Institutional Blockholder Networks and Corporate Acquisition Performance

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Abstract

We examine 17,207 U.S. mergers and acquisitions by public firms over the 1980–2019 period and find that the acquirer abnormal announcement returns are higher for firms held by more central investors in the network of active institutional blockholdings. This finding is robust to firm and deal characteristics, and it also extends to alternative network and return measures. To provide evidence on causality, we exploit extreme industry returns that lead to plausibly exogenous variation in investors' monitoring ability. The positive effect of blockholder centrality on acquirer abnormal announcement returns only exists in information-sensitive (i.e., private) deals and only among institutions that have a comparative advantage in exploiting monitoring information. Our findings suggests that institutional investors obtain an information advantage through the network, which increases their monitoring ability.

Keywords: Institutional investors; investor networks; monitoring; mergers and acquisitions; acquirer returns

JEL classification: G23, G30, G34

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1 Introduction

Agency theory predicts a natural conflict between managers and shareholders that arises from the separation of ownership and control over public firms (Berle and Means, 1932). While managers are expected to maximize shareholder value, they may engage in (suboptimal) self-serving decisions (Jensen and Meckling, 1976). These suboptimal decisions comprise "empire building," which includes value-destroying acquisitions that are not in the best interests of shareholders (Gantchev et al., 2020). Starting from Shleifer and Vishny (1986) and Agrawal and Mandelker (1990), a large body of literature has recognized the monitoring role of institutional blockholders as a potential solution to the agency problem.[1] Based on Chen et al.'s (2007, p. 280) notion that monitoring "*consists of both information gathering and efforts to influence management*," large shareholders have the means to effectively constrain managerial opportunism. First, they frequently hold many firms at the same time, thereby accumulating information advantages (Kang et al., 2018). Second, they are powerful in dealing with management as they can intervene directly ("voice") or threaten to sell their shares ("exit"), and their sizable stakes create incentives strong enough to internalize the costs of monitoring. This allows them to exploit their superior information set and improve deal quality.

Despite the importance of acquisitions to the firm, which typically represent sizable investments, the literature has so far neglected the role of the network created by institutional investors holding blocks in the same firms. In this paper, we argue that such networks' topological properties are likely to impact both dimensions of monitoring effectiveness, i.e., 1) the *availability of information* and 2) the *ability to use information* to affect management decisions. We conjecture that

[1] See Edmans (2014) and Edmans and Holderness (2017) for a survey of the literature.

institutions centrally located in the network have access to more timely and superior information, allowing them to detect managerial opportunism in the first place. Unlike investors in the periphery of the network, central institutions can more easily interact with other investors and persuade them to vote in the same direction (Bajo et al., 2020). This enhances their influence in dealing with management and enables them to translate information advantages into effective monitoring.

There is a large and multidisciplinary literature on information diffusion in social networks. Information-based models illustrate how network structures play an important role in disseminating information (Banerjee 1992; Bikhchandani et al., 1992; Welch 1992; Park and Sabourian, 2011). Buskens (2002) develops a stochastic model that predicts information dissemination as a function of the position of the node in the network. Fracassi (2017) argues that centrally located managers in the executive network can make more informed decisions. Cohen et al. (2008) use social networks to identify information transfer in security markets. They find that fund managers located centrally in the network of shared educational backgrounds earn abnormal returns. DiMaggio et al. (2019) show that centrally located brokers in the network of broker-investor relationships gather information, which is then leaked to their best clients to generate superior returns. Overall, literature suggests that information is disseminated through networks and allows centrally located actors to exploit their information advantage.

Building on this literature, we argue that an investor's position within the network of institutional blockholdings is a key determinant of access to monitoring information. We base our conjecture on evidence that institutional investors exchange information with their peers about investee firms (Shiller and Pound, 1989; Hong et al., 2004; Cohen et al., 2008; Pool et al., 2015). For example, in their survey of investor communication among U.S. institutions trading on the New York Stock Exchange, Shiller and Pound (1989) find that the most important reason for purchasing stocks is institutions' frequent communication with their peers. Pool et al. (2015) observe that funds whose managers live in the same neighborhood have a high portfolio overlap and conclude that this effect is driven by direct communication between shareholders. Similarly, Hong et al. (2004) document that fund managers' portfolio choices are affected by word-of-mouth information-sharing among institutional investors. Finally, Ozsoylev et al. (2014) find that central individual investors in the network of trading patterns earn higher returns and trade earlier with respect to information events than peripheral investors.

Besides institutions' access to information, central blockholders are also likely to have significant influence over management, i.e., the means to exploit their information advantages and improve decision quality. We base this premise on early studies in the social psychology literature showing that the leadership role in communication networks typically devolves upon to the person with the highest network centrality (Leavitt, 1951; Berkowitz, 1956). In line with these findings, studies in the social network literature generally assume network centrality to be equivalent to power (Mizruchi, 1982; Bonacich, 1987; Mintz and Schwartz, 1987). We expect an analogous relationship in institutional investor networks. First, central institutions' higher number of connections makes them more influential and strengthens their negotiating power vis-à-vis firm management as they can effectively discipline managers by persuading other investors to vote in the same direction (Bajo et al., 2020). Second, managers may fear that their opportunistic practices are exposed and propagated through the large networks of central institutions, resulting in reputational damage. Third, central institutions may facilitate deal quality by acting as advisors to the management (Bajo et al., 2020), given that information availability critically affects the quality of advice (Adams and Ferreira, 2007).

Overall, our main argument is that the presence of central institutions facilitates deal quality due to improvements in monitoring effectiveness. To test our predictions, we compile a comprehensive sample of 17,207 acquisitions by public U.S. firms over the 1980–2019 period. To capture deal quality, we rely on standard event study methods (Brown and Warner, 1985) and estimate cumulative abnormal acquirer returns (CAARs) around the deal announcement dates (Moeller et al., 2004; Harford et al., 2012; Dissanaike et al., 2020; Drobetz and Momtaz, 2020; among others). Next, we construct the network of institutional blockholdings. Following prior literature (Crane et al., 2019; Bajo et al., 2020), we consider two institutions to be connected if there exists at least one firm in which they both have an ownership stake of at least 5 percent of the firms' market capitalization. We focus on active institutions to ensure the network is not affected by mere replications of a benchmark indices. In line with Bajo et al. (2020), we consider "dedicated" and "transient" institutions as active and "quasi-indexer" as passive (Bushee, 1998, 2001; Bushee and Noe, 2000). Based on the resulting network, we capture blockholder centrality by using the number of first-degree links with other institutional investors, i.e., degree centrality, as our main measure (Cohen et al., 2008; Fracassi, 2017; Bajo et al., 2020).

We find that that the presence of central institutional blockholders is associated with improvements in deal quality. Our results survive a variety of alternative measures of CAARs and extend to different networks measure, for example, eigenvector, betweenness, and closeness centrality. We control for a wide range of ownership, deal, and firm characteristics and include time and industry fixed effects in all our regressions. Our findings are not only statistically significant but also economically meaningful: a one-standard-deviation increase in degree centrality is associated with an increase in abnormal announcement returns of 17.97% relative to the sample mean.

We implement several measures to address potential endogeneity concerns such as reverse causality, which is a frequent objection in empirical corporate governance research. We interpret our finding of a positive relation between CAARs and investor centrality as evidence that central institutional blockholders *cause* managers in their investee firms to make better acquisitions decisions. However, an alternative explanation, in which causality is reversed is also conceivable. If central blockholders prefer to invest in firms that conduct high-quality acquisitions, we should likewise observe such positive relation. To achieve valid inferences, we explain contemporaneous values of CAARs with lagged values of explanatory variables in all our regression analyses. Moreover, to allay any remaining doubts over reverse causality, we utilize plausibly exogenous variation in investor attention introduced by Kempf et al. (2017). We use their methodology to construct centrality measures among the subsets of firms' distracted and attentive investors. This identification strategy builds on the premise that investors lose the ability to exploit their privileged position in the network if they become distracted by exogenous industry shocks plausibly unrelated to the firm. Supporting a causal effect of investor networks on CAARs, we find variations in centrality to increase deal quality only when shareholder attention is devoted to the focal firm.

We proceed by evidencing that improvements in deal quality are driven by information advantages obtained through the institutional blockholder network. Private information is particularly important in private as opposed to public deals. While the market of corporate control for public targets already incorporates a substantial amount of information into stock prices, the lack of information on private targets creates opportunities for well-informed acquirers to exploit their information advantages and gain abnormal returns (Makadok and Barney, 2001; Capron and Chen, 2007). If central institutions gain informational advantages through the network, we should observe more pronounced effects on deal quality in information-sensitive (i.e., private) deals. We split the sample into private vs. public deals and rerun our baseline model. Supporting our conjecture, degree centrality facilitates abnormal acquirer announcement for the subsample of private targets while there is no effect for the subsample of public targets.

Next, we exploit heterogeneity across investor types to provide additional evidence for the role of information as a channel through which investor networks affect CAARs. As already explained, monitoring ability depends on the *availability of information* and the *ability to use information* for monitoring purposes (Chen et al., 2007). If network centrality is a valid proxy for the availability of monitoring information, its effect on deal quality should be stronger among types of institutional investors that are good at exploiting information for monitoring. Prior literature (Gaspar et al., 2005; Cornett et al., 2007; Chen et al., 2007; Koh, 2007; Ferreira and Matos, 2008; Harford et al., 2018) indicates that institutional investors are most likely to use information to monitor management when they do not have business relations with their portfolio firms or when they invest for the long run (hereafter, monitoring institutions). Accordingly, we construct firm-level centrality measures among heterogeneous investor types and re-run our main model. We find that only informed (i.e., central) monitoring institutions facilitate deal quality, while there is no such effect for informed institutions without special ability to exploit information for monitoring purposes. Again differentiating between private and public deals, we can only observe the effect of monitoring institutions' network centrality on CAARs for information-sensitive (i.e., private) deals. The effect vanishes in public deals for which information is already widely available to bidders. Overall, this line of analysis confirms that improvements in deal quality are driven by information advantages obtained through the institutional blockholder network.

Most closely related to our work are Crane et al. (2019) and Bajo et al. (2020). Bajo et al. (2020) study the relation between blockholder centrality and firm value, while Crane et al. (2019)

investigate the role of clique ownership in shaping firm governance. We note that investor cliques and investor centrality are different concepts. Cliques are complete subnetworks in which every member of the clique is connected to any other member of the clique. Clique ownership captures the total ownership of a firm held by institutions belonging to such highly clustered communities. Therefore, it is a proxy for coordination (Crane et al., 2019) rather than for the access to information like network centrality. To empirically disentangle both concepts, we control for clique ownership in all our regression analyses.

Our study is further related to the concept of common ownership (for example, Azar et al., 2018; Dennis et al., 2022). The common ownership literature emphasizes connections between firms which collaborate, coordinate and exchange information through an intermediary blockholder. Network centrality, in contrast, focuses on the connections of the firms' representative blockholder. The objective of our study is not to analyze how firms respond to the actions of their competitors, but to assess the impact of informed blockholders on monitoring ability and the quality of corporate acquisitions. To allay any remaining concerns, we control for common institutional ownership in all our regression analyses.

Our study complements the literature in several ways. First, we propose blockholder centrality as a novel determinant that affects acquirer abnormal announcement returns. Earlier research has put forward a range of factors that partially explain return differences in acquisitions, including means of payment (Travlos, 1987, Bhagat et al., 2005; Savor and Lu, 2009), bid type (Moeller et al., 2004; Bhagat et al., 2005; Offenberg and Pirinsky, 2015), the target's public or private status (Fuller et al., 2002; Conn et al., 2005; Capron and Shen, 2007), bidder competition (Schwert, 2000, Moeller et al., 2004; Masulis et al., 2007), industry specialization (Morck et al., 1990; Fan and Goyal, 2006), and acquirer size (Asquith et al., 1983; Moeller et al., 2004). However, the role of the institutional blockholder network has been overlooked so far.

Second, we augment research that explores the monitoring role of institutional investors and shed light on how they obtain valuable information. Existing studies typically rely on the overall level of institutional ownership, ownership concentration, or heterogeneity among institution types to explain monitoring intensity (for example, Gaspar et al., 2005; Cornett et al., 2007; Chen et al., 2007; Ferreira and Matos, 2008; Harford et al., 2018). These studies neglect the information diffusion that likely occurs between institutions as well as the role of the network in shaping investor's power in interacting with firm management.

Third, we add to the rising literature that explores financial outcomes through the concept of network centrality. While most studies focus on the social network (for example, Cohen et al., 2008; Fracassi, 2017), we analyze the implications of the network created by institutional investors holding blocks in the same firms.

The remainder of this paper is structured as follows: In Section 2, we introduce the measures of abnormal returns and blockholder centrality, and provide descriptive statistics of our data. We document our main empirical results in Section 3. Section 4 concludes the paper.

2 Data and Descriptive Statistics

2.1 M&A data

We compile a comprehensive sample of 17,207 acquisitions by public U.S. firms from 1980–2019. Following the literature (Moeller et al., 2004; Harford et al., 2012; Drobetz and Momtaz, 2020), we impose the following six sample requirements. (1) The transaction must be completed. (2) The deal value must exceed $1 million and must be at least 1% of the acquirer's market value. (3) The target must be a public or private firm or a non-public subsidiary of a public or private firm. (4) The acquirer must control less than 50% of the shares of the target firm prior to announcement of the acquisition and must end up with all the shares of the acquired firm. (5) The number of days between the announcement and completion dates must be between zero and one thousand. (6) Stock price and accounting data must be available from Compustat and CRSP, respectively.

Figure I shows the number of acquisitions over time. The overall number is depicted in red, while the green and blue lines indicate public and private acquisitions, respectively. The number of acquisitions does not increase monotonically but fluctuates over time. It increases during the 1980–1998 period and falls during the years 2000 and 2007. The number of public and private acquisitions behave similarly throughout the entire study period.

To estimate the impact of investor centrality on acquirer returns, we rely on standard event study methods (Brown and Warner, 1985). As in Moeller et al. (2004), we estimate three-day cumulative abnormal acquirer returns (CAARs) over the (−1, +1) event window and the (−205, −6) estimation window. We rely on the market model, where we use the CRSP equally-weighted returns as benchmark (Moeller et al., 2004; Mansulis and Wang, 2007; Tunyi, 2021).[2]

2.2 Network Centrality

To capture network centrality, we start by constructing an undirected and unweighted network formed by institutional investors holding stakes in the same firms. Such networks are

[2] In Table 6, we use alternative specifications and obtain qualitatively similar results. They comprise, e.g., market-adjusted returns and different estimation as well as event periods.

generally defined as a structure of nodes and dyadic ties between them.[3] As with Bajo et al. (2020), we define actors as active institutional blockholders. We assign a tie between two nodes if there exists at least one firm in which they both are invested with at least 5 percent of its market capitalization (Crane et al., 2019; Bajo et al., 2020). We visualize the resulting network as of 2019Q4 in Figure 2.

Based on the constructed network, we compute five network centrality measures to assess an investors' position in the network. First, we consider the number of blockholding ties an investor has to other investors, i.e., degree centrality (Cohen et al., 2008; Fracassi, 2017; Bajo et al., 2020). This measure is intuitive as it simply counts the number of first-degree ties that are connected to a node. Formally, degree centrality (unscaled) of institution k in quarter-year q is defined as:

$$DEGR\_UNSC_{kq} = \sum_{j \neq k}^{N_q} A_{kjq}, \tag{2}$$

where N_q is the number of nodes k in quarter-year q, and A_{kjq} is an indicator equal to one if there is a tie between nodes k and j. We plot average investor-level degree centrality (unscaled) in Figure 3a. The average investor in our sample is directly connected to 3.498 other institutional blockholders in 2019Q4. This number does not evolve monotonically over time, but it fluctuates from 1.336 in 2004Q2 to 15.073 in 1997Q2.

Degree centrality depends on the network potential—that is, the maximum number of ties $N - 1$ that a node can have with other nodes. If the number of nodes N fluctuates over time,

[3] Undirected information networks imply a mutual exchange of information among any two connected nodes. This is intuitive, as rational investors are only willing to provide information if they receive information in return (Ozsoylev and Walden, 2011; Han and Yang, 2013; Ozsoylev et al., 2014).

network potential also changes. Figure 3b illustrates that, on average, the universe of active blockholders fluctuates substantially over the sample period. Network potential shows a mean of 254 with a standard deviation of 70. It varies from 103 in 1981Q4 to 432 in 2001Q2. To avoid a potential time bias, we scale $DEGR\_UNSC_{kq}$ by $N_q - 1$ (Bajo et al. (2020)). The second centrality measure, scaled degree centrality for investor k at quarter-year q, is hence given by:

$$DEGR_{kq} = \frac{\sum_{j \neq k}^{N_q} A_{kjq}}{N_q - 1}. \tag{3}$$

The measure is defined on the interval (0, 1) and captures the percentage of network potential tied to an investor in a given year. Figure 3c reveals that scaled degree centrality, on average, varies from 0.00485 in 2012Q3 to 0.05640 in 1996Q2. The latter value implies that the average investor had ties to 5.64% of active institutional blockholders in the network.

Although degree centrality measures are the primary measures of network centrality in the literature, earlier studies use other measures (Ozsoylev et al., 2014; DiMaggio et al., 2019; Bajo et al., 2020). First, unlike $DEGR$, eigenvector centrality accounts for not only direct ties between investors but also indirect ones, placing more weight on the most central nodes. The rationale is that investors are likely to receive more monitoring-relevant information from network affiliates if the affiliates enjoy more access to information themselves. Therefore, our third measure of network centrality, eigenvector centrality, for investor k in quarter-year q is given as:

$$EIVEC_{kq} = \frac{1}{\lambda} \sum_{j \neq k}^{N_q} x_{kjq} \, EIVEC_{jq}, \tag{4}$$

where λ is a constant to prevent nonzero solutions, and $EIVEC$ is the eigenvector centrality score (Bonacich, 1987). Following Bajo et al. (2020), we scale $EIVEC$ by the maximum possible value for a network of size N.

Our fourth measure of network centrality, betweenness centrality, captures the extent to which a node acts as an interface between two other nodes. It proxies for the importance of an investor to information dissemination in the network. More central investors are exposed to more information and can control information flow within the network. Formally, betweenness centrality captures the percentage of the shortest paths between any pair of nodes in the network that pass through investor k:

$$BETW_{kq} = \sum_{k \neq j \neq z} \frac{b_{kjzq}}{b_{jzq}}, \tag{5}$$

where b_{kjzq} is the number of the shortest paths between nodes j and z that pass through investor k in quarter-year q, and b_{jzq} is the total number of shortest paths between j and z in time q.

Our fifth measure of network centrality, closeness centrality, captures a node's path length (i.e., inverse distance) to all other nodes in the network. Investors close to all other nodes in the network may obtain superior information because they can reach out to affiliated investors without being dependent on the mediation of many other nodes. Closeness centrality can also proxy for the speed with which an institution obtains information from the network. Formally, we define closeness centrality as the average of the shortest path length between investor k and all other nodes in the network:

$$CLOSE_{kq} = \frac{N_q - 1}{\sum_{j \neq k}^{N_q} d_{kjq}}, \tag{6}$$

where d_{kjq} is the length of the shortest path between nodes k and j in the network at time q.

Next, to aggregate the five centrality measures at the firm level. Our rationale is that central investors are good at monitoring managers, eventually inducing them to undertake fewer value-destroying acquisitions. Literature has established that monitoring effectiveness is driven by both the importance of the firm for the investor (Fich et al., 2015) and the importance of the investor for the firm (Goldstein, 2011). Therefore, we do not simply apply holding weights to the firm-level network measures, but adopt the weighting factor w_{kiq-1} as in Kempf et al. (2017).[4] It puts more weight on investor k if firm i takes a large position in k's portfolio (i.e., if i is important to k), or if k is a large shareholder of i (i.e., if k is important to i). Formally, investor centrality for firm i in quarter-year q is given by

$$CENTRALITY_{iq} = \sum_{k \in I_q} w_{kiq-1} CENTRALITY_{kq}, \tag{7}$$

with

$$w_{kiq-1} = \frac{QPFweight_{kiq-1} + QPercOwn_{kiq-1}}{\sum_{k \in I_{q-1}} \left(QPFweight_{kiq-1} + QPercOwn_{kiq-1} \right)}, \tag{8}$$

where $CENTRALITY$ represents one of our network centrality measures ($DEGR\_UNSC$, $DEGR$, $EIVEC$, $BETW$, or $CLOSE$). $PFweight_{kiq-1}$ and $PercOwn_{kiq-1}$ capture the fraction of i in k's portfolio and the fraction of i's market value of equity held by k, respectively. We measure both terms as of the previous quarter-year and sort them into quintiles Q to reduce the effect of possibly spurious outliers. Finally, we scale by the denominator so that the weights sum to one. Figure 3d plots average quarterly firm-level degree centrality. As is the case at the investor level, our final centrality measure $DEGR_{iq}$ does not behave monotonically but fluctuates significantly. It gradually builds up during the 1980–1998 period and declines markedly afterwards.

[4] Our results remain qualitatively unchanged when we use holding-weighting (see Section 3.3).

2.3 Distracted Investors

Facing attention constraints, investors must decide which firms to focus on. Extreme industry returns may cause investors to shift their focus to firms in these industries, temporarily distracting them from firms in other industries. Investors that experience extreme returns in parts (industries) or their portfolios will likely spend more time monitoring managers of firms in shocked industries while dedicating less time to firms in non-shocked industries. Such industry shocks occur plausibly exogenous to firms in non-shocked industries and temporarily loosen monitoring constraints (Kempf et al., 2017). Kempf et al. (2017) show that managers react to temporary institutional investor inattention by undertaking more value-destroying acquisitions.

We use this negative shock to monitoring activity to identify a plausibly exogenous effect of network centrality on acquirer abnormal announcement returns. We start by computing the Kempf et al. (2017) distraction measures at the investor-industry-year level. We then sort all distraction scores by industry-year to distinguish between distracted and attentive investors based on the median. Finally, we aggregate degree centrality scores at the firm level (see Equation (7)) using only observations of a given firm's distracted ($DEGR\_DIST$) or attentive ($DEGR\_ATT$) institutional shareholders. To ensure that the measures are not mechanically related to the focal firm, we exclude firm-year observations that experience the industry shocks (Kempf et al., 2017).

The premise of this study is that more central institutions prevent managers from engaging in value-destroying acquisitions. If network centrality captures monitoring ability, we only expect variations in $DEGR\_ATT$ to affect announcement returns, whereas $DEGR\_DIST$ should have no such effect. The idea is that central investors do not exploit their privileged and powerful position in the network to monitor managers once they become distracted. A reverse causality explanation is unlikely (i.e., successful acquirers attract investment only from central institutions that are attentive but not distracted) because investors are assigned to the groups of attentive or distracted shareholders based on exogenous variation plausibly unrelated to the focal firm itself.

2.4 Heterogeneity across Investors

We use the same methodology as above (see Section 3.3) to construct firm-level centrality measures for subsets of investors that differ in their monitoring preferences. Independence from firm management or investment horizon induce heterogeneity in the extent to which investors use available information for monitoring. Given that shareholder centrality captures investor excess to information, we only expect such monitoring institutions to utilize their information endowment and prevent managers from making bad acquisitions.

Grey institutions that have existing or potential business relationships with portfolio firms are less likely than independent institutions to challenge and pressure portfolio firms' managers for fear of losing business (Chen et al., 2007; Ferreira and Matos, 2008). As in Chen et al. (2007), we classify mutual funds, investment advisors, and public pension funds as independent, and banks, insurance companies, and all remaining institutions as grey.

Similarly, while short-term investors are mainly interested in realizing trading profits, long-term investors do not exit as easily but have incentives to use monitoring information and engage with managers (Gaspar et al., 2005; Chen et al., 2007; Koh, 2007; Harford et al., 2018). We classify long-term and short-term investors based on the portfolio churn rate (CR), which we compute in line with the literature (Gaspar et al., 2005; Döring et al., 2021). Formally, investor k's CR in quarter-year q is given by:

$$CR_{kq} = \frac{\sum_{i=1}^{C_{kq}} |S_{kiq}P_{iq} - S_{kiq-1}P_{iq-1} - S_{kiq}\Delta P_{iq}|}{\sum_{i=1}^{C_{kq}} \frac{S_{kiq}P_{iq} + S_{kiq-1}P_{iq-1}}{2}}, \tag{9}$$

where S_{kiq} is the number of firm i's shares held by investor k in quarter-year q, P_{iq} is firm i's stock price in quarter-year q, and C_{kq} is the number of firms investor k holds in quarter-year q. We sort all values by quarter-year and distinguish between long- and short-term institutions based on the median CR.

Finally, we aggregate degree centrality at the firm level (see Equation (7)) using only observations of independent ($DEGR\_IND$), grey ($DEGR\_GREY$), long-term ($DEGR\_LT$), and short-term ($DEGR\_ST$) institutional investors.

2.5 Sample Construction

We obtain data from several sources. The takeover sample is from Thomson Reuters' SDC Platinum M&A database. Data on institutional investors' holdings come from the Thomson Reuters Financial (F-13) database. Stock price and accounting data stem from Compustat and CRSP, respectively. We complement these data with Fama and French's (1997) 12-industry returns and institutional investor classification data based on Bushee (1998, 2001) and Bushee and Noe (2000), which is available from their websites.[5] We winsorize all continuous variables at the 1st and 99th percentiles. After imposing sample requirements and deleting observations for which we have missing data, our final sample consists of 17,207 acquisitions over the 1980–2019 period.

[5] For Kenneth French's industry return data, see http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. For Brian Bushee's investor classification data, see http://accounting-faculty.wharton.upenn.edu/bushee.

2.6 Control Variables

Following the literature, we construct a vector of investor control variables, denoted as IC, related to ownership and network structures. An institution's portfolio concentration is likely to affect the number of ties to other institutional investors. Whereas specialized institutions allocate their assets under management to a relatively small number of target stocks, a broader investment scope exposes an investor to more coinvestment relationships. Therefore, following Bajo et al. (2020), we incorporate the weighted Herfindahl index—that is, an investor's portfolio dispersion—as a control variable ($IHERF$).

The larger the number of blockholders in a firm, the larger the number of coinvestment ties among those institutions. In other words, institutional ownership concentration should be positively correlated with degree centrality. To proxy for institutional ownership concentration, we control for the firm-level Herfindahl index ($FHERF$; Crane et al., 2019; Bajo et al., 2020).[6] Network centrality is also likely correlated with an institution's assets under management. To realize the benefits of portfolio diversification, large investment firms are forced to allocate their holdings across various stocks, increasing the number of coinvestment relationships. We follow Crane et al. (2019) and Bajo et al. (2020) and control for firm size as captured by the weighted institution's natural logarithm of assets in millions of U.S. dollars reported in 13-F filings ($ISIZE$).

To empirically disentangle the effects of network centrality on acquirer returns from those of related network properties, we control for clique ownership. As in Crane et al. (2019), we construct a network of overlapping holdings ≥ 5% of the firms' market value of equity. We then apply the Louvain algorithm (Blondel et al., 2008) to approximate solutions to the problem of

[6] We apply holding weights to aggregate investor-level measures at the firm level to obtain $ISIZE$ and $IHERF$, respectively.

identifying cliques and define ownership by institutional investor cliques as the total fraction of the firm owned by all cliques each year (IO_CLIQUE). As in He and Huang (2017) and Ramalingegowda et al. (2021), we also control for the level of common ownership, as captured by block ownership by same-industry peer firms within the four-digit SIC (IO_COMMON). Following Bajo et al. (2020), we further control for the shares held by dedicated, transient, and quasi-indexer institutional investors as a percentage of the firm's shares outstanding (IO_DED, IO_TRA, IO_QIX) to ensure that the effects of network centrality on acquirer returns are not affected by a firm's institutional ownership composition.

Next, we construct a vector of deal controls (DC) that prior literature identifies as determinants of acquirer announcement returns. Because bidder competition and hostility can have negative effects on acquirer returns (Schwert, 2000; Moeller et al., 2004; Masulis et al., 2007), we add dummy variables indicating the presence of more than one bidder ($COMPETED$) and hostile deals ($HOSTILE$), respectively. Research finds that acquiring-firm shareholders gain more with tender offers (Moeller et al., 2004; Bhagat et al., 2005; Offenberg and Pirinsky, 2015). We thus incorporate a respective indicator variable to our sample ($TENDER$). Because diversifying acquisitions are shown to have lower abnormal returns (Morck et al., 1990; Moeller et al., 2004), we add a dummy variable indicating whether acquirer and target two-digit SIC industries are the same or not ($CONGLO$). Acquisitions paid for with equity are usually accompanied by lower announcement returns than those paid with cash (Myers and Majluf, 1984; Travlos, 1987, Bhagat et al., 2005; Savor and Lu, 2009). We thus add dummy variables indicating pure equity deals ($EQUITY$) or pure cash ($CASH$) deals, respectively. To proxy for M&A activity in the target and acquirer industries, we further add the liquidity index as in Moeller et al. (2004), and a dummy variable indicating prior industry merger activity ($DISTURB$) as in Tunyi (2020).

Finally, we construct a vector of acquirer controls, denoted as AC. Because Moeller et al. (2004) find that firm size is negatively related to abnormal bidder returns, we add the natural logarithm of firms' market capitalization in USD ($FSIZE$). Following Asquith et al. (1983), acquirer return regressions generally adjust for the impact of the takeover on the acquirers' market capitalization by controlling for the transaction value relative to the acquirers' size. To reduce any potential omitted variables bias when estimating effects on abnormal announcement returns, we add the relative size ($RELSIZE$) to the vector of acquirer controls. Finally, as in related literature (Moeller et al., 2004; Drobetz and Momtaz, 2020; Dissanaike et al., 2020), we control for standard fundamentals that have been shown to affect acquirer returns, namely operating cash flow (OCF), Tobins Q ($TOBINSQ$), liquidity (LIQ), leverage (LEV), market-to-book ratio (MTB), asset tangibility ($TANGIB$), and firm age (AGE).

2.7 Descriptive Statistics

Descriptive statistics for our main variables are in Table 1. Panel A shows statistics on abnormal returns for successful acquisitions over the sample period. With a mean of 1.032%, shareholders of acquiring firms, on average, slightly benefit from acquisitions, which is in line with previous literature (see, for example, Moeller et al., 2004). Panel B focuses on network characteristics and reveals significant variation in the network centrality measures. Unscaled degree centrality shows a median of 2.378, with 25th and 75th percentiles of 0.667 and 6.259, respectively. This indicates that the bottom quarter of sample firms are held by poorly connected shareholders with, on average, less than one link to active blockholders. Top quarter firms' shareholders, however, are well connected showing more than six such links. We also provide summary statistics on deal and acquirer characteristics in Panel C and Panel D, respectively, but do not comment on them for the sake of brevity.

Insert Table 1 about here

2.8 Investor-level Correlations

We provide pairwise correlation coefficients between centrality measures and different portfolio characteristics at the investor level in Table 2. Focusing on the network measures, we observe positive correlations among all five that are statistically significant at the 1% level. For example, scaled degree centrality shows pairwise correlation coefficients of 0.974 with unscaled degree centrality (see coefficient on $DEGR\_UNSC$ in column (1)) as well as 0.821 with eigenvector centrality (see coefficient on $EIVEC$ in column (1)). Acknowledging these high correlations, we focus on scaled degree centrality, $DEGR$ (see Equation (7)), as our main network centrality measure in the analyses below. However, we also use alternative network measures in Section 3.3 for robustness.

Insert Table 2 about here

Focusing on the pairwise correlations between network measures and portfolio characteristics, we find that $DEGR$ is positively correlated with the number of stocks in an investor's portfolio (see coefficient on $NSTO$ in column (1)) and an investors' total assets (see coefficient on $ISIZE$ in column (1)). These positive correlations are plausible, given that a high number of stocks and total assets increases the probability of blockholding ties with other institutions. However, these correlations are only of moderate magnitude, showing coefficients of 0.171 and 0.184, respectively. We also observe a negative correlation between $DEGR$ and the investor's portfolio Herfindahl with a coefficient of -0.042 (see coefficient on $IHERF$ in column (1)), indicating a negative relation between ownership concentration and the likelihood of blockholding ties. Overall, given these moderate correlations, network centrality appears to be a distinct construct that goes beyond standard portfolio characteristics.

3 Empirical Results

3.1 Univariate Statistics

To give a first overview of how deal and firm characteristics differ between acquirers held by central and decentral shareholders, we present univariate statistics in Table 3. In a first step, we sort $DEGR$ by quarter-year and split the sample based on the median. We then observe and test for differences between the two subsamples.

Insert Table 3 about here

Focusing on the equally-weighted abnormal return for our sample of successful offers (see Panel A), we find that centrally held firms, on average, gain 1.364 percentage points over the 3-day event window. The corresponding effect for decentrally held firms is considerably smaller with a $CAAR$ of 0.695. This indicates that firms held by institutions centrally located in the network of active blockholdings gain twice as much from acquisitions as their counterparts. The difference in means between both groups of 0.670 is statistically significant at the 1% level.

Next, in Panel B of Table 3, we examine whether ownership characteristics provide preliminary evidence on why abnormal returns differ between centrally and decentrally held firms. We find that, among other characteristics, the subsamples differ with respect to institutional investor size and ownership composition. Centrally held firms' weighted institution's assets in millions of U.S. dollars reported in 13-F filings ($ISIZE$) amounts to \$17.88 billion dollars, while $ISIZE$ for decentrally held firms averages to \$25.28 billion dollars. This finding may seem counterintuitive at first glance, given that a higher number of total assets increases the probability of blockholding ties with other institutions. Nevertheless, it can be explained by the composition of firms' institutional ownership. While centrally held firms have more ownership from dedicated and transient institutions, decentrally held firms have a 5.7 percentage points higher share of quasi-indexer institutions. Quasi-indexers above-average assets under management drive the differences in $ISIZE$, while we do not consider them in the calculation of active blockholder centrality, given their passive replicating investment strategy (see Section 3.2).

Turning to differences in deal characteristics in Panel C of Table 3, we find that average deal values are significantly smaller for centrally held firms ($DEALVAL$ of \$134.77 million vs. \$691.01 million), and that they acquire private targets more often ($PRIVATE$ of 53.51% vs. 41.63%). They complete acquisitions faster ($COMPLETE$ of 64 days vs. 81 days), less often have competing bidders ($COMPETE$ of 0.59% vs. 1.74%), hostile takeovers ($HOSTILE$ of 0.16% vs. 0.40%), tender offers ($TENDER$ of 2.45% vs. 4.83%), and diversifying deals ($CONGLO$ of 36.98% vs. 38.70%). They are also slightly more likely to pay with cash than with equity, however, the t-test of no differences in means cannot be rejected due to lack of statistical significance.

Finally, focusing on acquirer characteristics in Panel D of Table 3. We observe that firms held by central institutional investors are significantly smaller with $FSIZE$ of \$0.82 billion dollars compared to \$6.40 billion dollars for their decentrally held counterparts. In contrast, their average transaction value relative to the acquirers' size is larger ($RELSIZE$ of 16.20% vs. 13.70%), they have higher liquidity (LIQ of 0.19 vs. 0.14) and are younger (AGE of 14 years vs. 21 years).

3.2 Baseline Regressions

To test whether active blockholder centrality increases acquirers' abnormal announcement returns in a multivariate setting, we estimate several specifications of the following regression:

$$CAAR_{iq}^{(-1,+1)} = \beta_0 + \beta_1 DEGR_{iq-1} + \beta_2 IC_{iq-1} + \beta_3 DC_{iq-1} + \beta_4 AC_{iq-1} + FEs + \varepsilon_{iq-1}, \qquad (10)$$

where $CAAR_{iq}^{(-1,+1)}$ are the cumulative abnormal announcement returns for acquirer i at quarter-year q; $DEGR_{iq-1}$ is the weighted centrality among acquirer i's active institutional shareholders at quarter-year $q-1$; IC_{iq-1} is a vector of control variables on institutional ownership characteristics ($IHERF$, $FHERF$, $ISIZE$, IO_CLIQUE, IO_COMMON, IO_DED, IO_TRA, IO_QIX) at quarter-year $q-1$; DC_{iq-1} is a vector of control variables on deal characteristics ($COMPETED$, $HOSTILE$, $TENDER$, $CONGLO$, $EQUITY$, $CASH$, $LIQIDX$, $DISTURB$) at quarter-year $q-1$; and AC_{iq-1} is a vector of control variables on acquirer characteristics ($FSIZE$, $RELSIZE$, OCF, $TOBINSQ$, LIQ, LEV, MTB, $TANGIB$, AGE) at quarter-year $q-1$. FEs are quarter-year fixed effects and two-digit SIC industry fixed effects applied at both the acquirer and target levels. As in Momtaz and Drobetz (2020), we cluster heteroskedasticity-robust standard errors by target nation and the acquirer's two-digit SIC industry.

The results are in Table 4. We start by estimating the effects of shareholder centrality on acquirer returns in a setting without control variables to ensure the results of subsequently reported analyses are not driven by the inclusion of control variables alone. We add quarter-year fixed effects to all models to isolate the effects of $DEGR$ on $CAAR$ from time-series trends observed earlier in Figure 1 and Figure 3d. In this preliminary model (1), we observe a positive and statistically significant coefficient on $DEGR$ at the 1% level. Next, in models (2) to (4), we subsequently add the vectors of institutional ownership controls (IC), deal controls (DC), and acquirer controls (AC). We find that the presence of control variables reduces the magnitude of the estimated $DEGR$ coefficient, however, it remains statistically significant at the 1% level across all specifications. Finally, in models (5) and (6), we subsequently add acquirer-industry fixed effects and target-industry fixed effects. Notably, the coefficient estimates on $DEGR$ remain stable both in magnitude and statistical significance, indicating that unobserved heterogeneity at the industry level does not confound the results. The results indicate that shareholder centrality is positively associated with acquirer's cumulative announcement abnormal returns.[7]

Insert Table 4 about here

Focusing on the full model (6), hereafter referred to as the baseline model, we find that the effect of active blockholder centrality on acquirer's cumulative announcement abnormal return is also economically relevant. A one-standard-deviation increase in $DEGR$ (0.0239) is associated with an increase in $CAAR$ by 17.97% relative to the sample mean ($= 7.7648 \times 0.0239$ / 1.0321, where 1.0321 is the sample mean of $CAAR$). The standardized effect size falls within the range of known determinants of announcement abnormal returns, such as acquirer's Tobins Q (Moeller et al., 2004), with a respective effect of 22.06%. The remaining control variables are in line with the literature. Competed deals and diversifying acquisitions are negatively related to $CAAR$ (Morck et al., 1990; Schwert, 2000; Masulis et al., 2007). Acquisitions paid for with equity are accompanied by lower announcement returns than those paid with cash (Bhagat et al., 2005; Savor and Lu, 2009), small acquirers gain more than large acquirers (Moeller et al., 2004), and the transaction value relative to the acquirers' size is positively associated with $CAAR$ (Asquith et al., 1983).

[7] The results remain significant at the 1% level when we alternatively control for acquirer fixed effects or acquirer-industry $\times$ quarter-year fixed effects, respectively. They are available upon request from the authors.

Overall, the results provide evidence of a positive association between acquirer's cumulative announcement abnormal return and the degree of connectedness among their active institutional blockholders.

3.3 Identification

As in related empirical corporate finance studies, endogeneity is a concern to our inferences. In our setup, violations of the exogeneity condition are likely to result from measurement error or simultaneity. We take several steps to achieve valid inferences about a causal effect of investor centrality or acquirer abnormal announcement returns.

First, we address endogeneity stemming from measurement error by implement robustness tests with regards to measurement of investor centrality. In our main analyses, we proxy for the level of connectedness of a firm's representative active blockholder using scaled degree centrality ($DEGR$). We aggregate this to the firm level using Kempf et al.'s (2017) weighting scheme. To mitigate concerns about the measurement of investor centrality, we use alternative measurements instead. The results are in Table 5.

Insert Table 5 about here

In Panel A of Table 5, we rerun the baseline model, but use alternative centrality measures (see Section 3.2). They comprise unscaled degree centrality ($DEGR\_UNSC$), eigenvector centrality ($EIVEC$), betweenness centrality ($BETW$), and closeness centrality ($CLOSE$). As can be seen from columns (1) – (4), the coefficient estimates on centrality measures remain qualitatively unchanged both in sign and statistical significance. Next, to alleviate concerns over measurement error caused by the process of aggregating investor-level centrality measures at the firm level, in Panel B of

Table 5, we rerun the baseline model, subsequently using all five centrality measures as key explanatory variables but with holding weighting as an alternative weighting scheme. The results are in columns (5) – (9). Similarly, we observe positive and statistically significant estimates at the 1% level across all models. This indicates that our inferences are not sensitive to using alternative network measures and/or alternative weighting schemes. We conclude that endogeneity resulting from error in measurement of investor centrality is not a concern to our inferences.

Next, we address error in measuring acquirer abnormal announcement returns. Our main model is based on three-day CAARs, which we estimate over the (−1, +1) event window and the (−205, −6) estimation window relative to the CRSP equally-weighted benchmark. To test whether our findings are sensitive to alternative measurement of the dependent variable, we re-run the baseline mode but vary the above model parameters. The results are in Table 6.

Insert Table 6 about here

In column (1), we estimate CAARs relative to the CRSP value-weighted benchmark instead of the CRSP equally-weighted benchmark. In column (2), we use market-adjusted returns instead of market model returns. In column (3), we apply both modifications simultaneously, i.e., we estimate value-weighted market-adjusted returns. Models (4) – (5) estimate 5-day and 11-day CAARs over the (−2, +2) and (−5, +5) event windows, respectively. In models (6) – (7), we apply alterative estimation windows. In column (6), we use the (−210, −11) estimation window as in Mansulis et al. (2007). In model (7), we use the (−300, −91) estimation window as in Brooks et al. (2018) and Tunyi (2021). The baseline findings remain qualitatively unchanged across all seven models. This indicates that endogeneity resulting from measurement error in acquirer abnormal announcement returns does not affect our results.

Next, we address endogeneity resulting from simultaneity. We interpret our finding of a positive relation between investor centrality and acquirer abnormal announcement returns as evidence that central institutions *cause* firms to make better acquisitions decisions. However, reverse causality posits that central institutions choose to invest in firms that eventually become successful acquirers. To achieve valid inferences about a causal effect of $DEGR$ on $CAAR$, we avoid simultaneity by regressing contemporaneous values of acquirer abnormal announcement returns on one-quarter lagged explanatory variables in all our analyses. To allay any remaining concern about simultaneity, we utilize plausibly exogenous variation in investor attention (Kempf et al., 2017).

As constructed in Section 3.3, $DEGR\_DIST$ and $DEGR\_ATT$ capture the level of connectedness of a firm's representative distracted and attentive active blockholder, respectively. While attentive investors may exploit their privileged position in the network to monitor managers, distracted investors are unlikely to make any monitoring effort given their temporary inattention on the focal firm. If network centrality proxies for the availability of monitoring information, we should observe variations in $DEGR\_ATT$ to affect $CAAR$, whereas variations in $DEGR\_DIST$ should have no such effect. The underlying idea is that improvements in investor centrality can only mitigate managerial opportunism if investors utilize their privileged position in the network.

To test whether the relation between network centrality and announcement returns in sensitive to exogenous changes in investor attention, we rerun the baseline model but use $DEGR\_DIST$ and $DEGR\_ATT$ instead of $DEGR$. The results are in Table 7.

Insert Table 7 about here

In models (1) and (2), we use $DEGR\_DIST$ and $DEGR\_ATT$ as separate determinants. $DEGR\_DIST$ is insignificant with a coefficient estimate of 1.124, while $DEGR\_ATT$ is statistically significant close to the 1% level ($p = 0.012$) with a coefficient of 6.399. When we apply both measures simultaneously in model (3), the results persist both in sign and magnitude with estimated coefficients of 1.133 and 6.401, respectively. For reference, we also estimate the overall effect of investor centrality on abnormal returns based on the reduced sample in model (4)[8]. We still observe a $DEGR$ coefficient estimate of 8.022, statistically significant at the 1% level.

In terms of economic significance, the $DEGR$ estimate implies that a one-standard-deviation increase in a firm's overall investor centrality (0.0231) increases acquirer abnormal announcement returns by 18.10% relative to the sample mean ($=$ 8.0222 $\times$ 0.0231 / 1.0248, where 1.0248 is the sample mean of $CAAR$). Almost the entire effect can be attributed to network centrality of attentive investors, which facilitate CAARs by 15.74% relative to the sample mean ($=$ 6.4007 $\times$ 0.0252 / 1.0248). Given the lack of significance on the $DEGR\_DIST$ coefficient, there is no discernable effect of distracted investors' centrality on abnormal returns.

The findings indicate that acquirers' active blockholder centrality facilitates abnormal announcement returns if their attention is devoted to the firm. When shareholders are distracted, however, the effect vanishes as they cannot exploit their central position in the network for monitoring purposes. Overall, the results suggest that the baseline effect is causal.

[8] The sample is reduced because we followed Kempf et al. (2017) and removed all observations in the shocked industries to ensure that the distraction measure does not capture extreme industry sector performance (see Section 3.3).

3.4 Heterogeneity across Deal Type and Investors

Next, we substantiate that the effect of investor centrality on abnormal returns is driven by central investors' superior access to monitoring information. If $DEGR$ proxies for information availability, its effect on $CAAR$ should be strongest for information-sensitive (i.e., private) deals. Moreover, it should be most pronounced in the presence of investors that have comparative advantages in exploiting such information to monitor management. That is, the effect should be stronger for independent and long-term investors than for grey and short-term investors (see Section 3.4). To this aim, we rerun the baseline model using alternative deal types and measures of degree centrality aggregated among heterogeneous investor types. The results are in Table 8.

Insert Table 8 about here

We start by splitting our sample of successful acquisitions into private deals (Panel A) and public deals (Panel B) and rerun the baseline model among each subsample. We compare a $DEGR$ coefficient estimate of 18.051, which is significant at the 1% level in column (1), to an estimate of -0.545, which is insignificant in column (4). This indicates that the effect of investor centrality on abnormal returns does not exist per se but only for private deals. It provides initial evidence for the role of information in explaining deal quality.

Next, we estimate the same models but use measures of degree centrality disaggregated by institution type. Both $DEGR\_GREY$ coefficients are insignificant in columns (2) and (5), indicating that—regardless of the deal type—grey investors do not exert any effects on $CAAR$. For $DEGR\_IND$, however, we compare a highly significant coefficient estimate of 13.044 for the subsample of private deals to an insignificant coefficient estimate of -1.603 for the subsample of public deals. A similar pictures emerges when differentiating between network centrality of short-term vis-à-vis long-term investors. As shown in columns (3) and (6), we find no effects of $DEGR\_ST$ on $CAAR$ for both private and public deals, whereas the $DEGR\_LT$ coefficient estimate is positive and highly statistically significant at 10.637 for private deals but insignificant for private deals at 2.311. Unreported Wald-tests indicate that $DEGR\_GREY$ and $DEGR\_IND$ as well as $DEGR\_ST$ and $DEGR\_LT$ differ in magnitude for the subsample of private deals, while the tests fail to confirm the null hypotheses of no significant differences in means for the public deals subsample.

Taken together, our results suggest that only investors with comparative advantages in exploiting monitoring information (i.e., independent and long-term investors) facilitate deal quality, and only for those acquisitions that are considered information-sensitive (i.e., private). The heterogeneity across investors and deal types provides support for the notion that the investor centrality captures information advantages that translate into high-quality acquisitions.

4 Conclusion

Borrowing from the social network literature, we extend the literature on the role of institutional investors and the profitability of corporate acquisitions. Examining 17,207 acquisition decisions of public firms over the 1980–2019 period, we propose blockholder centrality as a novel determinant of acquirer returns. This finding is robust to a variety of firm and deal characteristics, and it also extends to alternative network and return measures. Using plausibly exogenous variation in investor attention, the observed effect seems to be causal. Providing credence to an information-based explanation, further analyses reveal that the effect does only persist in private deals and among investors with advantages in exploiting monitoring-relevant information.

Overall, our results suggest that central blockholders gain an information advantage through the network which increases their monitoring ability and eventually facilitates deal quality. Our study highlights the importance of the blockholder network as a governance mechanism that influences institutional monitoring in general and acquirer returns in particular. The findings shed light on how institutions obtain valuable information and identify a novel determinant of institutional investor monitoring.

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TABLES AND FIGURES

Table 1: Desciptive statistics

The table presents summary statistics of the main variables used in the study. The sample includes all completed mergers and acquisitions by publicly traded U.S. firms listed on SDC where the acquirer gains control of a public, private, or subsidiary target with a deal value exceeding $1 million and 1% of the acquirer's market value. The table depicts the number of observations (N), mean, standard deviation (SD), 25th percentile (P25), median, and 75th percentile (P75). We winsorize all continuous variables at the 1% and 99% percentiles to constrain the impact of outliers. Panel A reports summary statistics of our dependent variable, the 3-day cumulative abnormal announcement return. Panels B, C, D, and E report descriptive statistics of network, ownership, deal and acquirer characteristics, respectively. The sample consists of 17,207 firm-quarter-year observations over the 1980–2019 period.

	N	Mean	SD	P25	Median	P75
Panel A: Cumulative abnormal announcement returns						
$CAAR^{(-1,+1)}$	17,207	1.032	7.107	-2.341	0.502	3.787
Panel B: Network characteristics						
$DEGR$	17,207	0.018	0.024	0.002	0.008	0.022
$DEGR\_UNSC$	17,207	4.800	6.216	0.667	2.378	6.259
$EIVEC$	17,207	0.022	0.022	0.008	0.016	0.029
$BETW$	17,207	0.006	0.010	0.001	0.003	0.007
$CLOSE$	17,207	0.071	0.067	0.019	0.052	0.102
Panel C: Ownership characteristics						
$IHERF$	17,207	0.018	0.022	0.009	0.012	0.018
$FHERF$	17,207	0.122	0.151	0.041	0.065	0.129
$ISIZE$ *(in mil. $)*	17,207	21,554.185	22,943.288	5,956.662	14,549.639	28,566.848
IO_CLIQUE	17,207	0.370	0.195	0.222	0.387	0.514
IO_COMMON	17,207	0.050	0.072	0.000	0.000	0.082
IO_DED	17,207	0.054	0.080	0.000	0.012	0.084
IO_TRA	17,207	0.124	0.103	0.042	0.100	0.181
IO_QIX	17,207	0.258	0.164	0.124	0.245	0.379
Panel D: Deal characteristics						
$COMPETED$	17,207	0.012	0.107	0.000	0.000	0.000
$HOSTILE$	17,207	0.003	0.053	0.000	0.000	0.000
$TENDER$	17,207	0.036	0.187	0.000	0.000	0.000
$CONGLO$	17,207	0.378	0.485	0.000	0.000	1.000
$EQUITY$	17,207	0.154	0.361	0.000	0.000	0.000
$CASH$	17,207	0.281	0.449	0.000	0.000	1.000
$LIQIDX$	17,207	0.042	0.062	0.008	0.023	0.051
$DISTURB$	17,207	0.870	0.336	1.000	1.000	1.000
Panel E: Acquirer characteristics						
$FSIZE$ *(in mil. $)*	17,207	3,588.320	12,877.637	178.234	589.386	2,020.949
$RELSIZE$	17,207	0.150	0.221	0.030	0.067	0.164
OCF	17,207	0.118	0.128	0.054	0.105	0.167
$TOBINSQ$	17,207	2.262	2.134	1.139	1.595	2.443
LIQ	17,207	0.168	0.193	0.029	0.086	0.242
LEV	17,207	0.170	0.184	0.011	0.114	0.277
MTB	17,207	3.617	4.707	1.488	2.334	3.923
$TANGIB$	17,207	0.213	0.226	0.040	0.128	0.306
AGE *(in years)*	17,207	17.639	14.394	7.000	13.000	25.000

Table 2: Investor-level correlations

The table shows pairwise correlation coefficients among investor-level network characteristics and portfolio characteristics. Network characteristics include degree centrality scaled by network potential ($DEGR$), unscaled degree centrality ($DEGR\_UNSC$), eigenvector centrality ($EIVEC$), betweenness centrality ($BETW$), and closeness centrality ($CLOSE$). Institutional investor portfolio characteristics include number of stocks ($NSTO$), total assets reported in 13F filings ($ISIZE$), and portfolio Herfindahl measure ($IHERF$). The coefficients were calculated using quarterly data over the sample period 1980–2019. p-values are in parentheses. Pairwise correlation coefficients that differ significantly from zero at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Network characteristics								
(1) $DEGR$	1.000							
(2) $DEGR\_UNSC$	0.974***	1.000						
	(0.000)							
(3) $EIVEC$	0.821***	0.794***	1.000					
	(0.000)	(0.000)						
(4) $BETW$	0.734***	0.724***	0.668***	1.000				
	(0.000)	(0.000)	(0.000)					
(5) $CLOSE$	0.620***	0.619***	0.682***	0.287***	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)				
Portfolio characteristics								
(6) $NSTO$	0.171***	0.178***	0.151***	0.166***	0.093***	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
(7) $ISIZE$	0.184***	0.188***	0.204***	0.120***	0.206***	0.510***	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
(8) $IHERF$	-0.042***	-0.041***	-0.041***	-0.024***	-0.028***	-0.175***	-0.349***	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Table 3: Univariate statistics

The table reports univariate statistics of the main variables used in this study, sorted by the acquirers' weighted shareholder centrality. The sample includes all completed mergers and acquisitions by publicly traded U.S. firms listed on SDC where the acquirer gains control of a public, private, or subsidiary target with a deal value exceeding $1 million and 1% of the acquirer's market value. Column (1) shows variable means for acquirers held by central institutional investors, while column (2) depicts variable means for acquirers held by decentral institutional investors. We use median $DEGR_{it}$, i.e. Kempf et al. (2017, p. 1669) scaled degree centrality of the overall sample as the threshold to distinguish between centrally and decentrally held acquirers. Column (3) reports the differences in means between both subsamples, and column (4) provides p-values of t-tests where we test for differences in means. Panel A reports univariate summary statistics of our dependent variable, the 3-day cumulative abnormal announcement return. Panels B, C, and D report univariate descriptive statistics of ownership, deal and acquirer characteristics, respectively. The sample consists of 17,207 firm-quarter-year observations over the 1980–2019 period. Means that that differ significantly from each other at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	(1) Central	(2) Decentral	Δ (1) – (2)	p-value Δ
Panel A: Cumulative abnormal announcement returns				
$CAAR^{(-1,+1)}$	1.364	0.695	0.670	0.000***
Panel B: Ownership characteristics				
$IHERF$	0.018	0.018	0.001	0.120
$FHERF$	0.122	0.121	0.001	0.539
$ISIZE$ *(in mil. $)*	17,881.314	25,283.408	-7,402.094	0.000***
IO_CLIQUE	0.378	0.362	0.017	0.000***
IO_COMMON	0.058	0.042	0.016	0.000***
IO_DED	0.064	0.045	0.019	0.000***
IO_TRA	0.137	0.109	0.028	0.000***
IO_QIX	0.230	0.287	-0.057	0.000***
Panel C: Deal characteristics				
$DEALVAL$ *(in mil. $)*	134.991	691.405	-556.414	0.000***
$PRIVATE$	0.535	0.416	0.119	0.000***
$COMPLETE$	64.446	81.416	-16.970	0.000***
$COMPETED$	0.006	0.017	-0.011	0.000***
$HOSTILE$	0.002	0.004	-0.002	0.003***
$TENDER$	0.024	0.048	-0.024	0.000***
$CONGLO$	0.370	0.387	-0.017	0.025**
PCT_STOCK	0.495	0.503	-0.008	0.420
PCT_CASH	0.505	0.497	0.008	0.420
$LIQIDX$	0.043	0.041	0.002	0.036**
$DISTURB$	0.869	0.872	-0.003	0.555
Panel D: Acquirer characteristics				
$FSIZE$ *(in mil. $)*	823.524	6,395.537	-5,572.013	0.000***
$RELSIZE$	0.162	0.137	0.025	0.000***
OCF	0.113	0.124	-0.010	0.000***
$TOBINSQ$	2.284	2.240	0.044	0.179
LIQ	0.193	0.143	0.049	0.000***
LEV	0.168	0.173	-0.004	0.109
MTB	3.538	3.698	-0.161	0.025**
$TANGIB$	0.207	0.219	-0.012	0.000***
AGE *(in years)*	14.027	21.307	-7.280	0.000***

Table 4: Baseline regressions

The table reports results of multivariate OLS regressions of $CAAR^{(-1,+1)}$ on $DEGR$. The dependent variables in all models, $CAAR^{(-1,+1)}$, are the acquirers' 3-day cumulative abnormal announcement returns relative to the CRSP equally-weighted benchmark, calculated over the $(-1, +1)$ event window and the $(-205, -6)$ estimation window. $DEGR$ is institutional blockholders' scaled degree centrality which we aggregate to the firm level using the Kempf et al. (2017, p. 1669) (KMS) weighting factor. The sample includes all completed mergers and acquisitions by publicly traded U.S. firms listed on SDC where the acquirer gains control of a public, private, or subsidiary target with a deal value exceeding \$1 million and 1% of the acquirer's market value. All models include quarter-year fixed effects to control for unobserved heterogeneity across time. No control variables are included in model (1). Models (2), (3), and (4) subsequently control for the vector of investor controls IC, the vector of deal controls DC, and the vector of acquirer controls AC, respectively. In models (5) and (6), we subsequently add acquirer-industry fixed effects and target-industry fixed effects based on the 2-digit SIC code, respectively, to control for time-invariant industry characteristics. The sample consists of 17,207 firm-quarter-year observations over the 1980–2019 period. Heteroskedasticity-robust standard errors are clustered by target nation and the acquirer's two-digit SIC industry, and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: $CAAR^{(-1,+1)}$					
$DEGR$	26.287***	21.392***	16.728***	9.015***	7.680***	7.765***
	(1.166)	(1.555)	(0.990)	(1.253)	(1.268)	(1.376)
Ownership characteristics						
$IHERF$		-12.344***	-10.706***	-3.281*	-2.556	-2.748
		(2.408)	(2.065)	(1.730)	(2.041)	(2.007)
$FHERF$		4.195***	3.875***	1.884***	1.748***	1.777***
		(0.246)	(0.302)	(0.344)	(0.342)	(0.341)
$ISIZE$		-0.400***	-0.362***	-0.113**	-0.126**	-0.135**
		(0.031)	(0.035)	(0.051)	(0.049)	(0.052)
IO_CLIQUE		0.712***	0.236	-1.726***	-1.871***	-1.886***
		(0.226)	(0.172)	(0.296)	(0.249)	(0.269)
IO_COMMON		-2.858***	-1.987***	-2.471***	-1.618***	-1.513***
		(0.249)	(0.348)	(0.471)	(0.493)	(0.504)
IO_DED		0.809*	0.522	2.911***	2.348***	2.234***
		(0.427)	(0.528)	(0.471)	(0.584)	(0.614)
IO_TRA		0.230	0.657	2.045***	1.296**	1.281**
		(0.465)	(0.507)	(0.613)	(0.527)	(0.530)
IO_QIX		-0.588**	-0.977***	1.808***	1.450***	1.418***
		(0.260)	(0.290)	(0.430)	(0.379)	(0.367)
Deal characteristics						
$COMPETED$			-0.408	-0.554*	-0.508	-0.514*
			(0.324)	(0.322)	(0.324)	(0.307)
$HOSTILE$			-0.432	-0.782	-0.669	-0.448
			(0.523)	(0.522)	(0.502)	(0.469)
$TENDER$			-0.727***	-0.691***	-0.766***	-0.778***
			(0.188)	(0.176)	(0.194)	(0.205)
$CONGLO$			-0.209**	-0.197***	-0.267***	-0.378***
			(0.088)	(0.072)	(0.064)	(0.048)

Table 4 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: $CAAR^{(-1,+1)}$					
$EQUITY$			-1.730***	-1.650***	-1.415***	-1.373***
			(0.081)	(0.113)	(0.111)	(0.113)
$CASH$			0.352***	0.515***	0.504***	0.515***
			(0.075)	(0.077)	(0.073)	(0.075)
$LIQIDX$			0.032	-0.866**	-0.631	-0.319
			(0.450)	(0.417)	(0.488)	(0.566)
$DISTURB$			-0.740***	-0.543***	-0.240***	-0.233***
			(0.115)	(0.099)	(0.079)	(0.077)
Acquirer characteristics						
$FSIZE$				-0.418***	-0.394***	-0.382***
				(0.053)	(0.047)	(0.046)
$RELSIZE$				1.892***	1.805***	1.786***
				(0.284)	(0.305)	(0.305)
OCF				-1.732***	-1.757***	-1.835***
				(0.269)	(0.199)	(0.195)
$TOBINSQ$				0.149***	0.126***	0.121***
				(0.034)	(0.035)	(0.032)
LIQ				-0.850***	-1.177***	-1.136***
				(0.222)	(0.256)	(0.248)
LEV				1.396***	1.172***	1.137***
				(0.212)	(0.256)	(0.229)
MTB				0.011	0.011	0.013
				(0.012)	(0.011)	(0.011)
$TANGIB$				0.381	-0.087	-0.044
				(0.281)	(0.216)	(0.208)
AGE				0.171***	0.123***	0.122**
				(0.053)	(0.044)	(0.048)
Quarter-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry (acquirer) FE	No	No	No	No	Yes	Yes
Industry (target) FE	No	No	No	No	No	Yes
R-squared	0.016	0.027	0.037	0.047	0.055	0.059
Adjusted R-squared	0.007	0.018	0.027	0.037	0.041	0.041
Observations	17,207	17,207	17,207	17,207	17,207	17,207

Table 5: Robustness to alternative network measures and weighting schemes

The table reports the results of robustness tests and reruns the baseline model (see column (6) of Table 4) using alternative network measures and/or alternative weighting schemes to aggregate our investor-level network measures to the firm level. The sample includes all completed mergers and acquisitions by publicly traded U.S. firms listed on SDC where the acquirer gains control of a public, private, or subsidiary target with a deal value exceeding $1 million and 1% of the acquirer's market value. The dependent variables in all models, $CAAR^{(-1,+1)}$, are the acquirers' 3-day cumulative abnormal announcement returns relative to the CRSP equally-weighted benchmark, calculated over the $(-1, +1)$ event window and the $(205, -6)$ estimation window. In columns (1)–(4), we use unscaled degree centrality ($DEGR\_UNSC$), eigenvector centrality ($EIVEC$), and betweenness centrality ($BETW$) and closeness centrality ($CLOSE$) instead of scaled degree centrality ($DEGR$), respectively. In Panel B, we do not retain the Kempf et al. (2017, p. 1669) (KMS) weighting factor but alternatively use holding weighting to obtain firm-level measures of the aforementioned network centralities. We include year fixed effects, acquirer-industry fixed effects and target-industry fixed effects in all models to capture unobserved heterogeneity due to aggregate time-series trends and time-constant industry characteristics. Heteroskedasticity-robust standard errors are clustered by target nation and the acquirer's two-digit SIC industry, and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: KMS weighting				Panel B: Holding weighting				
	Dependent variable: $CAAR^{(-1,+1)}$								
$DEGR\_UNSC$	0.035***				0.026***				
	(0.004)				(0.004)				
$EIVEC$		5.272***				5.300***			
		(1.435)				(1.352)			
$BETW$			15.804***				8.575***		
			(3.512)				(1.780)		
$CLOSE$				1.875***				3.231***	
				(0.687)				(0.399)	
$DEGR$									6.611***
									(1.166)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry (acquirer) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry (target) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047
Adjusted R-squared	0.037	0.036	0.037	0.036	0.037	0.037	0.037	0.037	0.037
Observations	17,207	17,207	17,207	17,207	17,207	17,207	17,207	17,207	17,207

Table 6: Robustness to alternative return measures

The table reports the results of robustness tests and reruns the baseline model (see column (6) of Table 4) using alternative return measures. The sample includes all completed mergers and acquisitions by publicly traded U.S. firms listed on SDC where the acquirer gains control of a public, private, or subsidiary target with a deal value exceeding \$1 million and 1% of the acquirer's market value. Models (1) estimates CAARs relative to the CRSP value-weighted benchmark instead of the equally-weighted benchmark. Model (2) uses market-adjusted returns instead of market model returns. Model (3) applies both previous modifications simultaneously, i.e., it estimates value-weighted market-adjusted returns. Models (4)–(5) estimate 5-day and 11-day CAARs over the $(-2, +2)$ and $(-5, +5)$ event windows, respectively. Models (6)–(7) use the $(-210, -11)$ and $(-300, -91)$ estimation windows, respectively. All models include quarter-year fixed effects to control for unobserved heterogeneity across time, as well as industry fixed effects both at the acquirer and the target level and based on the 2-digit SIC code to control for time-invariant industry characteristics. Heteroskedasticity-robust standard errors are clustered by target nation and the acquirer's two-digit SIC industry and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: $CAAR$						
$DEGR$	8.214***	9.098***	9.498***	6.584***	10.499**	6.395***	6.874***
	(1.260)	(1.669)	(1.546)	(1.444)	(4.241)	(1.456)	(1.555)
Model	MM	MA	MA	MM	MM	MM	MM
Benchmark	VW	EW	VW	EW	EW	EW	EW
Event window	$(-1,+1)$	$(-1, +1)$	$(-1, +1)$	$(-2, +2)$	$(-5, +5)$	$(-1, +1)$	$(-1, +1)$
Estimation window	$(-205, -6)$	n/a	n/a	$(-205, -6)$	$(-205, -6)$	$(-210, -11)$	$(-300, -91)$
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry (acquirer) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry (target) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.060	0.067	0.069	0.049	0.042	0.059	0.061
Adjusted R-squared	0.042	0.050	0.052	0.031	0.024	0.041	0.042
Observations	17,207	17,207	17,207	17,207	17,207	17,151	16,280

Table 7: Distracted versus attentive investors' centrality

The table reports results of multivariate OLS regressions of $CAAR^{(-1,+1)}$ on measures of degree centrality where we distinguish between distracted and attentive investors. The dependent variables in all models, $CAAR_{(-1,+1)}$ are the acquirers' 3-day cumulative abnormal announcement returns relative to the CRSP value-weighted benchmark, calculated over the $(-1, +1)$ event window and the $(-205, -6)$ estimation window. $DEGR$ is active institutional blockholders' scaled degree centrality which we aggregate to the firm level using the Kempf et al. (2017, p. 1669) weighting factor. It presents the results of re-running the baseline model (see column (6) of Table 4), where we use the median to distinguish between distracted and attentive investors in each firm-year and industry, based on the Kempf et al. (2016) distraction measure. The sample includes all completed mergers and acquisitions by publicly traded U.S. firms listed on SDC where the acquirer gains control of a public, private, or subsidiary target with a deal value exceeding $1 million and 1% of the acquirer's market value. We remove all observations in the shocked industries to ensure that the distraction measure does not capture extreme industry sector performance. In columns (1) and (2), we calculate firm-level degree only among the subsamples of distracted ($DEGR_DIST$) or attentive ($DEGR_ATT$) investors, respectively. In model (3), we apply both measures simultaneously. We do not distinguish between distracted and attentive investors in model (4) but use the overall network centrality measure $DEGR$ instead. All models include quarter-year fixed effects to control for unobserved heterogeneity across time, as well as industry fixed effects both at the acquirer and the target level and based on the 2-digit SIC code to control for time-invariant industry characteristics. We perform a Wald test to determine whether the $DEGR\_ATT$ coefficient exceeds the $DEGR\_DIST$ coefficients in magnitude. Heteroskedasticity-robust standard errors are clustered by target nation and the acquirer's two-digit SIC industry and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

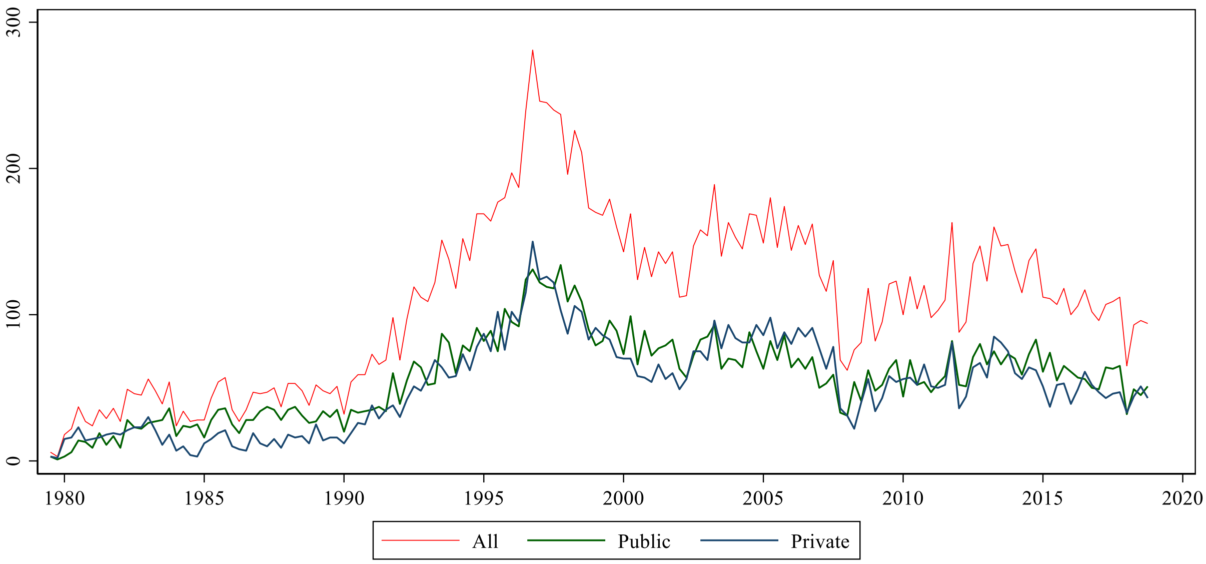
	(1)	(2)	(3)	(4)
	Dependent variable: $CAAR^{(-1,+1)}$			
$DEGR\_DIST$	1.124		1.133	
	(2.210)		(2.195)	
$DEGR\_ATT$		6.399**	6.401**	
		(2.423)	(2.485)	
$DEGR$				8.022***
				(2.520)
Controls	Yes	Yes	Yes	Yes
Quarter-year FE	Yes	Yes	Yes	Yes
Industry (acquirer) FE	Yes	Yes	Yes	Yes
Industry (target) FE	Yes	Yes	Yes	Yes
R-squared	0.068	0.069	0.069	0.069
Adjusted R-squared	0.045	0.045	0.045	0.045
Observations	12,968	12,968	12,968	12,968

Table 8: Heterogeneity across deal type and investors

The table reports results of multivariate OLS regressions of $CAAR^{(-1,+1)}$ on measures of degree centrality where we distinguish between investor and deal types. The dependent variables in all models, $CAAR_{(-1,+1)}$, are the acquirers' 3-day cumulative abnormal announcement returns relative to the CRSP value-weighted benchmark, calculated over the $(-1, +1)$ event window and the $(-205, -6)$ estimation window. $DEGR$ is active institutional blockholders' scaled degree centrality which we aggregate to the firm level using the Kempf et al. (2017, p. 1669) (KMS) weighting factor. The sample includes all completed mergers and acquisitions by publicly traded U.S. firms listed on SDC where the acquirer gains control of a public, private, or subsidiary target with a deal value exceeding $1 million and 1% of the acquirer's market value. We analyze private deals in Panel A and public deals in Panel B. Models (1) and (4) do not distinguish between different investor types but use the overall network centrality measure DEGR instead. In columns (2) and (5), we distinguish between grey ($DEGR_GREY$) and independent ($DEGR_IND$) investors. In columns (3) and (6), we calculate firm-level degree among short-term ($DEGR_ST$) and long-term ($DEGR_LT$) investors. All models include quarter-year fixed effects to control for unobserved heterogeneity across time, as well as industry fixed effects both at the acquirer and the target level and based on the 2-digit SIC code to control for time-invariant industry characteristics. We perform a Wald test to test for significant differences among investor types. Heteroskedasticity-robust standard errors are clustered by target nation and the acquirer's two-digit SIC industry and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

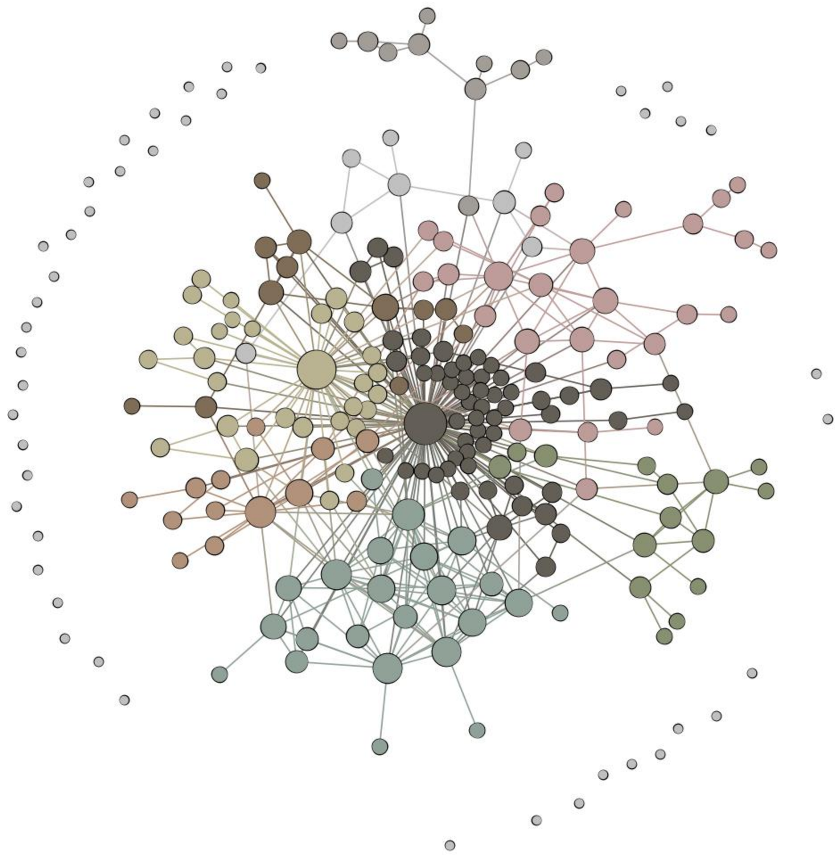
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Private deals			Panel B: Public deals		
	Dependent variable: $CAAR^{(-1,+1)}$					
$DEGR$	18.051***			-0.545		
	(3.780)			(2.695)		
$DEGR\_GREY$		-1.745			-10.469	
		(6.049)			(8.575)	
$DEGR\_IND$		13.044***			-1.603	
		(2.180)			(2.364)	
$DEGR\_ST$			1.870			-1.043
			(2.591)			(1.815)
$DEGR\_LT$			10.637***			2.311
			(2.582)			(3.325)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry (acquirer) FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry (target) FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.076	0.075	0.070	0.093	0.096	0.094
Adjusted R-squared	0.039	0.036	0.032	0.060	0.062	0.061
Observations	8,189	7,871	7,854	9,013	8,804	8,789

Figure 1: Number of acquisitions by announcement quarter-year



The figure shows the number of acquisitions by announcement quarter-year over the 1980–2019 study period. The sample includes all completed mergers and acquisitions by publicly traded U.S. firms listed on SDC where the acquirer gains control of a public, private, or subsidiary target with a deal value exceeding $1 million and 1% of the acquirer's market value. The red line depicts the overall number of acquisitions while the green and blue lines indicate acquisitions of public or private targets, respectively.

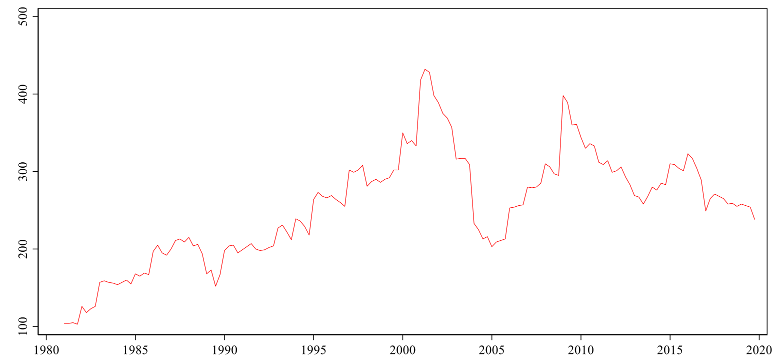
Figure 2: Visualization of the active institutional blockholder network



The figure visualizes the network formed by active institutional investors with blockholdings in the same firms as of 2019Q4. Circles on the graph indicate nodes, i.e., active institutional blockholders. Lines indicate ties, i.e., whether two active institutional blockholders are connected to eachother through investments in the same firms. The circle size scales with $DEGR$, i.e., the number of connections an investor has relative to the maximum possible number of connections. Colors represent modularity, i.e., different clusters.

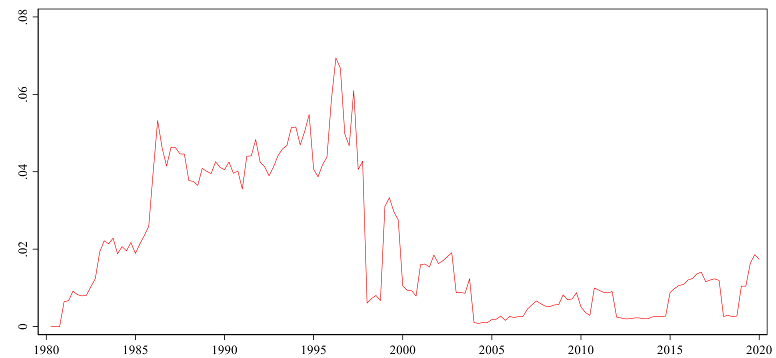
Figure 3: Network potential and average degree centrality

(a) $DEGR\_UNSC_{kt}$



(b) $N_t - 1$

(c) $DEGR_{kt}$



(d) $DEGR_{iq}$

The figure shows the network potential as well as average values of degree centrality at the investor and firm level over the 1980–2019 sample period. Figure 1a reports average investor-level degree centrality in absolute terms ($DEGR\_UNSC_{kt}$)—that is, the number of direct connections to other investors. Figure 1b shows network potential ($N_t - 1$)—that is, the maximum number of connections any investor can have. Scaling $DEGR\_UNSC_{kt}$) by $N_t - 1$ results in the normalized degree centrality ($DEGR_{kt}$), as shown in averages at the investor level in Figure 1c. Figure 1d reports averages of the normalized degree centrality at the firm level ($DEGR_{iq}$). Kempf et al. (2017, p. 1669) weighting factors are applied to aggregate investor-level measures at the firm level.