Carnegie Mellon University
Research Showcase @ CMU

Tepper School of Business

9-2009

Board Networks and Merger Performance

Robert Schonlau
University of Washington

Param Vir Singh
Carnegie Mellon University, psidhu@andrew.cmu.edu

Follow this and additional works at: http://repository.cmu.edu/tepper

Part of the Economic Policy Commons, and the Industrial Organization Commons

Recommended Citation
.

This Working Paper is brought to you for free and open access by Research Showcase @ CMU. It has been accepted for inclusion in Tepper School of Business by an authorized administrator of Research Showcase @ CMU. For more information, please contact research-showcase@andrew.cmu.edu.

Board Networks and Merger Performance*

Robert Schonlau[a,**] Param Vir Singh[b]

[a] Foster School of Business, University of Washington, WA 98195
[b] Tepper School of Business, Carnegie Mellon University, PA 15213

Abstract:
We compare the post-merger financial performance of acquiring firms that have well-connected (central) boards with the performance of less-connected (non-central) boards and find that central boards are associated with better performing acquisitions as evidenced by larger post-merger buy-and-hold abnormal returns, stronger improvements in the ROA, and a 7-12% annual abnormal return based on calendar time portfolios. Central firms are more likely to use cash, to make an acquisition, and to be acquired. Our results suggest that board networks affect the decision to acquire, the choice of target, the method of payment, and ultimately the financial performance of the firm around the merger.

JEL classification: G3, G34, G39, L14
Keywords: mergers and acquisitions, social networks, boards, directors

---

* We would like to thank Kathleen Carley, Jon Glover, Rick Green, Jarrad Harford, Jennifer Koski, David Krackhardt, Ray Reagans, Ed Rice, Andrew Siegel, Stephan Siegel, and other seminar participants at the University of Washington and Carnegie Mellon University for helpful comments.
** Corresponding author: Rob Schonlau, Department of Finance and Business Economics, Foster School of Business at the University of Washington, 269 Mackenzie Hall, UW Box 353200, Seattle, WA 98195-3200. Email: schonlau@u.washington.edu Phone: 206.619.3701

Electronic copy available at: http://ssrn.com/abstract=1322223

1. Introduction

Directors have the fiduciary duty to participate in all major firm decisions and are viewed as important managerial monitors and advisors. Any board characteristic that affects the directors' effectiveness can potentially influence firm performance—hence the literature's focus on board independence, board size, directors' ages, and busy directors (e.g., Yermack, 1996; Hermalin and Weisbach, 2003; Fich and Shivdasani, 2006). In this paper we draw attention to another characteristic—board networks—that has the potential to influence the board's effectiveness. Specifically, we hypothesize that better networked boards have access to important information via their networks that makes them more informed in both their monitoring and advising capacities and potentially leads to better firm performance.

When would more informed boards lead to better firm performance? Given that boards tend to meet relatively few times each year, and generally do not actively participate in the firm's day-to-day operations, their information set directly affects the firm only through a few important decisions such as CEO replacement, executive compensation, and major capital investments like acquisitions. In this paper we investigate the relation between board networks and firm performance specifically around mergers and ask the question: do better networked boards make better acquisitions? The motivation for this question builds on research that shows that information flows through board networks[1] and from our inference that the boards with better access to that information would be more effective and that this informational advantage would be observable through better firm performance around mergers.

[1] Board networks have been shown to be an important source of inter-organizational information about corporate practices, strategies, contacts, new business opportunities, and general business information. For a review of this literature refer to Mizruchi (1996).

Electronic copy available at: http://ssrn.com/abstract=1322223

To test this hypothesis we map the board network by tracing the web of inter-firm relationships created by board interlocks as shown and explained in Figure 1. We then use social network methods to systematically rank boards according to their centrality within the social network. As discussed in Freeman (1979), prior research shows that central positions within social networks tend to have better access to information flowing in the network. Hence, compared to non-central firms, we expect central acquiring firms to have relatively more information when making acquisition decisions. If central boards have informational advantages making them aware of acquisition opportunities and allowing them to face relatively lower acquisition information asymmetries, we hypothesize that central boards are more likely to acquire and that these acquisitions will perform relatively better than acquisitions made by non-central boards. Because more information is also available in the network about central firms, we hypothesize that central firms are more likely to be targets and to be associated with better performing acquisitions. In Section 2 we motivate these hypotheses in more detail and discuss the specific types of merger-relevant information available through board networks.

[Insert Figure 1]

Consistent with our predictions, we find that central firms are more likely to participate in merger activity and tend to have better post-acquisition performance, as measured by buy-and-hold abnormal returns (BHARs), calendar time portfolios, and changes in the ROA around mergers. For example, a one standard deviation increase in a firm's centrality is associated with approximately a 5% increase in its odds of making an acquisition in a given year and an 11% increase in the odds of being acquired. A standard deviation increase in centrality is associated with a 6% increase in post-

acquisition BHARs and a 1% increase in ROA around the acquisition.[2] We find that the odds of a firm without interlocks—which by definition is the least central type of firm in the network—acquiring another firm or being acquired are significantly less than a firm with interlocks. Using calendar-time portfolios with the Fama-French three-factor model, we find a 7-12% annual difference in abnormal returns between portfolios of central and non-central acquiring firms.

Our research contributes to a growing number of recent finance papers using social networks to explain managerial behavior and financial outcomes. For example, recent papers have explored how networks affect mutual fund performance (Cohen, Frazzini, and Malloy, 2008; Kuhnen, 2008), venture capital investments (Hochberg, Ljungqvist, and Lu, 2007), executive compensation (Barnea and Guedj, 2009), and firm governance (Fracassi and Tate, 2008; Hwang and Kim, 2008). These papers find mixed evidence on the performance implications of social networks.

Our paper contributes to several areas of literature. First, this paper adds to the finance merger literature by investigating the influence of inter-firm board networks on acquisition decisions and post-acquisition firm performance.[3] Specifically, using board networks this paper contributes to our understanding of which mergers are likely to be value creating in the long-run, which firms are likely to acquire other firms, which firms are likely to be targets, and when cash is likely to be used as the method of payment. Second, this paper adds to our understanding of the directors' influence on firm performance. Specifically, our results illustrate how better connected boards' are

[2] The results mentioned in this paragraph are based on different measures of centrality that will be introduced later in the paper.

[3] Fracassi and Tate (2008) also look at networks and mergers. However their research question and network measure captures the social networking ties between the CEO and the directors on the same board rather than measuring the effects of inter-firm social networks on acquisition activity.

associated with better performing acquisitions and how central boards are both more likely to acquire and to be acquired. We add to the literature investigating the relation between firm acquisition behavior and board networks by investigating the merger-related financial consequences of board networks, conducting our tests on larger samples of firms, and using network measures that capture more than just direct ties between firms.[4] Our results demonstrate that inter-firm board networks affect real business decisions and firm performance.

This paper is organized as follows. In Section 2 we cite related board literature, motivate our hypotheses, and describe our network measures. In Section 3 we describe our data. In Section 4 we empirically test the relation between board network measures and firm performance around mergers. In Section 5 we examine the relation between centrality and the probability of being acquired, making an acquisition, and using cash as the method of payment. In Sections 6 and 7 we discuss some robustness tests and then summarize the results and conclude.

2. Board networks and acquisitions: motivation, hypotheses, and measures

Directors are considered the shareholders' agents responsible for protecting their interests by monitoring and advising top management (Fama and Jensen, 1983; Linck, Netter, and Yang, 2008). Given the board's ability to influence important firm decisions, previous studies have investigated how board size, board independence, directors' ages, and busy directors affect firm performance (e.g., Yermack, 1996; Core, Holthausen, and Larcker, 1999; Hermalin and Weisbach, 2003; Fich and Shivdasani, 2006). Many of these same studies also explore the connection between these board characteristics and CEO

[4] Previous papers investigating board networks and acquisition behavior have mainly been outside the finance literature and, with the partial exception of Beckman and Haunschild (2002), have not investigated the financial implications of the inter-firm network-influenced acquisitions.

turnover, executive compensation, and acquisitions. In these papers, the relation between the board characteristics and firm performance or managerial behavior is often motivated with monitoring explanations where directors are considered to be less efficient monitors if they are too old, too busy, or part of a captured or large board. Along these lines, a director with multiple board seats would potentially be a non-effective monitor given the time constraints on his schedule.

However, from an advising standpoint, this same director may benefit from sitting on multiple boards and be able to pass along valuable current insights into how other firms are dealing, or have dealt, with similar issues. Indeed, a related stream of research has shown that corporate practices spread from firm-to-firm via board interlocks. Directors learn from their peers, get first-hand accounts of new strategies and their consequences and then provide advice to management. Along these lines, past research has shown that board interlocks affect the decision to acquire, the takeover premium paid (Haunschild, 1993; 1994), the formation of alliances (Gulati and Westphal, 1999), the adoption of multidivisional organization forms (Palmer, Barber, and Zhou, 1993) and the adoption of corporate practices like anti-takeover provisions and the back-dating of options (Davis and Greve, 1997; Bizjak, Lemmon, and Whitby, 2009). These papers clearly show that diverse and detailed information about other firms' previous merger experience, corporate structure, and corporate policies travels via board networks. Consistent with this research, we contend in this study that board networks provide access to information relevant for target selection and successful post-merger integration.

2.1. Board networks and merger information

What kinds of information could be available via board networks that would affect a firm's acquisition decisions and contribute to better post-merger performance? First, board networks provide information about other firms' merger-related experiences (Beckman and Haunschild, 2002). Directors can learn from their peers about negotiation strategies, investment banks, legal issues, post-acquisition activities, how to prepare for mergers, and how to approach targets. They can learn from others' past mistakes and successes in dealing with similar acquisition situations.

Second, board networks can provide information about potential target firms which leads to more efficient identification of actual targets and thus reduces potentially large search costs (Bruner, 2004). For example, if a bidding firm had a better understanding of the potential target firm's capabilities, existing governance practices, potential post-merger economies of scope or scale, possible merger-related synergies, or timely information about the willingness of the top management to be acquired, they would be able to better and more efficiently evaluate whether a potential target would be a valuable addition to the firm. Indeed, given that firms are known to expend considerable effort and resources in actively acquiring information about potential targets,[5] it is unlikely that they would not use, or be affected by, the information and perspectives gained via their networks. To the degree that this information makes their

[5] Bruner (2004) in chapter 7 indicates that acquisition targets are generally chosen after a search process that usually takes several months. As an example of this process, AlliedSignal reviewed 550 potential targets before initiating negotiations with 28 and finally buying 10. Even if many of the potential targets are initially suggested by an investment bank, the acquiring firm still would have to sift through the potential targets to make the final decision. Even small improvements in the search process could result in significant savings in time and resources.

search efforts more efficient they would save time and resources and be able to make better acquisition decisions.

Similarly, information gained via board networks about potential target firms and their management could make acquisition activities more attractive to firms by reducing information asymmetries and adverse selection issues associated with opportunistic behavior of targets (Akerlof, 1970; Myers and Majluf, 1984). Through board ties, firms can obtain reliable and possibly private information about the target firms and their management that is otherwise difficult to obtain. Previous knowledge about the target firm's capabilities and previously-formed opinions about target management would facilitate and affect the bidding firm early-on in considering whether and how to approach the target. Similarly, more information about the target would inform the bidder on how best to assimilate the target after the merger. Such questions as whether to retain key target firm management, how much autonomy to allow the target firm post-acquisition, and how to integrate possible differences in corporate cultures would be affected by how much information was available to the bidding firm. After the acquisition, awareness of key people—possibly outside the firm—could be important for successful post-acquisition performance.

And, lastly, given that merger activity is often associated with industry-level shocks (Mitchell and Mulherin, 1996; Harford, 2005), board networks can provide important current perspective and information on changing industry conditions and thus allow firms to be prepared and better positioned during the waves of merger activity. Whether the merger activity is in response to changes in regulation (Andrade, Mitchell, and Stafford, 2001), technological innovation, changes in capacity within the industry

(Andrade and Stafford, 2004), or in response to other recent mergers, having more informed directors advising management during these periods of rapid change could be particularly important.

Board networks are not the only source by which the above mentioned information is available. However, they are one such source which delivers information directly to decision makers and their impact would depend on the extent to which such knowledge is easily available to directors from outside the network. Much of the knowledge mentioned above is private, tacit, soft, and potentially costly to obtain. Although board networks do not replace other formal methods of acquiring information while attempting acquisitions, they do affect the boards' information set and the directors' perspectives.

2.2. Hypotheses

While board networks provide access to the above described information, this access is not equally available to all boards in the network. Hence, firms with better access to this information are advantaged in their acquisition activities. To determine which boards are better connected within the network, we systematically rank each board's connections using social network methods designed to show which boards are "central" within the network. These centrality measures have been used in social network research to assess actors' influence and centrality within social networks and represent an ideal way to estimate boards' centrality within the social network of boards.[6] Central positions in social networks are considered to have better access to the information in the network (Ebadi and Utterback, 1984; Sparrow, Liden, Wayne, and

[6] See Freeman (1979) and Borgatti (2005) for discussions of several centrality measures. For a textbook treatment see Wasserman and Faust (1994) chapter 5.

Kraimer, 2001; and Tsai, 2001). In this paper we specifically apply these ideas to boards and their acquisition decisions; if central boards have better access to merger-relevant information via their networks, then we expect central boards to be advantaged in their acquisition activity relative to less connected boards. Our specific hypotheses are described below. We discuss our measures of centrality in Section 2.3.

If central bidders have better access to the information described in Section 2.1 then we expect them to make more informed acquisition decisions and hence be associated with relatively better performing acquisitions. With greater access to information about the target and the acquisition process, central firms face relatively less information asymmetry about the post-acquisition target value and hence (1) are able to better avoid Akerlof's (1970) "lemons" problem, (2) become aware of additional attractive acquisition opportunities which would not have been taken without the additional information, and (3) are less likely to use stock. Hence,

H1: *Central bidding firms are associated with better performing acquisitions.*
H2: *Central firms are more likely to make an acquisition.*
H3: *Central bidding firms are more likely to use cash as the method of payment.*

The third prediction is generally consistent with Hansen's (1987) observation that a bidder has more incentive to use stock given the contingent pricing characteristics of a stock deal if the target has important information about its value not understood by the bidder.[7] Alternatively, the third prediction also follows from Shleifer and Vishny's (2003) theory of acquisitions based on rational managers and inefficient markets. In their

[7] The more uncertain the bidder is about the target value, the higher the risk of the bidder overpaying. As the risk of overpayment increases, the bidder's incentive to use cash decreases because in the event of overpayment the target management (knowing their own true value) willingly accepts the offer and the full cost of overpayment is born by the bidder. However, if stock is used as the method of payment, the target management bears part of the cost. If central positions in the network provide information to the bidder about the target then the bidder has relatively better understanding of the target's value than a non-central bidding firm and is thus relatively less likely to use stock.

paper, managers know when their own firm's stock is overvalued and rationally try to use the overvalued stock as the method of payment. Central bidding firms are less likely to be overvalued and hence are not as likely to be motivated in this way to use stock as their method of payment. To see why central firms are less likely to be overvalued, consider that information flows both to and from each board in the network. Central boards not only have relatively better access to network information about other firms, but information about the central firms is also more available to other firms (and by extension to the market) and hence information about central firms is more likely to already be priced.[8]

Having more information about central firms available in the network also suggests that central firms are more likely to be acquisition targets in as much as they are themselves examples of firms that as targets would have lower levels of information asymmetry. Along these lines, acquisitions of central targets are more likely to have good post-merger performance given that the acquisition was executed with relatively more information about the target available at the time of the merger. As before, having more information about the target is expected to be associated with a higher likelihood of the bidder using cash as the method of payment. Hence,

H4*: Central target firms are associated with better performing acquisitions.*
H5: *Central firms are more likely to be acquired.*
H6: *Central targets are more likely to be associated with cash deals.*

The hypotheses listed above are based on the idea that central network positions are associated with better access to information about other firms in the network and not just information about the observed bidder-target pair. In contrast, even a non-central

[8] This is related to Cohen et al. (2008)'s evidence of mutual fund managers taking positions based on private information shared via educational networks between corporate board members and fund managers. They argue that information shared via networks is one way that information is priced.

bidding firm might obtain information about a specific target in the network without necessarily having good access to network information in general if the bidding and target firms are "close" in the network even if both firms are not central.[9]

In this scenario, a non-central bidding firm would not benefit as much as a central firm from the network information in terms of general perspective, information about the industry as a whole, or about various potential targets, but the non-central firm could obtain merger-relevant information about a specific target which was close to the bidder within the network. Because information decays over network distance, this type of information may only travel across a few board interlocks. But to the extent that this information was available over short network distances, we would expect acquisitions made over shorter network distances to be more informed and hence associated with better performance and the use of cash. In Section 2.3 we explain how we measure network distance. Hence,

> **H7:** *Network distance between the bidding and target firms is negatively related to acquisition performance.*
> **H8:** *Network distance between the bidding and target firms is negatively related to the use of cash as the method of payment.*

2.3. Network measures

To empirically test hypotheses 1-6, we require a systematic way to measure centrality in board networks. Various centrality measures (degree, eigenvector, betweeness) have been used in recent finance research (see e.g., Hochberg, Ljungqvist, and Lu, 2007; Barnea and Guedj, 2009)). These measures tend to be correlated but are based on slightly different notions of what it means to be central and make different implicit assumptions about how information flows in the network (Borgatti, 2005).

[9] The number of interlock connections that separate two boards within the network is a measure of the network distance between them. Closer boards have fewer interlocks between them.

Given their extensive use in social networks research for assessing an actor's centrality in a network, we also choose to use these measures for our social network. Details of how degree, reach, betweeness and eigenvector centrality are calculated are provided in the appendix. Intuitively, degree measures the number of immediate connections (interlocks) a board has, reach looks beyond direct interlocks and measures how many boards can be reached across the shortest number of intermediaries, betweeness measures how many boards' connected paths connect via a given board, and eigenvector measures the centrality of a board by looking at the board's number of interlocks and weighting those connections by the centrality of the interlocked firms. Figure 2 provides a visual comparison of these centralities within a small example network as well as a picture of the 2004 board network immediately around an example firm (i.e., John Wiley and Sons, Inc.) The correlation between the various centrality measures is shown in Table 1.

[Insert Figure 2]

It is not clear from previous research in networks or mergers which of these four centrality measures best captures the type of information flow that would most affect acquisition decisions. Given the differences among acquisition deals, it is possible that different types of information affect individual deals differently. To the extent that all of these centrality measures proxy for information flow (and given their correlation) we would expect qualitatively similar results from the various measures in the general sample. Our basic idea remains the same for all four measures: central firms have more information which affects their acquisition decisions.

Rather than present four sets of results for every test using the different centralities, we tabulate our results using two measures—eigenvector and reach—to

facilitate comparison and make note of whether the tabulated results are consistent with the untabulated degree and betweeness measures. We chose eigenvector and reach centralities as our main measures for several reasons. First, unlike degree they both allow for influence across network distances greater than one. This is important given that previous research in networks has established the ability of even distant ties and the overall network structure to influence information flow in a network (Granovetter, 1973; Freeman, 1979). Eigenvector centrality has been widely used in social networks research with board interlocks (Faust, 1997) and is calculated with the idea that the centrality of an actor is proportional to the number of its contacts and the centrality of those contacts (Bonacich, 1972). In contrast, reach centrality is concerned with how many other actors can be reached over the shortest number of network steps and weights connections by how far away they are within the network rather than by their centrality.

We repeat our tests using the other centrality measures (degree and betweeness) and find that in most cases the qualitative results of our tests are not dependent on our choice of centrality measure. Given that each measure makes different implicit assumptions about the flow of information across the board network, the differences that are found in the test results based on choice of centrality measure provide information about the flow occurring in the network and are noted in the paper. The results for the untabulated centrality measures are available upon request. We chose not to use the principal component of the four measures given they are designed to capture different types of centrality and to preserve the interpretation of the centrality coefficients in the regressions.

For hypotheses 7 and 8 we require a systematic measure of network distance

between firms. For this measure, we count the number of interlocked boards between each observed bidder and target following the shortest connected path. In our tests we take the inverse of this number and deal with a measure of how "near" two firms are rather than how distant. Hence, *Nearness* is related to the number of interlocked firms between two boards in the network and is a measure of how close two firms are. Since information decays over distance, pairs of firms with high values of nearness have more timely and reliable access to information about each other in the network. As opposed to centrality measures which are not dependent on any particular target, nearness is only defined for a given bidder in terms of a particular target.

3. Data and sample characteristics

The merger data in this paper come from the U.S. Mergers and Acquisitions Database provided by Thompson Financial's Securities Data Company (SDC). We restrict the data to include the deals made by U.S. public bidders coded as having SDC form AA, AM, or M with announcement dates between 1991 and 2005. Additional sample-specific data filters are described in Section 3.1. The stock information and historical SIC codes come from CRSP, the financial information comes from Compustat, and the board membership information comes from Compact Disclosure.

The board membership data from Compact Disclosure are not limited to the S&P 500, or even the S&P 1500, but instead are larger than the CRSP and Compustat universe of firms.[10] Utilizing this data source allows us to investigate the influence that board networks have on merger deals of various sizes without having to limit our sample to

[10] Based on information in the 1998 Guide to Database Elements for the SEC Database, for a firm to appear in the database it must supply direct goods or services and file with the SEC, be listed on national securities exchanges or trade OTC, and have either a minimum of 500 shareholders of one class of stock or have at least $5 million in assets. If a firm has not filed with the SEC in the past 18 months it is dropped from their database for that year.

large firms. This is particularly important for an accurate representation of the network that alleviates concerns of network sampling bias affecting our centrality measures (Costenbader and Valente, 2003).

Compact Disclosure lists the names and ages of the directors and leading officers for firms that file with the SEC. Using this data, we identify board interlocks using a matching algorithm that compares information from the first, middle, and last names in addition to the reported age of directors and managers across firms. Because of the hundreds of thousands of individual-level observations listed by Compact Disclosure across the 15-year period an automated matching process was used followed by manual checks to improve the quality of the data.

3.1. Samples

We create two different samples to test the hypotheses discussed in Section 2. To facilitate the discussion and presentation of results in Sections 4 and 5, these samples are described and identified here. The specific control variables used in the samples are described in Section 3.2.

Sample 1 is at the acquisition-deal level and is restricted to include completed deals with public, private, or subsidiary targets having SDC transaction values greater than $1 million. Observations in this sample also require bidder CRSP return information at the time of announcement, Compustat information in the fiscal year prior to the announcement, and Compact Disclosure board information in the calendar year prior to the announcement date. We also require that the relative size of the target firm to the bidding firm be at least 1% leaving 4,339 deals in Sample 1. This sample is used for the tests associated with hypotheses 1, 3, 4, 6, 7 and 8 as described in Section 2.

Sample 2 is at the firm-year level and includes all firms each year that are in both CRSP and Compustat for which we also have board and centrality information from 1991-2005. This sample includes both firms that did, and did not, merge each year. We use Sample 2 to investigate the influence of board networks on a firm's likelihood of making an acquisition, and the likelihood of getting acquired. SDC merger information is added each year for each firm indicating whether the firm made an acquisition or was acquired. Compustat control variables and network and board information from Compact Disclosure are added from the prior year. If a firm from the CRSP/Compustat list does not appear in SDC in a given year as either an acquirer or target then we assume that the firm made no acquisitions that year and was not acquired. These data requirements result in more than 50,000 firm-year observations. Inferences from the tests based on Sample 2 are applicable to all firms in the CRSP and Compustat universe. This sample is used for the tests associated with hypotheses 2 and 5. The number of mergers differs between Samples 1 and 2 given the different data requirements.

3.2. Explanatory variables used in samples

The specific financial, deal, and network variables used in our tests are explained in this section. Most of the control variables described below are used in the tests but are not tabulated in the tables.

Previous research has shown that announcement merger returns are related to the public status of the target firm, whether cash or stock is used to buy the target (Fuller, Netter, and Stegemoller, 2002), whether the bidding firm has excessive amounts of cash (Harford, 1999), and the size of the acquirer (Moeller, Schlingemann, and Stulz, 2004). In addition to these variables, we control for the firm's expected growth opportunities,

past profitability, leverage, the relative size of the target to the bidder, whether the bidder is part of the S&P500, the acquisition year, the bidder's industry, whether the merger is diversifying, and several board characteristics. These variables have been used previously in the literature as control variables for the merger announcement market reaction as well as to explain long-term post-merger stock performance (e.g., Chen, Harford, and Li, 2007).

We obtain the target public status and method of payment information from SDC. We use the log of assets as a proxy for firm size and the log of the market-to-book ratio as an approximation of a firm's growth opportunities. We use ROA as a proxy for profitability and the ratio of the firm's long-term debt-to-book assets as a measure of the firm's leverage. The relative size of the target is calculated as SDC's transaction value divided by the bidding firm's previous year's market value of equity.

We control for industry using indicators for the Fama-French 48 industries (Fama and French, 1997). The board characteristics we control for include board size, the percentage of directors that are insiders, and indicator variables for whether the CEO is also chairman of the board and whether the board is busy.[11] The board control variables are based on information from Compact Disclosure. All control variables are from the year prior to the merger announcement.

We measure a firm's excess cash as the residual from a cash model similar to one used in Opler, Pinkowitz, Stulz, and Williamson (1999). The cash model shown below is estimated each year on all firms in Compustat:

[11] We classify a director as an insider if he was an officer prior to becoming a director or is an officer while being a director. The board is classified as busy if more than 50% of the directors have 3 or more directorships (Fich and Shivdasani, 2006).

$$Ln\left(\frac{Cash}{Assets}\right) = \beta_0 + \beta_1 \frac{Mkt}{Bk} + \beta_2 Size + \beta_3 \frac{Cshfl}{NtA} + \beta_4 \frac{NWC}{NtA} + \beta_5 \frac{CapExp}{NtA} + \beta_6 TLev + \beta_7 IndSg + \beta_8 \frac{RD}{Sales} + \beta_9 Div \quad (1)$$

In this cash model, *Cash* is cash and short-term investments, *Assets* is total assets, *Mkt/Bk* is market value to book value, *Size* is the log of total assets, *NtA* is net assets measured as total assets minus cash, *Cshfl* is cash flow measured as operating income before depreciation and interest less interest expense less tax less dividends paid, *NWC* is net working capital measured as current assets minus current liabilitites, *CapExp* is capital expenditures, *TLev* is total leverage including long-term and short-term debt divided by assets, *IndSg* is the mean industry standard deviation of cash flow measured over the previous 20 years with industries assigned at the 2-digit SIC level, *RD* is research and development, *Sales* is net sales, and *Div* is an indicator variable for whether or not dividends were paid during the year.

For our network measures, we include the normalized centrality for each firm from the year prior to the merger announcement. Hypotheses 1-3 require measures of the bidders' centralities, and hypotheses 4-6 require measures of the targets' centralities. We take the log of the eigenvector, degree, and betweeness centralities to reduce the strong right-skew in these measures and then standardize all the centrality measures to facilitate interpretation of the results. To ensure that our conclusions are not driven by these transformations, in untabulated tests we also estimate several specifications where we bin the underlying centrality measure into four discrete groups and treat the resulting index as an interval variable and obtain qualitatively similar results.

Consistent with hypotheses 7-8, we also include a measure of the network distance between the bidder and target. As explained earlier, rather than work directly with distance, we use a measure of nearness calculated as the inverse of the distance.

Hence, an interlocked bidder-target pair would have a nearness measure of 1 while boards that are two interlocks away have a nearness measure of 0.5. Bidder-target pairs that are not connected by any series of interlocks are assigned a nearness of 0.

We add an indicator variable for deals where the bidder and target are interlocked to account for possible legal and operational implications of having directly interlocked boards. We also add an indicator variable for boards with no director interlocks ("isolate boards"). We do this to control for possible underlying systematic differences between boards that share directors and those that do not.

We also interact the centrality measures with the S&P500 indicator to account for possible differences in how the information from board networks affects large and well-known firms' acquisition behavior relative to small and lesser-known firms' acquisition behavior. To the extent that S&P500 firms have more informational resources, or access to better information from alternative sources, the information from board networks would be less important in acquisition decisions (Haunschild and Beckman, 1998). We include the interaction of the centrality measure and the S&P500 indicator to control for this as well as possible differences associated with the S&P500 firms' greater following by institutional investors, brokers, and analysts; increased news coverage; greater access to business round tables; greater ability to act on information gained via their networks given their better access to capital; and the idea that network information gained by directors of smaller firms about larger firms is not likely to lead to the smaller firms' acquisition of the larger firms, whereas information gained by directors of large firms via networks could directly influence their potential acquisition of the smaller firms.

3.3. Descriptive statistics

Table 1 shows the correlation matrix between the network measures and the non-indicator control variables used in our specifications. As shown in the table, the network statistics tend to be highly correlated. For this reason we do not place them together in our tests. Most of the other variables do not appear to be highly correlated. To ensure our results are not driven by multicollinearity we examine the coefficients' variance inflation factors after each regression and confirm they are within acceptable ranges.

[Insert Table 1]

Table 2 shows the distribution of mergers across years for Samples 1 and 2. Table 3 presents sample information at the industry level. The number of mergers and the median normalized eigenvector, and reach centralities are shown for each industry. Approximately 13% of the firm-year observations in Sample 2 are firms with no interlocks (isolates). The tabulated industry median centrality measures include the isolate firms.

[Insert Table 2]

[Insert Table 3]

As shown in Table 3, there is variability from industry-to-industry in centrality and in the percent of isolate firms. In Section 2 we argue that boards with higher centrality have better information which in turn affects their acquisition behavior. Figure 3 explores this relation by visually comparing the median annual centrality measures for acquiring (acquired) and non-acquiring (non-acquired) firms in Sample 2 by industry and year. The reported medians are based on the centralities prior to any transformations and include isolate firms.

[Insert Figure 3]

To calculate the median centrality measures shown in Figure 3, each firm each year in Sample 2 is placed in either the acquiring (acquired) or non-acquiring (non-acquired) group. Then all the firm-year observations in these two groups are further sorted by industry or by year. We then calculate the median centrality statistics for these sorted groups. The centrality measure used each year for each firm is calculated using the board information from the prior year.

As shown on the left side of Figure 3, acquiring firms in almost all 48 industries tend to have higher reach centrality in the year prior to acquisitions than non-acquiring firms from the same industries. As shown on the right side of Figure 3, acquiring firms and acquired firms across industries tend to have higher centrality in the year prior to the acquisition than non-acquiring and non-acquired firms. Consistent with our hypotheses, in general it appears that both bidders and targets tend to have higher centrality measures in the year prior to acquisitions than non-bidders and non-targets in the same industries and years. This relation will be further explored in a multivariate setting in Section 5.

4. Merger performance and board networks

To explore the relation between board networks and firm performance around acquisitions we examine several measures of firm performance as a function of the boards' networks while controlling for other relevant variables from the merger literature as described in Section 3.2. Our measures of performance include both short-term and long-term stock performance, as well as changes in the firm's ROA around the merger. We explore the long-term stock performance implications of board networks using Lyon,

Barber, and Tsai's (1999) buy-and-hold abnormal returns (BHAR) methodology as well as the calendar-time portfolio approach discussed in Fama (1998).

Given the presence of large outliers in our data we use least-absolute-deviation regression techniques (median regression) for all of our performance-based tests (Tables 4-5, 7). As an alternative approach, we also estimate our regressions using OLS with data winsorized at the 5th and 95th percentiles with White's heteroskedasticity-robust standard errors clustered by firm and obtain qualitatively similar results.

4.1. Short-term performance

If the market recognizes that central firms make better acquisitions then the immediate market reaction to the merger announcement should be relatively more positive for central firms. We use the bidder three-day (-1,1) cumulative abnormal returns (CARS3) around the announcement date as our measure of short-term market reaction. The daily abnormal return is calculated using the market model with the CRSP value-weighted index. The market model parameters are estimated over the period 60 to 200 trading days before the merger announcement.

Table 4 shows the results from regressing CARS3 on the bidder's eigenvector and reach centrality in addition to various sets of control variables described in Section 3.2. Given space constraints, for the OLS regressions we report only the main network coefficients at the top of Table 4 for comparison with the median regression coefficients. Both the OLS and median regressions use the same control variables in each model. There is limited support for the idea that bidder centrality is associated with positive announcement returns (i.e., eigenvector model 5 and the reach model 1), but this conclusion is not robust for different time periods and in general is not supported by the

data. Overall, the CARS3 results suggest little or no relation between announcement returns and bidder or target centrality.[12] These results suggest that either board networks don't have merger performance implications, or the general market is unaware of the boards' relative centrality.

[Insert Table 4]

Given that we find evidence in other tests that centrality is positively associated with both long-term stock performance after mergers (Tables 5-6) as well as improvements in ROA around mergers (Table 7), we assume from the CARS3 results that market participants have imperfect perceptions of firms' relative centrality in the overall network and/or board centrality's association with firm performance around mergers.

4.2. Long-term stock performance – buy-and-hold abnormal returns

Following Lyon, Barber, and Tsai (1999), we calculate size and book-to-market value (B/M) decile cutoff points each year for NYSE firms. We then assign Nasdaq and AMEX firms to their respective size and B/M deciles each year based on these cutoff points. The decile of the smallest firms is then further partitioned into four subgroups making 140 total groups based on 14 size and 10 B/M groups each year. For each bidding firm in our sample, we then select the five firms from the same size and B/M group in the year before the merger announcement that experienced stock returns closest to the bidding firm.

[12] In untabulated tests we obtain similar results using degree and betweeness. In additional untabulated tests we use the CARS3 around the merger announcements using Schwert's (1996) method for anticipated merger events where the intercept is assumed to be zero and only the slope coefficient from the estimation period is used to calculate the abnormal return and obtain similar results.

To be included as part of the benchmark group, each firm is required to not have acquired another firm within the prior three years that was larger than 10% of its market capitalization. We use the mean return from these five firms matched on size, B/M, and recent past stock performance as the benchmark return. Each month we then define the abnormal return to the bidding firm as the difference between the bidding firm's return and this benchmark return. We calculate the three-year buy-and-hold returns (BHARs) starting the month after the merger completion date using these abnormal returns. We obtain qualitatively similar results using either the single closest return—as in Chen et al., (2007)—as we do using the mean return from the five closest firms.

4.2.1. Cumulative buy-and-hold abnormal return plots

To explore the relation between BHARs and pre-merger centrality, we categorize each bidding firm into High, Medium, Low, and Isolate groups in the year before the merger announcement using their centralities. The group assignments are done as follows: First, we sort all CRSP and Compustat firms—including the bidding firms—into eigenvector, degree, reach and betweeness deciles each year. Isolate firms are not linked to other firms via interlocks and hence do not have meaningful centrality statistics and are considered an eleventh group and not part of the decile formation. Firms from the bottom three deciles are assigned to the Low group, firms from the top three deciles are assigned to the High group, and the middle four deciles constitute the Medium group. In Figure 4, the cumulative BHARs across the three-year period following each merger are then plotted for each of the above mentioned groups for different sub-samples of Sample 1.

Using the full sample, the results in Figures 4A, 4E and 4F strongly suggest that the post-merger long-term benchmark-adjusted stock performance of central firms is better than that of non-central firms which is consistent with hypotheses 1 and 4. In these plots, the acquiring firms in the High group perform similarly to their non-acquiring benchmark group. The firms in the Low group underperform their benchmark by approximately 15-20% over the three years following the merger. Figures 4E and 4F show the same plot using centrality group assignments from the year before and from the same year as the acquisition, respectively.

[Insert Figure 4]

One question that could arise from these plots is whether the dispersion in outcomes is attributable to the interaction of the board networks and mergers. An alternative explanation could be that central boards typically perform better than non-central firms with or without mergers. To address this question we create a comparison sample of non-acquiring firms matched on industry, time, and size and plot their BHARs.

To create the comparison sample we do the following: For each of the bidding firms in Sample 1 we find the firm closest to the bidding firm in size that has the same centrality category (High, Med, Low, Isolate) in the previous year, comes from the same industry, and that did not acquire another firm within six months of the bidding firm's merger completion date. We add this comparison firm to the non-acquiring comparison sample on the same date that the original bidding firm was added to the acquiring sample. We then calculate the BHARs for this group in the same way as for the acquiring sample and plot the cumulative abnormal returns in Figure 4B. The monotonic ordering of the abnormal returns observed for the acquiring group (4A) is not observed in the non-

acquiring sample. From this we conclude that the dispersion in abnormal returns stems from the interaction of board networks with merger events and not from board networks alone.

As discussed in Section 3.2, in the multivariate tests we include both an indicator and interaction variable associated with the S&P500 to account for possible differences in how S&P500 firms use information from their networks in merger decisions. To further investigate this possibility, we plot the long-term BHARs using the full sample as well as the sub-sample of S&P500 acquirers. The lack of a visual relationship between the centrality groups and BHARs for S&P500 acquiring firms as shown in 4C supports the idea that board networks interact with S&P500 firms' acquisition behavior differently than for other firms. In Figure 4D the BHARs for the acquiring firms in the S&P1500 (excluding the S&P500) appear more consistent with the rest of the sample where better networked firms have better long-term BHARs following acquisitions.

4.2.2. Multivariate analysis of long-term buy-and-hold abnormal returns

To quantify the relationship between the post-merger BHARs with multivariate controls, we regress the 3-year post-acquisition BHARs on the centrality measures along with the controls used in Table 4. Table 5 shows the results controlling for the bidder's eigenvector and reach centrality in addition to various sets of control variables in different time periods. As in Table 4, we report only the main network coefficients from the winsorized OLS regressions for comparison with the median regression coefficients. Both the OLS and median regressions use the same control variables.

The positive significant coefficient associated with the bidder centrality for five of the OLS models and two of the median regression models suggests that even after

controlling for industry, year and all of the firm and deal variables shown in Table 4 that the bidder's centrality is positively associated with long-term post-merger abnormal returns. The coefficients from eigenvector model 1 indicate that a one standard deviation increase in bidder eigenvector centrality is associated with a 4-6% increase in 3-year BHARs even after controlling for bidder and deal characteristics. Eigenvector models 2 and 3 also provide evidence that target centrality is positively associated with post-merger BHARs. These results are consistent with hypotheses 1 and 4. The untabulated results using the other centrality measures show a positive relationship between bidder centrality and BHARs for the 1998-2005 period.

Network nearness is not found to consistently predict long-term post-merger stock performance. This suggests that whether or not the bidding and target firms are close together in the network does not significantly affect their post-merger performance. This is not consistent with hypothesis 7.

[Insert Table 5]

4.3. Long-term stock performance – calendar time portfolios

Although the buy-and-hold approach closely mirrors the experience of an actual investor and allows us to control for size, B/M, and recent stock performance when calculating the abnormal returns, it has some limitations. The buy-and-hold methodology does not easily allow the researcher to deal with correlation across events and may compound errors in estimation made soon after the event (Fama, 1998; Mitchell and Stafford, 2000). To ensure that the observed relation between long-run post-merger stock performance and board networks is not dependent on the BHARs approach we also

examine the long-term stock performance of our firms using the calendar-time portfolio approach discussed by Fama (1998).

For the calendar time approach we form portfolios of bidding firms each month based on the network centrality decile assignments from the year before the merger announcement. Each bidding firm's stock is added to its respective portfolio starting the month after the merger completion date. The firm remains in its assigned portfolio for 1-3 years after the merger. In each calendar month, for each portfolio, the mean return using equal-weighting and value-weighting approaches is calculated. For the value weighting approach, the relative weights are based on each firm's market value of equity from the year prior to its merger announcement. If a firm makes more than one bid within the post-merger period it enters the portfolio only once but remains in the portfolio until 1-3 years after the completion of the last merger.

For this test we are interested in the return difference each month between portfolios of central and non-central bidding firms. We define the central and non-central groups using the High and Low centrality groups described in Section 4.2.1. This monthly mean return difference is then regressed on monthly factors from the Fama-French three-factor model. We also tabulate results using a four-factor model including momentum. We interpret significant alphas in this model to be the returns not explained by the factors but related to differences in board networks. These results are shown in Table 6.

[Insert Table 6]

Results are shown in Panel A for various holding-periods ranging from 1 to 3 years after the merger completion date. As shown in the first column of the table, we

calculate the alphas with and without the S&P500 firms to be consistent with our earlier discussion as well as with various relative size filters. We implement the relative size filters to investigate the possibility that information attained via board networks becomes less important as the relative size of the target increases given the likely utilization of other information sources and heightened scrutiny involved with larger deals. Panel B shows the results from looking at the 1991-1997, 1995-2001, and 1998-2005 time periods while holding the firms in their respective portfolios for one year after the merger completion date.

Significant positive alphas are observed for the value weighted three- and four-factor models. The size and significance of the alphas in Table 6 tend to decrease as the holding-period increases from one to three years. Also, the size of the alphas tends to increase as the sample is limited to smaller relative size deals. For example, using the value-weighted portfolio results with reach centrality, the monthly alphas from the three-factor model estimated on the sample with deals with relative size smaller than 20% for the period 1991-2005 range from 95 basis points a month significant at the 5% level to 55 basis points a month significant at the 10% level as the holding period changes from one to three years. The size of the alphas decreases monotonically as the holding-period increases by each year. We interpret this to suggest that the merger-related benefits from the board networks are realized mostly in the first year after the merger and then decrease with time. The above mentioned monthly alphas correspond with annualized abnormal returns between 7 and 12% a year.

As shown in Table 6, we find almost no significant alphas using equal-weighted portfolios except for the subsample of the smallest relative size deals. Given the presence

of significant alphas in the value-weighted approach we conclude that for a given level of centrality that large firms' post-merger performance tends to systematically differ from smaller firms' post-merger performance and that the board network information is particularly important for relatively smaller deals. In untabulated tests using degree and betweeness we find almost no significant alphas using the same approach as shown in Table 6.

4.4. Changes in ROA

To ensure that the observed differences in long-term post-merger stock performance between highly and poorly networked firms are not due solely to differences in expectations of future performance, we also measure the change in ROA from three years before to three years after the merger by taking the difference between the mean annual ROA for years (t+1,t+3) and (t-1,t-3) where t is the year of the merger. We test for changes in mean ROA (Panel A) as well as changes in mean industry-adjusted ROA (Panel B) and tabulate the results in Table 7. We calculate the industry-adjusted ROA by first subtracting the median ROA for all firms with the same two-digit SIC code each year before then taking the three-year annual mean ROA for each firm before and after the acquisition year.

[Insert Table 7]

As shown in Table 7, the results in many of the OLS and median regression specifications in Panels A and B for models 1, 2, 3 using either eigenvector or reach centrality indicate that increases in bidder centrality are associated with positive changes in both industry-adjusted and non-adjusted ROA around mergers. For these models, a one standard deviation increase in bidder centrality is associated with approximately a

1% increase in ROA. Similarly a one standard deviation increase in target centrality is associated with a 1-2% increase in ROA around the acquisition.

The median reach results from Panel A model 3 suggest that both the bidder and target centrality remain significant when both measures appear in the regression. However, the results from the other models where both bidder and target centrality are included show that the bidder centrality loses its significance after controlling for the target connections. We are hesitant to interpret this as indicative that target centrality is the more important predictor for post-merger performance given both the large drop in sample size when we include target centrality and the reach results.

In untabulated tests using degree and betweeness centrality we find qualitatively similar although weaker results. Our qualitative conclusions are robust to using either EBIT/assets or EBITDA/assets for our measure of ROA. Nearness is not found to consistently predict changes in ROA. This is not consistent with hypothesis 7.

5. Centrality and the probability of acquiring, being acquired, and using cash

As motivated in Section 2.2, for hypotheses 2, 3, 5, 6 and 8 we expect central firms to have a higher likelihood of acquiring, being acquired, and to have cash used as the method of payment. The results from tests of these hypotheses are shown in Tables 8-9.

5.1. Centrality and the probability of making an acquisition or being acquired

The results shown in Table 8 are from multinomial logit models based on Sample 2 where the dependent variable is set to one of three values indicating whether the firm acquired, was acquired, or did not engage in acquisition activity in a given year. In these tests the firms are required to have at least $20 million in assets. We impose this filter

because we cannot capture in our sample the types of acquisitions that the very small firms might make. Our qualitative conclusions are not dependent on this size filter.

[Insert Table 8]

In untabulated models that control only for the year and both the firm's industry and centrality we find that all four measures of centrality are positively associated at the 1% level with the odds of making an acquisition and the odds of being acquired. After including additional firm-level control variables, eigenvector centrality ceases to be significant in explaining either the likelihood of making an acquisition or being acquired and hence is not included in Table 8. As shown in the table, reach ceases to be significant for non SP500 firms in explaining the odds of making an acquisition but remains significant in explaining the odds of being acquired. Both betweeness and degree are found to be significant and positive in explaining both outcomes.

The multinomial results are shown in relative risk format such that each odds ratio is relative to the comparison case noted in the table. Hence, for example, holding all the other variables constant, the reach results suggest that a one standard deviation increase in centrality is associated with a 13.4% increase in the odds of being acquired in a given year relative to the no-acquisition activity case. The betweeness results indicate that a one standard deviation increase in centrality is associated with a 5.3% increase in the odds of making an acquisition in a given year and an 11.3% increase in the odds of being acquired relative to the non-acquisition activity case.

Even after controlling for firm characteristics, as well as time and industry effects, the results using betweeness, degree, and to a lesser extent reach are consistent with our hypotheses that central firms are more likely to both make acquisitions and be acquired.

Additionally, the odds ratios associated with the isolate firms are consistent with our hypotheses in that the least central of firms are found to be less likely to acquire and less likely to be acquired. This is true using any of the centrality measures.

The differences in the way the various centrality measures relate to the probability of the outcomes of acquiring or being acquired taken together with the differences in the way the measures are calculated provide insight into the type of information flow affecting the outcomes. For example, degree only captures immediate connections and given its significant association with acquisition activity shows that information flow from direct board interlocks affects the probability of acquisition outcomes. Reach centrality is also significant in explaining the outcomes and measures how many firms can be reached over the shortest network distance—once again emphasizing that the information that matters for these outcomes is close within the network. A firm with high betweeness centrality has connections to diverse clusters of firms suggesting that the decision to acquire and the likelihood of being acquired increases with connections to diverse groups. And finally, a firm with high eigenvector centrality is a firm with connections to other firms which also have high centrality. Given that eigenvector centrality does not explain well the odds of the outcomes, this suggests that weighting a firm's connections by their respective centralities masks whatever underlying relation exists between the odds of the outcomes and the information flow that exists via those connections as already shown by the degree and reach results. Combined with the fact the eigenvector centrality does positively relate to post-acquisition performance, this suggests the possibility that the type of information flow that affects the decision to

acquire or not to acquire is different than the type of information that may lead to better performing acquisitions.

5.2. Centrality and the use of cash

To test whether centrality and nearness affect the likelihood of using cash as the method of payment we estimate a multinomial logit model for the choice to use 100% cash, 100% stock, or a mixture of cash and stock. In these models we control for bidder and target centrality as well as the distance between the bidder and target. Although not tabulated, we also control for the variables introduced in Section 3.2. The results are shown in Table 9 and provide evidence that target centrality is positively associated with the likelihood of using cash. This is consistent with hypothesis 6.

For example, compared to the 100% stock case, the odds of using 100% cash are 39.2% larger for each standard deviation increase in target centrality. The lack of significance for nearness after controlling for target centrality suggests that whatever information in the network that is relevant for the choice of using cash or stock is disseminated generally in the network rather than across any direct path of interlocked boards between the bidder and target. In untabulated results, if target centrality is not included in the model then nearness is positive and significantly associated with the odds of using 100% cash. The results using the other centralities are qualitatively similar to those shown for eigenvector centrality. Overall the results suggest that cash is more likely to be used for more central targets.

[Insert Table 9]

6. Alternative explanations and robustness tests

We recognize that board connections are the outcome of complex interactions of people and competitive forces at the firm-, industry-, and market-level over time. It is possible that the centrality measures we are using are actually proxying for other underlying variables in our models such as director ability, or that centrality is in some way endogeneously determined along with merger activity and performance. In this section we investigate these possibilities.

6.1. Centrality and director ability

An alternative explanation of our performance results is that centrality is a proxy for director ability. This could occur if more capable directors over time are more successful and hence are offered multiple directorships. Given that a firm's centrality is related to how many of its directors, or managers, also sit on other boards, it is possible that boards with high centrality are the same boards with directors that have higher-than-average ability as evidenced by their multiple directorships. Hence, the association between superior post-acquisition performance and centrality may be a function of director ability rather than information available via the network.

To test whether our results are related to ability we construct a measure of director ability and add it as another control in our ROA regressions. To construct the measure we assume that a firm's performance is a reflection of the ability of its directors. We recognize that this leads to an imperfect measure of ability but suggest that it is likely that boards and shareholders also form opinions about new potential directors precisely based on the performance of the firms in recent years where they have worked. Hence measuring ability based on past firm performance likely mirrors some of the selection criteria used to find new directors. Each year we calculate the stock returns for all firms

in our sample and then create yearly director-level weighted averages of the returns for the firms the directors were associated with over the last five years. We then aggregate the directors' weighted average ability measures at each board each year to form a board-level measure of the directors' ability.

[Insert Table 10]

As shown in the median results in column 1 of Table 10, the bidder and target centrality measures remain significant in explaining the change in ROA around the acquisition even after controlling for ability. The inclusion of ability does not affect the coefficients or standard errors associated with the bidder centrality in the OLS results. In untabulated tests we observe qualitatively similar results using other centrality measures.

6.2. Endogeneity

Another potential concern involves the possible endogeneity associated with centrality, merger activity, and merger performance. For example, one question that could be asked is whether some underlying firm characteristic leads both to boards with higher centrality prior to acquisitions as well as more frequent and relatively better performing mergers. To investigate this possibility we discuss three robustness checks below that address variations of this concern.

First, if firms retain the best directors after acquisitions then over time the subset of firms that tend to acquire frequently would accumulate the type of directors that are sought after for their ability and their acquisition experience and hence likely to have multiple directorships. Thus over time the serial acquirers may end up being central in the network and the observed relation between board centrality and both the probability of making an acquisition as well as post-acquisition performance could be driven by the

subset of firms that make a lot of acquisitions. To investigate this possibility we eliminate serial acquirers (i.e., firms that have made three or more acquisitions within three years) from our sample and re-estimate the model shown in Table 8. In untabulated tests we find that the Table 8 results remain unchanged with or without the serial acquirers. We also find that serial acquirers, on average, do have significantly larger centrality measures than non-serial acquirers.

A related concern that is not addressed simply by removing the serial acquirers involves reverse causality where firms' merger preparations may in fact lead to increased centrality. This could occur in various ways including if directors with special skill sets or experience are sought after in preparation for acquisitions. If these directors are in demand then they likely have multiple board seats and thus the board's preparations lead both to higher centrality and better performing mergers. To address this concern we need either an exogenous shock to the industry that leads immediately to acquisitions and does not allow the boards time to change board composition or an instrument for bidder centrality that is uncorrelated with the board's preparation for impending merger activity.

Accordingly, for an exogenous shock test, we limit the deals in Sample 1 to those within the relatively few industries that had merger waves in the 1990s where the mergers occur within two years of the dates listed in Table 2 of Harford (2005). We assume that the industry shocks initiating these waves were unexpected and hence argue that the directors on these firms' boards at that time were not likely placed there years in advance of planned merger activity. These time and industry filters in addition to the data requirements for the centrality calculations result in a severe reduction in sample size. Despite the reduction in observations, as shown in the OLS results in column 2 of Table

10, the relation between target centrality and change in ROA remains significant. The loss in significance for the bidder centrality may be an indication that bidder centrality is related to board preparations in advance of mergers, or more likely is due to the dramatic reduction in sample size combined with numerous control variables.

For the instrumental variable approach, we need an instrument that is correlated with the bidder centrality but not correlated with the bidder's preparations. While a bidder certainly prepares for merger activity, it is unlikely that the bidder starts these preparations more than a year in advance. Yet, given that most directors sit on a board for multiple years the bidder's centrality three years prior to the merger is correlated with its centrality in the year before the merger, but is not directly connected with the board's recent preparation for merger activity. Accordingly, we use the bidder's centrality from three years prior to the merger as an instrument for its centrality in the year prior to the merger in a two stage least squares (2SLS) framework. In the first stage, bidder centrality at time t is regressed on its instrument and other control variables. The predicted value of bidder centrality from this regression is used as a covariate in place of actual bidder centrality in the second stage regression which predicts change in bidder's ROA.

To ensure our instrument is valid we confirm that the bidder reach at year t-3 significantly predicts bidder reach at year t-1. The F-statistic for the first stage regression is 24.26 which is much larger than the rule of thumb proposed by Stock, Wright, and Yogo (2002). As a second check, we find that the partial r-square for bidder centrality is 0.2983 which is also higher than the suggested cutoff value of 0.1. Column 3 of Table 10 reports the second stage results of the 2SLS. Both bidder and target centrality significantly predict the change in bidder's post-merger ROA. These results suggest that

the loss of significance for the bidder reach in the shock test as reported in column 2 was due to the dramatic reduction in sample size.

As a third robustness check, we also re-estimate centrality's relation to the change in ROA around acquisitions using firm fixed-effects to account for the possibility that some underlying time-invariant firm-level characteristic accounts for both the firm's centrality and post-acquisition performance. As shown in column 4 of Table 10 the target centrality remains significant in explaining the change in ROA but the bidder centrality coefficient becomes insignificant. Given that centrality tends to be highly correlated from year-to-year it is not surprising that it looses its significance in a fixed-effect framework. As noted by Plumper and Troeger (2007) and Wooldridge (page 286) the coefficient estimate on bidder centrality is inefficient and potentially imprecise using fixed-effects given that centrality displays relatively little variation through time at the firm level.[13] Following Plumper and Troeger's (2007) method, we perform a panel fixed-effect regression with vector decomposition where we treat bidder centrality as an almost time-invariant variable. Column 5 in Table 10 reports the results for this test. Using this method, both bidder and target centralities are found to significantly predict the change in post-merger ROA.

Other comments related to endogeneity concerns include the following: First, in all of our tests we try to mitigate this concern by calculating each firm's centrality using board connections from the year prior to the merger announcement rather than the current-year's connections. Second, a board's betweeness, eigenvector, and reach centralities are not only a function of their own choice of directors but are also largely determined by the structure of the overall network based on other boards' year-to-year

[13] Using Sample 2, the reach centrality autocorrelation is .77.

election of directors. Hence, a board's centrality, as measured in this paper, is not directly under the control of the board.

7. Summary and conclusions

In this paper, we argue that well-networked boards have access to merger-relevant information via their networks and show that central positions in board networks are associated with statistically significant and economically meaningful superior post-merger financial performance. Better networked boards do, on average, make better acquisition decisions.

Not only are board networks found to relate to post-acquisition performance, but we also find that higher centrality within the board network significantly increases the odds of a firm making an acquisition, the odds of being acquired, and the odds of using cash as the method of payment. These conclusions are robust to various specifications, control variables, and several different performance measures.

Indeed, these results demonstrate the effect that directors' knowledge and interactions can have on firm performance and emphasize the influence that directors have through their advisory role as opposed to just their monitoring role; a board's ability to acquire information from its social network influences merger decisions, firm performance, and hence shareholder wealth. Our results suggest that executives and directors may be valuable to boards not only for their qualifications and past experience, but also for the social connections they have.

In future research, we plan to investigate how directors' connections affect their value in the director labor market. It appears interlocked directorships simultaneously provide informational benefits as well as requirements on the time of the director. This

begs the question how to reconcile the positive information-based interpretation of inter-firm director connections and the negative monitoring-based interpretation of busy directors.

Our research demonstrates that board networks can be an important source of acquisition-related information but there are many questions left for future research. For example, what are the costs of having too many connections outside the firm? Does the value of board networks vary with different industry and macro conditions? If central positions provide informational advantages to firms in making acquisition decisions, then do they also provide informational advantages in business decisions unrelated to mergers? Do directors' connections with political groups, investment banks, lobby groups, or suppliers also affect firm performance? These questions are left for future research.

References

Akerlof, G., 1970. The market for lemons: Quality uncertainty and the market mechanism. The Quarterly Journal of Economics 84, 488-500.

Andrade, G., Stafford, E., 2004. Investigating the economic role of mergers. Journal of Corporate Finance 10, 1-36.

Andrade, G., Mitchell, M., Stafford, E., 2001. New evidence and perspectives on mergers. Journal of Economic Perspectives 15, 103-120.

Barnea, A., Guedj, I., 2009. Director networks. Unpublished working paper. University of Texas, Austin.

Beckman, C., Haunschild, P., 2002. Network learning: The effects of partners' heterogeneity of experience on corporate acquisitions. Administrative Science Quarterly 47, 92-124.

Bizjak, J., Lemmon, M., Whitby, R., 2009. Option backdating and board interlocks. Review of Financial Studies (forthcoming).

Bonacich, P., 1972. Factoring and weighing approaches to status scores and clique identification. Journal of Mathematical Sociology 2, 113-120.

Borgatti, S., 2005. Centrality and network flow. Social Networks 27, 55-71.

Bruner, R., 2004. Applied Mergers and Acquisitions. Hoboken, New Jersey: John Wiley & Sons, Inc.

Chen, X., Harford, J., Li, K., 2007. Monitoring: Which institutions matter? Journal of Financial Economics 86, 279-305.

Cohen, L., Frazzini, A., Malloy, C., 2008. The small world of investing: Board connections and mutual fund returns. Journal of Political Economy 116, 951-979.

Core, J., Holthausen, R., Larcker, D., 1999. Corporate governance, chief executive officer compensation, and firm performance. Journal of Financial Economics 51, 371-406.

Costenbader, E., Valente, T., 2003. The stability of centrality measures when networks are sampled. Social Networks 25, 283-307.

Davis, G., Greve, H., 1997. Corporate elite networks and governance changes in the 1980s. American Journal of Sociology 103, 1-37.

Ebadi, Y., Utterback, J., 1984. The effects of communication on technological innovation. Management Science 30, 572-585.

Fama, E., 1998. Market efficiency, long term returns and behavioral finance. Journal of Financial Economics 49, 283-303.

Fama, E., French, K., 1997. Industry costs of equity. Journal of Financial Economics 43, 153-193.

Fama, E., Jensen, M., 1983. Agency problems and residual claims. Journal of Law and Economics 26, 327-349.

Faust, K., 1997. Centrality in affiliation networks. Social Networks 19, 157-191.

Fich, E., Shivdasani, A., 2006. Are busy board effective monitors? The Journal of Finance 61, 689-724.

Fracassi, C., Tate, G., 2008. External networking and internal firm governance. Unpublished working paper. University of California, Los Angeles.

Freeman, L., 1979. Centrality in social networks: Conceptual clarification. Social Networks 1, 215-239.

Fuller, K., Netter, J., Stegemoller, M., 2002. What do returns to acquiring firms tell us? Evidence from firms that make many acquisitions. The Journal of Finance 57, 1763-1793.

Granovetter, M., 1973. The strength of weak ties American journal of sociology. American Journal of Sociology 78, 1360-1380.

Gulati, R., Westphal, J., 1999. Cooperative or controlling? The effects of CEO-board relations and the content of interlocks on the formation of joint ventures. Administrative Science Quarterly 44, 473-506.

Hansen, R., 1987. A theory for the choice of exchange medium in mergers and acquisitions. The Journal of Business 60, 75-95.

Harford, J., 1999. Corporate cash reserves and acquisitions. The Journal of Finance 54, 1969-1997.

Harford, J., 2005. What drives merger waves? Journal of Financial Economics 77, 529-560.

Haunschild, P., 1993. Interorganizational imitation: the impact of interlocks on corporate acquisition activity. Administrative Science Quarterly 38, 564-592.

Haunschild, P., 1994. How much is that company worth? Interorganizational relationships, uncertainty, and acquisition premiums. Administrative Science Quarterly 39, 391-411.

Haunschild, P., Beckman, C., 1998. When do interlocks matter? Alternative sources of information and interlock influence. Administrative Science Quarterly 43, 815-844.

Hermalin, B., Weisbach, M., 1991. The effects of board composition and direct incentives on firm performance. Financial Management 20, 101-112.

Hermalin, B., Weisbach, M., 2003. Boards of directors as an endogenously determined institution: a survey of the economic literature. Economic Policy Review 9, 7-26.

Hochberg, Y., Ljungqvist, A., Lu, Y., 2007. Whom you know matters: Venture capital networks and investment performance. The Journal of Finance 62, 251-301.

Hwang, B., Kim, S., 2009. It pays to have friends. Journal of Financial Economics 93, 138-158.

Kraft, A., Leone, A., Wasley, C., 2006. An analysis of the theories and explanations offered for the mispricing of accruals and accrual components. Journal of Accounting Research 44, 297-339.

Kuhnen, C., 2008. Business networks, corporate governance and contracting in the mutual fund industry. Journal of Finance (forthcoming).

Linck, J., Netter, J., Yang, T., 2008. The determinants of board structure. Journal of Financial Economics 87, 308-328.

Lyon, J., Barber, B., Tsai, C., 1999. Improved methods for tests of long-run abnormal stock returns. The Journal of Finance 54, 165-201.

Mitchell, M., Mulherin, J., 1996. The impact of industry shocks on takeover and restructuring activity. Journal of Financial Economics 41, 193-229.

Mitchell, M., Stafford, E., 2000. Managerial decisions and long-term stock price performance. Journal of Business 73, 287-329.

Mizruchi, M., 1996. What do interlocks do? An analysis, critique, and assessment of research on interlocking directorates. Annual Review of Sociology 22, 271-298.

Moeller, S., Schlingemann, F., Stulz, R., 2004. Firm size and the gains from acquisitions. Journal of Financial Economics 73, 201-228.

Myers, S., Majluf, N., 1984. Corporate financing and investment decisions when firms have information that investors do not have. Journal of Financial Economics 13, 187-221.

Opler, T., Pinkowitz, L., Stulz, R., Williamson, R., 1999. The determinants and implications of corporate cash holdings. Journal of Financial Economics 52, 3-46.

Palmer, D., Barber, B., Zhou, X., 1993. Late adoption of the multidivisional form by larger U.S. corporations: Institutional, political and economic accounts. Administrative Science Quarterly 38, 100-131.

Plumper, T., Troeger, V., 2007. Efficient estimation of time-invariant and rarely changing variables in finite sample panel analyses with unit fixed effects. Political Analysis 15, 124-139.

Schwert, G., 1996. Markup pricing in mergers and acquisitions. Journal of Financial Economics 41, 153-192.

Shleifer, A., Vishny, R., 2003. Stock market driven acquisitions. Journal of Financial Economics 70, 295-311.

Sparrow, R., Liden, R., Wayne, S., Kraimer, M., 2001. Social networks and the performance of individuals and groups. The Academy of Management Journal 44, 316-325.

Stock, J., Wright, J., Yogo, M., 2002. A survey of weak instruments and weak identification in generalized method of moments. Journal of Business and Economic Statistics 20, 518-529.

Tsai, W., 2001. Knowledge transfer in intraorganizational networks: Effects of network position and absorptive capacity on business unit innovation and performance. The Academy of Management Journal 44, 996-1004.

Wasserman, S., Faust, K., 1994. Social Network Analysis: Methods and Applications. Cambridge: Cambridge University Press.

Woolridge, J., 2002. Econometric analysis of cross section and panel data. The MIT Press.

Yermack, D., 1996. Higher market valuation of companies with a small board of directors. Journal of Financial Economics 40, 185-211.

Appendix – How to calculate centrality measures

Each year we construct a board network as shown in Figure 1. From this network, a board overlap matrix (B) is created. Matrix B is an M-by-M symmetric matrix where M is the number of all firms in the network for that year. The elements in this matrix can have a value of zero or one. A value of one for matrix element b_{ij} indicates the presence of a tie between firms *i* and *j*. This matrix is then used to calculate the network distance between firms and to construct the eigenvector, reach, betweeness, and degree centrality measures as described below. We calculate the centrality measures using the UCINET software.

Eigenvector centrality is constructed with the idea that the centrality of an actor is proportional to the number of its contacts and the centrality of those contacts (Bonacich 1972). The eigenvector centrality (E_i) for firm *i* is calculated through the following equations:

$$E_i = \frac{1}{\lambda}\sum_j b_{ij}E_j \qquad (A1)$$

In this equation λ is a constant. The centrality scores that satisfy the above relation form a system of simultaneous linear equations. The solution to which can be obtained by solving the standard eigenvalue-eigenvector problem ($\boldsymbol{BE} = \boldsymbol{\lambda E}$). Here *E* is the vector of centralities and λ is the largest eigen value of *B*. To be comparable across yearly networks, the eigenvector centrality is normalized by dividing it by the maximum difference possible expressed as a percentage.

Reach centrality is a measure of how close a board is to all other boards in the network. Firms with higher values of reach centrality can reach the greatest number of other firms through the fewest number of intermediaries. The reach centrality of firm *i* is calculated

as follows:

$$Reach\ Centrality_i = 1 + \sum_{j=1}^{M} \frac{1}{g_{ij}} \quad for\ \ i \neq j \qquad (A2)$$

where g_{ij} is the number of intermediate boards between boards *i* and *j* following the shortest connected path (i.e. the number of "geodesics" between *i* and *j*). The reach centrality as calculated above is normalized by dividing it by the maximum reach centrality observed in the network each year.

<u>*Betweeness centrality*</u> measures the extent to which a firm lies on the shortest path between other firms. The betweeness centrality of firm *i* is estimated as

$$BC(i) = \sum_{j<k} g_{jk}(i) / g_{jk}. \qquad (A3)$$

Here, g_{jk} is the number of geodesics between *j* and *k* and $g_{jk}(i)$ is the number of geodesics between firms *j* and *k* on which firm *i* falls. The betweeness centrality calculated above is normalized by dividing it by the maximum possible number of geodesics.

<u>*Degree centrality*</u> measures the number of boards connected to each board. Hence the degree centrality for firm *i* is just the number of boards directly interlocked with firm *i*. This measure is normalized by dividing by the maximum degree each year.

Figure1: Mapping board networks

Figure 1a shows an affiliation network based on four firms (spheres) and 12 directors (diamonds). Lines between firms and directors indicate which board(s) the directors sit on. Most of the directors (e.g., Stan) sit on the board of only one firm, whereas a few (Rob, Julie, Erica, and Jacob) sit on multiple boards. A director or manager who is affiliated with multiple firms creates interlocks between these firms. Figure 1b shows the inter-firm network created by these board interlocks. In this paper, we refer to these inter-firm networks as board networks. In this example, Firms 2 and 3 are connected because Erica sits on both boards. Given that information can flow in either direction between boards, the inter-firm connections are shown with bi-directional arrows. Note that although Firms 1 and 3 are not directly connected with each other, they can still receive information about each other through intermediaries (e.g., Firm 2). In our network we consider two firms to be connected if a manager or director of one firm sits on the board of another firm.

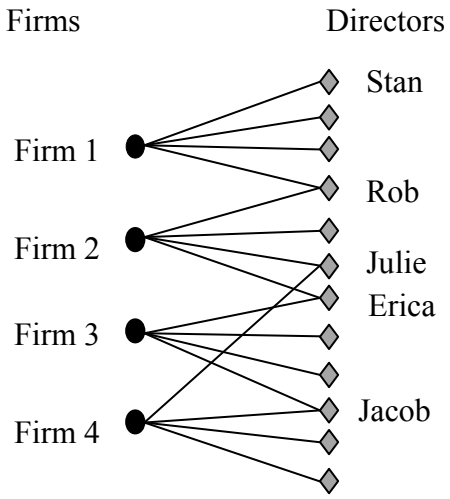


Figure 1a: Affiliation Network

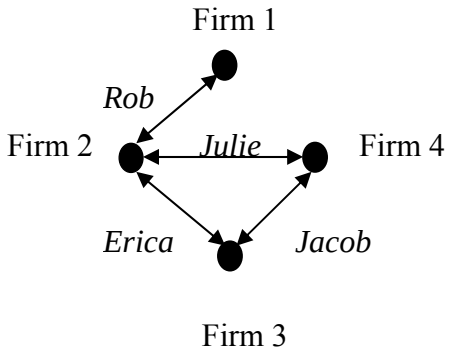
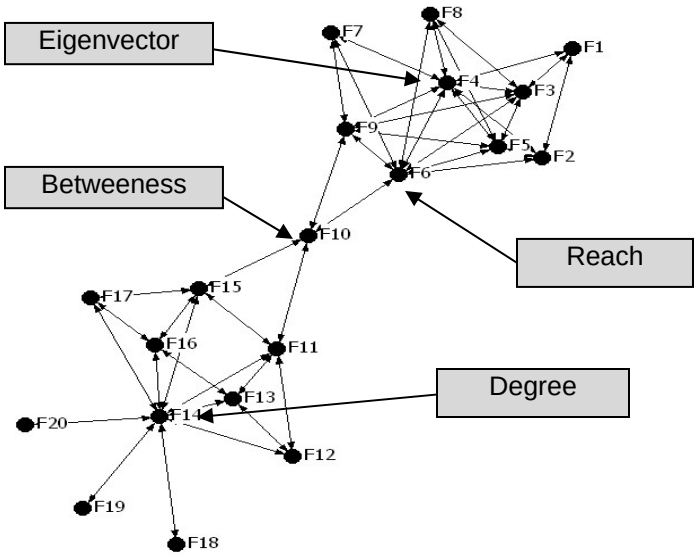


Figure 1b: Board Network

Figure 2: Centrality measures and board networks

In these figures, each sphere represents a board and each line represents a director, or a manager, at a given firm that also sits on the board of another firm. In Panel A the network positions which correspond to the maximum value of each of the four centralities used in this paper are identified. In Panel B an image of the board network immediately around John Wiley and Sons, Inc. (JWB) is shown. This image represents a small piece of the overall network where the chosen firms are all within a network distance of 2 board lengths from JWB. To provide a sense of the centralities of each these boards based on their connections within the greater network, the spheres are scaled by their reach centrality with larger spheres corresponding with more central firms.

Panel A:



Panel B:

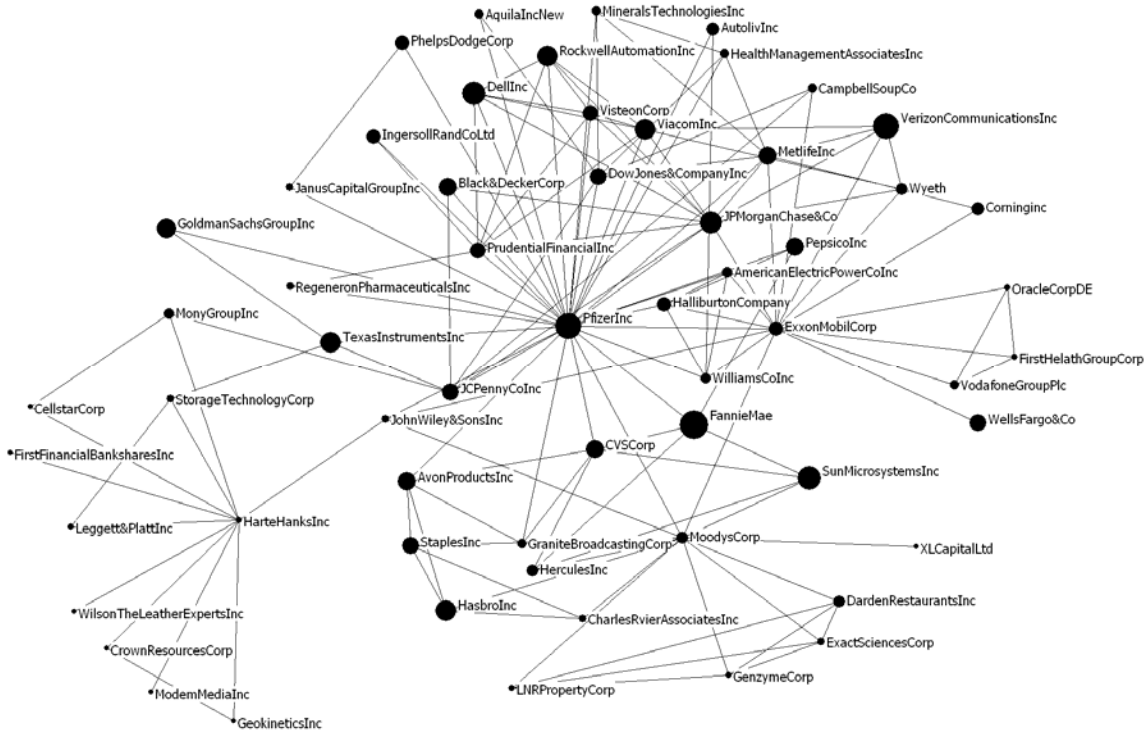


Figure 3: Median centralities by industry and year for acquiring (acquired) and non-acquiring (non-acquired) firms

Median normalized centralities are shown for each industry and for each year in Sample 2. Sample 2 contains more than 50,000 firm-year observations from 1991-2005 based on the firms in the CRSP/Compustat universe for which we also have director information. The centralities are measured in the year prior to the observed acquisition for both acquiring (acquired) and non-acquiring (non-acquired) firms. On the left, the median annual reach centrality for acquiring and non-acquiring firms is shown by industry. On the right the median annual reach centrality is shown each year from 1991-2005 for acquiring/non-acquiring (top) firms and acquired/non-acquired (bottom) firms.

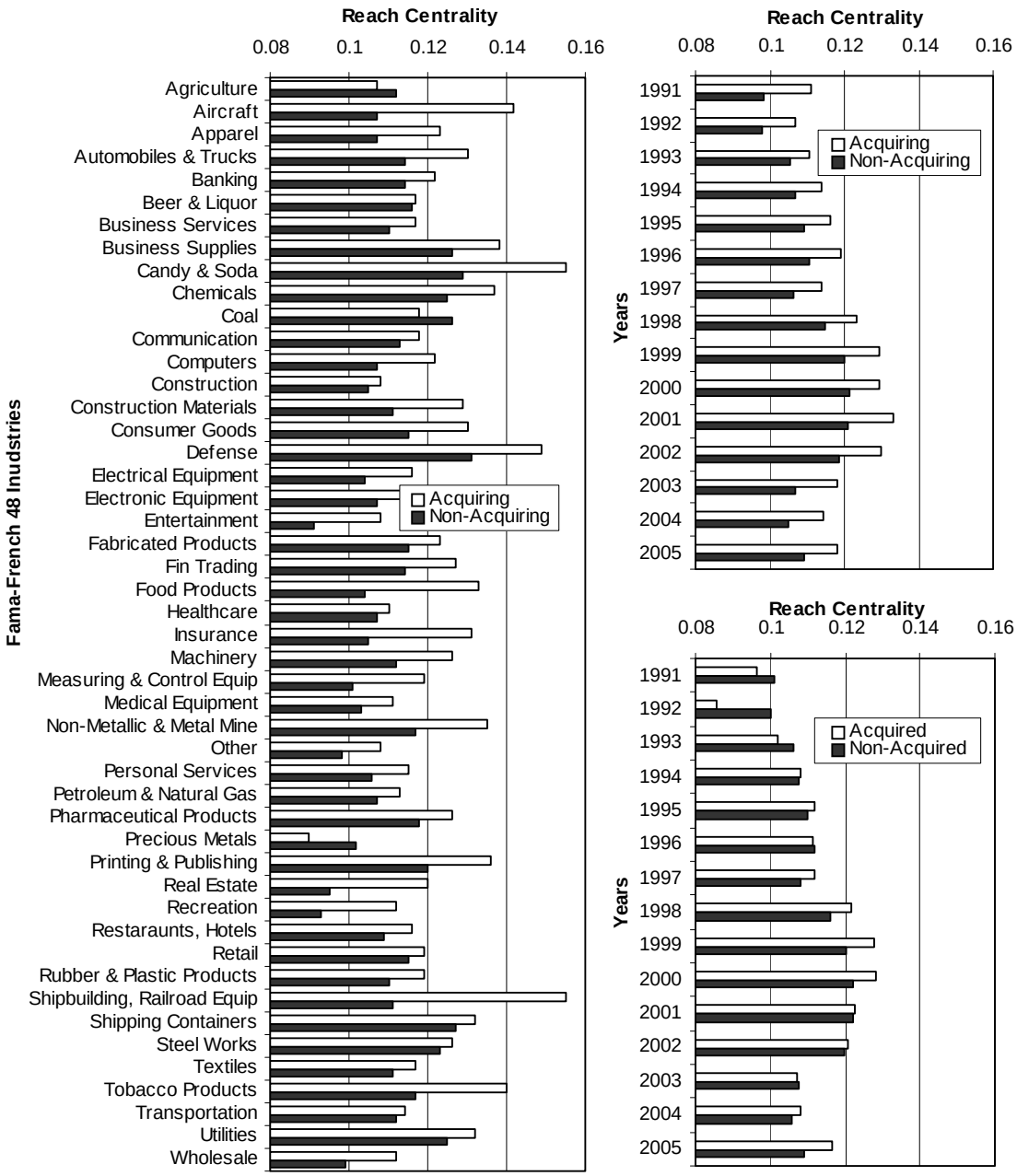
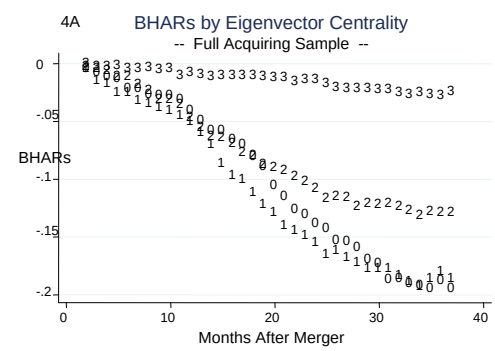
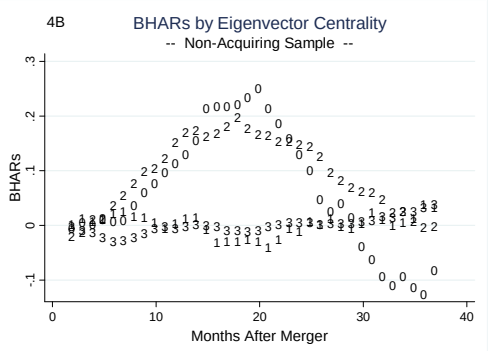


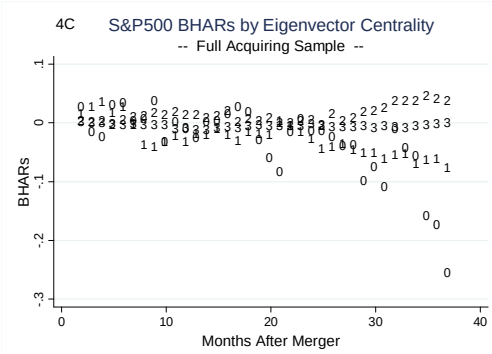
Figure 4: Three-year buy-and-hold abnormal returns after acquisitions

All firms in the CRSP-Compustat-Compact Disclosure universe are sorted each year into High (3), Medium (2), Low (1), and Isolate (0) centrality groups as described in Section 4.2.1 for years 1991-2005. Using these centrality group assignments, the acquiring firms' post acquisition three-year buy-and-hold abnormal returns are then plotted using subsets of Sample 1 as noted below. In all plots, except 4F, the acquiring firms are sorted into their centrality groups based on their network centralities from the year before the merger announcement. In 4F the sorting is done in the same year as the announcement. The BHARs are calculated using Lyon, Barber, and Tsai's (1999) methodology.

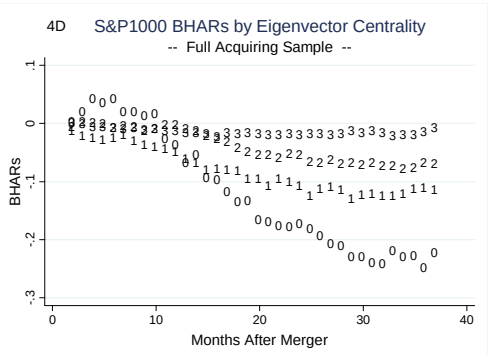


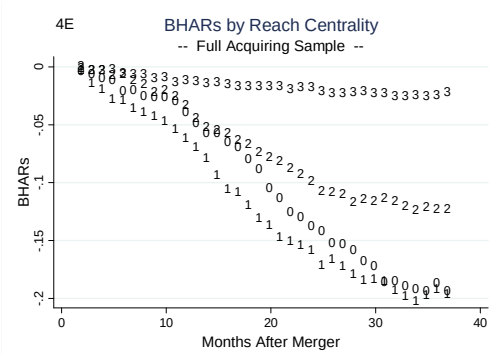
Abnormal returns for acquiring firms (left) versus non-acquiring firms (right) of similar size from the same industries and time periods



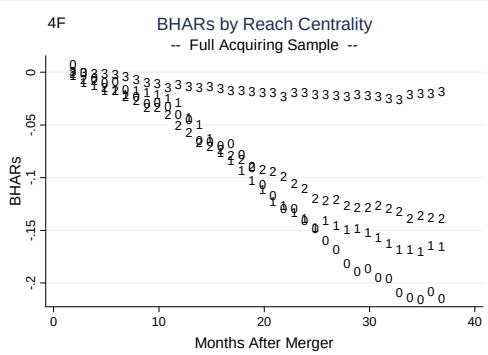


Abnormal returns for S&P500[14] acquiring firms (left) versus S&P1000 (S&P1500 excluding S&P500) firms (right)





Abnormal returns for firms with centrality groups identified in the year prior to acquisition (left) versus firms with groups identified in same year as acquisition (right)



[14] In an earlier version of this paper the S&P500 firms were identified using the original Compustat zlist variable. As noted in Kraft, Leone, and Wasley (2006) using this variable to identify historical S&P500 firms introduces a predictable bias in the BHARs. In this version of the paper the S&P500 firms are identified using Compustat's Index Constituents list with historical dates of when firms were added and left the S&P500.

Table 1: Correlation and descriptive statistics for acquisition sample

The correlations and descriptive statistics shown below are for acquiring firms in Sample 1 based on 4,339 acquisition deals from 1991-2005. All variables are measured from the year prior to the merger announcement. The correlations are calculated using a pairwise approach. *Eigenvector* is the standardized log of the firm's normalized eigenvector centrality. *Betweeness* is the standardized log of the firm's normalized betweeness centrality. *Reach* is the standardized firm's normalized reach centrality. *Degree* is the standardized log of the firm's normalized degree centrality. *Nearness* is the inverse of the number of interlocks between the bidder and target firms. *%Insider* is the percent of the board classified as insiders. *Board Size* is the number of directors on the board. *Relative Size* is the SDC transaction value divided by the bidding firm's market value of equity from the year before the acquisition. *ROA* is the firm's EBIT divided by the firm's total assets. *Firm size* is the log of the firm's total assets. *Excess Cash* is the residual from a cash model. *Leverage* is the firm's long-term debt divided by its assets. *M/B* is the log of the firm's market value of assets divided by its total book assets. *Tval* is SDC's transaction value. *Firm Size* and *M/B* are not logged in the lower portion of the table.

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Eigenvector	1												
2	Betweeness	0.63	1											
3	Reach	0.68	0.73	1										
4	Degree	0.67	0.82	0.68	1									
5	Nearness	0.21	0.24	0.26	0.30	1								
6	%Insider	-0.37	-0.41	-0.39	-0.42	-0.16	1							
7	Board Size	0.42	0.42	0.41	0.54	0.25	-0.34	1						
8	Relative Size	-0.20	-0.18	-0.20	-0.23	0.09	0.08	-0.16	1					
9	ROA	0.09	0.06	0.07	0.07	0.03	-0.04	0.13	-0.17	1				
10	Firm Size	0.53	0.49	0.54	0.62	0.32	-0.34	0.60	-0.38	0.29	1			
11	Excess Cash	0.04	0.08	0.06	0.04	-0.03	0.00	-0.13	-0.14	-0.10	-0.09	1		
12	Leverage	0.07	0.04	0.06	0.09	0.05	-0.06	0.17	0.10	0.05	0.24	-0.31	1	
13	M/B	0.00	0.04	0.07	0.03	-0.02	0.04	-0.09	-0.36	0.01	-0.06	0.31	-0.23	1

	SD	25th Percentile	Mean	Median	75th Percentile
%Insiders	0.16	0.20	0.31	0.29	0.40
Board Size	2.88	6	8.21	8	10.00
Tval($millions)	3307	13	476	45	176
ROA	0.19	0.04	0.06	0.09	0.14
Firm Size ($millions)	8776	78	2474	297	1242
Excess Cash	1.71	-0.88	0.23	0.36	1.46
Leverage	0.18	0.01	0.18	0.13	0.29
M/B	3.87	1.31	2.65	1.80	2.83

Table 2: Yearly sample distribution

Sample 1 is restricted to include completed deals with public, private, or subsidiary targets having SDC transaction values greater than $1 million. Observations in this sample also require CRSP return information at the time of announcement, Compustat information in the fiscal year prior to the announcement, Compact Disclosure bidder board information in the calendar year prior to the announcement date, as well as some deal-level information used to account for the relative size of the deal, the public status of the target, and the method of payment used. Sample 2 includes all firms—acquirers and non-acquirers—each year that are in both CRSP and Compustat for which we also have board and centrality information. SDC information about how many acquisitions each firm did each year is added to Sample 2 as well as information about whether the firm was acquired.

Year	Number of deals in Sample 1	Number of deals in Sample 2	Number of firms in Sample 2
1991	172	689	3,062
1992	179	831	3,042
1993	232	1,017	3,185
1994	304	1,262	3,508
1995	343	1,465	3,774
1996	375	1,840	3,930
1997	355	2,200	4,063
1998	371	2,222	3,962
1999	402	2,233	4,417
2000	329	1,656	4,294
2001	229	1,118	4,020
2002	253	1,055	3,700
2003	251	1,037	3,522
2004	298	1,250	3,369
2005	246	1,335	3,354

Table 3: Sample and network statistics by industry

Column 1 lists the Fama-French 48 industries. The next four columns report the number of mergers in Sample 1, the number of firm-year observations in Sample 2, the percent of those firm-year observations associated with isolate firms (i.e., firms without interlocks), and the number of mergers in Sample 2 by industry. The last two columns show the median values for the normalized eigenvector and reach centrality measures. These centralities are based on all the firms in Sample 2 and not just the subset of merging firms.

Industry	Number of Mergers in Sample 1	Number of firm-years in Sample 2	% of Isolate firm-years in Sample 2	Number of Mergers in Sample 2	Eigenvector Centrality	Reach Centrality
Agriculture	14	154	13.0%	36	0.004	0.120
Aircraft	41	251	18.7%	128	0.011	0.129
Apparel	77	777	12.9%	181	0.006	0.123
Automobiles & Trucks	93	766	15.8%	274	0.011	0.127
Banking	22	143	5.6%	53	0.010	0.127
Beer & Liquor	7	197	17.8%	32	0.004	0.125
Business Services	1,190	7,192	12.0%	3,672	0.007	0.126
Business Supplies	90	710	9.7%	214	0.045	0.138
Candy & Soda	16	154	10.4%	41	0.169	0.148
Chemicals	109	1,062	11.2%	471	0.043	0.136
Coal	10	102	18.6%	25	0.038	0.132
Communication	296	1,520	9.1%	1,023	0.011	0.129
Computers	270	2,077	9.9%	823	0.007	0.123
Construction	64	402	14.2%	170	0.003	0.118
Construction Materials	157	1,295	18.5%	461	0.007	0.126
Consumer Goods	104	1,134	10.4%	325	0.014	0.128
Defense	15	119	9.2%	52	0.150	0.143
Electrical Equipment	204	1,969	12.9%	489	0.003	0.118
Electronic Equipment	392	3,134	12.0%	1,068	0.006	0.122
Entertainment	107	775	21.5%	256	0.001	0.115
Fabricated Products	39	215	10.7%	83	0.012	0.125
Fin Trading	99	738	14.5%	381	0.013	0.128
Food Products	79	921	16.8%	282	0.006	0.121
Healthcare	320	1492	14.7%	1,321	0.003	0.120
Insurance	68	340	15.3%	428	0.024	0.128
Machinery	270	2,141	9.8%	728	0.015	0.129
Measuring & Control Equipment	144	1,289	17.1%	337	0.006	0.117
Medical Equipment	247	2,033	13.1%	625	0.003	0.118
Non-Metallic & Metal Mining	25	243	7.4%	62	0.031	0.132
Other	118	751	15.3%	543	0.001	0.112
Personal Services	106	678	17.7%	319	0.003	0.122
Petroleum & Natural Gas	456	2,506	17.8%	998	0.004	0.118
Pharmaceutical Products	255	2,687	9.8%	524	0.016	0.133
Precious Metals	15	214	17.8%	33	0.003	0.112
Printing & Publishing	105	673	12.2%	404	0.037	0.138
Real Estate	28	212	25.5%	72	0.001	0.116
Recreation	50	660	28.6%	129	0.000	0.108
Restaurants, Hotels, Motels	179	1,527	13.2%	364	0.005	0.120
Retail	272	3,202	11.5%	869	0.009	0.126
Rubber & Plastic Products	59	603	15.4%	185	0.007	0.124
Shipbuilding, Railroad Equip	15	76	9.2%	33	0.026	0.137
Shipping Containers	31	230	6.5%	95	0.082	0.139
Steel Works	111	897	8.1%	263	0.022	0.134
Textiles	46	384	6.8%	78	0.009	0.122
Tobacco Products	3	51	5.9%	4	0.025	0.144
Transportation	125	1,411	16.1%	396	0.006	0.124
Utilities	165	1,983	7.2%	489	0.053	0.134
Wholesale	367	3,112	18.7%	1,371	0.002	0.115

Table 4: Three-day cumulative abnormal returns around merger announcements

The dependent variable in all models is the 3-day cumulative abnormal return around the merger announcement dates. Eigenvector and reach centrality are standardized such that a unit increase corresponds with a one standard deviation increase in the underlying variable. Results using eigenvector and reach centrality are shown on the left and right side of the tables, respectively. All models use the same control variables and are estimated using both OLS and median regression approaches. For the OLS models, the non-indicator variables are winsorized at the 5th and 95th percentiles and only the main centrality coefficients are reported (top two rows). The median regression control variables are tabulated below and are based on non-winsorized data. The sample years are indicated in the column header. For example, models 4-6 are estimated using acquisitions from 1991-1997, 1995-2001, and 1998-2005, respectively. The centrality measure is from the year prior to the merger announcement. *Nearness* is the inverse of the number of intermediate boards between the bidder and target. *Interlock* is an indicator that the bidder and target firms are interlocked. *S&P500*, *Isolate*, *Busy Board*, and *CEO Chair* are bidder indicator variables for being part of the S&P500, having no interlocks, having a busy board, and having a CEO that is also the chairman of the board. *Private Target* and *Public Target* are indicator variables for the public status of the target using SDC's method of categorizing targets into public, private, or subsidiary firms. *%Insider*, *Board Size*, *Relative Size*, *ROA*, *Firm Size*, *Excess Cash*, *Leverage* and *M/B* are described in Section 3.2 and represent measures of the percentage of the board that are insiders, the number of directors on the board, the relative size of the target to the bidder, the bidder's past ROA, the bidder's size, a measure of the bidder's excess cash, the bidder's leverage, and the bidder's M/B. The *Cash Deal* and *Stock Deal* variables are indicators for the use of 100% cash or stock as the method of payment. The variables marked with the vertical line in the left margin are used as untabulated controls in other tables and are subsequently referred to as Table 4 controls. Standard errors are shown in brackets with significance at the 1%, 5%, and 10% levels marked with ***, **, and *, respectively.

	Bidder	**Target**	**Bidder Target**	**Bidder**	**Bidder**	**Bidder**	**Bidder**	**Target**	**Bidder Target**
Years:	**91-05**	**91-05**	**91-05**	**91-97**	**95-01**	**98-05**	**91-05**	**91-05**	**91-05**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**
Eigenvector OLS Results:							Reach OLS Results:		
Bidder Centrality	0.005		0.005	0.005	0.009	0.003	0.007**		0.008
	[0.003]		[0.006]	[0.005]	[0.006]	[0.005]	[0.004]		[0.009]
Target Centrality		-0.003	-0.002					-0.002	-0.002
		[0.005]	[0.005]					[0.005]	[0.005]
Eigenvector Median Regression Results:							Reach Median Regression Results:		
Bidder Centrality	0.003		0.007	0.002	0.005*	0.002	0.004		0.011
	[0.002]		[0.006]	[0.002]	[0.002]	[0.004]	[0.003]		[0.009]
Target Centrality		-0.000	0.000					-0.001	0.001
		[0.004]	[0.004]					[0.004]	[0.004]
S&P500*Centrality	-0.002		0.003	-0.003	-0.004	0.002	-0.003		-0.003
	[0.004]		[0.006]	[0.003]	[0.005]	[0.009]	[0.007]		[0.010]
Nearness	-0.014	-0.000	-0.010	-0.019*	-0.022*	-0.024	-0.015	0.004	-0.010
	[0.012]	[0.029]	[0.030]	[0.010]	[0.012]	[0.019]	[0.013]	[0.031]	[0.033]
Isolate	0.001	0.030**	0.035**	0.009**	-0.001	-0.012	0.007	0.029**	0.056***
	[0.005]	[0.012]	[0.014]	[0.004]	[0.005]	[0.010]	[0.008]	[0.012]	[0.021]
S&P500	0.001	0.003	0.002	-0.000	0.001	0.001	0.001	0.004	0.003
	[0.005]	[0.006]	[0.008]	[0.004]	[0.005]	[0.010]	[0.007]	[0.006]	[0.010]

Interlock	-0.010	-0.003	0.007	0.013	-0.006	-0.019	-0.008	-0.005	0.005
	[0.014]	[0.027]	[0.027]	[0.011]	[0.014]	[0.023]	[0.015]	[0.027]	[0.029]
Busy Board	-0.001	-0.018*	-0.016	-0.003	0.004	0.000	-0.000	-0.017	-0.015
	[0.005]	[0.011]	[0.011]	[0.004]	[0.005]	[0.008]	[0.005]	[0.011]	[0.011]
CEO Chair	0.001	-0.001	-0.002	0.001	-0.005*	-0.001	0.001	-0.001	-0.002
	[0.002]	[0.005]	[0.005]	[0.002]	[0.002]	[0.004]	[0.002]	[0.005]	[0.005]
%Insiders	0.003	0.016	0.017	-0.003	-0.013	0.002	-0.000	0.015	0.016
	[0.011]	[0.022]	[0.022]	[0.009]	[0.012]	[0.018]	[0.012]	[0.022]	[0.021]
Board Size	0.000	-0.000	-0.001	-0.000	0.001	0.001*	0.000	-0.000	-0.001
	[0.001]	[0.001]	[0.001]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Private Target	-0.007**	-0.018	-0.017	-0.005**	-0.009***	-0.011**	-0.007**	-0.019	0.000
	[0.003]	[0.046]	[0.043]	[0.002]	[0.003]	[0.005]	[0.003]	[0.045]	[0.044]
Public Target	-0.019***	-0.011*	-0.013**	-0.019***	-0.019***	-0.021***	-0.019***	-0.011*	-0.012**
	[0.004]	[0.006]	[0.006]	[0.003]	[0.004]	[0.006]	[0.004]	[0.006]	[0.006]
Diversifying	-0.002	0.005	0.004	-0.003*	-0.002	0.000	-0.001	0.004	0.004
	[0.002]	[0.005]	[0.005]	[0.002]	[0.002]	[0.004]	[0.002]	[0.005]	[0.005]
Cash Deal	0.005*	0.011*	0.008	0.005**	0.005*	0.004	0.005*	0.011**	0.009
	[0.003]	[0.006]	[0.006]	[0.002]	[0.003]	[0.004]	[0.003]	[0.006]	[0.006]
Stock Deal	-0.003	-0.012*	-0.013*	0.001	-0.002	-0.005	-0.003	-0.012*	-0.013*
	[0.003]	[0.007]	[0.007]	[0.002]	[0.003]	[0.005]	[0.003]	[0.007]	[0.007]
Relative Size	0.003***	-0.005**	-0.004**	0.005***	0.002*	0.001	0.003***	-0.005**	-0.005**
	[0.001]	[0.002]	[0.002]	[0.001]	[0.001]	[0.002]	[0.001]	[0.002]	[0.002]
ROA	0.001	0.002	0.013	0.012**	-0.002	-0.012	0.002	0.003	0.012
	[0.006]	[0.029]	[0.029]	[0.005]	[0.006]	[0.009]	[0.006]	[0.028]	[0.028]
Firm Size	-0.005**	-0.009*	-0.010*	-0.000	-0.008***	-0.008**	-0.006**	-0.008	-0.011**
	[0.002]	[0.005]	[0.005]	[0.002]	[0.002]	[0.004]	[0.002]	[0.005]	[0.005]
Excess Cash	-0.001	0.002	0.001	-0.001**	0.000	0.000	-0.001	0.002	0.001
	[0.001]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]
Leverage	0.001	0.032**	0.030*	0.004	0.011	0.009	0.001	0.032**	0.033**
	[0.007]	[0.015]	[0.016]	[0.006]	[0.007]	[0.011]	[0.007]	[0.015]	[0.015]
M/B	-0.003	-0.006	-0.008	0.005**	-0.001	-0.005	-0.003	-0.006	-0.008
	[0.002]	[0.006]	[0.006]	[0.002]	[0.002]	[0.003]	[0.002]	[0.006]	[0.006]
Constant	0.022*	-0.001	0.008	0.024***	0.024*	0.010	0.012	-0.016	0.000
	[0.013]	[0.025]	[0.025]	[0.009]	[0.012]	[0.021]	[0.014]	[0.027]	[0.029]
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4339	1322	1322	1960	2404	2379	4339	1322	1322
R-squared	0.061	0.165	0.166	0.070	0.065	0.078	0.061	0.165	0.166
OLS Adj R2	0.043	0.114	0.113	0.034	0.035	0.048	0.043	0.114	0.113
Median Pseudo R2	0.025	0.080	0.081	0.033	0.027	0.035	0.025	0.080	0.081

Table 5: Buy-and-hold returns and long-term post-merger stock performance

The dependent variable in all specifications is the post-acquisition three-year buy-and-hold cumulative abnormal return. The abnormal return is calculated relative to a benchmark return from a portfolio of firms matched with the bidder on size, B/M, and recent past stock performance as explained in Lyon, Barber, and Tsai (1999). The same control variables used in Table 4 are used here but are not tabulated. The eigenvector and reach centrality variables are standardized such that a one unit increase corresponds with a one standard deviation increase in the underlying measure. All models are estimated using OLS and median regression approaches. For the OLS models the non-indicator variables are winsorized at the 5th and 95th percentiles and only the main network variables are tabulated in the top two rows of each panel. *Nearness* is the inverse of the number of intermediate boards between the bidder and target. *S&P500* and *Isolate* are bidder indicator variables for being part of the S&P500 and having no interlocks. Standard errors are shown in brackets with significance at the 1%, 5%, and 10% levels marked with ***, **, and *, respectively.

	Bidder	Target	Bidder Target	Bidder	Bidder	Bidder	Bidder	Target	Bidder Target
Years:	**91-05**	**91-05**	**91-05**	**91-97**	**95-01**	**98-05**	**91-05**	**91-05**	**91-05**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**
Eigenvector OLS Results:							Reach OLS Results:		
Bidder Centrality	0.056*		0.115*	0.042	0.035	0.104**	0.081*		0.195**
	[0.029]		[0.070]	[0.044]	[0.047]	[0.043]	[0.041]		[0.093]
Target Centrality		0.129**	0.140**					-0.010	0.008
		[0.064]	[0.066]					[0.083]	[0.079]
Eigenvector Median Regression Results:							Reach Median Regression Results:		
Bidder Centrality	0.040**		0.051	0.032	0.021	0.052*	0.029		0.070
	[0.019]		[0.050]	[0.020]	[0.024]	[0.027]	[0.026]		[0.076]
Target Centrality		0.030	0.030					0.021	0.022
		[0.034]	[0.033]					[0.032]	[0.031]
S&P500*Centrality	-0.005		0.003	0.028	0.028	-0.075	-0.072		-0.102
	[0.037]		[0.055]	[0.034]	[0.045]	[0.065]	[0.059]		[0.105]
Nearness	0.011	-0.076	-0.152	0.076	-0.229*	-0.030	-0.018	-0.029	-0.157
	[0.101]	[0.262]	[0.261]	[0.114]	[0.119]	[0.141]	[0.105]	[0.272]	[0.275]
Isolate	0.079*	-0.105	-0.023	0.031	0.105**	0.139*	0.086	-0.088	0.038
	[0.045]	[0.135]	[0.151]	[0.044]	[0.051]	[0.072]	[0.067]	[0.134]	[0.205]
S&P500	-0.029	-0.031	-0.030	-0.056	0.002	0.043	0.021	-0.021	0.031
	[0.046]	[0.066]	[0.072]	[0.045]	[0.047]	[0.075]	[0.056]	[0.065]	[0.102]
Table 4 Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4195	1293	1293	1916	2310	2279	4195	1293	1293
OLS Adj R2	0.016	-0.008	-0.007	0.008	0.009	0.033	0.016	-0.011	-0.010
Median Pseudo R2	0.077	0.082	0.082	0.076	0.070	0.113	0.077	0.081	0.082

Table 6: Calendar-time portfolios and long-term post-merger stock performance

Monthly alphas from three- and four-factor models (Fama-French and momentum) are shown below. The dependent variable for all columns is the difference between the monthly mean return from a High and a Low centrality portfolio of recently acquiring firms. High and Low assignments are based on the top and bottom three centrality deciles of all CRSP/Compustat firms for which we have director information as described in Section 4.2.1. All centrality measures are from the year prior to the acquisition. Equal weighted and value weighted portfolio alphas are shown below using eigenvector and reach centrality deciles. Firms enter the High and Low centrality portfolios the month following the completion of the merger and remain in their respective portfolios for 1-3 years as indicated below. The results shown in Panel A show how the estimated alphas change depending on whether the firms are retained in their centrality portfolios for 1, 1.5, 2, or 3 years after the acquisition. Panel B results are from specifications where the firms are retained in their respective portfolios for 1 year after the acquisition but are based on sub-periods of the overall sample. All acquisitions in the sample have a relative target-to-bidder size of at least 1%. The alphas in both Panel A and B are shown using (a) all acquisitions in the sample, (b) acquisitions with relative size < 75%, (c) acquisitions with relative size < 20%, and (d) acquisitions by firms not in the S&P500. Significance at the 1%, 5%, and 10% levels is marked with ***, **, and *, respectively.

	Reach Equal Weighted		Reach Value Weighted		Eigenvector Equal Weighted		Eigenvector Value Weighted	
Additional sample filters	**3-Factor Model Alpha**	**4-Factor Model Alpha**	**3-Factor Model Alpha**	**4-Factor Model Alpha**	**3-Factor Model Alpha**	**4-Factor Model Alpha**	**3-Factor Model Alpha**	**4-Factor Model Alpha**
Panel A: Vary number of years firms stay in portfolio. All results based on deals from 1991-2005.								
Firms remain in portfolio for 1 year after acquisition								
(a) All deals	-0.0003	-0.0015	0.0073**	0.0064*	0.0005	-0.0013	0.0072**	0.0052
(b) Relative Size< 75%	0.0005	-0.0002	0.0077**	0.0068*	0.0013	0.0000	0.0076**	0.0055
(c) Relative Size< 20%	0.0038	0.0025	0.0095**	0.0092**	0.0042	0.0026	0.0093**	0.0084**
(d) Non-S&P500 deals	0.0005	-0.0002	0.0077**	0.0068*	0.0013	0.0000	0.0076**	0.0055
Firms remain in portfolio for 1.5 years after acquisition								
(a) All deals	0.0017	0.0006	0.0055*	0.0051	0.0021	0.0004	0.0049*	0.0029
(b) Relative Size< 75%	0.0023	0.0016	0.0057*	0.0054	0.0028	0.0013	0.0053*	0.0033
(c) Relative Size< 20%	0.0056**	0.0043	0.0064*	0.0059	0.0054*	0.0036	0.0064*	0.0042
(d) Non-S&P500 deals	0.0023	0.0016	0.0057*	0.0054	0.0028	0.0013	0.0053*	0.0033
Firms remain in portfolio for 2 years after acquisition								
(a) All deals	0.0017	0.0007	0.0046*	0.0043*	0.0023	0.0006	0.0037	0.0020
(b) Relative Size< 75%	0.0020	0.0015	0.0047*	0.0043	0.0027	0.0014	0.0043*	0.0024
(c) Relative Size< 20%	0.0051**	0.0039	0.0059*	0.0055*	0.0052**	0.0032	0.0054*	0.0035
(d) Non-S&P500 deals	0.0020	0.0015	0.0047*	0.0043	0.0027	0.0014	0.0043*	0.0024
Firms remain in portfolio for 3 years after acquisition								
(a) All deals	0.0012	-0.0001	0.0040*	0.0029	0.0017	0.0000	0.0025	0.0010
(b) Relative Size< 75%	0.0020	0.0011	0.0045*	0.0031	0.0026	0.0011	0.0034	0.0015
(c) Relative Size< 20%	0.0048**	0.0031	0.0055*	0.0042	0.0047*	0.0026	0.0041	0.0024
(d) Non-S&P500 deals	0.0020	0.0011	0.0045*	0.0031	0.0026	0.0011	0.0034	0.0015
Panel B: Vary sample period. All results based on firms staying in portfolio for 1 year after acquisition.								
Results based on deals from 1991-1997								
(a) All deals	0.0001	-0.0002	0.0027	0.0044	0.0014	0.0007	0.0001	0.0019
(b) Relative Size< 75%	0.0031	0.0039	0.0032	0.0048	0.0041	0.0046	0.0006	0.0024
(c) Relative Size< 20%	0.0085**	0.0089**	0.0057	0.0072	0.0084**	0.0086**	0.0024	0.0042
(d) Non-S&P500 deals	0.0031	0.0039	0.0032	0.0048	0.0041	0.0046	0.0006	0.0024
Results based on deals from 1995-2001								
(a) All deals	-0.0026	-0.0042	0.0121**	0.0109*	-0.0009	-0.0035	0.0118**	0.0086
(b) Relative Size< 75%	-0.0029	-0.0040	0.0127**	0.0113*	-0.0018	-0.0039	0.0121**	0.0087
(c) Relative Size< 20%	-0.0009	-0.0028	0.0133**	0.0135**	0.0002	-0.0022	0.0136**	0.0128**
(d) Non-S&P500 deals	-0.0029	-0.0040	0.0127**	0.0113*	-0.0018	-0.0039	0.0121**	0.0087
Results based on deals from 1998-2005								
(a) All deals	-0.0010	-0.0021	0.0095*	0.0086	-0.0004	-0.0021	0.0111**	0.0089*
(b) Relative Size< 75%	-0.0018	-0.0027	0.0096*	0.0086	-0.0011	-0.0026	0.0110**	0.0087*
(c) Relative Size< 20%	-0.0003	-0.0018	0.0113*	0.0112*	0.0003	-0.0013	0.0130**	0.0121**
(d) Non-S&P500 deals	-0.0018	-0.0027	0.0096*	0.0086	-0.0011	-0.0026	0.0110**	0.0087*

Table 7: Change in industry-adjusted three-year mean ROA around acquisitions

The dependent variable used in the Panel A (Panel B) specifications is the change in the firm's three-year (industry-adjusted) mean annual ROA based on data from years (t+1,t+3) and (t-1, t-3) where t is the year of the merger. The eigenvector and reach centralities are standardized such that a one unit increase corresponds with a one standard deviation increase in the underlying measures. All models are estimated separately using both OLS and median regression approaches. For the OLS models, the non-indicator variables are winsorized at the 5th and 95th percentiles and only the main centrality coefficients are reported (top two rows). With the exception of ROA, all the same control variables used in Table 4 are used in both the OLS and median regressions but are not tabulated. *Nearness* is the inverse of the number of intermediate boards between the bidder and target. *S&P500* and *Isolate* are bidder indicator variables for being part of the S&P500 and having no interlocks. The fit statistics are similar using either adjusted or unadjusted ROA and are only tabulated for Panel B. Significance at the 1%, 5%, and 10% levels is marked with ***, **, and *, respectively.

	Bidder	**Target**	**Bidder Target**	**Bidder**	**Bidder**	**Bidder**	**Bidder**	**Target**	**Bidder Target**
Years:	**91-05**	**91-05**	**91-05**	**91-97**	**95-01**	**98-05**	**91-05**	**91-05**	**91-05**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**
Panel A: Eigenvector OLS Results:			**Using non-adjusted ROA**				Reach OLS Results:		
Bidder Centrality	0.019**		-0.001	0.008	0.026**	0.035***	0.018		0.030
	[0.008]		[0.013]	[0.011]	[0.013]	[0.012]	[0.012]		[0.019]
Target Centrality		0.018***	0.018**					0.026***	0.028***
		[0.007]	[0.007]					[0.008]	[0.008]
Eigenvector Median Regression Results:							Reach Median Results:		
Bidder Centrality	0.006**		0.012*	0.003	0.009	0.014***	0.008**		0.021**
	[0.002]		[0.006]	[0.002]	[0.006]	[0.005]	[0.003]		[0.009]
Target Centrality		0.004	0.006					0.007*	0.009**
		[0.005]	[0.005]					[0.004]	[0.004]
S&P500*Centrality	-0.001		0.003	0.001	0.000	-0.002	-0.005		-0.005
	[0.005]		[0.007]	[0.004]	[0.010]	[0.011]	[0.007]		[0.012]
Nearness	0.012	0.003	-0.024	0.015	0.020	0.001	0.012	-0.031	-0.060*
	[0.013]	[0.030]	[0.032]	[0.014]	[0.028]	[0.022]	[0.012]	[0.031]	[0.036]
Isolate	0.013**	-0.003	0.006	-0.004	0.030**	0.034***	0.022***	-0.013	0.027
	[0.006]	[0.018]	[0.020]	[0.006]	[0.012]	[0.012]	[0.008]	[0.018]	[0.024]
S&P500	0.008	0.006	0.002	0.006	-0.005	0.012	0.009	0.005	0.011
	[0.006]	[0.008]	[0.009]	[0.006]	[0.011]	[0.011]	[0.007]	[0.008]	[0.012]
Panel B: Eigenvector OLS Results: :			**Using industry-adjusted ROA**				Reach OLS Results:		
Bidder Centrality	0.018**		-0.005	0.008	0.027**	0.034***	0.018		0.023
	[0.008]		[0.013]	[0.011]	[0.013]	[0.012]	[0.012]		[0.020]
Target Centrality		0.017**	0.016**					0.027***	0.029***
		[0.007]	[0.007]					[0.008]	[0.008]
Eigenvector Median Regression Results:							Reach Median Results:		
Bidder Centrality	0.007***		0.008	0.001	0.011***	0.015***	0.009***		0.018
	[0.002]		[0.008]	[0.005]	[0.004]	[0.004]	[0.004]		[0.012]
Target Centrality		0.008*	0.008*					0.009**	0.010**
		[0.005]	[0.005]					[0.004]	[0.005]
S&P500*Centrality	-0.003		0.006	0.004	-0.003	-0.001	-0.004		-0.001
	[0.003]		[0.008]	[0.008]	[0.007]	[0.010]	[0.007]		[0.014]
Nearness	0.013	-0.014	-0.030	0.018	0.035*	-0.017	0.011	-0.022	-0.056
	[0.008]	[0.032]	[0.035]	[0.027]	[0.019]	[0.020]	[0.014]	[0.035]	[0.039]
Isolate	0.014***	0.005	0.014	-0.004	0.036***	0.041***	0.024***	0.000	0.032
	[0.004]	[0.019]	[0.023]	[0.011]	[0.009]	[0.011]	[0.009]	[0.018]	[0.033]
S&P500	0.008**	0.000	-0.005	0.012	-0.001	-0.003	0.009	0.003	0.002
	[0.004]	[0.009]	[0.010]	[0.011]	[0.008]	[0.010]	[0.007]	[0.009]	[0.014]
Table 4 Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3257	1023	1023	1716	2050	1541	3257	1023	1023
OLS Adj R2	0.026	0.019	0.018	0.029	0.023	0.028	0.024	0.027	0.027
Median Pseudo R2	0.037	0.063	0.064	0.045	0.047	0.056	0.037	0.064	0.067

Table 8: Centrality and the probability of making an acquisition or being acquired.

This table presents the results from estimating a multinomial logit model for firm-years where the firm makes an acquisition, is acquired, or does not engage in any acquisition activity in a given year. The sample includes all firm-years from 1991-2005 for which we have the financial and board information. Results are shown using both reach centrality (left) and betweeness centrality (right). The heading of each column indicates which of the three cases the odds ratios and p-values relate to. For each section of rows the base case is indicated. Hence, for example, in the top betweeness section using the no acquisition activity as the comparison group, the odds of a firm making an acquisition in a given year relative to a firm not engaging in any acquisition activity is 1.053 times larger for a one standard deviation increase in bidder centrality. The reach and betweeness centralities are standardized such that a one unit increase is associated with a standard deviation increase in the underlying measures. Although not tabulated, these models also include bidder controls for CEO-chairs, busy boards, percent of board that were insiders, board size, ROA, firm size, excess cash, leverage, and M/B as well as industry and year controls. Significance at the 1%, 5%, and 10% levels is marked with ***, **, and *, respectively.

	Using Reach Centrality						Using Betweeness Centrality					
	Firm-years without acquisition activity		Firm-years making acquisitions		Firm-years being acquired		Firm-years without acquisition activity		Firm-years making acquisitions		Firm-years being acquired	
Variables	odds ratio	p-value	odds ratio	p-value	odds ratio	p-value	odds ratio	p-value	odds ratio	p-value	odds ratio	p-value
	Comparison category: no acquisition activity						Comparison category: no acquisition activity					
Bidder Centrality			1.006	0.86	1.134**	0.04			1.053***	0.01	1.113***	0.00
S&P500*Centrality			1.233**	0.03	1.557	0.11			1.035	0.76	1.303	0.34
Isolate			0.801***	0.01	0.955	0.76			0.843***	0.00	0.838**	0.05
S&P500			0.916	0.38	0.236***	0.00			1.063	0.62	0.282***	0.00
	Comparison category: making an acquisition						Comparison category: making an acquisition					
Bidder Centrality	0.994	0.86			1.127*	0.065	0.950***	0.01			1.057	0.11
S&P500*Centrality	0.811**	0.03			1.263	0.401	0.966	0.76			1.259	0.43
Isolate	1.249***	0.01			1.192	0.275	1.186***	0.00			0.994	0.95
S&P500	1.091	0.38			0.258***	0.000	0.941	0.62			0.265***	0.00
	Comparison category: being acquired						Comparison category: being acquired					
Bidder Centrality	0.882**	0.04	0.887*	0.06			0.898***	0.00	0.946	0.11		
S&P500*Centrality	0.642	0.11	0.792	0.40			0.767	0.34	0.794	0.43		
Isolate	1.047	0.76	0.839	0.28			1.193**	0.05	1.006	0.95		
S&P500	4.234***	0.00	3.879***	0.00			3.552***	0.00	3.775***	0.00		
	Observations					50785	Observations					50785
	Pseudo R2					0.0646	Pseudo R2					0.0646
	Log-Likelihood					-33761	Log-Likelihood					-33758

Table 9: Method of payment as a function of centrality

This table presents the results from estimating a multinomial logit model for whether the acquirer used 100% cash, a mixture of cash and stock, or 100% stock as the method of payment. The sample includes all acquisitions in Sample 1 for which we also have the target board information. The results shown in the first set of columns are the odds ratios and associated p-values for the 100% cash case. The second and third sets of columns show the odds ratios and associated p-values for the mixed payment and 100% stock cases, respectively. For each section of rows the base case is indicated. Hence, for example, in the top section using 100% cash as the comparison group, the odds of an acquirer using 100% stock relative to using 100% cash is .719 times smaller for a one standard deviation increase in target centrality. Eigenvector centrality is standardized such that a one unit increase is associated with a standard deviation increase in the underlying measure. Although not tabulated, these models also include all of the Table 4 control variables with the exception of the method of payment variables. This means that we include controls for CEO-chairs, busy boards, percent of board that are insiders, board size, ROA, firm size, excess cash, leverage, M/B, as well as the public status of the target, the relative size of the deal, whether the deal was diversifying, and industry and year controls. Significance at the 1%, 5%, and 10% levels is marked with ***, **, and *, respectively.

	Acquisitions with 100% cash		Acquisitions with mixed payment		Acquisitions with 100% stock	
	odds ratio	p-value	odds ratio	p-value	odds ratio	p-value
Comparison category: acquisitions with 100% cash						
Bidder Eigenvector			0.963	0.85	1.015	0.95
Target Eigenvector			0.746**	0.04	0.719**	0.046
S&P500*Eigenvector			0.777	0.30	0.920	0.77
Nearness			1.106	0.92	3.042	0.34
Isolate			0.391*	0.08	0.838	0.77
S&P500			1.210	0.54	1.648	0.17
Comparison category: acquisitions with mixed payment						
Bidder Eigenvector	1.039	0.85			1.055	0.78
Target Eigenvector	1.341**	0.04			0.964	0.80
S&P500*Eigenvector	1.288	0.30			1.184	0.51
Nearness	0.904	0.92			2.750	0.35
Isolate	2.557*	0.084			2.143	0.15
S&P500	0.826	0.54			1.362	0.31
Comparison category: acquisitions with 100% stock						
Bidder Eigenvector	0.985	0.95	0.948	0.78		
Target Eigenvector	1.392**	0.04	1.037	0.80		
S&P500*Eigenvector	1.087	0.77	0.845	0.51		
Nearness	0.329	0.34	0.364	0.35		
Isolate	1.193	0.77	0.467	0.15		
S&P500	0.607	0.17	0.734	0.31		
Observations	1322					
Pseudo R2	0.271					
Log-Likelihood	-1051					

Table 10: Robustness Checks

This table contains a series of robustness checks. The dependent variable in all columns is the change in the firm's three-year mean annual ROA using data from years (t+1,t+3) and (t-1, t-3) where t is the year of the merger. Reach centrality is standardized such that a one unit increase corresponds with a one standard deviation increase in the underlying measure. Although untabulated, in all models the Table 4 control variables (except ROA) are included in addition to the bidder-target nearness and indicator variables for whether the bidder is an isolate firm or is part of the S&P500. For the robustness test in column 1 we also control for the directors' collective ability using the weighted average of the stock returns for all the firms at which the directors worked over the last 5 years as explained in Section 6.1. For the robustness test in column 2, we estimate the change in ROA as done in Table 7 but limit the sample to the industries with merger waves as identified in Harford (2005) Table 2. For the robustness test in column 3, we repeat the analysis in Table 7 using the full sample with instrumental variables. In this specification we use the bidder's past centrality (t-3) and isolate status (t-3) as instruments for the bidder centrality and isolate dummy. Column 4 reports the results from a firm fixed effect model. The FE-VD results in column 5 are estimated using a panel fixed effects regression with variable decomposition as explained in Plumber and Troeger (2007). The models in columns 1-2 are estimated separately using both OLS and median regression approaches. For the OLS models, the non-indicator variables are winsorized at the 5th and 95th percentiles and only the main centrality coefficients are reported. Significance at the 1%, 5%, and 10% levels is marked with ***, **, and *, respectively.

	Ability	**Shock**	**IV**	**FE**	**FE-VD**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
OLS Regression Results					
Bidder Reach Centrality	0.030	0.056	0.057*	-0.020	0.054***
	[0.020]	[0.077]	[0.032]	[0.031]	[0.010]
Target Reach Centrality	0.029***	0.057**	0.021*	0.014**	0.021***
	[0.008]	[0.026]	[0.012]	[0.006]	[0.005]
Ability	0.076				
	[0.056]				
Median Regression Results					
Bidder Reach Centrality	0.021**	0.001			
	[0.010]	[0.060]			
Target Reach Centrality	0.010**	0.023			
	[0.004]	[0.019]			
Ability	0.027				
	[0.019]				
Table 4 Controls	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes
Year Controls	Yes	Yes	Yes	Yes	Yes
Observations	1021	170	794	1023	1014
OLS Adj R2	0.0477	-0.0388	0.1108	0.527	0.625
Median Pseudo r2	0.0695	0.159			