Central Hub M&A Advisors

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ABSTRACT

This paper examines whether acquiring firms benefit from advisor network centrality. Consistent with central network positions conveying an information advantage, more centrally positioned advisors are associated with higher acquirer abnormal returns, lower takeover premia and superior post-merger operating performance. The effect of advisor network centrality is stronger when there is greater information asymmetry surrounding the target firm, and when the acquirer advisor's network contacts possess firm- or industry-specific information about the target firm. The results hold when a difference-in-differences technique and instrumental-variable approach are employed. Finally, the economic rent from advisor networking is shared between acquirers and central advisors.

JEL classification: G14, G24, G34

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1. Introduction

Recent advances in corporate finance attest to the importance of social connections in explaining variation in acquisition outcomes. Cai and Sevilir (2012), for instance, show that having a board connection between the merging firms facilitates information flow, leading to improved acquisition outcomes. In contrast, EI-Khatib, Fogel and Jandik (2015) find that acquirer CEOs use the power achieved through their networks to entrench themselves, resulting in greater value losses to both the acquirer and the combined entity. In this paper, we explore the value of networks of another important player in mergers and acquisitions (hereafter M&As): investment banks. Despite fierce competition, investment banking firms tend to cooperate with a fairly stable group of banks over time (Pichler and Wilhelm, 2001; Corwin and Schultz, 2005). The horizontal structure of investment banking industry is thus characterized by relationships. We investigate whether these horizontal relationships matter to acquiring firms, and if so, through what channels.

The extant evidence indicates that networking improves information access and facilitates knowledge sharing (e.g., Freeman, 1978; Rauch, 2001; Sorenson, 2003; Ferriani, Cattani, and Baden-Fuller, 2009). In our context, horizontal relationships can enable a financial advisor to gain privileged access to the private information owned by other investment banks. Specifically, each investment bank represents an information source that contains private knowledge about a number of firms. Such private information could be obtained through either repeated interactions with particular firms, or specialization in the firm's markets or products (Eccles, 1987; Anand and Galetovic, 2000, 2006). When a financial advisor is more centrally positioned in the network of investment banks (i.e., better networked), it can more efficiently extract information useful for a takeover bid from other investment banks, and use it to aid an acquirer in scouting for profitable acquisition opportunities, evaluating potential merger synergies, and/or identifying deals that are likely to be value-destroying. We therefore hypothesize that more centrally positioned financial advisors provide better advisory service and create greater value for acquiring firms, all else being equal. We term this conjecture as the "*information production*" hypothesis.

Investment banks can be connected in many ways, e.g., through social connection among employees such as CEOs and directors, or formal business ties at the firm level. We,focus on networks that arise when investment banks form *business ties* at the firm level by syndicating M&A deals in the past. The reason is twofold. First, social ties between individual investment bankers are typically hidden and costly to identify. In contrast, syndicate relationships are publicly observable. Hence, by making use of publicly available data sources such as media releases and business press, market participants can easily observe syndicate ties formed between investment banks and identify which investment banks are well (or poorly) networked at virtually no cost. The publicity of syndicate relationships adds to the practical importance of our empirical findings. Second, despite high investment banker turnover,[1] investment banking firms tend to maintain stable syndicate relationships over time with a strong emphasis on long-term reciprocal exchange (e.g., Pichler and Wilhelm, 2001; Corwin and Schultz, 2005; Ljungqvist, Marston, and Wilhelm, 2009). The ongoing nature of syndicate relationships reflects the interdependence among investment banks in the M&A market, which is an important element affecting the incentives for information sharing (e.g., Corwin and Schultz, 2005; Hochberg, Ljungqvist, and Lu, 2007). Naturally, investment banks would be reluctant to share valuable, private information with their rivals unless they are bound to relationships that are expected to persist into the future.[2] We argue that the information value of business ties at the firm level should be at least as important as that of interpersonal ties. In such a network, we characterize each financial advisor's relative network position by the following three centrality measures: the number of ties that an advisor has with other investment banks (*degree centrality*); its access to other investment banks that are network-powerful themselves (*eigenvector centrality*); and the extent to which it acts as a "bridge" along the shortest paths between unconnected investment banks (*betweenness centrality*).

Using a sample of U.S. M&A transactions announced between 1990 and 2016, we find strong support for the "*information production*" hypothesis. Acquiring firms experience significantly higher cumulative abnormal returns (CARs) around the announcement date when they are advised by investment

[1] See "Banks face talent crisis amid mounting costs of employee turnover: report", *Reuters News*, 18 January 2017.
[2] For example, investment banks may poach one another's valuable employees, clients and/or financial innovation. The consensus in the literature is that the weak property rights of investment banks over their human assets along with the possible spillover effect precludes perfect competition in the investment banking industry. Investment banks, therefore, prefer to establish ties with and stick to those banks with which they are familiar (Persons and Warther, 1997; Anand and Galetovic, 2000; Benveniste, Ljungqvist, Wilhelm, and Yu, 2003).

banks that are more centrally positioned in the network of investment banks. The effects are economically sizable. Holding other factors constant, acquirers experience a 0.252- to 0.332-percentage-point increase in the announcement abnormal returns for every one-standard-deviation increase in advisor network centrality. This corresponds to U.S. $14.662- to 19.301-million incremental shareholder wealth for an average-sized acquirer in our sample.

Perhaps the biggest challenge in our analysis is that some unobservable factors (e.g., advisor skill) may simultaneously contribute to strong advisor network positioning and high acquirer abnormal returns, leading to omitted variable bias. We have taken great care to adopt a combination of different strategies to mitigate this concern. First, we explicitly control for confounding factors that may drive our results. It is possible that centrally positioned advisors are also those highly reputed or skilled financial advisors. We thus examine acquirer CAR of financial advisors experiencing a change in network centrality in the announcement year and control for advisor fixed effects. This approach allows us to explore time-series variation in advisor network centrality while absorbing the average effect of unobservable, time-invariant advisor traits such as reputation and skill. We find that a change in acquirer advisor centrality is positively and significantly associated with acquirer CAR, consistent with the network effects.

The second explanation for our finding is that centrally positioned advisors prefer to syndicate M&A deals, such that improvements in information production in fact stem from syndication rather than variation in network position. Our test results suggest, however, that advisor network centrality continues to positively affect acquirer CAR after controlling for whether a given deal is syndicated. In addition, using degree centrality as a proxy for an advisor's access to deal flow (Hochberg *et al.*, 2007), we show that network centrality boosts acquirer returns regardless of degree centrality scores. Thus, the network effect we document is unlikely to be explained by privileged access to high-quality deals.

Second, we exploit the 2008 sudden collapse of Lehman Brothers, which created a plausibly exogenous decrease in the network centrality for the group of financial advisors affiliated with Lehman Brothers. Using a difference-in-differences (DiD) approach, we find that affiliated financial advisors, whose network position was weakened due to the loss of an important business connection, generated significantly lower acquirer abnormal returns after the shock, relative to unaffiliated advisors that were exposed to similar market conditions but unaffected by Lehman's collapse. These results hold up to the common methodological concerns such as the parallel-trends assumption and falsification tests. As an alternative identification strategy, we implement a two-stage least squares (2SLS) regression analysis, using geographical location of financial advisors as an instrument for advisor network centrality. Once again, the results confirm a positive link between advisor network centrality and acquirer abnormal returns.

Third, we investigate whether the positive effect of advisor network centrality on acquirer CAR exhibits heterogeneity in the cross-section. In line with the "*information production*" hypothesis, we find that the positive association between advisor network centrality and acquirer abnormal returns is more evident in deals involving a higher level of information opacity, as indicated by whether the target firm is from an unrelated industry, has above-average idiosyncratic return volatility, lacks a credit rating, or is a non-Standard & Poor's (S&P) 1500 firm. While advisor network centrality could still capture the effects of other relevant variables such as advisor reputation, any such omitted variable would have to produce similarly heterogeneous effects on acquirer CAR across the four information asymmetry environments explored here.

Next, we analyze the types of information an acquirer advisor can extract from its *network contacts*. Towards this end, we consider three types of target information that a network contact may have: (i) firm-specific information obtained from past dealings; (ii) industry-specific information acquired as a result of specialization in the target's industry; and (iii) regional-specific information obtained as a result of specialization in the target's states. We find that the positive effect of advisor network centrality on acquirer CAR is stronger when the acquire advisor is connected to one or more investment banks that either provided the target firm with equity underwriting services before or have expertise in the target's industry. These findings lend further support to the argument that central financial advisors utilize network contacts to extract information useful for a takeover bid.

Finally, we examine whether advisor network centrality affects other acquisition outcomes. We find that acquiring firms generally pay lower takeover premiums and enjoy better post-merger operating performance (i.e., higher profitability and greater asset turnover) when more centrally positioned financial advisors are employed. Moreover, the superior service of central financial advisors comes at a premium price. All else being equal, a one-standard-deviation increase in advisor centrality is associated with 0.141- to 0.182-percentage-point increase in advisory fees, suggesting that the information value of a financial advisor's network position is recognized by acquiring firms and that the economic rents of advisor networking are shared between acquirers and central financial advisors.

The remainder of the paper proceeds as follows. Section 2 discusses the related literature and the contribution of the current paper relative to the literature. Section 3 describes the data and variables used in our empirical analysis. In Section 4, we examine the impact of advisor network centrality on acquirer returns and perform tests to verify the robustness of our results. Section 5 explores the channels through which advisor network centrality operates, and Section 6 studies the impact of advisor network centrality on other acquisition outcomes. Section 7 concludes the paper.

2. Related Literature and Relative Contribution

This study is related to three main strands of literature. The first strand explores various characteristics of financial advisors in explaining cross-sectional variation in M&A outcomes, e.g., advisor reputation (Bowers and Miller, 1990; Servaes and Zenner, 1996; Rau, 2000; Rau and Rodgers, 2002; Kale, Kini, and Ryan, 2003; Walter, Yawson, and Yeung, 2008; Bao and Edmans, 2011; Golubov, Petmezas, and Travlos, 2012), provision of fairness opinions (Kisgen, "Qj" Qian, and Song, 2009), specialization in the M&A market (Song, Wei, and Zhou, 2013) and dual agency (Agrawal, Cooper, Lian, and Wang, 2013).It is widely believed that financial advisors generate valuable information for acquirers, but the literature presents mixed evidence on the information value of financial advisors. For instance, Servaes and Zenner (1996) compare the performance of "in-house" M&As with those advised by investment banks. They find no significant difference in acquirer abnormal returns between deals with and without investment banks. Rau (2000) reports that top-tier investment banks produce lower announcement-period returns for their acquirer clients than do lower-tier investment banks. In contrast, Kale *et al.* (2003) and Golubov *et al.* (2012)

show that acquiring firms advised by top-tier financial advisors experience higher abnormal returns in public acquisitions. Using a novel fixed effects approach, Bao and Edmans (2011) document significant bank fixed effects in the acquirer abnormal returns, indicating that certain banks do possess superior ability of providing value-enhancing M&A advice. We contribute to this debate by presenting new evidence that a financial advisor's position in the network of investment banks is a key factor affecting their ability to enhance the shareholder value of acquiring firms.

The paper closest to our work is a contemporaneous paper by Chaudhry, Kontonikas, and Vagenas-Nanos (2017), which examines financial advisory firms that are connected through *social links* between their board members. They find that better connected advisory firms are associated with a higher frequency of acquisitions, are more likely to work on the acquirer's side, and advise on more complex transactions. However, acquirer abnormal returns do not appear to be affected by advisor centrality, whereas target firms receive a lower takeover premium and poorer abnormal returns when a central financial advisor is used. [3] Our paper differs from theirs in that we focus on *business connections* among investment banking firms (as opposed to interpersonal ties), and we reach different conclusions. We show that a financial advisor's business connections are economically beneficial from an acquirer client's perspective. Acquiring firms experience better acquisition outcomes - in terms of announcement abnormal returns, takeover premiums and post-merger performance - when enlisting the services of central hub financial advisors that are connected to a larger number of investment banks, more banks that are network-influential, and "standing" more frequently between other banks that are not directly linked. The effect is more pronounced when there is greater information uncertainty surrounding the target firm and when the network contacts of the financial advisor had previously acted as underwriters on the target's equity offerings or specialize in the target industry. These findings support the notion that being a central hub, instead of on the periphery of the

[3] When matching high and low centrality advisors through propensity score matching on the basis of both acquirer size and target public status, Chaudhry *et al.* (2017) report a negative and significant impact of advisor centrality on acquirer abnormal returns.

network of investment banks, allows a financial advisor to utilize its network contacts to extract information useful for making value-creating acquisition decisions.

Our paper is also related to the emerging research on social connections between merging firms in M&As, e.g., board connectedness where the acquirer and the target share a common director (Cai and Sevilir, 2012); social ties between directors and CEOs of the acquiring and the target firms (Ishii and Xuan, 2014); cross-directorships between the merging firms (Renneboog and Zhao, 2014); and personal connections of acquirer CEOs (El-Khatib, Fogel, and Jandik, 2015). To the best of our knowledge, the present study is the first to empirically examine the implications of an acquirer financial advisor's business connections with other investment banks. This makes an important difference, given that investment banks as financial advisors play a critical role in M&A activities and that a financial advisor's horizontal connections should be at least as important as the social networks of the board and CEOs of the merging firms. [4] By focusing on connections at the firm level, our work also suggests that personal connections need not be the only channel for transmission of ideas and knowledge. Rather, ongoing business relationships characterized by trust and long-term reciprocity influence the incentives for information sharing, thereby representing an important conduit over which information transmits between investment banks.

Beyond the importance of our results for the M&A literature, the current work speaks to the literature on the economic networks prevailing in the investment banking industry. The major strand of this literature focuses on the impact of bank-firm relationships on firm value (e.g., Riordan and Williamson, 1985; Boot and Thakor, 2000; Asker and Ljungqvist, 2010; Ogura, 2010; Degryse, Masschelein, and Mitchell, 2011; Engelberg, Gao, and Parsons, 2012; Hale, 2012). In contrast, research on the role of interbank cooperation and the resulting networks is relatively scarce. Anand and Galetovic (2000, 2006), for instance, model how investment banks cooperate to prevent free riding on costly information gathering efforts and avoid price competition. Corwin and Schultz (2005) empirically document that the strength of past syndicate relationships between the lead IPO underwriter and the prospective syndicate members is

[4] Over our sample period of 1990-2016, for example, over 62% of U.S. M&A transactions involve one or more investment banks acting as financial advisors to the acquirers. Source: Thomson Financial SDC.

the single most important determinant of syndicate memberships. In a similar vein, Ljungqvist *et al*. (2009) report that, for both equity and debt offerings, a candidate bank's prior-year syndicate relationships with the lead manager is positively associated with the probability of winning a co-management appointment.[5]

Perhaps most closely related to our work is the study by Bajo *et al*. (2016), which examines how a centrally positioned *lead* underwriter affects various aspects of IPOs. They find that more central lead underwriters are associated with more favorable IPO outcomes such as offer price revision, IPO market valuation and initial returns. The superior performance of central lead underwriters is attributed to their ability to introduce greater investor attention and to more efficiently disseminate and extract information about the IPO firms from institutional investors. It should be noted that, although Bajo *et al*. (2016) show that firms underwritten by more central lead underwriters receive more pre-IPO attention in the news media, they do not empirically distinguish between the information dissemination and extraction roles of IPO underwriting networks. We provide clean evidence on the information extraction role of interbank networking by exploiting the uniqueness of the M&A setting. Namely, we directly observe the level of information opacity surrounding the target firm in question and the group of investment banks possessing private knowledge of that target firm due to past interaction or specialization. In addition to documenting cross-sectional effects that are consistent with the information production channel, we identify the exact types of *network contacts* that are informationally valuable, i.e., investment banks having either provided the target firm with equity underwriting services before or had expertise in the target's industry. These findings are new to our paper. Moreover, compared to IPOs, acquisitions affect massive reallocations of capital and create substantially greater value at stake (e.g., Moeller, Schlingemann, and Stulz, 2005; Devos, Kadapakkam, and Krishnamurthy, 2009; Wang and Xie, 2009; Bonaime, Gulen, and Ion, 2018). For instance, the year 2016 alone saw $736.4 billion worth of takeover activity domestically, which is approximately 57 times more than the gross U.S. IPO proceeds ($12.8 billion).[6] In this sense, our study

[5] Ljungqvist *et al*. (2009) measure syndicate relationship as the candidate bank's participation rates in the lead manager's prior-year syndicates and its reciprocal relationship with the lead manager.

[6] Sources: M&A data are obtained from Thomson Financial SDC. Gross IPO proceeds data come from Jay R. Ritter at https://site.warrington.ufl.edu/ritter/files/2017/08/IPOs2016Statistics.pdf.

have important implications for practitioners by providing evidence on the economic importance of interbank networks for value creation and the efficiency of resource allocation involved in corporate takeovers.

3. Data and Variable Definitions

3.1. Sample and Data

We use the *Thomson Financials Securities Data Collection Platinum (SDC)* database to collect data on the U.S. M&A transactions announced between January 1990 and December 2016 (rumored deals are excluded). Following Golubov *et al*. (2012), we clean the sample of deals that are classified as bankruptcies, liquidations, self-tenders, leveraged buyouts, privatizations, repurchases, restructurings, reverse takeovers and going private transactions. For the remaining observations, we exclude deals that: (i) involve no investment bank acting as a financial advisor to the acquirer; (ii) have a missing payment method; (iii) have a transaction value less than $1 million or 1% of the acquirer market value; (iv) involve an acquirer having more than 10% of the initial stake in the target or seeking to own less than 50% of the target after the transaction; and (v) were made by acquirers having missing financial information necessary for constructing the main variables for our analysis. After imposing these restrictions, we are left with a sample of 7,207 observations.

3.2. Variable Definitions

3.2.1. Measurement of Acquisition Performance

Following prior studies, we use the acquirer three-day cumulative abnormal return (CAR) around the deal announcement as our primary measure of acquisition performance (e.g., Bowers and Miller, 1990; Walter *et al.*, 2008; Ismail, 2010; Wang, Xie, and Zhang, 2014). Acquirer CAR is computed as returns in excess of those predicted by the market model, using the CRSP value-weighted index as a benchmark. Panel A, Table 1, reports the descriptive statistics of the acquirer three-day CAR for the full sample. The mean (median) CAR is 0.50% (0.00%), with a standard deviation of 8.40%.

3.2.2. *Measurement of Network Centrality*

We define interbank network based on whether investment banks have formed business ties in the past by serving as part of syndicated M&A deals either on the acquirer or target side. To characterize each financial advisor's relative position in the network of investment banks, we employ three common centrality measures, namely, *degree*, *betweenness* and *eigenvector* centrality (e.g., Sabidussi, 1966; Bonacich, 1972; Freeman, 1978).[7] Each measure describes a unique property of a financial advisor's relationships with other investment banks. Specifically, *degree centrality* measures the number of ties that a financial advisor has with other investment banks (e.g., Freeman, 1978; Hochberg *et al.*, 2007; Hochberg, Ljungqvist, and Lu, 2010). Intuitively, the more relationships an advisor has, the more investment banks it can reach and, by symmetry, the more banks can reach it, so the more capable the advisor is to receive or disseminate information from and to other investment banks in the network. Formally, let $\mathrm{N}_t = \{1, 2 \dots, n\}$ be the set of investment banks active at time *t*; $\mathcal{G}(N_t)$ be the network describing all the pairwise links between investment banks; $\mathbb{R}_t$ be a $\mathrm{n} \times \mathrm{n}$ matrix of $\mathcal{G}(N_t)$, where $R_{ij} = 1$ if investment banks, *i* and *j*, are linked via past syndication; and $R_{ii} = 0$ (i.e., all the diagonal elements are zeros). Degree centrality for advisor *i* at time *t* is given by:

$$D_{i,t} = \sum_{j=1}^{N_t} R_{ij,t}\,; \qquad \text{for } \mathrm{N}_t \geq 2 \text{ } and \text{ } i, j \in \mathcal{G}(N_t) \tag{1}$$

[7] Another widely used measure of network centrality is closeness, which reflects the distance between a financial advisor and all other investment banks in the network (Marsden and Campbell, 1984). Though closeness increases the probability of receiving information from a close-by agent, we expect it to play less of a role in determining the information value of a financial advisor. According to the social network theory (e.g., Granovetter, 1973; Yakubovich, 2005), information is more likely to be redundant when it flows through strong rather than weak ties. The intuition is that close-by investment banks tend to move in the same circles as a financial advisor does. The information the advisor receives is, therefore, likely to overlap significantly with what it already knows. Instead, being connected to acquaintances allows the advisor to gain more novel information from investment banks with whom it does not know. For this reason, we do not employ closeness centrality in our study.

Since degree centrality increases with network size, we normalize this measure by the maximum logically possible degree in a network of N actors (i.e., $N_t - 1$) to ensure that degree is comparable over time (e.g., Hochberg *et al.*, 2007, 2010). This normalized measure of degree centrality is:

$$D_{i,t}^{*} = \frac{1}{N_t - 1} \sum_{j=1}^{N_t} R_{ij,t} \; ; \qquad \text{for } \mathrm{N}_t \geq 2 \; and \; i, j \in \mathcal{G}(N_t) \qquad (2)$$

A shortcoming of degree centrality is that it merely counts the number of connections a financial advisor has, without considering the "quality" of each relationship (Robinson and Stuart, 2007). For example, a financial advisor could be connected to investment banks that are located at the center of the network (i.e., well networked) and, hence, possess more information than those occupying peripheral positions (i.e., poorly connected). To capture such an element, we construct *eigenvector centrality*, which is essentially a recursive measure of degree centrality. It measures a financial advisor's centrality as the sum of its ties to other investment banks, weighted by centrality scores of the banks it is tied to (e.g., Hochberg *et al.*, 2007, 2010). Mathematically, eigenvector centrality is defined as follows:

$$E_{i,t} = \lambda_t \sum_{j=1}^{N_t} R_{ij,t} \, E_{j,t}; \qquad \text{for } \mathrm{N}_t \geq 2 \; and \; i, j \in \; \mathcal{G}(N_t) \qquad (3)$$

Where λ_t is the largest eigenvector element value for the adjacency matrix $\mathbb{R}_t$ at time t, and $E_{j,t}$ is the corresponding eigenvector (Bonacich, 1972, 1987; Hochberg *et al.*, 2007; Ljungqvist *et al.*, 2009). To ensure comparability, $E_{i,t}$ is normalized by the highest possible eigenvector centrality value in an *N*-actor network. A financial advisor with higher eigenvector centrality has greater information advantage over other investment banks because it is connected to well-informed peers that are centrally positioned themselves.

Finally, *betweenness centrality* quantifies the extent to which a financial advisor acts as a "bridge" along the shortest path between two or more disconnected investment banks. Under this measure, financial advisors are considered central if they are hubs of information, requiring others to communicate through them. To illustrate, consider a star-shaped network structure where each bank is linked to no one else but a central hub advisor. Information can then flow through the network only if the central hub advisor serves as a conduit to transmit the messages (Jason and Powell, 2004). Thus, having a high betweenness score implies that a financial advisor is in an advantageous position to extract information, control the type of information transmitted, and manage the relationships among others that lack direct ties between them (Freeman, 1978; Ferriani *et al*., 2009; Bajo, Chemmanur, Simonyan, and Tehranian, 2016). Formally, advisor *i*'s betweenness at time *t* is given by:

$$B_{i,t} = \sum\nolimits_{j<k}^{N_t} \frac{P_{ijk,t}}{P_{jk,t}}; \qquad \text{for } \mathrm{N}_t \geq 2 \; and \; i,j,k \in \mathcal{G}(N_t) \tag{4}$$

Where $P_{jk,t}$ denotes the number of shortest paths from advisor *j* and *k* at time *t*; and $P_{ijk,t}$ is the number of shortest paths between advisor *j* and *k* that advisor *i* lies upon at time *t*. Once again, we normalize this measure by the maximum betweenness in a network of *N* actors to ensure comparability.

Our centrality measures are constructed based on undirected (or symmetric) ties between investment banks. Theoretically, a tie could be *directed* from one investment bank (the "originator") to another (the "receiver"). In the IPO market, for instance, a lead underwriter that invites other investment banks to join an underwriting syndicate could be considered as the "originator" of the interbank relationships. In this paper, we do not consider the direction of interbank relationships because M&A advisory syndicates rarely have a formally appointed lead advisor. Our review of news articles and merging firms' SEC filings reveals that only 67 of 1,111 syndicated M&A deals (6%) have clearly identified lead advisors over our sample period.

Networks are dynamic, with investment banks breaking up old ties and establishing new ones over time. To capture these dynamics, we construct network for each year *t* based on the syndicate relationships that investment banks have established over the last three years before year *t*.[8] When an acquirer hires a syndicate involving multiple financial advisors, we assign the highest centrality score among these advisors to a deal (e.g., Rau, 2000). Our sample period has also seen a substantial number of M&As among investment banks. To take this into account, we follow Ljungqvist *et al*. (2009) and allow the surviving investment bank to inherit the peer relationships of their "predecessors". For instance, Merrill Lynch and

[8] Our results continue to hold when alternative windows such as one-year and five-years are used to construct measures of advisor network centrality.

Banc of America Securities LLC merged in 2008. Thus, the combined firm, Bank of America Merrill Lynch, is considered as having relationships with the banks to which both Merrill Lynch and Banc of America Securities LLC were tied before the merger. [9]

Panel B, Table 1, indicates that the mean (median) centrality score of an acquirer financial advisor is 8.5% (6.9%), 20.5% (21.8%), and 5.1% (3.3%), respectively, when using normalized *degree*, *eigenvector*, and *betweenness* as centrality measures. To illustrate, consider the two ends of the spectrum. Over the three years ending in 2016, Goldman Sachs was one of the most centrally positioned financial advisors. It was connected to approximately 21.7% of the other investment banks (*degree*), stood "between" 11.6% of all possible pairs of investment banks (*betweenness*), and had the largest normalized *eigenvector* of 39.8%. Another example is Evercore Partners, a non-bulge bracket financial advisor. Though it was connected to only 9.1% of the other investment banks (*degree*) and stood between 2.1% of all possible pairs of investment banks, Evercore's connections were highly network-influential as indicated by its large normalized *eigenvector* of 25.1%. At the other end of the spectrum, Cowen, a middle-market bank, was not connected to any of the investment banks for the network constructed for year 2016 and, hence, had zero centrality scores.

Though *degree*, *eigenvector* and *betweenness* centrality capture different properties of an acquirer advisor's network position, they exhibit significant correlations with each other. We therefore follow EI-Khatib *et al.* (2015) and create two additional transformed centrality variables. First, we perform a principal component analysis (PCA) to identify the first principal component of the three centrality measures, which is roughly equally-weighted and explains 94.12% of the total variance. This variable is designed to capture the most important "common element" shared by all the centrality measures. Second, using the modified Gram–Schmidt process (Golub and Van Loan, 1996), we orthogonalize the *degree*, *eigenvector* and *betweenness* centrality measures into a set of mutually orthogonal variables, such that the effects of the

[9] SDC occasionally uses different names for the same advising bank (e.g., deals advised by "Citi" are regarded as different from those advised by "Citigroup"). To ensure consistency, the advisors' names are combined into one in such cases.

preceding variables are removed from the subsequent variable. The order of the orthogonalization process we used is: *degree- eigenvector-betweenness*, although the choice of other orders does not alter our results. These orthogonally transformed centrality measures reflect the unique impact of a particular centrality dimension that is uncorrelated with the other two centrality factors.

3.2.3. Other Control Variables

The extant literature shows that reputable financial advisors offer high-quality advice for public acquisitions (e.g., Kale *et al.*, 2003; Golubov *et al.*, 2012). We thus control for advisor reputation, defined as an acquirer financial advisor's market share of M&A deals (measured in transaction value) over the last three years before the deal announcement (e.g., Rau, 2000; Bao and Edmans, 2011). [10] M&As among investment banks themselves are taken into account when computing this measure. [11] As shown in Panel B, Table 1, acquirer advisor's market share has a mean (median) of 3.7% (1.2%). Since this variable is highly correlated with our centrality measures, we include the residuals from a regression of advisor market share on the three advisor centrality measures in our regression models (*xMktShare*), similar to Bajo *et al*. (2016).

We further control for a comprehensive set of firm- and deal-specific characteristics that are important determinants of acquirer CAR (e.g. Kale *et al.*, 2003; Moeller, Schlingemann, and Stulz, 2004; Masulis, Wang, and Xie, 2007; Moeller, Schlingemann, and Stulz, 2007; Golubov *et al.*, 2012; Alexandridis, Fuller, Terhaar, and Travlos, 2013; Song *et al.*, 2013). The firm-specific attributes include acquirer size, stock price run-up, free cash flow, leverage, and Tobin's Q. The deal-specific characteristics are relative transaction size, number of competing bidders, industry relatedness, a set of dummy variables indicating whether a deal is tender offer, hostile or cross-border, and six interaction terms between target listing status and means of payment.[12] Panels C and D, Table 1, report the sample summary statistics for these control variables. The average acquiring firm has a size of $5,818.2 million, with a stock price run-

[10] For robustness, we follow Golubov *et al*. (2012) and employ a top-eight classification as an alternative measure of advisor reputation. Our results remain unchanged.

[11] Consistent with Rau (2000), we give full credit to an investment bank working on either the acquirer or the target side. When there are multiple financial advisors hired by an acquirer, each advisor receives equal credit.

[12] To avoid any multicollinearity problems, we do not control for acquirer stock price volatility (sigma), which is highly correlated with relative transaction size in our sample (at the level of 67.82%).

up of 12.0% before the deal announcement. The mean (median) free cash flow ratio is approximately 5.1% (7.6%), and the mean (median) leverage ratio is around 20.2% (15.9%). Tobin's Q is positively skewed, with a mean value of 2.4 versus a median of 1.5. Transaction size is, on average, 41.4% of the acquirer size, and there are about 1.04 bidders for an average deal. Industry-related transactions, tender offers, hostile deals, public and cross-border transactions comprise 65.7%, 7.7%, 2.2%, 43.6% and 12.9% of sample deals, respectively. Approximately one-third of the transactions are all-cash paid. Appendix A provides a detailed description of the variables used in our empirical analysis.

[Please Insert Table 1 Here]

4. Advisor Network Position and Acquisition Performance

As discussed earlier, investment banks routinely cooperate with each other through syndication. These syndicate relationships give rise to a communication network that allows investment banks to share information, contacts and other valuable resources at a low cost. In such a setting, a financial advisor's position in the network of investment banks is valuable because successful acquisition outcomes require the advisor to obtain not just an intimate understanding of the acquirer's needs, but also detailed knowledge of the potential target. Vertical interactions with the acquiring firm usually contribute to the former, whereas the latter can be facilitated through horizontal networking among investment banks. For instance, a financial advisor may pick up useful information about a potential target when it is connected to investment banks that possess "inside" knowledge of the target's business through past dealings (e.g., provision of underwriting services and/or advice on corporate matters). Alternatively, the advisor may gain a nuanced understanding of the target's operating environment – such as potential regulatory trends, local competition and market opportunities – if some of its network contacts closely operate in the target firm's industry or geographical region. This information advantage enhances the advisor's ability to accurately assess the compatibility between the merging firms and related synergy gains, leading to improved M&A advice (Uysal, Kedia, and Panchapagesan, 2008). However, because individual financial advisors occupy heterogonous positions in the network, they are unlikely to have equal ability to extract acquisition-related information (e.g., Renneboog and Zhao, 2014; El-Khatib *et al.*, 2015; Bajo *et al.*, 2016). All else being equal, a financial advisor that is better networked with other investment banks should have better ability to efficiently extract information from its network contacts and, hence, create value for acquiring firms. We formally test this hypothesis by examining the impact of advisor network position on acquirer abnormal returns around the deal announcement.

4.1. Baseline Results

In Table 2, we regress the acquirer three-day CAR on advisor network centrality and a vector of advisor-, deal- and acquirer-specific characteristics identified in Table 1 for the full sample. Since the centrality measures are collinear, we estimate five separate regression models, adding one centrality measure at a time. Acquirer advisor centrality is measured by *degree* in column (1), *eigenvector* in column (2), *betweenness* in column (3), the principal component in column (4), and the orthogonal versions of the centrality measures in column (5). The *t*-statistics reported in parentheses are adjusted for heteroskedasticity and acquirer clustering. In all regression models, we control for industry and year fixed effects whose coefficients are suppressed for brevity.

The results, reported in Table 2, indicate that acquirer advisor centrality generates a positive, significant (at the 5% level) impact on acquirer announcement abnormal returns (columns (1) through (3)). Of the three advisor network centrality measures, *degree* and *eigenvector* have the largest economic effects. All else being equal, a one-standard-deviation increase in these two centrality measures is associated with 0.279- and 0.332-percentage point increases in acquirer CAR, equating to U.S. $16.218 - $19.301 million incremental shareholder wealth for an average-sized acquirer in our sample (columns (1) and (2)).[13] On the other hand, although *betweenness* centrality has the largest magnitude of coefficient estimate, it produces the smallest economic effect, with a one-standard-deviation increase in this centrality measure leading to

[13] Take *eigenvector* as an example. The percentage increase in acquirer CAR is calculated as the coefficient estimate for *eigenvector* (0.0194) times the corresponding standard-deviation increase in *eigenvector* (0.171). The incremental shareholder wealth is equal to the percentage increase in acquirer CAR (0.0194×0.171=0.332%) times the average size of acquiring firms in our sample ($5818.186 million). The economic effect of the other two centrality measures is calculated in a similar way.

0.252-percentage point increases in acquirer CAR, *ceteris paribus* (column (3)). In column (4), we see that the coefficient on the first principal component of centralities is positive and significant at the conventional levels, suggesting that the three centrality measures jointly and favorably affect acquirer abnormal returns. Despite this, the results reported in column (5) reveal that an advisor's *degree* centrality makes a distinct contribution to the improvement of acquirer CAR, unrelated to the other two centrality measures.

The parameter estimates of our control variables are generally consistent with the findings of prior studies. Similar to Moeller *et al*. (2004, 2007), we find that acquiring firms with larger market capitalization and greater pre-announcement stock price run-up experience significantly lower abnormal returns around the deal announcement, whereas more heavily leveraged acquirers are associated with higher CARs. Moreover, acquirers garner higher announcement abnormal returns when the target is relatively large, but lower returns when the management of the target firm is against the offer. These findings are in line with Asquith *et al.* (1983) and Schwert (2000). Among the six acquisition types based on target listing status and M&A currency, stock-financed public acquisitions produce the lowest acquirer announcement returns, confirming the evidence documented in Masulis *et al*. (2007). Other controls such as industry relatedness and acquirer Tobin's Q do not appear to significantly influence acquirer returns. Overall, the baseline regression results are consistent with the notion that centrally positioned advisors enhance the shareholder value of acquiring firms. However, this finding can be biased if a financial advisor's network position is correlated with other relevant variables. In the following section, we explore possible mechanical explanations for this finding. To conserve space, our attention is limited to the three individual centrality measures, i.e., *degree*, *eigenvector* and *betweenness*. [14]

[Please Insert Table 2 Here]

[14] In unreported analysis, we find that the first principal component of centralities and the orthogonally transformed centrality variables generate similar effects on acquirer abnormal returns in all the subsequent analyses, both in terms of signs and statistical significance.

4.2. Possible Explanations

4.2.1. Advisor reputation

We have shown that the centrality measures are correlate with advisor reputation, which is one of the key determinants of acquirer abnormal returns (e.g., Kale *et al.*, 2003; Golubov *et al.*, 2012). In our baseline regression models, we have controlled for residuals from a regression of advisor market share on the three centrality measures. For robustness, we examine acquirer CAR of financial advisors whose average network centrality over a three-year rolling window changes from year *t*-1 to year *t* and include advisor fixed effects in our model. In doing so, we mitigate the threat of omitted variable bias arising from observable or unobservable differences across acquirer financial advisors such as advisor reputation or skill that have been relatively stable over time (e.g., Servaes and Zenner, 1996; Rau, 2000; Golubov *et al.*, 2012). To be included in the analysis, an advisor must have advised on at least one deal in the year before the announcement year (year *t*). Panel A, Table 3, reports the results, with control variables omitted for brevity. We find that a change in acquirer advisor centrality is positively and significantly associated with acquirer CAR, consistent with the networking effects.

In Table B.1, Appendix B, we control for the possibility that the centrality measures capture the reputation effect using two alternative methods: (i) inclusion of an additional indicator variable for large bank sizes, defined as those banks with the top 10% of market share over the last three years; and (ii) excluding deals advised by large banks. The results are qualitatively similar. Thus, it is unlikely that our baseline findings merely identify the advisor reputation effect.

4.2.2. Preference for Syndication

Another explanation for better performance of central financial advisors is their preference for syndication. Since we use syndicate relationships to proxy for interbank networks, financial advisors with higher centrality scores are naturally those having previously syndicated deals more frequently. Meanwhile, a growing body of research indicates that syndication, which brings together financial intermediaries with different information sources, leads to improved information production and higher returns in various capital markets, e.g., IPOs (Corwin and Schultz 2005); debt offerings (Song 2004), and venture capital

(Tian 2012). Accordingly, if a better-networked financial advisor is more likely to syndicate a given deal, the positive link between advisor network centrality and acquirer returns could reflect the information value of syndication rather than that of networking. We address this issue by augmenting our CAR regression model with an additional control for whether the current deal involves multiple investment banks jointly acting as financial advisors to the acquirer, i.e., *Syndicated*. The results, presented in Panel B, Table 3, show that the coefficient estimates for our centrality measures are similar to those reported in Table 2, in terms of both magnitude and statistical significance. Moreover, the syndicated dummy variable is statistically insignificant in all regression models, suggesting that the information value of a well-networked financial advisor is unlikely to be explained by a preference for syndication.

4.2.3. Access to Deal Flow

Better networked financial advisors may have access to a larger deal flow, which permits them to cherry pick and work only on deals that are *ex ante* value-creating. This offers another possible reason for our baseline finding. To investigate this possibility, we follow Hochberg *et al*. (2007) and assume that high *degree* centrality is, in part, an indicator of an advisor's access to deal flow. Recall that *degree* centrality counts the number of ties a financial advisor has established with other investment banks. If relationships encourage investment banks to share M&A mandates through syndication, then a financial advisor with more ties should have greater access to other investment banks' deal flow to which it would otherwise have no access. Accordingly, we create a dummy variable, *high degree centrality,* indicating whether an acquirer advisor is in the top-quintile of the degree centrality distribution, and interact this variable with the other two centrality measures, *eigenvector* and *betweenness*. Panel C, Table 3, regresses acquirer CAR on these two centrality variables and their interaction with *high degree centrality*, controlling for the same vector of variables as in Table 2. We find that *eigenvector* and *betweenness* centrality measures are positive and significant at the 5% and 10% level, respectively. The interaction terms are statistically insignificant throughout the table. Thus, network centrality improves acquirer returns even if the financial advisor does not enjoy access to a better selection of deals.

[Please Insert Table 3 Here]

4.3. Identification

The previous section indicates that advisor reputation, preference for syndication and access to high-quality deal flow are unlikely to be the driving force behind the positive link between network centrality and acquirer returns. In this section, we further attenuate the endogeneity concern by employing two different identification strategies: a difference-in-differences (DiD) technique and a two-stage least squares (2SLS) regression approach.

4.3.1. A Quasi-Natural Experiment with the 2008 Collapse of Lehman Brothers

We begin by implementing a quasi-experimental approach to gauge the real effect of advisor network position on acquirer CAR following the 2008 collapse of Lehman Brothers (then the fourth-largest investment bank in U.S.).[15] On Sunday night, September 14, 2008, the Federal Reserve and the SEC pressed Lehman Brothers to file for bankruptcy protection, which Lehman did early on Monday, September 15, 2008. The sudden collapse of Lehman Brothers created a plausibly exogenous change in advisor network centrality. Investment banks that were affiliated with Lehman could be expected to suffer a decrease in their network position because of the loss of an important business partner. In addition to an obvious reduction in the number of ties, the permanent "exit" of Lehman Brothers caused an unexpected disruption to the network, breaking the interconnections of many investment banks that were linked through Lehman either directly or indirectly. With lower centrality scores, affiliated advisors' ability to extract information from other investment banks should be weakened. Thus, if the positive association between advisor centrality and acquirer CAR is truly attributable to the information production channel, affiliated

[15] An alternative quasi-experiment could be M&As among investment banks over our sample period. For example, apart from the bankruptcy of Lehman Brothers, Merrill Lynch, Bear Stearns, and Wachovia were taken over in 2008 because of the financial crisis (Kovner, 2012). We, however, do not use these bank mergers as experiments for a couple of reasons. First, shocks are, by definition, meant to be sudden and unpredicted. Many bank mergers do not meet this definition since they are well anticipated before they actually occur, largely because of the release of public information through various channels, e.g., rumors and news articles. Second, bank mergers may span a long time, making it difficult to pin down a precise event date for many of these events in our sample (e.g., He and Tian, 2013). Third, merging investment banks may continue to operate as individual entities, i.e., retain control over the management and direction of how to conduct their own business, after the merger. In this case, pre-merger relationships with other investment banks may continue post-merger. Finally, even if a tie is terminated due to bank mergers, such a termination is potentially endogenous because the surviving bank makes the choice to severe the tie.

financial advisors should produce lower acquirer abnormal returns, relative to unaffiliated financial advisors, following the "Lehman shock".

To test this prediction, we construct the treatment group by identifying affiliated investment banks as those having syndicated one or more M&A deals with Lehman Brothers over the last five years preceding the Lehman shock. The remaining investment banks are assigned to the control group. [16] The sample period is limited to three years before and three years after Lehman's bankruptcy to be consistent with the construction of our centrality variables. Moving further away from the event may increase the probability of inducing confounding factors (Roberts and Whited, 2013). For robustness, we experiment with using one year of data before and after the Lehman shock and find similar results.

Table B.2, Appendix B, reports the centrality scores before and after Lehman's bankruptcy. Panel A reports the change in *degree* centrality for affiliated advisors experiencing a negative shock to their network position (the treatment group) and, for comparison, unaffiliated investment banks that were exposed to similar market conditions but unaffected by the event (the control group). We see a sizable and significant drop in *degree* centrality among affiliated financial advisors, averaging 5.78 percentage points (p = 0.0351). On the other hand, the change in *degree* centrality is small and statistically insignificant for the group of unaffiliated advisors (p = 0.5510). Panels B and C, respectively, present the change in *eigenvector* and *betweenness* centrality before and after Lehman's collapse for the two groups. We find similar patterns, confirming that the network positioning of affiliated financial advisors was weakened after the shock.

Next, we estimate the following specification by a DiD estimator:

$$Acquirer\ CAR_i = \alpha_0 + \beta Affiliated_i + \gamma Post + \delta Affiliated_i \times Post + \theta X_i + \varepsilon_i; \qquad (5)$$

Where $Acquirer\ CAR_i$ is the acquirer's three-day cumulative abnormal returns; $Affiliated_i$ is an indicator variable equal to one if the acquirer advisor was affiliated with Lehman (the treated group) and zero otherwise (the control group). *Post* is a dummy variable coded as one if a deal was announced after

[16] Using an alternative window such as a three- or ten-year period does not alter our results.

the treatment date and zero otherwise. Our main variable of interest is the interaction term, $Affiliated_i$ × *Post*, whose coefficient (δ) estimates the impact on acquirer CAR brought by the changes in the network positioning of those affiliated financial advisors (the treated group). More precisely, it indicates to what extent changes in acquirer abnormal returns of affiliated financial advisors (the treated group) differ from the pre- to post-treatment period, relative to the same changes of unaffiliated financial advisors (the control group). We expect δ to be negative if our results are attributable to the information channel. X_i is a set of controls; and ε_i is the error term.

Table 4 presents the estimation results. Column (1) includes industry fixed effects to control for unobservable time-invariant industry-specific effects (e.g., industry shocks). Year fixed effects are also included to capture time-varying effects on the outcome of all deals. The estimate for *Affiliated* × *Post* is negative and significant at the 5% level, suggesting that acquirers advised by affiliated financial advisors lost substantially greater shareholder value around the deal announcements following the shock, as compared to those advised by unaffiliated investment banks.

It is possible that the change in acquirer CAR we observe is driven by coincident changes in acquirer-, deal-, or advisor-specific characteristics unrelated to advisor network centrality (Heider and Ljungqvist, 2015). In column (2), we include a full vector of deal-, acquirer-, and advisor-specific variables as additional controls and find similar results.

[Please Insert Table 4 Here]

The consistency of the DiD strategy hinges on the "*parallel trends*" assumption, i.e., the average change in the outcome variable would follow the same trend for both treated and control groups in the absence of treatment (Roberts and Whited, 2013). In our setting, this means that, to make a causal inference from our DiD estimator, we need to ensure that the acquirer CARs would have evolved in a similar fashion across affiliated and unaffiliated advisors absent Lehman's collapse. Such an assumption would be violated, for example, if affiliated financial advisors differ systematically from unaffiliated advisors along certain pre-treatment dimensions that were correlated with the differential changes in acquirer CAR regardless of the shock.[17] We rule out this concern in several ways. First, with more than one period of pre-treatment data, we inspect whether affiliated and unaffiliated financial advisors share parallel trends in acquirer CAR during the pre-treatment era (e.g., Heider and Ljungqvist, 2015). Panel A, Table 5, reports the difference in mean acquirer CAR between affiliated and unaffiliated financial advisors across the last three years prior to Lehman's bankruptcy, along with the corresponding t-test statistics. The difference in average acquirer CARs between these two groups is statistically indistinguishable in each of the three pre-treatment years, indicating that the parallel-trends assumption is likely to hold.[18]

To more formally verify the credibility of our DiD approach, we conduct falsification tests by "falsely" assuming that the Lehman shock occurred around a placebo period dated one-, two-, or three-year(s) earlier. This analysis allows us to examine whether the decline in acquirer CAR for the treated group (affiliated advisors), as shown in Table 4, is isolated only to the post-treatment year. If the observed change in acquirer CAR is due to time trends among the treated group, then the interaction term, *Affiliated* × *Post*, should remain significantly negative even after we shift the event-timing. If, on the other hand, the "exit" of Lehman adversely affecting the network positions of affiliated advisors has a real effect on acquirer returns, we should observe no significantly differential trends in acquirer CAR between affiliated and unaffiliated advisors in a false event year. Panel B, Table 5, presents the results on a year-by-year basis, with the controls the same as those shown in Table 4. For brevity, only the coefficient on *Affiliated* × *Post* is reported. We find that the estimated treatment effect, as indicated by the coefficient of *Affiliated* × *Post*, is economically small and statistically indistinguishable from zero for all the false event years.

Next, we augment our DiD model with advisor fixed effects to fully control for any confounding caused by unobservable fixed differences (e.g., skill or reputation) between affiliated and unaffiliated

[17] Note that although affiliated advisors may have different characteristics from unaffiliated ones, the parallel-trends assumption is violated only if such characteristics are *also* correlated with changes in the outcome variable, i.e., acquirer CAR.
[18] The analysis indicates that affiliated advisors are generally associated with higher acquirer CAR than unaffiliated advisors in the pre-treatment era, as indicated by the positive differences in acquirer CAR between the treated and control groups. These different levels (as opposed to trends) do not undermine the validity of our DD analysis since the differences between the treated and control groups as well as common trends affecting both groups are differenced out in the DiD estimation (He and Tian, 2013; Roberts and Whited, 2013).

investment banks (Bertrand and Mullainathan, 2003). The *Affiliated* and *Post* dummy variables are dropped from the model since their effects are absorbed by the advisor and year fixed effects. Panel C, Table 5, summarizes the results. We continue to observe a negative, significant (at the 10% level) coefficient estimate of *Affiliated* × *Post*, similar to the results reported in Table 4.

In Panel D, we employ a propensity score matching procedure to ensure that the affiliated and unaffiliated financial advisors are comparable along certain key dimensions. A large body of literature shows that market share is a key determinant of a financial advisor's ability to provide value-enhancing M&A advice (e.g., Servaes and Zenner, 1996; Rau, 2000). Accordingly, we match the two groups on the dimension of the average market share over the last three years. To ensure the robustness of the estimator, we restrict the matching to be the nearest one neighborhood and caliper equal to 0.001. The pairwise t-tests indicate that, before the propensity score matching, the average market share of the treatment group is 1.14%, which is significantly higher than that of the control group (0.02%). After matching, the difference between the two groups is small in terms of magnitude (0.0000) and statistical significance (p = 0.9970). Using this matched sample does not materially alter our results. Despite the reduction in sample size, the coefficient on the interaction term, *Affiliated* × *Post*, is negative and significant at the 10% and 5% level, respectively, in the specification without and with a full control of deal-, acquirer-, and advisor-specific characteristics (columns (1) and (2)).

Finally, the sudden collapse of Lehman Brothers may raise the possibility of contagion from one bank to another that transmits across the network. Consequently, investment banks affiliated with Lehman Brothers could be exposed to greater systemic risk than unaffiliated banks. For instance, prior studies find that investment banks having co-syndicated loans with Lehman were more prone to bank runs and asset write-downs (Ivashina and Scharfstein, 2010; De Haas and Van Horen, 2012). If investment banks doing business with Lehman were in worse shape after the failure of Lehman Brothers, then the observed decrease in acquirer CAR among affiliated advisors can be driven by the market perception that these advisors are more problematic than unaffiliated advisors.

We address this concern by reconstructing a new control group to be investment banks that were affiliated with Lehman through either equity or debt issue syndication, but not M&A deals, over the last five years preceding the shock. In doing so, we are able to compare investment banks that had been similarly affected by Lehman's bankruptcy, but the new control group contains banks that were not tied with Lehman in the M&A market. If the change in acquirer CAR shown above is attributable to the systemic risk-related concern common to all the banks doing business with Lehman, then we should observe no significant difference in acquirer abnormal returns between the treated and the new control group. If, instead, the effect is driven by the structural change in the advisor networks, then advisors affiliated with Lehman in the M&A market should deliver poorer acquirer abnormal returns following the "exit" of Lehman, relative to the control group. The results, laid out in Panel E of Table 5, support the latter. The interaction term, *Affiliated* × *Post*, remains negative and significant at the 10% level.

[Please Insert Table 5 Here]

4.3.2. A Two-stage Least Squares Regression Approach

As an alternative identification strategy, we perform a 2SLS regression analysis, which relies on instrumental variables (IVs) to correct for the potential bias arising from the endogenous nature of advisor network centrality. This approach has been widely employed in the corporate finance literature to address endogeneity concerns (e.g., Bennedsen, Nielsen, Perez-Gonzalez, and Wolfenzon, 2007; Hochberg *et al.*, 2010). To identify the model, we need an instrument that affects the endogenous regressor, advisor centrality, but is uncorrelated with acquirer CAR except through the channel of the acquirer advisor's network position (Fletcher and Lehrer, 2011). The instrumental variable we employ here is *geographical location*, which is an indicator variable equal to one if the acquirer advisor is headquartered in a Federal State where a major financial center - such as New York City, Chicago, Los Angeles and Boston - is present; and zero otherwise.[19] A financial center is well known as a hub for major investment banks and other

[19] We follow Wang, Xie and Zhang (2014) and identify the following States as ones including a major financial center: New York (NY), Illinois (IL), California (CA), Massachusetts (MA), New Jersey (NJ), Connecticut (CT), Rhode Island (RI), Maine (ME), Vermont (VT), and New Hampshire (NH).

significant financial service providers. When an acquirer financial advisor locates near a major financial hub, it is likely to enjoy a geographical advantage to build ties with other investment banks, especially those that are well-networked. For instance, being located near the cluster of investment banks makes it easier for a financial advisor to meet and interact with other banks (e.g., through social interaction or participation in local professional associations or meetings). This, in turn, increases the probability that the advisor will be called upon when a syndicate is needed to put together a complex M&A deal, thereby increasing its centrality scores. We thus expect an acquirer financial advisor to have higher centrality scores if it is headquartered in a State in which a major financial center is present. Meanwhile, there is no obvious reason to believe that simply locating close to a financial center, which often emerges historically, would affect acquirer abnormal returns other than operating *indirectly* through its impact on networking among investment banks, if there is any.

Table 6 reports the 2SLS regression results for the full sample, with acquirer advisor centrality measured by *degree* in model (1), *eigenvector* in model (2), and *betweenness* in model (3). For each model, the first column presents the first-stage regression of the centrality measure on the IV introduced above and a full vector of controls; whereas the second column contains the second-stage regression results of acquirer CAR. Control variables are the same as those shown in Table 2. For brevity, only the coefficients on the centrality measures are reported. The first-stage regression results reveal that all the three centrality measures are positively and strongly correlated with a financial advisor's *geographical location* (statistically significant at the 1% level). At the bottom of Table 6, we present the F-statistics for the weak identification tests, along with the corresponding Stock-Yogo critical values for a 10% maximal LIML size distortion (Staiger and Stock, 1997). [20] The F-test statistics far exceed the Stock-Yogo critical value in each regression model, indicating that our instrumentation is strong. The second-stage regression results reveal that the three centrality measures (instrumented) generate a positive and highly significant (at the 5% level)

[20] With cluster-robust statistics, the Cragg-Donald-based weak instruments test is no longer valid. We thus report corresponding Kleibergen-Paap Wald RK F statistics for the weak identification tests.

impact on acquirer abnormal returns. Collectively, these findings are consistent with the causal link between advisor network position and acquirer returns.

[Please Insert Table 6 here]

4.4. Other Robustness Tests

We perform additional robustness tests to verify the validity of our baseline results. First, our centrality measures are computed based on the *existence* of ties between investment banks. The extant literature on social networks suggests, however, that the strength of ties may also matter. For instance, strong ties may increase the willingness of sharing costly private information, such that investment banks having stronger ties would have a higher priority to receive such information before acquaintances (i.e., banks sharing weak ties). We thus re-estimate our CAR models using value-weighted centrality measures, where each tie is weighted by the number of times that two investment banks have syndicated M&A deals over the last three years before the deal announcement. The results, reported in Panel A, Table B.3, Appendix B, are similar to those reported in Table 2.

Second, our centrality measures based on syndicate relationships in the M&A market may not capture the information value of interbank relationships formed in other markets. To address this concern, we examine syndicate relationships across a wider set of transaction types including equity and debt offerings. Specifically, we construct interbank networks for each year *t* based on the ties that investment banks have formed by participating in the same syndicate(s) organized for underwriting equity and debt issues, respectively, over the last three years prior to year *t*. We then calculate centrality scores for each underwriter by transaction type and assign the scores to acquirer financial advisors based on the matching of investment bank names.

Panel B, Table B.3, Appendix B, repeats our baseline regression controlling for the acquirer financial advisor's centrality scores in the equity and debt market, respectively. [21] The results indicate that

[21] The results would be more informative if we control for the acquirer advisor's network centrality in the equity and debt markets in the same regression model. However, we are unable to do so because centrality measures in the equity and debt markets are highly correlated.

the improvement in acquirer returns primarily stems from interbank ties formed in the M&A market but not in other markets. In unreported results, we separately regress the acquirer three-day CAR on advisor network centrality in the equity and debt market. We find that none of these centrality measures are statistically significant, indicating that an acquirer advisor's network position in the securities markets plays little role in explaining cross-sectional variation in acquirer abnormal returns.

Third, because of the bargaining nature of a takeover contest, whether an acquirer has a strategic advantage of hiring a central financial advisor may depend on the network positioning of the financial advisor on the target side (Kale *et al.*, 2003). As shown in Panel C, Table B.3, Appendix B, the centrality measures of target financial advisors do not appear to significantly affect acquirer CAR. After controlling for such an effect, acquirer advisor centrality continues to exert a positive, significant (at the 5% level) impact on acquirer abnormal returns.

Finally, we conduct the following robustness tests: (i) using advisor centrality measures based on alternative length of connections (e.g., over the last one or five years); (ii) employing the equally-weighted CRSP index (as opposed to value-weighted) as the market return; and (iii) using acquirer CAR computed over alternative event windows (-2, +2) and (-5, +5). In all the tests, our main results regarding the positive effect of advisor centrality on acquirer CAR hold.

5. What Explains Central Acquirer Advisors' Ability to Deliver Superior Performance?

Our theoretical framework posits that an acquirer financial advisor's network position improves acquisition outcomes because it creates a competitive advantage in information production. In this section, we provide direct evidence on this argument by performing two analyses. First, we investigate whether the beneficial effect of advisor network centrality on acquirer abnormal returns is more pronounced among more informationally opaque deals as our theoretical framework suggests. Second, we explore whether and what types of network contacts contribute to a central advisor's superior ability of producing target-related information.

5.1. Cross-sectional Heterogeneity

If the economic effect of network centrality on acquirer CAR goes through the information channel, it should be stronger for deals involving a higher level of information opacity. Towards this end, we examine cross-sectional differences in the degree of information asymmetry across target firms, as proxied by industry relatedness, target idiosyncratic stock return volatility, whether the target firm has credit ratings, and whether it is in the Standard & Poor's (S&P) 1500 index. Except for industry relatedness, all the cross-sectional tests are performed for a sample of public acquisitions for which we can obtain the relevant data on target share price, credit ratings and S&P 1500 membership. As before, we control for advisor-, deal- and acquirer-specific characteristics along with year and industry fixed effects whose coefficients are suppressed for brevity. [22]

An acquirer operating in a different industry from the target firm is likely to face greater information asymmetry because of unfamiliarity with the target's operating environment (Faccio and Masulis, 2005). We therefore expect the positive relation between advisor centrality and acquirer abnormal returns to be more evident in cross- than in same- industry deals. Panel A, Table 7, investigates this possibility for the full sample split by industry relatedness, defined by the 2-digit Standard Industrial Classification (SIC) codes. We find that all the three centrality variables are positive and significant at the 5% level for the subsample of cross-industry deals (columns (1) through (3)). In addition, the economic magnitudes of these centrality measures are about 1.5 times larger than those reported in Table 2; holding other factors constant, an acquirer undertaking a cross-industry deal experience 0.414-0.454 percentage points higher abnormal returns for every one-standard-deviation increase in its financial advisor's centrality scores. In contrast, there is either an insignificant or marginally significant impact of advisor network centrality on acquirer CAR in same-industry transactions (columns (4) through (6)). This finding is consistent with the interpretation that the information advantage of a financial advisor's network position is less important for

[22] The control variables are the same as those in Panel A, Table 9, except that we exclude the interaction terms between target status and payment method since the sample involves only public targets.

acquirers that are in the same industry as the targets and, hence, well acquainted with the target's business operations, growth prospects and risks.

In Panel B, Table 7, we conduct CAR analysis for a sample of public acquisitions split based on whether the target firm has above- or below-average idiosyncratic stock return volatility. Target idiosyncratic return volatility is computed as the standard deviation of the market-adjusted daily returns of the target's stock over a 200-day window (-210, -11). We expect advisor network centrality to be more valuable for deals in which target firms have higher idiosyncratic return volatility because these deals involve greater uncertainty about the target's firm value and future earnings (Officer, Poulsen, and Stegemoller, 2009). Consistent with this expectation, we find that the favorable effect of advisor network centrality is absent in deals involving targets with below-average idiosyncratic return volatility (columns (4) through (6)). For target firms with above-average idiosyncratic stock return volatility, *betweenness* centrality is positive and significant at the conventional levels, whereas the other two centrality measures generate a positive but weak impact on acquirer CARs (columns (1) through (3)).

Panels C and D, Table 7, examine the impact of advisor network centrality on acquirer returns for the sample of public deals divided based on whether the target firm has credit ratings and S&P 1500 membership, respectively. The extant literature suggests that firms with a credit rating are less informationally opaque because rating agencies regularly provide forward-looking opinions on the firm's financial performance and credit risk (e.g., Tang, 2009; Xia, 2014). Similarly, memberships in the S&P 1500 reduce information asymmetry because of improved transparency and increased flow of public information from information intermediaries such as media, financial analysts and "watchdogs" (e.g., Chen, Noronha, and Singal, 2004; Mola, Rau, and Khorana, 2013). Accordingly, we expect the information production role of central financial advisors to be less important for acquisitions of rated firms and firms in the S&P 1500. In line with this conjecture, we find that all the three centrality variables have a positive, significant effect on acquirer CAR only among deals involving unrated and non-S&P 1500 target firms (columns (1) through (3)).

In sum, across all the four different measures of target information opacity, we find that, consistent with the information production channel, more centrally positioned advisors lead to greater improvement in acquirer abnormal returns when there is more severe information asymmetry surrounding the target firm. These findings are difficult to reconcile with an alternative explanation in which advisor network centrality simply proxies for other unobservable factors such as advisor ability, since such an explanation would have the burden of explaining why these omitted variables exhibit stronger effects in the high information asymmetry situations only.

[Please Insert Table 7 Here]

5.2. Information Channels

To strengthen the information channel interpretation of our results, we explore the types of network contacts that are informationally valuable to acquirer advisors. Specifically, we ask whether a centrally positioned financial advisor utilizes its connections with other investment banks to gather acquisition-related information, and if so, what types of information contribute to the observed improvement in acquirer abnormal returns. To this effect, we consider acquirer advisor's network contacts that: (i) had direct interaction with the target firm in the past; (ii) specialize in the target firm's industry; and (iii) specialize in the target geographical region.

The extant literature suggests that past dealings are the primary avenues for investment banks to gather "inside" information about a corporate client (e.g., Fang, 2005; Fernando, May, and Megginson, 2012; Corwin, Larocque, and Stegemoller, 2017). We thus expect an acquirer advisor to derive firm-specific information at least in part from its network contacts that had previously been hired by the target firm for investment banking services. We start by identifying investment banks that have acted as a lead underwriter or co-manager on the target firm's equity or debt issues, or have provided the target with M&A advisory services, over the last three years preceding the deal announcement (the acquirer financial advisor is not included). [23,24] When one or more of these investment banks and the acquirer advisor are linked via past M&A syndication, we label the acquirer advisor with the corresponding type of information channel. For instance, in 2000, ConAgra Inc. engaged Gleacher & Co LLC to act as its financial advisors in connection with the acquisition of International Home Foods Inc. One of Gleacher's network contacts was Morgan Stanley, which helped International Home Foods with its equity offerings in 1997. Accordingly, Gleacher is classified as having target information from the *equity underwriting* channel. It is noted that although we can identify investment banks that had previously provided M&A services for both public and private target firms, only public targets have data on past equity and debt transactions. To be consistent, the analysis is restricted to a sample of 3,704 public acquisitions. [25] Of these deals, 12.9% involve acquirer advisors having information partially derived from the equity underwriting channel, 8.5% from the debt underwriting channel, and 7.7% from the M&A advisory channel.

Columns (1) through (3), Table 8, provide the results for each of these three firm-specific information channels. The control variables are the same as those shown in Table 4, and we present only results using *degree* centrality of acquirer financial advisors for the sake of brevity. Using other centrality measures produces similar results (Appendix B, Table B.5). Column (1) reports the results for the equity underwriting channel, where *degree* centrality is broken into two mutually exclusive variables: (i) *degree* centrality scores for acquirer advisors having an equity underwriting channel, and zero otherwise; and (ii) *degree* centrality scores for acquirer financial advisors without such a channel, and zero otherwise. We find that *degree* centrality is positive and significant at the 5% level for acquirer advisors with an equity underwriting channel. For every one-standard-deviation increase in *degree* centrality, acquirer CAR increases by 0.626% when one or more network contacts of the acquirer advisor have acquired target information during the past equity underwriting process. In the absence of such network contacts, an

[23] As before, the acquirer advisor cannot have a tie with itself and therefore does not form a part of its network contacts.
[24] We obtain similar results when an alternative window such as a one- or five-year window is used. We do not consider a longer window since the information obtained by a network contact, say, ten years ago is unlikely to be relevant for the assessment of the target's conditions today.
[25] For the M&A advisory channel, including private targets does not change our results.

acquirer advisor's *degree* centrality is positive and significant at the 10% level. The effect is also smaller economically, with a one-standard-deviation increase in this centrality measure being associated with 0.321-percentage point increases in acquirer abnormal returns.

In columns (2) and (3), we observe that the other two channels, i.e., debt underwriting and M&A advisory, contribute either weakly or insignificantly to the information-production role of a central financial advisor. One possible explanation for this result is that the equity issuer-underwriter relationships carry greater information value than do other investment banking relationships (e.g., Burch, Nanda, and Warther, 2005; Fang, 2005; Fernando *et al.*, 2012; Corwin and Stegemoller, 2014). For example, Fernando *et al.* (2012) indicate that IPO underwriters must acquire firm-specific information about the issuer in order to credibly certify the firm's IPO to outside investors. In contrast, the information-production role of debt underwriters diminishes because of debt ratings offered by rating agencies. In a similar vein, private information collected during the M&A process is mainly related to the target firm, which largely vanishes after the target is successfully acquired. Thus, our results reconcile the existing evidence, suggesting that the information advantage of an acquirer financial advisor is most evident when it has access to private target information obtained by other investment banks through the provision of equity underwriting services.

Besides firm-specific information, the acquirer advisor may obtain useful information about the target firm's operating environment when it is tied to investment banks specializing in the target industry or geographic region. To test this proposition, we rank each investment bank based on the percentage of M&A transaction value it has advised on in the target industry (defined based on the 3-digit SIC codes) over the last three years preceding the deal announcement.[26] We then classify those ranked 1st to 15th as specialists in the target industry.[27] When one or more of these industry specialist investment banks are tied to the acquirer financial advisor via past M&A syndication, we label the acquirer advisor with the industry-specific information channel. Column (4), Table 8, summarizes the results for the industry-specific

[26] We choose the 3-digit SIC classification since it is neither too coarse compared with the 2-digit SIC partition, nor too narrow compared with the 4-digit SIC classification. The results are, however, robust to the alternative industry classifications, although the effect becomes weaker when the 2-digit SIC partition is used.
[27] Our results continue to hold when we change the cut-off point of the 15th to the 5th or the 20th.

information channel. Consistent with our expectations, *degree* centrality exhibits a stronger effect on acquirer CAR, both economically and statistically, when one or more network contacts of the acquirer advisor have strong expertise in the target industry.

We use the same procedure to identify network contacts specializing in the target geographical region, defined based on the state in which the target firm operates. Column (5) of Table 8 reports the results for the subsample of domestic deals for which target State information is available. We find that *degree* centrality with and without the regional-specific information channel are both positive and significant at the 10% level. Thus, the relation between *degree* centrality and acquirer CAR does not appear to differ on whether the acquirer advisor "knows" regional specialists. One possible explanation for this finding is most investment banks have branches across state lines.

In column (6), Table 8, we present the results for the *combined* channel, which is equal to one if the acquirer advisor has any of the aforementioned information channels, and zero otherwise. The results indicate that the positive effect of *degree* centrality on acquirer CAR is stronger among financial advisors having access to firm-, industry- or regional-specific information of the target firm. While we do not exhaust all possible information channels, [28] these findings lend strong support to the argument that acquirer financial advisors utilize their connections with other investment banks to extract valuable information about the target firms.

[Please Insert Table 8 Here]

Taken together, the cross-sectional tests performed in this section further attenuate the endogeneity concerns: If unobservable advisor skill is the underlying force driving our results, the effect should be present regardless of target information asymmetry. We, however, show that the positive effect of advisor network centrality on acquirer CAR is more evident among deals characterized by greater information asymmetry surrounding the target firm. Moreover, much of value creation comes from acquire advisor's

[28] For example, an acquirer advisor may extract acquisition-related information from network contacts that have provided the target firm with other ancillary services such as marketing and cash management in the past.

network contacts that have either provided the target firm with equity underwriting services before or had expertise in the target's industry. These findings are consistent with the information channel.

6. Other Acquisition Outcomes

6.1. Takeover Premium, Synergy Gain and Post-Merger Performance

Having established the robustness of our findings, we now proceed to examine the impact of acquirer advisor network centrality on other major acquisition outcomes. Table 9 investigates whether advisor network centrality affects takeover premium for a sample of public deals for which the data on target stock price are available. Takeover premium is defined as a *percentage* premium of offer price over target market value four weeks before the deal announcement (e.g., Officer *et al.*, 2009; Golubov *et al.*, 2012). We control for the same variables as in the CAR analysis, except that the interaction terms between target listing status and payment method are replaced by the *payment include stock* variable since the sample here includes public targets only.

According to the "*information production*" hypothesis, a centrally positioned financial advisor has preferential access to the private knowledge of a potential target owned by other connected investment banks. It is, therefore, better informed about the profitability and true value of the target than a peripheral advisor. All else being equal, more centrally positioned financial advisors should be associated with more accurate deal evaluation. The results, shown in columns (1) through (3) of Table 9, confirm this conjecture. The three centrality measures all generate a significant, negative impact on takeover premium, with the *degree* centrality producing the largest effect both economically and statistically (significant at the 1% level). Holding other factors constant, an acquiring firm can expect a 2.086-percentage-point reduction in premium for every one-standard-deviation increase in its financial advisor's degree centrality (column (1)).[29] The first principal component and the orthogonally transformed degree centrality are also negative and significant (columns (4) and (5)). Thus, the information advantage of a central financial advisor helps an acquirer to accurately evaluate a deal and lower the cost of acquisition.

[29] Note that takeover premium is stated in percentage points, not in decimals.

[Please Insert Table 9 Here]

Better information could also imply better ability to construct synergistic deals. To explore this possibility, we study the impact of acquirer advisor network centrality on total takeover synergy gain, defined as the combined announcement returns received by the acquirer and the target shareholders over a three-day event window (e.g.,Wang and Xie, 2009; Cai and Sevilir, 2012). [30] As shown in Table B.5, Appendix B, the coefficient estimates of our centrality measures are statistically insignificant throughout the table, indicating that advisor network position has little impact on total synergy gains. Recent research shows that, at the time of the deal announcement, the market may fail to recognize and impound synergy gains from a merger which are often longer-term and more uncertain in nature (e.g., Bernile and Bauguess, 2011; Dutordoir, Roosenboom, and Vasconcelos, 2014; Dasgupta, Harford, and Ma, 2019). Specifically, managers are reluctant to provide precise synergy estimates because of the concern about potential lawsuits in relation to misleading synergy disclosure (Dasgupta *et al.*, 2019). Indeed, using news articles and press releases, Bernile and Bauguess (2011) find that only about 23% of public deals are accompanied by management forecasts of synergies. Dutodoir *et al*. (2014) report that only 2% of public deals provide a present value estimate of synergy value. The lack of management disclosure of synergy estimates can make it difficult for market participants to draw inference about the existence and magnitude of merger-related efficiencies, even if such synergies exist (Bernile and Bauguess, 2011). We therefore investigate whether deals advised by more centrally positioned financial advisors are accompanied by *real* improvements in operating performance after the merger.

Following Hoberg and Phillips (2010), we focus only on the acquirer's change in operating performance *after* the transaction's effective date. Though this approach is likely to understate the true impact of our centrality variables, it avoids bias from trying to measure *ex ante* performance of the two separate firms before the corporate takeover (Hoberg and Phillips, 2010; Maksimovic, Phillips, and

[30] We follow Wang and Xie (2009) and construct a value-weighted portfolio of the acquirer and the target, with the weights being the market capitalization of the respective firms 11 days before the deal announcement. The target's weight is adjusted for the value of target equity held by the acquiring firm before the announcement date. We then compute the takeover synergy gain as the portfolio's cumulative abnormal returns over a three-day event window.

Prabhala, 2011). The analysis is restricted to a sample of completed deals. Our main measure of *ex post* operating performance is the change in return on assets (ROA) from year t+1 to t+4 (a three-year horizon), where ROA is computed as the operating income before depreciation divided by total assets (e.g., Eisenberg, Sundgren, and Wells, 1998; Harford, Humphery-Jenner, and Powell, 2012). ROA is commonly used as an indicator of how efficiently an acquiring firm uses a given amount of assets to generate earnings. Thus, increases in ROA can be interpreted as improvements in operating efficiency. We further decompose ROA into return on sales (ROS) and asset turnover (ATO) to gain a better understanding of the source(s) driving the change in ROA if there is any. ROS is measured as operating income before depreciation scaled by sales, and ATO is computed as sales divided by total assets. The post-takeover changes in these two ratios reflect improvements in operating margin and productive asset utilization, respectively. To control for the effect of outliers, we truncate all the performance variables to lie in the interval [-1, +1] (Hoberg and Phillips, 2010). Since improvements in post-merger performance could be driven by economy-wide and industry factors (Healy, Palepu, and Ruback, 1992), we include industry and year fixed effects in the regression models to control for time-invariant industry effects and year-specific variation in operating performance changes. Other controls are the same as those employed in our CAR analysis.

Table 10 provides the results for post-merger operating performance. We find that more centrally positioned financial advisors are associated with a significant improvement in ROA in the post-merger period (Panel A, Table 10). As shown in Panels B and C, the increase in ROA is attributable to more productive use of assets by the combined firm, i.e., ATO, but not improvement in profit margins, i.e., ROS.

[Please Insert Table 10 Here]

To provide a complete picture of the benefits of central financial advisors, we extend our analysis to non-value-added acquisition outcomes measured by completion probability and deal duration (e.g., Golubov *et al.*, 2012; Song *et al.*, 2013; Chaudhry, Kontonikas, and Vagenas-Nanos, 2017). [31] The results,

[31] The probability of completing a deal and time to completion are considered as "non-value-added" performance dimensions because value creation depends on the quality of a deal, not on whether and how fast a deal is completed. For instance, it is detrimental to acquirer shareholders if a central financial advisor merely pushes through a deal that is value-destructive.

reported in Table B.6, Appendix B, indicate that the impact of acquirer advisor centrality on the probability of completing a deal is negative but generally statistically insignificant. Thus, despite the well-known problem of misaligned incentives arising from the contingent-fee structure (McLaughlin, 1992; Bao and Edmans, 2011), central financial advisors do not seem to be merely motivated to consummate a deal in order to get completion payments. In terms of deal duration, Table B.7, Appendix B, shows that the coefficient estimate of advisor network centrality is positive and significant at the 1% level. Thus, more centrally positioned financial advisors appear to take longer to gather and process the information necessary for providing high-quality advice on M&A deals.

Overall, the results presented in this section support the information value of advisor network centrality. Apart from higher abnormal returns, acquiring firms pay lower takeover premiums and experience better post-merger operating performance when enlisting the services of a financial advisor that is more centrally positioned in the network of investment banks. Moreover, there is no evidence that central financial advisors are hired to merely push through or execute deals quickly without making valuable inputs into the M&A decision making.

6.2. Advisory Fee

If central financial advisors provide superior service, an interesting question is whether such service comes at a premium fee. M&A advisory fees are a major source of revenue for investment banks (Kolasinski and Kothari, 2008; Golubov *et al.*, 2012). Consequently, investment banks would have an incentive to invest costly resources in maintaining connectivity only when such an investment is rewarded by corporate clients. Evidence of this also addresses the question as to why not all acquirers hire centrally positioned financial advisors.

Table 11 provides the results for advisory fees, defined as the total advisory fee paid by the acquirer as a percentage of deal value. We use Tobit model regressions to take care of the non-negative nature of advisory fees. McLaughlin (1990) documents a negative association between percentage advisory fee and transaction size due to economies of scale. We control for this effect by including the natural logarithm of deal value in our fee regression model. Other control variables are the same as those shown in Table 2. We find that advisor network centrality is positively and significantly (at the 1% level) related to advisory fees. Holding other factors constant, a one-standard-deviation increase in *degree*, *eigenvector* and *betweenness* centrality is associated with 0.182-, 0.181-, and 0.141-percentage point increases in advisory fees, respectively. This translates into U.S. $1.348-1.743 million in premium fees for an average deal ($959.092 million) in our sample. Compared with the mean incremental gain of $14.662 -19.301 million that a central advisor brought for an average-sized acquiring firm, our results indicate that financial advisors share in economic rents (8.263% - 9.704%) arising from their position in the network of investment banks. [32]

[Please Insert Table 11 Here]

7. Conclusion

Like many other financial intermediaries, investment banks routinely cooperate with one another and are bound into webs of relationships. Though the prevalence of interbank networking is well documented in the literature, the performance consequences of this organizational structure have received little attention empirically. Using a comprehensive sample of U.S. M&A transactions announced over 1990-2016, we examine, for the first time in the literature, whether networking among investment banks is economically beneficial from an acquirer client's perspective.

Our results indicate that when acquirer financial advisors have a more influential position in the network of investment banks, acquiring firms experience significantly better acquisition performance, as measured by announcement abnormal returns, offer premium and post-merger operating performance. These findings are robust to alternative definitions of advisor network centrality, as well as various empirical strategies that address the endogeneity problems. Consistent with the "*information production*" hypothesis, the positive effect of an advisor's network position on acquisition performance is more pronounced when the information asymmetry surrounding the target firm is more severe. Moreover, the

[32] The share of rent accruing to a central hub financial advisor is equal to the premium fee (that is, $1.743 million, $1.738 million and $1.348 million, respectively, for a one-standard-deviation increase in degree, eigenvector and betweenness centrality), divided by the total gain arising from the advisor's central position in the network of investment banks, i.e., 17.961 (1.743+16.218) million for degree, $21.039 (1.738+19.301) million for eigenvector, and $16.010 ($1.348+$14.662) for betweenness.

information advantage of central financial advisors appears to stem primarily from their network contacts that had previously served the target firm in the equity market or specialized in the target industry. Finally, the economic rent from advisor networking is shared between acquirers and central hub advisors, with central hub financial advisors charging a premium price for their superior service.

Overall, our study suggests that the position of a financial advisor in the network of investment banks is one of the possible drivers of the cross-sectional variation in acquisition outcomes. The findings have important implications for practitioners undertaking M&As. Given the large returns to the use of a well-networked investment bank, for instance, acquiring firms should consider network position as one of the selection criteria when selecting their financial advisors.

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Table 1. Summary Statistics

This table presents the descriptive statistics for the sample of U.S. M&A transactions announced between 1/1/1990 and 31/12/2016. Panels A, B, C and D report the number of observations (*N*), mean, standard deviation (*Std. Dev.*), minimum (*Min.*), median, and maximum (*Max.*) for acquirer abnormal returns, advisor-, acquirer- and deal-specific characteristics, respectively. Appendix A provides a description of all the variables.

	N	Mean	Std. Dev.	Min.	Median	Max.
Panel A: Acquirer returns						
CAR (-1, +1)	7207	0.005	0.084	-0.234	0.000	0.314
Panel B: Advisor characteristics						
Degree	7207	0.085	0.077	0.000	0.069	0.271
Eigenvector	7207	0.205	0.171	0.000	0.218	0.715
Betweenness	7207	0.051	0.056	0.000	0.033	0.233
Advisor Market Share	7207	0.037	0.045	0.000	0.012	0.187
Panel C: Acquirer characteristics						
Acquirer Size (in $mil)	7207	5818.186	20816.576	0.315	876.760	564801.688
Run-up	7207	0.120	0.577	-0.960	0.025	8.772
FCF	7207	0.051	0.171	-4.150	0.076	0.775
Leverage	7207	0.202	0.197	0.000	0.159	1.896
Tobin’s Q	7207	2.384	3.638	0.194	1.526	137.308
Panel D: Deal characteristics						
Relative Size	7207	0.414	1.450	0.010	0.198	88.589
Number of Competing Bidders	7207	1.043	0.243	1.000	1.000	4.000
Related	7207	0.657	0.475	0.000	-	1.000
Tender	7207	0.077	0.267	0.000	-	1.000
Hostile	7207	0.022	0.146	0.000	-	1.000
Public Target	7207	0.436	0.496	0.000	-	1.000
Private Target	7207	0.329	0.470	0.000	-	1.000
Subsidiary Target	7207	0.235	0.424	0.000	-	1.000
Cross Border	7207	0.129	0.336	0.000	-	1.000
All Cash	7207	0.312	0.464	0.000	-	1.000
Payment include Stock	7207	0.553	0.497	0.000	-	1.000

Table 2. Advisor Centrality and Acquirer Abnormal Returns

This table reports the results from the OLS regression of the acquirer three-day CAR on the measures of acquirer financial advisor centrality and other advisor-, deal- and acquirer- characteristics for a sample of U.S. acquisitions over 1990-2016. The dependent variable is the cumulative abnormal return (CAR) on the acquirer's stock over the event window (-1, +1). Acquirer advisor centrality is measured as *degree* in column (1), *eigenvector* in column (2), *betweenness* in column (3), the principal component (PC) score in column (4), and the orthogonally transformed centrality measures in column (5). Other variables are defined in Appendix A. Year and industry fixed effects are included in all the models, but the coefficients are suppressed for brevity. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. Symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Dep. Var.= Acq. CAR	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Centrality	Degree	Eigenvector	Betweenness	PC	Ortho
Degree	0.0362**				0.0026**
	(2.2397)				(2.0822)
Eigenvector		0.0194**			0.0024
		(2.3928)			(1.3378)
Betweenness			0.0450**		0.0006
			(2.1668)		(0.5800)
PC				0.0018**	
				(2.3600)	
xMktShare	0.0244	0.0287	0.0235	0.0257	0.0313
	(0.4120)	(0.4805)	(0.3971)	(0.4340)	(0.5149)
Ln (Acquirer Size)	-0.0053***	-0.0055***	-0.0052***	-0.0054***	-0.0054***
	(-7.3035)	(-7.0944)	(-7.3425)	(-7.2717)	(-7.2358)
Run-up	-0.0080***	-0.0079***	-0.0080***	-0.0079***	-0.0079***
	(-3.1842)	(-3.1569)	(-3.2052)	(-3.1736)	(-3.1834)
FCF	-0.0123	-0.0123	-0.0124	-0.0123	-0.0123
	(-1.2857)	(-1.2847)	(-1.2920)	(-1.2882)	(-1.2874)
Leverage	0.0181***	0.0179***	0.0186***	0.0182***	0.0181***
	(3.1612)	(3.1262)	(3.2534)	(3.1734)	(3.1430)
Tobin's Q	0.0004	0.0004	0.0004	0.0004	0.0004
	(0.8583)	(0.8600)	(0.8531)	(0.8552)	(0.8618)
Relative Size	0.0042***	0.0042***	0.0042***	0.0042***	0.0042***
	(3.9120)	(3.9177)	(3.9219)	(3.9163)	(3.9426)
Related	0.0030	0.0031	0.0029	0.0030	0.0031
	(1.3052)	(1.3526)	(1.2741)	(1.3086)	(1.3807)
Tender	0.0043	0.0041	0.0044	0.0043	0.0040
	(0.7579)	(0.7419)	(0.7673)	(0.7575)	(0.7415)
Hostile	-0.0137**	-0.0135**	-0.0138**	-0.0137**	-0.0134**
	(-2.1401)	(-2.1276)	(-2.1489)	(-2.1391)	(-2.1304)
Cross-border	-0.0010	-0.0008	-0.0011	-0.0010	-0.0008
	(-0.3521)	(-0.2872)	(-0.3710)	(-0.3291)	(-0.2617)
Number of Competing Bidders	-0.0038	-0.0040	-0.0037	-0.0038	-0.0041
	(-0.6144)	(-0.6682)	(-0.5948)	(-0.6263)	(-0.7041)
Pub. × All cash	-0.0053	-0.0051	-0.0052	-0.0052	-0.0049
	(-1.4548)	(-1.4135)	(-1.4449)	(-1.4370)	(-1.3814)
Priv. × All cash	0.0003	0.0003	0.0003	0.0003	0.0003
	(0.0594)	(0.0608)	(0.0565)	(0.0636)	(0.0486)
Sub. × All cash	0.0011	0.0011	0.0012	0.0012	0.0011
	(0.3265)	(0.3217)	(0.3532)	(0.3379)	(0.3303)
Pub. × Pmt. incl. Stock	-0.0418***	-0.0418***	-0.0419***	-0.0418***	-0.0418***
	(-13.7784)	(-13.7667)	(-13.7854)	(-13.7827)	(-13.7474)
Priv. × Pmt. incl. Stock	0.0013	0.0014	0.0013	0.0014	0.0015
	(0.3670)	(0.3952)	(0.3653)	(0.3796)	(0.4106)
Intercept	0.0449***	0.0449***	0.0440***	0.0480***	0.0477***
	(3.9799)	(4.0342)	(3.8872)	(4.2852)	(4.1920)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
N	7207	7207	7207	7207	7207
Adjusted R^2	0.094	0.094	0.094	0.094	0.094

Table 3. Alternative Explanations

Panel A of this table examines the acquirer three-day CAR for acquirer financial advisors whose network centrality changes from year *t*-1 to year *t*, controlling for advisor fixed effects. Year *t* refers to the announcement year. A change in acquirer advisor centrality is measured as the change in *degree* between year *t*-1 and year *t* in column (1), the change in *eigenvector* in column (2), and the change in *betweenness* in column (3). To be included in the analysis, an acquirer advisor must have advised on at least one deal in the previous year. Panel B controls for *Syndicated*, which is a dummy variable equal to one if the current deal involves multiple acquirer financial advisors and zero otherwise. In Panel C, we control for a central advisor's access to deal flow, as proxied by its level of degree centrality. *High degree centrality* is an indicator variable equal to one if an acquirer advisor is in the top-quintile of the degree centrality distribution, and zero otherwise. All specifications control for the same set of variables as in Table 2, whose coefficients are suppressed for brevity. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. Symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Advisor reputation versus networking

Dep. Var.= Acq. CAR	**(1)**	**(2)**	**(3)**
Change in Centrality	Degree	Eigenvector	Betweenness
Change in Degree	0.1198**		
	(2.4115)		
Change in Eigenvector		0.0421**	
		(1.9897)	
Change in Betweenness			0.0820*
			(1.6793)
Controls	Yes	Yes	Yes
Advisor Fixed Effect	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
N	5285	5258	5103
adj. R^2	0.113	0.114	0.116

Panel B: Syndication versus networking

Dep. Var.= Acq. CAR	**(1)**	**(2)**	**(3)**
Centrality	Degree	Eigenvector	Betweenness
Degree	0.0350**		
	(2.2128)		
Eigenvector		0.0190**	
		(2.4381)	
Betweenness			0.0433**
			(2.1265)
Syndicated	0.0011	0.0008	0.0014
	(0.3070)	(0.2314)	(0.3865)
Controls	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
N	7207	7207	7207
Adjusted R^2	0.094	0.094	0.094

Panel C: Access to deal flow versus information

Dep. Var.= Acq. CAR	**(1)**	**(2)**
Centrality	Eigenvector	Betweenness
Eigenvector	0.0203**	
	(1.9899)	
Eigenvector × High Degree Centrality	-0.0016	
	(-0.1822)	
Betweenness		0.0597*
		(1.7343)
Betweenness × High Degree Centrality		-0.0176
		(-0.5560)
Controls	Yes	Yes
Industry Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
N	7207	7207
Adjusted R^2	0.094	0.094

Table 4. Advisor Centrality and Acquirer CAR: A Difference-in-differences Approach

This table presents the results from the difference-in-differences cross-sectional regressions for a sample of deals announced between 14 September 2005 and 14 September 2011, which involves three years of data before and after the bankruptcy date of Lehman Brothers (14 September, 2008). In each column, the dependent variable is the acquirer three-day CAR. *Post* is a dummy variable equal to one if a deal is announced after the bankruptcy date of Lehman Brothers; and zero otherwise. *Affiliated* is a dummy variable equal to one if an acquirer financial advisor was affiliated with Lehman Brothers five years prior to the bankruptcy date; and zero otherwise. The main variable of interest is the interaction term, *Affiliated* x *Post*, which denotes the difference-in-differences coefficient. Other variables are defined in Appendix A. Year and industry fixed effects are included in all the models, but the coefficients are unreported. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. Symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Dep. Var.= Acq. CAR	(1)	(2)
Affiliated × Post	-0.0193**	-0.0203**
	(-2.1374)	(-2.3074)
Post	0.0389**	0.0438***
	(2.5359)	(2.9478)
Affiliated	0.0079	0.0114**
	(1.3720)	(1.9659)
xMktShare		-0.1293
		(-1.4716)
Ln (Acquirer Size)		-0.0007
		(-0.5132)
Run-up		-0.0354***
		(-4.4641)
FCF		-0.0175
		(-1.4215)
Leverage		0.0668***
		(3.8339)
Tobin's Q		0.0003
		(0.1231)
Relative Size		0.0251***
		(5.1279)
Related		0.0082*
		(1.8058)
Tender		0.0153
		(1.6382)
Hostile		-0.0057
		(-0.4027)
Cross-border		0.0020
		(0.3527)
Number of Competing Bidders		-0.0125
		(-1.3912)
Pub. × All cash		-0.0079
		(-1.0508)
Priv. × All cash		-0.0034
		(-0.4436)
Sub. × All cash		-0.0018
		(-0.2568)
Pub. × Pmt. incl. Stock		-0.0346***
		(-5.2666)
Priv. × Pmt. incl. Stock		0.0033
		(0.4284)
Intercept	-0.0043	-0.0032
	(-0.2826)	(-0.1582)
Industry Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
N	1390	1390
Adjusted R^2	0.020	0.092

Table 5. Robustness Tests

Panel A of this table investigates the parallel trends before the bankruptcy date of Lehman Brothers. Panel B conducts a placebo test which replicates the difference-in-differences analysis in Table 4, but "falsely" assumes that the Lehman shock was occurred around a placebo period dated one-, two- or three-years earlier (i.e., 2007 through 2005). In Panel C, we include advisor fixed effect as an additional control to fully capture unobservable, time-invariant differences between affiliated and unaffiliated investment banks. The *Affiliated* and *Post* dummy variables are excluded from the model since their effects are absorbed by advisor and year fixed effects. Panel D performs the DiD analysis for a sample of affiliated and unaffiliated financial advisors matched on the basis of their average market share over the last three years. In Panel E, the control group is redefined as investment banks that were affiliated with Lehman Brothers in either the equity or debt market, but not in M&A advisory market, over the last five years preceding the shock. For brevity, only the coefficient on *Affiliated* × *Post* is reported. Control variables in all the regression models are the same as those shown in Table 4. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. Symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Parallel trends

Years relative to 14/09/2008	Average Acquirer CAR for Treatment Group (1)	Average Acquirer CAR for Control Group (2)	Difference in Acquirer CAR (1)-(2)	*p*-value of Difference t-test (3)
t=-1	-0.0065	-0.0106	0.0041	0.7195
t=-2	0.0152	0.0029	0.0123	0.1294
t=-3	-0.0050	-0.0105	0.0056	0.4007

Panel B: Falsification tests

Dep. Var.= Acq. CAR	**Coefficient on *Affiliated* × *Post***	
False Event Year	(1)	(2)
2007	-0.0120	-0.0112
	(-1.4215)	(-1.3627)
2006	0.0048	0.0075
	(0.5944)	(0.9246)
2005	0.0094	0.0124
	(1.1930)	(1.5606)
Controls	No	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Panel C: Controlling for advisor fixed effects

Dep. Var.= Acq. CAR	(1)	(2)
Affiliated × Post	-0.0150*	-0.0156*
	(-1.6588)	(-1.7576)
Controls	No	Yes
Advisor Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
N	1390	1390
Adjusted R^2	0.029	0.080

Panel D: Matched group

Dep. Var.= Acq. CAR	(1)	(2)
Affiliated × Post	-0.0468*	-0.0588**
	(-1.9556)	(-2.4066)
Controls	No	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
N	194	194
Adjusted R^2	0.038	0.093

Panel E: Alternative control group

Dep. Var.= Acq. CAR	(1)	(2)
Affiliated × Post	-0.0202*	-0.0200*
	(-1.6472)	(-1.6710)
Controls	No	Yes

Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
N	1057	1057
Adjusted R^2	0.013	0.090

Table 6. Advisor Centrality and Acquirer CAR: Two-stage Least Square Regression

This table reports the results of the two-stage least square regression (2SLS) of the acquirer three-day CAR for the full sample, where the measures of acquirer advisor centrality are instrumented by the geographical location of acquirer advisor headquarters. Advisor centrality is measured as *degree* in model (1), *eigenvector* in model (2), and *betweenness* in model (3). For each model, the first column reports the first-stage regression results, where the dependent variable is the measure of the advisor centrality under question, whereas the second column presents the second-stage regression results of acquirer CAR with the centrality measure instrumented. We control for the same set of variables as in Table 2. For brevity, only the coefficients on the centrality measures are reported. Variables are defined in Appendix A. The z-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. Symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Dep. Var.= Acq. CAR	**(1)**		**(2)**		**(3)**	
Centrality	Degree		Eigenvector		Betweenness	
Degree		0.1120**				
		(2.5312)				
Eigenvector				0.0488**		
				(2.5330)		
Betweenness						0.1519**
						(2.5307)
Geographical Location	0.0484***		0.1110***		0.0357***	
	(-27.2947)		(-26.3942)		(-29.1864)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Instrument strength test (F-test)	745.002		696.656		851.843	
Stock-Yogo threshold (10% maximal LIML size)	16.38		16.38		16.38	
Centered R^2	0.097		0.099		0.097	
UncenteredR^2	0.100		0.101		0.099	
N	7207		7207		7207	

Table 7. Advisor Centrality, Acquirer CAR and Target-firm Information Asymmetry

This table summarizes the results of the OLS regressions of the three-day acquirer CAR on measures of acquirer advisor centrality and other control variables for the sample split based on different proxies for the degree of target information asymmetry. Columns (1) through (3) of Panel A present the results for the cross-industry deal subsample, where acquirer advisor centrality is measured as *degree* in column (1), *eigenvector* in column (2), and *betweenness* in column (3). Columns (4) through (6) repeat the analysis for the subsample of same-industry transactions. Panels B, C and D report the results for the sample split based on whether the target firm has above- or below-average idiosyncratic return volatility (sigma), with or without credit ratings, and is in the S&P 1500 index or not, respectively. These three analyses are restricted to the sample of public acquisitions for which data on target firms' share price, credit rating and S&P 1500 memberships are available. All the regression models control for advisor reputation, deal characteristics, acquirer characteristics, year and industry fixed effects as before, but their coefficients are not reported for brevity. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. Symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Cross- versus same-industry deals

Dep. Var.= Acq. CAR	**Cross-industry Deals**			**Same-industry Deals**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Centrality	Degree	Eigenvector	Betweenness	Degree	Eigenvector	Betweenness
Degree	0.0589**			0.0222		
	(2.2856)			(1.1382)		
Eigenvector		0.0242**			0.0144*	
		(1.9986)			(1.7061)	
Betweenness			0.0746**			0.0268
			(2.2154)			(1.0601)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	2471	2471	2471	4736	4736	4736
Adjusted R^2	0.101	0.101	0.101	0.092	0.092	0.092

Panel B: Target firm with above- versus below-average idiosyncratic return volatility (sigma)

Dep. Var.= Acq. CAR	**Above-average Target Sigma**			**Below-average Target Sigma**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Centrality	Degree	Eigenvector	Betweenness	Degree	Eigenvector	Betweenness
Degree	0.0893*			0.0050		
	(1.6969)			(0.1876)		
Eigenvector		0.0386*			-0.0057	
		(1.7701)			(-0.4781)	
Betweenness			0.1310**			0.0218
			(2.0711)			(0.6160)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	902	902	902	1419	1419	1419
Adjusted R^2	0.089	0.089	0.090	0.120	0.120	0.120

Panel C: Target firm without versus with credit ratings

Dep. Var.= Acq. CAR	**Without Credit Ratings**			**With Credit Ratings**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Centrality	Degree	Eigenvector	Betweenness	Degree	Eigenvector	Betweenness
Degree	0.0569**			0.0290		
	(2.3357)			(0.4020)		
Eigenvector		0.0202**			0.0105	
		(1.9836)			(0.3188)	
Betweenness			0.0824***			0.0456
			(2.6534)			(0.5576)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	2695	2695	2695	444	444	444
Adjusted R^2	0.090	0.089	0.091	0.133	0.132	0.133

Panel D: Target firm with versus without S&P 1500 membership

Dep. Var.= Acq. CAR	**Without S&P 1500 Membership**			**With S&P 1500 Membership**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Centrality	Degree	Eigenvector	Betweenness	Degree	Eigenvector	Betweenness
Degree	0.0576**			0.0120		
	(2.2841)			(0.2046)		
Eigenvector		0.0208**			-0.0073	
		(1.9867)			(-0.2514)	
Betweenness			0.0795**			0.0381
			(2.4663)			(0.5502)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	2597	2597	2597	542	542	542
Adjusted R^2	0.084	0.083	0.084	0.135	0.135	0.136

Table 8. Information Channels

This table presents the results from the OLS regressions of the acquirer three-day CAR on acquirer advisor degree centrality, different information channels and other controls. Columns (1) through (3) examine individual firm-specific information channels, where *Equity underwriting, Debt underwriting,* and *M&A advisory* indicate whether the acquirer advisor is connected to investment banks that have provided the target with equity underwriting, debt underwriting and M&A services, respectively, during the last three years. The sample here is restricted to public deals for which data on the target firm's equity and debt transactions are available. In Column (4), we investigate the industry-specific information channel for the full sample, where *Industry-specific channel* indicate whether one or more network contacts of the acquirer advisor have expertise in the target industry. Column (5) explores *Regional-specific channel*, defined as whether the acquirer advisor's network contacts have specialized in the target Federal State. The analysis is performed for domestic deals only since information about target state is unavailable for cross-border deals. In column (6), we use a combined information channel measure (*Combined*), which is equal to one if the acquirer advisor is connected to any of the information channels above and zero otherwise. All the models control for advisor reputation, deal characteristics, acquirer characteristics, year and industry fixed effects as before, but their coefficients are not reported for brevity. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. Symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Dep. Var.= Acq. CAR	**Firm-specific**			**Industry/Regional-specific**		**Combined**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Degree Centrality	Equity	Debt	M&A	Industry	Regional	Combined
with Equity Underwriting Channel	0.0813**					
	(2.3915)					
without Equity Underwriting Channel	0.0417*					
	(1.7869)					
with Debt Underwriting Channel		0.0719*				
		(1.7063)				
without Debt Underwriting Channel		0.0486**				
		(2.1138)				
with M&A Advisory Channel			-0.0160			
			(-0.3818)			
without M&A Advisory Channel			0.0583**			
			(2.5698)			
with Industry-specific Channel				0.0390**		
				(2.0934)		
without Industry-specific Channel				0.0333*		
				(1.8336)		
with Regional-specific Channel					0.0320*	
					(1.6699)	
without Regional-specific Channel					0.0355*	
					(1.6881)	
with Combined Channel						0.0399**
						(2.4035)
without Combined Channel						0.0104
						(0.4556)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	3139	3139	3139	7207	6225	7207
Adjusted R^2	0.092	0.091	0.093	0.094	0.096	0.094

Table 9. Advisor Centrality and Takeover Premium

This table provides OLS regression estimates of takeover premium on measures of acquirer financial advisor centrality and other control variables for a sample of U.S. public acquisitions over 1990-2016. Takeover premium is defined as a percentage premium of offer price over target market value four weeks before the deal announcement, stated in percentage points not in decimals. Acquirer advisor centrality is measured as *degree* in column (1), *eigenvector* in column (2), *betweenness* in column (3), the principal component (PC) score in column (4), and the orthogonally transformed centrality measures in column (5). Other variables are defined in Appendix A. Year and industry fixed effects are included in all the models, but the coefficients are unreported. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. Symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Dep. Var.= Takeover Premium	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Centrality	Degree	Eigenvector	Betweenness	PC	Ortho
Degree	-27.0854***				-2.4843***
	(-2.6461)				(-2.9939)
Eigenvector		-9.5085**			1.2817
		(-2.0476)			(1.5744)
Betweenness			-24.9226**		1.4113*
			(-1.9844)		(1.8466)
PC				-1.0382**	
				(-2.2963)	
xMktShare	12.8963	9.9769	11.7265	11.6274	17.5022
	(0.4586)	(0.3552)	(0.4167)	(0.4137)	(0.6189)
Ln (Acquirer Size)	-0.8695*	-0.9822**	-1.0765**	-0.9529**	-0.8281*
	(-1.8524)	(-2.0874)	(-2.3638)	(-2.0391)	(-1.7434)
Run-up	5.7777***	5.8319***	5.8636***	5.8155***	5.7372***
	(3.8208)	(3.8541)	(3.8726)	(3.8437)	(3.7930)
FCF	3.4943	3.5026	3.6475	3.5655	3.0090
	(0.4400)	(0.4395)	(0.4574)	(0.4481)	(0.3794)
Leverage	-16.3108***	-16.4905***	-16.8111***	-16.5121***	-15.8519***
	(-4.1827)	(-4.2243)	(-4.3072)	(-4.2345)	(-4.0330)
Tobin's Q	0.2397	0.2341	0.2360	0.2369	0.2484
	(1.1714)	(1.1423)	(1.1542)	(1.1578)	(1.2086)
Relative Size	-2.6166***	-2.6936***	-2.7544***	-2.6750***	-2.5492***
	(-3.1594)	(-3.2053)	(-3.2791)	(-3.2053)	(-3.0996)
Related	0.3295	0.2826	0.3264	0.3159	0.3588
	(0.2188)	(0.1875)	(0.2167)	(0.2097)	(0.2380)
Tender	7.5247***	7.6076***	7.5737***	7.5554***	7.5524***
	(3.5510)	(3.5935)	(3.5755)	(3.5666)	(3.5554)
Hostile	-1.9829	-1.9920	-1.9129	-1.9643	-2.0212
	(-0.7475)	(-0.7487)	(-0.7217)	(-0.7402)	(-0.7610)
Cross-border	3.7084	3.7423	3.7269	3.7162	3.7922
	(1.3400)	(1.3519)	(1.3464)	(1.3430)	(1.3659)
Number of Competing Bidders	6.7697***	6.7558***	6.7092***	6.7481***	6.8113***
	(2.9100)	(2.9065)	(2.8879)	(2.9024)	(2.9277)
Pmt. incl. Stock	-4.9850***	-4.9781***	-4.9822***	-4.9706***	-5.1869***
	(-3.0361)	(-3.0291)	(-3.0335)	(-3.0263)	(-3.1522)
Intercept	55.1681***	55.9212***	56.2449***	53.7821***	51.2447***
	(6.7641)	(6.8624)	(6.9177)	(6.5051)	(6.1532)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
N	2748	2748	2748	2748	2748
Adjusted R^2	0.081	0.080	0.080	0.080	0.081

Table 10. Advisor Centrality and Post-Merger Performance of Acquirers

This table reports the OLS regression results of post-merger operating performance for a sample of complete deals over 1990-2016. The dependent variable in Panel A is changes in return on assets (ROA) over the three-year post-period after the M&A transaction is effective. Panel B and C report the results for the ex post three-year changes in return on sales (ROS) and asset turnover (ATO), respectively. The control variables are the same as those shown in Table 2. For brevity, only the coefficients on the five centrality measures are reported. Appendix A provides a description of all the variables. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. Symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Advisor centrality and the ex post three-year change in ROA

Dep. Var.= 3-Year ΔROA	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Centrality	Degree	Eigenvector	Betweenness	PC	Ortho
Degree	0.0578**				0.0046**
	(2.0486)				(2.1872)
Eigenvector		0.0149			-0.0042
		(1.1547)			(-1.6449)
Betweenness			0.0808**		0.0007
			(2.0474)		(0.3221)
PC				0.0024*	
				(1.8142)	
Controls	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
N	5165	5165	5165	5165	5165
Adjusted R^2	0.047	0.046	0.047	0.047	0.048

Panel B: Advisor centrality and the ex post three-year change in ROS

Dep. Var.= 3-Year ΔROS	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Centrality	Degree	Eigenvector	Betweenness	PC	Ortho
Degree	0.0076				0.0004
	(0.1889)				(0.1169)
Eigenvector		0.0093			0.0030
		(0.5041)			(0.9635)
Betweenness			0.0046		-0.0001
			(0.0914)		(-0.0212)
PC				0.0005	
				(0.2761)	
Controls	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
N	5160	5160	5160	5160	5160
Adjusted R^2	0.050	0.050	0.050	0.050	0.050

Panel C: Advisor centrality and the ex post three-year change in ATO

Dep. Var.= 3-Year ΔATO	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Centrality	Degree	Eigenvector	Betweenness	PC	Ortho
Degree	0.1576**				0.0117**
	(2.0685)				(2.0323)
Eigenvector		0.0588*			-0.0020
		(1.6560)			(-0.3004)
Betweenness			0.2204**		0.0039
			(2.1018)		(0.6473)
PC				0.0071**	
				(2.0073)	
Controls	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
N	5335	5335	5335	5335	5335
Adjusted R^2	0.053	0.053	0.053	0.053	0.053

Table 11. Advisor Centrality and Advisory Fees

This table reports the Tobit regression estimates of advisory fees on measures of acquirer financial advisor centrality and other control variables for a sample of U.S. acquisitions over 1990-2016. Advisory fee is defined as total advisory fee paid by the acquirer as a percentage of deal value from Thomson Financial SDC. Acquirer advisor centrality is measured as *degree* in column (1), *eigenvector* in column (2), and *betweenness* in column (3). Other variables are defined in Appendix A. Year and industry fixed effects are controlled for in all models but the coefficients are unreported. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. Symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Dep. Var.= Advisory Fee	**(1)**	**(2)**	**(3)**
Centrality	Degree	Eigenvector	Betweenness
Degree	0.0236^{***}		
	(5.4097)		
Eigenvector		0.0106^{***}	
		(4.5106)	
Betweenness			0.0251^{***}
			(4.3770)
xMktShare	0.0079	0.0105	0.0075
	(0.7189)	(0.9296)	(0.6836)
Ln (Deal Size)	-0.0032^{***}	-0.0032^{***}	-0.0031^{***}
	(-3.9690)	(-4.0754)	(-3.8135)
Relative Size	0.0000	0.0001	0.0001
	(0.0839)	(0.1159)	(0.1067)
Related	-0.0025	-0.0024	-0.0025
	(-1.3918)	(-1.3805)	(-1.3921)
Tender	-0.0013	-0.0014	-0.0012
	(-0.9612)	(-1.0712)	(-0.8997)
Hostile	0.0013	0.0013	0.0011
	(1.0009)	(0.9959)	(0.8979)
Cross-border	-0.0001	-0.0001	-0.0000
	(-0.0383)	(-0.0422)	(-0.0083)
Number of Competing Bidders	0.0012^{*}	0.0013^{*}	0.0012^{*}
	(1.8622)	(1.9393)	(1.8837)
Pub. × All cash	0.0006	0.0006	0.0005
	(0.4244)	(0.4353)	(0.3778)
Priv. × All cash	-0.0055^{***}	-0.0057^{***}	-0.0053^{***}
	(-3.3173)	(-3.3159)	(-3.1779)
Sub. × All cash	-0.0105^{***}	-0.0104^{**}	-0.0104^{***}
	(-2.6139)	(-2.4697)	(-2.6138)
Pub. × Pmt. incl. Stock	-0.0010	-0.0010	-0.0010
	(-0.8367)	(-0.8713)	(-0.8565)
Priv. × Pmt. incl. Stock	0.0020	0.0021	0.0021
	(0.6165)	(0.6318)	(0.6388)
Ln (Acquirer Size)	0.0002	0.0002	0.0002
	(0.1582)	(0.1865)	(0.1746)
Run-up	-0.0025^{*}	-0.0025^{*}	-0.0025^{*}
	(-1.7412)	(-1.7722)	(-1.7973)
FCF	-0.0075^{**}	-0.0077^{**}	-0.0076^{**}
	(-2.1565)	(-2.1786)	(-2.1722)
Leverage	0.0009	0.0010	0.0012
	(0.5489)	(0.6047)	(0.7646)
Tobin's Q	-0.0003^{*}	-0.0003^{*}	-0.0003^{*}
	(-1.8548)	(-1.8754)	(-1.8517)
Intercept	0.0255^{***}	0.0251^{***}	0.0250^{***}
	(6.5555)	(6.4426)	(6.3854)
Industry Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
N	1218	1218	1218
Adjusted R^2	0.141	0.143	0.140

Appendix A

Variable	Definition
Panel A: Dependent Variables	
CAR (-1, +1)	Cumulative abnormal returns of the acquiring firm stock over the event window (-1, +1) around the announcement date, using the market model. The market model parameters are estimated using the CRSP value-weighted index as the benchmark for the period (-210, -11).
Takeover Premium	A percentage premium of offer price over the target's market value four weeks prior to the deal announcement from Thomson Financial SDC.
3-Year ΔROA	Three-year changes in return on assets (ROA) from year t + 1 to t + 4, where t is the year in which the transaction is effective. ROA is defined as operating income before depreciation (Compustat data item 13) scaled by total assets.
3-Year ΔROS	Three-year changes in return on sales (ROS) from year t + 1 to t + 4, where t is the year in which the transaction is effective. ROS is defined as operating income before depreciation (Compustat data item 13) divided by sales.
3-Year ΔATO	Three-year changes in asset turnover (ATO) from year t + 1 to t + 4, where t is the year in which the transaction is effective. ATO is defined as sales divided by total assets.
Advisory Fee	Total advisory fee paid by the acquirer as a percentage of deal value from Thomson Financial SDC.
Panel B: Advisor Characteristics	
Degree Centrality	The number of ties that a financial advisor has with other investment banks over the last three years prior to the year of announcement, normalized by the maximum logically possible degree in a network of N actors (i.e., $N_t - 1$).
Eigenvector Centrality	The sum of a financial advisor's ties to other investment banks over the last three years prior to the year of announcement weighted by centralities of the banks it is tied to, normalized by the highest possible eigenvector centrality value in an N-actor network.
Betweenness Centrality	The extent to which a financial advisor acts as a "bridge" along the shortest path between two or more disconnected investment banks over the last three years prior to the year of announcement, normalized by the maximum betweenness in a network of N actors.
Advisor Market Share	The fraction of overall M&A deals (measured in transaction value) advised by an investment bank over the last three years prior to the year of announcement from the SDC.
Panel C: Deal Characteristics	
Relative Size	The deal value (from the SDC) divided by the market value of the bidding firm's equity six trading days before the deal announcement (from CRSP)
Relatedness	A dummy variable being 1 if the bidder and the target are operating in the same industries with a common 2-digit SIC code and 0 otherwise (from the SDC).
Public Target	A dummy variable being 1 if the bid is for public target and 0 otherwise.
Private Target	A dummy variable being 1 if the bid is for private target and 0 otherwise.
Subsidiary Target	A dummy variable being 1 if the bid is for subsidiary target and 0 otherwise.
Foreign Target	A dummy variable being 1 if the bid is for foreign target and 0 otherwise.
Pmt. Incl. Stock	A dummy variable being 1 if the acquisition is either partially or fully financed with stock and 0 otherwise.
All Cash	A dummy variable being 1 if the acquisition is fully financed with cash and 0 otherwise.
Tender Offer	A dummy variable being 1 if the deal is a tender offer and 0 otherwise.
Hostile	A dummy variable equal to 1 if the deal is "hostile" or "unsolicited" as reported by SDC; and 0 otherwise.
Number of Competing Bidders	The number of bidders competing for the deal.
Panel D: Acquirer Characteristics	
Acquirer Size	The market value of the acquiring firm's equity six days before the announcement date in millions of U.S. dollars (from CRSP).
Tobin's Q	Market value of assets divided by book value of assets, where the market value of assets is equal to book value of assets plus market value of common stock minus book value of common stock minus balance sheet deferred taxes (from CRSP and Compustat).
Run-up	Market-adjusted buy-and-hold returns of the acquirer's stock over a 200-day window (-210, -11) from CRSP.

Leverage	The sum of long-term debt and short-term debt divided by the market value of the acquirer's total assets.
Free Cash Flow	Acquirer's operating income before depreciation minus interest expense minus income tax plus changes in deferred taxes and investment tax credits minus dividends on both preferred and common share divided by the book value of total assets at the fiscal year-end immediately before the announcement date from Compustat.

Appendix B

Table B.1. Controlling for Advisor Reputation Effect

This table re-conducts the baseline regressions in Table 2, using two different measures to control for advisor reputation effects. In Panel A, we control for large banks (instead of xMktShare), which is equal to one if a financial advisor has the top 10% of market share over the last three years, and zero otherwise. In Panel B, we exclude deals advised by those large banks. The control variables are the same as those listed in Table 2. For brevity, only the coefficients on the centrality measures are reported. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. Symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Controlling for large banks

Dep. Var.= Acq. CAR	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Centrality	Degree	Eigenvector	Betweenness	PC	Ortho
Degree	0.0303*				0.0021
	(1.7671)				(1.5228)
Eigenvector		0.0173**			0.0024
		(2.2619)			(1.3498)
Betweenness			0.0367		0.0004
			(1.5591)		(0.3276)
PC				0.0015**	
				(1.9943)	
Large Banks	0.0030	0.0027	0.0029	0.0025	0.0035
	(0.6287)	(0.6311)	(0.5672)	(0.5409)	(0.6850)
Controls	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
N	7207	7207	7207	7207	7207
Adjusted R^2	0.094	0.094	0.094	0.094	0.094

Panel B: Excluding deals advised by large banks

Dep. Var.= Acq. CAR	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Centrality	Degree	Eigenvector	Betweenness	PC	Ortho
Degree	0.0324*				0.0024*
	(1.8550)				(1.7300)
Eigenvector		0.0145**			0.0010
		(1.9656)			(0.7153)
Betweenness			0.0465*		0.0009
			(1.9168)		(0.7417)
PC				0.0016**	
				(1.9711)	
Controls	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
N	6496	6496	6496	6496	6496
Adjusted R^2	0.089	0.089	0.089	0.089	0.089

Table B.2. Change in Advisor Centrality surrounding the Lehman Shock

This table summarizes the differences in centrality scores measured based on interbank ties over a three-year window before and after the collapse of Lehman Brothers for affiliated and unaffiliated financial advisors, along with the corresponding t-test statistics. Panels A through C report the differences in *degree*, *eigenvector* and *betweenness* centrality, respectively.

	Before (1)	After (2)	Difference (2)-(1)	P-value of Difference t-test (3)
Panel A: Degree centrality				
Affiliated group (treated)	0.1436	0.0888	-0.0548	0.0351**
Unaffiliated group (control)	0.0243	0.0184	-0.0059	0.5510
Panel B: Eigenvector centrality				
Affiliated group (treated)	0.2958	0.1845	-0.1113	0.0243**
Unaffiliated group (control)	0.0569	0.0457	-0.0111	0.5789
Panel C: Betweenness centrality				
Affiliated group (treated)	0.0815	0.0472	-0.0343	0.0661*
Unaffiliated group (control)	0.0080	0.0024	-0.0055	0.4377

Table B.3. Other Robustness Tests

This table verifies the robustness of our baseline results reported in Table 2. Panel A re-conducts the CAR analyses using value-weighted advisor network centrality measures, where each tie is weighted by the number of times that two investment banks had syndicated M&A deals over the last three years prior to the announcement. Panel B controls for acquirer advisor centrality in the equity market and in the debt market, respectively. In columns (1) through (3) (columns (4) through (6)), acquirer advisor centrality in the equity (debt) market is computed based on the ties formed between investment banks that have jointly underwritten one or more equity (debt) offerings over the last three years before the M&A announcement. Panel C re-estimates the CAR regression models controlling for the measures of target financial advisor centrality. Other control variables are the same as those shown in Table 2, whose coefficients are omitted for brevity. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. Symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Acquirer three-day CAR and value-weighted advisor centrality

Dep. Var.= Acq. CAR	**(1)**	**(2)**	**(3)**
Centrality	Degree	Eigenvector	Betweenness
Degree	0.0135**		
	(2.1474)		
Eigenvector		0.0123**	
		(2.2181)	
Betweenness			0.0529**
			(2.2405)
Controls	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
N	7207	7207	7207
Adjusted R^2	0.094	0.094	0.094

Panel B: Controlling for advisor centrality in the equity and debt underwriting markets

Dep. Var.= Acq. CAR	**Equity Market**			**Debt Market**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Centrality	Degree	Eigenvector	Betweenness	Degree	Eigenvector	Betweenness
Degree	0.0341**			0.0305*		
	(2.1112)			(1.8679)		
Eigenvector		0.0198**			0.0188**	
		(2.5086)			(2.3193)	
Betweenness			0.0439**			0.0407**
			(2.1401)			(1.9894)
Degree in Equity (Debt) Market	0.0042			0.0111		
	(0.4524)			(1.2952)		
Eigenvector in Equity (Debt) Market		-0.0040			0.0067	
		(-0.2121)			(0.3291)	
Betweenness in Equity (Debt) Market			0.0164			0.0513
			(0.1796)			(0.7326)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	7207	7207	7207	7207	7207	7207
Adjusted R^2	0.094	0.094	0.094	0.094	0.094	0.094

Panel C: Controlling for target advisor centrality

Dep. Var.= Acq. CAR	**(1)**	**(2)**	**(3)**
Centrality	Degree	Eigenvector	Betweenness
Degree	0.0357**		
	(2.2046)		
Target Advisor Degree	0.0035		
	(0.2281)		
Eigenvector		0.0191**	
		(2.3646)	
Target Advisor Eigenvector		0.0021	
		(0.3133)	
Betweenness			0.0462**
			(2.2327)
Target Advisor Betweenness			-0.0178
			(-0.8619)
Controls	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
N	7207	7207	7207
Adjusted R^2	0.094	0.094	0.094

Table B.4. Information Channels using Other Centrality Measures

Panels A and B of this table replicate the CAR analysis in Table 8 using *eigenvector* and *betweenness* centrality measure, respectively. Columns (1) through (3) examine individual firm-specific information channels, where *Equity underwriting, Debt underwriting,* and *M&A advisory* indicate whether the acquirer advisor is connected to investment banks that have provided the target with equity underwriting, debt underwriting and M&A services, respectively, during the last three years. The sample here is restricted to public deals for which data on the target firm's equity and debt transactions are available. In Column (4), we investigate the industry-specific information channel for the full sample, where *Industry-specific channel* indicate whether one or more network contacts of the acquirer advisor have expertise in the target industry. Column (5) explores *Regional-specific channel*, defined as whether the acquirer advisor's network contacts have specialized in the target State. The analysis is performed for domestic deals only since information about target state is unavailable for cross-border deals. In column (6), we use a combined information channel measure (*Combined*), which is equal to one if the acquirer advisor is connected to any of the information channels above, and zero otherwise. All the models control for advisor reputation, deal characteristics, acquirer characteristics, year and industry fixed effects as before, but their coefficients are not reported for brevity. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. Symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively

Panel A: Eigenvector Centrality

Dep. Var.= Acq. CAR	**Firm-specific**			**Industry/Regional-specific**		**Combined**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Eigenvector Centrality	Equity	Debt	M&A	Industry	Regional	Combined
with Equity Underwriting Channel	0.0283*					
	(1.8836)					
without Equity Underwriting Channel	0.0145					
	(1.4828)					
with Debt Underwriting Channel		0.0282				
		(1.5453)				
without Debt Underwriting Channel		0.0165*				
		(1.6965)				
with M&A Advisory Channel			-0.0149			
			(-0.8183)			
without M&A Advisory Channel			0.0202**			
			(2.0902)			
with Industry-specific Channel				0.0212**		
				(2.4290)		
without Industry-specific Channel				0.0180**		
				(1.9852)		
with Regional-specific Channel					0.0194**	
					(1.9922)	
without Regional-specific Channel					0.0168*	
					(1.8408)	
with Combined Channel						0.0223***
						(2.6557)
without Combined Channel						0.0072
						(0.7562)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	3139	3139	3139	7207	6225	7207
Adjusted R^2	0.091	0.091	0.092	0.094	0.097	0.094

Panel B: Betweenness Centrality

Dep. Var.= Acq. CAR	**Firm-specific**			**Industry/Regional-specific**		**Combined**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Betweenness Centrality	Equity	Debt	M&A	Industry	Regional	Combined
with Equity Underwriting Channel	0.1326***					
	(2.7720)					
without Equity Underwriting Channel	0.0584**					
	(1.9637)					
with Debt Underwriting Channel		0.0926				
		(1.5248)				
without Debt Underwriting Channel		0.0723**				
		(2.4865)				
with M&A Advisory Channel			-0.0250			
			(-0.4216)			
without M&A Advisory Channel			0.0860***			
			(2.9982)			
with Industry-specific Channel				0.0535**		
				(2.0812)		
without Industry-specific Channel				0.0379		
				(1.6052)		
with Regional-specific Channel					0.0420	
					(1.6197)	
without Regional-specific Channel					0.0487*	
					(1.8118)	
with Combined Channel						0.0516**
						(2.3374)
without Combined Channel						0.0109
						(0.3646)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	3139	3139	3139	7207	6225	7207
Adjusted R^2	0.093	0.092	0.093	0.094	0.097	0.094

Table B.5. Advisor Centrality and Combined CAR

This table provides OLS regression estimates of total synergy gain on measures of acquirer financial advisor centrality and other control variables for the public acquisitions in our sample. Total synergy gain is measured by the combined announcement returns received by the acquirer and the target shareholders over a three-day event window. Acquirer advisor centrality is measured as *degree* in column (1), *eigenvector* in column (2), *betweenness* in column (3), the principal component (PC) score in column (4), and the orthogonally transformed centrality measures in column (5). Other variables are defined in Appendix A. Year and industry fixed effects are included in all the models, but the coefficients are unreported. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. Symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Dep. Var.= Combined CAR	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Centrality	Degree	Eigenvector	Betweenness	PC	Ortho
Degree	0.0284				0.0019
	(1.1180)				(0.9132)
Eigenvector		0.0066			-0.0022
		(0.6073)			(-1.2294)
Betweenness			0.0448		0.0015
			(1.4110)		(0.8307)
PC				0.0012	
				(1.0905)	
xMktShare	-0.0596	-0.0576	-0.0590	-0.0585	-0.0653
	(-0.8528)	(-0.8249)	(-0.8438)	(-0.8370)	(-0.9319)
Ln (Acquirer Size)	-0.0063***	-0.0061***	-0.0064***	-0.0063***	-0.0061***
	(-5.5258)	(-5.2733)	(-5.7779)	(-5.5232)	(-5.3091)
Run-up	-0.0118***	-0.0120***	-0.0118***	-0.0118***	-0.0119***
	(-3.4962)	(-3.5330)	(-3.4927)	(-3.5024)	(-3.5055)
FCF	0.0173	0.0169	0.0173	0.0172	0.0173
	(1.0081)	(0.9957)	(1.0034)	(1.0040)	(0.9994)
Leverage	0.0161*	0.0166*	0.0164*	0.0163*	0.0170*
	(1.6614)	(1.7071)	(1.6989)	(1.6789)	(1.7481)
Tobin's Q	-0.0001	-0.0000	-0.0001	-0.0001	-0.0001
	(-0.1093)	(-0.0944)	(-0.1086)	(-0.1047)	(-0.1225)
Relative Size	0.0141***	0.0142***	0.0141***	0.0141***	0.0142***
	(4.9732)	(4.9698)	(4.9991)	(4.9779)	(4.9975)
Related	-0.0001	-0.0000	-0.0001	-0.0001	-0.0002
	(-0.0252)	(-0.0051)	(-0.0315)	(-0.0206)	(-0.0604)
Tender	0.0011	0.0010	0.0013	0.0011	0.0014
	(0.2461)	(0.2070)	(0.2729)	(0.2431)	(0.3111)
Hostile	0.0168	0.0168	0.0166	0.0167	0.0168
	(1.3140)	(1.3103)	(1.2972)	(1.3068)	(1.3102)
Cross-border	-0.0175**	-0.0176**	-0.0174**	-0.0175**	-0.0178**
	(-2.0608)	(-2.0736)	(-2.0476)	(-2.0559)	(-2.0870)
Number of Competing Bidders	-0.0085	-0.0084	-0.0085	-0.0085	-0.0087
	(-1.4603)	(-1.4421)	(-1.4647)	(-1.4555)	(-1.4929)
Pmt. incl. Stock	-0.0272***	-0.0272***	-0.0273***	-0.0272***	-0.0271***
	(-7.6524)	(-7.6503)	(-7.6688)	(-7.6591)	(-7.5793)
Intercept	0.0593***	0.0578**	0.0595***	0.0613***	0.0604***
	(2.5969)	(2.5333)	(2.6087)	(2.6509)	(2.5913)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
N	2069	2069	2069	2069	2069
Adjusted R^2	0.141	0.141	0.142	0.141	0.142

Table B.6. Advisor Centrality and Completion Probability

This table presents the results from the probit regression of deal completion on measures of acquirer financial advisor centrality and other control variables for the full sample. Deal completion is a dummy variable equal to one if a given deal is completed and zero otherwise. Acquirer advisor centrality is measured as *degree* in column (1), *eigenvector* in column (2), *betweenness* in column (3), the principal component (PC) score in column (4), and the orthogonally transformed centrality measures in column (5). Other variables are defined in Appendix A. Year and industry fixed effects are controlled for in all models but the coefficients are unreported. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. Symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Dep. Var.= Deal Completion	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Centrality	Degree	Eigenvector	Betweenness	PC	Ortho
Degree	-0.4032				-0.0342
	(-1.0623)				(-1.1263)
Eigenvector		-0.2959*			-0.0528*
		(-1.7569)			(-1.7279)
Betweenness			-0.1388		0.0423
			(-0.2806)		(1.4926)
PC				-0.0180	
				(-1.0635)	
xMktShare	0.3873	0.3133	0.4071	0.3735	0.2263
	(0.3301)	(0.2697)	(0.3409)	(0.3180)	(0.1896)
Ln (Acquirer Size)	0.0312*	0.0363*	0.0250	0.0310*	0.0352*
	(1.6548)	(1.9256)	(1.3709)	(1.6534)	(1.8593)
Run-up	0.0677	0.0665	0.0703	0.0679	0.0699
	(1.2044)	(1.1828)	(1.2482)	(1.2072)	(1.2428)
FCF	-0.1013	-0.1018	-0.1019	-0.1012	-0.1085
	(-0.5846)	(-0.5874)	(-0.5864)	(-0.5840)	(-0.6197)
Leverage	-0.1158	-0.1075	-0.1266	-0.1173	-0.0951
	(-0.7948)	(-0.7376)	(-0.8682)	(-0.8050)	(-0.6481)
Tobin's Q	-0.0064	-0.0064	-0.0065	-0.0064	-0.0067
	(-1.0922)	(-1.0899)	(-1.1068)	(-1.0932)	(-1.1323)
Relative Size	-0.0365***	-0.0356***	-0.0378***	-0.0366***	-0.0359***
	(-2.9905)	(-3.0125)	(-2.9958)	(-2.9984)	(-3.0235)
Related	0.1024*	0.1007*	0.1035*	0.1025*	0.0959*
	(1.8639)	(1.8318)	(1.8828)	(1.8651)	(1.7437)
Tender	0.4978***	0.5004***	0.4980***	0.4980***	0.5102***
	(3.9426)	(3.9632)	(3.9414)	(3.9436)	(4.0439)
Hostile	-1.9998***	-2.0049***	-1.9971***	-2.0001***	-2.0135***
	(-15.3759)	(-15.4017)	(-15.3499)	(-15.3737)	(-15.4447)
Cross-border	-0.1782**	-0.1829**	-0.1754**	-0.1785**	-0.1886***
	(-2.5060)	(-2.5707)	(-2.4672)	(-2.5092)	(-2.6555)
Number of Bidders	-0.8209***	-0.8190***	-0.8220***	-0.8211***	-0.8120***
	(-8.6570)	(-8.6561)	(-8.6614)	(-8.6584)	(-8.6520)
Pub. × All cash	-0.2708***	-0.2731***	-0.2714***	-0.2713***	-0.2795***
	(-2.9597)	(-2.9814)	(-2.9676)	(-2.9652)	(-3.0428)
Priv. × All cash	0.2766**	0.2756**	0.2795**	0.2770**	0.2778**
	(2.3428)	(2.3257)	(2.3691)	(2.3449)	(2.3323)
Sub. × All cash	0.2792***	0.2785***	0.2791***	0.2788***	0.2812***
	(2.8171)	(2.8102)	(2.8155)	(2.8123)	(2.8445)
Pub. × Pmt. incl. Stock	-0.2249***	-0.2250***	-0.2266***	-0.2249***	-0.2334***
	(-3.1112)	(-3.1111)	(-3.1337)	(-3.1107)	(-3.2306)
Priv. × Pmt. incl. Stock	0.1657*	0.1633*	0.1665*	0.1652*	0.1618*
	(1.8914)	(1.8627)	(1.9011)	(1.8860)	(1.8465)
Intercept	2.0427***	2.0416***	2.0598***	2.0145***	1.9626***
	(7.5679)	(7.5895)	(7.6417)	(7.3589)	(7.1288)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
N	7207	7207	7207	7207	7207
Pseudo R^2	0.200	0.200	0.200	0.200	0.202

Table B.7. Advisor Centrality and Time to Completion

This table reports the OLS regression results for the time to completion on measures of acquirer financial advisor centrality and other control variables for the completed sample. The time to completion is measured as the time it takes from the announcement date to the effective date from a deal (in units of 100 days). Acquirer advisor centrality is measured as *degree* in column (1), *eigenvector* in column (2), *betweenness* in column (3), the principal component (PC) score in column (4), and the orthogonally transformed centrality measures in column (5). Other variables are defined in Appendix A. Year and industry fixed effects are controlled for in all models but the coefficients are unreported. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. Symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Dep. Var.= Time to Resolution	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Centrality	Degree	Eigenvector	Betweenness	PC	Ortho
Degree	0.6203***				0.0530***
	(3.9459)				(4.3299)
Eigenvector		0.2391***			-0.0155
		(3.2734)			(-1.0407)
Betweenness			0.5796***		-0.0302**
			(2.8310)		(-2.3853)
PC				0.0247***	
				(3.4785)	
xMktShare	0.9324*	0.9554*	0.8938*	0.9326*	0.8992*
	(1.7475)	(1.7880)	(1.6735)	(1.7468)	(1.6605)
Ln (Acquirer Size)	0.0064	0.0080	0.0113	0.0079	0.0058
	(0.6595)	(0.8294)	(1.2131)	(0.8247)	(0.5960)
Run-up	-0.0186	-0.0193	-0.0204	-0.0192	-0.0185
	(-1.0578)	(-1.0990)	(-1.1616)	(-1.0914)	(-1.0520)
FCF	-0.1892**	-0.1898**	-0.1908**	-0.1899**	-0.1866**
	(-2.2215)	(-2.2310)	(-2.2314)	(-2.2279)	(-2.1986)
Leverage	0.1141	0.1158	0.1234*	0.1174*	0.1050
	(1.6168)	(1.6401)	(1.7541)	(1.6651)	(1.4743)
Tobin's Q	-0.0097***	-0.0097***	-0.0097***	-0.0097***	-0.0096***
	(-3.4613)	(-3.4517)	(-3.4463)	(-3.4551)	(-3.4631)
Relative Size	0.0688***	0.0697***	0.0709***	0.0696***	0.0681***
	(3.5949)	(3.6284)	(3.6494)	(3.6159)	(3.5824)
Related	0.0974***	0.0982***	0.0964***	0.0973***	0.0983***
	(4.3614)	(4.3979)	(4.3140)	(4.3578)	(4.3897)
Tender	-0.1457***	-0.1486***	-0.1449***	-0.1462***	-0.1460***
	(-3.0811)	(-3.1831)	(-3.0471)	(-3.1003)	(-3.0989)
Hostile	0.6779***	0.6771***	0.6703***	0.6756***	0.6827***
	(2.9919)	(2.9876)	(2.9533)	(2.9799)	(3.0218)
Cross-border	-0.0376	-0.0375	-0.0400	-0.0379	-0.0396
	(-1.2238)	(-1.2195)	(-1.2966)	(-1.2331)	(-1.2857)
Number of Bidders	0.3035***	0.3022***	0.3054***	0.3034***	0.3051***
	(3.3330)	(3.3559)	(3.3363)	(3.3412)	(3.3416)
Pub. × All cash	0.2597***	0.2620***	0.2599***	0.2607***	0.2553***
	(6.0852)	(6.1408)	(6.0820)	(6.1060)	(6.0257)
Priv. × All cash	-0.0998**	-0.1014**	-0.1012**	-0.1005**	-0.1005**
	(-2.1605)	(-2.2083)	(-2.1851)	(-2.1775)	(-2.1692)
Sub. × All cash	-0.0313	-0.0322	-0.0306	-0.0311	-0.0342
	(-0.7346)	(-0.7562)	(-0.7193)	(-0.7309)	(-0.8057)
Pub. × Pmt. incl. Stock	0.5953***	0.5961***	0.5951***	0.5954***	0.5963***
	(18.0323)	(18.0537)	(17.9943)	(18.0272)	(18.0232)
Priv. × Pmt. incl. Stock	0.0991***	0.0991***	0.0980***	0.0990***	0.0977***
	(3.1087)	(3.1028)	(3.0668)	(3.1013)	(3.0684)
Intercept	0.6332***	0.6233***	0.6109***	0.6697***	0.7164***
	(3.3787)	(3.3341)	(3.2551)	(3.5642)	(3.7875)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
N	6690	6690	6690	6690	6690
Adjusted R^2	0.269	0.269	0.268	0.269	0.270