Social Connections and Information Leakage: Evidence from Target Stock Price Run-Ups in Takeovers

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This version: June, 2017

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Abstract

We propose that information leakage in a target's social networks contributes to the increase in its stock price prior to a merger announcement (hereafter, target run-up). Our findings show that a target with better social connections indeed experiences a higher pre-announcement target run-up. However, the social-connection effect does not exist during the merger announcement, after the announcement, or in windows two months prior to the announcement. We further find that the social-connection effect is more pronounced among targets with more severe asymmetric information or weaker corporate governance. It is weaker when public information about an upcoming merger is available prior to the merger announcement, such as when the bidder accumulates more than five percent of the target's share or when there are news reports on the merger prior to the announcement. The target social-connection effect is also weaker in tender offers, probably because targets are unaware of upcoming tender offers prior to their announcements. Overall, our results show that private information on an upcoming merger can be leaked and transmitted via a target's social networks prior to its announcement, thereby causing target stock price run-up.

1. Introduction

Target stock prices typically increase substantially prior to merger announcements.[1] This price increase attracts considerable public attention because it is usually perceived to be associated with the leakage of inside information. In recent years, in fact, the Securities and Exchange Commission (SEC) has charged numerous individuals and entities with trading on inside information about potential mergers and acquisitions (M&As).

One of the common themes of these SEC cases is leakage of confidential information via social connections prior to merger announcements. In many cases, senior executives or board members initiate the leaks, which spread among social networks that are either directly or indirectly linked to them. For example, in a case filed on September 20, 2012, the SEC alleged that a former board member of the Mercer Insurance Group shared confidential information with a business associate about Mercer's negotiations regarding the company's acquisition by United Fire. This business associate later shared the information with his golfing partner, and together they made more than $83,000 by trading on the information.[2] In another case filed on August 18, 2014, the SEC alleged that a then senior vice president at Eastern Bank told a fellow golfer with whom he socialized at a local country club about his bank's intention to acquire Wainwright Bank & Trust Company.[3] These and other SEC cases suggest that confidential information about upcoming mergers can leak and spread through the social connections of senior executives and board members prior to merger announcements.

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[1] See, for example, Asquith (1983); Asquith, Bruner, and Mullins (1983); Dennis and McConnell (1986); Dodd (1980); and Keown and Pinkerton (1981).
[2] See SEC press release "SEC Charges Three in North Carolina with Insider Trading" at www.sec.gov.
[3] See SEC press release "SEC Charges Former Bank Executive and Friend with Insider Trading Ahead of Acquisition" at www.sec.gov.

A bidder typically pays a substantial premium for a target.[4] Thus, people who find out about an upcoming merger through their social networks prior to a merger announcement can profit by buying the target stock ahead of the announcement.[5] However, an empirical question so far unanswered in the literature is whether the above-cited and similar anecdotes about social connections and pre-announcement information leakage reflect special situations, during special time periods, for special firms — or whether they reflect the general reality of M&As. The goal of this paper is to find the answer. Specifically, we study how target social connections affect target stock price run-ups (hereafter "target run-up"). We also test the information dissemination explanation that private information transmitted via the social networks of executives and directors drives target run-up.

We first hypothesize that targets whose executives and directors have more widespread social connections experience stronger stock price run-ups prior to merger announcements. This is because any confidential information on an upcoming merger can be leaked and disseminated more widely if the target's executives and board directors are socially better connected. To test this hypothesis, we measure the work, school, or other social ties (such as country club memberships and participation in nonprofit organizations) for each target's senior executives and directors. We discuss the calculation of the social-connection variables in detail in section 2.[6] We

[4] Schwert (1996) documents that between 1975 and 1991, a target experienced on average a cumulative abnormal return of 23.1% in the window of trading days from two months prior to a merger announcement to six months after the announcement. Using a more recent sample from 1984 to 2004, Chatterjee, John, and Yan (2013) find that the average cumulative abnormal target stock is 30.4% in the window from three months prior to six months after the merger announcement. They also find that the premium of the offer price over the stock price on trading day -63 is, on average, 62.4%.

[5] It is worth noting that the aim of this study is not to discuss the legal context of the increase in the pre-announcement target stock prices. It is beyond the scope of this study to identify whether disseminating information in social networks prior to merger announcements is illegal and constitutes insider trading.

[6] Our social-connection variables capture only the connections in a target's direct social network. However, these variables can also proxy for the target's indirect connections beyond its direct social network. Any social peer in the target's direct network can also serve as an intermediary to social peers in other networks to which he or she belongs. Thus, if a target has many direct social connections, information can also spread more widely to other social networks

calculate target run-up as the increase in the target stock's price in the week(s) prior to the merger announcement. This calculation generally follows the definition in the literature (e.g., Schwert 1996), which defines target stock price run-up as the increase in a target stock's price between the pre-announcement date, when the price is unaffected by the upcoming merger, and the announcement date.

Our empirical findings are consistent with our hypothesis. They show that target run-up prior to a merger announcement is significantly higher if the target's top executives and board members are more socially connected. For example, our sorted portfolio results suggest that when the degree of a target's social connections increases from the bottom quintile to the top quintile, its cumulative abnormal returns (*CAR*s) increase by 4.24% in window [-16, -2] (i.e., a three-week trading-day window from the 16th to the second trading day prior to the merger announcement). These results are robust to the control of various target firm characteristics and industry and year dummies. They hold even after we use the death of a board member or an executive as an exogenous event to control for any potential endogeneity in our estimation. We also find that the positive effect of target social connections on target stock price run-up does not exist prior to day -42 (i.e., two months prior to the merger announcement), nor does it exist after the merger announcement. Thus, the social-connection effect on target price run-up exists only during the short window prior to a merger announcement.

Next, we propose and test an information dissemination explanation that the target's social networks transmit inside information about an upcoming merger prior to a merger announcement. The information could be direct information about an upcoming merger, such as confirmation of the merger or the stand-alone value of the target determined during the due diligence. It could also

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not directly linked to the target. Our previous example of the Mercer Insurance Group provides anecdotal evidence that information can easily spread outside a firm's direct social network.

be indirect information helpful for estimating the probability of a merger. With inside information, some network members could then buy the target's stock prior to the merger announcement, in anticipation of an increase in the target's stock price once the merger is announced. This pre-announcement increase in stock purchases leads to a pre-announcement run-up in the target's stock price.

We run four tests on this information dissemination explanation. First, we study the cross-sectional variation in the effect of target social connections on target run-up from the perspective of information asymmetry. Leakage of private information is more likely and more pervasive if a firm's insiders, such as its executives and directors, have more private information than do outside investors. Thus, if private information leaked in social networks indeed drives how targets' social connections affect target run-up, then we expect the social-connection effect to be more pronounced for targets facing more information asymmetry.

Our findings are consistent with this expectation. We find that the positive effect of target social connections on target run-up is more pronounced for targets with higher analyst forecast dispersion, higher analyst forecast error, or higher stock return volatility (i.e., targets with more information asymmetry).

Second, we test the information dissemination explanation from the corporate governance perspective that strong corporate governance can mitigate information leakage. We find that the positive effect of target social connection on target run-up is less pronounced when institutional investors hold a larger fraction of the target's stock. Institutional investors may have more incentive to monitor a firm and be more effective at doing so compared to retail investors.[7] In this sense, our finding is consistent with the information dissemination explanation, suggesting that

[7] See, for example, Shleifer and Vishny (1986); Huddart (1993); Admati, Pfleiderer, and Zechner (1994); Maug (1998); Edmans and Manso (2011); and McCahery, Sautner, and Starks (2016).

information leakage through target social connections is less likely to happen in better-governed firms.[8]

Third, we find some evidence (although somewhat weak) that a positive social-connection effect does not exist when public information on the upcoming merger is available in the capital markets, such as when the bidder accumulates at least five percent of a target's shares prior to the merger announcement (so that the bidder must file a Schedule 13D with the SEC) or when news reports are available prior to the merger announcement. These results suggest that the information causing the social-connection effect is related to the upcoming merger.

Fourth, we find that the positive social-connection effect does not exist for tender offers. In those situations, the target is typically unaware of an upcoming tender offer before it is announced by the bidder. Thus, any information leakage about an upcoming tender offer is unlikely to occur in the target's social networks prior to the announcement of the tender offer. The above findings on information availability to either the target's outsiders or insiders support the information dissemination explanation.

Jarrell and Poulsen (1989) suggest that target stock price run-ups may result from market speculation, such as rumors and "street talk." Thus, an alternative explanation for our results is that market speculation transmitted via social networks drives target run-up. Such an explanation, however, is no different from our information dissemination explanation if social peers speculate on inside information disseminated via social networks. However, it is also possible that investors

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[8] It is also possible that the negative effect of institutional investor holding on information leakage is due to the information advantage enjoyed by institutional investors over retail investors. Institutional investors are more informed and have more access to the information helpful to predict a merger. They are also more skillful and resourceful to analyze the information to more accurately predict a merger. Thus, information transmission through a target's social networks could help the target's social peers gain less information advantage over institutional investors and more over retail investors. In other words, any private information on an upcoming merger disseminated through social networks is less profitable for the target's social peers and induces fewer trading prior to the merger announcement if the target has more institutional investors and less retail investors holding its stock. This possibility is also consistent with our information dissemination explanation.

can anticipate merger announcements from publicly available information such as 13D filings (filed with the SEC when more than five percent of a target firm's stock is acquired). If so, this market-speculation explanation differs from our information dissemination explanation, because the former focuses on public and the latter focuses on inside information.

We argue that our earlier findings on information asymmetry and the social-connection effect are inconsistent with the market-speculation explanation. Outside investors can better anticipate upcoming mergers based on public information when they face less severe information asymmetry. Thus, if market anticipation from public information does indeed drive target run-up, we expect the effect of social connections on target run-up to be stronger for targets facing less severe asymmetric information. However, our earlier results on information asymmetry contradict this expectation.[9]

Finally, we also study how bidder social networks affect changes in pre-announcement target stock prices, as well how target social networks affect changes in pre-announcement bidder stock prices. We find little empirical impact from these studies. We discuss these results in detail later.

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[9] Our results suggest that the information leaked in social networks could cause target run-up by inducing network members to revise their expectations on the likelihood and value of a future merger. Alternatively, one may argue that the impacts of social connections unrelated to leaked information could drive investors' expectations on the likelihood and value of a future merger. In particular, a firm's strong social connections could enhance the trustworthiness of potential bidders on the firm. Or it could reduce the cost of information exchange between the firm and potential bidders. Both the enhanced trustworthiness and reduced cost of information exchange could facilitate a valuable merger to occur. However, we argue that this alternative argument is unlikely to explain our results. Social connections themselves, as well as the trustworthiness and the reduced cost of information exchange associated with them, are public information that should be fully incorporated in pre-merger stock prices. This public information should not drive any change in pre-merger stock prices such as target run-up. Instead, any change in pre-merger stock prices should be caused by new information. It is possible that a firm adds new social connections prior to merger announcements, which could change the firm's trustworthiness or cost of information exchange. However, we find in unreported tests that target social connections do not change significantly in months prior to takeover announcements. Unlike this alternative argument, our explanation is that the new information is about the upcoming merger, because the changes in pre-merger prices related to social connections occur only in the windows immediately prior to merger announcements but not in two months prior to merger announcements.

The remainder of the paper is organized as follows. We discuss the relationship of our study to the literature in Section 2. In Section 3, we discuss our sample construction and present variable definitions. In Section 4, we study the effect of social connections on target stock price run-up. The information dissemination explanation for the social-connection effect is examined in Section 5. In Section 6, we study the effect of bidder social connections on target price run-up. Section 7 concludes the paper.

2. Relationship of the Study to the Literature

Our paper contributes to the large amount of literature on corporate takeovers, particularly the literature on mergers and insider trading. For example, Keown and Pinkerton (1981) examine a sample of over 200 U.S. takeovers and show that the pre-announcement target price run-up is a result of widespread, illegal trading on inside information. Meulbroek (1992) finds supporting evidence that almost half of observed target run-ups occur on days when insiders are trading. Similarly, Chakravarty and McConnell (1997) document a positive and significant relationship between insider trades and pre-announcement target run-ups. A more recent study by Augustin, Brenner, and Subrahmanyam (2016) also estimates that 25 percent of M&A announcements are preceded by illegal insider trading in equity options. Xin, Shekhar, Tam, and Yao (2015) further suggest that, due to concerns about information leakage, acquirers usually avoid sharing M&A advisors with other firms in the same industry. Bhattacharya (2014) provides an overview of the literature on insider trading. While previous studies primarily focus on the existence of insider trading, our paper focuses on social networks as an important channel for information leakage (and potentially for insider trading) prior to a merger announcement.

There is also a large amount of literature on insider trading in nonmerger situations. The most closely related paper is Ahern (2016), which examines a sample of illegal insider trading cases filed by the SEC and the Department of Justice (DOJ). Ahern (2016) finds that social relationship plays an important role in these cases. Our paper is different in three ways, however. First, our paper studies information leakage from the perspective of targets in M&As; Ahern (2016) studies it from the perspective of insider traders. Accordingly, our paper sheds light on which firm characteristics contribute to information leakage, such as information asymmetry, retail investor holdings, etc. In comparison, Ahern (2016) focuses on the demographic profile of insider traders.

Second, while Ahern's (2016) sample consists of only the cases brought by the SEC and DOJ, our sample includes both the charged and the uncharged cases. We also provide evidence that the positive impact of target social networks on target run-up holds even after we remove all charged cases and keep only the uncharged cases.[10] Thus, our paper generalizes to a larger population of information-leakage cases beyond the illegal and charged insider trading cases. Our findings point out the possibility of information leakage even in merger deals not involving SEC and DOJ charges.

Third, while Ahern (2016) shows that the leaked information in the charged cases tends to flow from the lower-status members in social hierarchies to the higher status members, we show that leaked information could flow laterally among network members with similar (and the highest) social status in firm hierarchies. Thus, information leakage is more widespread and beyond the social connections that have been charged by the SEC.

Our paper also contributes to the literature on target run-up and mark-up in M&As. Target mark-up can be viewed as the offer price premium over the target stock price immediately prior to

[10] Our sample also differs from Ahern's (2016) sample in that ours consists of only M&As, but Ahern's (2016) sample consists of both M&A tips and nonmerger tips (such as earnings tips).

the merger announcement. It is often calculated in the literature as the target stock return in certain post-announcement windows. We find that target social connections have little effect on the target's stock returns in post-announcement windows (i.e., the post-announcement mark-up). This insignificant effect is in contrast to the positive effect of target social connections on the pre-announcement target run-up.

Our findings on both run-up and mark-up are consistent with those in Schwert (1996). Schwert (1996) finds that the increase in the pre-announcement target stock price is of similar magnitude to the increase in the final offer price, so that the post-announcement mark-up is unaffected by the pre-announcement run-up (see also Betton, Eckbo, and Thorburn, 2008). His interpretation of this "mark-up pricing" phenomenon is that both the pre-announcement target stock price and the offer price increase in response to the new public information on the target's stand-alone value. Our findings are consistent with the mark-up pricing argument in that the private information disseminated in social networks could be related to the target's stand-alone value discovered during due diligence. The private information may induce a bidder to mark up its final offer price, but at the same time, the pre-announcement target stock price would increase if the information leaks in social networks prior to the merger announcement. The post-announcement mark-up would remain unchanged when both the pre-announcement target stock price and the final offer price increase in response to the private information on the target's stand-alone value.

Another line of thought on target run-up and mark-up in the literature is that the information incorporated in target run-up may be based on rumors regarding the upcoming merger. If so, the pre-announcement target stock price would increase. The offer price would remain unchanged, because there is no change in the bidder's valuation of the target's stand-alone value and the synergy. As a result, the pre-announcement target run-up would substitute for the post-announcement mark-up (see, e.g., Betton, Eckbo, and Thorburn, 2008). Our findings could also be consistent with this substitution argument in that the information leaked in social networks prior to the merger announcement could also be the private information on the upcoming merger. In a perfect world, if a bidder can infer and prove that leaked information on the upcoming merger drives the pre-announcement target run-up, the bidder could negotiate its offer price to be unchanged (as predicted by the substitution argument). However, in reality, the bidder is likely to be uncertain about the cause of target run-up and cannot assume the existence of insider trading during its negotiations with the target. This is especially the case when traders with leaked information commonly disguise their trading to avoid hefty SEC penalties in the future. In this case, if the bidder perceives the pre-announcement target run-up as reflecting new, unknown information, it may increase its final offer price in response to the run-up. As a consequence, the post-announcement mark-up would remain unchanged.

Our paper is also related to the role of social networks in M&As. For example, Ishii and Xuan (2014) document that social ties between bidders and targets in M&As negatively affect short-run merger performance. In contrast, Cai and Sevilir (2012) document that the connections between bidders and targets through common directors can benefit bidders via value creation. Recently, El-Khatib, Fogel, and Jandik (2015) show that the position of a bidder's CEO in his/her social network is also significant in M&As. Our paper differs in that it focuses on the general social connections on the target side rather than on a bilateral connection between bidder and target (as in both Ishii and Xuan, 2014, and Cai and Sevilir, 2012) or on connections on the bidder side (as in El-Khatib, Fogel, and Jandik, 2015). Moreover, our paper studies information leakage in social networks to nontransacting parties rather than information exchanges between transacting parties, as in the previous studies.

An important stream of literature also studies the role social networks play in various investing and financing decisions other than M&As. Most studies focus on the role of social networks to facilitate information transmission.[11] Some studies focus on the effect of social connections on corporate governance,[12] and others on the transmission of knowledge in social networks.[13] The above-cited studies focus on various bilateral connections between transacting parties, which is a different focus from that of our study.

3. Sample Construction and Variable Definition

3.1. Social network sample

We obtain the firm social network data from the BoardEx database, as provided by Management Diagnostics Limited. The BoardEx database provides biographical information on executive-level leadership and board members of public companies in the United States and Europe. The biographical information includes demographic information (date of birth, date of death, gender, nationality), employment information (workplaces and job title), educational information (school, degree, and major), and other social information, including club memberships, professional associations, and charities.

[11] For example, Engelberg, Gao, and Parsons (2012) find that social ties between firms and commercial banks can help firms obtain larger loans and better loan terms from connected commercial banks. Cohen et al. (2008) show that social connections between firms and mutual fund managers help those fund managers trade more profitably. Cai et al. (2016) document higher costs of trading stocks of firms that are more connected to the traders.

[12] For example, studies show that CEO-director connections (see, e.g., Hwang and Kim, 2009; Fracassi and Tate, 2012; Nguyen, 2012; and Chidambaran, Kedia, Prabhala, 2012) and CEO-fund connections (e.g., Butler and Gurun, 2012) are associated with a weaker corporate governance. Recently, Schmidt (2015) considers the joint effect of both information exchange and weak corporate governance on corporate policies.

[13] For example, firms with connected boards are more likely to adopt similar governance structures (Davis, 1991 and Davis and Greve, 1997) or similar accounting techniques (Reppenhagen, 2010, and Bizjak, Lemmon, and Whiteby, 2009). They are also more likely to manage earnings and thereby more likely to restate earnings or be sued for fraud (Chiu, Teoh, and Tian, 2013; and Fich and Shivdasani, 2007). Hochberg et al. (2007) show venture capital (VC) syndication networks help improve VC performance.

Based on this information, we identify school ties, work ties, and other social ties for individuals in the BoardEx sample. We identify a school tie when two individuals graduated within a year of each other from the same school or received the same professional (J.D. or MBA), master, or doctoral degree. Restricting graduation year and degree maximizes the possibility that the individuals know one another as a consequence of their respective educations (Fracassi, 2016). A work tie is identified when two individuals have been employed by the same company. An "other" social tie is identified when two individuals hold memberships in the same country club, charity, or governmental or other nonprofit organization. For ties through nonprofit organizations, we also require the individuals to hold ranking titles in those organizations, such as "trustee," "president," "advisor," or "board member." This requirement ensures active and engaged membership, and thus increases the likelihood of a social connection.

We next examine the starting and ending dates for the three types of ties. We drop work ties and social ties that end five years before our testing year, as we believe that most individuals linked through work and other social contexts are less likely to maintain their connections five years after the conclusion of their ties. However, we do not impose such a restriction on school ties, as individuals often maintain connections with their classmates after graduation, through alumni networks and other university social events.

Finally, we calculate a firm's social connections based on the three ties among top executives and directors (i.e., the individuals with high-level job titles) (Fracassi, 2016). Our final sample of social connections consists of 6,940 firms and 59,962 firm-years from 1999 to 2010.

To address any potential endogeneity concern, we also construct the sample of deaths of directors and senior executives. The sample of deaths covers 1,546 firms and 1,816 deaths of senior executives and directors.

3.2. Merger sample

We obtain our initial merger sample from Securities Data Corporation's (SDC) U.S. mergers and acquisitions database. We include in the merger sample both completed and failed mergers from 1999 to 2010. We match the merger sample to Standard & Poor's Compustat files to extract financial statement information; to the Center for Research in Securities Prices (CRSP) to extract stock prices and stock trading volume; to the Institutional Brokers Estimate System (IBES) to extract data on analyst coverage; and finally to the CDA/Spectrum Mutual Funds Historical Files to extract data on mutual fund holdings. We then clean our merger sample based on the following criteria: 1) the target is a publicly traded firm with stock price data available; 2) the bidder acquires more than 50% of the shares of the target at the announcement date; 3) the deal value is above $10,000; 4) SDC classifies the deal as either successful, unconditional, or withdrawn. Our merger sample consists of 1,926 mergers.

Finally, we match our merger sample to the sample of social connections. Our final sample consists of 377 publicly traded target stocks. Table 1 reports the annual breakdown on the number of mergers and the mean and the median of target market capitalizations. In our empirical analysis, we may miss part of the final sample because of incomplete information on certain variables.

3.3. Measuring firm social connection

A central point of interest in our study is firm social connection. We use four variables to measure how a firm's senior management and board members are socially connected to their peers in other firms. The first variable is *Degree*, measuring the sum of all direct connections a firm has with other firms in the network covered by the BoardEx database. It is calculated as the logarithm of the number of a firm's connections normalized by the highest possible number of connections a firm could have in the network of BoardEx firms. We denote $c(i)$ as the number of firm i's connections and *n* as the number of firms in the network; *n -1* is the number of all other firms that a firm could be connected to in the network. *Degree* for firm *i* is:

$$Degree(i) = Log(\frac{100 \times c(i)}{n-1}). \qquad (1)$$

The second variable is *Closeness*, measuring a firm's ability to interact quickly with the other firms in the network (i.e., how closely the firm is connected to other firms). Two firms are more closely connected if there are fewer intermediary firms between them. In particular, *Closeness* is calculated as the logarithm of the inverse of the sum of graph theoretic distances from a firm to all other firms, normalized by the inverse of the smallest possible graph theoretic distance a firm could have. We can obtain the smallest graph theoretic distance if a firm is directly connected to all other firms without any intermediaries (i.e., *n-1*). We define *U* as the set of all firms in the network other than firm *i* and *d(i, j)* as the number of edges in the shortest path connecting firms *i* and *j*. Then *Closeness* of firm *i* is defined by:

$$Closeness(i) = Log(\frac{100 \times (n-1)}{\sum_{j \epsilon U} d(i,j)}) \; . \qquad (2)$$

The third variable is *Betweenness*, measuring a firm's ability to serve as an intermediary between the connections of any two other firms. It is calculated as the logarithm of the sum of all possibilities that a firm can serve as an intermediary between all possible firm pairs' shortest connections, normalized by the number of all possible firm pairs. In particular, *Betweenness* of firm *i* is defined by:

$$Betweenness(i) = Log(\frac{100 \times \sum_{j \cong k \;\&\; j,k \epsilon U} \frac{m(j,k;i)}{m(j,k)}}{(n-1)(n-2)/2}) \; , \qquad (3)$$

where *m(j, k; i)* is the number of the shortest paths between firms *j* and *k* through firm *i*, and *m(j, k)* is the number of the shortest paths between *j* and *k*. We denote $(n-1)(n-2)/2$ as the maximum number of possible firm pairs that can go through firm *i* in the network of *n* firms.

Finally, we also use common-factor analysis to construct *Social Connection Factor* (*SCF*) to capture the common factor among the three social-connection variables (*Degree, Closeness*, and *Betweenness*). We present in Table 2 the results of the common-factor analysis. We present in Panel A starting communalities, calculated as the squared multiple correlations from the regression of *Degree, Closeness*, or *Betweenness* against the other two connection variables. Panel B reports the eigenvalues of the reduced correlation matrices. According to Harman (1976), the number of factors needed to approximate the original correlations among individual measures is equal to the number of summed eigenvalues needed to exceed the sum of communalities. In our sample, the summed communalities are less than the eigenvalues for the first factor in the factor analysis, suggesting that one factor will be sufficient to explain the intercorrelations among *Degree, Closeness*, and *Betweenness.* Thus, we calculate *SCF* based on the first factor in the factor analysis. We report in Panel C the correlations between *SCF* and the three social-connection variables used to calculate *SCF*. The summary statistics of *SCF* are reported in Panel D.

3.4. Construction of the other variables

We calculate targets' cumulative abnormal stock returns (*CAR*s) in the following pre-announcement event windows: the one-week trading-day window [-6, -2], the two-week trading-day window [-11, -2], the three-week trading-day window [-16, -2], and the four-week trading-day window [-21, -2]. We also calculate *CARs* in the three-day window [-1, 1] around merger announcements and four post-announcement event windows: the one-week window [2, 6], the two-week window [2, 11], the three-week window [2, 16], and the four-week window [2, 21]. Here, day 2 stands for the second trading day after the merger announcement date; day -2 stands for the second trading day prior to the merger announcement date, etc. We calculate the abnormal returns using standard event-study methodology. In particular, we first estimate the market model parameters for each target, using daily returns over the event-day window [-250, -42] relative to the merger announcement date. We use these market model parameters to estimate daily abnormal stock returns. We then cumulate daily abnormal target returns to compute target *CAR*s in the above event windows.

We also calculate the following control variables. Book-to-market ratio (*BM*) is calculated as the logarithm of the book value of equity divided by the market value of equity. The book value of equity is the book value of stockholders' equity plus deferred taxes and investment tax credit (if available), minus the book value of preferred stock at the end of the last fiscal year. Depending on availability, we use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. The market value of equity is calculated at trading day -42. Firm size (*Size*) is the logarithm of market capitalization at day -42. Lagged return (*Past Return*) is the cumulative abnormal stock returns in trading-day window [-250, -42]. The Amihud illiquidity ratio (*Amihud Illiquidity*) is the ratio of daily absolute stock return to daily dollar trading-volume averaged in window [-250, -42]. The Amihud illiquidity ratio is scaled by 10^3.

Our first two information asymmetry variables are the dispersion of financial analysts' forecasts of a firm's one-year-ahead earnings (*Dispersion*) and the error in financial analysts' earnings forecasts (*Forecast Error*). Analyst forecast dispersion is the standard deviation of analysts' earnings forecasts on the last reporting date prior to the merger announcement date, scaled by the market price at day -42. Forecast error is the absolute value of the difference between mean earnings forecasts and actual earnings per share on the last reporting date prior to the merger announcement date, scaled by the market price at day -42. We code *DISPERSION* and *ERROR* as missing if there are fewer than three financial analysts covering the firm. Information asymmetry between the firm and outside investors could induce both forecast error and analyst dispersion.

Higher forecast error or analyst dispersion indicates higher information asymmetry (Thomas, 2002, and Krishnaswami and Subramaniam, 1999). Our third information asymmetry variable is the volatility of daily market-adjusted stock returns in window [-250, -42]. Higher idiosyncratic stock return volatility is associated with higher information asymmetry (Krishnaswami and Subramaniam, 1999).

To study institutional investor holdings, we calculate both the fraction of a firm's stock held by institutional investors and the number of institutional investors holding the stock. We measure both variables in the quarter prior to day -42.

We provide in Table 3 the sample statistics of the above variables for all target firms in our sample. The average size of our target firms is $1.95 billion, which is larger than the average target size in our full merger sample. This is because the BoardEx database tends to cover large firms.

4. Target Social Connection and Target Stock Price Run-Up

In this section, we study the effect of a target's social connections on stock price run-up prior to a merger announcement, using both portfolio sorts and panel regressions.

4.1. Univariate analysis

We begin by sorting all target firms into five quintiles based on the four social-connection variables (*Degree, Closeness, Betweenness*, and *SCF*). For each quintile, we calculate the average target stock price run-up, measured by target *CAR*s in four pre-announcement windows [-6, -2], [-11, -2], [-16, -2], and [-21, -2]. We also calculate the difference in each of these four target *CAR*s between the High and the Low quintiles (High-Low).

We report the results from the portfolio sorts in Table 4, with Panels A, B, C, and D based on *Degree, Closeness, Betweenness*, and *SCF* respectively, as the social-connection variable. In general, our results are similar in four panels. They show that target firms with higher social connectivity experience higher *CAR*s during all four pre-announcement event windows. For example, in Panel A with *Degree* as the social connection variable, target stock price run-up in the week before the merger announcement (i.e., *CAR*[-6, -2]) increased from an insignificant -1.21% in the Low quintile (the quintile with the lowest *Degree*) to a significant 1.64% in the High quintile (the quintile with the highest *Degree*). The average difference in *CAR*[-6, -2] between the High and the Low quintiles is 2.84%, and it is significant at the 5% level. Similarly, in Panel A, the differences between the High and Low quintiles of *Degree* are 3.85% and 4.24%, respectively, in *CAR*[-11, -2] and *CAR*[-16, -2]. They are both statistically significant. The difference in *CAR*[-21, -2] is 2.05%, although it is insignificant. These results show a positive relationship between target social connection and target stock price run-up.

4.2. Multivariate regressions

We further study the relation between target social connection and target stock price run-up by estimating the following regression model:

$$Target\ CAR = \gamma_0 + \gamma_1 Connection + \gamma_2 Size + \gamma_3 BM + \gamma_4 Past\ Return + \gamma_5 Illiquidity + \varepsilon, \quad (4)$$

where *Target CAR* is target stock price run-up in one of the four pre-announcement windows: [-6, -2], [-11, -2], [-16, -2], and [-21, -2]. *Connection* is one of our four target social-connection variables (*Degree*, *Closeness*, *Betweenness*, or *SCF*). The control variables consist of *Size* (firm size), *BM* (book-to-market ratio), *Past Return* (lagged stock returns), and *Amihud Illiquidity* (Amihud illiquidity ratio). All controlled variables are calculated for target firms. We also control for both industry and year dummies. Industries are defined by two-digit SIC codes. The statistical inference is based on robust standard errors. If a target with better social connections is more likely to experience information leakage and thus a higher target stock price run-up, then we expect γ_1, the coefficient of *Connection*, to be positive.

We present the regression results in Table 5. In Panel A, the social-connection variable is *Degree*. As expected, the coefficients of *Degree* are positive and significant for target *CAR*s in all four pre-announcement event windows. For example, in the second column with *CAR*[-6, -2] as the target run-up variable, the coefficient of *Degree* is 0.010 and it is statistically significant at the 1% level. This coefficient of *Degree* is also economically significant. The standard deviation of *Degree* in the regression sample is 1.66 and the standard deviation of *CAR*[-6, -2] is 8%. Thus, our results in the second column indicate that an increase of one standard deviation in *Degree* is associated with an increment of 1.66% in *CAR*[-6, -2], which is about 20% of the standard deviation of *CAR*[-6, -2]. Similar statistical and economic significance exist as well for the other target run-up variables: *CAR*[-11, -2], *CAR*[-16, -2], and *CAR*[-21, -2].

In Panels B, C and D of Table 5, we report the results with *Closeness, Betweenness*, and *SCF* respectively, as the target social-connection variables. Again, the coefficients of *Closeness, Betweenness*, and *SCF* are positive for all target run-up variables. They are also significant both statistically and economically, except for the coefficient of *Betweenness* in the last column in Panel C with *CAR*[-21, -2] as the target run-up variable. Overall, our results in Table 5 are consistent with those in Table 4. They show that a target's stock price run-up prior to its merger announcement is positively related to the magnitude of the target's social connections.

4.3. Death of a senior executive or director as an exogenous event

One potential concern about our regressions above is that both target run-up and target social connection may be endogenous variables determined by other factors. If such is the case, the relationship between these two variables as shown in the previous subsections may not necessarily imply any causality. To address this concern, we consider an event that exogenously changes a target's social connections: the deaths of senior executives and directors.

In particular, we calculate *Connection (Post-Pre)*. This is the change in a target's social connections (*Connection*) from the year immediately prior to the executive or director death (*Connection (Pre)*) to the years after the death (*Connection (Post)*).[14] *Connection* is one of our four social-connection variables, namely, *Degree*, *Closeness*, *Betweenness*, or *SCF*. We argue that *Connection (Post-Pre)* can help address concerns about the potential endogeneity of *Connection* if the change in a target's social connections around the executive or director death was driven only by the exogenous death and if the death is unrelated to any future M&As.

We run OLS regressions on target *CARs* against *Connection (Post-Pre)*. In addition to the control variables in regression (4), we also control for target social connection prior to the director or executive death, i.e., *Degree(Pre)*, *Closeness(Pre)*, *Betweenness(Pre)*, or *SCF(Pre)*. We continue controlling for year and industry dummies. However, due to the constraint of the size of the death sample (35 observations), here we define industry dummies by the first digit of SIC codes rather than the first two digits as elsewhere in the paper. For the same reason, we gradually control for industry and year dummies to understand how the controls affect the statistical power of our regressions.

We present the results in Table 6. In Panel A, *Connection (Post-Pre)* is *Degree (Post-Pre)* in the first three columns and it is *Closeness (Post-Pre)* in the next three columns. In Panel B, *Connection (Post-Pre)* is *Betweenness (Post-Pre)* in the first three columns and it is *SCF (Post-*

[14] An alternative method is to use a dummy variable of *death* to capture the exogenous change in firm social connection. However, it is uncertain whether the death of a senior executive or director increases or decreases firm social connections, because any death could be accompanied with the appointment of a new executive or director. In unreported tests, we find that the death of a senior executive or director is associated with an increase in firm social connections in around 60% of the death sample and a decrease in around 40% of the sample. Thus, a *death* dummy variable cannot accurately capture the change in firm social connections around death for all sample firms.

Pre) in the last three columns. To save space, we only present the results with *CAR*[-6, -2] as the target run-up variable. The results based on the other target run-up variables are qualitatively similar and are available upon request from the authors.

As can be seen, the coefficients of *Degree (Post-Pre)* are all positive and statistically significant as well as economically significant. For example, according to the results in the second column in Panel A, an increase of one standard deviation in *Degree (Post-Pre)* (i.e., 2.42) increases *CAR*[-6, -2] by 6.8%, around 80% of the standard deviation of *CAR*[-6, -2] in the regression sample. Similarly, the coefficients of *Closeness (Post-Pre), Betweenness (Post-Pre),* and *SCF (Post-Pre)* are also positive. They are mostly significant as well, with the exception of the coefficient of *Closeness (Post-Pre)* in Column (4) of Panel A, the coefficient of *Betweenness (Post-Pre)* in Column (3) of Panel B, and *SCF (Post-Pre)* in Column (6) of Panel B.

Overall, our results using executive or director death as an exogenous event are consistent with our earlier results. They show that a target experiences a higher stock price run-up prior to its merger announcement if the target is socially better connected.

4.4. The target social-connection effect in cases without charges of insider trading

Our sample includes both cases where the SEC or DOJ filed charges and uncharged cases. There is no doubt that social relationship plays an important role in the cases with charges for insider trading. However, it is an empirical question on whether target social network affects target run-up in the uncharged cases as well.

To study this, we repeat the multivariate regression analysis in Table 5 by removing all cases with charges of insider trading. We focus on the one-week pre-announcement window [-6, -2] in this test. Table 7 reports the results. The coefficients of *Degree, Closeness, Betweenness*, and *SCF*, our social-connection variables, are all positive and significant at the 1% or 5% level. The results show that the positive impact of target social network on target run-up holds even after we remove all charged cases and keep only the uncharged cases. They suggest that information leakage prior to M&As could exist not only in the cases with charges of illegal insider trading, but also in the cases where charges are not filed by the SEC or the DOJ.

4.5. The target social-connection effect in other event windows

In this subsection, study the post-announcement mark-ups in four post-announcement windows [2, 6], [2, 11], [2, 16], and [2, 21], the announcement period target stock return in window [-1, 1], and the pre-merger target stock return in window [-250, -42]. Schwert (1996) shows that target stock return on average is not affected by any rumor or leaked information about the upcoming merger prior to day -42. Thus, we can view target stock return in [-250, -42] as the return not influenced by any merger-related information.

We first sort portfolios following the same procedure discussed in Section 4.1. We report the results in Table 8. Our results show mostly no significant difference in target *CAR*s between the High and Low social-connection groups for the announcement period window [-1, 1], the pre-merger window [-250, -42], and the four post-announcement windows. We then run regressions on target stock returns in these windows. The specification of the regressions is similar to that in regression (4). We present the results in Table 9. As can be seen, the coefficients of all four social-connection variables are insignificant in both the announcement period and post-announcement windows. During the pre-merger window [-250 -42], the coefficient of *Closeness* is the only significant coefficient among all four social-connection measures. These results are generally consistent with the results in Table 8. Overall, our results in this subsection show that target social connection does not affect target stock return during the announcement, after the announcement, or in the period without any influence by mergers. These results are in contrast to our earlier results that target social connection positively affects target return in the pre-announcement windows.

5. Information dissemination Explanation

In Section 4, we show that a target's social connections positively affect its stock price run-up prior to a merger announcement. We conjecture that private information leaked and transmitted pre-announcement in social networks drives this social-connection effect. The private information could be either directly related to an upcoming merger or be any nonmerger new information that helps accurately predict a merger. When the private information leaks via social networks, some network members buy the target's stock prior to the announcement if they anticipate from the private information that the target's stock price will increase. Consequently, the target's pre-announcement stock price will increase prior to the merger announcement.

We also find in Section 4 that target social connection has no impact on target returns in the event window prior to day -42 or after the announcement. We argue that the target social-connection effect does not exist in the event window prior to day -42 because private information on the upcoming merger or the target's stand-alone value may not have emerged yet. The target social-connection effect does not exist during the announcement or in the post-announcement windows, because any information on the merger or the target's stand-alone value has already been incorporated into stock prices once the merger is announced. Thus, target social connection plays no role in information leakage or transmission in the window prior to day -42, in the announcement period window, and in the post-announcement windows.

5.1. Target run-ups, target social connection, and information asymmetry

In this subsection, we test the information dissemination explanation from the perspective of information asymmetry faced by the target. We argue that leaks of private information in social networks is more likely and more pronounced if the target has more private information than outside investors do. Thus, if the leaks of private information indeed drive the positive effect of target social connection on target run-up, the effect should be stronger for targets facing more severe information asymmetry.

To test this hypothesis, we use the following proxies for information asymmetry: stock return volatility, analyst forecast dispersion, and analyst forecast error. Higher analyst dispersion, forecast error, or idiosyncratic stock return volatility indicates higher information asymmetry. We interact each information asymmetry variable with one of our social-connection variables. According to the information dissemination explanation, we expect the coefficient of the interaction variable to be positive.

We present the results from the above test in Table 10. In Panel A, we use analyst dispersion (*Dispersion*) to proxy for information asymmetry. The target connection variable is *Degree*, *Closeness*, *Betweenness,* or *SCF*. We run regressions on target *CARs* against *Dispersion*, one of the target connection variables, the interaction term between *Dispersion* and the target connection variable, and the control variables as in regression (4). To save space, we present only the results with target *CARs* measured in window [-6, -2]. As can be seen, the coefficients of all four interaction variables (i.e., *Degree*×*Dispersion*, *Closeness*×*Dispersion*, *Betweenness*× *Dispersion*, and *SCF*×*Dispersion*) are positive. They are also statistically significant at either the 5% or 1% level. These results imply that the positive effect of target social connection on target run-up is more pronounced for firms with higher analyst forecast dispersion, and thus they support the information dissemination explanation.

In Panels B and C, we use analyst forecast error (*Forecast Error*) and stock return volatility (*Volatility*) to proxy for information asymmetry. Again, we focus on the interaction term between the information asymmetry variables and the target-connection variables. Similar to the results in Panel A, all coefficients of the interaction terms in both Panels B and C are positive. Most of the coefficients are also statistically significant. In general, our results in Panels B and C support the information dissemination explanation as well.

In all three panels, the coefficients of the target connection variables either remain significantly positive or become insignificant. The insignificance of some coefficients could be due to the fact that the statistical power of these coefficients is subsumed by that of the interaction variables. Also, the coefficients of the asymmetric information variables are all positive, and most of them are statistically significant. The latter results suggest that stock price run-up in a merger is higher for targets with more severe information asymmetry.

5.2. Target run-ups, target social connection, and institutional holdings

In this subsection, we investigate how institutional investors affect the relation between the target's social connections and its stock price run-up. Institutional investors have more incentive to monitor and govern a firm. Thus, information leakage is less likely to happen in target with more institutional ownership. In other words, we expect that the positive effect of target social connection on target run-up is weaker among targets with higher institutional ownership and smaller retail ownership.

We use two variables to measure institutional ownership: the percentage of a target's outstanding shares held by institutional investors (*Institutional Holding*) and the number of institutional investors holding the target's shares (*Institutions Number*). We interact each of these two variables with a connection variable. We then run regressions on target *CARs* against the interaction term. We expect the coefficient of the interaction term to be negative.

We present the results in Table 11. In Panel A, the dependent variable is target *CARs* in window [-6, -2] in the left four columns and [-11, -2] in the right four columns. The institutional investor variable is *Institutional Holding*. In the left four columns, as expected, the coefficients of the interaction variables are negative in all columns. However, only the coefficient of *Betweenness*× *Institutional Holding* is statistically significant. In the right four columns where the dependent variable is *CAR*[-11, -2], both the statistical and economic powers of the coefficients of the interaction variables improve. For example, the coefficient of *Degree*×*Institutional Holding* decreases from -0.012 to -0.026 and it becomes statistically significant.

In Panel B, we repeat the regressions in Panel A but measure institutional investors by *Institutions Number*. Similarly, in the right four columns where the dependent variable is *CAR*[-11, -2], most coefficients of the interaction terms are negative and significant, except for *Closeness*×*Institutions Number*.

In unreported results, we also run regressions of target *CAR*[-16, -2] against the interaction terms between the institutional investor variable and the connection variable. The coefficients of the interaction terms from these regressions are also statistically more significant than those from the regressions with target *CAR*[-6, -2] as the dependent variable. In general, our results in Table 11 show that the positive social-connection effect on target run-up is more pronounced when the target has lower institutional ownership. This finding is consistent with our information dissemination explanation.

5.3. Target run-up, target social connection, and public information on upcoming mergers

In this subsection, we study whether the social connection effect on target run-up holds when information about the possibility of an upcoming merger is publicly available. When investors outside social networks can learn of an upcoming merger from publicly available information, network peers lose the information advantage from any leaked information on the upcoming merger. In this case, if information leakage does explain the social-connection effect on target run-up, we expect that effect to be weaker when public information on an upcoming merger is available to outside investors prior to the merger announcement.

We first study the argument from the perspective of bidder toehold. A bidder has to file a Schedule 13(d) with the Securities and Exchange Commission to disclose stake purchases of 5% or more in the target. Thus, a pre-announcement toehold of more than 5% could publicly signal an upcoming merger to all participants in the capital markets prior to the announcement of the merger. According to our discussion, we expect the social-connection effect to be weaker in those mergers where bidders accumulate at least a toehold of 5% of the target's shares and stronger in those mergers without such a toehold.

To test, we first extract from the SDC the information on the bidder's ownership in the target prior to the merger announcement. We then construct two dummy variables: *Toehold* and *Non Toehold*. *Toehold* equals one if the bidder owns more than 5% of the target's shares prior to the merger announcement. *Non Toehold* is one minus *Toehold*. We interact both *Toehold* and *Non Toehold* with the social-connection variables and run regressions on target *CAR* against these interaction variables. We expect the coefficients of the connection variables interacting with *Non Toehold* to be positive and larger than those interacting with *Toehold*.

We present the results from the above regressions in Panel A of Table 12. Again, to save space, we only report the results with target *CAR*[-6, -2] as the dependent variables. The coefficients of *Degree×Non Toehold*, *Closeness×Non Toehold*, *Betweenness×Non Toehold*, and *SCF×Non Toehold* are positive, and they are all statistically significant. In contrast, the coefficients of *Degree×Toehold*, *Closeness×Toehold*, *Betweenness×Toehold*, and *SCF×Toehold* are all insignificant. These results suggest that the social-connection effect on target run-up does not exist in mergers where the bidder purchases at least 5% of the target's shares prior to the merger announcement, and it exists only in the mergers when the bidder accumulates less than 5% of the target's shares prior to the merger announcement.

We also check the significance of the differences in the coefficients between the social-connection variables interacting with *Toehold* and those interacting with *Non Toehold* (e.g., the difference in the coefficients between *Degree×Toehold* and *Degree×Non Toehold*). In nonreported tests, we find that the differences are insignificant for all four connection variables. We argue that the insignificance is due to the small number of mergers with at least a 5% toehold (i.e., six in our regression sample). The small number reduces the statistical power of our tests on the differences. Nevertheless, our results on bidder toehold are consistent with the information dissemination explanation.

Second, we study the public information on upcoming mergers from the perspective of news reports. We search the Factiva database for any news reports prior to each merger in our sample. We construct two dummy variables: *News* and *No News*. *News* (*No News*) equals one (zero) if there is at least one news report on the upcoming merger prior to the merger announcement and zero (one) otherwise. We then interact *News* and *No News* with our social-connection variables and run regressions of target *CARs* against these interaction variables.

We present the results from the above regressions in Panel B of Table 12. Again, we present only the results based on target *CAR*[-6, -2]. Our results based on target *CAR* in the other event windows are similar to the results presented in Table 12. They are available upon request from the authors. Overall, we find that the coefficients of the interaction variable between target social connections and *No News* remain positive and highly significant. However, the coefficients of the interaction variables between target social connections and *News* are mostly insignificant. These results suggest that the social-connection effect on target run-up holds only in the mergers without pre-announcement merger news releases, but not in those with pre-announcement merger news.

However, similar to the results on bidder toehold, we find from unreported tests insignificant differences in the coefficients between the social-connection variables interacting with *News* and those interacting with *No News* (e.g., in the coefficients between *Degree*×*News* and *Degree*×*No News*). The reason for the insignificance is due to the small sample size of the mergers with pre-announcement news, similar to the results on toehold.

Overall, our results in this subsection show that information leakage in social networks has a weaker effect on target run-up if public information on the upcoming merger is available prior to the merger announcement, such as when the bidder acquires more than 5% of the target's shares and files a Schedule 13(d) with the SEC prior to the merger announcement, or when news outlets have already reported the possibility of an upcoming merger prior to the merger announcement. However, these results are statistically weakened by the small sample of such cases. Nevertheless, they still provide evidence supporting the information dissemination explanation.

5.4. Target run-ups, target social connection, and tender offers

In this subsection, we study the information dissemination explanation from the perspective of tender offers, which often occur without the bidder consulting with the target. If a target does not know of an upcoming tender offer before it is announced, no information about the offer can be leaked and disseminated among the target's social connections. We thus expect the social-connection effect on target run-up to be weaker in tender offers than in nontender offers.

We follow the same steps as in the previous tests. We first construct two dummy variables: *Tender* and *Non Tender*. *Tender* (*Non Tender*) equals one (zero) if the SDC classifies the merger as a tender offer; it equals zero (one) otherwise. We then interact *Tender* and *Non Tender* with the social-connection variables. Finally, we run regressions on target *CAR* against these interaction variables. We expect the coefficients of the connection variables interacting with *Non Tender* to be positive and larger than those interacting with *Tender*.

We present the results in Table 13, with target *CAR*[-6, -2] as the dependent variable. We find that the coefficients of the interaction variables between target social connection and *Non Tender* remain positive and highly significant. In contrast, the coefficients of the interaction variables between target social connection and *Tender* are mostly insignificant. In unreported tests, we also study the differences in the coefficients between the connection variables interacting with *Tender* and those interacting with *Non Tender*. We find that the difference in the coefficients between *Degree*×*Tender* and *Degree*×*Non Tender*, between *Betweenness*×*Toehold* and *Betweenness*×*Non Toehold*, and between *SCF*×*Toehold* and *SCF*×*Non Toehold* are statistically significant. However, the difference in the coefficients between *Closeness*×*Toehold* and *Closeness*×*Non Toehold* is insignificant. In general, these results suggest that the social-connection effect on target run-up holds in tender offers but not in nontender offers. They support the information dissemination explanation.

5.5. Alternative market–speculation explanation

An alternative interpretation of target run-ups is that market speculations are transmitted in social networks, thereby affecting target stock prices. Jarrell and Poulsen (1989) suggest that target run-up results from market speculations, such as rumors and "street talk." As we discussed at the beginning of this section, the information dissemination explanation considers the leakage of private information via social networks. The leaked private information is then used by network peers to anticipate mergers. Thus, the market speculation explanation differs from the information dissemination explanation only when network peers rely on public instead of private information to anticipate mergers and when such anticipation is transmitted via social networks.

It is worth noting that social networks can still affect target run-up even if network peers' speculations are based on the same set of public information as investors outside those networks. Network peers could be able to evaluate the probability and the value of an upcoming merger more accurately and in a timelier manner than investors outside those networks can, even if their evaluations are based on the same set of public information.

Network peers could also place greater trust in public information transmitted in social networks than outside investors do. Many studies suggest that individuals in the same social network tend to trust one another to take predictable and mutually acceptable actions (Uzzi, 1996 and 1999). Any network member passing along unreliable information thus risks losing his or her reputation and business opportunities in his/her social circles. Consequently, the same set of public information, once analyzed and certified for trustworthiness within social networks, is more likely to induce network members rather than outside investors to buy the target's stock.

Our findings on information asymmetry in Section 5.1 are inconsistent with the market-speculation explanation, however. Outside investors can better anticipate upcoming mergers from public information when they face less severe asymmetric information. Thus, if transmitting market speculation from public information drives the social-connection effect, then we expect the effect to be stronger in the targets facing less severe asymmetric information. However, as we show in Table 10, our results contradict this expectation.

6. The Bidder Social-Connection Effect on Run-Up

We have shown that a target with more social connections experiences a higher stock price run-up prior to a merger announcement. We have also provided evidence that the social-connection effect contributes to information leakage in a target's social networks. Another interesting question is whether the bidder's social networks could leak information on upcoming mergers. To answer this question, we repeat the analysis in Section 4.2 but replace target social-connection variables with bidder social-connection variables. In other words, we regress target *CAR* against one of the four bidder social-connection variables, namely, *Degree_Bidder*, *Closeness_Bidder*, *Betweenness_Bidder*, or *SCF_Bidder*.

We present the results in the first three columns in Table 14. To save space, we present only the results with target *CAR* [-6, -2] as the dependent variable. The coefficients of all four bidder connection variables are insignificant. These results show that a target's pre-announcement run-up is not affected by the degree of connectedness of its bidder. They suggest that no information leakage on the upcoming merger occurs in a bidder's social networks prior to takeover announcements. One possible explanation is that bidders do not want to leak information to drive up the acquisition prices that they have to pay for their targets.[15]

[15] It is possible that self-serving managers of a bidder could have an incentive to leak the information on the bidder's upcoming merger to pursue private benefits. However, by leaking information, the managers could suffer a loss in the value of their equity in the bidder because the leak could force the bidder to overpay for the target. Managers leaking information could also face a hefty penalty if they face SEC/DOJ charges. Thus, whether information leakage happens depends on the tradeoff among the managers' private benefits, equity benefits, and litigation risk. Our results suggest that the costs of information leakage outweigh the benefits for a bidder's board members and senior executives.

It is also empirically interesting to determine whether social connections, either on the side of the bidder or the target, affect bidder stock price run-up prior to the merger announcement. We run regressions on bidder *CAR* in window [-6, -2] against either target social-connection variables or bidder social-connection variables.[16] We present the results from these regressions in the Columns 5-11 in Table 14. Our results show that both the coefficients of the bidder and the target social-connection variables are insignificant from zero. They suggest that neither the target's nor the bidder's social connections affect the bidder's stock prices prior to a merger announcement. Previous studies show that, on average, a bidder experiences either an insignificant or a negative return upon the announcement of its merger. Thus, even if network peers know of an upcoming merger through information leakage via social networks, they may have no incentive to buy the bidder's stock.

7. Conclusions

This paper investigates how a target's social networks affects its stock price run-up (i.e., the increase in the target's stock price) prior to a merger announcement. We use the social connections of a firm's board members and senior executives to measure a firm's social connectedness. We find that a target with better social connections experiences a higher target run-up. This result holds after we address the endogeneity concern by using the death of board members and senior executives as an exogenous shock. We also find, however, that the target social-connection effect on target run-up does not exist during the merger announcement, after the announcement, or before the merger negotiation is initiated. The latter findings suggest that the

[16] The results based on bidder *CAR* in the other event windows are similar to those presented in the paper.

information related to the upcoming merger drives the target social-connection effect in the pre-announcement windows.

We propose an information dissemination explanation for the existence of a target social-connection effect. In this explanation, private information on the upcoming merger is leaked and transmitted via a target's social networks. The leaked information induces network members to buy the target's shares prior to the merger announcement, thus contributing to target run-up. Our findings support this information dissemination explanation. First, we find that the target social-connection effect on target run-up is more pronounced when the target faces severe information asymmetry. Second, the target social-connection effect is more pronounced when the target's retail ownership is greater than its institutional ownership, probably because institutional investors can monitor a firm better than retail investors. Third, the target social-connection effect is weaker when public information on the possibility of an upcoming merger is available prior to the merger announcement, such as when a bidder acquires more than 5% of the target's shares or when there are news reports on the merger possibility prior to the announcement. Fourth, the effect is also weaker for tender offers, probably because the target is unaware of the tender offer prior to its announcement.

Overall, our results present strong evidence that a target's social networks can transmit leaked private information on an upcoming merger prior to its announcement and that this phenomenon is a primary contributor to a target's stock price run-up.

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Table 1: Sample distribution by years

This table reports by year the number of mergers and acquisitions and the average size of the targets in our sample. The sample consists of targets that are U.S. public companies from 1999 to 2010.

		Target Market Value ($ billions)	
Year	Sample Size	Mean	Median
1999	12	0.50	0.28
2000	9	4.44	0.33
2001	10	1.60	1.21
2002	7	8.46	0.47
2003	13	3.96	0.77
2004	26	2.65	0.93
2005	38	2.27	0.35
2006	47	1.63	0.42
2007	53	1.14	0.58
2008	65	2.70	0.24
2009	43	1.45	0.39
2010	54	0.60	0.23
Full Sample	377	1.95	0.42

Table 2: Selected statistics related to the common-factor analysis

The sample includes all U.S. public targets with social-connection information available from 1999 to 2010. *SCF* is the social connection factor score obtained using common-factor analysis on *Degree*, *Closeness*, and *Betweenness*. *Degree* is the log of the sum of a firm's connections with other firms, normalized by the highest possible number of connections; *Closeness* is the log of the number of the other firms in the network divided by the sum of graph theoretic distances from the firm to all other firms; and *Betweenness* is the log of the sum of all possible firm pairs connected in the shortest paths through the firm normalized by the number of all possible firm pairs.

Panel A: Estimated communalities of three social-connection measures

	Degree	Closeness	Betweenness
Communalities	0.6549	0.0379	0.6508

Panel B: Eigenvalues of the reduced correlation matrix of three social-connection measures

	1	2	3
Eigenvalues	3.0000	0.0012	-0.0012

Panel C: Correlations between *SCF* and three social-connection measures

	Degree	Closeness	Betweenness
SCF	0.9999	0.2018	0.8173

Panel D: Descriptive statistics of SCF

Mean	Median	Std. Dev.	Q25	Q75
0.000	0.162	0.994	-0.615	0.764

Table 3: Summary statistics

This table reports the summary statistics for the targets in our sample. The sample includes all U.S. public targets with social-connection information available from 1999 to 2010. *Degree* is the logarithm of the number of a firm's connections, normalized by the highest possible number of connections the firm could have in the network of the BoadEx firms. *Closeness* is calculated as the logarithm of the inverse of the sum of graph theoretic distances from a firm to all other firms, normalized by the inverse of the smallest possible graph theoretic distance a firm could have. *Betweenness* is calculated as the logarithm of the sum of all possibilities that a firm can serve as an intermediary between all possible firm pairs' shortest connections, normalized by the number of all possible firm pairs. Book-to-market ratio is the ratio of the book value to the market value of equity. Book-to-market and market capitalization are calculated at day -42. Past return is cumulative abnormal return in window [-250, -42]. The Amihud illiquidity ratio is the ratio of daily absolute stock return to daily dollar trading volume averaged over window [-250, -42].

Variable Name	Mean	Median	Standard Deviation	25th Percentile	75th Percentile
Stock characteristics					
Market capitalization ($ billion)	1.95	0.42	5.94	0.13	1.38
Book-to-market ratio*10^3	0.72	0.56	0.001	0.34	0.87
Past return (%)	10.70	-3.89	132.08	-28.37	24.10
Amihud illiquidity ratio*10^6	2.07	0.01	11.90	0.002	0.15
Social-connection measures					
Degree	-4.65	-4.30	1.67	-5.57	-3.37
Closeness	-4.01	-4.01	0.74	-4.32	-3.66
Betweenness	-10.52	-10.07	2.67	-11.77	-8.48

Table 4: Target social connection and target stock price run-up – univariate sort

The sample includes all U.S. public targets with social-connection information available from 1999 to 2010. The sample is sorted into five quintiles based on one of the three connection variables and the common factor. Average target cumulative abnormal returns (CARs) are calculated for each quintile, as well as the difference in CARs between the high and low quintiles. The connection variables are *Degree*, the log of the sum of a firm's connections with other firms, normalized by the highest possible number of connections; *Closeness*, the log of the number of the other firms in the network divided by the sum of graph theoretic distances from the firm to all other firms; *Betweenness*, the log of the sum of all possible firm pairs connected in the shortest paths through the firm normalized by the number of all possible firm pairs; and *SCF*, the social-connection factor score, obtained using common factor analysis on *Degree*, *Closeness*, and *Betweenness*. CARs are calculated for trading-day windows [-6, -2], [-11, -2], [-16, -2], and [-21, -2] where -2 stands for the second day prior to the merger announcement, etc. All CAR numbers are in percentage. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

Panel A: Average target cumulative abnormal returns (CARs) sorted by *Degree*

Connection	[-21, -2]	[-16, -2]	[-11, -2]	[-6, -2]
1 (Low)	1.25	0.04	0.01	-1.21
2	-0.76	-1.46	-1.00	-0.86
3	1.71	1.98	2.57*	2.48**
4	2.57*	3.03***	3.24***	2.68***
5 (High)	3.30**	4.28***	3.86***	1.64**
High - Low	2.05	4.24**	3.85**	2.84**

Panel B: Average target cumulative abnormal returns (CARs) sorted by *Closeness*

Connection	[-21, -2]	[-16, -2]	[-11, -2]	[-6, -2]
1 (Low)	1.78	0.80	1.14	0.27
2	1.93	2.23	2.04*	1.34
3	3.30**	3.27***	2.74**	1.12
4	-0.22	-0.51	0.24	0.93
5 (High)	1.29	2.13*	2.58**	1.14
High - Low	-0.50	1.33	1.44	0.86

Panel C: Average target cumulative abnormal returns (CARs) sorted by *Betweenness*

Connection	[-21, -2]	[-16, -2]	[-11, -2]	[-6, -2]
1 (Low)	0.18	-0.72	0.54	-0.61
2	2.15	0.63	0.80	0.26
3	1.16	1.88	2.02	2.80***
4	3.15*	3.41**	2.76**	1.67
5 (High)	3.02**	3.58***	3.65***	1.69**
High - Low	2.31	3.11**	4.30*	2.84**

Panel D: Average target cumulative abnormal returns (CARs) sorted by *SCF*

Connection	[-21, -2]	[-16, -2]	[-11, -2]	[-6, -2]
1 (Low)	1.96	-0.63	-0.02	-0.83
2	-0.97	-0.93	-0.71	-0.48
3	2.90	3.15	3.71**	2.64**
4	2.46*	2.71***	2.64***	2.59***
5 (High)	3.47**	4.53***	4.18***	1.88**
High - Low	1.51	5.17**	4.20**	2.71**

Table 5: Target social connection and target stock price run-ups – multivariate regression

This table reports the results from OLS regressions of target cumulative abnormal returns (CAR) in windows [-6, -2], [-11, -2], [-16, -2], and [-21, -2] on target social-connection variables. The connection variables are *Degree*, the log of the sum of a firm's connections with other firms, normalized by the highest possible number of connections; *Closeness*, the log of the number of the other firms in the network divided by the sum of graph theoretic distances from the firm to all other firms; *Betweenness*, the log of the sum of all possible firm pairs connected in the shortest paths through the firm normalized by the number of all possible firm pairs; and *SCF*, the social-connection factor score obtained using common factor analysis on *Degree*, *Closeness*, and *Betweenness*. For the control variables, *Size* is the log of market capitalization on day -42; *BM* is the log ratio of the book value to the market value of equity on day -42; *Past return* is target CAR in window [-250, -42]; the Amihud illiquidity ratio is the ratio of daily absolute stock return to daily dollar trading volume averaged over window [-250, -42] and scaled by 10^3. Industries are defined by two-digit SIC codes. T-statistics are provided in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

Panel A: The target social connection variable is *Degree*

Dep. Variables:	CAR[-6, -2]	CAR[-6, -2]	CAR[-11, -2]	CAR[-16, -2]	CAR[-21, -2]
Intercept	0.129***	0.252***	0.324***	0.258**	0.407***
	[4.738]	[3.249]	[2.968]	[2.118]	[2.697]
Degree	0.010***	0.010***	0.014***	0.013***	0.009**
	[4.13]	[4.134]	[3.549]	[3.112]	[2.011]
Size		-0.007**	-0.004	-0.004	-0.011*
		[-2.367]	[-0.632]	[-0.834]	[-1.704]
BM		-0.001	0	-0.009	-0.016
		[-0.082]	[0.020]	[-0.658]	[-0.944]
Past return		-0.019**	-0.052***	-0.062***	-0.065**
		[-2.031]	[-3.562]	[-3.634]	[-2.590]
Amihud illiquidity		-1.535**	-1.171	-0.808	-1.811**
		[-2.222]	[-1.176]	[-1.088]	[-1.974]
Industry dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.21	0.25	0.23	0.26	0.22
N	377	369	369	369	369

Panel B: The target social connection variable is *Closeness*

Dep. Variables:	CAR[-6, -2]	CAR[-6, -2]	CAR[-11, -2]	CAR[-16, -2]	CAR[-21, -2]
Intercept	0.202***	0.294***	0.350***	0.280**	0.456***
	[4.157]	[3.618]	[2.993]	[2.233]	[3.000]
Closeness	0.023***	0.020***	0.019*	0.017*	0.021**
	[2.604]	[2.765]	[1.748]	[1.771]	[2.201]
Size		-0.006**	-0.003	-0.003	-0.01
		[-1.973]	[-0.421]	[-0.604]	[-1.563]
BM		0	0.002	-0.008	-0.016
		[0.014]	[0.134]	[-0.569]	[-0.916]
Past return		-0.018*	-0.050***	-0.060***	-0.065**
		[-1.956]	[-3.488]	[-3.554]	[-2.578]
Amihud illiquidity		-1.248**	-0.946	-0.617	-1.492
		[-2.165]	[-1.019]	[-0.722]	[-1.620]
Industry dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.2	0.23	0.21	0.24	0.22
N	377	369	369	369	369

Panel C: The target social connection variable is *Betweenness*

Dep. Variables:	CAR[-6, -2]	CAR[-6, -2]	CAR[-11, -2]	CAR[-16, -2]	CAR[-21, -2]
Intercept	0.130***	0.263***	0.336***	0.298**	0.424***
	[4.338]	[3.287]	[2.921]	[2.362]	[2.689]
Betweenness	0.004***	0.004***	0.006**	0.007**	0.005
	[2.841]	[2.872]	[2.149]	[2.427]	[1.449]
Size		-0.007**	-0.005	-0.006	-0.012*
		[-2.401]	[-0.690]	[-1.058]	[-1.740]
BM		0	0	-0.009	-0.017
		[0.002]	[0.003]	[-0.648]	[-0.967]
Past return		-0.022**	-0.056***	-0.066***	-0.069***
		[-2.251]	[-3.783]	[-3.728]	[-2.609]
Amihud illiquidity		-0.926	-0.425	-0.961	-1.382
		[-1.181]	[-0.332]	[-0.803]	[-0.997]
Industry dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.19	0.23	0.22	0.25	0.21
N	359	351	351	351	351

Panel D: The target social connection variable is *SCF*

Dep. Variables:	CAR[-6, -2]	CAR[-6, -2]	CAR[-11, -2]	CAR[-16, -2]	CAR[-21, -2]
Intercept	0.086***	0.218***	0.272***	0.225*	0.375**
	[3.186]	[2.803]	[2.598]	[1.837]	[2.466]
SCF	0.015***	0.015***	0.023***	0.024***	0.014*
	[3.515]	[3.479]	[3.134]	[3.224]	[1.654]
Size		-0.007**	-0.005	-0.006	-0.012*
		[-2.456]	[-0.736]	[-1.106]	[-1.763]
BM		0	-0.001	-0.009	-0.017
		[0.023]	[0.042]	[0.677]	[0.966]
Past return		-0.022**	-0.057***	-0.066***	-0.069***
		[-2.259]	[-3.790]	[-3.755]	[-2.602]
Amihud illiquidity		-0.901	-0.387	-0.92	-1.357
		[-1.107]	[-0.289]	[-0.762]	[-0.971]
Industry dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.2	0.24	0.24	0.26	0.21
N	359	351	351	351	351

Table 6: Target stock price run-up and the change in target social connection before and after the death of a CEO

This table reports the results from OLS regressions of target cumulative abnormal returns in window [-6, -2] on the change in target social-connection variables before and after the death of a CEO. The sample consists of the U.S. publicly listed targets experiencing death(s) of senior executive(s) and/or director(s). *Degree* is the log of the sum of all direct connections between a firm and other firms, normalized by the highest possible number of connections. *Closeness* is the log of the number of firms in the network minus one, divided by the sum of graph theoretic distances from the firm to all other firms. Betweenness is the log of the sum of all possible firm pairs connected in the shortest paths through the firm normalized by the number of all possible firm pairs. *SCF* is the social-connection factor score obtained using common-factor analysis on *Degree*, *Closeness*, and *Betweenness*. *Post-Pre* measures the change from the most recent year prior to the death of an executive or director to the post-death years. The control variables are identical to those included in table 5, and their coefficients are not reported. In Panel A, the connection variables are *Degree* and *Closeness*; in Panel B, the connection variables are *Betweenness* and *SCF*. Industries are defined by 1-digit SIC codes. *T*-statistics based on robust standard errors clustered by firm are provided in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

Panel A: Connection measured by *Degree* and *Closeness*

	Dep. Variable: CAR [-6, -2]					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.434**	0.722***	0.986***	0.301*	0.575**	0.795**
	[2.336]	[2.962]	[3.169]	[1.813]	[2.165]	[2.088]
Degree (Post-Pre)	0.015**	0.022**	0.028**			
	[2.072]	[2.466]	[2.774]			
Degree (Pre)	0.01	0.011	0.006			
	[1.347]	[1.318]	[0.633]			
Closeness (Post-Pre)				0.013	0.024*	0.067***
				[1.178]	[1.847]	[2.904]
Closeness (Pre)				0.019	0.038	0.074*
				[0.956]	[1.345]	[1.921]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	Yes	No	No	Yes
Year dummies	No	Yes	Yes	No	Yes	Yes
R^2	0.28	0.42	0.57	0.19	0.27	0.46
N	42	42	42	42	42	42

Panel B: Connection measured by *Betweenness* and *SCF*

	Dep. Variable: CAR [-6, -2]					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.722***	1.113***	1.343***	0.606**	1.068***	1.321***
	[2.913]	[3.771]	[4.330]	[2.604]	[3.936]	[4.245]
Betweenness (Post-Pre)	0.010***	0.008*	0.005			
	[3.127]	[2.019]	[0.596]			
Betweenness (Pre)	0.009	0.006	0.002			
	[1.573]	[1.019]	[0.186]			
SCF(Post-Pre)				0.040*	0.035*	0.013
				[2.004]	[1.880]	[0.398]
SCF (Pre)				0.015	0.013	-0.003
				[0.892]	[0.891]	[0.118]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	Yes	No	No	Yes
Year dummies	No	Yes	Yes	No	Yes	Yes
R^2	0.39	0.63	0.78	0.35	0.62	0.77
N	35	35	35	35	35	35

Table 7: Target social connection and target stock price run-up – subsample without insider trading

This table reports the results from OLS regressions of target cumulative abnormal returns (CAR) in windows [-6, -2] on target social-connection variables. The sample includes only takeovers without insider trading charges. The connection variables are *Degree*, the log of the sum of a firm's connections with other firms, normalized by the highest possible number of connections; Closeness, the log of the number of the other firms in the network divided by the sum of graph theoretic distances from the firm to all other firms; *Betweenness*, the log of the sum of all possible firm pairs connected in the shortest paths through the firm normalized by the number of all possible firm pairs; and *SCF*, the social-connection factor score obtained using common factor analysis on *Degree*, *Closeness*, and *Betweenness*. The control variables are identical to those included in Table 5. Industries are defined by two-digit SIC codes. *T*-statistics based on robust standard errors clustered by firm are provided in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

	Dep. Variable: CAR [-6,-2]			
	(1)	(2)	(3)	(4)
Intercept	0.281***	0.308***	0.280***	0.238***
	[3.500]	[3.511]	[3.383]	[2.973]
Degree	0.011***			
	[4.510]			
Closeness		0.020**		
		[2.192]		
Betweenness			0.005***	
			[2.790]	
SCF				0.017***
				[3.828]
Size	-0.006**	-0.005	-0.006*	-0.006*
	[-2.028]	[-1.561]	[-1.830]	[-1.964]
BM	0.003	0.003	0.004	0.004
	[0.437]	[0.440]	[0.530]	[0.540]
Past return	-0.020*	-0.020*	-0.024**	-0.025**
	[-1.952]	[-1.876]	[-2.273]	[-2.271]
Amihud illiquidity	-1.462**	-1.192**	-0.82	-0.788
	[-2.084]	[-1.975]	[-1.018]	[-0.933]
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
R^2	0.27	0.24	0.24	0.26
N	343	343	326	326

Table 8: Target social connection and target stock return in other windows – univariate sort

The sample includes all U.S. public targets with social-connection information available from 1999 to 2010. The sample is sorted into five quintiles based on each connection variable. Average target cumulative abnormal returns (CARs) (in percentage) are calculated for each quintile, as well as the difference in CARs between the high and low quintiles. The connection variables are *Degree*, the log of the sum of a firm's connections with other firms, normalized by the highest possible number of connections; *Closeness*, the log of the number of the other firms in the network divided by the sum of graph theoretic distances from the firm to all other firms; *Betweenness*, the log of the sum of all possible firm pairs connected in the shortest paths through the firm normalized by the number of all possible firm pairs; and *SCF*, the social connection factor score obtained using common factor analysis on *Degree*, *Closeness*, and *Betweenness*. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

Panel A: Average target cumulative abnormal returns (CARs) sorted by *Degree*

Connection	[-250, -42]	[-1, 1]	[2, 6]	[2, 11]	[2, 16]	[2, 21]
1 (Low)	-6.30	23.57***	0.74	-0.38	-0.20	-0.02
2	36.26	24.33***	0.27	0.55	0.77	0.66
3	7.71	27.45***	0.34	0.41	-0.27	0.40
4	-3.57	24.85***	0.26	0.08	-0.01	0.29
5 (High)	19.40*	21.49***	0.81	0.78	0.49	-0.51
High - Low	25.70**	-2.08	0.07	1.16	0.68	-0.49

Panel B: Average target cumulative abnormal returns (CARs) sorted by *Closeness*

Connection	[-250, -42]	[-1, 1]	[2, 6]	[2, 11]	[2, 16]	[2, 21]
1 (Low)	2.93	16.85***	-0.10	-0.96	-1.51	-0.41
2	12.12***	13.74***	-0.20	0.26	0.27	-0.44
3	-1.79	23.66***	1.24	0.73	0.68	0.77
4	6.26	31.99***	0.64	0.70	1.53	1.83
5 (High)	33.98***	35.44***	0.82	0.72	-0.19	-0.96
High - Low	31.04**	18.59***	0.92	1.68	1.32	-0.55

Panel C: Average target cumulative abnormal returns (CARs) sorted by *Betweenness*

Connection	[-250, -42]	[-1, 1]	[2, 6]	[2, 11]	[2, 16]	[2, 21]
1 (Low)	-3.10	24.01***	0.05	-0.62	-0.59	0.51
2	34.66	22.39***	0.33	0.09	-0.18	-0.91
3	17.18*	23.07***	0.82	0.72	-0.06	0.23
4	1.36	25.01***	-0.01	0.20	0.34	0.74
5 (High)	9.10	22.40***	1.07*	0.99	0.65	0.11
High - Low	12.20	-1.61	1.02	1.61	1.24	-0.40

Panel D: Average target cumulative abnormal returns (CARs) sorted by *SCF*

Connection	[-250,-42]	[-1, 1]	[2, 6]	[2, 11]	[2, 16]	[2, 21]
1 (Low)	-1.46	20.34***	0.37	-0.63	-1.12	-0.72
2	39.28	22.89***	0.45	0.61	0.94	1.09
3	1.52	28.02***	0.19	0.30	-0.38	0.31
4	0.84	23.36***	0.33	0.12	-0.03	0.26
5 (High)	18.96*	22.20***	0.92	0.95	0.70	-0.35
High - Low	20.42	1.86	0.56	1.58	1.82	0.37

Table 9: Target social connection and target stock returns in other windows – multivariate regression

This table reports the results from OLS regressions of target cumulative abnormal returns (CARs) in windows [-250, -42], [-1, 1], [2, 6], [2, 11], [2, 16], and [2, 21] on target social-connection variables. The connection variables are *Degree*, the log of the sum of a firm's connections with other firms, normalized by the highest possible number of connections; *Closeness*, the log of the number of the other firms in the network divided by the sum of graph theoretic distances from the firm to all other firms; *Betweenness*, the log of the sum of all possible firm pairs connected in the shortest paths through the firm normalized by the number of all possible firm pairs; and *SCF*, the social-connection factor score obtained using common factor analysis on *Degree*, *Closeness*, and *Betweenness*. Control variables are identical to those in Table 5 and are unreported. Both industry and year dummies are controlled for. Industries are defined by two-digit SIC codes. *T*-statistics based on robust standard errors clustered by firm are provided in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

Panel A: The target social connection variable is *Degree*

	[-250, -42]	[-1, 1]	[2, 6]	[2, 11]	[2, 16]	[2, 21]
Intercept	-1.525***	0.016	0.012	0.073	0.107	0.038
	[-3.089]	[0.072]	[0.225]	[0.931]	[1.159]	[0.372]
Degree	0.027*	-0.01	0	0.002	0.002	0.002
	[1.710]	[-1.125]	[0.003]	[0.907]	[0.783]	[0.596]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.87	0.29	0.27	0.23	0.28	0.29
N	377	377	369	369	369	369

Panel B: The target social connection variable is *Closeness*

	[-250, -42]	[-1, 1]	[2, 6]	[2, 11]	[2, 16]	[2, 21]
Intercept	-1.291**	-0.132	0.014	0.072	0.119	0.05
	[-2.567]	[-0.532]	[0.227]	[0.921]	[1.292]	[0.487]
Closeness	0.084**	-0.047*	0	0.002	0.005	0.005
	[2.403]	[-1.922]	[0.070]	[0.310]	[0.658]	[0.657]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.87	0.3	0.27	0.23	0.28	0.29
N	377	377	369	369	369	369

Panel C: The target social connection variable is *Betweenness*

	[-250, -42]	[-1, 1]	[2, 6]	[2, 11]	[2, 16]	[2, 21]
Intercept	-1.395***	0.086	0.016	0.065	0.106	0.045
	[-2.782]	[0.368]	[0.299]	[0.776]	[1.071]	[0.416]
Betweenness	0.011	0.002	0	0.001	0.001	0
	[1.236]	[0.367]	[0.397]	[0.608]	[0.520]	[0.209]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.88	0.29	0.27	0.23	0.27	0.3
N	359	359	351	351	351	351

Panel D: The target social connection variable is *SCF*

	[-250, -42]	[-1, 1]	[2, 6]	[2, 11]	[2, 16]	[2, 21]
Intercept	-1.450***	0.083	0.02	0.052	0.104	0.051
	[-2.849]	[0.381]	[0.383]	[0.693]	[1.174]	[0.510]
SCF	0.024	0.008	0	0.002	0.004	0.001
	[0.887]	[0.636]	[0.123]	[0.610]	[0.781]	[0.156]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.88	0.3	0.25	0.24	0.28	0.32
N	351	351	349	349	349	349

Table 10: Target run-up, target social connection, and information asymmetry

This table reports the results from OLS regressions of target cumulative abnormal returns (CARs) in event window CAR[-6, -2] and CAR[-11, -2] against target social-connection variables and their interactions with measures of information asymmetry. The connection variables are *Degree*, the log of the sum of a firm's connections with other firms, normalized by the highest possible number of connections; *Closeness*, the log of the number of the other firms in the network divided by the sum of graph theoretic distances from the firm to all other firms; *Betweenness*, the log of the sum of all possible firm pairs connected in the shortest paths through the firm normalized by the number of all possible firm pairs; *SCF*, the social-connection factor score obtained using common factor analysis on *Degree*, *Closeness*, and *Betweenness*. For the information asymmetry variables in Panels A to C, *analyst forecast dispersion* is the standard deviation of analyst forecast scaled by the actual EPS at event day -42; *analyst forecast error* is the absolute difference between the analyst forecast and the actual EPS, scaled by the actual EPS at event day -42; and *volatility* is the standard deviation of the target's daily stock returns over window [-250, -42]. The control variables are identical to those included in Table 5. The coefficients of the control variables are unreported. Both year and industry dummies are controlled for. Industries are defined based on two-digit SIC codes. *T*-statistics based on robust standard errors clustered by firm are provided in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

Panel A: Information asymmetry is proxied by analyst forecast dispersion.

	Dep. Variable: CAR [-6,-2]			
Intercept	0.224*	0.296**	0.245**	0.239**
	[1.950]	[2.561]	[2.065]	[2.087]
Degree*Dispersion	0.082***			
	[4.310]			
Degree	0.007**			
	[2.246]			
Closeness*Dispersion		1.132***		
		[3.398]		
Closeness		0.011		
		[1.408]		
Betweenness*Dispersion			0.322**	
			[2.142]	
Betweenness			0.002	
			[0.732]	
SCF*Dispersion				0.366**
				[2.581]
SCF				0.012*
				[1.938]
Dispersion	0.461***	4.260***	3.166**	-0.025
	[4.100]	[3.401]	[2.205]	[-0.316]
Control variables	Yes	Yes	Yes	Yes
R^2	0.27	0.25	0.26	0.28
N	224	224	215	215

Panel B: Information asymmetry is proxied by analyst forecast error.

	Dep. Variable: CAR [-6,-2]			
Intercept	0.270***	0.353***	0.285***	0.275***
	[2.861]	[3.842]	[2.844]	[2.860]
Degree*Forecast Error	0.034***			
	[2.840]			
Degree	0.008**			
	[2.399]			
Closeness*Forecast Error		0.631***		
		[4.422]		
Closeness		0.015***		
		[3.006]		
Betweenness*Forecast Error			0.165**	
			[1.986]	
Betweenness			0.001	
			[0.664]	
SCF*Forecast Error				0.308**
				[2.303]
SCF				0.011*
				[1.861]
Forecast Error	0.140***	2.312***	1.567**	-0.142**
	[3.144]	[4.449]	[2.002]	[-2.112]
Control variables	Yes	Yes	Yes	Yes
R^2	0.28	0.28	0.26	0.29
N	242	242	230	230

Panel C: Information asymmetry is proxied by return volatility

	Dep. Variable: CAR [-6,-2]			
Intercept	0.224*	0.296**	0.245**	0.239**
	[1.950]	[2.561]	[2.065]	[2.087]
Degree*Volatility	0.260*			
	[1.956]			
Degree	0.001			
	[0.222]			
Closeness*Volatility		0.916***		
		[3.209]		
Closeness		-0.014		
		[-1.423]		
Betweenness*Volatility			0.198**	
			[2.030]	
Betweenness			-0.002	
			[0.599]	
SCF*Volatility				0.656**
				[2.424]
SCF				-0.005
				[-0.551]
Volatility	1.379*	3.608***	2.148*	0.086
	[1.762]	[3.097]	[1.907]	[0.209]
Control variables	Yes	Yes	Yes	Yes
R^2	0.29	0.26	0.28	0.3
N	344	344	327	327

Table 11: Target stock price run-up, target social connection, and institutional holdings

This table reports the results from OLS regressions on target cumulative abnormal returns (CARs) in event windows CAR[-6, -2] and CAR[-11, -2]. The connection variables are *Degree*, the log of the sum of a firm's connections with other firms, normalized by the highest possible number of connections; *Closeness*, the log of the number of the other firms in the network divided by the sum of graph theoretic distances from the firm to all other firms; *Betweenness*, the log of the sum of all possible firm pairs connected in the shortest paths through the firm normalized by the number of all possible firm pairs; and *SCF*, the social-connection factor score obtained using common factor analysis on *Degree*, *Closeness*, and *Betweenness*. *Institutional Holding* is the fraction of the target's stock held by institutional investors. *Institutions Number* is the logarithm of the number of institutions holding the target's stock. The control variables are identical to those included in Table 5. The coefficients of the control variables are unreported. Both year and industry dummies are controlled for. Industries are defined by two-digit SIC codes. *T*-statistics based on robust standard errors clustered by firm are in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

Panel A: Interaction between the connection variables and the institutional investor holdings

	Dep. Variable: CAR [-6,-2]				Dep. Variable: CAR [-11,-2]			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.332***	0.354**	0.407***	0.277***	0.463***	0.445**	0.541***	0.338**
	[3.674]	[2.587]	[4.230]	[3.183]	[3.477]	[2.458]	[3.953]	[2.560]
Degree*Institutional Holding	-0.012				-0.026**			
	[-1.600]				[-2.541]			
Degree	0.018***				0.032***			
	[2.990]				[3.880]			
Closeness*Institutional Holding		-0.008				-0.021		
		[-0.305]				[-0.618]		
Closeness		0.023				0.03		
		[1.011]				[1.077]		
Betweenness*Institutional Holding			-0.010**				-0.016**	
			[-2.142]				[-2.475]	
Betweenness			0.011***				0.017***	
			[3.029]				[3.329]	
SCF*Institutional Holding				-0.022				-0.038**
				[-1.547]				[-2.030]
SCF				0.030***				0.049***
				[2.863]				[3.483]
Institutional Holding	-0.073*	-0.043	-0.124**	-0.015	-0.141**	-0.097	-0.193**	-0.02
	[-1.733]	[-0.434]	[-2.215]	[-0.738]	[-2.369]	[-0.725]	[-2.337]	[-0.621]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.29	0.26	0.3	0.3	0.31	0.27	0.31	0.32
N	305	305	289	289	305	305	289	289

Panel B: Interaction between the connection variables and the number of institutions

	Dep. Variable: CAR [-6,-2]				Dep. Variable: CAR [-11,-2]			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.367**	0.430**	0.385**	0.289**	0.612***	0.528*	0.676***	0.369*
	[2.550]	[2.032]	[2.576]	[2.245]	[2.988]	[1.780]	[3.142]	[1.938]
Degree*Institutions Number	-0.003				-0.010**			
	[-1.349]				[-2.547]			
Degree	0.024**				0.060***			
	[2.062]				[3.182]			
Closeness*Institutions Number		-0.006				-0.009		
		[-0.846]				[-0.969]		
Closeness		0.044				0.059		
		[1.301]				[1.301]		
Betweenness*Institutions Number			-0.001				-0.006*	
			[-0.917]				[-1.934]	
Betweenness			0.01				0.032**	
			[1.500]				[2.431]	
SCF*Institutions Number				-0.004				-0.017**
				[-0.997]				[-2.190]
SCF				0.033*				0.103***
				[1.682]				[2.828]
Institutions Number	-0.015	-0.027	-0.015	0.001	-0.046*	-0.045	-0.062*	0.002
	[-0.884]	[-0.955]	[-0.731]	[0.046]	[-1.731]	[-1.102]	[-1.684]	[0.080]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.29	0.26	0.28	0.29	0.32	0.27	0.31	0.33
N	305	305	289	289	305	305	289	289

Table 12: Target stock price run-up, target social connection, and public information

This table reports the results from OLS regressions of target cumulative abnormal returns (CARs) in windows [-6, -2] and [-11, -2] on target social-connection variables and their interactions with measures of public information. Toehold (Non Toehold) is a dummy variable equal to one if the bidder owns more (less) than 5% of the target's shares prior to the merger announcement. News (No News) is a dummy variable equal to one if there are (no) news reports about the upcoming merger prior to the merger announcement, and zero otherwise. The connection variables are *Degree*, the log of the sum of a firm's connections with other firms, normalized by the highest possible number of connections; *Closeness*, the log of the number of the other firms in the network divided by the sum of graph theoretic distances from the firm to all other firms; *Betweenness*, the log of the sum of all possible firm pairs connected in the shortest paths through the firm normalized by the number of all possible firm pairs; and *SCF*, the social-connection factor score obtained using common factor analysis on *Degree*, *Closeness*, and *Betweenness*. The control variables are identical to those included in Table 5. The coefficients of the control variables are unreported. Both year and industry dummies are controlled for. Industries are defined based on two-digit SIC codes. *T*-statistics based on robust standard errors clustered by firm are in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

Panel A: Interaction between the connection variables and the dummies of *Toehold* or *Non toehold*

	Dep. Variable: CAR [-6, -2]			
Intercept	0.251***	0.293***	0.262***	0.216***
	[3.220]	[3.602]	[3.276]	[2.773]
Degree*Toehold	0.005			
	[0.687]			
Degree*Non Toehold	0.010***			
	[4.072]			
Closeness*Toehold		0.06		
		[0.910]		
Closeness*Non Toehold		0.020***		
		[2.765]		
Betweenness*Toehold			0.004	
			[0.797]	
Betweenness*Non Toehold			0.004***	
			[2.854]	
SCF*Toehold				0.008
				[0.704]
SCF*Non Toehold				0.015***
				[3.448]
Toehold	-0.037	0.147	-0.018	-0.014
	[0.869]	[0.563]	[0.272]	[0.853]
Control variables	Yes	Yes	Yes	Yes
R^2	0.25	0.23	0.23	0.24
N	369	369	351	351

Panel B: Interaction between the connection variables and the dummies of *News* or *No News*

	[-6, -2]	[-11, -2]	[-6, -2]	[-11, -2]	[-6, -2]	[-11, -2]	[-6, -2]	[-11, -2]
Intercept	0.248***	0.379***	0.263***	0.379***	0.267***	0.424***	0.238**	0.359***
	[2.664]	[3.005]	[2.772]	[2.902]	[2.702]	[3.173]	[2.528]	[2.833]
Degree*News	0.020**	0.02						
	[2.434]	[1.565]						
Degree*No News	0.010***	0.016***						
	[3.476]	[3.768]						
Closeness*News			-0.002	-0.027				
			[-0.081]	[-0.772]				
Closeness*No News			0.019**	0.020*				
			[2.353]	[1.797]				
Betweenness* News					0.011***	0.01		
					[2.633]	[1.097]		
Betweenness*No News					0.003	0.007**		
					[1.412]	[2.202]		
SCF* News							0.038***	0.044*
							[2.803]	[1.689]
SCF*No News							0.013**	0.024***
							[2.244]	[3.006]
News	0.051	0.038	-0.081	-0.165	0.088	0.05	0.006	0.018
	[1.094]	[0.560]	[-1.046]	[-1.347]	[1.576]	[0.491]	[0.409]	[0.849]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.3	0.28	0.27	0.25	0.27	0.27	0.28	0.28
N	296	296	296	296	280	280	280	280

Table 13: Target stock price run-up, target social connection, and tender offer

This table reports the results from OLS regressions on target cumulative abnormal returns (CARs) in windows [-6, -2] and [-11, -2]. *Tender* (*Non Tender*) is a dummy variable equal to one if the takeover involves a (no) tender offer. The connection variables are *Degree*, the log of the sum of a firm's connections with other firms, normalized by the highest possible number of connections; *Closeness*, the log of the number of the other firms in the network divided by the sum of graph theoretic distances from the firm to all other firms; *Betweenness*, the log of the sum of all possible firm pairs connected in the shortest paths through the firm normalized by the number of all possible firm pairs; and *SCF*, the social-connection factor score obtained using common factor analysis on *Degree*, *Closeness*, and *Betweenness*. The control variables are identical to those included in Table 5. The coefficients of the control variables are unreported. Both year and industry dummies are controlled for. Industries are defined based on two-digit SIC codes. *T*-statistics based on robust standard errors clustered by firm are in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

	Dep. Variable: CAR [-6, -2]			
	(1)	(2)	(3)	(4)
Intercept	0.260***	0.302***	0.283***	0.219***
	[3.380]	[3.686]	[3.595]	[2.871]
Degree*Tender Offer	0			
	[0.076]			
Degree*Non Tender Offer	0.011***			
	[4.146]			
Closeness*Tender Offer		0.015		
		[1.248]		
Closeness*Non Tender Offer		0.021**		
		[2.496]		
Betweenness*Tender Offer			-0.005	
			[-0.831]	
Betweenness*Non Tender Offer			0.005***	
			[3.342]	
SCF*Tender Offer				-0.006
				[-0.332]
SCF*Non Tender Offer				0.016***
				[3.597]
Tender Offer	-0.022	0.004	-0.076	0.027
	[-0.600]	[0.075]	[-1.249]	[1.613]
Control variables	Yes	Yes	Yes	Yes
R^2	0.27	0.25	0.25	0.26
N	369	369	351	351

Table 14: The bidder social connection effect on run-up

This table reports the results from OLS regressions of target or bidder cumulative abnormal returns in event window [-6, -2] against the social connections of the bidder or target. The connection variables are *Degree*, the log of the sum of a firm's connections with other firms, normalized by the highest possible number of connections; *Closeness*, the log of the number of the other firms in the network divided by the sum of graph theoretic distances from the firm to all other firms; *Betweenness*, the log of the sum of all possible firm pairs connected in the shortest paths through the firm normalized by the number of all possible firm pairs; and *SCF*, the social-connection factor score obtained using common factor analysis on *Degree*, *Closeness*, and *Betweenness*. The control variables are identical to those included in Table 5. The coefficients of the control variables are unreported. Both year and industry dummies are controlled for. Industries are defined based on two-digit SIC codes. *T*-statistics based on robust standard errors clustered by firm are provided in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

Dep. Variables:	Target CAR [-6, -2]				Bidder CAR[-6, -2]						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	0.230***	1.32	0.221**	0.215**	-0.034	0.464	-0.039	-0.021	0.008	-0.024	-0.025
	[2.634]	[0.423]	[2.458]	[2.485]	[-0.588]	[0.203]	[-0.658]	[-0.401]	[0.161]	[-0.443]	[-0.497]
Degree_Bidder	0.001				0.001						
	[0.331]				[0.650]						
Closeness_Bidder		0.235				0.108					
		[0.352]				[0.221]					
Betweenness_Bidder			0.001				0.001				
			[0.316]				[0.555]				
SCF_Bidder				0.002							
				[0.300]							
Degree_Target								0.001			
								[0.532]			
Closeness_Target									0.008***		
									[2.718]		
Betweenness_Target										0	
										[0.140]	
SCF_Target											-0.001
											[-0.280]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.21	0.21	0.22	0.22	0.2	0.2	0.21	0.2	0.21	0.21	0.21
N	346	346	329	329	342	342	325	356	356	338	338