer connections for an insurance company with few connections (Hoosier Motor Club), an average number of connections (Grange), and a high number of connections (Independence). The width of each connection edge in the network corresponds to the fraction of the insurer's trading volume that was executed with the respective dealer in 2018.

Figure 2 visually depicts examples of dealer trading networks using pie charts to rep-

[9]For example, if we see trades by insurance companies A and B, both of which are owned by parent company P, we assign all trades to P. For ease of exposition, we use the terms "insurer," "insurance company," and "investor" interchangeably to refer to the parent company.

resent the distribution of each brokerage firm's trading volume across trading clients who are insurers. The figure focuses on two example brokerage firms' trading in 2019. Panel A shows the insurer trading client base of Goldman Sachs. For illustrative purposes, the figure breaks out the top 20 insurer trading clients. Goldman's top 20 insurers by trading volume make up more than half of its total corporate bond trading volume with insurers. Panel B shows the insurer trading client base of Nomura. Nomura's top 20 insurers by trading volume make up more than 75% of its total corporate bond trading volume with insurers. In both panels, there is significant variation in the strength of the trading connection even among the dealer's top 20 insurer trading clients.

Table 1 presents summary statistics of the dealer networks in our sample. Panel A presents measures of insurance companies' dealer networks. For each insurer-year, we obtain the insurer's trading volume, number of trades, and number of dealers with whom they transact. The average trading volume across all insurer-years is \$266.027 million. On average, insurers execute 163.886 trades across 12.785 dealers per year.

Panel B of Table 1 presents measures of dealers' insurer trading networks. For each dealer-year, we obtain the dealer's trading volume, number of trades with insurers, and the number of insurers with whom they transact. The average trading volume with insurers across all dealer-years is \$1.314 billion. On average, dealers execute 774.265 trades across 58.650 insurers per year.

We also report measures of the strength of the trading connection between insurers and dealers. Panel C of Table 1 provides descriptive statistics of the connection strength at the dealer-insurer-year level. Trading volume with each insurer, on average, represents 1.359% of the total trading volume of a brokerage during the year (% of Dealer Volume). Trading volume with each brokerage, on average, represents 7.796% of the total trading volume of an insurer during a year (% of Insurer Volume).

3.2. Transaction-level Sample

Our sample selection process for the transaction-level analysis begins with the sample of approximately 2.0 million bond transactions described in Section 3.1. To study differences in decision-making based on trading connections, we compute each insurance company's number of unique dealer connections in the rolling 12-month window before the transaction. We require future credit ratings data, from Mergent FISD, to compute whether the bond is downgraded in the future (i.e., transactions for bonds that are not rated in the month after the transaction are dropped). We also require data to compute control variables: the rating level of the bond, the remaining time-to-maturity, and the natural logarithm of the bond offering amount (all from Mergent FISD). After these data requirements, our final transaction-level sample consists of 1,598,694 transactions.[10] The first panel in Appendix A defines all variables used in the transaction-level analyses.

Panel A of Table 2 presents summary statistics for the main variables we use in our transaction-level analyses. The average *Sell* is 0.450, indicating that 45% of transactions are sell transactions. Panel A also reports the other variables we use in our transaction-level analyses, all of which are in line with expectations and prior studies.

[10] This sample measures downgrades in the next 3 months. The sample size is slightly reduced when we use specifications that require measures computed over a longer horizon after the trade (e.g., downgrades over a 12-month window in the future). The sample size slightly increased when we use specifications that examine defaults, which do not require data on future downgrades.

3.3. Event-level Sample

In addition to our transaction-level analyses, we perform several analyses at the event level around M&A announcements. To construct our sample for the event-level analyses, we supplement our dealer network data with SDC Platinum data on M&A deals, which include 1,327 deals larger than $5 million where the target company has bonds outstanding at the time of the deal announcement (e.g., Beneish, Harvey, Tseng, and Vorst, 2022). We apply a series of filters to focus our sample on deals likely to be informationally relevant for the bonds. We require the acquirer to obtain a controlling stake (i.e., more than 50% of shares in the target). We further exclude divestitures, spinoffs, splitoffs, and acquisitions as part of a bankruptcy process. This sample selection procedure leaves us with a final sample of 540 M&A deals.

Based on these events, we create a dataset of trading opportunities at the insurer-event level. Specifically, we examine the trading activity of all insurers in the bonds of the acquired company in the 30 trading days before the deal announcement. Critically, the SDC data contain the names of the investment banks that advise the target and the acquirer in a deal. We use these names to identify investment banks with a dealer arm in our trading network data. Using these data, we measure whether an insurance company has a trading connection with any of the advising investment banks and the number of advising investment banks with which they have trading connections over the prior 12 months.

The above aggregation process results in a sample of 854,789 insurer-event observations for all M&A deals. Panel B of Table 2 covers variables measured at the insurer-event level, which we use for our analyses of the relation between insurers' connections to dealers and their trading activity in target company bonds prior to the affiliated investment bank's M&A deal announcements. The third panel in Appendix A defines all variables used in the insurer-event level analyses. For each insurer-event, we compute their aggregate buy-sell imbalance in the 30 trading days before the event (*Insurer BSI*) as the difference between the insurer's buy volume and the insurer's sell volume, scaled by the sum of the insurer's buy and sell volume and multiplied by 100, and set to zero if the insurer has no trading volume in target bonds. The average *Insurer BSI* is -0.027% (i.e., approximately neutral). On average, 36.7% of insurers have a trading relationship with a deal-affiliated dealer during the 12-month window prior to the deal announcement. The average number of unique deal-affiliated dealers with which insurers have trading relationships is 0.695. On average, 0.066% of deal-affiliated dealers' trading volume is with each insurer (*Deal Connection Strength*). The average M&A event return for target company bonds is -4.683%, with most (i.e., 76.5%) of the events accompanied by negative returns. Finally, 2.2% of the events are followed by downgrades for target company bonds within the next 3 months.

4. Dealer Network Size and Trading Performance

4.1. Dealer Network Size and Future Credit Downgrades

We begin by exploring the relation between the size of insurers' dealer networks and the informativeness of their trading decisions for future credit rating downgrades. Future credit rating downgrades provide a powerful setting for exploring the impact of network size on decision-making with respect to trading performance for two reasons. First, credit rating downgrades significantly impact bond values and, therefore, directly impact insurer companies' portfolios (e.g., Hand et al., 1992; Cornaggia et al., 2018; Bonsall et al., 2024). Second, insurers have significant incentives to hold higher-rated securities, given the ratings directly impact their risk-based capital (RBC) charges (Kisgen and Strahan, 2010; Becker and Ivashina, 2015, see Appendix B).[11]

To explore the above, we estimate the following linear probability model using our sample of insurer transactions described in Section 3.2:

$$
\begin{aligned}
Downgrade_{b,t+h} = {} & \beta_1 Sell_{i,b,t} \times Connection\ Rank_{i,t} + \beta_2 Connection\ Rank_{i,t} + \beta_3 Sell_{i,b,t} \\
& + \gamma Controls_{b,t} + \Sigma\beta_r Rating_{r,b,t} + \Sigma\beta_t Year \times Month_t + \Sigma\beta_i Insurer_i \\
& + \Sigma\beta_b Bond_b + \epsilon_{i,b,t+h}, \qquad (1)
\end{aligned}
$$

where $Downgrade_{b,t+h}$ is one of several indicators for whether the bond b has a rating downgrade in the next h=3 or 12 months after transaction date t. *Sell* is an indicator variable set to one if the transaction is a sell transaction and zero if it is a buy transaction. *Connection Rank* is the quintile rank of the number of dealers with whom the insurer traded in the 12-month window prior to the transaction date.[12]

Our coefficient of interest is β_1, which measures how insurers' sell transactions', relative to their buy transactions', ability to predict future ratings downgrades varies with their network size. A positive β_1 indicates that insurers with more extensive dealer networks are more likely

[11]The RBC requirement is a statutory minimum level of capital based on the riskiness of its financial assets and its underwriting risk (Koijen and Yogo, 2023). The formula to calculate the exact amount of required capital is complex, but as the RBC bond factor increases, so will the required risk-based capital.

[12]We use the quintile rank for ease of interpretation. Untabulated results using the number of dealers are qualitatively similar.

to sell, rather than purchase, securities before upcoming credit rating downgrades. Said differently, it implies insurers' network size influences their ability to improve their trading performance in terms of predicting future credit rating downgrades.

To control for potential differences in insurers' bond portfolios, we include a vector of controls for bond characteristics, *Controls*, including the remaining time-to-maturity and the bond size (natural logarithm of the bond offering amount). We also include fixed effects indicating each round credit rating level r. Our primary and most stringent specification also includes year-month t fixed effects, insurer i fixed effects, and bond b fixed effects. The inclusion of these additional fixed effects subsumes any variation constant for each trading month, insurance company, and bond. Insurer fixed effects account for time-invariant insurance company characteristics, such as an insurer's time-invariant in-house research capabilities. More than 25% of the insurers in our sample change *Connection Rank* during the sample period. The inclusion of bond fixed effects holds constant securities in which insurers trade, only capturing time-dynamics in insurers' abilities to predict downgrades.

Table 3 presents regression estimates for multiple variations of Equation (1). Panel A presents results for insurers' trading prior to downgrades in the next 3 months. Panel B presents results when using a longer measurement window of 12 months. An inherent advantage of this longer measurement window is statistical power, given there is substantially more variation in the propensity to observe credit rating downgrades over longer periods.[13]

[13] Another advantage is that it reduces the possibility that an insurer may simply be trading in response to credit rating changes from another credit rating agency. Specifically, we focus on S&P rating changes in these analyses. However, insurers in our sample may subscribe to other ratings, such as Egan Jones, which might be timelier in some cases (Beaver, Shakespeare, and Soliman, 2006, see Bonsall, Koharki, and Neamtiu, 2017 for arguments otherwise). If better-connected insurers are more likely to subscribe to other credit ratings agencies, it is possible the predictability we document is simply them reacting to alternative, timelier ratings. This is significantly less likely over longer periods (i.e., an Egan Jones rating action is unlikely to lead S&P by more than a year).

Our results show that the transactions of better-connected insurers are more informative about future credit rating downgrades. Specifically, across nearly all specifications, we find positive and statistically significant coefficients on β_1, implying that the sell transactions of well-connected insurers (i.e., those with more trading connections in the past year) are relatively (compared to buy transactions) more positively associated with the probability that the bond has a future downgrade than the sell transactions of less well-connected insurers. These estimates are statistically significant at the 5% level or lower threshold, except for column 4 in Panel A (the analyses with the least amount of statistical power).

In addition to being statistically significant, our findings are also economically significant. For instance, column 4 of Panel B suggests that the sales of insurers with the largest dealer network (quintile 5) are approximately 37% more likely to be followed by a downgrade over the next twelve months than those with the smallest dealer network (quintile 1).[14] Moreover, column 4 includes bond fixed effects, highlighting that well-connected insurers sell at the most important times within the bond's life. This finding rules out many alternative explanations, such as well-connected insurers' ability to purchase "better" bonds.

4.2. Dealer Network Size and Severe Adverse Credit Events

We provide further evidence of the relation between insurers' dealer network size and trading decisions by leveraging the fact that more severe downgrades are significantly more important for insurers to avoid in their holdings. In particular, insurers have significant regulatory incentives to hold investment-grade securities (e.g., Becker and Ivashina, 2015),

[14] Note that the baseline is 0.526 for the 12-month horizon for the lowest quintile. Moving to the highest quintile adds 0.192 (i.e., $4 \times (0.142 - 0.094) \approx 0.192$).

which is highlighted by the fact that $\approx 95\%$ of total bonds held by insurers at the end of 2022 were investment-grade bonds (NAIC, 2022). Therefore, those downgrades to non-investment-grade (i.e., "junk") are particularly important for them to avoid, partially because it may lead to forced fire sales for them at a loss (Ellul, Jotikasthira, and Lundblad, 2011). At the extreme, avoiding defaults is most important for regulatory reasons and because of the extreme dollar losses associated with these events.

Based on the above, we investigate the relation between the size of insurers' dealer networks and the propensity to trade profitably before a future downgrade to non-investment-grade status or future default over various measurement windows. To do so, we re-estimate multiple variations of Equation (1) that replace the dependent variable with an indicator that the bond is downgraded to junk status or has a future default.[15] Table 4 presents our estimates for junk downgrades and defaults in Panels A and B, respectively.

Panel A shows that well-connected insurers' bond sale transactions, relative to their bond purchases, tend to predict downgrades to junk status to a greater extent than the bond sale transactions of less-connected insurers. Specifically, the coefficient on *Sell* × *Connection Rank* is positive and statistically significant at the 5% level or lower threshold in for all estimates. As before, we find evidence that these results are robust to the inclusion of bond-level fixed effects, which highlights that these differences in decision-making cannot be explained by different access to securities. These differences are also economically significant, as the sales of insurers in the highest quintile based on network size are approximately 51.5% ($\frac{4\times(0.038-0.025)}{0.101} \approx 0.515$) larger than those in the lowest in predicting junk rating downgrades

[15] Our default tests exclude bond fixed effects because they absorb nearly all of the variation in the dependent variable and are, therefore, impracticable. For instance, in the case of defaults before maturity, such fixed effects would absorb 100% of the variation, because a bond either does or does not default before maturity.

12 months in the future (see column 4 of Panel A).

Our findings in Panel B on future defaults mirror those in Panel A. All coefficients on the interaction term *Sell* × *Connection Rank* are positive and statistically significant at the 1% level of significance. The propensity for insurers' bond sales, relative to their bond purchases, to predict defaults over various periods is increasing in their dealer network size. As before, our estimates are also economically significant, given our evidence implies the high-connections insurers' sales are 236.4% ($\frac{4\times(0.022-0.009)}{0.022} \approx 2.364$) more predictive of defaults within one year than the low-connections insurers (see column 2 of Panel B).

4.3. Aggregate Portfolio Analyses

The findings in the prior subsections highlight that insurers with larger dealer networks make more informed trading decisions regarding future adverse credit events. In this section, we investigate the aggregate economic effect of the improved decision-making by well-connected insurers on their portfolio performance. To provide evidence on this issue, based on similar analyses in Di Maggio et al. (2019), we calculate the risk-adjusted abnormal performance of insurers with large dealer networks and compare it to that of insurers with smaller dealer networks.

We obtain monthly bond returns data from the Wharton Research Data Services (WRDS) Bond Returns database.[16] Using these data, at the beginning of each month, we construct long-short value-weighted portfolios that purchase (sell) bonds in the highest (lowest) decile of buy-sell imbalance across bonds traded by two groups: (1) high-connections insurers

[16]These data are increasingly used in academic research to explore a variety of corporate bond-related research questions (e.g., Li, 2022; deHaan, Li, and Watts, 2023; Gad, Nikolaev, Tahoun, and van Lent, 2024). A detailed description of the data, cleaning steps, and associated code can be found on WRDS: `https://wrds-www.wharton.upenn.edu/pages/get-data/wrds-bond-returns/`.

and (2) low-connections insurers. Similar to our other analyses, we measure each insurer's dealer network based on the previous 12-month trading window in all bonds in the previous month, separating insurers into those in the highest quintile of dealer network size ("high-connections") and all other insurers ("low-connections").[17] This long-short portfolio approximates the trading performance by emulating insurers' decision-making in each connectedness group.

We first compute the average monthly returns of the high-connections long-short portfolio and obtain alphas from regressions on common risk factors. Panel A of Table 5 reports the results of these regressions. We provide five specifications: raw returns, and alphas from a one-factor excess bond-market portfolio as suggested by Dickerson, Mueller, and Robotti (2023), the two-factor bond-market model of French and Fama (1989), the inclusion of the traded Pastor and Stambaugh (2003) liquidity factor following Becker and Ivashina (2015), and the inclusion of all factors. Across all specifications, we find a positive and statistically significant alpha for the high-connections portfolio. In column 5, after including all factors, the alpha is approximately 6.5 basis points monthly or 0.78% on an annualized basis. While moderate in economic magnitude, given average monthly returns of approximately 38 basis points across bonds in our sample period (untabulated), this performance still constitutes approximately 17% of outperformance relative to total bond returns in any given month.

Next, we use a similar process to compare the outperformance of high-connection insurers to others. Specifically, in Panel B of Table 5, we present the alphas of a portfolio that purchases the high-connections portfolio and sells the low-connections portfolio. The returns

[17] To ensure there are sufficient bonds to be formed in each long-short portfolio in each month, the low-connections group aggregates all insurers who are not in the highest quintile. Given the relative illiquidity in these markets, trades are uncommon, particularly for those insurers with fewer dealer connections (which tend to be smaller insurers with less trading activity).

from these long-short portfolios approximate the difference in the trading performance of high-connections insurers versus low-connections insurers.

Across all specifications in Panel B of Table 5, we find a positive and statistically significant alpha for the portfolio that takes a long position in the high-connections portfolio and a short position in the low-connections portfolio. In column 5, the alpha is approximately 7.0 basis points monthly or 0.84% on an annualized basis. Similar to our findings in Panel A, given average monthly returns of approximately 38 basis points across bonds in our sample period (untabulated), this outperformance still constitutes approximately 18% of outperformance relative to total bond returns in any given month.[18]

5. Mechanism

Our findings thus far highlight that insurers who trade with more dealers appear to be more informed. In this section, we provide evidence that an important mechanism for these information advantages is information flow from dealers to insurers. We begin by providing evidence that the dealers themselves are likely the sources of some of this private information. We then provide insights into dealers' incentives to provide this information to insurers.

[18] In untabulated analyses, we estimate the alphas of monthly returns for a portfolio based on the trading activity of low-connections (i.e., insurers in the bottom four quintiles of trading relationships) and find insignificant alphas in all specifications.

5.1. *Dealers as Sources of Private Information*

5.1.1. *Cross-sectional Analyses*

To provide initial evidence that investors with large dealer networks are obtaining information advantages from dealers themselves, we first explore cross-sectional variation across dealers. We exploit the heterogeneity across dealers in their likelihood of having novel information that would be useful to investors. Specifically, we exploit the fact that many dealers are stand-alone trading desks, whereas others have additional divisions that are likely to have useful information for investors.

To explore the above, we re-estimate Equation (1), replacing the trading connectedness variable with two separate variables measuring investors' trading connections to informed and uninformed dealers. These dealers are those expected to be likely to have or unlikely to have value-relevant information, respectively. We identify informed dealers in two ways. First, we identify the dealers whose investment banking division advised at least one M&A deal in the Thomson Reuters SDC database in the previous 12 months. Second, we perform a similar process for equity research arms using IBES.[19]

Panel A of Table 6 reports our estimates for these regressions when using splits based on whether a dealer has been active in the M&A market. Across all columns, we find a positive and statistically significant coefficient on the interaction *Sell* × *M&A Connection Rank*, consistent with a positive effect of investors' connections with M&A-affiliated dealers on the predictive ability of investors' sell transactions (relative to their buy transactions) for

[19]We focus on equity research arms rather than fixed income for several reasons. Data limitations make identifying the full universe of trading desks challenging, and single-name coverage for individual bond securities is rare, particularly for the high-grade bonds that insurers hold (e.g., De Franco et al., 2009). Additionally, discussions with industry practitioners confirm that equity research analysts are an important source of information for fixed-income investors in credit markets.

future downgrades, downgrades to junk, and defaults. In contrast, the coefficient on the interaction *Sell* × *Non-M&A Connection Rank* is insignificant in all columns except column 1, where it is negative and marginally significant. Therefore, we do not find that investors' connections with less-informed dealers positively impact the predictive ability of investors' sell transactions for future adverse credit events.

Panel B of Table 6 reports the results of these regressions when using splits based on whether a firm has a research division. We find a positive and significant coefficient on the interaction *Sell* × *Research Connection Rank*, consistent with a positive effect of investors' connections with research-affiliated dealers on the predictive ability of investors' sell transactions (relative to their buy transactions) for future downgrades to junk and defaults (columns 2 through 4). In column 1, when we investigate future 3-month downgrades, the coefficient on the interaction term is insignificant (but we note that the coefficient is positive and significant in untabulated results using 12-month downgrades). In contrast, the coefficient on the interaction *Sell* × *Non-Research Connection Rank* is insignificant in all columns except column 3, where it is statistically significantly negative. Overall, we do not find that investors' connections with uninformed dealers positively impact the predictive ability of investors' sell transactions for future adverse credit events.

5.1.2. Event-study Analyses

We add to the above evidence by focusing on a setting commonly used to explore the presence of informed trading—M&A events (e.g., Bhattacharya, 2014; Augustin and Subrahmanyam, 2020; Suk and Wang, 2021).[20] Although rare compared to many of the other

[20] These behaviors constitute a regulatory "grey zone" in which it is often difficult to prove that traders possess material non-public information.

types of information insurers are likely to learn through their dealer networks, M&A events provide an ideal setting to explore dealer-insurer information flows for several reasons. First, the information is non-public but known to the dealers, and therefore, dealers are likely to be the primary source of this information for insurers. Second, we can observe how we would expect information to flow along specific trading connections, strengthening our inferences regarding the likely source of information. Third, M&As can have important effects on bond prices and credit ratings (e.g., Asquith and Wizman, 1990; Bodnaruk and Rossi, 2016; Eisenthal-Berkovitz, Feldhütter, and Vig, 2020), so insurers have powerful incentives to trade on this information.[21]

Using an event-study design on the sample we describe in Section 3.3, we assess whether the trading clients of deal-affiliated dealers are more likely to trade in an informed manner in the short window (30 trading days) before the deal is publicly announced. Specifically, we estimate the following regression:

$$\begin{aligned} Insurer\ BSI_{i,e} &= \beta_1 DealConnection_{i,e} + \beta_2 DealConnection_{i,e} \times NegativeEvent_e \\ &+ \Sigma\beta_e Event_e + \Sigma\beta_i Insurer_i + \epsilon_{i,e}, \end{aligned} \tag{2}$$

where $Insurer\ BSI_{i,e}$ is the insurer i's pre-event buy-sell imbalance in corporate bonds for the firm that is the target of the deal event e and $DealConnection_{i,e}$ is one of several variables denoting the number of trading connections between the deal-affiliated dealer and insurer i for the deal event e. Although we use the same measurement window of 12 months

[21] For example, 76.5% of M&A deals we study are accompanied by negative returns, and 2.2% are accompanied by a downgrade for the target company's bonds within three months of the deal announcement. The downgrade probability increases to 19% in the 12 months after the deal announcement, during which time the terms of the deal might become effective.

before the event, this analysis deviates from our previous analyses that simply count the total size of the dealer network, by instead investigating the presence of connections to dealers actually involved in the deal and privy to non-public information. $NegativeEvent$ is one of several variables indicating whether or not the M&A deal is a negative event for the target company's bonds.

Following Haselmann, Leuz, and Schreiber (2023), the above specification uses non-adverse events as a baseline to which to compare adverse events. A negative β_2 suggests that when insurers are connected to a dealer affiliated with the deal, they decrease their net demand prior to the deal announcement to a greater extent for negative events. We include event fixed effects, which hold constant other factors with limited variation in the short window around the event (i.e., time-varying controls such as time to maturity) and also subsume the lower-order negative event effect. In our most stringent specification, we also include insurer fixed effects, which subsume any time-invariant insurance company characteristics that could confound our interpretation. For example, it allows us to rule out the alternative explanation that some insurers are better at trading prior to M&A deal announcements because they consistently have better in-house resources.

Table 7 presents regression results for multiple variations of Equation (2). In Panel A, we define $NegativeEvent$ as an M&A event with negative target company bond returns. The sample size is reduced slightly due to the requirement of return data in TRACE transactions. In Panel B, we define $NegativeEvent$ as a M&A event that is followed by a downgrade for target company bonds in the following 3 months after the event.

Across all specifications, we find evidence that private information about forthcoming M&A deals flows from deal-affiliated dealers to their trading clients. Our findings in columns

1 and 2 of both panels indicate that when an insurer has a trading connection with a dealer who is affiliated with an M&A deal, that insurer tends to sell bonds to a greater extent ahead of deal announcements accompanied by negative value implications. The coefficients are negative and statistically significant at the 1% level even when including insurer fixed effects, consistent with a deal connection explaining trading patterns even within a given insurer.

Additionally, as we would expect if insurers are sourcing this information from their dealer network, we see these results are more pronounced for insurers with a greater number of unique connections to the dealers affiliated with the deal. Specifically, in columns 3 and 4 of each panel, the coefficient on β_2 is negative and statistically significant at the 1% level. Altogether, these findings highlight that as insurers are more important clients for deal-affiliated dealers, they have access to the information privy to those dealers and make better decisions ahead of important credit-related events.

5.2. Dealer Incentives: Payment for Order Flow

Based on the above, an important question we explore relates to dealers' incentives to provide information to their trading clients and in which cases we expect these information transfers to be prevalent. We posit that information flow occurs due to "soft dollar" arrangements whereby dealers reward their most important trading clients for order flow. The possibility of such arrangements is supported by prior studies in other settings (e.g., Irvine, 2000; Frankel et al., 2006; Green et al., 2014), as well as by the institutional setting (e.g., see Section 2). We provide evidence on these issues by focusing on the M&A setting described in the prior section. This setting is ideal for exploring whether these information transfers are payment-for-order flow because it allows us to observe the information transfers and total order flow between each insurer-dealer pair.

To test the above, we re-estimate Equation (2) after replacing *DealConnection* with one of several variables measuring how important an insurer's trading flow is to a dealer (i.e., how important of a trading client a specific insurer is to a particular dealer affiliated with the M&A deal). We construct measures of this importance based on the proportion of the dealer's total trading flow with insurers the particular insurer comprises in the 12-month window before the deal announcement. To the extent that the private information transfers we document in prior analyses are soft dollar payments for order flow, we expect β_2 to be negative, indicating M&A-affiliated dealers' best trading clients appear to be most informed about upcoming announcements.

Table 8 presents regression results for these estimations. Our evidence is consistent with deal-affiliated dealers providing information to their best trading clients in all specifications. Specifically, we find a negative and statistically significant (at the 5% level or lower threshold) coefficient on β_2. This indicates that the prevalence of informed trade by insurers before an M&A announcement with adverse credit consequences increases with past order flow between the insurer and deal-affiliated dealer. Overall, these results are consistent with dealers rewarding their best trading clients with private information for order flow.

Figure 3 displays the above findings graphically. Across both panels, we see a clear relation between the importance of the insurer to the dealer and the insurer's propensity to sell target bonds before M&As with adverse credit-related consequences are publicly announced. Consistent with the above findings, in the case of no connection, we see neutral buy-sell activity. As the importance of the insurer to the dealer increases (based on the rank of the insurer's trading flow as a proportion of the dealer's total trading flow with insurers), insurers appear increasingly likely to avoid the losses associated with these events.

5.3. Robustness: Downgrade Events

Although the M&A setting provides us with an ideal laboratory by focusing on a specific type of information that can be traced to a limited set of informed parties, the rarity of these events raises questions about the economic significance of the documented mechanism. To alleviate this concern, we conduct an additional set of analyses examining profitable trading ahead of credit rating downgrades. Downgrades are more common than M&A events, and are particularly salient to insurance companies because of their regulatory implications. For these analyses, we consider the universe of all downgrade events over our sample period, and follow a similar approach as in our event-study analyses for the M&A events.[22] In particular, we examine whether insurance companies more connected to the original underwriter of the downgraded bond are more likely to trade profitably ahead of the downgrades. Specifically, we estimate:

$$\begin{aligned} Insurer\ BSI_{i,e} = {} & \beta_1 UnderwriterConnection_{i,e} + \beta_2 UnderwriterConnection_{i,e} \times toJunk_e \\ & + \Sigma\beta_e Event_e + \Sigma\beta_i Insurer_i + \epsilon_{i,e}, \end{aligned} \tag{3}$$

where $Insurer\ BSI_{i,e}$ is the insurer i's pre-downgrade buy-sell imbalance in the bond that

[22]We only consider the first downgrade between S&P, Moody's, and Fitch following Ellul et al. (2011).

is being downgraded in event e and $UnderwriterConnection_{i,e}$ is one of several variables measuring the trading connections between the issue-affiliated dealer and insurer i for the downgrade event e.[23] $toJunk$ is an indicator variable equal to one if the focal bond is downgraded from investment grade to speculative status.

The results of these analyses are summarized in Table 9. First, unlike in the M&A analyses we do not have a neutral event as a control group because all events are downgrades, as such the main effect is negative and significant across all three specifications, indicating that insurers that are connected to the original underwriter are more likely to sell a bond ahead of it being downgraded. Notably, we find these effects to be significantly more pronounced ahead of downgrades to junk status. Lastly, columns (2) and (3) highlight that it is not just the existence of a connection but also the importance of the connection for the dealer that determines more informed trading–consistent with a notion of payment for order flow.

6. Concluding Remarks

Our study explores the informational value of trading networks in OTC markets. Leveraging novel data allowing us to observe U.S. insurance companies' trading in corporate bond markets, we provide evidence that insurers gather private information about corporate fundamentals by leveraging their dealer networks. This information advantage allows them to avoid losses from adverse credit events and yield higher risk-adjusted trading performance. Collectively, our findings are consistent with dealers providing private information to their best trading clients as payment for order flow.

[23] We do not include a specification using the number of underwriter connections because unlike in an M&A event, there is typically only one underwriter.

We highlight several important caveats when interpreting our findings. First, our inferences are based on analyses of a single investor type: insurance companies. This focus has important advantages, namely data availability, but it has limitations related to generalizability to other investor types. Insurance companies are typically regarded as less active (e.g., buy-and-hold) and, therefore, are likely to engage in less information-based trading compared to other market participants, such as hedge funds. Therefore, we believe that our inferences likely present a conservative estimate of the informational value of OTC trading relationships. Conversations with practitioners confirm this belief, although we recognize this need not be the case.

Second, we recognize that an insurer's decision to develop a more extensive dealer network and acquire private information is endogenous. Intuitively, more active traders are likely to develop a larger dealer network for trade intermediation and are also more likely to acquire private information. Although several of our empirical analyses and anecdotal evidence support our inferences that insurers obtain information through their dealer network, we acknowledge that some of our estimates capture this joint decision by insurers.

The above caveats aside, our focus on documenting whether and why private information flows through investors' dealer networks is informative to both academics and regulators. While prior studies have primarily focused on their role in trade intermediation, which is their primary purpose, we provide evidence of another critical function they play in the marketplace regarding information dissemination. Our evidence also highlights potentially unfair advantages being garnered by informed traders in these markets through investors' dealer networks, some indicative of breakdowns of "ethical walls" established by the Glass Steagall Act. These findings caution for greater scrutiny in these marketplaces by regulators.

Appendix A. Variable Definitions

This table contains descriptions of the primary variables used throughout this paper. Sources include S&P Capital IQ (S&P), Mergent FISD (Mergent), Bond Returns by WRDS (WRDS Bond), Fama-French portfolios and factors on WRDS (WRDS FF), Dickerson et al. (2023) data, SDC Platinum (SDC), TRACE transactions (TRACE), and IBES. All continuous variables, except returns, are winsorized at the 1st and 99th percentiles to mitigate the effect of outliers.

Variable	**Definition**
	Transaction-level analyses
Bond Size	The natural log of the bond's offering amount, in $ billions. (WRDS Bond)
Connection Rank	Quintile rank (0=Low, 4=High) of the number of dealers with whom the insurer transacts in the 12-month window prior to the transaction. (S&P)
Default^h	Indicator variable set to 100 if the bond's issuer defaults over the next h years. Superscript h indicates the measurement horizon: 1 year and time prior to the bond's maturity. (Mergent)
Downgrade^h	Indicator variable set to 100 if the bond experienced a downgrade by S&P over the next h months. Superscript h indicates the measurement horizon: 3 months and 12 months. (Mergent)
Junk Downgrade^h	Indicator variable set to 100 if the bond experienced a downgrade to junk status, defined as a downgrade from BB- or higher to B+ or lower, by S&P over the next h months. Superscript h indicates the measurement horizon: 3 months and 12 months. (Mergent)
M&A Connection Rank	Quintile rank (0=Low, 4=High) of the number of M&A advisor-affiliated dealers with whom the insurer transacts in the 12-month window prior to the transaction. M&A advisor-affiliated dealers are those whose investment banking division advised at least one M&A deal in the previous 12 months. (S&P, SDC)
Non-M&A Connection Rank	Quintile rank (0=Low, 4=High) of the number of non-M&A advisor-affiliated dealers with whom the insurer transacts in the 12-month window prior to the transaction. (S&P, SDC)
Non-Research Connection Rank	Quintile rank (0=Low, 4=High) of the number of non-research-affiliated dealers with whom the insurer transacts in the 12-month window prior to the transaction. (S&P, IBES)
Rating	Credit rating level for the bond, where Rating=1 denotes a AAA rating and Rating=22 denotes a D rating. The WRDS Bond Returns data assigns the value of S&P ratings, if available, Moody's if S&P is missing, and Fitch if both S&P and Moody's are missing. (Mergent)
Research Connection Rank	Quintile rank (0=Low, 4=High) of the number of research-affiliated dealers with whom the insurer transacts in the 12-month window prior to the transaction. (S&P, IBES)
Sell	Indicator variable set to one if the transaction is a sell transaction for the insurer. (S&P)
Time to Maturity	The bond's remaining time to maturity, in years. (Mergent)
	Monthly portfolio-level analyses
Default premium	Return difference between the market portfolio of long-term corporate bonds and long-term government bonds (French and Fama, 1989). (Dickerson et al., 2023)
Excess market return	Average return on all bonds, weighted by their amounts outstanding (Dickerson et al., 2023). (Dickerson et al., 2023)

Liquidity factor	Traded liquidity factor (Pastor and Stambaugh, 2003). (WRDS FF)
Portfolio return	Monthly portfolio returns of either a portfolio based on the buy-sell imbalances of high-network insurers or a portfolio that takes a long position in the buy-sell high-network portfolios and shorts a buy-sell low-network portfolio, measured in basis points. (S&P, WRDS Bond)
Term spread	Return difference between long-term government bonds and the one-month T-Bill rate (French and Fama, 1989). (Dickerson et al., 2023)
	Insurer-event level analyses
# Deal Connections	Number of deal-affiliated dealers with which the insurer transacted in the 12-month window prior to the event. Deal-affiliated dealers are those affiliated with deal advisors of either the target or acquirer. (S&P, SDC)
Deal Connection	Indicator variable set to one if the insurer transacted with a deal-affiliated dealer in the 12-month window prior to the event. Deal-affiliated dealers are those affiliated with deal advisors of either the target or acquirer. (S&P, SDC)
Deal Connection Rank	Quintile rank (0=None, 1=Low, 5=High) of the proportion of the deal-affiliated dealer's transaction volume that is with the insurer in the 12-month window prior to the event, measured in percentage points. We determine the rank of this proportion within the dealer's insurer clients with nonzero trading volume with that dealer within the same window. Then, we take the maximum rank across all deal-affiliated dealers, where deal-affiliated dealers are those affiliated with deal advisors of either the target or acquirer. Deal Connection Rank is set to zero if Deal Connection Strength=0. (S&P, SDC)
Deal Connection Strength	Proportion of the deal-affiliated dealer's transaction volume that is with the insurer in the 12-month window prior to the event, measured in percentage points. This proportion is the insurer-year's maximum across all deal-affiliated dealers, where deal-affiliated dealers are those affiliated with deal advisors of either the target or acquirer. (S&P, SDC)
Downgrade$^{3mo.}$	Indicator variable set to 1 if any of the target company's bonds experienced a downgrade by S&P over the next 3 months after the deal announcement. (Mergent)
Insurer BSI	The aggregate buy-sell imbalance of the insurer in the 30 trading days prior to the deal announcement, measured in percentage points. The buy-sell imbalance is calculated as the difference between the insurer's buy volume and sell volume, scaled by the sum of the buy and sell volume and multiplied by 100. (S&P)
Negative Return	Indicator variable set to 1 if the weighted average deal announcement return for the target company's bonds is negative. For each outstanding bond, we calculate its deal announcement return as the percentage difference between the earliest price available in the 10 trading days before the deal announcement and the earliest price available in the 10 trading days after the deal announcement. The average deal announcement return is the weighted average across all outstanding target company bonds, weighted based on the the offering amount of each bond. (TRACE)

Appendix B. Risk-Based Capital Factors

Table B-1
S&P Ratings and Risk-Based Capital Factors

S&P Rating	**NAIC Designation**	**RBC Factors (%)** Life	P&C and Health
AAA AA+ AA AA- A+ A A-	1	0.39	0.30
BBB+ BBB BBB-	2	1.26	1.00
BB+ BB BB-	3	4.46	2.00
B+ B B-	4	9.70	4.50
CCC+ CCC CCC-	5	22.31	10.00
CC	6	30.00	30.00

This table summarizes the risk-based capital (RBC) requirement for corporate bond holdings of insurance companies for the fiscal year 2021. The RBC factors (i.e., the capital charges) depend on the NAIC designation of the security, which is determined by its credit rating. The factors differ between life insurers and property & casualty (P&C) and health insurers. (Sources: S&P, NAIC)

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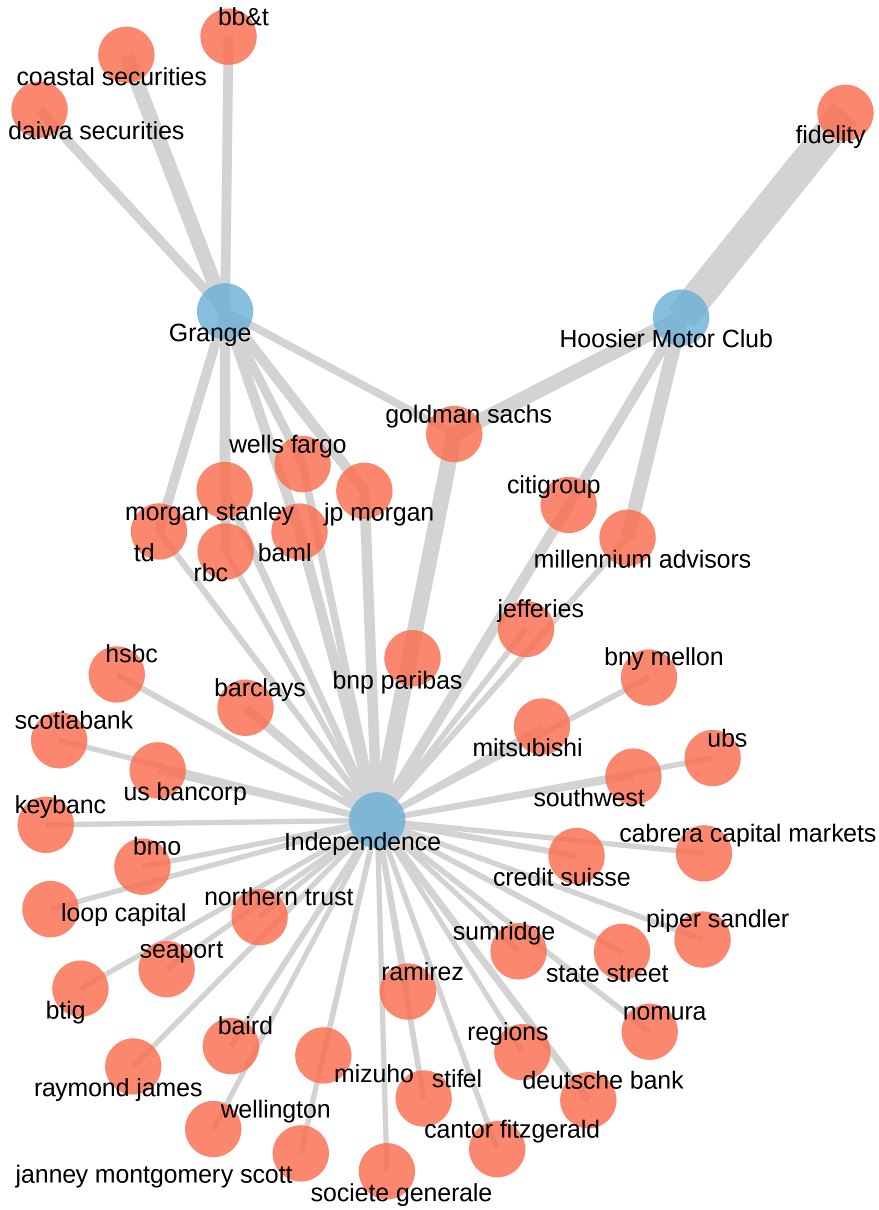
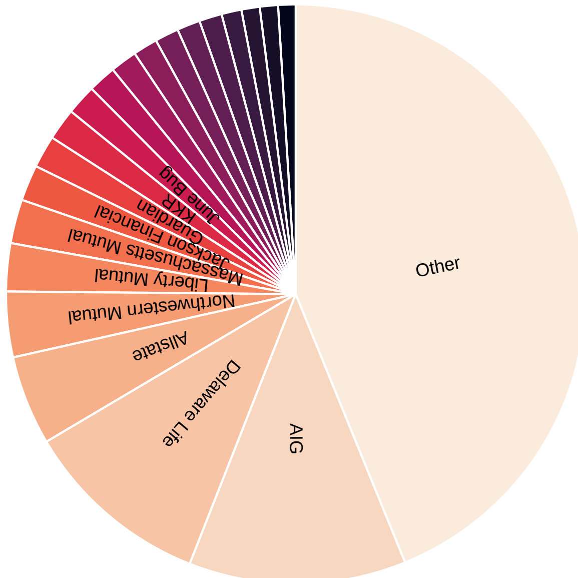
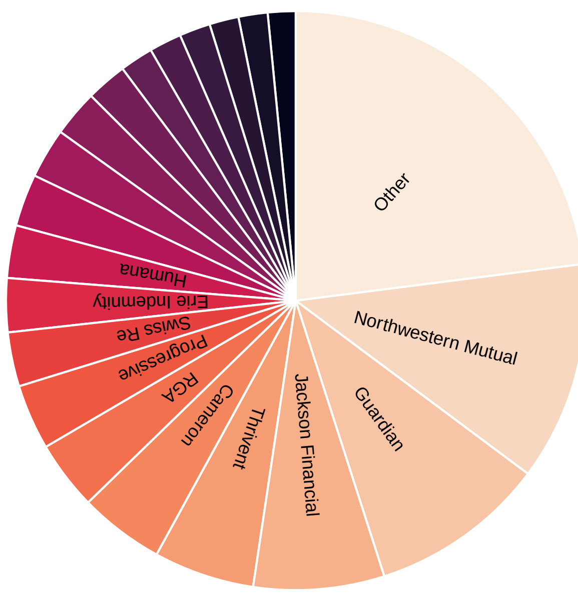


Fig. 1 Examples of Insurers' Dealer Networks

This figure presents the dealer networks of three insurers (blue), Grange, Independence, and Hoosier Motor Club, with their dealers (orange) in 2018. The edge widths in the network correspond to the fraction of the insurer's trading volume executed with the respective dealer in 2018.

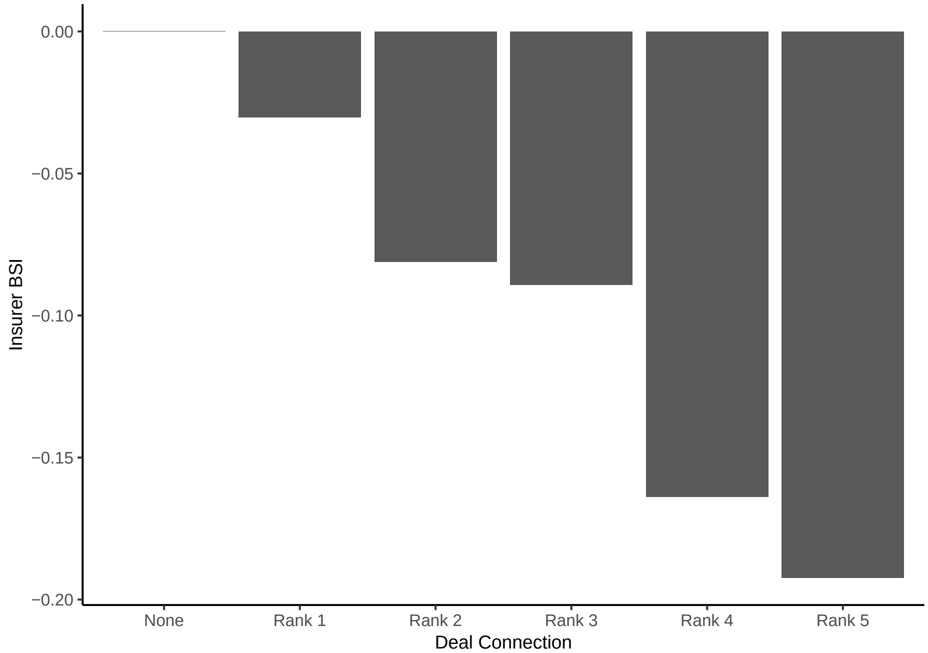


(a) Goldman Sachs

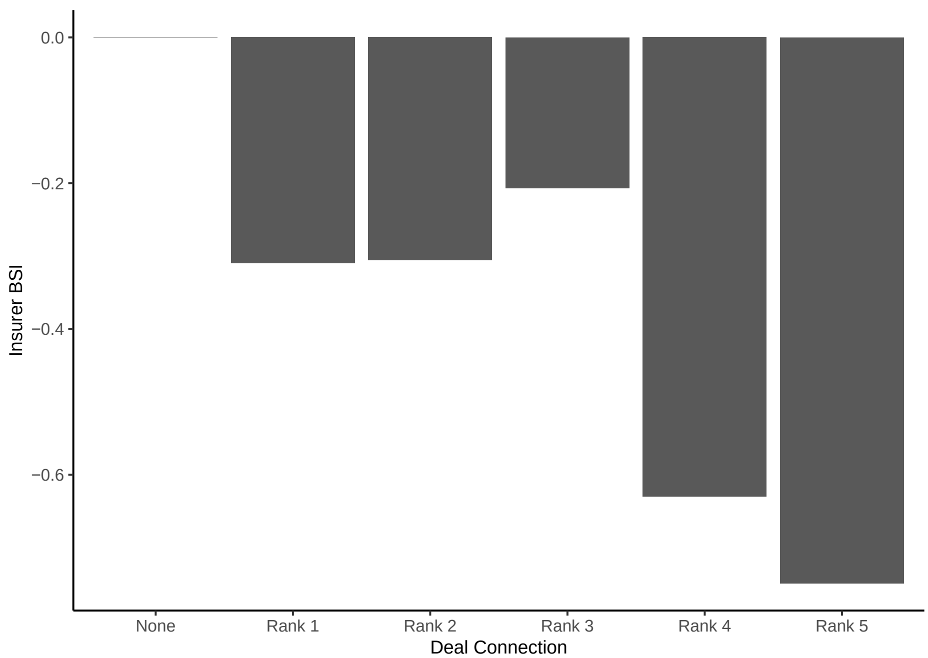


(b) Nomura

Fig. 2 Dealer Connections Examples
This figure presents the distribution of intermediated trading volume for two example brokerage firms across each brokerage's trading clients who are insurers in 2019. Panel (a) shows the insurer customer base of Goldman Sachs, and Panel (b) shows the insurer customer base of Nomura. For illustrative purposes, the top 20 connections, ranked based on the insurer's % of the brokerage's trading volume, are separately broken out. The remaining connections are aggregated in the *Other* category.



(a) M&As with Negative Returns



(b) M&As with Downgrades

Fig. 3 Insurers' Buy-sell Imbalances in Bonds of M&A Targets
This figure presents the average of $Insurer\ BSI$ in M&A target bonds over the $[-30,-1]$ window of deal announcements based on the rank of the strength of the insurers' trading connections with deal-affiliated dealers. Each panel focuses on a subset of M&A transactions with adverse credit-related consequences for targets. Panel (a) presents the BSI for M&As with negative announcement returns in the target bonds. Panel (b) presents the BSI for M&As where the target bonds experience a ratings downgrade in the following 3 months. Insurers in the deal connection category of "None" do not have any trading activity with the deal-affiliated dealer in the 12-month window before the announcement. Insurers in the deal connection category of "Rank K" have nonzero trading activity with the deal-affiliated dealer in the 12-month window before the M&A announcement that is in the Kth quintile of that dealer's insurer clients within the same window.

Table 1
Network Summary Statistics

Panel A: Insurer networks

	Mean	StDev	$p^{5\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{95\%}$	Obs.
Trading Volume ($MM)	266.027	792.673	0.240	2.130	12.677	89.067	1,712.814	14,851
No. of Trades	163.886	345.228	2.000	12.000	37.000	129.000	825.000	14,851
No. of Dealers	12.785	11.976	1.000	2.000	10.000	20.000	37.000	14,851

Panel B: Dealer networks

	Mean	StDev	$p^{5\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{95\%}$	Obs.
Trading Volume ($MM)	1,314.309	4,858.561	0.500	6.020	43.141	305.405	5,802.424	3,229
No. of Trades	774.265	2,631.785	1.000	14.000	54.000	282.000	3,717.400	3,229
No. of Insurers	58.650	129.407	1.000	1.000	3.000	30.000	376.600	3,229

Panel C: Dealer-insurer connection strength

	Mean	StDev	$p^{5\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{95\%}$	Obs.
% of Dealer Volume	1.359	6.481	0.001	0.011	0.064	0.377	3.766	190,560
% of Insurer Volume	7.796	15.917	0.072	0.764	2.867	8.074	26.955	190,560

This table reports summary statistics of the annual dealer trading networks of insurance companies. Panel A and Panel B present descriptives at the insurance-year level and the dealer-year level, respectively. Panel C provides descriptive statistics of the Connection Strength at the dealer-insurer-year level. Panel C presents both the fraction of the total trading volume of a dealer that is with the insurer during the year (% of Dealer Volume) or the fraction of the total trading volume of an insurance company that is with a dealer in a year (% of Insurer Volume), both measured in percentage points. All variables are winsorized at the 1st and 99th percentiles.

Table 2
Sample Summary Statistics

Panel A: Transaction level summary statistics

	Mean	StDev	$p^{5\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{95\%}$	Obs.
Sell	0.450	0.497	0.000	0.000	0.000	1.000	1.000	1,618,524
No. of Dealers	31.698	14.615	2.000	23.000	33.000	42.000	54.000	1,618,524
$\text{Downgrade}^{12mo.}$	10.501	30.656	0.000	0.000	0.000	0.000	100.000	1,525,435
$\text{Junk Downgrade}^{12mo.}$	0.983	9.868	0.000	0.000	0.000	0.000	0.000	1,525,435
Default^{1Y}	0.193	4.383	0.000	0.000	0.000	0.000	0.000	1,618,524
Time to Maturity (Years)	8.526	7.401	1.211	3.975	6.666	9.844	28.581	1,618,524
Bond Size ($BN)	1.037	0.817	0.250	0.500	0.750	1.250	3.000	1,618,524
Rating	8.439	3.102	4.000	6.000	8.000	10.000	14.000	1,618,524

Panel B: Insurer-event level summary statistics

	Mean	StDev	$p^{5\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{95\%}$	Obs.
Insurer BSI	-0.027	4.415	0.000	0.000	0.000	0.000	0.000	854,789
Deal Connection	0.367	0.482	0.000	0.000	0.000	1.000	1.000	854,789
# Deal Connections	0.695	1.118	0.000	0.000	0.000	1.000	3.000	854,789
Deal Connection Strength	0.066	0.258	0.000	0.000	0.000	0.005	0.337	854,789
Event Return	-4.683	8.504	-23.610	-6.481	-1.644	-0.074	2.325	486,044
Negative Return	0.765	0.424	0.000	1.000	1.000	1.000	1.000	486,044
$\text{Downgrade}^{3mo.}$	0.022	0.147	0.000	0.000	0.000	0.000	0.000	854,789

This table reports descriptive statistics of observations used in the study. Panel A presents descriptive statistics of variables used in our transaction-level analyses. For ease of interpretation, we report the raw, unranked version of the variable *Connection Rank*, which is labeled "No. of Dealers". Panel B presents descriptive statistics of variables measured at the insurer-event level. In addition to descriptive statistics for the variable *Negative Return*, we also report the continuous event return, which is labeled "Event Return". In both panels, all continuous variables, except returns, are winsorized at the 1st and 99th percentiles. The logged variable Bond Size is presented unlogged in this table.

Table 3
Investors' Connections and Future Downgrades

Panel A: 3-month horizon

	Downgrade$^{3mo.}$			
	(1)	(2)	(3)	(4)
Sell × Connection Rank	0.150***	0.167***	0.088**	0.057
	(3.330)	(3.857)	(2.032)	(1.506)
Connection Rank	-0.266***	-0.283***	-0.129***	-0.015
	(-8.524)	(-9.539)	(-2.922)	(-0.400)
Sell	0.377*	0.368**	0.750***	0.466***
	(1.948)	(1.990)	(4.067)	(2.746)
Controls	Yes	Yes	Yes	Yes
Rating fixed effects	Yes	Yes	Yes	Yes
Year × Month fixed effects	No	Yes	Yes	Yes
Insurer fixed effects	No	No	Yes	Yes
Bond fixed effects	No	No	No	Yes
Observations	1,598,694	1,598,694	1,598,694	1,598,694
R^2	0.008	0.034	0.037	0.207

Panel B: 12-month horizon

	Downgrade$^{12mo.}$			
	(1)	(2)	(3)	(4)
Sell × Connection Rank	0.281***	0.382***	0.185**	0.142**
	(2.920)	(4.240)	(2.139)	(2.236)
Connection Rank	-0.723***	-0.715***	-0.440***	-0.094
	(-9.623)	(-10.185)	(-5.012)	(-1.569)
Sell	1.082***	0.720**	1.428***	0.526**
	(3.360)	(2.398)	(4.944)	(2.347)
Controls	Yes	Yes	Yes	Yes
Rating fixed effects	Yes	Yes	Yes	Yes
Year × Month fixed effects	No	Yes	Yes	Yes
Insurer fixed effects	No	No	Yes	Yes
Bond fixed effects	No	No	No	Yes
Observations	1,525,435	1,525,435	1,525,435	1,525,435
R^2	0.021	0.057	0.061	0.429

This table presents analyses that examine the effect of insurers' network connections on the predictive ability of their bond sales for future downgrades. We estimate several versions of Equation (1) using the sample of transactions described in Section 3. Panel A presents results for downgrades that happen within 1 month of the trade. Panel B presents results for downgrades that happen within 12 months of the trade. *Controls* include the remaining time-to-maturity, and the bond size (natural logarithm of the bond offering amount). All variables are defined in Appendix A. t-statistics based on standard errors clustered by insurer are in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 4
Investors' Connections and Future Adverse Credit Events

Panel A: Downgrades to junk status

	Junk Downgrade$^{3mo.}$		Junk Downgrade$^{12mo.}$	
	(1)	(2)	(3)	(4)
Sell × Connection Rank	0.039***	0.041***	0.054***	0.038**
	(4.569)	(4.848)	(2.809)	(2.465)
Connection Rank	-0.036***	-0.024***	-0.077***	-0.025
	(-8.504)	(-3.231)	(-7.422)	(-1.451)
Sell	0.052**	-0.020	0.258***	0.101*
	(2.072)	(-0.717)	(4.416)	(1.886)
Controls	Yes	Yes	Yes	Yes
Rating fixed effects	Yes	Yes	Yes	Yes
Year × Month fixed effects	No	Yes	No	Yes
Insurer fixed effects	No	Yes	No	Yes
Bond fixed effects	No	Yes	No	Yes
Observations	1,598,694	1,598,694	1,525,435	1,525,435
R^2	0.032	0.171	0.096	0.444

Panel B: Defaults

	Default^{1Y}		Default^{Maturity}	
	(1)	(2)	(3)	(4)
Sell × Connection Rank	0.026***	0.022***	0.063***	0.054***
	(3.776)	(3.077)	(2.981)	(2.948)
Connection Rank	-0.016***	-0.009	-0.079***	-0.035
	(-3.623)	(-1.104)	(-4.864)	(-1.074)
Sell	-0.002	0.022	-0.009	0.041
	(-0.076)	(0.709)	(-0.098)	(0.588)
Rating fixed effects	Yes	Yes	Yes	Yes
Year × Month fixed effects	No	Yes	No	Yes
Insurer fixed effects	No	Yes	No	Yes
Observations	1,618,524	1,618,524	1,618,524	1,618,524
R^2	0.130	0.133	0.056	0.064

This table presents analyses that examine the effect of insurers' network connections on the predictive ability of their bond sales for future adverse credit events. We estimate several versions of Equation (1) using the sample of transactions described in Section 3. Panel A presents effect on future downgrades to junk status. Panel B presents the effect on future defaults. *Controls* include the remaining time-to-maturity, and the bond size (natural logarithm of the bond offering amount). All variables are defined in Appendix A. t-statistics based on standard errors clustered by insurer are in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 5
Portfolio Analyses

Panel A: High connections buy-sell portfolio

	Portfolio return				
	(1)	(2)	(3)	(4)	(5)
α	12.861***	6.828***	6.644***	6.235***	6.450***
	(3.647)	(3.175)	(3.274)	(3.270)	(3.403)
Excess market return		0.200***		0.094***	0.087***
		(16.486)		(4.630)	(4.253)
Default premium			0.171***	0.098***	0.099***
			(14.013)	(5.048)	(5.143)
Term spread			0.128***	0.081***	0.084***
			(16.952)	(6.572)	(6.811)
Liquidity factor					0.011*
					(1.836)
Observations	154	154	154	154	154
R^2		0.641	0.683	0.722	0.729

Panel B: High connections buy-sell vs. low connections buy-sell portfolio

	Portfolio return				
	(1)	(2)	(3)	(4)	(5)
α	7.798***	7.510***	6.871***	7.125***	6.966***
	(3.522)	(3.338)	(3.114)	(3.283)	(3.208)
Excess market return		0.010		-0.058**	-0.053**
		(0.753)		(-2.525)	(-2.270)
Default premium			0.037***	0.082***	0.081***
			(2.771)	(3.701)	(3.667)
Term spread			0.013	0.042***	0.040***
			(1.565)	(2.982)	(2.799)
Liquidity factor					-0.008
					(-1.183)
Observations	154	154	154	154	154
R^2		0.004	0.049	0.087	0.096

This table reports the estimates of the monthly portfolio alphas of the buy-minus-sell (e.g., high net buying minus high net selling) portfolios of high-connections and low-connections insurers. In Panel A, we present the alphas and factor loadings of portfolios based on buy-sell imbalances of high-connections portfolios (those in the top quintile of network connections). In Panel B, we present the alphas and factor loadings for a portfolio that takes a long position in the buy-sell high-connections portfolios and shorts a buy-sell low-connections portfolio (those in the remaining connections quintiles). Value-weighted portfolios are constructed based on the decile ranks of bonds at the beginning of each month, where the decile ranks are based on buy-sell imbalances from the prior month of trading. For each investor category (i.e., high-connections and low-connections), a buy-sell portfolio is constructed by taking a long (short) position in bonds with the highest net buying (selling), measured as the top (bottom) decile of buy-sell imbalances, by insurers in that connectedness category. Monthly returns for each portfolio are regressed on common bond risk factors: Excess market return (Dickerson et al., 2023), Default premium and Term spread factors (French and Fama, 1989), and the Liquidity factor (Pastor and Stambaugh, 2003). t-statistics are in parentheses, and levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 6
Dealers as Information Sources for Credit-related Information

Panel A: Dealer M&A transaction activity

	Downgrade$^{3mo.}$ (1)	Junk Downgrade$^{3mo.}$ (2)	Default^{1Y} (3)	Default^{Maturity} (4)
Sell × M&A Connection Rank	0.136**	0.035***	0.039***	0.093***
	(2.429)	(2.963)	(3.569)	(3.552)
Sell × Non-M&A Connection Rank	-0.094*	0.009	-0.017	-0.036
	(-1.840)	(0.731)	(-1.494)	(-1.271)
Controls	Yes	Yes	Yes	Yes
Rating fixed effects	Yes	Yes	Yes	Yes
Year × Month fixed effects	Yes	Yes	Yes	Yes
Insurer fixed effects	Yes	Yes	Yes	Yes
Bond fixed effects	Yes	Yes	No	No
Observations	1,598,694	1,598,694	1,618,524	1,618,524
R^2	0.207	0.171	0.133	0.064

Panel B: Dealer research activity

	Downgrade$^{3mo.}$ (1)	Junk Downgrade$^{3mo.}$ (2)	Default^{1Y} (3)	Default^{Maturity} (4)
Sell × Research Connection Rank	0.066	0.041***	0.050***	0.079**
	(0.991)	(2.609)	(3.935)	(2.414)
Sell × Non-Research Connection Rank	-0.024	0.002	-0.028**	-0.032
	(-0.372)	(0.125)	(-2.035)	(-0.870)
Controls	Yes	Yes	Yes	Yes
Rating fixed effects	Yes	Yes	Yes	Yes
Year × Month fixed effects	Yes	Yes	Yes	Yes
Insurer fixed effects	Yes	Yes	Yes	Yes
Bond fixed effects	Yes	Yes	No	No
Observations	1,598,694	1,598,694	1,618,524	1,618,524
R^2	0.207	0.171	0.133	0.064

This table presents analyses that examine the effect of insurers' network connections to different type of dealers on the predictive ability of their bond sales for future adverse credit events. We estimate several versions of Equation (1) using the sample of transactions described in Section 3. Panel A ranks insurers separately based on their network with M&A deal-advising and non-M&A deal advising connections. Panel B ranks insurers separately based on their network connections with dealers that have and that don't have a research practice. All regressions include main effects, which are omitted from the output for parsimony. *Controls* include the remaining time-to-maturity, and the bond size (natural logarithm of the bond offering amount). All variables are defined in Appendix A. *t*-statistics based on standard errors clustered by insurer are in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 7
Investors' Connection to Dealers Affiliated with Deal Advisors and M&A Transactions

Panel A: Negative announcement returns

	Insurer BSI			
	(1)	(2)	(3)	(4)
Deal Connection × Negative Return	-0.260***	-0.261***		
	(-5.630)	(-5.654)		
Deal Connection	0.066	0.161***		
	(1.615)	(3.965)		
# Deal Connections × Negative Return			-0.130***	-0.131***
			(-5.188)	(-5.210)
# Deal Connections			-0.009	-0.023
			(-0.410)	(-1.076)
Event fixed effects	Yes	Yes	Yes	Yes
Insurer fixed effects	No	Yes	No	Yes
Observations	486,044	486,044	486,044	486,044
R^2	0.009	0.013	0.009	0.013

Panel B: Post-deal downgrades

	Insurer BSI			
	(1)	(2)	(3)	(4)
Deal Connection × Downgrade$^{3mo.}$	-0.453***	-0.456***		
	(-4.533)	(-4.543)		
Deal Connection	-0.068***	-0.018		
	(-5.318)	(-1.565)		
# Deal Connections × Downgrade$^{3mo.}$			-0.219***	-0.218***
			(-3.882)	(-3.846)
# Deal Connections			-0.059***	-0.067***
			(-6.377)	(-6.012)
Event fixed effects	Yes	Yes	Yes	Yes
Insurer fixed effects	No	Yes	No	Yes
Observations	854,789	854,789	854,789	854,789
R^2	0.009	0.011	0.009	0.011

This table presents analyses that examine the relationship between existing trading connections to the dealers affiliated with banks that are advisors on an M&A deal and the insurer's buy-sell imbalance in the target company bonds during the 30 trading day period before the announcement of a takeover. We estimate several versions of Equation (2) using the sample of insurer-event observations described in Section 3. Panel A presents results that estimate the differences in trading patterns of deal-connected insurers separately for M&A events with and without negative deal returns. Panel B presents results that estimate the differences in trading patterns of deal-connected insurers separately for M&A events with and without post-deal target company bond downgrades. All variables are defined in Appendix A. *t*-statistics based on standard errors clustered by insurer are in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 8

Additional Analyses: Payment for Order Flow and M&A Transactions

Panel A: Negative announcement returns

	Insurer BSI			
	(1)	(2)	(3)	(4)
Deal Connection Strength × Negative Return	-0.449**	-0.451**		
	(-2.195)	(-2.204)		
Deal Connection Strength	0.082	0.129		
	(0.431)	(0.594)		
Deal Connection Rank × Negative Return			-0.090***	-0.090***
			(-4.717)	(-4.726)
Deal Connection Rank			0.026	0.051***
			(1.494)	(2.819)
Event fixed effects	Yes	Yes	Yes	Yes
Insurer fixed effects	No	Yes	No	Yes
Observations	486,044	486,044	486,044	486,044
R^2	0.009	0.013	0.009	0.013

Panel B: Post-deal downgrades

	Insurer BSI			
	(1)	(2)	(3)	(4)
Deal Connection Strength × $Downgrade^{3mo.}$	-0.891**	-0.890**		
	(-2.026)	(-2.020)		
Deal Connection Strength	-0.108**	-0.063		
	(-1.967)	(-0.823)		
Deal Connection Rank × $Downgrade^{3mo.}$			-0.140***	-0.141***
			(-3.358)	(-3.361)
Deal Connection Rank			-0.021***	-0.011*
			(-3.920)	(-1.874)
Event fixed effects	Yes	Yes	Yes	Yes
Insurer fixed effects	No	Yes	No	Yes
Observations	854,789	854,789	854,789	854,789
R^2	0.009	0.011	0.009	0.011

This table presents analyses that examine the relationship between the importance of insurers' trading volume to the dealers affiliated with banks that are advisors on an M&A deal and the insurer's buy-sell imbalance in the target company bonds during the 30 trading day period before the announcement of a takeover. We estimate several versions of Equation (2) using the sample of insurer-event observations described in Section 3. Panel A presents results that estimate the differences in trading patterns of deal-connected insurers separately for M&A events with and without negative deal returns. Panel B presents results that estimate the differences in trading patterns of deal-connected insurers separately for M&A events with and without post-deal target company bond downgrades. All variables are defined in Appendix A. *t*-statistics based on standard errors clustered by insurer are in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 9
Investors' Connection to Issue Underwriters and Issue Downgrades

	Insurer BSI		
	(1)	(2)	(3)
Underwriter Connection	-0.071***		
	(-9.719)		
Underwriter Connection × to Junk	-1.221***		
	(-18.482)		
Underwriter Connection Rank		-0.052***	
		(-13.278)	
Underwriter Connection Rank × to Junk		-0.497***	
		(-18.486)	
Underwriter Connection Strength			-0.450***
			(-13.755)
Underwriter Connection Strength × to Junk			-4.458***
			(-19.156)
Event fixed effects	Yes	Yes	Yes
Insurer fixed effects	Yes	Yes	Yes
Observations	180,727,800	180,727,800	180,727,800
R^2	0.049	0.050	0.050

This table presents analyses that examine the relationship between existing trading connections to the dealers affiliated with banks that underwrote a bond issue and the insurer's buy-sell imbalance in the target company bonds during the 30 trading day period before a downgrade. We estimate several versions of Equation (2) using the sample of insurer-event observations described in Section 3. All variables are defined in Appendix A. *t*-statistics based on standard errors clustered by insurer are in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.