Interbank Networking, Peer Pressure and the Performance of Investment banking Syndicates in M&As

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Abstract

We examine whether the cooperation network arising from investment banking syndication in mergers and acquisitions (M&A hereafter) helps explain the cross-sectional variation in acquirer announcement abnormal returns. We hypothesize that inter-investment bank (interbank hereafter) networking raises the ability of investment banks in a syndicate to monitor each another, and sanction free riders through exclusion from future cooperation. This facilitates the operation of the peer pressure mechanism, resulting in improved effort incentives and acquisition performance. We find that syndicates characterized by a higher degree of interconnections among participating investment banks are indeed associated with higher acquirer abnormal returns at the deal announcement. The effect is, however, concentrated in deals where information asymmetry between the acquirer and the advisors is at its strongest, and hence, where free-riding is most likely to occur. Furthermore, interbank networking has a more pronounced effect on acquirer returns in hot markets, in which peer penalty is strengthened through a higher level of expected payoffs from future cooperation. With additional implicit incentives created by peer pressure, interbank networking lowers the acquirer's cost of promoting advisor efforts through advisory fees.

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"[T]he strategy of investment banks *[is] to incur substantial costs in sharing resources with partner* banks *- in the form of technical advice, special studies, and market information - as a way of creating obligations that are hopefully converted into transaction fees from future cooperation" (Crane and Eccles, 1993, p.142).*

1 Introduction

Peer relationships are at the heart of most investment banking firms. Investment banks routinely cooperate by sharing market information, referring deals to each other, and syndicating deals in various financial markets. A considerable amount of research has examined the "reciprocity" element of interbank relationships in explaining membership stability across syndicates (e.g. Corwin and Schultz, 2005; Ljungqvist, Marston and Wilhelm, 2009). Others have studied the collusive nature of interbank relationships in generating excess profits necessary for preserving the incentives to gather information (Anand and Galetovic, 2000; Chen and Ritter, 2000; Anand and Galetovic, 2006). Less clear is, however, the role of interbank networks in counteracting the free-riding problem that is salient in peer cooperation, or more specifically, investment banking syndication. Indeed, many investment banking studies suggest that ongoing peer relationships may attenuate the non-cooperation problem internal to investment banking syndicates (Pichler and Wilhelm, 2001; Corwin and Schultz, 2005). Yet, to the best of our knowledge, no empirical research has been undertaken to investigate whether this is the case and how interbank networks influence the syndicate incentive structure and ultimately, the value creation for clients.

In this paper, we explore the governance role of interbank relationships in the context of mergers and acquisitions (M&A hereafter). We ask whether the interconnections between investment banks of a syndicate increase the incentives to cooperate and thus create value for acquirer clients. To motivate the empirical analysis, we employ a theoretical framework based on prominent models of moral hazard and peer pressure in teams (e.g. Kandel and Lazear, 1992; Che and Yoo, 2001; Rayo, 2007). In these models, a basic assumption is that an investment bank's effort, while unobservable to the acquiring firm, is more or less observable by other banks in the syndicate. In these situations, the fact that investment banks share a joint fee, which is largely contingent on the final acquisition success, induces externalities: if one advisor shirks (i.e., provides low effort), the probability that other advisors in a syndicate will receive lower fees increases.[1] This elicits endogenous (implicit) incentives for investment banks to exert peer pressure, that is, to monitor their co-workers, encourage them to exert the best effort and punish those who free ride.

Peer pressure can take on many forms. Given that investment banks interact repeatedly across deals (e.g. Pichler and Wilhelm, 2001; Corwin and Schultz, 2005; Ljungqvist et al., 2009), a natural form of peer pressure is to contingent future cooperation on whether or not a member bank free rides in the current deal.[2] Specifically, if any of other investment banks in the syndicate shirks, an advisor can take revenge by refusing to syndicate with the offender(s) for one or more consecutive periods. With this simple "tit-for-tat" strategy, a shirking investment bank is more severely punished: it is penalized not only by an increased probability of receiving a lower fee (as in the standard one-shot game), but also by a loss of expected profits from future syndication with other investment banks in the syndicate (Barron and Gjerde, 1997). Consequently, it is not surprising that each investment bank has stronger incentive to provide work effort when peer pressure is present rather than absent (Kandel and Lazear, 1992; Che and Yoo, 2001). Nonetheless, a potential downside to the peer pressure mechanism is that it puts syndicate members at an obvious cost which arises due to the activities of monitoring and sanctioning of their co-workers. This coupled with the fact that it is social and non-contractible raises the possibility that peer pressure may not take place in reality (Barron and Gjerde, 1997; Mas and Moretti, 2009). However, this ignores an important advantage to relationship investment banks, namely, network externalities.

Interbank networks in a syndicate facilitate the operation of the peer pressure mechanism in at least two ways. First, they enable investment banks to accumulate fine-grained information about one another through past interaction (Chassang, 2010). This, in turn, reduces the information asymmetry between two partner banks, allowing one to more effectively monitor the other (Sobel, 2002). Second,

[1] Mclaughlin (1990, 1992) finds that in a typical fee contract, more than 80% of the advisory fees are contingent on deal completion. This suggests that an advisor in a syndicate will receive lower fees if the deal fails to be successfully closed.

[2] There is considerable evidence showing that interbank relationships are the single most important determinant of future syndicate memberships (e.g. Pichler and Wilhelm, 2001; Corwin and Schultz, 2005; Ljungqvist et al., 2009). In the context of this study, although acquiring firms play a dominant role in making the decision about whether to form a syndicate and in what size, the lead advisor and other syndicate members may influence its choice of co-advisors by recommending the banks with which they have prior relationships.

interbank networks raise the power of mutual sanctioning (Fudenberg and Maskin, 1986; Kandori, 1992b). A notable phenomenon in the investment banking industry is that syndication memberships are remarkably stable, with investment banks placing a strong emphasis on long-term reciprocity (e.g. Pichler and Wilhelm, 2001; Corwin and Schultz, 2005; Ljungqvist et al., 2009). Reciprocity benefits relationship investment banks in that it conveys greater potential for future cooperation. Meanwhile, this benefit must be balanced against more credible and rapid retaliation if one free rides on its immediate ties (Fudenberg and Maskin, 1986; Kandori, 1992a; Fehr, Simon and Kirchsteiger, 1997; Hochberg, Ljungqvist and Lu, 2010). Moreover, reciprocity may encourage relationship investment banks to co-invest in certain assets such as sources of information sharing, common language and communication channels (Riordan and Williamson, 1985; Huberman, 2001; Nooteboom, 2004; Granovetter, 2005). To the extent that these co-investments are relationship-specific, i.e., lost if two banks "broke up" the relationship, they aggravate peer penalty (Rauch, 2001; Brown, Falk and Fehr, 2004; Rayo, 2007; Gilsing, Nooteboom, Vanhaverbeke, Duysters and van den Oord, 2008). An investment bank has a lower incentive to free ride when it jointly advises a deal with someone it "knows" because a valuable relational asset is placed at risk. This line of reasoning leads us to expect that syndicates consisting of more tightly networked investment banks have greater incentives to cooperate. All else equal, this should lead to greater effort provision and better acquisition performance measured by acquirer cumulative abnormal returns (CAR). If the primary value of interbank networking stems from its ability to reduce free-riding, it should have a more pronounced effect on acquirer abnormal returns when the information asymmetry between the acquirer and the advisors of a syndicate is more severe, in which case free-riding is more likely to occur. We proxy the degree of information asymmetry by employing two variables: (i) the absence of the ties between the acquirer and the advisors in the syndicate (i.e., vertical tie); and (ii) transaction size.

The empirical analysis of the association between interbank networking and acquisition performance is, however, challenging. The first factor complicating our analysis is that not all interbank relationships are publicly observable. Following common practice in corporate finance (e.g. Hochberg, Ljungqvist and Lu, 2007; Ljungqvist et al., 2009; Hochberg et al., 2010), we use past syndication relationships as a proxy for how investment banks in a syndicate are interdependent with each other. We quantify interbank network by density, defined as the relative degree of adjacent ties within a syndicate, where a tie arises if two investment banks in a syndicate have jointly advised on one or more M&A deals during the last year prior to the deal announcement (e.g. Freeman, 1978; Hochberg et al., 2007, 2010).

The second complication stems from the fact that investment banks tend to syndicate with a fixed group of partners over time, which makes interbank networking potentially endogenously determined (e.g. Pichler and Wilhelm, 2001; Corwin and Schultz, 2005; Ljungqvist et al., 2009; Shipilov, 2009). Furthermore, we include in our sample only a subpopulation of syndicate-advised deals. Given that these syndicated deals may differ in certain important unobservable ways from those non-syndicated deals, there is an additional problem of sample selection bias which cannot be easily addressed by a simple instrumental variables (IV) estimator. We tackle these issues by employing a novel three-stage, selection-adjusted IV approach, as suggested in the econometric literature (e.g. Vella, 1993; Vella and Verbeek, 1999; Semykina and Wooldridge, 2010; Bettin, Lucchetti and Zazzaro, 2012).

We test our hypotheses on a sample of U.S. syndicated M&A transactions announced from 1/1/1990 to 31/12/2012. Consistent with our expectations, we find that more densely networked syndicates are associated with significantly higher acquirer announcement abnormal returns after controlling for the reputation of participating advisors and other known determinants of acquirer CAR. Notably, the effect is evident only when the information asymmetry between an acquirer and the advisors of a syndicate is at its strongest, for deals in which the vertical tie is absent and for large deals. Thus, to the extent that the free-rider problem is more severe in these types of deals, our result offers strong support for the notion that interbank networking boosts effort incentives by supporting the operation of the peer pressure mechanism. The economic value of interbank networks is sizable: depending on the specifications, a one-standard-deviation increase in network density increases the acquirer three-day CAR by 1.98-3.12 percentage points, translating into $193.01-$304.71 million incremental shareholder wealth for an average-sized acquirer in our sample. The empirical results are robust to a wide range of alternative specifications.

Next, we explore various possible explanations for our findings regarding the positive relation between network density and acquirer abnormal returns. First, the positive acquirer CARs may arise because relationships investment banks possess superior knowledge about one another's attributes, leading to better matched syndicate members. Alternatively, networks may have evolved through a process of selection such that only peers that have demonstrated themselves as capable and honest partners can maintain their relationships over time (Li and Rowley, 2002). While we have employed an estimation strategy designed specifically to address this type of endogeneity, we further verify this issue by examining whether the effort incentive of a densely networked syndicate varies according to market conditions. If interbank networking indeed leads to better matching or a greater fraction of high-quality advisors to participate in a syndicate, then the positive density-acquirer CAR relation we document above should be indifferent under any market conditions. Contrary to this prediction, however, we find that the positive effect of interbank networks on acquirer CAR concentrates mainly in the peak but not the non-peak years of M&A cycles. This finding suggests that peer pressure does play a key role in determining the value of interbank networks. In hot markets where syndication activities occurs more often, peer pressure is more powerful because exclusion from a relationship is associated with a greater loss of expected payoffs from future cooperation.

Second, existing research suggests that lead advisor reputation helps curb moral hazard in syndicates. A reputable lead advisor may have the incentive to discipline other members in a syndicate because it has greater reputational stake at risk than others (Alchian and Demsetz, 1972; Benveniste, Busaba and Wilhelm, 1996; Aggarwal, 2000; Pichler and Wilhelm, 2001; Benveniste, Ljungqvist, Wilhelm and Yu, 2003). Thus, the positive association between network density and acquirer returns may merely capture the governance effect of lead advisor reputation rather than that of interbank netowrks. We address this issue by investigating the stand alone effects of lead advisor reputation and interbank networking using hand-collected data on lead-managed deals. We find that our results continue to hold after controlling for the presence of a prestigious lead advisor. Moreover, the use of a reputable lead advisor does not lead to higher acquirer abnormal returns. Thus, there is evidence that investment banking syndicates rely primarily on the *collective* efforts of investment banks in a syndicate, rather than the effort of a central monitor, to deter free riding, at least in M&As.

Third, interbank networks may affect the incentive structure through channels other than the peer pressure mechanism. Specifically, Pichler and Wilhelm (2001) study the moral hazard problem pertaining to investment banking syndicates organized for the purpose of underwriting security offerings. In their model, the issuer can mitigate the free-rider problem by implementing an incentive-pay scheme which aligns the bankers' incentives with that of the issuer through a payment of excess fees. Under this framework, interbank networking may improve acquisition performance by creating a relationship barrier to entry that helps an acquirer to preserve the quasi-rents provided to promote efforts. We discriminate this alternative from the "peer-pressure" explanation by examining the level of fees paid to a more densely networked syndicate. Our results indicate that the degree of interbank connections has either a negative or insignificant impact on the percentage of advisory fees. The finding, therefore, provides little support for the "incentive-pay" interpretation in which case one would expect the advisory fee to be higher for a syndicate characterized by a higher degree of interbank connections and hence, a stronger barrier to entry. Instead, it is more consistent with the argument that by inducing additional implicit incentives through mutual monitoring and sanctioning, interbank networking lowers the acquirer's cost of providing incentives through fees.

Our study contributes directly to the literature on the role of financial intermediation in M&As. It is the first study, to the best of our knowledge, to empirically examine the impact of interbank networking on acquisition performance. Prior research in this strand of literature has largely focused on the single-advisor setting, and explored various advisor characteristics in explaining cross-sectional difference in acquirer announcement returns, e.g., advisor reputation (Servaes and Zenner, 1996; Rau, 2000; Kale, Kini and Ryan, 2003; Walter, Yawson and Yeung, 2008; Bao and Edmans, 2011; Golubov, Petmezas and Travlos, 2012), specialization in the M&A market (Song, Wei and Zhou, 2013), dual agency (Agrawal, Cooper, Lian and Wang, 2013), and the provision of fairness opinion (Kisgen, Qian and Song, 2009). We depart from this strand of literature and instead investigate the economic value of interbank networking in a team setting. We show that syndicates consisting of more densely networked members display stronger incentives to exert a high level of effort and lead to better acquirer abnormal returns in large deals and in deals in which the acquirer-advisor tie is absent. The results support the notion that by facilitating mutual monitoring and sanctioning, interbank networking encourages effort provision in situations where the free-rider problem is exacerbated by the presence of asymmetric information between the acquirer and the advisors of a syndicate. These conclusions are supportive of the general peer pressure theory (e.g. Kandel and Lazear, 1992; Che and Yoo, 2001; Rayo, 2007; Mohnen, Pokorny and Sliwka, 2008; Winter, 2010), and in line with a number of empirical studies which show that the peer effect is more pronounced when team members are "close" to each other (e.g. Spagnolo, 1999; Mas and Moretti, 2009).

Beyond the importance of our results for the M&A literature, our study speaks to the broad literature on the value of networks of relationships embedded in the investment banking industry. The major strand of this literature focuses on the impact of the bank-firm (or vertical) relationships on firm value (e.g. Boot and Thakor, 2000; Asker and Ljungqvist, 2010; Ogura, 2010; Degryse, Masschelein and Mitchell, 2011; Engelberg, Gao and Parsons, 2012). Only a handful of studies have considered the importance of interbank cooperation and relationships. Anand and Galetovic (2000), for instance, study how information non-excludability affects the structure of financial intermediation markets. In their model, because information is non-excludable, i.e., the property rights over which are weak, investment banks are induced to cooperate to prevent one another from free riding on costly information-gathering efforts. In a later study, Anand and Galetovic (2006) model a similar case where investment banks collude to avoid price competition. Given that bank-firm relationships are generally featured by a "loose linkage" between relationship costs and deal revenues, collusion helps investment banks to appropriate most returns from their costly investments in networking with client firms. Pichler and Wilhelm (2001), on the other hand, model the moral hazard problem inherent in the security underwriting syndicates. They suggest that membership stability across deals may elicit a potential barrier to entry, which enables the incentive-pay strategy to operate as an effective tool against free-riding in an underwriting syndicate.

Empirically, Corwin and Schultz (2005) provide evidence showing that the strength of relationships between the lead bank and prospective syndicate members is the single most important determinant of syndicate memberships in the IPO market. This finding is further confirmed by Ljungqvist et al. (2009) who investigate the impact of analyst behavior on a bank's probability of being selected as a co-manager. They document that for both equity and debt offerings, a candidate bank's syndication relationships with the lead manager significantly increase its chance of winning a co-management appointment.

The current paper is similar in its scope to the above papers in that it too considers interbank cooperation and relationships. But to the best of our knowledge, it presents the first empirical evidence which shows that interbank networking is economically beneficial from a client firm's perspective. Moreover, our explicit attention to interbank networking as an endogenously emerged device which enhances peer pressure effect is novel compared with the arguments adopted in prior studies. Corwin and Schultz (2005), for instance, consider the possibility that free-riding is limited through private reporting. They argue that co-managers have incentives to "whisper" the lead underwriter's misconduct in the issuer's ear, because doing so may allow them to win more lucrative lead appointments in the issuer's follow-on underwriting transactions. Consistent with this argument, Corwin and Schultz (2005) find that the offer price is more likely to be revised in response to information revealed during the filing period if the underwriting syndicate contains more co-managers. The current work differs from theirs in that it focuses on an alternative mechanism, namely, peer pressure and how it interacts with the interbank networks to influence the incentive structure of investment banking syndicates.

Finally, and on a more general level, our study contributes to the emerging literature on peer effects. Peer pressure is found to be highly effective in encouraging work efforts in farms (Bandiera, Barankay and Rasul, 2005), contest between groups (Abbink, Brandts, Herrmann and Orzen, 2010), firms (Mas and Moretti, 2009; Hochberg and Lindsey, 2010), and many public good experiments (Fehr et al., 1997; Carpenter, Bowles, Gintis and Hwang, 2009). The current work is the first to uncover significant effects of peer pressure in the investment banking industry. More importantly, our study yields a host of new insights that are absent in the extant literature. We show that although the profit-sharing scheme provides syndicate members with *a motivation* to exert peer sanction, it may not be enough to effectuate mutually beneficial peer effects as many studies suggest (e.g. Fitzroy and Kraft, 1987; Che and Yoo, 2001). Investment banks do not voluntarily bear the costs of monitoring and punishing fellow members who shirk when these activities are costly. Instead, they display cooperative behavior only when they are mutually connected, and thus, able to monitor and sanction each other at a relatively low cost. We further show that the positive peer effect concentrates in hot markets where there exist ample opportunities for a pair of investment banks to cooperate in the foreseeable future. These findings indicate that even if investment banks in a syndicate are linked to one another, they do not cooperate out of pure altruism, i.e., truly care about their friends' wellbeing and payoffs. Rather, the dynamics in the scope of future interaction introduce variations in the level of peer sanction across investment banks which, in turn, leads to differences in the strength of peer pressure and the resulting level of implicit incentives. Finally, we show that interbank networks can have a significant influence over the level of advisory fees. By supporting the operation of peer pressure, interbank networks generate implicit incentives beyond those created under an explicit fee contract, allowing an acquirer to pay less to motivate optimal efforts. This evidence echoes the predictions of many economic models which explore the effect of the interaction between explicit and implicit incentives on optimal contract design (e.g. Che and Yoo, 2001; Rayo, 2007; Winter, 2010).

The reminder of this study proceeds as follows. Section 2 outlines the theoretical framework. Section 3 describes the data and variables used in our empirical analysis. Section 4 presents the econometric model. Section 5 examines the relation between interbank networking and acquisition performance. Section 6 considers alternative explanations for our results. Section 7 perfroms robustness checks, and Section 8 concludes.

2 Theoretical Framework

2.1 Moral Hazard and Peer Pressure

The difficulty of observing individual agents' effort and the resulting moral hazard problem are the key aspects of economic models that explain variations in team production (e.g. Alchian and Demsetz, 1972; Holmstrom, 1979, 1982; Rayo, 2007; Mohnen et al., 2008; Mas and Moretti, 2009). Pichler and Wilhelm (2001) relate the problem of moral hazard to investment banking syndicates organized for underwriting securities. In their model, whether an IPO can be successfully issued largely depends on the amount and the quality of the information produced by an underwriting syndicate. Such information production, however, requires individual bankers to devote day-to-day efforts in networking with their respective investors, which are overlapping with each another and difficult to monitor. As a result, shirking is tempting because part of the cost of exerting low effort in information production is borne by other investment banks in a syndicate rather than fully internalized by the free rider itself.

Some of these key insights apply directly to our case. When an M&A deal is jointly advised by multiple investment banks, an acquiring firm may easily observe the quality of the final acquisition outcome (e.g. whether the proposed deal ends up with an increase in shareholder value). But it is generally harder for the acquirer to tell how much effort each investment bank has exactly contributed to the final output given that in a team production, the marginal contributions of individual investment banks are not directly and separably observable (Alchian and Demsetz, 1972; Richardson, Yawson and Zhang, 2015). Thus, when the outcome is confounded by other factors and cannot be stated as a deterministic function of the effort exerted by the syndicate members, rewarding the entire syndicate based on the realized outcome induces the problem of moral hazard. Each investment bank in the syndicate has the incentive to free ride since the opportunistic behavior can be easily concealed behind the uncertainty concerning who is “at fault” (Alchian and Demsetz, 1972; Oxley, 1997; Maskin and Tirole, 1999; Hochberg and Lindsey, 2010). In the absence of effective governance mechanisms, this will lead to inadequate effort supplies and inefficient acquisition outcomes (Holmstrom, 1979, 1982).

To resolve the problem, an acquirer may directly monitor each advisor’s effort, but at a cost. In principle, direct monitoring reduces information asymmetry between the acquirer and the advisors, therefore allowing the acquirer to write an efficient contract that rewards and punishes individual advisors in a syndicate based on their respective efforts (e.g. Alchian and Demsetz, 1972). In practice, however, an acquirer’s ability to control free-riding through direct monitoring is limited. As M&As are fairly infrequent and complex in nature, monitoring is unavoidably costly for many acquiring firms that do not have adequate expertise in the areas in which individual advisors can add value. In these circumstances, the peer pressure mechanism, which exploits the strategic interaction and mutual monitoring capability of members in a team, provides an alternative solution to the problem of moral hazard (Fitzroy and Kraft, 1987; Kandel and Lazear, 1992).[3]

The notion that peer pressure can reduce free-riding and foster effort provision is not new (e.g. Kandel and Lazear, 1992; Barron and Gjerde, 1997; Spagnolo, 1999; Mohnen et al., 2008; Mas and Moretti, 2009; Winter, 2010). Perhaps the most prominent paper in this strand of the literature is Kandel and Lazear (1992) who first introduce the function of peer pressure in economic teams. In their model, the profit-sharing rule, which ties an agent's compensation to her own effort as well as that of her co-workers, induces the agent to monitor others in the team and to punish those who shirk. The introduction of peer pressure in effect alters the utility function of individual agents. If an agent shirks, she suffers a disutility that arises not only from the monetary penalty set under the compensation rule, but also from peer sanction which may take various forms including membership suspension (e.g. Che and Yoo, 2001; Rayo, 2007), feelings of guilt or shame (Kandel and Lazear, 1992; Mas and Moretti, 2009), and reputational damage (Chemmanur and Tian, 2011). In this setup, Kandel and Lazear (1992) show that individual agents' equilibrium effort provision is higher than it otherwise would be when peer pressure is absent.

Applying the idea to the context of M&A syndicates, we argue that peer pressure may operate for two reasons. First, by working directly with each other, investment banks of a syndicate are arguably better able to observe one another's contribution than the acquirer. Second, investment banking syndicates typically share a joint fee that is largely contingent on the final acquisition success (McLaughlin, 1990; McLaughlin, 1992). This coupled with potential damages on one's reputation following poor performance creates a strong incentive for individual advisors to deter free-riding through the exertion of peer pressure (Williamson, 1993; Corwin and Schultz, 2005; Golubov et al., 2012). As discussed, a natural strategy that each syndicate member can employ is to threaten (implicitly) to abstain from syndication with the cheater(s) in subsequent periods (Holmstrom, 1982;

[3] Another strategy is to delegate the monitoring responsibility to a lead advisor, who regulates the behavior of other investment banks in the syndicate on behalf of the acquirer. We discuss and explore this possibility in Section 6.2.

Fitzroy and Kraft, 1987). [4] The Nash equilibrium strategy for each bank is, therefore, a function of : (i) the expected payoff from exerting a high level of effort, given that other members also contribute; (ii) the chance of being caught; and (iii) the expected payoff from unilaterally shirking in the current deal and being subsequently excluded from the syndicates of victim members (Fudenberg and Maskin, 1986; Fudenberg and Levine, 1991; Che and Yoo, 2001; Hamilton, Nickerson and Owan, 2003; Rayo, 2007). Obviously, for this form of peer pressure to be effective, the expected penalty must be severe enough. That is, the probability of being caught and the long-run profits of cooperation with other syndicate members must be sufficiently high. Furthermore, while the profit-sharing rule provides syndicate members with a motivation to exert peer pressure, the intended monitoring actions and the resulting punishment for shirking may not actually take place (Kandel and Lazear, 1992; Barron and Gjerde, 1997). As costs must be incurred to detect and penalize free-riders, syndicate members can have little incentive to do so if the costs outweigh the resulting benefits from reduced free-riding (Mas and Moretti, 2009). This is plausible given that peer pressure is social and non-contractible (Kandel and Lazear, 1992; Barron and Gjerde, 1997; Mas and Moretti, 2009). In this case, we argue that interbank networking facilitates the operation of the peer pressure mechanism, for the reasons outlined below.

2.2 Endogenously Emerged Networks

In the investment banking industry, syndicate members are rarely faceless banks operating at arm's length. Rather, investment banks tend to cooperate with the same partners over time, with the consequence that syndicate memberships are thoroughly dominated by a group of investment banks that are familiar with each other through historical transactions (Pichler and Wilhelm, 2001; Corwin and Schultz, 2005; Ljungqvist et al., 2009).[5] One possible explanation for this phenomenon is that investment banks strategically network with each other so as to facilitate the operation of the peer pressure mechanism necessary for deterring free-riders (Persons and Warther, 1997; Anand and

[4] There is a potential implicit collusion problem where connected banks may collude to work against the best interest of the acquirer. We however believe that reputational concern reinforced through repeated dealings will serve as such a mechanism which prevents this collusion problem.

[5] This is consistent with the practice that investment banks often maintain a record of favors that they have both given to and received from their partnering banks; banks that do not reciprocate appropriately are considered to be uncooperative and hence, need to be punished (Shipilov, 2009).

Galetovic, 2000; Benveniste et al., 2003; Morrison and Wilhelm, 2008).[6] In particular, peer relationships permit investment banks to, as a by-product of past cooperation, gain private information about one another's conduct, capability and unique skill sets (Hamilton et al., 2003; Robinson and Stuart, 2007; Chassang, 2010; Parise and Rollag, 2010). This information is valuable in that it circumvents information asymmetry between two investment banks in a syndicate, allowing one to more effectively monitor the other at virtually no incremental cost. A considerable number of economic studies, for example, model the information about others' past conduct as valuable inputs that individual agents can utilize to draw statistical inference on the expected outcome (e.g. Holmstrom, 1982; Kandori, 1992b). In this sense, the mutual knowledge embedded in direct ties facilitates the formation of a "benchmark" against which a syndicate member can use to properly evaluate other members' effort. This, in turn, eases mutual monitoring, making any deviation from the anticipated outcome more likely to be detected (e.g. Kogut, 1989; Abreu, Milgrom and Pearce, 1991; Kandel and Lazear, 1992; Kandori, 1992b; Mody, 1993; Barron and Gjerde, 1997). We thus expect mutual monitoring to be more effective in a more densely linked syndicate where each member is monitored by a larger number of "informed" co-workers (i.e., those who know better about the member's performance potential and can better read its effort signals).

In addition, peer relationships raise the *ex post* sanctioning capabilities of investment banks in a syndicate. The phenomenon of the stable peer cooperation sketched above indicates that reciprocity is expected and that existing ties confer greater probabilities of long-run cooperation (e.g. Pichler and Wilhelm, 2001; Corwin and Schultz, 2005; Ljungqvist et al., 2009; Shipilov, 2009). Hence, the tacit threat of membership suspension is likely to be more credible when it is made by a related rather than an unrelated investment bank in a syndicate. Moreover, reciprocity may encourage relationship-specific investments which further amplify the peer sanction (Riordan and Williamson, 1985; Huberman, 2001; Nooteboom, 2004; Granovetter, 2005). It is not unusual, for instance, that relationship investment banks co-invest in common language, specific communication channels and

[6] There are additional concerns that cooperation may create chances for partnering banks to poach a bank's valuable employees, clients and/or financial innovation. The consensus in the literature is that the weak property rights of investment banks over their human assets along with the possible spillover effect that causes their financial innovations to be easily reverse-engineered precludes perfect competition in the investment banking industry. This implies that investment banks would prefer to cooperate with and stick to those banks which they are familiar with (Persons and Warther, 1997; Anand and Galetovic, 2000; Benveniste et al., 2003).

routines in order to increase the efficiency gains from long-run cooperation (e.g., through reduced costs and complexities in streamlining the decision making process) (Nooteboom, 1992; Teece, 1992; Huberman, 2001; Rauch, 2001). Given that a breakup is associated with a loss of these relationship-specific assets, free-riding is particularly costly for investment banks that are cooperating with someone they know (Rauch, 2001; Brown et al., 2004; Rayo, 2007). We thus hypothesize that the peer pressure mechanism is more effective in more densely networked syndicates. All else being equal, this should translate into greater effort provision and better acquisition outcomes.

2.3 Conditional Effects

If the primary value of interbank networking resides in its ability to reduce agency costs, then one can only detect its favorable effect on acquisition performance when there is *some* scope for free-riding (e.g. Kandel and Lazear, 1992; Prendergast, 2002). If the advisors in a syndicate are all well incentivized to exert high-level effort, interbank networking and the resulting peer pressure should not matter. Accordingly, we conjecture that the network effect is more evident in deals where the information asymmetry between the acquirer and the advisors is severe, and therefore, where the acquirer cannot rely on direct monitoring to cheaply attenuate the problem of moral hazard (e.g. Prendergast, 2002). To proxy for the severity of asymmetric information, we construct two variables: (i) the existence of vertical exchange relationships (i.e., the ties between the acquirer and the advisors in the syndicate) and (ii) transaction size.

Generally, the level of information asymmetry is lower when the acquirer-advisor relationships are present rather than absent (Prendergast, 2002). Similar to interbank networks, past interaction allows an acquiring firm to directly observe an advisor's behavior and accumulate information about the advisor. This increased information availability helps the acquirer to better detect whether that advisor has misbehaved in the current deal which, in turn, discourages shirking. Thus, all else equal, peer pressure is less important for acquirers that have more extensive ties with the advisors working in a syndicate and *vice versa*.

Pichler and Wilhelm (2001) suggest that the potential for moral hazard in syndicates also increases with deal size. Larger transactions typically involve higher complexity and uncertainty, which unavoidably expose an acquiring firm to greater information asymmetry (e.g. Oxley, 1997;

Prendergast, 2002; Kaplan and StroMberg, 2004). For instance, a target firm of larger size often has more divisions, lines of business and geographic regions. In this case, individual advisors of a syndicate are more likely to simultaneously carry out multiple activities, some of which can be poorly observed (Prendergast, 2002). Larger deals may also require more sophisticated financial due diligence for which acquiring firms do not have the necessary competence to understand. This, in turn, heightens the advisors' incentive to free ride since neither individual activities nor the joint outcome can be easily understood and related to the advisors' effort provision with any precision (e.g. Oxley, 1997; Kaplan and StroMberg, 2004; Hochberg and Lindsey, 2010). We thus hypothesize that *ceteris paribus,* the effect of interbank networks on acquisition performance is most evident in deals in which the acquirer-advisor tie is absent, and in deals that are considerably large.

To test the conditional effects of interbank network on acquisition performance, we run regressions separately for the sample divided by the existence of vertical ties and the size of the transactions.

3 Data and Variable Definitions

3.1 Sample and Data

We use the *Thomson Financials Securities Data Collection Platinum (SDC)* database to collect data on U.S. M&A transactions announced between January 1990 and December 2012 (rumored deals are excluded). Following Golubov et al. (2012), we clean the sample of deals that are classified as bankruptcies, liquidations, self-tenders, leveraged buyouts, privatizations, repurchases, restructurings, reverse takeovers and going private transactions. For the remaining observations, we exclude the deals that: (i) involved less than two investment banks advising the acquirer; (ii) had payment method missing; (iii) had a transaction value less than $1 million or 1% of acquire market value; (iv) were made by acquirers having insufficient data from CRSP database to measure abnormal returns at the announcement date; and (v) involved an acquirer having more than 10% of the initial stake in the target or seeking to own less than 50% of the target after the transaction. After imposing these restrictions, we are left with a sample of 1,138 syndicated transactions.

3.2 Variable Definitions

3.2.1 Measure of Acquisition Performance

We follow prior studies and measure acquisition performance by acquirer announcement abnormal returns (e.g. Bowers and Miller, 1990; Walter et al., 2008; Ismail, 2010). We use the standard event study methodology to compute the acquirer three-day cumulative abnormal return (CAR) around the deal announcement. The CAR is measured as returns in excess of those predicted by the market model, where the CRSP value-weighted index is used as the benchmark and the parameters are estimated over a period from 300 to 91 days prior to the announcement. Panel C of Table 1 reports the descriptive statistics of the acquirer three-day CAR for the sample. The mean (median) CAR is 0.3% (-0.3%), with a standard deviation of 10.00%.

3.2.2 Measure of Interbank Networks

We measure interbank network by density, defined as a relative degree of adjacent ties within a syndicate (Freeman, 1978). A tie arises if two of the member banks had syndicated one or more M&A deals before.[7] We compute network density by first constructing a symmetric "adjacency" matrix for each syndicate at the date of deal announcement. Each cell of the matrix is coded as one if two of the member banks has a tie and zero otherwise.[8] By convention, we assume that a bank has no relationship with itself and hence, all diagonal elements in a matrix are set to zero. We then compute the sum of ties for each matrix. Clearly, the more adjacent ties, the greater the extent to which investment banks in a syndicate are interconnected. Given that density increases with syndicate size, we normalize this measure by the maximum logically possible ties in an n-sized syndicate to ensure comparability across syndicates (e.g. Hochberg et al., 2007, 2010). Formally, the measure of network density can be written as follows:

$$D_S = \sum_{j=1}^{n} \sum_{i=1}^{n} \tau_{ijS} / \big(n(n-1)\big) \quad for\ n \geq 2 \quad and\ ij \in S \qquad (1)$$

Where:

[7] Here the relationships are "undirected" and all the matrices are symmetric. As a robustness check, we repeat our main regression analysis of acquirer CAR using a measure of asymmetric network density for a hand-collected sample of lead-managed deals. The results are qualitatively similar to those reported here.

[8] We also compute value-weighted network density by constructing an adjacency matrix for each syndicate, in which each cell reflects how frequently a member bank has worked with other members in the past. Our main results continue to hold when this alternative network measure is used.

$D_S =$ density of syndicate S;

n = syndicate size;

$$\tau_{ijS} = \begin{cases} 1 & \textit{if member bank i and j in syndicate S have a tie; and} \\ 0 & \textit{otherwise} \end{cases}$$

$n(n-1) =$ the maximum logically possible ties in an $n-$sized syndicate.

To gain further intuition for density, Figure 1a depicts the networks for two hypothetical syndicates, "S_a" and "S_b". Each syndicate has four investment banks, which are represented by nodes in the figure. The links between nodes indicate the existence of ties between two syndicate members. Obviously, the network of syndicate "S_a" is relatively dense, where each member has one or more ties to other members; while the network of syndicate "S_b" is relatively sparse, with only one of the members being tied to another.

Figure 1b shows the adjacency matrix for each syndicate. For a syndicate comprising four investment banks, the maximum possible ties are 12 (4x3). Given that the sum of existing ties in syndicate "S_a" is 10, its relative degree of density is 10/12 (ten out of twelve possible ties). The degree of density in syndicate "S_b" is 2/12 (two out of twelve possible ties). Thus, consistent with the visual inspection, our measure of networks indicates that member banks in syndicate "S_a" are more tightly networked than those in syndicate "S_b".

Networks are clearly dynamic, with investment banks breaking up old ties and establishing new ones over time. We capture these dynamics by constructing an adjacency matrix for each syndicate over a trailing one-year window. The sample period also saw a substantial number of mergers and acquisitions in the investment banking industry. To take this into account, we follow Ljungqvist et al. (2009) and allow surviving banks to inherit the peer relationships of their "predecessors". For instance, Merrill Lynch and Banc of America Securities LLC merged in 2008. Thus, the combined firm, Bank of America Merrill Lynch, is considered as having relationships with investment banks to which Merrill Lynch and Banc of America Securities LLC were tied prior to the merger.[9] Panel A of Table 1 indicates that in an average syndicate, the network density is 30.60%. The standard deviation in density across syndicates is 43.80%.

3.2.3 Other control variables

We control for various acquirer- and deal-specific characteristics that are found in prior studies to be important determinants of acquirer CAR (e.g. Kale et al., 2003; Moeller, Schlingemann and Stulz, 2004; Masulis, Wang and Xie, 2007; Golubov et al., 2012; Alexandridis, Fuller, Terhaar and Travlos, 2013). These include acquirer size, run-up, free cash flow, leverage, Tobin's Q, transaction size, relative size, industry relatedness, number of competing bidders, target listing status, all-cash offer, tender offer, hostility of target management, and whether the deal is cross-border. Table 1, Panels B and C, report the summary statistics for these control variables for the sample. The average acquiring firm has a size of $9,770.973 million, with a stock price run-up of 8.5% before the deal announcement. The mean (median) free cash flow ratio is about 8% (9.8%) and the mean (median) leverage ratio is around 18.8% (16%). Tobin's Q is positively skewed, with a mean value of 2.070 versus a median of 1.507. The targets are large for syndicated deals, accounting for 66.2% of the average acquirer size. Public and industry-related transactions make up 55.1% and 63.6% of the sample deals, respectively. Finally, approximately one-third of the transactions are paid by all cash.

To ensure that the performance effect of interbank networks is not driven by any omitted variables that affect acquirer CAR and in some cases, the choice of network structure of a syndicate, we include the following three variables as additional controls. The first variable indicates whether a reputable advisor is present in a syndicate. Prior research shows that reputable advisors offer high-quality advice for public acquisitions (e.g. Kale et al., 2003; Golubov et al., 2012). Meanwhile, prestigious investment banks may be better-networked than less prestigious ones, presumably because they have more deals to share with and to be reciprocated by other banks. Thus, if this variable is omitted from the model, any positive relation between network density and acquisition performance could be spurious. That is, it could be driven by the fact that greater network density is more likely to be observed for syndicates in which high-quality advisors are present than it would be when they are

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

absent. As a measure of advisor reputation, we rank individual advisors based on the value of the transactions each advisor has advised. We then classify an advisor as reputable if it is ranked among the top 8. The mergers and acquisitions among investment banks themselves over the sample period are taken into account when assigning the reputation measure to each deal (Golubov et al., 2012). Panel A of Table 1 indicates that about 64% of syndicated deals involve a top 8 advisor, suggesting that reputable banks are indeed key players in the syndication market.

The second control variable is syndicate size. Richardson et al. (2015) show that syndication itself has an independent and significant impact on various acquisition outcomes. At the same time, the number of investment banks may positively correlate with density. It is possible, for example, that a densely networked syndicate is more desirable when the syndicate is larger and hence, more susceptible to free riding. We measure syndicate size as the number of acquirer advisors reported by the SDC. The mean (median) size of M&A syndicate in our sample is 2.23 (2) with a standard deviation of 63.7%, as shown in Panel A of Table 1.

Finally, we control for the density of vertical relationships, defined as the fraction of all logically possible ties between the acquiring firm and its advisors in the syndicate. As noted earlier, vertical ties may affect an acquirer's choice of syndicate network structure since the acquirer having denser relationships with its advisors may possess superior knowledge about the advisors' capabilities. This, in turn, improves the acquirer's monitoring ability, lessening the importance of interbank networks to promoting advisor incentives. Meanwhile, that acquirer is likely to experience better acquisition outcomes as a result of reduced free-riding. We measure vertical relationship density by constructing an adjacency matrix for each deal, similar to the measurement of interbank network density. The cells in each matrix are coded as one if there is a vertical tie between the acquirer and the incumbent advisor in the syndicate; and zero otherwise. A vertical tie exists if an incumbent investment bank has advised the acquirer on M&A transactions one year before the announcement year (our results are robust to alternative 3- and 5-year windows). It is worth noting that the network here is different from interbank networks in that it involves the acquirer in addition to the advisors in a syndicate. Moreover, the adjacency matrix is "asymmetric", that is, a vertical tie is directed from acquirer (the "originator" of a tie) to each advisor of the syndicate (the "receiver"), and not *vice versa*.

To account for the possibility that stronger vertical relationships have a greater impact on acquisition performance, we weigh each vertical tie by the frequency that an investment bank of a syndicate has worked for the acquirer in the past. Again, bank mergers are considered, so that an acquirer's tie to a "surviving" syndicate member is equal to the sum of the acquirer's ties to the "predecessor" banks before the merger. Panel B of Table 1 indicates that the mean (median) vertical relationship density is 10.00% (0.00%) in our sample, with a standard deviation of 30.90%.

Appendix A summarizes all the variables used in our empirical analysis. In untabultated results, we compute the variance inflation factors (VIF) for these variables and find none of the VIF values exceed the critical value of 10 (Gujarati, 2003). Thus, multicollinearity is unlikely to be a concern here.

[Please Insert Table 1 Here]

4 An Empirical Framework for Analysing Network Density

4.1 Endogeneity and Sample Selection

There are two fundamental concerns troubling our empirical analysis on the association between syndicate network structure and acquisition performance. First, the fact that investment banks prefer to cooperate with those they know indicates that the network structure of a syndicate (i.e., sparse or dense) is unlikely to be exogenously emerged. Endogeneity can also arise if an acquirer's choice regarding the desired level of network density is influenced by certain unobservable factors such as the firm's monitoring technology and contracting environment (Kaplan and StroMberg, 2004). For instance, acquirers with access to superior monitoring technology may rely on explicit fee contracts rather than internal peer pressure to motivate efforts (Himmelberg, Hubbard and Palia, 1999). Meanwhile, one may expect these firms to experience higher abnormal returns because of the improved advisor effort provision. In these situations, the superiority of an acquiring firm's monitoring technology simultaneously makes a dense syndicate less desirable while deal performance more favorable. Failure to account for this unobserved heterogeneity in monitoring technology across acquiring firms would cause us to underestimate the true effect of network density on acquisition performance.

Second, given that we include only syndicated deals in our sample, the problem of sample selection bias is obvious. The essential issue here is that if certain omitted variables determining whether an observation is included in the selected sample are also correlated with those affecting acquisition outcomes, the estimates from a simple ordinary least squares (OLS) regression will be inconsistent and biased (Heckman, 1979, pp. 153-154). For example, unobserved variation in deal quality may affect both deal performance and the choice of a syndicate. More problematic deals are likely to produce poorer acquisition outcomes. At the same time, they may have greater difficulties in attracting multiple investment banks which may refuse to participate due to reputational concerns. If this is the case, the syndicated deals "selected" into our sample would involve a larger fraction of high-quality deals that are more likely to be syndicated (i.e., attracting multiple advisors). We therefore employ an econometric model that considers both endogeneity and sample selection bias, as discussed below.

4.2 Econometric Model

Estimating models with endogenous variables and sample selection bias has been comprehensively explored in the econometric literature (e.g. Vella, 1993; Vella and Verbeek, 1999; Semykina and Wooldridge, 2010; Bettin et al., 2012). We follow Semykina and Wooldridge (2010) and adopt a three-stage, selection-adjusted IV approach. In particular, we consider the model with the following form:

$$y_i = \alpha_0 + Density_i\delta + X_i\theta + \varepsilon_i \; ; \qquad (2)$$

$$Density_i = \beta_0 + Z_{2i}\omega + X_i\pi + \mu_i; \qquad (3)$$

$$Syndicate_i^* = \varphi_0 + Z_{1i}\gamma + v_i; \qquad (4)$$

$where$:

$Syndicate_i = 1;$ $Density_i$ is observed if $Syndicate_i^* > 0 \, , and$

$Syndicate_i = 0;$ $Density_i$ is unobserved if $Syndicate_i^* \leq 0$

Equation (2) is the structural equation which relates acquirer CAR (y_i) to the degree of network density in a syndicate ($Density_i$). X_i denotes a set of exogenous variables as described in Section 3.2.3; and ε_i is the error term. Equation (3) is the reduced form equation for the endogenous regressor, $Density_i$. Z_{2i} denotes a vector of exogenous instruments (introduced below); β_0 is the intercept; and μ_i is the disturbance term.[10] In Equation (4), we model the sample selection by specifying a selection rule based on whether a syndicate is observed or not. Specifically, the unobserved latent variable, $Syndicate_i^*$, is related to the selection binary variable, $Syndicate_i$, in a way that if $Syndicate_i^* > 0$, syndicate is formed for the i^th deal ($Syndicate_i = 1$), and the value of $Density_i$ for that syndicate is observed; otherwise, $Syndicate_i = 0$ and $Density_i$ is missing. In essence, $Density_i$ is a censored endogenous variable, the observability of which is conditional on whether a syndicate is established. φ_0 is the intercept; Z_{1i} denotes a set of factors affecting the probability of forming a syndicate; and v_i is the error term. Equations (2) through (4) form a simultaneous equations system. Following the discussion in the previous subsection, the key feature of this system is that the error terms ε_i may correlate with μ_i, making $Density_i$ endogenous, while the correlation between ε_i and v_i implies the realization of a syndicate ($Syndicate_i$) is informative about ε_i, leading to the problem of sample selection bias (Chib, Greenberg and Jeliazkov, 2009).

We estimate the system in two steps. First, we estimate the sample selection equation (Equation (4)) by probit for a sample of M&A deals announced over the period between 1990 and 2012, regardless of whether a syndicate is formed or not. The dependent variable is a binary variable equal to one if syndication is realized, and zero otherwise. Following Richardson et al. (2015), we employ three categories of explanatory variables. First, we expect syndicates to be more likely to be hired in more complicated deals in which their combined networks and expertise of multiple investment banks are of greater value. We measure transaction complexity by deal size, hostility of target management towards a deal, target listing status, number of competing bidders, industry relatedness, and whether the acquirer and the target are from different countries.

Second, syndicates bring together the capital and distribution channels of different investment banks, thus broadening an acquiring firm's set of financing choice alternatives (e.g. bank loan, equity and debt underwriting) and improving the ability to help raise acquisition-related financing. We therefore expect that acquiring firms are more likely to hire a syndicate when they have a higher

[10] We note that the main objective here is to address the issue regarding the endogeneity of network density, rather than to identify all of the possible determinants of network density.

demand for external financing. Given that acquiring firms with more financial slack are less likely to turn to external financing which is relatively more expensive (Myers, 1984), we measure an acquirer's demand for external financing by *cash shortfall*, defined as the difference between the dollar cash component of an offer and the acquirer's free cash flows. Intuitively, the larger is the cash shortfall, the greater is the requirement for external financing.

Lastly, we control for factors that may render the formation of a syndicate unnecessary. These include acquirer size, stock price volatility, leverage ratio, acquisition experience and the presence of a top 8 advisor in a syndicate. All else being equal, a syndicate is less important for larger and safer acquiring firms which are less informationally opaque, and hence, have access to a wider range of alternative financing channels through which they can raise money at reasonable costs even on an "at arm's length" basis (Petersen and Rajan, 1994; Patrick and Xavier, 2000). To proxy for firm risk, we employ the acquirer's stock price volatility and leverage ratio (Demsetz and Lehn, 1985; Hadlock and James, 2002; Bharadwaj and Shivdasani, 2003; Song, 2004). We expect firms with a less volatile stock price and a lower leverage ratio to be less risky and hence, less likely to employ a syndicate.

When an acquiring firm experiences strong stock price run-up prior to the deal announcement, the probability of hiring a syndicate reduces because the acquirer is more likely to use its own stock rather than external fund to finance the deal (Martynova and Renneboog, 2009).

Compared with firms with little or no acquisition experience, better-experienced acquirers possess stronger in-house M&A expertise, which lessens the importance of obtaining enhanced expertise through syndication. Similarly, the presence of a reputable advisor reduces the need to hire additional investment banks because reputable advisors are often considered as having the expertise to offer high-quality M&A advice alone (Golubov et al., 2012).

As exclusive restrictions, we employ lagged syndicate size *(Syndicate size lag)*, measured as the number of advisors hired by an acquirer in its most recent deal, and its interaction with the ratio of the current and previous deal size *(Weighted size lag)*. These two variables are constructed to capture unobserved factors that may affect the propensity to hire a syndicate across acquiring firms over time (Corwin and Schultz, 2005). They are excluded on the basis that an acquirer's prior use of a syndicate should have no direct impact on the current deal's performance. Based on the probit estimates, we compute the generalized residuals.

Next, we estimate Equations (2) and (3) simultaneously using an IV approach for a sample of syndicated deals only. The endogenous regressor, $Density_i$, is instrumented with a set of "exogenous" variables (Z_{2i}), while the generalized residual computed from the first step is inserted as an additional regressor in Equation (2) to correct for sample selection bias if any (Vella and Verbeek, 1999).

4.3 Identification

To identify the IV model, we employ multiple instruments which are related to the endogenous regressor, $Density_i$, but uncorrelated with the error term in the structural equation of acquire CAR (Equation (2)). Our first instrument comes from the variation of geographic proximity among investment banks in a syndicate. Geographic proximity may increase network density in that investment bankers from the same geographical region may have a greater chance to meet and interact with each other (e.g. through the participation of the same local associations and professional meetings). This increases the probability for these bankers to establish ties (Hochberg et al., 2010; Huang, Jiang, Lie and Yang, 2011; Tian, 2012). Meanwhile, there is no obvious reason to believe that simply having geographic proximity would directly affect the current deal's performance. We measure geographic proximity by the fraction of syndicate members from the same Federal State, where the State data are obtained from the SDC database.

The second instrument captures the fraction of syndicate members that have participated in one another's syndicates in the debt market prior to the announcement year.[11] We expect that prior debt-underwriting relationships facilitate the formation of interbank ties in M&As, but should not affect the M&A deal outcome other than operating *indirectly* through their impact on the current M&A syndicate network structure if there is any. To account for the possibility that the degree of network density in an M&A syndicate is influenced by both the duration and the strength of underwriting relationships in the debt market, we construct two variables. The first variable is an

[11] Similar instruments are constructed based on the prior interbank ties formed in the equity market over the last one year and five years before the announcement year. These instruments, however, do not appear to offer any additional explanatory power in identifying any of the specifications of network density throughout our analysis. The instrument redundancy test for the full sample, for example, indicates that these instruments are redundant with a p-value of 0.1294. We therefore do not use these variables, given that including irrelevant instruments may increase the biases of instrumental-variables estimators (Fletcher and Lehrer, 2011).

unweighted measure, computed based on the *existence* of the most recent ties formed between syndicate members in the debt market one year before the announcement year. The second variable is a weighted measure, which takes into account the number of times that two investment banks have interacted with each other in the debt market over the last five years before the announcement year.

Our third model identification follows the intuition that the choice of a syndicate network structure (i.e., dense or sparse) is likely to be localized. The recent study by Francis et al. (2012) indicates that acquiring firms prefer local financial advisors even in cross-border deals. If that is the case, the probability that an acquirer will form a densely networked syndicate is likely to be higher if its local advisors are relatively more tightly networked. We thus include a measure of the density of interbank networks present in the acquirer's Federal State as an additional instrument ("*local network density*"). It is computed as a proportion of logically possible ties that exist among *all* the investment banks active in the acquirer's State, where a tie exists if two investment banks have syndicated M&A deals one year before the announcement year. [12] This variable is excluded on the basis that an acquirer's deal performance should not be directly affected by the pre-existing population density of local investment banks.

Since using a large set of instruments can make an estimator to have poor finite sample performance, we demonstrate the strength of our results by employing the full set of the instruments listed above (Fletcher and Lehrer, 2011). [13] With this relatively large instrument set, we estimate our IV model (Equation (2) and (3)) by limited information maximum likelihood (LIML). Compared with traditional estimators such as 2SLS and GMM, the advantage of the LIML estimator is that it is median-unbiased and hence, more asymptotically efficient when there are many instruments (e.g. Anderson, 2005; Ackerberg and Devereux, 2006). Anderson, Kunitomo and Sawa (1982), for instance, provide Monte Carlo evidence showing that the LIML estimator is efficient regardless of the number of instruments, while the bias of 2SLS estimator increases with the size of the instrument set. In

[12] Note that our first IV (*geographic proximity*) measures the percentage of syndicate members from the same Federal State (which may or may not be the same as the acquirer's State), whereas *local network density* measures the degree of connections between all the investment banks headquartered in the acquirer's Federal State.

[13] Since the exclusion of redundant instruments improves the reliability of our estimates (Fletcher and Lehrer, 2011), our preferred set of IVs is a subset of the instruments which allows us to achieve stronger results. To demonstrate the strength of our findings, however, we consider the most difficult test with our sample data by employing the full set of the instruments and maintaining the same set in every analysis involved this study.

addition, the LIML estimator is more robust to weak instruments (i.e., instruments which are correlated with endogenous regressor but only weakly), when compared to other estimators such as 2SLS (Stock, Wright and Yogo, 2002; Anderson, 2005).

Our identification relies on the assumption that our instruments affecting the level of observed interbank network density are not correlated with the unobserved component of the acquirer CAR equation (ε_i in Equation (2)). While possible, we are unaware of any existing evidence suggesting that the instruments considered here affect the performance of mergers and acquisitions. Moreover, our identification strategy is valid so long as the set of our instruments affects acquirer CAR only through the degree of network density, but not via other channels (Fletcher and Lehrer, 2011). To more formally test our instruments for statistical exogeneity, however, we conduct the Hansen-J test which tests the joint null hypothesis that: (i) the instruments are uncorrelated with the structural error term, ε_i ; and (ii) the model is correctly specified (i.e., the instruments are correctly excluded from the structural equation) (Hochberg and Lindsey, 2010; Fletcher and Lehrer, 2011).

Having satisfied the exclusion restriction is not sufficient for the LIML estimator to be consistent in a finite sample. The instruments must also be "strongly" correlated with the included endogenous regressor(s) (Staiger and Stock, 1997). We test for instrument strength using the Stock and Yogo (2002) test. Under the null hypothesis that the set of instruments is jointly weak (even if the model is identified), the Stock and Yogo (2002) test provides critical values that vary according to factors such as the IV estimator used, the size of instrument set, and the number of endogenous variables (Stock et al., 2002). With the LIML estimator, the instrumentation is considered "strong" if the test statistic exceeds the Stock and Yogo (2002) critical value for a maximal size bias that one is willing to tolerate with the estimator (e.g. the worst-case limiting rejection rate for a nominal 5% Wald test of a null that the coefficients of the instruments are jointly equal to zero).

5 Network Density and Acquirer CAR

5.1 OLS Regression Analysis

To compare with later models, we first estimate a simple OLS regression of the acquirer three-day CAR on network density and the control variables listed in Section 3.2.3. The results are presented in Table 2. In each specification, the year dummies are included but not reported. The t-statistics are adjusted for heteroskedasticity and acquirer clustering. Column (1) provides the results for the full sample. Columns (2) and (3) report the results from splitting the sample according to whether vertical ties are absent (hereafter the vertically unrelated and vertically related subsample, respectively). In columns (4) and (5), we present the results from splitting the sample based on transaction size, where deals above the 60^{th} percentile of the size distribution are classified as large (hereafter the large deal subsample), and the remaining deals are classified as ordinary (hereafter the ordinary deal subsample).

In all five columns, the density variable is statistically insignificantly different from zero. This is not surprising given the problems of sample selection and endogeneity identified above. In the next subsection, we examine more precisely the relation between network density and acquisition performance by employing the selection-adjusted IV approach outlined in Section 4.2.

[Please Insert Table 2 Here]

5.2 Selection-adjusted Instrumental Variable Approach

We begin with probit estimation of Equation (4) for a sample of deals in which at least one advisor is employed. The dependent variable is equal to one if a syndicate is used, and zero otherwise. Column (1) of Table 3 presents the results. We find that although its weighted measure exhibits no influence, the lagged syndicate size variable is positive and highly significant (at the 1% level). This suggests that identification problems are unlikely to be a concern here. On average, a syndicate is more likely to be hired when acquiring firms have a larger cash shortfall and hence, greater demand for external financing. This finding supports the argument that by combining fundraising capacity of different investment banks, syndicates facilitate acquisition-related financing. We also find that the probability of syndicate use is significantly higher in larger deals (both relatively and absolutely), cross-border transactions, deals with more competing bidders, and acquisitions of public (as opposed to unlisted) targets. These findings suggest that syndicates, which combine various resources of different investment banks, are more likely to get involved in complex deals. Consistent with our univariant analysis, reputable investment banks are important participants of syndicated deals: other things being equal, the likelihood of using a syndicate increases by 34.69% if a top-8 advisor is present. Finally, acquiring firms with larger market capitalization, smaller stock volatility (sigma) or lower leverage ratio are less likely to employ a syndicate. This is consistent with the idea that syndicates are less valuable for larger and safer firms which usually have easier access to multiple forms of cheap financing options.

Next, we estimate Equations (2) and (3) jointly by LIML for a sample of syndicated deals, conditional on the syndication decision modeled in column (1). Columns (2) through (6) of Table 3 report the estimates for the reduced form equation (Equation (3)). For space reasons, we present the estimates of the structural equation of acquirer CAR separately in Table 4. The dependent variable in each specification of Table 3 is the degree of network density at the syndicate level. The explanatory variables include the four exogenous instruments listed in Section 4.3, and a vector of full controls from the structural equation of acquirer CAR (Equation (2)). Note that we maintain the same set of instruments across samples to avoid the possibility that any observed difference in network effects is driven by the selection of instruments. Year fixed effects are controlled for in all specifications but not reported. The z-scores in parentheses are adjusted for heteroskedasticity and clustering at the firm level.

Column (2) of Table 3 presents the regression results for the full sample. Consistent with the intuition that acquiring firm's choice of syndicate network structure is positively affected by the extent of networking among its local advisors, we find that the coefficient of the local network density variable is positive and highly significant (at the 1% level). The same is true for the fraction of syndicate members from the same State variable: all else equal, syndicates exhibit a significantly higher degree of density when a larger number of member banks are located in the same Federal State. The density of syndicate members' debt underwriting relationships over the preceding one year and five years prior to the announcement year are positive and significant at the 10% and 1% level, respectively. Thus, syndicate members' ties in the debt market indeed have a favorable impact on the formation of ties in M&As.

In columns (3) through (6), we provide the results for the subsamples based on whether there is a vertical tie between the acquirer and the advisors, and whether the deal size is above the 60th percentile. The effects of our instruments largely mirror those presented in column (2), except that: (i) the fraction of syndicate members from the same State variable is not statistically significant in the vertically related subsample (column (4)); (ii) the prior-year density of the debt underwriting relationship variable is insignificant in the vertically related and ordinary deal subsamples (columns (4) and (6)), but positive and significant at the 5% level in both the vertically unrelated and large deal subsamples (columns (3) and (5)); and (iii) the coefficient on the weighted density of syndicate members' ties in the debt market over the preceding five years is only borderline significant in the large deals subsample (column (5)).

At the bottom of Table 3, we report the Hensen-J test statistics for our instruments for each specification. In all five columns, the p-value of the J statistics is greater than 10%. Thus, there is little evidence that our set of instruments violates the over-identifying restrictions. In characterizing weak instrumentation, we report the F-statistics for the joint significance of our instruments, along with the corresponding Stock-Yogo critical values for a 10% maximal LIML size distortion. In all but the vertically related subsample, the F-test statistics are well above the Stock-Yogo threshold of 5.44. Thus, even with this relatively large set of instruments, the LIML estimator does not perform poorly in finite samples and that we can reject the null hypothesis of weak instruments.

In terms of the covariates from the structural equation of acquirer CAR (Equation (2)), the participation of a top-8 advisor is positively associated with density, though this is evident in the vertically unrelated subsample only (column (3)). Thus, there is some evidence that reputable advisors are better networked than less prestigious ones, i.e., on average, they are more likely to connect with other investment banks in a syndicate. Furthermore, density is significantly higher when an acquirer has stronger ties to its incumbent syndicate members, as indicated by the positive and significant coefficient on the vertical relationship density variable. One interpretation of this result is that frequent interaction with the same acquirer in the past increases the opportunity for the investment banks to interact and establish ties with one other. We also find that density is positively affected by acquiring firms' Tobin's Q, although the effect is significant in the vertically unrelated subsample only (column (3)). Interestingly, cross-border deals are, on average, associated with less densely networked syndicates (columns (2), (4) and (6)). A possible reason is that cross-border deals increase the need for involving a foreign advisor in a syndicate to whom local advisors are less likely to form a tie due to geographical distance. Lastly, we find that hostile offers are associated with lower density in the ordinary deal subsample (column (6)). For large deals, the degree of density is higher for all-cash offers, but lower for private transactions (column (5)). Other control variables generate either no or only a marginally significant effect on network density. Overall, the results presented in Table 3 indicate that the choices of syndicate formation and network structure are both strongly influenced by advisor-, firm- and deal-specific characteristics. This suggests that the coefficients estimated by the selection-adjusted IV estimator should be more reliable than those estimated by a simple OLS estimator.

[Please Insert Table 3 Here]

In Table 4, we report estimates for the structural model of acquirer three-day CAR (Equation (2)). The full sample analysis in column (1) indicates that conditional on the use of syndicate, the density variable (instrumented) has a positive but borderline significant impact on acquirer announcement abnormal returns. An interesting observation emerges, however, when considering the subsamples with and without vertical relationships. Specifically, the estimates presented in column (2) indicate that when a vertical tie is absent, there is a significant increase in acquirer abnormal returns if a more densely networked syndicate is hired. The effect is also economically large: holding other factors constant, increasing network density by one standard deviation (43.80%), for instance, increases acquirer abnormal returns by 1.98 percentage points (43.80% x0.0451x1%). This is a nontrivial improvement compared to the average three-day CAR of 0.3% in our sample. In terms of the dollar wealth creation, a one-standard-deviation increase in density is associated with a $193.01-million ($32.79-million) increase in shareholder value for a mean-(median-) sized acquirer in our sample.

While there is a strong positive effect of interbank networking on acquirer CAR in the vertically unrelated subsample, we find no such effect for the deals where acquirers are tied to one or more advisors in a syndicate. As seen in column (3) of Table 4, the coefficient on the density variable is statistically indistinguishable from zero. In addition, the magnitude is about one-third smaller than that observed in the vertically unrelated subsample.

A similar pattern is observed in columns (4) and (5) which focus on the sample split at the 60th percentile of the transaction size distribution. The positive effect of network density on acquirer announcement abnormal returns is mainly concentrated in deals above the 60th percentile (column (4)), but not in others (column (5)). The differences in the association between density and acquirer CAR for deals in which acquirers and advisors are vertically unrelated versus related, and for large versus ordinary deals, are consistent with our predictions. Specifically, interbank networks increase acquirer CAR precisely in the type of deals where the level of information asymmetry between the acquirer and the advisors is high, and hence, where peer pressure is likely to add value through reductions in free-riding.

The parameter estimates of most of the control variables in Table 4 mirror the findings of prior studies. Specifically, we find that larger syndicate size is associated with higher acquirer abnormal returns, and the effect is most pronounced in the large deal subsample. Golubov et al. (2012) document a positive association between advisor reputation and bidder returns for public takeovers. We find that the participation of a top-8 advisor is statistically positive in the subsample of ordinary deals. Moreover, vertical relationship density negatively affects acquirer abnormal returns, particularly when transaction size is large. One possible interpretation is that a strong bank-firm relationship insulates investment banks of a syndicate from the discipline of competitive product markets, and hence, harms acquisition performance (Himmelberg et al., 1999; Ongena and Smith, 2001; Asker and Ljungqvist, 2010; Ogura, 2010). Consistent with Moeller et al. (2004) and Moeller et al. (2007), acquiring firms with higher Tobin's Q are related to lower CARs. The abnormal returns are however significantly higher if an acquirer experiencing greater stock price run-up undertakes a deal at or below the 60th percentile of the size distribution (column (5)), and if an acquirer with greater free cash flows makes a large acquisition that falls above the 60th percentile (column (4)). In line with Alexandridis et al. (2013), we find that larger deals are, on average, associated with lower acquirer abnormal returns, although the effect reverses in the vertically related subsample where acquirer CAR appears to be positively affected by the absolute deal size and negatively influenced by the relative transaction size. The relation between the number of competing bidders and acquirer CAR is significantly negative for large deals while positive for ordinary-sized deals. Finally, public acquisitions are associated with lower acquirer announcement returns in almost all of our specifications, confirming the evidence documented in Masulis et al. (2007). Other controls, such as industry relatedness, the hostility of target management, and whether the deal is a tender offer or cross-border, generate either no or borderline significant impacts on acquirer returns. The correction term, *general residuals*, is also insignificant in all columns. Thus, the form of selectivity does not appear to be a major issue here.

[Please Insert Table 4 Here]

5.3 Variation in Cutoff Points of Transaction Size

The selection of the 60^{th} percentile of the transaction size as a cutoff point is obviously arbitrary. Therefore, a natural concern about the above analysis is whether the relative strength of the density-acquirer CAR association varies if an alternative cutoff point of transaction size is selected. If deal size indeed proxies well for the severity of information asymmetry, a given increase in network density should matter more (less) in deals that lie above a higher (lower) percentile of the size distribution, in which case the risk of free-riding is more (less) substantial. In Table 5, we test this conjecture by repeating our CAR analysis on the subsamples split at the 50^{th} and 75^{th} percentile, respectively. Again, Equations (2) and (3) are jointly estimated by LIML, conditional on the use of a syndicate. The instruments are the same as before. We present only the estimates for the main equation of acquirer CAR here, with the estimates for the selection and reduced form equation suppressed for the sake of brevity. In all specifications, the Hensen-J test statistics fail to reject the null of instrument validity. The F-test statistics are far beyond the Stock-Yogo critical value for a 10% maximal LIML size distortion, indicating that the instrumentation is collectively strong.

Columns (1) and (2) estimate the regression over the subsample of deals above and at/below the 50^{th} percentile, respectively. We find that while there is a positive association between the density variable and acquirer CAR, it is statistically insignificant or marginally significant. Moving to the subsamples split at the 75^{th} percentile, however, we observe a strong, positive, and statistically significant (at the 1% level) impact of network density on the acquirer three-day CAR for deals above the 75^{th} percentile (column (3)). The coefficient on the density variable is 0.0712, which is nearly double the effect documented in Table 4 for the subset of deals above the 60^{th} percentile of transaction size (0.0427). For a one-standard-deviation increase in network density, this corresponds to a 3.12-percentage-point increase in the acquirer three-day CAR (43.80%x0.0712 x1%), which equates to

$304.71 million ($51.77 million) in incremental shareholder wealth creation for an average-(median-) sized acquirer in our sample. The effect is not only sizable economically, but also dwarfs the effects of network density on the subset of deals at or below the 75th percentile of the size distribution (column (4)). Collectively, these findings add to the evidence suggesting that the impact of interbank network on acquirer abnormal returns is present only when the information asymmetry problem is severe enough to make the interbank networks a valuable device against free-riding. Other control variables exhibit effects on acquirer CAR similar to those presented in Table 4. In the empirical analysis that follows, we explore alternative explanations for our main findings. We focus our attention on the full sample and the subsamples where the network effect is found to be most evident, namely, the vertically unrelated and the large deal subsamples.

[Please Insert Table 5 Here]

6. Alternative Explanations

6.1 Endogenous Matching and Selective Networking

We have argued that proximal relationships help investment banks to gain better information about one another's unique skill and capabilities. This eases the mutual monitoring necessary for motivating advisor effort provision. However, even without motivation effects, better information may mean better matching since relationship banks may know better about what requisite attributes to look for when selecting their syndicate partners. This offers an alternative explanation to the positive effect of density on acquirer returns documented above. Alternatively, it could be argued that as relationships evolve over time, investment banks discover peers that they can trust and work well with and those they cannot, so they disengage in favor of peers that are more capable and cooperative (Li and Rowley, 2002). In this case, our results may be driven by the fact that a more densely networked syndicate involves a larger fraction of high-quality investment banks that are more likely to network with each other. Whilst plausible, these alternative interpretations are unlikely to explain our empirical results for two reasons. First, in addition to explicitly controlling for the participation of a reputable (presumably high-quality) advisor, we employ an estimation strategy designed specifically to address this type of endogeneity. Second, if networking improves the match among syndication members or leads to a greater fraction of high-quality advisors to participate in a syndicate, we should observe a positive effect of density on acquirer abnormal returns irrespective of deal types. The results presented in Tables 4 and 5 are, however, inconsistent with this prediction. The density variable is broadly significant in the full sample, and exhibits a differentially more significant impact on acquirer CAR in precisely the type of deals in which peer pressure is most likely to be valuable (i.e., in vertically unrelated and large deals). This indicates that the economic value of interbank networks lies at least partially in its support for peer pressure, and that the density effect we document is unlikely to be a mere result of better matching or having a larger fraction of high quality advisors.

To further disentangle these effects, however, we analyze the time-varying pattern of peer effects. The “peer-pressure" hypothesis predicts that more densely networked syndicates produce a more pronounced effect on acquisition performance in hot rather than cold markets. The reason is that there are more foreseeable syndication opportunities during market booms. This strengthens the sanctioning ability of relationship investment banks necessary for deterring free-riders because exclusion from a relationship is related to a larger loss of expected profits from future cooperation (Pichler and Wilhelm, 2001). Accordingly, if the primary driver of the positive relation between density and acquirer returns is peer pressure, we expect the relation to be more (less) evident during market peaks (downturns). Meanwhile, it is difficult to reconcile this cyclical pattern with the endogenous matching and selective networking arguments, in which case one would expect an unconditional, monotonic and positive relation between density and acquirer returns.

We test this conjecture by examining whether the favorable impact of network density on the acquirer three-day CAR concentrates only in the peak years of M&A cycles. Our sample encompasses two peak periods: (i) the doc-com bubble of 1998-2000; and (ii) the recent merger wave 2003-2007 (Maksimovic, Phillips and Yang, 2013; Ahern and Harford, 2014). We create an indicator variable, *Peak Year*, coded as one for these years and zero otherwise. To allow the coefficient of network density to differ for the peak and non-peak years of M&A cycles, we follow Hochberg and Lindsey (2010) and break our density measure into two mutually exclusive variables: (i) the degree of density during market peaks and zero otherwise; and (ii) the degree of density during non-market peaks and zero otherwise. We then estimate our acquirer CAR model conditional on the choice of a syndicate, with both density measures endogenized. Thus, the selection model predicts the probability of using a syndicate; the reduced-form model predicts the level of network density during the peak and non-peak years, respectively; and the primary equation predicts the acquirer three-day CAR. In a system with two or more endogenous regressors, strong identification depends on cross-correlations of the instruments (Hochberg and Lindsey, 2010). Therefore, to achieve stronger model identification, we expand our instrument set to include the interaction of the *Peak Year* dummy with each of the instruments described in Section 4.3 as additional instruments for our two density measures (Bun and Harrison, 2014). We control for the same set of variables as in Table 4 except that the year dummies are excluded here, given that the *Peak Year* dummy is a time indicator itself. [14] Table 6 presents our estimates for the primary equation for the full sample, the vertically unrelated subsample and the subsample of large deals above the 60th percentile of the size distribution, respectively (our results are robust to alternative cutoff points for transaction size). The estimates for the reduced-form models are omitted for the sake of brevity.

The regression diagnostics, reported at the bottom of Table 6, provide support for our choice of instruments. The smallest of the p-values for the Hansen-J tests is 0.384. Thus, there is little evidence against the overidentifying restrictions. The Kleibergen-Paap rank Wald F-test statistic for weak identification is 10.107 for the full sample (column (1)), 8.362 for the vertically unrelated subsample (column (2)), and 6.088 for the large deal subsample (column (3)). All the test statistics exceed the Stock-Yogo critical value of 3.78 for a 10% maximal size distortion, indicating that our instruments are collectively strong.

Turning to the main results reported in Table 6, it is remarkable to observe that the network effect documented in Tables 4 and 5 comes almost entirely from the peaks of the market. The coefficient on the density variable during non-peak periods is insignificant or marginally significant throughout the table, indicating that interbank networks have virtually little impact on acquirer abnormal returns when there are limited opportunities for future cooperation. In comparison, we find a consistently positive and statistically significant (at the 5% level) relation between network density and acquirer CAR during peak years across all specifications. The point estimates suggest that all else

[14] Our results continue to hold when year fixed effects are controlled for.

being equal, increasing density by one-standard-deviation during the peak years increases the acquirer three-day CAR by 2.69-3.17 percentage point, depending on the specification. This corresponds to a \$263.20- to \$309.85-million incremental shareholder wealth for an average-sized acquirer in our sample. Overall, these findings lend support for the “peer-pressure” interpretation that market booms, which create more syndication opportunities in the foreseeable future, enhance the incumbent syndicate members’ ability to deter free-riders through the threat of exclusion from a relationship that would not be seen in cold markets. Such a time-varying pattern is hard to be explained through the “matching” and “selective networking” hypotheses.

[Please Insert Table 6 Here]

6.2 Lead Advisor Reputation

In practice, syndicates are often lead-managed by an investment banker who takes the major responsibility of organizing the activities of a syndicate (e.g. Corwin and Schultz, 2005). Compared with other investment banks in a syndicate, lead investment banks are often more visible and have greater reputational capital at risk. This induces them to actively monitor other syndicate members and punish those who slacken effort even at a cost (Alchian and Demsetz, 1972; Benveniste et al., 1996; Aggarwal, 2000; Pichler and Wilhelm, 2001; Benveniste et al., 2003). In our context, a lead advisor may act as an “endogenous principal” who governs the effort provision of other syndicate members on behalf of the acquirer.[15] If this is the case, one may expect less free riding if a syndicate is led by a more reputable advisor that has stronger incentive to exert effort monitoring. Thus, a natural question is whether the positive density-acquirer CAR association we document in Tables 4 and 5 is driven by this omitted lead advisor reputation effect. It is interesting to note that both lead advisor reputation and interbank network affect the incentive structure by way of exerting peer pressure. They are, however, different in that the lead advisor reputation mechanism emphasizes the effort of a *single* advisor who is motivated to regulate other members purely out of its own reputational concerns. The power of interbank networks, on the other hand, resides in the efforts of *all* the syndicate members to exert peer pressure *mutually*. This difference makes it important to

[15] Corwin and Schultz (2005) consider the possibility that co-managers may monitor the behavior of the lead manager and report low effort to the acquirer in order to win future lead mandates.

empirically distinguish these two alternative governance mechanisms and the associated effects on syndicate incentive structure.

To address this issue, we hand-collect data on the identity of lead investment banks from the *SDC* and *Factiva* databases, following the procedure outlined in Appendix B. Of 1,138 syndicate-advised transactions, 347 acquisitions are identified as lead-managed (lead sample hereafter). Notably, the mean absolute (relative) deal size in this lead sample is around 1.65 (1.39) times larger than in the full sample (the summary statistics are not reported here for space reasons). Stock-financed and public transactions account for 70.3% and 75.8% of the sample deals, respectively, each of which is approximately 20% higher than those in the full sample. This indicates a potential sample selection bias that arises due to missing data.

To measure lead advisor reputation, we create a dummy variable (*top-8 lead advisor*), which equals one if the lead advisor is ranked among the top 8 according to the value of transactions it has advised. Again, bank mergers are considered when assigning this lead reputation measure to each deal. The data indicates that the participation of a top-8 advisor variable provides a close approximation for the presence of a reputable lead advisor, with both variables highly correlated at the level of 68.30%.

We directly control for lead advisor reputation and re-estimate our acquirer CAR models for the lead sample, the vertically unrelated subsample and the subsample of large deals above the 60th percentile of the size distribution, respectively.[16] In addition to network density, the top-8 lead advisor is endogenized in each specification to account for the possibility that the choice of a top 8 advisor is likely to be non-randomly determined (Fang, 2005; Golubov et al., 2012). We instrument the degree of network density by the same exogenous variables as those shown in Table 4. The selection on a top-8 versus a non-top 8 lead advisor is instrumented by the scope variable, which is constructed to capture the history of an acquiring firm that has hired a reputable lead investment bank in different capital markets (Fang, 2005; Golubov et al., 2012). Specifically, it is equal to three if an acquirer has engaged a top-8 lead investment bank in all of the following three types of transactions: equity issue, bond issue and M&A, over the last five years prior to the deal announcement; two if it has employed a top-8 lead investment bank in two of the three types of transactions; one if it has hired a top-8 lead

[16] Again, our results are not sensitive to the choice of the cutoff points for transaction size.

investment bank in one of the three types of transactions; and zero if the acquirer had never used a top-8 lead investment bank for any of its corporate transactions. As an additional instrument, we include the average use of a top-8 lead advisor by the acquiring firm's peers, defined as those acquirers located in the same Federal State as the acquirer, over the last three years prior to the announcement year. Our logic for using this variable as an instrument is that an acquiring firm's choice of lead advisor can well be influenced by its local peers (Kaustia and Rantala, 2015). For instance, managers of acquiring firms from the same geographical region are arguably easier to observe and learn from one another about which investment bank is a good leader. This "knowledge-spillover" effect may, in turn, cause the choice of the lead advisor to be geographically correlated. Meanwhile, this *priori* belief prevailing in an acquirer's local area should not directly affect the acquirer's deal performance.

Table 7 reports estimates for the primary CAR equation, with the estimates for the selection and reduced-form equations omitted here for the sake of brevity. The Hensen-J statistics fail to reject the null that the excluded instruments are valid at conventional levels. Due to the significant drop in sample size, however, the Kleibergen-Paap rank Wald F-test statistic for weak identification is problematic in all sets of models. Nevertheless, we note that the weak-instrument robust inference tests, such as the Anderson-Rubin (1949) Wald test, are significant at the 5% level in all the specifications indicating valid inferences even in the presence of weak identification. Additionally, the correction term (i.e., *general residuals*) is significant at the 5% level throughout the table. Thus, consistent with our observation in the univariant analysis, the choice of syndication is endogenous to the CAR determining process, at least for the lead sample. The negative coefficient on this term suggests that some unobservable factors increasing the probability of using a syndicate negatively affect acquirer announcement abnormal returns.

Turning to the main results presented in Table 7, we find that after controlling for the presence of a reputable lead advisor, more densely networked syndicates continue to be associated with significantly higher acquirer announcement abnormal returns. Thus, our main explanatory variable does not appear to be a mere manifestation of lead advisor reputation. Contrary to conventional economic wisdom, the top-8 lead advisor variable is negative and insignificant in all of our specifications, suggesting that lead advisor reputation does not necessarily limit free-riding internal to a syndicate. Overall, the results indicate that it is the *collective* effort, as opposed to the effort of any single member, which is important to fostering cooperation and creating value for acquiring firms. Other control variables exhibit effects on acquirer CAR similar to those presented in Table 4.

[Please Insert Table 7 Here]

6.3 Peer Pressure versus Incentive Pay

We have argued that interbank networks improve acquisition performance because they facilitate the operation of peer pressure and create implicit incentives to apply adequate effort. Alternative literature suggests, however, that network density may affect the incentive structure through other channels. Specifically, Pichler and Wilhelm (2001) show that the free-rider problem inherent in security underwriting syndicates can be mitigated by implementing an incentive-pay scheme, which involves the principal (e.g. acquirer) to offer an amount of fees exceeding individual member banks' incentive compatibility constraint (i.e., the cost of exerting a high level of effort). For this strategy to be effective, the entry into a syndicate must be restricted. If banks were allowed to freely join a syndicate, competition would drive the fees down until the incentive rents were dissipated, and the problem of moral hazard would emerge again. It is thus possible that interbank connections in a syndicate improve acquisition performance because they create a relationship barrier to entry that helps an acquirer to preserve the quasi-rents provided to promote efforts.

Can we empirically determine the underlying mechanism through which interbank networks add value to acquiring firms? The primary distinction between the "incentive-pay" and the "peer-pressure" hypotheses is that the former assumes a one-shot game, so that each advisor's effort decision is guided solely by the level of fee premiums offered by an acquirer. In contrast, the "peer-pressure" hypothesis recognizes the possibility that additional implicit incentives can be generated through peer monitoring and sanctioning in a repeated play (Che and Yoo, 2001). Consequently, these two alternative explanations have opposite predictions on the level of fees paid to a densely networked syndicate. If the incentive-pay scheme is the primary driver of the positive density-acquirer CAR association we document, then a more tightly networked syndicate should be associated with a higher percentage of fees since it presents a stronger relationship barrier to entry needed to preserve the incentive rents. The opposite is true, however, if the positive impact of network density on acquirer CAR stems from the peer pressure effect. In particular, by inducing implicit incentives beyond those provided by an explicit fee contract, interbank networking in effect reduces an acquirer's incremental costs of incentivizing advisors (Che and Yoo, 2001; Rayo, 2007). That is, if both implicit and explicit incentives are to promote effort provisions by individual members in a syndicate, one becomes a substitute for the other. The problem faced by an acquirer is therefore altered to the selection of a sharing rule that uses the least amount of fees to motivate optimal efforts, taking into account the implicit incentives generated under peer pressure (Arya, Fellingham and Glover, 1997; Rayo, 2007; Mohnen et al., 2008). In this case, the more densely networked is a syndicate, *ceteris paribus*, the stronger are the implicit incentives and, generally, the lower is the amount of fee premium required to motivate best efforts. Note that this does not necessarily mean that acquiring firms selecting relatively more costly incentive-pay contracts are inefficient. As previously discussed, peer pressure is social and non-contractible. This implies that the associated implicit incentives are subject to manipulation and uncertainty. Peer pressure is therefore less optimal for an acquiring firm which can utilize contracts to efficiently align the advisors' incentives. We explore this issue by estimating the impact of network density on advisory fees using the selection-corrected IV approach.

Table 8 presents the LIML estimation results for the full sample, the vertically unrelated subsample, and the subsample of large deals defined as those above the 60^{th} percentile of the size distribution. The estimates for the selection and reduced-form equations are suppressed for brevity. In each specification, the dependent variable is the advisory fees paid by an acquirer as a percentage of transaction value. We instrument network density by the same set of instruments as shown in Table 4. As controls, we include syndicate size, the presence of a top-8 advisor in a syndicate, the level of vertically relationship density, the natural logarithm of absolute deal size, the relative transaction size, and a set of binary variables indicating whether the deal is cross-industry, financed by stock, hostile or a tender offer, similar to Golubov et al. (2012). Year fixed effects are included in all models but not reported. The z-scores are adjusted for heteroskedasticity and firm clustering. Again, the Hensen-J tests of over-identifying restrictions fail to reject the null of valid instruments. The F-test statistics for weak instrumentation are well above the Stock-Yogo threshold of 5.44 in all but the full sample.[17]

The results reported in columns (1) and (2) indicate that density has a statistically insignificant impact on the percentage of advisory fees in the full sample and the vertically unrelated subsample. For large deals above the 60th percentile of the size distribution, however, the density variable is negative and significant at the 5% level (column (3)). The magnitude of the coefficient estimates indicates that holding other factors constant, increasing network density by one standard deviation (43.80%) reduces fees by about 0.14 percentage points (-0.0031x43.80%x100) This is approximately a $3.71 ($0.77)-million-reduction in advisory fees for a mean (median)-sized acquisition in our sample. As for our control variables, advisory fees are significantly affected by the absolute (and sometimes relative) transaction size. This confirms the findings of McLaughlin (1990) that advisory fees increase with deal size at a decreasing rate. Similar to Golubov et al. (2012), we find that fees are lower for deals financed with stock. Other variables such as industry relatedness and hostility of target management do not have any significant influence over the percentage fees.

Overall, the evidence does not appear to support the argument that the incentive-pay scheme is the underlying mechanism through which interbank networks add value to an acquirer client. Instead, the insignificant or even negative impact of network density on advisory fees is more nearly consistent with network density generating additional implicit incentives through peer pressure, which allows an acquirer to pay less to motivate efforts.

[Please Insert Table 8 Here]

6.4 Other Alternative Explanations

The main finding of this paper is that the interbank connections in a syndicate improve acquisition performance, but this occurs only when a vertical tie is absent and when the deal is considerably large. We interpret this as evidence that interbank networking encourages effort provision through the support of the operation of the peer pressure mechanism when the free-rider problem is an important concern. We also provide evidence showing that the primary driver of the

[17] The Anderson-Rubin (1949) Wald and the Stock-Wright (2000) S statistic is 3.50 (*p*-value 0.48) and 2.72 (*p*-value 0.61), respectively, for the full sample, both of which fail to reject the null hypothesis. Thus, the results presented in column (1) should be interpreted with some caution.

positive density-performance association is peer pressure and not endogenous matching, selective networking, lead advisor reputation or incentive pay. A potential caveat of our study is that we do not observe which investment bank free rides in a syndicate. This prevents us from examining the actual means by which syndicate members employ to punish free riders. While exclusion from relationships is a natural enforcement device in a repeated setting, other alternative forms of peer sanction may exist. For instance, with the mutual monitoring possibility, an acquiring firm may implement an information revelation scheme which encourages investment banks of a syndicate to report their observations on others' effort (e.g. Alvi, 1988; Ma, 1988). Because this scheme alleviates the problem of information asymmetry between the acquirer and the advisors, the acquirer can now induce best efforts by simply penalizing free-riders based on private reports (Che and Yoo, 2001). Indeed, Corwin and Schultz (2005) explore this possibility in the context of IPO underwriting syndicates. They argue that co-managers may "whisper" the book manager's misconduct in the issuer's ear so as to win more lucrative lead appointments in the issuer's follow-on underwriting business. Whilst plausible, this story appears difficult to explain our results for two reasons. First, the private-reporting scheme assumes that investment banks are *rivals*, and hence, motivated to "whisper in the acquirer's ear" in order to cut against each another. In our case where investment banks in a syndicate are closely related with each other, however, private reports are presumably difficult to be solicited by an acquirer (Kandel and Lazear, 1992). Second, if private reporting is the primary force mitigating free-riding, whether and to what extent investment banks in a syndicate are interconnected should not matter. Rather, one would expect acquirers to experience better announcement returns so long as there are more than one investment bank participating in a syndicate, in which case one bank could possibly report on another's effort to the acquirer. The results in this study show that the level of interbank connections present in a syndicate does positively and significantly affect acquirer abnormal returns, which provide clear evidence against this alternative interpretation.

Another possible form of peer pressure is empathy. Mas and Moretti (2009), for instance, argue that workers feel more shame when they cheat co-workers to whom they are close than others about whom they care less. Thus, interbank networks may enhance the peer pressure effect by creating stronger empathy among investment banks in the syndicate. That is, investment banks have less incentive to free ride when cooperating with someone they know because they truly care about one another's payoffs rather than fear punishment or retaliation by peers. Although we cannot definitely rule this possibility out, our results documented in Table 8 do not seem to support this interpretation. If density reduces free-riding through empathy, more densely networked syndicates should perform strictly better than less densely networked ones even if the prospects for future cooperation are limited due to market conditions. The fact that we observe a significantly positive association between density and acquirer abnormal returns only in hot markets suggests, however, that peer sanction is likely to occur at least partially through the discontinuation of future syndication.

7 Robustness

We perform a set of additional robustness checks to ensure the validity of our findings. These include: (i) using acquirer CAR computed over alternative event windows (-2, +2) and (-5, +5); (ii) employing the equally-weighted CRSP index (as opposed to the value-weighted) as the market return; (iii) measuring density over alternative trailing 3-year and 5-year windows; (iv) utilizing a density measure that is weighted by past interaction frequency over the last 1, 3 and 5 years prior to the announcement year; (v) employing a asymmetric (as opposed to symmetric) network density measure; and (vi) excluding general residuals from the estimation model and using a simple IV approach (unadjusted for selection bias). None of these variations significantly change the results reported in this study.

8 Conclusion

Similar to many other financial markets such as venture capital and commercial banking, the investment banking industry is markedly featured by relational rather than arm's-length, transactional cooperation. We examine the economic implications of this cooperation networks that investment banking syndication gives rise to in the context of M&As. We expect that more densely networked syndicates create greater value for acquirer clients, not only because relationship investment banks can more effectively monitor each other than unrelated banks, but also because they have superior *ex post* abilities to sanction free-riders through discontinuation of future cooperation.

We find that acquiring firms do indeed enjoy higher abnormal returns at the deal announcement when investment banks in the syndicate are more tightly networked. The effect is, however, not uniform across deals. Instead, the positive performance effect of interbank network occurs only when the acquirer-advisor tie is absent and when the transaction is considerably large. This lends strong support for the notion that interbank networks improve effort provision when the free-rider problem is exacerbated due to information asymmetry between the acquirer and the advisors. The results are robust to endogeneity and a wide range of alternative specifications.

We also provide evidence for several ancillary predictions of our hypothesis which is hard to reconcile with alternative explanations. Specifically, we find that the positive effect of the interbank network on acquirer abnormal returns is concentrated mainly in hot markets, and there is little-to-no performance effect at other times. These findings suggest that even with interbank ties, investment banks display cooperative behavior only when the level of peer sanction arising from withdrawal of future cooperation is sufficiently high. Meanwhile, they do not appear consistent with other interpretations such as endogenous matching or selective networking, as in these cases the positive network effect should be significant regardless of deal type or market conditions.

Using a hand-collected sample of lead-managed transactions, we also explore lead advisor reputation as an alternative tool to reduce free-riding through peer pressure. We find that acquirer announcement abnormal returns are unaffected by lead advisor reputation but continue to be positively associated with network density after controlling for the presence of reputable lead advisor. The evidence suggests that investment banking syndicates mostly rely on the collective efforts of relationship investment banks in a syndicate instead of the effort of a central monitor to deter free riding, at least in M&As.

Finally, we explore the possibility that interbank networks operate through a mechanism other than peer pressure, i.e., the incentive-pay scheme, as proposed by Pichler and Wilhelm (2001). We find that contrary to the incentive-pay hypothesis, density exhibits a negative or insignificant impact on advisory fees. This provides additional evidence in favor of the "peer pressure" explanation, which purports that with implicit incentives generated under mutual monitoring and sanctioning, interbank networks lower an acquirer's cost of motivating additional advisor effort through explicit fees.

To the best of our knowledge, this is the first study to empirically investigate how interbank networking maximizes the value of investment banking clients. Our findings that interbank networks help mitigate the free-riding problem in a syndicate and even offset fees offer important implications for the network structure that an acquirer should employ to maximize shareholder value through mergers and acquisitions. An unanswered question is whether a free-rider is indeed excluded from the syndicated deals of other relationship banks in subsequent periods. We are unable to address this issue in this study due to the limitation of the data on hand. However, we hope that our work motivates further investigation into this and other forms of peer sanction.

References:

Abbink, K., Brandts, J., Herrmann, B., Orzen, H. 2010. Intergroup conflict and intra-group punishment in an experimental contest game. The American Economic Review,420-447.

Abreu, D., Milgrom, P., Pearce, D. 1991. Information and timing in repeated partnerships. Econometrica 59,1713-1733.

Ackerberg, D.A., Devereux, P.J. 2006. Comment on 'the case against jive'. Journal of Applied Econometrics 21,835-838.

Aggarwal, R. 2000. Stabilization activities by underwriters after initial public offerings. The Journal of Finance 55,1075-1103.

Agrawal, A., Cooper, T., Lian, Q., Wang, Q. 2013. Common advisers in mergers and acquisitions: Determinants and consequences. Journal of Law and Economics 56,691-740.

Ahern, K.R., Harford, J. 2014. The importance of industry links in merger waves. The Journal of Finance 69,527-576.

Alchian, A.A., Demsetz, H. 1972. Production, information costs, and economic organization. The American Economic Review 62,777-795.

Alexandridis, G., Fuller, K.P., Terhaar, L., Travlos, N.G. 2013. Deal size, acquisition premia and shareholder gains. Journal of Corporate Finance 20,1-13.

Alvi, E. 1988. Information revelation and principal-agent contracts. Journal of Labor Economics 6,132-146.

Anand, B.N., Galetovic, A. 2000. Information, nonexcludability, and financial market structure. The Journal of Business 73,357-402.

Anand, B.N., Galetovic, A. 2006. Relationships, competition and the structure of investment banking markets. The Journal of Industrial Economics 54,151-199.

Anderson, T.W. 2005. Origins of the limited information maximum likelihood and two-stage least squares estimators. Journal of Econometrics 127,1-16.

Arya, A., Fellingham, J., Glover, J. 1997. Teams, repeated tasks, and implicit incentives. Journal of Accounting and Economics 23,7-30.

Asker, J., Ljungqvist, A. 2010. Competition and the structure of vertical relationships in capital markets. Journal of Political Economy 118,599-647.

Bandiera, O., Barankay, I., Rasul, I. 2005. Social preferences and the response to incentives: Evidence from personnel data. The Quarterly Journal of Economics 120,917-962.

Bao, J., Edmans, A. 2011. Do investment banks matter for m&a returns? Review of Financial Studies 24,2286-2315.

Barron, J.M., Gjerde, K.P. 1997. Peer pressure in an agency relationship. Journal of Labor Economics 15,234-254.

Benveniste, L.M., Busaba, W.Y., Wilhelm, W.J. 1996. Price stabilization as a bonding mechanism in new equity issues. Journal of Financial Economics 42,223-255.

Benveniste, L.M., Ljungqvist, A., Wilhelm, W.J., Yu, X. 2003. Evidence of information spillovers in the production of investment banking services. The Journal of Finance 58,577-608.

Bettin, G., Lucchetti, R., Zazzaro, A. 2012. Endogeneity and sample selection in a model for remittances. Journal of Development Economics 99,370-384.

Bharadwaj, A., Shivdasani, A. 2003. Valuation effects of bank financing in acquisitions. Journal of Financial Economics 67,113-148.

Boot, A.W.A., Thakor, A.V. 2000. Can relationship banking survive competition? The Journal of Finance 55,679-713.

Bowers, H.M., Miller, R.E. 1990. Choice of investment banker and shareholders' wealth of firms involved in acquisitions. Financial Management 19,34-44.

Brown, M., Falk, A., Fehr, E. 2004. Relational contracts and the nature of market interactions. Econometrica 72,747-780.

Bun, M., Harrison, T. 2014. Ols and iv estimation of regression models including endogenous interaction terms. UvA-Econometrics Working Paper.

Carpenter, J., Bowles, S., Gintis, H., Hwang, S.-H. 2009. Strong reciprocity and team production: Theory and evidence. Journal of Economic Behavior & Organization 71,221-232.

Chassang, S. 2010. Building routines: Learning, cooperation, and the dynamics of incomplete relational contracts. American Economic Review 100,448-465.

Che, Y.-K., Yoo, S.-W. 2001. Optimal incentives for teams. The American Economic Review 91,525-541.
Chemmanur, T.J., Tian, X. 2011. Peer monitoring, syndication, and the dynamics of venture capitalist interactions. Working paper,1-53.
Chen, H.-C., Ritter, J.R. 2000. The seven percent solution. The Journal of Finance 55,1105-1131.
Chib, S., Greenberg, E., Jeliazkov, I. 2009. Estimation of semiparametric models in the presence of endogeneity and sample selection. Journal of Computational and Graphical Statistics 18,321-348.
Corwin, S.A., Schultz, P. 2005. The role of ipo underwriting syndicates: Pricing, information production, and underwriter competition. The Journal of Finance 60,443-486.
Crane, D.B., Eccles, R.G. 1993. Customer relationships in the 1990s. In: Hayes, S.L.I. (Ed), Financial services - perspectives and challenges. Harvard Business School Press: Boston, Massachusetts; 1993.
Degryse, H., Masschelein, N., Mitchell, J. 2011. Staying, dropping, or switching: The impacts of bank mergers on small firms. Review of Financial Studies 24,1102-1140.
Demsetz, H., Lehn, K. 1985. The structure of corporate ownership: Causes and consequences. Journal of Political Economy 93,1155-1177.
Engelberg, J., Gao, P., Parsons, C.A. 2012. Friends with money. Journal of Financial Economics 103,169-188.
Fang, L.H. 2005. Investment bank reputation and the price and quality of underwriting services. Journal of Finance 60,2729-2761.
Fehr, E., Simon, G., Kirchsteiger, G. 1997. Reciprocity as a contract enforcement device: Experimental evidence. Econometrica 65,833-860.
Fitzroy, F.R., Kraft, K. 1987. Cooperation, productivity, and profit sharing. The Quarterly Journal of Economics 102,23-35.
Fletcher, J.M., Lehrer, S.F. 2011. Genetic lotteries within families. Journal of Health Economics 30,647-659.
Freeman, L.C. 1978. Centrality in social networks conceptual clarification. Social Networks 1,215-239.
Fudenberg, D., Levine, D.K. 1991. An approximate folk theorem with imperfect private information. Journal of Economic Theory 54,26-47.
Fudenberg, D., Maskin, E. 1986. The folk theorem in repeated games with discounting or with incomplete information. Econometrica 54,533-554.
Gilsing, V., Nooteboom, B., Vanhaverbeke, W., Duysters, G., van den Oord, A. 2008. Network embeddedness and the exploration of novel technologies: Technological distance, betweenness centrality and density. Research Policy 37,1717-1731.
Golubov, A., Petmezas, D., Travlos, N.G. 2012. When it pays to pay your investment banker: New evidence on the role of financial advisors in m&as. Journal of Finance 67,271-312.
Granovetter, M. 2005. The impact of social structure on economic outcomes. The Journal of Economic Perspectives 19,33-50.
Gujarati, D.N., Basic econometrics. McGraw Hill: NewYork; 2003.
Hadlock, C.J., James, C.M. 2002. Do banks provide financial slack? The Journal of Finance 57,1383-1419.
Hamilton, Barton H., Nickerson, Jack A., Owan, H. 2003. Team incentives and worker heterogeneity: An empirical analysis of the impact of teams on productivity and participation. Journal of Political Economy 111,465-497.
Heckman, J.J. 1979. Sample selection bias as a specification error. Econometrica 47,153-161.
Himmelberg, C.P., Hubbard, R.G., Palia, D. 1999. Understanding the determinants of managerial ownership and the link between ownership and performance. Journal of Financial Economics 53,353-384.
Hochberg, Y.V., Lindsey, L. 2010. Incentives, targeting, and firm performance: An analysis of non-executive stock options. Review of Financial Studies 23,4148-4186.
Hochberg, Y.V., Ljungqvist, A., Lu, Y. 2007. Whom you know matters: Venture capital networks and investment performance. The Journal of Finance 62,251-301.

Hochberg, Y.V., Ljungqvist, A., Lu, Y. 2010. Networking as a barrier to entry and the competitive supply of venture capital. Journal of Finance 65,829-859.

Holmstrom, B. 1979. Moral hazard and observability. The Bell Journal of Economics 10,74-91.

Holmstrom, B. 1982. Moral hazard in teams. The Bell Journal of Economics 13,324-340.

Huang, Q., Jiang, F., Lie, E., Yang, K. 2011. The role of investment banker directors in m&a: Can experts help? Journal of Financial Economics, Forthcoming.

Huberman, G. 2001. Familiarity breeds investment. The Review of Financial Studies 14,659-680.

Ismail, A. 2010. Are good financial advisors really good? The performance of investment banks in the m&a market. The Review of Quantitative Finance and Accounting 35.

Kale, J.R., Kini, O., Ryan, H.E. 2003. Financial advisors and shareholder wealth gains in corporate takeovers. Journal of Financial and Quantitative Analysis 38,475-501.

Kandel, E., Lazear, E.P. 1992. Peer pressure and partnerships. Journal of Political Economy 100,801-817.

Kandori, M. 1992a. Social norms and community enforcement. The Review of Economic Studies 59,63-80.

Kandori, M. 1992b. The use of information in repeated games with imperfect monitoring. The Review of Economic Studies 59,581-593.

Kaplan, S.N., StroMberg, P.E.R. 2004. Characteristics, contracts, and actions: Evidence from venture capitalist analyses. The Journal of Finance 59,2177-2210.

Kaustia, M., Rantala, V. 2015. Social learning and corporate peer effects. Journal of Financial Economics 117,653-669.

Kisgen, D.J., Qian, J., Song, W. 2009. Are fairness opinions fair? The case of mergers and acquisitions. Journal of Financial Economics 91,179-207.

Kogut, B. 1989. The stability of joint ventures: Reciprocity and competitive rivalry. The Journal of Industrial Economics 38,183-198.

Li, S.X., Rowley, T.J. 2002. Inertia and evaluation mechanisms in interorganizational partner selection: Syndicate formation among u.S. Investment banks. The Academy of Management Journal 45,1104-1119.

Ljungqvist, A., Marston, F., Wilhelm, W.J. 2009. Scaling the hierarchy: How and why investment banks compete for syndicate co-management appointments. Review of Financial Studies 22,3977-4007.

Ljungqvist, A., Wilhelm, W.J., Jr. 2003. Ipo pricing in the dot-com bubble. The Journal of Finance 58,723-752.

Ma, C. 1988. Unique implementation of incentive contracts with many agents. The Review of Economic Studies 55,555-571.

Maksimovic, V., Phillips, G., Yang, L.I.U. 2013. Private and public merger waves. The Journal of Finance 68,2177-2217.

Martynova, M., Renneboog, L. 2009. What determines the financing decision in corporate takeovers: Cost of capital, agency problems, or the means of payment? Journal of Corporate Finance 15,290-315.

Mas, A., Moretti, E. 2009. Peers at work. American Economic Review 99,112-145.

Maskin, E., Tirole, J. 1999. Unforeseen contingencies and incomplete contracts. The Review of Economic Studies 66,83-114.

Masulis, R.W., Wang, C., Xie, F. 2007. Corporate governance and acquirer returns. The Journal of Finance 62,1851-1889.

McLaughlin, R.M. 1990. Investment-banking contracts in tender offers: An empirical analysis. Journal of Financial Economics 28,209-232.

McLaughlin, R.M. 1992. Does the form of compensation matter?: Investment banker fee contracts in tender offers. Journal of Financial Economics 32,223-260.

Mody, A. 1993. Learning through alliances. Journal of Economic Behavior & Organization 20,151-170.

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

Mohnen, A., Pokorny, K., Sliwka, D. 2008. Transparency, inequity aversion, and the dynamics of peer pressure in teams: Theory and evidence. Journal of Labor Economics 26,693-720.

Morrison, A.D., Wilhelm, W.J. 2008. The demise of investment banking partnerships: Theory and evidence. The Journal of Finance 63,311-350.
Myers, S.C. 1984. The capital structure puzzle. The Journal of Finance 39,574-592.
Nooteboom, B. 1992. Towards a dynamic theory of transactions. Journal of Evolutionary Economics 2,281-299.
Nooteboom, B. 2004. Governance and competence: How can they be combined? Cambridge Journal of Economics 28,505-525.
Ogura, Y. 2010. Interbank competition and information production: Evidence from the interest rate difference. Journal of Financial Intermediation 19,279-304.
Ongena, S., Smith, D.C. 2001. The duration of bank relationships. Journal of Financial Economics 61,449-475.
Oxley, J.E. 1997. Appropriability hazards and governance in strategic alliances: A transaction cost approach. Journal of Law, Economics, & Organization 13,387-409.
Parise, S., Rollag, K. 2010. Emergent network structure and initial group performance: The moderating role of pre-existing relationships. Journal of Organizational Behavior 31,877-897.
Patrick, B., Xavier, F. 2000. Equity, bonds, and bank debt: Capital structure and financial market equilibrium under asymmetric information. Journal of Political Economy 108,324-351.
Persons, J.C., Warther, V.A. 1997. Boom and bust patterns in the adoption of financial innovations. The Review of Financial Studies 10,939-967.
Petersen, M.A., Rajan, R.G. 1994. The benefits of lending relationships: Evidence from small business data. The Journal of Finance 49,3-37.
Pichler, P., Wilhelm, W. 2001. A theory of the syndicate: Form follows function. The Journal of Finance 56,2237-2264.
Prendergast, C. 2002. The tenuous trade-off between risk and incentives. Journal of Political Economy 110,1071-1102.
Rau, P.R. 2000. Investment bank market share, contingent fee payments, and the performance of acquiring firms. Journal of Financial Economics 56,293-324.
Rauch, J.E. 2001. Business and social networks in international trade. Journal of Economic Literature 39,1177-1203.
Rayo, L. 2007. Relational incentives and moral hazard in teams. The Review of Economic Studies 74,937-963.
Richardson, G., Yawson, A., Zhang, H.Z. 2015. Are two heads better than one? Evidence on the role of investment banking syndicates in m&as. Working paper,1-60.
Riordan, M.H., Williamson, O.E. 1985. Asset specificity and economic organization. International Journal of Industrial Organization 3,365-378.
Robinson, D.T., Stuart, T.E. 2007. Network effects in the governance of strategic alliances. Journal of Law, Economics, and Organization 23,242-273.
Semykina, A., Wooldridge, J.M. 2010. Estimating panel data models in the presence of endogeneity and selection. Journal of Econometrics 157,375-380.
Servaes, H., Zenner, M. 1996. The role of investment banks in acquisitions. Review of Financial Studies 9,787-815.
Shipilov, A.V. 2009. Firm scope experience, historic multimarket contact with partners, centrality, and the relationship between structural holes and performance. Organization Science 20,85-106.
Sobel, J. 2002. Can we trust social capital? Journal of Economic Literature 40,139-154.
Song, W.-L. 2004. Competition and coalition among underwriters: The decision to join a syndicate. The Journal of Finance 59,2421-2444.
Song, W., Wei, J., Zhou, L. 2013. The value of "boutique" financial advisors in mergers and acquisitions. Journal of Corporate Finance 20,94-114.
Spagnolo, G. 1999. Social relations and cooperation in organizations. Journal of Economic Behavior & Organization 38,1-25.
Staiger, D., Stock, J.H. 1997. Instrumental variables regressions with weak instruments. Econometrica 65,557-586.
Stock, J.H., Wright, J.H., Yogo, M. 2002. A survey of weak instruments and weak identification in generalized method of moments. Journal of Business & Economic Statistics 20,518-529.

Teece, D.J. 1992. Competition, cooperation, and innovation: Organizational arrangements for regimes of rapid technological progress. Journal of Economic Behavior & Organization 18,1-25.

Tian, X. 2012. The role of venture capital syndication in value creation for entrepreneurial firms. Review of Finance 16,245-283.

Vella, F. 1993. A simple estimator for simultaneous models with censored endogenous regressors. International Economic Review 34,441-457.

Vella, F., Verbeek, M. 1999. Two-step estimation of panel data models with censored endogenous variables and selection bias. Journal of Econometrics 90,239-263.

Walter, T.S., Yawson, A., Yeung, C.P.W. 2008. The role of investment banks in m&a transactions: Fees and services. Pacific-Basin Finance Journal 16,341-369.

Williamson, O.E. 1993. Transaction cost economics and organization theory. Industrial and Corporate Change 2,107-156.

Winter, E. 2010. Transparency and incentives among peers. The RAND Journal of Economics 41,504-523.

Figure 1. Examples of Density in Two Hypothetical Syndicates

This figure depicts the networks for two hypothetical syndicates, "S_a" and "S_b". Each syndicate has four investment banks, which are represented by nodes in the figure. The links between nodes indicate the existence of ties between two syndicate members. The adjacency matrix for each syndicate is shown below the figure. In each matrix, a cell is coded as one if two of the member banks has a tie and zero otherwise. By convention, a syndicate member has no relationship with itself and hence, all diagonal elements in a matrix are set to zero.

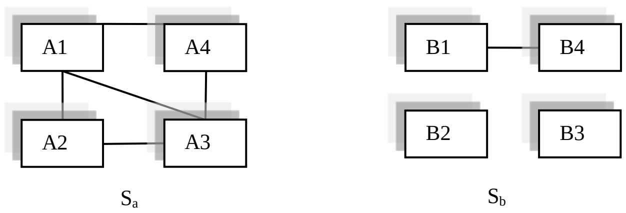

Figure 1a

$$S_A = \begin{bmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{bmatrix} \qquad S_B = \begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix}$$

Figure 1b

Table 1. Descriptive Sample Statistics

This table presents the descriptive statistics for the sample of US M&A transactions involving two or more investment banks on the acquirer side during the period from 1/1/1990 to 31/12/2012. Panels A, B and C report the number of observations (*N*), the mean, median and standard deviation (*Std. Dev)* for syndicate-, acquirer- and deal-characteristics, respectively. The data on M&A transactions are drawn from the Thomson Financial SDC database; share price data are obtained from CRSP; and accounting data are collected from Computstat.

	N	Mean	Median	Std. Dev.
Panel A: Syndicate characteristics				
Density	1138	0.306	0.000	0.438
Syndicate size	1138	2.230	2.000	0.637
Participation of Top 8	1138	0.640	-	0.480
Panel B: Acquirer characteristics				
Vertical relationship density	1138	0.100	0.000	0.309
Acquirer size (in $mil)	1138	9770.973	1660.162	29460.685
Run-up	1138	0.085	0.029	0.407
FCF	925	0.080	0.098	0.145
Leverage	968	0.188	0.160	0.164
Tobin's Q	969	2.070	1.507	2.494
Panel C: Deal characteristics				
Deal size (in $mil)	1138	2644.377	547.061	8593.413
Relative size	1138	0.662	0.345	1.462
Num. of bidders	1138	1.117	1.000	0.386
Public target	1138	0.551	-	0.498
Private target	1138	0.184	-	0.387
Subsidiary target	1138	0.265	-	0.442
Cross border	1138	0.193	-	0.395
All cash	1138	0.293	-	0.455
Related	1138	0.636	-	0.481
Tender	1138	0.155	-	0.362
Hostile	1138	0.061	-	0.239
CAR (-1, +1)	1138	0.003	-0.003	0.100
Advisory fee (in $mil)	249	9.490	4.575	11.611

Table 2. Network Density and Acquirer CAR: Ordinary Least Squares

This table reports the results from the OLS regressions of the 3-day acquirer CAR for the full sample as well as the sample split by the existence of vertical relationship and deal size, respectively. The vertically unrelated (related) subsample contains deals in which the acquirer-advisor tie is absent (present). The large (ordinary) deal subsample consists of deals in (below) the top two size quintiles. The dependent variable is the acquirer's 3-day CAR. Density at the syndicate level is calculated based on interbank syndication relationships 1 year prior to the announcement year. A description for each variable is provided in Appendix A. Year fixed effects are controlled for in all models but the coefficients are unreported. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Full	Vertically Unrelated	Vertically Related	Large Deals (>60%)	Ordinary Deals (<=60%)
	(1)	(2)	(3)	(4)	(5)
Density	0.0014	0.0049	-0.0076	0.0047	0.0108
	(0.1852)	(0.5862)	(-0.4492)	(0.4655)	(1.0530)
Vertical relationship density	-0.0082			-0.0101	-0.0059
	(-1.3578)			(-1.4249)	(-0.4587)
Syndicate size	0.0073*	0.0070	0.0106	0.0095*	0.0076
	(1.7123)	(1.5693)	(0.6909)	(1.9549)	(0.8488)
Participation of Top 8	0.0177**	0.0166**	0.0128	0.0049	0.0262***
	(2.3365)	(2.0242)	(0.5897)	(0.3669)	(2.9088)
Ln (Acquirer size)	-0.0024	-0.0022	-0.0172*	0.0115**	-0.0097***
	(-0.8214)	(-0.7292)	(-1.8285)	(2.4558)	(-2.6290)
Run-up	0.0032	0.0003	0.0213	0.0093	0.0059
	(0.2872)	(0.0265)	(0.8342)	(0.4747)	(0.4199)
FCF	0.0141	0.0152	0.0469	0.0880	0.0206
	(0.3585)	(0.3881)	(0.3847)	(1.3891)	(0.4939)
Leverage	0.0065	0.0092	-0.0434	0.0761*	-0.0284
	(0.2738)	(0.3616)	(-0.6824)	(1.9095)	(-0.9949)
Tobin's Q	-0.0019	-0.0021	0.0037	-0.0022	-0.0000
	(-1.3569)	(-1.3471)	(0.4675)	(-1.1274)	(-0.0049)
Ln (Deal size)	-0.0081**	-0.0094***	0.0179*	-0.0121*	-0.0028
	(-2.5825)	(-2.8139)	(1.7594)	(-1.9566)	(-0.5962)
Relative size	0.0055**	0.0057**	-0.0275	0.0058	0.0074***
	(2.0747)	(2.2008)	(-1.4735)	(1.0034)	(3.6574)
Related	0.0059	0.0087	-0.0101	-0.0009	0.0148*
	(0.9493)	(1.2925)	(-0.5443)	(-0.0957)	(1.8701)
Tender	0.0265***	0.0310***	-0.0025	0.0192	0.0382***
	(2.7863)	(3.0118)	(-0.1120)	(1.5610)	(2.9916)
Hostile	-0.0044	-0.0107	0.0343	-0.0025	0.0051
	(-0.3880)	(-0.8380)	(1.2543)	(-0.1668)	(0.2931)
All cash	0.0128*	0.0112	0.0121	0.0083	0.0133
	(1.7955)	(1.4202)	(0.7075)	(0.6693)	(1.4998)
Public deals	-0.0419***	-0.0412***	-0.0487*	-0.0178	-0.0563***
	(-5.4573)	(-4.9048)	(-1.8899)	(-1.3969)	(-5.7654)
Private deals	0.0055	0.0031	0.0128	0.0509**	-0.0098
	(0.5672)	(0.2915)	(0.5268)	(2.3179)	(-0.9043)
Cross-border	-0.0010	-0.0038	0.0291	-0.0021	0.0028
	(-0.1239)	(-0.4809)	(1.3954)	(-0.2026)	(0.2732)
Num. of bidders	-0.0075	-0.0040	-0.0092	-0.0219**	0.0198*
	(-0.9907)	(-0.4646)	(-0.4230)	(-2.0470)	(1.8543)
Intercept	0.0454	0.0447	0.1023	-0.0335	0.0175
	(1.4654)	(1.3903)	(1.5373)	(-0.3114)	(0.3715)
Year fixed effects	YES	YES	YES	YES	YES
Diagnostics					
R^2	0.207	0.214	0.403	0.215	0.237
Adj. R2	0.170	0.172	0.168	0.112	0.178
N	923	791	132	356	567

Table 3. Selection and Reduced-Form Models

Column (1) of this table estimates the determinants of syndication decision (Equation (4)) by probit regression, where the dependent variable is a dummy variable equal to 1 if a syndicate is used; and 0 otherwise. Columns (2) through (6) of the table estimate the reduced-form equation for the endogenous regressor, density (Equation (3)), conditional on the syndication decision, for the full sample as well as the sample split by the existence of a vertical relationship and deal size, respectively. The dependent variable, *density*, is computed as the relative degree of interbank relationships within a syndicate that had formed through M&A syndication over the last one year prior to the announcement date. The reduced-form and structural equations (Equation (2) and (3)) are jointly estimated by LIML. The vertically unrelated (related) subsample contains deals in which the acquirer-advisor tie is absent (present). The large (ordinary) deal subsample consists of deals in (below) the top two size quintiles. A description for each variable is provided in Appendix A. Year fixed effects are controlled for in all models. The coefficients are however suppressed for brevity. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Selection (1)	Full (2)	Vertically Unrelated (3)	Vertically Related (4)	Large Deals (>60%) (5)	Ordinary Deals (<=60%) (6)
Instruments						
Lagged syndicate size	0.3214***					
	(6.2760)					
Weighted lagged syndicate size	-0.0008					
	(-0.3767)					
Local network density		0.3884***	0.3869***	0.4530***	0.3097***	0.8937***
		(3.7585)	(3.1177)	(2.8988)	(3.7342)	(3.1730)
Fraction of members from the same State		0.1519***	0.1642***	0.0875	0.2294***	0.1034**
		(3.9019)	(3.9007)	(0.8704)	(3.7936)	(2.1573)
Prior-year debt underwriting relationship density		0.1007*	0.1351**	-0.1191	0.2042**	0.0604
		(1.9298)	(2.4731)	(-0.7947)	(2.2852)	(0.9686)
Prior-5year debt underwriting relationship density weighted by frequency		0.0006***	0.0005***	0.0014***	0.0003*	0.0008***
		(4.9099)	(4.1944)	(2.8418)	(1.8653)	(4.5247)
Covariates from Third-Stage						
Syndicate size		-0.0081	-0.0072	-0.0361	-0.0028	-0.0001
		(-0.4800)	(-0.4039)	(-0.5073)	(-0.1266)	(-0.0018)
Participation of Top 8	0.3469***	0.0661	0.1102**	0.0432	0.1392*	-0.0062
	(6.2203)	(1.3879)	(2.0878)	(0.3509)	(1.7358)	(-0.0926)
Vertical relationship density		0.1264***			0.1373***	0.1380*
		(3.2307)			(2.6495)	(1.8380)
Cash shortfall	0.0205**					
	(2.3038)					
Ln (Acquirer size)	-0.1173***	0.0069	-0.0055	0.0191	-0.0251	0.0438*
	(-3.9113)	(0.3326)	(-0.2476)	(0.3430)	(-0.6850)	(1.7110)
Run-up	0.0150	-0.0582	-0.0464	-0.0562	-0.0801	-0.0527
	(0.2528)	(-1.3949)	(-1.0217)	(-0.5360)	(-1.1736)	(-0.9575)
Sigma	5.9677**					
	(2.5137)					
FCF		-0.0358	-0.0960	1.2025*	-0.1569	0.0666
		(-0.2706)	(-0.7522)	(1.9443)	(-0.4684)	(0.4135)
Leverage	0.6523***	-0.0515	-0.0442	0.0443	-0.0077	-0.2394
	(3.5247)	(-0.4144)	(-0.3379)	(0.1284)	(-0.0348)	(-1.4445)
Tobin's Q		0.0097*	0.0106**	-0.0048	0.0124*	-0.0134
		(1.9283)	(2.0226)	(-0.2099)	(1.9257)	(-0.9943)
Ln (1+Acquirer experience)	0.0306					
	(0.6421)					
Ln (Deal size)	0.2825***	0.0153	0.0496	-0.0701	0.0625	-0.0102
	(8.7461)	(0.4715)	(1.4538)	(-0.9165)	(1.1817)	(-0.2390)
Relative size	0.1301**	0.0141	0.0241	0.0020	0.0339	0.0109
	(2.5370)	(0.8323)	(1.4519)	(0.0214)	(1.0747)	(0.2457)
Related	-0.0288	0.0116	0.0223	0.0772	0.0044	0.0048
	(-0.5473)	(0.3281)	(0.5643)	(1.0800)	(0.0781)	(0.1001)
Hostile	0.2363*	-0.0813	-0.0902	0.0910	-0.0138	-0.1524**
	(1.7498)	(-1.2157)	(-1.2113)	(0.4999)	(-0.1532)	(-2.1569)
Cross-border	0.3298***	-0.1080**	-0.0337	-0.2234**	-0.0741	-0.1668**
	(4.9056)	(-2.1306)	(-0.6056)	(-2.0697)	(-0.9032)	(-2.4181)
Num. of bidders	0.2197***	-0.0360	-0.0301	-0.0628	0.0088	-0.0794
	(2.7540)	(-0.8385)	(-0.5827)	(-0.6498)	(0.1373)	(-1.4892)
All cash		0.0266	0.0534	-0.0749	0.1505**	-0.0302
		(0.7439)	(1.2928)	(-0.7806)	(2.1568)	(-0.7059)
Tender		-0.0207	-0.0357	-0.1904*	-0.0271	-0.0603
		(-0.4219)	(-0.6387)	(-1.8745)	(-0.3137)	(-0.9228)
Public deals	0.1405**	-0.0552	-0.0439	-0.0760	-0.1378*	0.0145
	(2.5440)	(-1.1760)	(-0.8545)	(-0.5947)	(-1.6710)	(0.2524)
Private deals		-0.0340	-0.0387	-0.0511	-0.2109**	0.0388
		(-0.6770)	(-0.6998)	(-0.3269)	(-2.0569)	(0.6558)
General residuals		-0.0740	0.0878	-0.4980*	0.0903	-0.2359
		(-0.6539)	(0.7284)	(-1.8347)	(0.5681)	(-1.4954)
Intercept	-3.8236***	-0.1546	-0.6169	0.7944	-0.9634	0.4444
	(-8.8865)	(-0.3523)	(-1.3367)	(1.0503)	(-1.0961)	(0.7704)
Year fixed effects	YES	YES	YES	YES	YES	YES

Diagnostics						
Hansen J Chi2	-	3.030	2.028	0.233	1.142	0.227
p-value	-	0.387	0.567	0.972	0.767	0.973
Instrument strength test (F-test)	-	18.590	17.989	4.630	12.228	13.655
Stock-Yogo critical values:	-	10% maximal LIML size 5.44	10% maximal LIML size 5.44	10% maximal LIML size 5.44	10% maximal LIML size 5.44	10% maximal LIML size 5.44
R^2	-	0.330	0.348	0.524	0.330	0.356
Adj. R^2 (Pseudo R^2)	0.164	0.281	0.289	0.307	0.209	0.267
N	4383	665	533	132	294	371

Table 4. Network Density and Acquirer CAR: Selection-adjusted IV Approach

This table presents the LIML estimation results for the structural equation (Equation (2)), conditional on the syndication decision and with network density endogenized. In each column, the dependent variable is the cumulative abnormal return (CAR) on the acquirer's stock over the event window (-1, +1). Column (1) reports the estimates for the full sample; column (2) ((3)) provides the results for the vertically unrelated (related) subsample of deals in which the acquirer-advisor tie is absent (present); column (4) ((5)) presents the results for the subsample of deals above (at or below) the 60th percentile of the transaction size distribution. A description for each variable is provided in Appendix A. Year fixed effects are controlled for in all models, but the coefficients are suppressed for brevity. Intercepts are not shown. The z-scores in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Full	Vertically Unrelated	Vertically Related	Large Deals (>60%)	Ordinary Deals (<=60%)
	(1)	(2)	(3)	(4)	(5)
Density	0.0370*	0.0451**	0.0163	0.0427**	0.0607*
	(1.7241)	(1.9794)	(0.4467)	(2.0023)	(1.7436)
Syndicate size	0.0081*	0.0076*	0.0132	0.0134***	0.0022
	(1.8953)	(1.6839)	(0.9618)	(2.7829)	(0.2119)
Participation of Top 8	0.0185*	0.0144	0.0163	-0.0035	0.0379***
	(1.7002)	(1.1720)	(0.8488)	(-0.2301)	(2.7202)
Vertical relationship density	-0.0144**			-0.0189***	-0.0070
	(-2.0959)			(-2.7287)	(-0.4629)
Ln (Acquirer size)	-0.0011	0.0015	-0.0205**	0.0049	-0.0107
	(-0.2475)	(0.3105)	(-2.3495)	(0.9865)	(-1.4418)
Run-up	0.0207*	0.0186	0.0237	0.0247	0.0273**
	(1.8394)	(1.6113)	(1.1062)	(1.4119)	(2.1022)
FCF	0.0278	0.0302	0.0134	0.1297**	0.0081
	(1.0301)	(1.0611)	(0.1210)	(2.1506)	(0.2367)
Leverage	0.0117	0.0171	-0.0221	0.0832*	0.0098
	(0.3914)	(0.5134)	(-0.4126)	(1.8368)	(0.2390)
Tobin's Q	-0.0031**	-0.0037***	0.0043	-0.0038**	0.0033
	(-2.3668)	(-2.8087)	(0.6255)	(-2.2094)	(0.8065)
Ln (Deal size)	-0.0110*	-0.0171**	0.0247**	-0.0096	-0.0033
	(-1.7913)	(-2.5650)	(2.1564)	(-1.2661)	(-0.3301)
Relative size	0.0022	0.0026	-0.0278*	-0.0049	0.0130
	(0.3186)	(0.3722)	(-1.7941)	(-0.7015)	(0.7252)
Related	0.0023	0.0062	-0.0119	-0.0055	0.0106
	(0.3452)	(0.8109)	(-0.7935)	(-0.5897)	(1.1557)
Tender	0.0147	0.0201*	0.0028	0.0091	0.0259*
	(1.4904)	(1.7805)	(0.1502)	(0.7398)	(1.7670)
Hostile	0.0076	0.0028	0.0370	0.0094	0.0224
	(0.5880)	(0.1900)	(1.4766)	(0.6314)	(1.1721)
Cross-border	0.0059	-0.0033	0.0404*	0.0122	0.0214
	(0.5609)	(-0.2985)	(1.7328)	(0.9943)	(1.2620)
Num. of bidders	-0.0129	-0.0114	-0.0061	-0.0345***	0.0338**
	(-1.4179)	(-1.0938)	(-0.3136)	(-2.7141)	(2.2728)
All cash	0.0091	0.0047	0.0141	-0.0003	0.0144
	(1.2046)	(0.5351)	(1.0243)	(-0.0223)	(1.5016)
Public deals	-0.0219**	-0.0177*	-0.0425**	-0.0119	-0.0311**
	(-2.3918)	(-1.6954)	(-2.0531)	(-0.9248)	(-2.4456)
Private deals	0.0123	0.0103	0.0169	0.0459	-0.0034
	(1.0729)	(0.8099)	(0.7805)	(1.5787)	(-0.2512)
General residuals	0.0072	-0.0036	0.0364	0.0047	0.0425
	(0.3436)	(-0.1608)	(1.0325)	(0.1872)	(1.3699)
Year fixed effects	YES	YES	YES	YES	YES
"Excluded" Instruments: Local network density; Fraction of members from the same State; Prior-1 year (unweighted) and prior-5year (weighted) debt underwriting relationship density.					
Diagnostics					
Centered R^2	0.224	0.079	0.219	0.141	0.045
UncenteredR^2	0.225	0.079	0.219	0.141	0.045
F	3.799	4.393	2.219	2.884	2.521
N	665	533	132	294	371

Table 5. Network Density, Acquirer CAR and Transaction Size

This table reports the LIML estimation results for the structural equation (Equation (2)), for the sample split at the 50th and 75th percentile of the size distribution, respectively, conditional on the syndication decision and with network density endogenized. The reduced-form estimation results are suppressed here for the sake of brevity. In each column, the dependent variable is the cumulative abnormal return (CAR) on the acquirer's stock over the event window (-1, +1). Columns (1) and (2) provide the results for the subsample of deals above or at/below the 50th percentile; columns (3) and (4) present the results for subsample of deals above or at/below the 75th percentile. A description for each variable is provided in Appendix A. Year fixed effects are controlled for in all models, but the coefficients are suppressed for brevity. Intercepts are not shown. The z-scores in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	50% size cutoff		75% size cutoff	
	Large Deals	Ordinary Deals	Large Deals	Ordinary Deals
	(1)	(2)	(3)	(4)
Density	0.0323	0.0632*	0.0712***	0.0225
	(1.4487)	(1.6573)	(2.7309)	(0.8045)
Syndicate size	0.0113**	-0.0028	0.0179***	0.0003
	(2.4425)	(-0.2226)	(3.9486)	(0.0306)
Participation of top 8	0.0089	0.0314**	-0.0284*	0.0384***
	(0.5904)	(2.0626)	(-1.8509)	(2.9634)
Vertical relationship density	-0.0148**	-0.0189	-0.0433***	-0.0109
	(-2.2424)	(-0.9603)	(-2.8043)	(-1.3962)
Ln (Acquirer size)	0.0012	-0.0079	0.0159**	-0.0073
	(0.2554)	(-1.0007)	(2.2304)	(-1.3989)
Run-up	0.0287*	0.0178	0.0286*	0.0227*
	(1.8822)	(1.2614)	(1.7042)	(1.9054)
FCF	0.0942*	0.0253	0.1062*	0.0250
	(1.7199)	(0.8264)	(1.6763)	(0.8608)
Leverage	0.0429	0.0199	0.0237	0.0334
	(1.0526)	(0.4410)	(0.4634)	(0.9013)
Tobin's Q	-0.0036**	0.0018	-0.0052***	0.0022
	(-2.4006)	(0.3293)	(-3.0827)	(0.5483)
Ln (Deal size)	-0.0080	-0.0069	-0.0246**	-0.0062
	(-1.1141)	(-0.6558)	(-2.5629)	(-0.7761)
Relative size	-0.0070	0.0173	0.0021	0.0060
	(-1.0371)	(0.7134)	(0.2484)	(0.7991)
Related	0.0004	0.0046	-0.0057	0.0048
	(0.0409)	(0.4427)	(-0.5305)	(0.5841)
Tender	0.0129	0.0232	0.0078	0.0229*
	(1.0975)	(1.5227)	(0.4798)	(1.8015)
Hostile	0.0156	0.0059	0.0249	-0.0148
	(1.0589)	(0.3065)	(1.5386)	(-0.7334)
Cross-border	0.0196	0.0102	0.0089	0.0129
	(1.5587)	(0.5629)	(0.6469)	(0.9763)
Num. of bidders	-0.0276**	0.0278*	-0.0467***	0.0047
	(-2.3386)	(1.6728)	(-3.6228)	(0.4389)
All cash	-0.0039	0.0200*	-0.0079	0.0118
	(-0.3422)	(1.9401)	(-0.6194)	(1.3585)
Public deals	-0.0174	-0.0271*	-0.0043	-0.0230**
	(-1.4775)	(-1.8757)	(-0.2342)	(-2.1301)
Private deals	0.0249	0.0044	-0.0005	0.0099
	(1.3809)	(0.2663)	(-0.0114)	(0.8009)
General residuals	0.0115	0.0268	-0.0230	0.0278
	(0.4463)	(0.8701)	(-0.8184)	(1.0640)
Year fixed effect	YES	YES	YES	YES
"Excluded" Instruments: Local network density; Fraction of members from the same State; Prior-1 year (unweighted) and prior-5year (weighted) debt underwriting relationship density.				
Diagnostics				
Hansen J Chi2	1.598	0.238	4.058	1.050
p-value	0.660	0.971	0.255	0.789
Instrument strength test	13.637	10.389	10.286	17.792
Stock-Yogo critical values:	10% maximal LIML size 5.44	10% maximal LIML size 5.44	10% maximal LIML size 5.44	10% maximal LIML size 5.44
Centered R^2	0.123	0.055	0.125	0.087
UncenteredR^2	0.123	0.055	0.125	0.087
F	3.214	1.981	2.233	2.211
N	367	298	200	465

Table 6. Network Density and Acquirer CAR in Hot Markets

This table presents the LIML estimation results for the structural model of acquirer CAR, measured as the cumulative abnormal return on the acquirer's stock over the event window (-1, +1). The main variables of interest are density during peak and non-peak years, both are endogenized in each specification. Peak years include the dot-come bubble of 1998-2000, and the recent merger wave 2003-2007. Column (1) reports the estimates for the full sample; columns (2) and (3) provide results for the vertically unrelated subsample and the large deal subsample based on the 60th percentile size cutoff point, respectively. In each specification, the selection model predicts the probability of using a syndicate; the reduced-form model predicts the level of network density during peak and non-peak years, respectively; and the primary equation predicts the acquirer three-day CAR. The estimates for the selection and reduced-form models are unreported for brevity. Other variables are defined in Appendix A. Intercepts are not shown. The z-scores in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Full (1)	Vertically Unrelated (2)	Large Deals (>60%) (3)
Density during peak years	0.0615**	0.0724**	0.0707**
	(2.2985)	(2.3818)	(2.2454)
Density during non-peak years	0.0386	0.0472*	0.0183
	(1.5700)	(1.8599)	(0.7316)
Syndicate size	0.0089**	0.0084*	0.0137***
	(2.1342)	(1.9054)	(3.0079)
Participation of Top 8	0.0100	0.0062	-0.0083
	(0.9417)	(0.4887)	(-0.5978)
Vertical relationship density	-0.0259***		-0.0257***
	(-3.3083)		(-3.1442)
Ln (Acquirer size)	0.0036	0.0056	0.0088*
	(0.8221)	(1.2479)	(1.9523)
Run-up	0.0219*	0.0200	0.0233
	(1.7828)	(1.5316)	(1.3810)
FCF	0.0451	0.0563*	0.1432**
	(1.5952)	(1.9422)	(2.0048)
Leverage	0.0133	0.0178	0.1001**
	(0.4504)	(0.5449)	(2.2916)
Tobin's Q	-0.0038***	-0.0042***	-0.0046***
	(-2.8830)	(-3.1161)	(-2.7994)
Ln (Deal size)	-0.0229***	-0.0281***	-0.0170**
	(-3.4282)	(-3.8343)	(-2.4721)
Relative size	0.0030	0.0030	0.0067
	(0.5253)	(0.5303)	(1.5273)
Related	-0.0014	0.0020	-0.0043
	(-0.1884)	(0.2349)	(-0.4459)
Tender	0.0197	0.0257*	0.0024
	(1.5264)	(1.8435)	(0.1858)
Hostile	-0.0002	-0.0095	0.0163
	(-0.0148)	(-0.5555)	(0.9723)
Cross-border	-0.0049	-0.0126	0.0156
	(-0.4212)	(-1.0506)	(1.3358)
Num. of bidders	-0.0133	-0.0102	-0.0348***
	(-1.3331)	(-0.8821)	(-3.0395)
All cash	0.0097	0.0025	0.0008
	(1.2328)	(0.2710)	(0.0626)
Public deals	-0.0249***	-0.0220**	-0.0118
	(-2.7345)	(-2.1014)	(-0.8921)
Private deals	0.0194	0.0174	0.0409
	(1.4076)	(1.1838)	(1.3194)
General residuals	-0.0268	-0.0342	0.0124
	(-1.4437)	(-1.6230)	(0.6705)
Diagnostics			
Hansen J Chi2	6.360	4.606	5.269
p-value	0.384	0.595	0.510
Instrument strength test *(KP rank)*	10.107	8.362	6.088
Stock-Yogo critical values:	10% maximal LIML size 3.78	10% maximal LIML size 3.78	10% maximal LIML size 3.78
Centered R^2	0.137	0.138	0.131
UncenteredR^2	0.139	0.138	0.217
F	4.127	4.678	3.546
N	665	533	294

Table 7. Top-8 Lead, Density and Acquirer CAR: Selection-adjusted IV Approach

This table presents the results of the LIML estimation from an IV-style regression of acquirer 3-day CAR, conditional on the syndication decision modeled in Table 3, with both top-8 lead advisor and network density endogenized. The sample consists of deals with hand-collected data on the identity of the lead advisor. The results are presented in structural form, with both the *density* variable and the *top-8 lead advisor* variable endogenized. Column (1) reports the estimates for the lead sample; columns (2) and (3) present results for the sample split according to whether the vertical tie is absent and whether the deal size is above the 60th percentile of the deal size distribution, respectively. Network density is computed based on inter-bank syndicate relationships 1 year prior to the announcement year. A description for each variable is provided in Appendix A. Year fixed effects are controlled for in all models, but the coefficients are suppressed for brevity. Intercepts are not shown. The z-scores in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Full (1)	Vertically Unrelated (2)	Large Deals (>60%) (3)
Density	0.1628**	0.1860**	0.1433**
	(2.1269)	(2.0050)	(2.0119)
Syndicate size	0.0180*	0.0198*	0.0204**
	(1.8509)	(1.8103)	(2.2304)
Top-8 lead advisor	-0.0531	-0.0673	-0.0770*
	(-1.3486)	(-1.3780)	(-1.6800)
Vertical relationship density	-0.0291*		-0.0212
	(-1.7955)		(-1.1807)
Ln (Acquirer size)	0.0361**	0.0412**	0.0213
	(2.2898)	(2.3644)	(1.1643)
Run-up	-0.0004	-0.0275	0.0217
	(-0.0140)	(-0.8248)	(0.6270)
FCF	0.0180	-0.0024	0.3618***
	(0.2216)	(-0.0256)	(3.0305)
Leverage	-0.1137	-0.1264	-0.0849
	(-1.5614)	(-1.5146)	(-0.9942)
Tobin's Q	-0.0091***	-0.0124***	-0.0124***
	(-3.0803)	(-3.1899)	(-4.1584)
Ln (Deal size)	-0.0673***	-0.0713***	-0.0503**
	(-2.7170)	(-2.6094)	(-2.0034)
Relative size	-0.0210	-0.0059	-0.0562*
	(-0.9276)	(-0.2028)	(-1.8018)
Related	0.0055	0.0015	0.0012
	(0.2892)	(0.0657)	(0.0570)
Tender	-0.0013	-0.0078	0.0640
	(-0.0535)	(-0.2909)	(1.4139)
Hostile	0.0185	0.0344	-0.0195
	(0.5935)	(0.8650)	(-0.7021)
Cross-border	-0.0765***	-0.0766***	-0.0613
	(-2.6789)	(-2.7433)	(-1.3315)
Num. of bidders	-0.0740***	-0.0664**	-0.1287***
	(-3.3976)	(-2.5700)	(-4.0706)
All cash	0.0015	0.0096	-0.0519
	(0.0527)	(0.3200)	(-1.1048)
Public deals	-0.1455***	-0.1312***	-0.1242**
	(-3.6324)	(-3.2816)	(-2.1797)
Private deals	0.0344	0.0526	0.1332***
	(0.6871)	(0.8987)	(3.0319)
General residuals	-0.1447**	-0.1565**	-0.1708**
	(-2.3171)	(-2.1762)	(-2.5001)
Year fixed effects	YES	YES	YES
Diagnostics			
Hansen J Chi2	5.713	6.965	9.277
p-value	0.222	0.138	0.055
Instrument strength test	3.382	3.082	2.088
(KP rank Wald F-test)			
Stock-Yogo critical values:	10% maximal LIML size 4.06	10% maximal LIML size 4.06	10% maximal LIML size 4.06
Centered R^2	-0.023	-0.056	0.231
UncenteredR^2	-0.023	-0.056	0.231
F	3.968	3.341	4.596
N	170	141	94

Table 8. Network Density and Advisory Fee: Selection-adjusted IV Approach

This table presents the results of LIML estimation from an IV-style regression of advisory fee on network density, conditional on the syndication decision modeled in Table 3. The results are presented in structural form, with the selection and reduced-form estimation results omitted for brevity. The dependent variable in each specification is advisory fees paid by acquirer as a percentage of transaction value. Column (1) reports the estimates for the full sample; columns (2) and (3) present the results for the subsample of deals in which the vertical tie is absent; and the subsample of large deals defined as those above the 60th and 75th percentiles of the size distribution, respectively. Network density is computed based on inter-bank syndicate relationships 1 year prior to the announcement year. A description for each variable is provided in Appendix A. Year fixed effects are controlled for in all models, but the coefficients are suppressed for brevity. Intercepts are not shown. The z-scores in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Full (1)	Vertically Unrelated (2)	Large Deals (>60%) (3)
Density	-0.0020	-0.0031	-0.0031**
	(-0.9676)	(-1.1711)	(-2.0400)
Syndicate size	-0.0006	-0.0007	-0.0007*
	(-1.3891)	(-1.3585)	(-1.8327)
Participation of top8	0.0001	-0.0000	0.0012
	(0.0745)	(-0.0154)	(1.0282)
Vertical relationship density	0.0002		0.0003
	(0.2609)		(0.3542)
Ln (Deal size)	-0.0021***	-0.0022***	-0.0010***
	(-5.3906)	(-5.0656)	(-3.1492)
Relative size	-0.0012**	-0.0011*	-0.0000
	(-2.1141)	(-1.7316)	(-0.1152)
Related	-0.0009	-0.0020	0.0001
	(-0.8710)	(-1.5068)	(0.1640)
Payment incl. stock	-0.0050**	-0.0047*	-0.0035*
	(-2.2834)	(-1.8263)	(-1.6669)
Hostile	-0.0001	0.0009	0.0015
	(-0.0585)	(0.3615)	(0.7238)
Tender	-0.0006	-0.0005	-0.0024
	(-0.3271)	(-0.2433)	(-1.5052)
General residuals	-0.0028	-0.0028	0.0020
	(-1.2723)	(-0.9589)	(0.8402)
Year fixed effects	YES	YES	YES
Diagnostics			
Hansen J Chi2	1.374	3.747	2.859
p-value	0.712	0.290	0.414
Instrument strength test (F-test)	5.243	5.624	8.268
Stock-Yogo critical values	10% maximal LIML size 5.44	10% maximal LIML size 5.44	10% maximal LIML size 5.44
Centered R^2	0.413	0.417	0.160
UncenteredR^2	0.413	0.417	0.160
F	6.388	5.662	2.276
N	135	110	83

Appendix A Variable Definition

Variable	Definition
Panel A: Dependent Variables	
CAR (-1, +1)	Cumulative abnormal returns of the acquiring firm stock over the event window (-1, +1) around the announcement date. The return is calculated using the market model with the benchmark being the CRSP value-weighted index. The model parameters are estimated over the (-300, -91) period prior to the announcement.
Advisory Fee	The advisory fees paid by an acquirer as a percentage of transaction value, from SDC.
Panel B: Advisor Characteristics	
Density	The relative degree of adjacent ties within a syndicate, where a tie exists if two of the investment banks in the syndicate had syndicated one or more deals one year before the deal announcement.
Participation of Top 8	A dummy variable equal to 1 if one of the investment banks in a syndicate is ranked as top 8 according to the value of transactions; and 0 otherwise.
Panel C: Acquirer Characteristics	
Vertical Relationship Density	The fraction of all logically possible (asymmetric) ties between the acquiring firm and the advisors in a syndicate, where a vertical tie exists if the acquirer had been advised by an incumbent advisor in the syndicate one year before the deal announcement.
Bidder Size	The market value of the bidding firm's equity 11 days before the announcement date in millions of $US dollars..
Tobin's Q	The market value of assets divided by the book value of assets, where the market value of assets is equal to the book value of assets plus market value of common stock minus the book value of common stock minus balance sheet deferred taxes.
Run-up	Market-adjusted buy-and-hold returns of the bidder's stock over a 200-day window (-210, -11) from CRSP.
Sigma	Standard deviation of the market-adjusted daily returns of the bidder's stock over a 200-day window (-210, -11) from CRSP.
Leverage	The sum of long-term debt and short-term debt divided by the market value of total assets.
Free Cash Flow	Operating income before depreciation minus interest expense minus income tax plus changes in deferred taxes and investment tax credits minus dividends on both preferred and common share divided by the book value of total assets at the fiscal year-end immediately before the announcement date from Computstat.
Acquirer Experience	The total number of acquisitions made by the acquirer over the 5 years preceding the year of acquisition.
Panel D: Deal Characteristics	
Deal Size	The value of the transaction in millions of $US dollars.
Relative Size	The deal value divided by the market value of the bidding firm's equity 11 trading days before the announcement date.
Relatedness	A dummy variable equal to 1 if the bidder and the target are operating in the same industries with a common 3-digit SIC code and 0 otherwise.
Public Target	A dummy variable equal to 1 if the bid is for public target and 0 otherwise.
Private Target	A dummy variable equal to 1 if the bid is for private target and 0 otherwise.
Subsidiary Target	A dummy variable equal to 1 if the bid is for subsidiary target and 0 otherwise.
Foreign Target	A dummy variable equal to 1 if the bid is for foreign target and 0 otherwise.
All-Cash Deals	A dummy variable equal to 1 if the payment is pure cash and 0 otherwise.
Pmt. Incl. Stock	A dummy variable equal to 1 if the acquisition is either partially or fully financed with stock and 0 otherwise.
Cash Shortfall	The difference between the cash component of the payment in takeover bid and the acquirer's free cash flows measured in billions of $US dollars.
Tender Offer	A dummy variable equal to 1 if the deal is a tender offer and 0 otherwise.
Hostile	A dummy variable equal to 1 if the deal is "hostile" or "unsolicited" as reported by SDC; and 0 otherwise.
Number of Competing bidders	The number of bidders competing for the deal.

Appendix B The Procedure for Collecting Data on the Identity of Lead Advisors

We manually collect information on the identity of the lead investment bank for each M&A transaction from the *SDC* and the *Factiva* databases. The following data are obtained from the *SDC* database: the acquirer fee per advisor, the explanation for multiple M&A financial advisors, the advisor assignment, and the multiplier assigned to each advisor in a syndicate.[18] Where possible, we classify a lead advisor as the member bank which receives the largest share of advisory fee in a syndicate. This designation is consistent with both practice and empirical evidence observed in the literature (e.g. Ljungqvist and Wilhelm, 2003; Song, 2004; Corwin and Schultz, 2005). When the fee information is absent, we classify a member bank as lead advisor if it acts as the "lead", "exclusive", or "principal" advisor on a transaction according to the explanation provided by the *SDC*. If the *SDC* reports that a member initiates the deal, we consider it as the lead advisor since it is more likely to get involved in the strategic planning process and have a significant influence over the choice of other syndicate members. In the case where a syndicate involves two advisors only, we designate a member bank as co-advisor if it advises a "minority shareholder" in a firm, reasoning that its advice is likely to be less influential than that provided by a member bank advising the board or top management of the firm.[19] This procedure allows us to identify lead advisors for 287 out of 1,138 sample syndicate-advised transactions.

For those observations for which we cannot locate the above information from the *SDC*, we manually collect the data on the lead advisor from the *Factiva* database. We search for the news released six months surrounding the announcement of the takeover bid under the subject heading "Acquisitions/Mergers/Takeovers". The key words we use for searching are "adv*", "investment bank*", "investment firm*" "lead*", "principal*", "exclusive*", "co-adv*", "co-fin*", "joint adv*" or "joint fin*". We carefully read the text surrounding each matched key word to determine whether or not an investment bank plays a lead role in a transaction. It is noted that while most news announcements provide a detailed description for the financial advisors participating in a syndicate, the information on who leads the syndicate is often unreported. Consequently, we are able to identify only 60 additional deals as lead-managed. This together with the *SDC* data gives us a total of 347 acquisitions in which the lead advisor can be identified.

[18] The *SDC* assigns a multiplier of less than 1 to an advisor if the advisor represents a minority interest of a firm and 1 otherwise.
[19] We verify whether this method of identifying a lead advisor is reliable by searching the Factiva database. We find that where the information is available, the identity of the lead advisor is identical according to both methods.