Working in Teams: Evidence on the Role of Investment Banking syndicates in Mergers and Acquisitions

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Abstract

This thesis explores the role of investment banking syndication and the cooperation network that it gives rise to in the context of mergers and acquisitions (hereafter M&A). We hypothesize that by combining information channels, expertise and fundraising capacity of different investment banks, syndicates enhance acquisition-related services, primarily in generating information useful for screening and pricing a potential target and in helping acquirers obtain the external funds needed to finance a deal. Because of the free-riding problem inherent in team production, however, the value of a syndicate deteriorates as the scope for free riding increases.

Using a large sample of U.S. M&A transactions announced from 1990 to 2012, we find strong support for our hypotheses. Syndicates are more likely to be hired in difficult situations, where acquiring firms face greater transaction complexity and where they have a higher need for external financing. The choice between a syndicate and a single advisor has a profound impact on transaction outcomes. Compared with individual advisors, syndicates produce higher acquirer abnormal returns when the potential for free riding in a syndicate, as proxied by transaction size, target listing status and information opacity of target industry, is limited. In contrast, when advisors in a syndicate have considerable opportunities to act opportunistically, syndicates are associated with lower acquirer returns. Contrary to common economic wisdom, the lead advisor reputation mechanism does not help mitigate this moral hazard problem. Further analysis reveals that although acquiring firms advised by a syndicate do not pay lower takeover premiums, they create greater shareholder value by making more synergistic deals if their advisory syndicate is

less susceptible to free riding. Moreover, syndicates are better able to complete a deal when the acquirer requires external funds to finance the cash component of the offer. The results are robust to the endogeneity of syndication choice and a wide array of specifications. Overall, these findings suggest that, in M&As, investment banking syndicates perform a very different role from individual advisors. The non-linear association between syndicates and various acquisition outcomes highlights the benefits as well as the nontrivial agency costs associated with the use of M&A syndicates.

In light of the above results, this thesis next examines whether the cooperation network arising from investment banking syndication in M&As helps mitigate the moral hazard problem. 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 year before the deal announcement. We hypothesize that inter-investment bank (interbank hereafter) networking raises the ability of investment banks in a syndicate to monitor each other and sanction those shirking members through the withdrawal of subsequent cooperation. This, in turn, facilitates the operation of the peer pressure mechanism leading to improved effort and acquisition performance.

Controlling for the endogenous nature of interbank networking and other likely determinants of acquirer abnormal returns, we find that syndicates characterized by a higher degree of interconnections among participating investment banks are indeed associated with higher acquirer returns. Consistent with peer pressure playing a dominant role in determining the value of interbank networks, we find that such an effect is concentrated mainly in deals where information asymmetry between the acquirer and the advisors is severe and, hence, where free-riding is most likely to occur. Moreover, even if investment banks in a syndicate are linked to one another, they cooperate only when the expected peer sanction is severe, as indicated by sufficiently frequent interbank interaction in the past and ample opportunities for cooperation in the foreseeable future during market booms. Finally, we find that, with additional implicit incentives generated by peer pressure, interbank networking lowers the acquirer's cost of promoting advisor efforts through advisory fees.

The thesis contributes to the literature by extending existing research beyond the traditional focus on the attributes of individual advisors to the salient feature of peer cooperation in investment banking. Evidence in this thesis identifies syndication as an important organizational form that allows investment banks to enhance acquisition-related services. However, this competitive advantage is hampered if scope exists for an advisor to free ride on the efforts of others in a syndicate. In these situations, interbank networking is valuable in that it turns mutual dependence and relational capital into powerful peer pressure that reduces the cost of moral hazard. These findings offer important implications for the hiring choice of a syndicate versus a single advisor and the syndicate structure that an acquirer can employ to maximize shareholder value through M&As.

DECLARATION

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CHAPTER 1: GENERAL INTRODUCTION

1. Motivation and Research Objective

Cooperation among investment banks is a pervasive and striking feature of the investment banking industry. Considerable research, both theoretical and empirical, has explored why investment banks cooperate through syndication and how this organizational form affects the value of client firms (see e.g., Chowdhry and Nanda, 1996; Chen and Ritter, 2000; Song, 2004; Corwin and Schultz, 2005; Ljungqvist, Marston and Wilhelm, 2009; Shivdasani and Song, 2011). However, the focus of the extant literature is largely confined to the context of securities offerings. In addition, most studies hypothesize a positive role of investment banking syndicates. With the exception of Shivdasani and Song (2011) who investigate the negative impact of using multiple *lead* managers on the quality of bond issues, no prior research has explicitly examined the potential cost of syndication that arises through the internal free-riding problem inherent in joint production. This is striking given that ever since Alchian and Demsetz (1972), economic theorists have recognized the disastrous effect of moral hazard on team efficiency (see e.g., Alchian and Demsetz, 1972; Holmstrom, 1982; Rayo, 2007).

This thesis fills this research gap by examining the role of investment banking syndication and the cooperation network that it gives rise to in the context of mergers and acquisitions (hereafter M&A). Our data indicate that approximately 42% of M&A transactions (measured in transaction value) were advised by two or more investment banks over the 1990-2012 period. Surprisingly, the M&A literature makes no distinction between syndicates and individual advisors, thus leaving unaddressed the fundamental question of whether the form of investment banking syndication matters to acquiring firms (see e.g., Bowers and Miller, 1990; Servaes and Zenner, 1996; Rau, 2000; Hunter and Jagtiani, 2003; Kale, Kini and Ryan, 2003; Walter, Yawson and Yeung, 2008; Golubov, Petmezas and Travlos, 2012). We address this issue in our first empirical study by comparing the characteristics and performance of acquiring firms advised by a syndicate to those advised by a single bank. As an important departure from prior studies that typically assume a monotonic effect of syndicate on client value, we test directly whether the relation between the choice of a syndicate and acquisition performance varies according to factors that are likely to exacerbate free-riding.

Specifically, we conjecture that collaboration among investment banks creates two major efficiency gains that are unattainable in a single-advisor setting. First, syndicates provide enhanced M&A advice to an acquiring firm by permitting investment banks to best utilize one another's network of contacts that are essential for generating valuable information on target candidates. The interactive nature inherent in a team production process also increases the probability of detecting errors, omissions and anomalies when evaluating the potential target and pricing the deal (Sah and Stiglitz, 1986; Brander, Amit and Antweiler, 2002; Hamilton, Nickerson and Owan, 2003). Ignoring any incentive problems, this "capability-pooling" argument implies that acquirers advised by a syndicate should make better acquisition decisions and, thus, receive more favorable market reactions around the deal announcement than those acquirers advised by a single advisor (Hamilton et al., 2003). Second, by combining multiple investment banks' lending capacity and security distribution networks, a syndicate enhances its ability to help acquiring firms raise funds needed to finance a deal (Corwin and Schultz, 2005;

Grullon, Underwood and Weston, 2014). All else being equal, this should lead to a higher probability of bid success.

The most obvious disadvantage of using a syndicate is that advisors have greater incentives to free ride than they otherwise would if they acted alone (see e.g., Alchian and Demsetz, 1972; Groves, 1973; Holmstrom, 1982; Pichler and Wilhelm, 2001; Rayo, 2007). The benefits derived by a shirking member bank (e.g., time and resources that can be used to do other business) accrue entirely to the bank itself. However, the costs of its opportunistic behavior, presumably lower advisory fees and reputational cost, are shared across the syndicate. This, coupled with the difficulty of observing and separating an advisor's effort from that of others, heightens the incentive for free-riding when there are multiple investment banks jointly advising on a deal. We thus expect that the impact of syndicate use on acquisiton performance differs based on the scope for moral hazard. Specifically, the greater the scope for members to act opportunistically, the less sufficient are the effort supplies and, other things being equal, the lower is the added value of a syndicate to an acquirer client.

If free-riding presents a major obstacle to the maximum value that a syndicate can create for its acquirer clients, it is important to consider what mechanisms exist to overcome free-riding and its negative impact on acquisition performance. In the second empirical study of this thesis, we explore this issue by investigating whether interbank networking offers a solution to the team incentive problem through the support of the peer pressure mechanism. In the investment banking industry, investment banks cooperate with a fairly stable group of banks over time and are therefore bound into webs of relationships with their peers (e.g., Pichler and Wilhelm, 2001; Corwin and Schultz, 2005; Ljungqvist et al., 2009; Shipilov, 2009). Though the literature documents the prevalence of interbank networking, the performance consequences of this organizational structure have received relatively little attention empirically. In particular, we are unaware of any studies that have empirically assessed the governance role of interbank networks. This is despite the recent development of network economics, which explicitly recognizes peer relationships as a powerful tool to curb free-riding and promote cooperative incentives in teams (see e.g., Hart and Kurz, 1983; Montgomery, 1991; Kandori, 1992a; Teece, 1992; Greif, 1993; Rauch, 2001; Gujarati, 2003; Zuckerman, 2003; Granovetter, 2005).

Following the intuition set forth in this stream of research, we argue that because syndicate members' payoffs are contingent upon joint acquisition performance, shirking imposes a cost directly on all members. If one member shirks, the probability that other members in the syndicate will receive a lower share of advisory fees (and potentially incur a reputational cost) increases. This induces individual investment banks in a syndicate to exert peer pressure, that is, to monitor each other and to punish those who free ride when the anticipated risk of free-riding is high. Given repeated interaction among investment banks across deals, we consider a simple "tit-for-tat" strategy in which a syndicate member deters its co-workers from free riding in the current deal by threatening (implicitly) to terminate cooperation with the defector(s) in consecutive periods. Clearly, no syndicate member would cheat to maximize a one-shot gain if the probability of being caught shirking is high and the penalty, in the form of a loss of future revenue from syndicating with other members, is severe (Fudenberg and Maskin, 1986; Fudenberg and Levine, 1991; Hamilton et al., 2003).

In this setup, interbank networking enhances the peer pressure function for two reasons. First, direct ties allow investment banks of a syndicate to more effectively monitor one another, owing to the familiarity and mutual knowledge that they have developed through past interaction. Second, peer relationship plays an important role in determining future syndicate memberships (e.g., Pichler and Wilhelm, 2001; Corwin and Schultz, 2005; Ljungqvist et al., 2009). Thus, when a bank cooperates with someone it knows, the threat of terminating future cooperation presents a more credible deterrent against shirking. Moreover, breaking off trade with a relationship bank may result in a loss of valuable relationship-specific investments such as sources of information sharing, thereby aggregating the penalty for free riding on direct ties (Rauch, 2001; Brown, Falk and Fehr, 2004; Rayo, 2007; Gilsing, Nooteboom, Vanhaverbeke, Duysters and van den Oord, 2008). This line of reasoning leads us to conjecture that syndicates characterized by a higher degree of interconnections among participating investment banks are less prone to free-riding and, hence, produce better acquisition performance, all else being equal.

2. Summary of the Major Findings

Chapters 3 and 4 of this thesis empirically test our hypotheses on a sample of U.S. M&As announced between 1990 and 2012.[1] Chapter 3 examines the economic rationale for the use of an M&A advisory syndicate and the impact of this choice on acquisition performance. The results indicate that, compared with individual advisors, syndicates are more likely to be employed in more complicated deals, specifically cross-border deals, public acquisitions, deals that are absolutely or relatively larger, and deals with more

[1] This sample period is chosen because it covers the most up-to-date data that were available at the time when data were collected.

competing bidders. They are also more likely to be hired when acquiring firms have insufficient internal cash reserves to fund a deal. The choice between syndicates and individual advisors has profound implications for various acquisition outcomes. Syndicates generate significantly higher (lower) acquirer abnormal returns and total synergy gains when the scope for internal free-riding, as proxied by transaction size, target listing status and information opacity of target industry, is limited (sizable). Such non-linear relations continue to hold after we take into account the endogeneity of syndication choice. By employing a unique hand-collected dataset of lead-managed M&A deals, we further find that hiring a reputable lead advisor does not help curb the free-rider problem. Although there is no significant difference between syndicate- and individual-advised deals in takeover premiums, syndicates are, on average, associated with higher completion probability when external funds are required for a deal.

In Chapter 4, we investigate investment bank networking as a possible solution to the group moral hazard problem identified above. We characterize interbank networks at the syndicate level by density, measured as the fraction of adjacent ties within a syndicate (e.g., Freeman, 1978; Hochberg, Ljungqvist and Lu, 2007, 2010). A tie is present if two investment banks in a syndicate have jointly advised one or more M&A deals over the last year before the announcement year.[2] Understanding the consequence of interbank networking for acquisition performance, however, presents several challenges to our empirical analysis, owing to sample selection and endogeneity issues that arise from omitted variable problems. The novel approach that we take in our empirical analysis is a

[2] Past syndication relationships are a natural starting point because: (i) they are publicly observable; and (ii) they reflect the level of interdependence among investment banks in the M&A market (e.g., Corwin and Schultz, 2005; Hochberg et al., 2007).

three-stage, selection-adjusted instrumental variables (IV) estimation model (see e.g., Vella, 1993; Vella and Verbeek, 1999; Semykina and Wooldridge, 2010; Bettin, Lucchetti and Zazzaro, 2012).

Using the sample of syndicate-advised deals, our empirical analysis reaches four major conclusions. First, interbank networks at the syndicate level do positively affect acquirer announcement abnormal returns when free-riding is more likely to occur, for deals where there exists severe information asymmetry between the acquirer and the advisors of a syndicate. In contrast, the estimated impact for interbank networking is rarely significant when the scope for free-riding is limited, as is the case where the acquirer either has better knowledge about the advisors as a result of direct interaction in the past, or faces relatively less transaction complexity and uncertainty. Second, even with the presence of interbank relationships, cooperative behavior occurs only when the past interaction between investment banks in a syndicate takes place over a relatively short idle time period. This finding suggests that investment banks care more about relationships with their peers with whom they interact more frequently, and less about those with whom they rarely interact. Third, we find that the positive effect of interbank networking on acquirer abnormal returns is concentrated mainly in peak (as opposed to non-peak) years of M&A cycles, over which considerable future interactions are expected to occur and, hence, free-riding is associated with a higher level of peer penalty. Finally, network density at the syndicate level has either a negative or insignificant impact on the percentage of advisory fees. Thus, by inducing additional implicit incentives through peer pressure, interbank networking lowers an acquirer's explicit cost of providing incentives.

Overall, our findings lend strong support to the idea that interbank networks reduce free-riding and lead to improved effort provision through the exertion of peer pressure.

3. Contribution

The contribution of this thesis is fivefold. First, it provides new insights into the debate over whether it pays to pay for financial advisors. Our focus on the salient feature of peer cooperation in the investment banking industry differs radically from much of the existing literature, which emphasizes the attributes of individual advisors such as overall reputation (e.g., Bowers and Miller, 1990; Golubov et al., 2012), specialization (e.g., Song, Wei and Zhou, 2013) and dual agency (e.g., Agrawal, Cooper, Lian and Wang, 2013). We present the first evidence on the "two-faces" of an M&A syndicate. On the one hand, syndication creates efficiencies through collaboration. On the other hand, the problem of internal free-riding places a limit on the extent to which syndicate efficiencies can be achieved and translated into improvements in acquisition outcomes. These findings suggest that syndicates play a very different role from individual advisors, highlighting the importance of differentiating these two groups when assessing the value of investment banks in M&As.

Second, we add to a growing body of research on syndication among financial intermediaries in various market settings, e.g., bank loans (Sufi, 2007), venture capital (VC) (Sahlman, 1990; Lerner, 1994; Lockett and Wright, 2001; Tian, 2012), initial public offerings (IPOs) (Chowdhry and Nanda, 1996; Chen and Ritter, 2000; Corwin and Schultz, 2005), and offerings of equity and debt securities (Song, 2004; Ljungqvist et al., 2009; Shivdasani and Song, 2011). This thesis is the first to examine the economic implications of investment banking syndicates in the M&A context. We show that, in addition to traditional functions identified in prior research, such as the improvement in information production and the provision of "second opinion", syndicates facilitate acquisition-related financing. More importantly, to the best of our knowledge, it is the first study to empirically assess, quantify and uncover empirical evidence on the moderating effect of free-riding on the performance of investment banking syndicates.

Third, economic networks have long been considered important to the understanding of market interaction and exchange outcomes (see e.g., Hart and Kurz, 1983; Montgomery, 1991; Kandori, 1992a; Teece, 1992; Greif, 1993; Rauch, 2001; Zuckerman, 2003; Granovetter, 2005). Zuckerman (2003), for example, argues that economic networks emerging endogenously to fulfil a need unmet by the market have profound implications for firm behavior and performance. Consistent with this argument, a large body of empirical research has reported evidence in industries such as chemicals and biotechnology (Robinson and Stuart, 2007), mutual funds (Cohen, Frazzini and Malloy, 2008), commercial banking (e.g., Sharpe, 1990; Ogura, 2010; Engelberg, Gao and Parsons, 2012) and venture capital (Hochberg et al., 2007). In the investment banking field, however, the main stream of research has focused on the impact of vertical (i.e., bank-client) relationships on the quality of investment banking services provided to client firms (see e.g., Boot and Thakor, 2000; Ogura, 2010; Degryse, Masschelein and Mitchell, 2011; Riordan and Williamson, 1985; Engelberg et al., 2012; Hale, 2012). When peer (i.e., bank-bank) relationships are considered, the focus is generally confined to the analysis of how peer connections influence the performance of financial immediacies themselves (see e.g., Corwin and Schultz, 2005; Ljungqvist et al., 2009).[3] This thesis contributes to this strand of literature by showing that interbank networking serves as an important additional factor to help assess the value of financial intermediaries added to a client firm. In contrast to most investment banking studies that implicitly view lead bank reputation as a prominent countervailing force against free-riding (see e.g., Fang, 2005; Ljungqvist, Marston and Wilhelm, 2006), we show that a reputable lead investment bank may not have the incentive to exert costly effort to regulate other members' behavior if its identity is not released to the general public through different sources such as business press and media. In these situations, interbank networking, which turns mutual dependency and relational capital into powerful peer pressure, provides a valuable device to mitigate the free-rider problem in teams identified originally by Holmstrom (1982). Our findings provide important empirical evidence on a number of theoretical arguments regarding the role of economic networks as a tool for transactional governance (Greif, 1993; Oxley, 1997; Rayo, 2007).

Fourth, and on a more general level, the thesis contributes to the emerging literature on peer effects. Peer pressure is found to be highly effective in encouraging work effort 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 (see e.g., Fehr, Simon and Kirchsteiger, 1997; Carpenter, Bowles, Gintis and Hwang, 2009). This thesis is the first to uncover significant effects of peer pressure in the investment banking industry. Moreover, our

[3] A number of strategic management researchers also examine interbank network effects in the investment banking context. The main research interest, however, has been limited to the impact of peer networks on the performance of investment banks themselves (see e.g., Combs and Ketchen, 1999; Shipilov, 2009).

study yields a host of new insights absent from 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 effect mutually beneficial peer effects as many prior studies suggest (see 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 therefore, able to monitor and sanction each other at a relatively low cost. We further show that the positive peer effect is concentrated in ties where the interaction among investment banks in a syndicate is frequent, and 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, 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. This, in turn, leads to differences in the strength of peer pressure and the resulting level of implicit incentives. Our results, therefore, underscore mutual sanctioning as an important condition for peer pressure to operate.

Finally, this thesis offers important implications for practitioners undertaking takeovers and mergers. Specifically, the results of this thesis suggest a potential nontrivial agent cost that an acquiring firm should take into account when choosing between a syndicate and a single advisor. For instance, when the scope for free-riding is expected to be limited, hiring a syndicate is beneficial because it enables an acquiring firm to exploit a wide variety of sources of value created by collaboration across investment banks. When the anticipated risk of free-riding is high, however, hiring a syndicate that consists of more densely networked investment banks appears to be the better choice. In addition, the findings of this thesis indicate that the conventional wisdom of hiring a reputable lead banker may not hold in the market for M&As. Since the identity of the lead advisor is not disclosed to the public in most circumstances, the general market cannot effectively punish lead advisors with poor performance as in other markets such as IPOs. This, in turn, weakens the lead advisor's incentive to expend costly effort to monitor other syndicate members.

4. Thesis Structure

The remainder of this thesis is structured as follows. Chapter 2 reviews the prior literature relevant to the thesis. Chapter 3 investigates the determinants of syndicate choice and the impact of this choice on acquisition outcomes. Chapter 4 explores the role of interbank networking in resolving the free-rider problem in M&A syndicates and Chapter 5 concludes the thesis.

CHAPTER 2: LITERATURE REVIEW

1. Introduction

This chapter provides a broad review of the literature relevant to the thesis. The aim is to identify the research gaps and offer an overview of the key theories used to develop the hypotheses for each empirical chapter of this thesis. In Section 2, we discuss prior research on the role of financial advisors in M&As. Section 3 reviews the literature that investigates the determinants of investment banking syndicate membership and the primary functions of investment banking syndicates in markets other than M&As. Section 4 discusses the main theoretical models of moral hazard in teams, and Section 5 provides a summary.

2. M&A Financial Advisors

There is growing interest among scholars in investigating whether investment banks provide merging firms with valuable advice that justifies their substantial advisory fees. The main strand of this literature has focused on whether individual investment banks' quality, typically measured by name prestige, has an effect on the shareholder value of acquiring firms. The evidence is mixed. Bowers and Miller (1990), for instance, explore the value of the top-tier financial advisors (also known as "bulge bracket" investment banking firms). They find that compared with less prestigious investment banks, top-tier advisors do not deliver higher abnormal returns for their acquirer clients, although the total wealth gains accruing to the acquirer and the target are larger if either of the merging parties employs a top-tier bank.

McLaughlin (1990) investigates the structure of M&A advisory fee contracts used in 195 tender offers from 1978 to 1985. The author reports that, on average, the advisory fee is about 1.29% of the value of a completed deal and that over 80% of the advisory fee is contingent on deal completion in a typical contract. In a subsequent study, McLaughlin (1992) examines whether the use of this contingent-fee structure creates a conflict of interest between clients and financial advisors in a tender offer. As a measure of bank reputation, the author partitions investment banks into three groups based on the rank assigned by Carter and Manaster (1990). It is documented that, although completion rates do not differ across bank reputation, a bidding firm advised by a less reputable advisor pays significantly lower takeover premiums and also experiences higher announcement abnormal returns. The author concludes that the contingent-fee payment contract indeed creates misaligned incentives and that financial advisors are motivated to complete a deal rather than to create value for their clients. However, the author acknowledges that the results could be driven by top-tier banks being: "*associated with more difficult transactions, requiring higher premiums and with lower benefits to bidding firms*" (p. 258).

Servaes and Zenner (1996) compare the performance of "in-house" M&As with those advised by investment banks for a period from 1981 to 1992. They find that an advisor is more likely to be used when acquirers undertake more complex deals and when acquirers are less experienced. Nevertheless, acquirer abnormal returns do not differ significantly between deals with and without investment banks. This result holds even when a top-tier investment bank is used. A potential limitation of their study is that the sample, which consists of only the 100 largest transactions per year, may not be representative of the underlying population.

Rau (2000) extends McLaughlin's (1990, 1992) studies and examines the proportion of contingent fees charged by different tiers of investment banks in both tender and merger offers from 1980 to 1994. The author reports that about 66% of the total fees are contingent on deal completion in tender offers and 39% in mergers, indicating that the average investment bank has a stronger incentive to complete tender offers than mergers. In addition, top-tier advisors, classified as those having the largest market share, charge a greater proportion of contingent fees in both tender and merger offers than do less prestigious advisors. Accordingly, Rau (2000) posits that this choice of a contingent-fee structure encourages top-tier investment banks to subordinate deal quality to deal completion. Consistent with this conjecture, Rau (2000) finds that top-tier investment banks complete more tender offers than lower-tier investment banks, but they consistently produce lower announcement-period returns for their acquirer clients. Hunter and Jagtiani (2003) provide further evidence that top-tier bidder advisors are more likely to get a deal completed and to complete it in less time, and that acquirers are associated with lower synergistic gains when a top-tier advisor is used.

Kale et al. (2003) argue that the failure of previous studies to uncover a significant role of top-tier advisors in acquirer returns is probably due to the negligence of the adversarial nature inherent in a takeover contest. Since both bidders and targets can hire advisors, a client firm can have a strategic advantage only if the reputation of its advisor is *relatively* higher than that of the opposing side's advisor. The authors therefore construct a relative measure of advisor reputation, computed as a ratio of the bidder advisor's market share in the year of the takeover to that of the target advisor. Using a sample of 324 successful U.S. public takeovers, they find that bidder advisors that are relatively more reputable than the target advisors generate higher total wealth gains and extract a larger share of gains for their bidder clients. Walter et al. (2008), on the other hand, argue that the static ranking methodology employed in prior research may neglect the dynamics of the M&A advisory market. [4] They address this problem by sorting advisors based on contemporaneous market share over a three-year rolling window. Like previous studies, however, they find that top-tier investment banks fail to deliver superior bidder abnormal returns when compared to lower-ranked advisors. This holds even after accounting for the reputation of the target advisor.

The recent study by Golubov et al. (2012) provides new evidence on the performance of top-tier investment banks in different types of acquisitions classified by target listing status. They find that acquiring firms advised by a top-tier advisor experience higher abnormal returns around the deal announcements but only in public acquisitions. Top-tier investment banks are also able to complete public deals faster than lower-tier banks, although they do not lead to a higher probability of bid success. Golubov et al. (2012) interpret these results as evidence that advisors' reputational concerns are not uniform across acquisition types. Since public acquisitions involve greater reputation exposure than do acquisitions of private and subsidiary targets, top-tier investment banks seeking to protect their reputation capital have greater incentive to work diligently in public deals.

[4] Static ranking system refers to the practice of assigning a constant ranking to each financial advisor over the entire sample period. For example, Rau, 2000) ranks each advisor every year on the basis of the value of announced deals advised during the year and then assigns the average yearly rankings across the sample period to each advisor.

As a departure from previous studies of advisor reputation, Kisgen, Qian and Song (2009) explore the use and consequences of a third-party assessment of the fairness of an M&A transaction rendered by an investment bank over the period 1994- 2003. They show that, though fairness opinions (FOs) do not affect transaction outcomes when used by a target firm, they have a significant impact on deal premiums, announcement abnormal returns and the probability of deal completion when used by an acquiring firm. Specifically, the takeover premium is significantly lower when acquirers obtain a FO and is further reduced if the acquirers have multiple advisors providing a FO. In light of this latter result, the authors argue that the multi-opinion structure may be beneficial to an acquiring firm because, in these situations, it is difficult for multiple investment banks to provide a similarly biased FO. Finally, they report that transactions with an acquirer FO are more likely to be completed, but the acquirer announcement-period returns are significantly lower for these deals than those without an acquirer FO. The use of the multi-opinion structure, on the other hand, has no significant impact on both deal completion and acquirer announcement abnormal returns.

Bao and Edmans (2011) contend that the measures employed in most prior studies, such as market share and the league table ranking, may be mis-specified proxies for advisor quality. To investigate the issue whether investment banks matter for M&A outcomes, they employ a novel fixed effects approach. Using a sample of investment banks that had at least advised 10 deals over the period 1980-2007, they find significant bank fixed effects in the acquirer announcement-period returns. Furthermore, the difference in average acquirer returns across investment banks persists over time, with the top quintile of banks (sorted based on the average acquirer CAR over the last two years) significantly outperforming the bottom quintile for the next two years. Bao and Edmans (2011) conclude that investment banks do have a significant impact on M&A outcomes. The persistence in M&A performance implies that acquirer clients do not chase advisors with superior track records, but tend to award future mandates to those banks with the largest prior market share.

Song et al. (2013) explore the choice of hiring a “boutique”, i.e., those specializing in M&As only, versus a full-service advisor, and the impact of this choice on subsquent merger performance. They find that boutique advisors are more likely to be used in stock offers and in deals where the acquiring firm is confronted with target management resistance. Where a deal is diversifying or has competing bidders, however, acquiring firms are more likely to employ a mixed team consisting of both full-service and boutique advisors. With regard to acquisition outcomes, Song et al. (2013) find that acquiring firms pay lower premiums to targets when a boutique advisor, as opposed to a full-service advisor, is hired. Though there is no significant difference in deal completion probablity between boutique and full-service advisors, acquirer boutique advisors take longer to complete a deal.

Agrawal et al. (2013) investigate the role of individual investment banks that simultaneously advise the acquirer and target firms (i.e., a common advisor) in M&As. They report that acquirers and targets are more likely to hire a common advisor when a deal is absolutely smaller but relatively large, paid by stock, involves private targets, has multiple advisors, uses a top-tier advisor and when one merging firm has prior investment banking relationships with the counterpart’s advisors. After accounting for the endogenous choice of advisors, the authors find that common advisors are associated with a longer time to completion and lower bid premiums than separate advisors. However, the relation between the use of a common advisor and acquirer announcement abnormal returns is either insignficant or weakly positive.

Overall, the extant literature contributes signficantly to our understanding of how different individual advisor attributes help explain cross-sectional variations in M&A outcomes. However, with the exception of Kisgen et al. (2009) and Song et al. (2013) who have, to some extent, explored a *specific form* of advisory teams, most studies treat syndicates as individual advisors. In the next section, we discuss the important role played by investment banking syndicates in capital markets other than M&As.

3. Investment Banking Syndicates in Markets other than M&As

A syndicate is a hybrid organizational form that can be broadly defined as "*a group of individual decision makers who must make a common decision under uncertainty, and who, as a result, will receive jointly a payoff to be shared among them*" (Wilson, 1968, p. 119). In the investment banking industry, a syndicate is widely used to facilitate short-term collaboration necessary for accomplishing a narrow set of activities involved in a single transaction (Pichler and Wilhelm, 2001).

3.1. Determinants of Syndicate Formation

An important feature associated with investment banking syndicates is that their structure arises endogenously. Thus, to understand the functions of a syndicate, it is often important to consider factors affecting syndicate formation. The extant literature conveys little information about how syndicates are established in M&As. However, prior research examining other investment banking services sheds some light on this issue. Generally, the formation of a syndicate starts with the selection of a lead bank by the client firm. The firm may or may not have a choice of lead banks depending on the attractiveness of its deal (Danos, Eicheneseher and Holt, 1989). In the IPO market, for instance, large and profitable offerings often permit issuing firms to select the lead manager from a number of underwriters participating in the “bake sale” (Corwin and Schultz, 2005). When selecting the lead banker, the issuer considers factors such as the general reputation, prior relationships and the industry knowledge of the candidate banks. Once the lead banker is appointed, the issuer may choose some of the remaining underwriters as co-managers (Corwin and Schultz, 2005). In a typical offering of corporate securities, co-managers are included to facilitate the distribution of issues and to increase aftermarket services such as analyst coverage and price stabilization (e.g., Chen and Ritter, 2000; Narayanan, Rangan and Rangan, 2004). There are also occasions in which non-managing syndicate members are appointed on the basis of prior relationships with the client firm or lead manager (Ljungqvist et al., 2009). An investment bank, for example, may get a place in a syndicate because it has lent money to the client firm, or purchased research from the lead bank (Corwin and Schultz, 2005).

Empirical work examining the determinants of syndicate membership largely confirms these features involved in the formation process. In the IPO market, for instance, Corwin and Schultz (2005) find that the strength of relationships between the lead bank and the prospective syndicate members is the single most important determinant of syndicate inclusion. Underwriters that have a higher participation rate in the lead manager’s last syndicates, or possess more reciprocal relationships with the lead manager, are more likely to be selected as co-managers in a syndicate.[5] The influence of interbank relationships on co-manager selection is considered "*somewhat puzzling*", given that it is primarily the issuer who decides the choice of co-managers (Corwin and Schultz, 2005; p.462). Corwin and Schultz (2005), however, suggest that lead managers may affect the decision indirectly by advising the issuer on which candidates should be included as co-managers. In these circumstances, relationships with the lead underwriter are critical.

To provide further evidence on the effect of bank-bank relationships, Corwin and Schultz (2005) investigate whether the frequencies of lead manager-syndicate member pairs differ between those syndicates that do and do not involve a top-10 lead underwriter in their sample. The results indicate that most pairs maintain the same combination of lead and syndicate members across deals. Thus, lead managers appear to prefer underwriters with whom they have worked in the past and *vice versa*. One possible reason for this phenomenon, as Corwin and Schultz (2005) purport, is that ongoing relationships help mitigate the non-cooperative problems inherent in an investment banking syndicate. Lead managers, for example, may cut back on selling credits after syndicate members have expended time and effort on share distribution. Likewise, co-managers may shirk or undermine the lead underwriter's reputation by talking to the issuer behind the lead underwriter's back. These opportunistic behaviors may be minimized if relationships are built on a long-term basis. When opportunistic behaviors occur, a victim bank can refuse to participate or not include a non-cooperative underwriter in future syndicates. Despite

[5] Reciprocal relationships refer to the case where the underwriter invited the lead manager in its recent syndicates (see e.g., Corwin and Schultz, 2005; Ljungqvist et al., 2009).

its intuitive appeal, this conjecture is not empirically assessed in Corwin and Schultz's (2005) study.

In addition to interbank relationships, Corwin and Schultz (2005) report that highly prestigious underwriters or underwriters with top-ranked analysts are more likely to be included as syndicate members or co-managers when IPOs are relatively large. In small IPOs, these banks are more likely to participate as co-managers. Syndicate memberships are also affected by the geographic distribution of underwriters. An underwriter is more likely to be included in a syndicate if it is in or adjacent to the issuer's State. However, the probability of participating as syndicate members is significantly lower for underwriters that operate in the same State as the lead manager. Moreover, regional underwriters have a significantly lower chance of winning an appointment as a syndicate member or co-manager compared with those with a national presence. These results indicate that underwriters with different information sources from the lead manager are preferred because of their ability to provide incremental information about the local demand for an offering.

Ljungqvist et al. (2009) explore whether analyst behavior affects a bank's probability of being selected as a co-manager. They posit that analyst behavior is influenced by a bank's hope of winning future appointments as co-manager rather than that of lead bank. This argument appears counter-intuitive, at first glance, given that the average rewards to co-managers are modest. Ljungqvist et al. (2009), however, contend that since a co-management position enables underwriters to build relationships with client firms as well as a reputation for good judgment, it increases their chance to compete for future more lucrative lead appointments. Using 8,303 U.S. equity and debt offerings completed from 1/12/1993 to 30/06/2002, the authors find evidence supporting their assertions. All else being equal, analyst optimism or even mere research coverage enhances a bank's ability to win a co-management position in both equity and debt offerings. This, in turn, increases the probability for that bank to win subsequent lead-management appointments. Such an effect holds even in the "hardest-to-win" situation, where the issuing firm had previously appointed another bank as an exclusive lead manager. Ljungqvist et al. (2009) conclude that, in security offering markets where reputational consideration constitutes a substantial barrier to entry, analyst coverage and optimism provide a viable means for less prestigious banks to "*scale the hierarchy*". That is, by improving the chance to be appointed as a co-manager, analyst optimism opens the door for these banks to future lucrative lead positions that have been traditionally dominated by bulge-bracket underwriters.

Apart from analyst optimism, Ljungqvist et al. (2009) report that for both equity and debt offerings, a candidate bank's participation rate in the lead manager's prior-year syndicates as well as its reciprocal relationship with the lead manager positively affect its chance to win a co-management appointment. This result confirms Corwin and Schultz's (2005) argument that the lead manager influences an issuer's choice of co-managers in favor of those banks with whom the lead bank has frequently cooperated in the past. Furthermore, a potential co-manager's position in interbank networks, measured by eigenvector centrality, has a significant positive impact on the bank's chance to win both current co-management mandates and future lead-management offers.[6] When a bank has strong underwriting or lending relationships with the issuing firm, the bank is more likely to be selected as a co-manager. By contrast, reputation in the debt or equity underwriting market does not help a candidate bank win a co-management appointment, unless the reputation is derived from significant lending capacity. This suggests that lead managers may negatively influence an issuer's choice of co-managers by cutting against their more reputable competitors. Finally, lead banks are reluctant to work with co-managers that have a significantly lower reputation than themselves. In the equity underwriting market, for example, a one-standard deviation increase in the absolute difference in reputation between the candidate bank and the lead manager nearly wipes out the bank's chance to be a co-manager.

Shivdasani and Song (2011) study the determinants of an emerging syndicate structure that involves multiple lead underwriters, i.e., co-lead. Compared to the traditional sole-led form, co-led syndicates are more likely to be present in industries with high commercial bank penetration. The probability of using a co-led syndicate also increases with the issuer's credit rating and the fraction of bank loans from the underwriter. Shivdasani and Song (2011) interpret this finding as evidence that commercial banks leverage their lending relationships with issuers to win co-lead mandates. However, when issues are non-shelf registered, the likelihood of forming a co-lead syndicate is significantly lower. One possible reason, as the authors suggest, is that the underwriter and the issuer may have developed a close relationship over the SEC-filing period, which makes it difficult for other underwriters to participate as an additional lead manager.

[6] Eigenvector centrality is measured as the number of times that a bank has syndicated with other peers that are themselves well networked (Ljungqvist et al., 2009).

Finally, underwriters participating in a co-led syndicate are, on average, less reputable than those involved in a sole-led syndicate. This indicates that issuers employing co-led syndicates are less concerned about underwriters' certification reputation, but rather stand to benefit from other non-certification benefits provided by multiple lead managers.

Overall, prior studies on underwriting syndicates suggest that the appointment of syndicate members is endogenously influenced by the preferences of both the issuing firm and the lead manager.

3.2. Primary Functions of Syndicates in the Security Underwriting Market

The extant literature reveals serveral potential functions of investment banking syndicates, but the knowledge is limited only to syndicates organized for underwring security offerings. Chowdhry and Nanda (1996), for instance, propose a theoretical rationale for using an IPO underwriting syndicate to stabilize the stock price in after-market trading. In their model, uninformed investors face the problem of adverse selection and are, therefore, reluctant to participate in the IPO market.[7] To induce these investors to participate, underwriters must compensate them through one of the following two strategies: (i) *ex ante* underpricing; or (ii) *ex post* price stabilization, i.e., repurchasing shares at the offer price in the after-market. The latter strategy is more efficient than the former in that underpricing benefits both informed and uninformed investors, whereas price stabilization compensates only uninformed investors. Based on this recognition, Chowdhry and Nanda (1996) develop a model in which a reputable underwriter promises

[7] The problem of adverse selection arises because of information asymmetry. It causes a larger allocation of "lemons" than "peaches" in the uninformed investors' portfolio as a result of excessive bidding for an overvalued IPO (Rock, 1986).

the issuer to stabilize the price by repurchasing shares in the after-market if the share price falls below the offer price.[8] Since this price is unknown *ex ante*, the underwriter is confronted with the problem of how much funds are required to be set aside for share buybacks. Committing excessive funds than what is received from the issuer is obviously suboptimal. However, having insufficient commitment of funds exposes the underwriter to the risk of dishonoring the promise if the actual cost of share repurchases exceeds the expected cost. To resolve this dilemma, the underwriter can form a syndicate. By including one more investment banks in a syndicate, the fund available for price stabilization increases which, in turn, enhances the capacity of absorbing losses in the event of share repurchases. Because the improved loss capacity allows more uninformed investors to be compensated by stock repurchase, the need for *ex ante* underpricing is also reduced. This benefits the issuer who can now enjoy greater revenue from its choice of going public. Thus, Chowdhry and Nanda's (1996) study suggests a positive role in using a syndicate in diversifying risk and increasing loss capacity necessary for price stabilization.

Chen and Ritter (2000) empirically investigate the pattern of gross spreads on 3,203 equity IPOs from 1985 to 1998. They find that the spreads are clustered at exactly seven percent, with the degree of concentration increasing gradually over the sample period.[9] Though these spreads are competitive for IPOs ranging from $20 to $30 million, they appear to exceed the competitive levels for those above $30 million. In explaining these excessive spreads, the authors contend that an underwriting syndicate in itself does not

[8] In Chowdhry and Nanda's (1996) model, underwriter reputation ensures that the promise of price stabilization of the issue is credible.
[9] The sample was restricted to domestic IPOs with gross proceeds of at least $20 million, where gross proceeds are the commissions paid to investment banks or underwriting discounts.

amount to a factor conducive to a reduced competitive environment required for high spreads. While fees are shared among syndicate members in a typical IPO, competition for the lead position is still fierce among investment banks. It is more likely that a syndicate is formed to obtain other aftermarket services. Given that underwriting fees are a fixed (seven) percent of the total proceeds, issuing firms paying excessive spreads may benefit from using a syndicate, which brings additional services at no incremental cost. Consistent with this argument, Chen and Ritter (2000) find that issuers receive an additional 0.36-0.55 net analyst coverage for every one more co-manager included in a syndicate.

Corwin and Schultz (2005) study the effect of underwriting syndicates in pricing 1,638 IPOs from January 1997 to June 2002. They report that the offer price is more likely to be revised in response to information revealed during the filing period when the underwriting syndicate contains more co-managers. They interpret this finding as evidence that using a syndicate improves information production and, hence, the accuracy of IPO pricing. They further investigate the possibility that underwriting syndicates improve IPO pricing by providing additional certification beyond that offered by the lead underwriter. In particular, the authors contend that because an underwriter's reputation could be severely damaged if the syndicate in which it participates mispriced an offering, individual member banks, especially those with greater reputation at risk, will have stronger incentives to ensure that the IPO is properly priced based on their own assessment of market demand. Consistent with this conjecture, Corwin and Schultz (2005) find that the size of offer price revision increases as more highly ranked co-managers are included in the syndicate. Moreover, for every additional co-manager involved in a syndicate, there is one more market maker and 0.8 more analysts issuing reports after the IPO, *ceteris paribus*.

In response to the relaxation of the Glass-Steagall Act in the 1990s, another research strand has explored the role of hybrid syndicate structure involving both investment and commercial banks.[10] The focus is on the performance consequence of including commercial banks in an underwriting syndicate. On the one hand, commercial banks have a natural competitive advantage in certifying the quality of the security offerings issued by their borrowers because they have private information about the issuers obtained through prior lending relationships. On the other hand, these banks may gain at the expense of investors by abusing the private information and misrepresenting the issue's quality. Consequently, when the perceived risk of conflicts of interest is high, investors may severely discount an issue if it is underwritten by a commercial bank (Puri, 1999). To alleviate this problem, Narayanan et al. (2004) posit that lending banks may use a syndicate to obtain credible certification of their issues from an independent (i.e., non-lending) and prestigious lead investment bank. Using 1,640 seasoned equity offerings from 1994 to 1997, they find that commercial banks indeed co-manage a greater proportion of their issues with highly reputable lead investment banks when lending relationships are present. With the use of this "co-branding" structure, problematic issues do not suffer from a price discount when compared to issues underwritten by syndicates with pure lending banks. Thus, when the opportunistic risk is high, commercial banks can

[10] The Glass-Steagall provisions prohibited commercial banks from simultaneously performing lending and underwriting activities either directly or indirectly through affiliations. In the early 1990s, the provisions were gradually relaxed, leading to the re-entry of commercial banks into the underwriting market (See Benston, 1994; Narayanan et al., 2004).

credibly commit against opportunism and reduce issue underpricing by co-managing issues with a reputable lead investment bank.

Song (2004), on the other hand, examines the hybrid syndicate structure in the context of public bond offerings.[11] The author argues that the coalition between investment and commercial banks is driven by the motive to enhance the underwriting services provided to a group of clients with special needs. Specifically, because the capabilities of investment and commercial underwriters are complementary, a hybrid syndicate combining these two types of underwriter should serve a different clientele from that of a pure-investment bank syndicate. In support of this service enhancement hypothesis, Song (2004) finds that, compared with pure-investment bank syndicates, hybrid syndicates serve firms that are smaller, have lower S&P common stock rankings, and rely more on bank loans than bond issues as a source of debt before the current bond issuance. Because these firms' issues are more difficult to underwrite, the result indicates that hybrid syndicates enhance underwriting capabilities, permitting services to be provided for a more challenging market segment that has a greater information problem or less prior access to the public debt market. When compared to commercial bank-lead (CB-lead) syndicates, hybrid syndicates are more likely to serve clients with a lower level of investment in capital expenditure and, hence, a greater risk of borrower moral hazard. In spite of this, hybrid syndicates raise more capital for this group of clients than their CB-lead counterparts. In the case where the interest expense increases, hybrid underwritten issues do not suffer a price discount while CB-lead underwritten issues do. This finding holds even when the risk for commercial bank underwriters to opportunistically use

[11] In Song's (2004) study, a hybrid syndicate refers to the arrangement where an investment bank leads the transaction with commercial banks participating as co-managers.

lending-generated information is high. The results thus support the “co-branding” role of hybrid syndicates in Narayanan et al.’s (2004) study, suggesting that the use of prestigious lead investment banks helps alleviate the opportunism problem associated with commercial underwriters.

Taken together, prior research in the field of security underwriting suggests that forging a syndicate is economically desirable from an issuing firm’s point of view. An exception to this point of view is Shivdasani and Song (2011)’s study which investigates a co-led syndicate structure involving multiple intermediaries as lead underwriters. They argue that the emergence of this co-led structure reflects increased competition for the lead position as a result of the relaxation of the Glass-Steagall Act in the 1990s, which led to the re-entry of commercial banks into the securities underwriting market. Because increased competition lowers underwriting fees, underwriters have less incentive to screen bond issue quality. Furthermore, when an offering is jointly led by multiple underwriters, individual members’ reputation may not be observed perfectly by outsiders. This information asymmetry encourages individual lead managers to free ride on one another’s reputation, further reducing the incentive to screen the quality of the issuer (Tirole, 1996). Shivdasani and Song (2011) find that, during the boom period between 1996 and 2000, issuing firms are indeed more likely to engage in financial misrepresentation in industries in which commercial banks have high levels of penetration. In addition, issues underwritten by co-led syndicates are subject to a greater probability of subsequent class-action lawsuits and earnings restatements compared with sole-led offerings. These results are consistent with the notion that the use of the co-led syndicate structure lowers screening standards, permitting poor quality issuers to raise capital via "cooking" their books.

4. Moral Hazard in Syndicates

Despite the several positive roles identified in prior research, economic theorists have long recognized that syndicates are subject to the problem of free-riding and, hence, insufficient effort supplies (see e.g., Alchian and Demsetz, 1972; Holmstrom, 1979; Prendergast, 2002). One of the first studies to investigate the moral hazard problem in a team-based framework is Holmstrom (1982). In this study, a team is loosely defined as a group of agents organized to jointly produce a monetary output. When individual inputs cannot be perfectly observed and contracted for, Holmstrom (1982) shows that there is no such a sharing rule that yields efficient Pareto optimal Nash equilibria while satisfying budget-balancing, even when the joint outcome is certain. As a result, agents always have the incentive to free ride on others' contributions whenever they share with one another the returns of their effort. To resolve this problem, Holmstrom (1982) suggests that the principal can create a contract that punishes the team if the team output falls below some arbitrary target.

Pichler and Wilhelm (2001) link this moral hazard problem to underwriting syndicates in which multiple investment banks coordinate in gathering and disseminating the information necessary to sell the securities offering at hand. In this context, moral hazard arises because individual banks' capacity to produce high-quality information depends on their day-to-day efforts in developing and nurturing relationships with investors and clients, which overlap one another and are difficult to monitor. Hence, Pichler and

Wilhelm (2001) consider a staged game where each player (i.e., bankers and issuers) tries to maximize its expected utility from the offering. The joint outcome (i.e., the realized proceeds) is obervable by all players, but the effort level is known only by the banker exerting the effort. That is, although the issuer and other bankers know whether a bank has exerted effort, they cannot determine the exact level of effort that the banker has put forward. The presence of this information asymmetry prevents efficient contracts that can reward and punish bankers based on individual effort. As a result, underwriting fees can be tied only indirectly to the overall effort as reflected in the realized outcome. In these circumstances, individual bankers are motivated to exert *some* effort necessary to be included in a syndicate. The fact that each banker bears the full cost of his or her own effort but receives only a share (1/M) of the returns in an M-banker syndicate, however, heightens the incentive to free ride.

To mitigate this problem, Pichler and Wilhelm (2001) consider an incentive pay scheme under the condition of restricted versus free entry and lead versus no-lead regime. The timing of the game is modeled as follows. Initially (at time zero), whether the entry into a syndicate is free or restricted and whether the syndicate has a lead bank are assumed to be exogenously determined. At time one, the issuer selects the sharing rule that specifies how to share the gross proceeds with the syndicate members. Given the sharing rule, individual banks then rationally select from one of the following three effort levels at time two: none, low or high. The effort level is private knowledge, i.e., known only by the banker himself. At time three, the issuer randomly chooses syndicate members (including the lead banker, if any) based on observations from previous periods. Bankers who have exerted no effort are excluded from the syndicate whereas those having exerted *some* effort have an equal probablity of being chosen as a syndicate member. The use of the random selection rule is consistent with the model construction where erroneous inclusion of low-effort bankers in the syndicate is possible due to imperfect observability of banker effort. At time four, the offer is priced and each syndicate member recieves a share of the total syndicate fee. The game is then over.

To isolate the economic benefit of restricted entry from that of a lead banker, Pichler and Wilhelm (2001) first consider a no-lead regime, i.e., a syndicate without a lead banker. When moral hazard is present, the issuer seeking to maximize expected net proceeds is confronted by two problems: (i) how to induce a sufficient number of bankers to participate in the syndicate, i.e., the participation constraint; and (ii) for a banker who wishes to participate, how to motivate it to contribute at a high-effort level, i.e., the incentive-compatibility constraint. Resolving these two problems requires the issuer to offer a share of fees exceeding the equality of both constraints for a high-effort level effort. In essence, the excess fee serves to encourage more bankers to participate at an effort level close to the first best solution. Although the issuer shares its surplus with the syndicate, it is better off because the improvement in bankers' incentives increases the total proceeds far more than offset the issuer's cost of movitating the best effort. For this strategy to be feasible, however, the number of syndicate applicants must be restricted. If bankers were allowed to compete freely for syndicate membership, they would join until the quasi-rents were driven to zero in which case the moral hazard problem would re-emerge. Pichler and Wilhelm (2001) suggest that the practice of maintaining stable syndicate memberships among investment banks across deals may present a natural barrier to entry and allow investment banks to earn quasi-rents.

In the second part of their study, Pichler and Wilhelm (2001) explore the role of the lead banker in moderating the effect of moral hazard under the condition of limited entry into a syndicate. As before, whether individual members' effort levels are high or low are unknown by others. The issuer selects the lead bank randomly from a set of bankers that have exerted *some* effort during previous periods. The lead banker then chooses the remaining syndicate members. Given that lead banks are more visible than other syndicate members in reality, Pichler and Wilhelm (2001) assume that after the deal is completed, the lead banker's effort level is revealed to the public, whereas other members' individual effort levels are not.

The introduction of a lead banker, in effect, changes individual bankers' payoff functions. Each banker having exerted *some* effort, now has an equal chance of being chosen to lead the deal. The expected fees are, therefore, the sum of: (i) the lead banker's payoff multiplied by the probability of being chosen as lead banker; and (ii) a non-lead syndicate member's payoff multiplied by the probability of being chosen as a non-lead. Because the lead banker's effort level is publicly revealed, its payoff function involves an additional penalty for shirking which equals the loss of expected profits from participating (at high-effort level) in future deals. This effectively discourages individual bankers from participating and contributing at a low-effort level and increases the efficiency of the incentive scheme implemented under the condition of restricted entry. More specifically, the excess fee serves two functions: it improves the bankers' incentives as in the no-lead case, and increases the value of reputation and thus the impact of the penalty. The issuer can, therefore, use the same amount of excess fees to form an even larger syndicate (with all members exerting high effort) than the maximum syndicate size under the no-lead regime. However, the lead banker requires a strictly larger share of total syndicate fees than the average fee for other syndicate members to compensate for its higher reputational risk exposure. Pichler and Wilhelm (2001) conclude that barriers to entry together with the use of a lead bank represent a Pareto-optimal syndicate structure.

Apart from incentive pay schemes, economic theorists have advocated peer pressure as a highly-effective solution to the free-rider problem identified by Holmstrom (1982). Kandel and Lazear (1992), for example, consider the case where team members can take certain actions to raise the cost of shirking for other team members (e.g., mutual monitoring and sanctioning). In this framework, they show that the equilibrium effort is strictly higher than it would be if peer pressure was absent due to the increased disutility of shirking. However, for peer pressure to be effective, two conditions must be met. First, some form of profit sharing must exist to provide team members with the necessary motive to exert peer pressure on one another. If members were paid independently, the choice of one's effort would not affect the payoff of others. Team members would have no motivation to exert pressure. Second, team members must have the means to extert pressure (e.g., peer sanction) or, by default, peer pressure cannot create an additional incentive to work. Kandel and Lazear (1992) suggest that partnerships or firms that make individual workers' compensation contingent on firm profit are common instances where peer pressure is likely to operate as a major motivational device. For example, they observe that partnerships formed among relatives or friends are in practice often less prone to free-riding. One explanation is that when partners are family members or friends, empathy is strong, so individual partners feel guiltier when cheating "their own kind" than when cheating others. This raises the (nonpecuniary) cost of shirking, resulting in higher effort provisions.

Barron and Gjerde (1997) extend Kandel and Lazear (1992)'s work by investigating the role of peer pressure in influencing the design of the optimal incentive scheme in a principal-agent setting. It is assumed that an agent's monitoring effort and work effort substitue each other, so that an increase in the agent's monitoring induces a higher work effort of his co-workers, but, at the same time, leads to a lower level of his own work effort. The model is developed based on a three-stage sequential game. In stage one, the principal selects the compensation rule which specifies: (i) the lump-sum payment that each agent makes to the principal; and (ii) the share of total output distributed to each agent. In stage two, the agents choose the monitoring effort necessary to create a "peer pressure environment". Specifically, an agent first establishes a "standard" concerning the work effort of his co-workers. He then obtains the signals needed to evaluate his peers' actual work effort through monitoring. Finally, the agent imposes a penalty on a co-worker if the perceived work effort of the co-worker is lower than the previously set standard. In the third stage, the agents independently choose their work effort, taking into account both the compensation rule set by the principal, and the peer pressure environment set by the extent of monitoring by co-workers. The payoff occurs and the game ends. Barron and Gjerde (1997) show that, in this setup, peer pressure introduces a productive gain if each agent is risk-averse. When agents are risk-neutral, however, agents tend to select too much (inefficient) peer pressure that is not advantageous to the principal. The reason is that, when selecting the level of monitoring effort, each agent does not consider the cost that peer pressure imposes on the other agents, a cost that must be compensated by the principal. Consequently, the principal has the desire to discourage "inefficient" peer pressure by reducing the share of profit distributed to each agent. This leads to a weakened link between output and compensation in a team setting.

Che and Yoo (2001) introduce the possibility of repeated interaction among agents, and study the value of joint performance evaluation (JPE) in exploiting agents' mutual monitoring and sabotage abilities. They show that the JPE scheme, which makes an agent dependent on his co-workers to obtain reward, can lead to strong incentives because it provides not only a motivation but also a built-in means for agents to exert peer pressure. Specifically, the authors model a game where two agents are involved in a repeated interaction and the joint project is synergistic. Each agent plays the "start and keep playing work" strategy unless one shirks in which case, both agents shirk in subsequent periods. In this setup, shirking is more severely punished because, in addition to the reduced chance of getting a good signal as in the standard game, an agent is penalized by the subsequent shirking of his peer. Thus, the "sabotage" ability, i.e., the ability of agents to punish one another through their effort provisions, increases the effectiveness of the JPE-type group incentives. Che and Yoo (2001) conclude that the finding is consistent with the Gujarati's (2003) view that: "*even if it is unnecessary on technological ground, a team-based job design is efficient whenever the firm can rely on internal monitoring and peer pressure*" (Che and Yoo, 2001, p. 324).

A potential limitation of Che and Yoo (2001)'s study is that the agents are assumed to be unable to directly side contract with each other and, hence, can interact only through their effort decisions. Rayo (2007) relaxes this assumption and explores the role of relational contracts between agents in generating effort incentives in a team-based framework. In this model, the principal and the agents meet repeatedly for an infinite time period. In addition to the joint output, individual agents in the team can observe a noisy signal concerning each other's effort. Although these signals are too “soft” to be contracted on, they provide a basis for agents to penalize and reward each other via relational contracts. Specifically, a relational contract prescribes, among other things, the effort decisions for individual agents, the voluntary payments that the agents agree to make to each other at the end of every play (which could be either positive or negative), and the penalty rule where an agent who dishonors the contract is punished by exclusion from the team in all subsequent periods. Clearly, by transferring voluntary payments between agents based on individual effort signals, relational contracts generate additional effort incentives. However, because these payments are not court-enforceable, an agent may dishonor the payments if the continuation payoff from future interaction (i.e., penalty) is not high enough. Rayo (2007) shows that when team members’ efforts are less noisy or when the team enjoys higher net continuation surplus, relational contracts yield a higher level of effort incentives.

Mohnen, Pokorny and Sliwka (2008), on the other hand, provide a theoretical explanation for peer pressure effects based on agents’ inequity aversion. They develop a two-period model involving two agents who are both inequity averse. That is, each agent dislikes making a contribution to the final output more or less than his partner. Thus, besides the monetary motive, an agent’s effort decision is influenced by the expected utility loss from inequity, which is a function of his own effort and the effort of his team partners. When the contributions of the agents are transparent at an interim stage, inequity aversion can yield strong peer effects. An agent exerts more effort because: (i) a higher level of effort induces his colleague to contribute more effort in the second period when this colleague is also inequity averse; and (ii) the incentive to free ride is weaker given that shirking in the first period can be credibly punished by the colleague's reduction of effort in the second period. Mohnen et al. (2008) further test these implications in a real effort experiment. They find that participants do adjust their effort levels to match their teammates' contributions observed in the previous period. The reaction is, however, asymmetric. Participants exerting more effort than their peers tend to reduce effort significantly in subsequent periods, whereas participants exerting lower effort increase their future effort only slightly. The authors conclude that, in addition to the factors identified in prior studies, transparency is an important factor affecting the development and the effectiveness of peer pressure in teams.

5. Summary

In this chapter, we provide an overview of prior research on the role of investment banks in various capital markets such as M&As and IPOs. The evidence identifies underwriting syndicates as an important device that allows investment banks to diversify risk, improve underwriting service and provide valuable aftermarket services to issuing firms. However, the extant literature is silent on how syndicates form and function in the M&A market. Furthermore, although the theoretical models reviewed in this chapter have predicted a moderating effect of free-riding on syndicate efficiency, the empirical evidence of such an effect is relatively thin in general.

To shed light on these issues, Chapter 3 explores the determinants of the choice of investment banking syndicates and the performance consequences of this choice in the M&A context. In the light of the free-rider problem highlighted theoretically in the literature, we examine directly how this factor influences relationships between syndicate choice and various acquisition outcomes. In Chapter 4, we investigate whether interbank networking helps alleviate this free-rider problem and, hence, secure efficient acquisition outcomes for acquirer clients.

CHAPTER 3: ARE TWO HEADS BETTER THAN ONE? EVIDENCE ON THE ROLE OF INVESTMENT BANKING SYNDICATES IN M&AS

"*Large efficiency gains can arise when efforts from multiple parties are combined towards a common goal. An inescapable consequence of joint production, however, is that profits must be shared across parties. When efforts cannot be contracted upon, this sharing leads to a non-trivial incentive problem that is now paradigmatic in modeling organizational design.*"

- Rayo, 2007, p.937.

1. Introduction

As a prominent feature in the investment banking industry, syndication is often considered important for understanding the value of investment banks in different capital markets (e.g., Song, 2004; Corwin and Schultz, 2005; Sufi, 2007; Ljungqvist et al., 2009). In M&As, however, the forms and functions of investment banking syndicates remain largely unknown. Prior research typically does not distinguish between deals advised by a syndicate versus a single advisor, instead treating syndicates as a singular advisor that has the highest league table ranking in the team (e.g., Servaes and Zenner, 1996; Rau, 2000; Walter et al., 2008; Golubov et al., 2012).[12] The fact that M&A advisory syndicates are relatively infrequently employed may have been the major reason why this organizational form has been ignored in the literature.[13] Yet, the role of advisory syndicates is important given the economic importance of syndicated M&A activities. The year 2012 alone, for

[12] For example, McLaughlin (1992) measures banker quality for an acquiring firm as "*the highest-quality banker representing it*" if the firm hires more than one banker (p.239).
[13] Over our sample period 1990-2012, about 14% of M&A transactions were advised by a syndicate.

instance, has seen $124.226 billion worth of syndicated deals, accounting for more than 52% of the total transaction value for that year. The decision to use a syndicate also appears to be strategic rather than random. In the 2001 merger between Phillips Petroleum Co. and Conoco Inc., for example, Phillips hired Goldman Sachs, J.P. Morgan Chase and Merrill Lynch & Co. as its financial advisers. Conoco, on the other hand, was advised by Salomon Smith Barney, Credit Suisse First Boston and Morgan Stanley. The formation of an "all-star" syndicate by each merging firm was considered as a strategy to: (i) prevent potential rival bids by tying up all of the major M&A advisors in the energy sector; and (ii) ensure a smooth merger process that was expected to be troubled by a bundle of financing and accounting issues.[14]

The purpose of this chapter is to bridge the gap by investigating why acquiring firms hire a syndicate rather than a single advisor and how this choice affects subsequent acquisition performance such as acquirer abnormal announcement returns. We define an M&A syndicate as a group of investment banks organized to accomplish a narrow set of activities involved in a single M&A transaction and, as a consequence, share a joint fee (Wilson, 1968; Pichler and Wilhelm, 2001). We conjecture two primary distinctions between M&A syndicates and individual advisors in creating value for their respective acquirer clients.[15] First, syndication combines the heterogeneous information, networks, skills and expertise of individual investment banks, enhancing M&A advice provided to an acquirer (Anand and Galetovic, 2000; Corwin and Schultz, 2005; Grullon et al., 2014).

[14] See "Big Oil Deal Ties Up, Well, Almost Everyone: Busload of advisors for Conoco/Phillips just happen to be conflicted", *Investment Dealers Digest*, Tomson Financial, 26 November 2001.

[15] We focus on the performance of acquiring firms since the majority of acquiring firms appear to experience a loss in mergers and acquisitions, whereas target firms generally make a gain (e.g., Moeller, Schlingemann and Stulz, 2005).

Compared with a single advisor, a syndicate allows multiple investment banks to jointly produce information on a potential target based on their respective networks, consult with each other and exchange opinions on important issues such as target choice, related synergies and offer price (Sah and Stiglitz, 1986; Anand and Galetovic, 2000; Brander et al., 2002; Cooper and Kagel, 2005). All else being equal, this should permit syndicates to handle more complex deals and help acquiring firms to make better acquisition decisions. We term this conjecture the "service enhancement" hypothesis.

Second, syndicates facilitate the financing process. Apart from M&A advice, investment banks typically provide a wide range of financing services, with access to unique contacts of investors from whom to raise capital (Corwin and Schultz, 2005; Grullon et al., 2014). Thus, by bringing together the capital and distribution networks of different investment banks, a syndicate expands the financing channels through which an acquiring firm can obtain adequate funds needed to complete a deal (Chowdhry and Nanda, 1996). In addition, the participation of additional investment banks may provide incremental certification that helps reduce informational opacity between an acquiring firm and outside investors, and hence, transaction costs of external funds (e.g., Song, 2004; Corwin and Schultz, 2005). We therefore expect that syndicates are more likely to be employed when acquiring firms are in higher need of external financing. If syndicates are better able to arrange adequate financing for a deal, they should have higher completion rates than individual advisors, *ceteris paribus*. We label this possibility the "acquisition-related financing" hypothesis.

A potential downside to the choice of syndicates is that advisors may free ride on one others' contributions. It is in no individual syndicate member's interest to work because each advisor bears the full costs of supplying efforts, but the benefits are dispersed among the syndicate (e.g., Alchian and Demsetz, 1972; Groves, 1973; Holmstrom, 1982; Pichler and Wilhelm, 2001; Rayo, 2007). In contrast, the free-rider probable is less severe in a single-advisor setting where the advisor knows that it has to internalize the benefits and costs of all its activities. This reasoning leads us to conjecture that, as the potential for free-riding increases, the value that a syndicate can add to an acquirer client diminishes. We term this argument the "moral hazard destruction" hypothesis.

In practice, moral hazard is clearly difficult to observe and verify. In the spirit of Demsetz and Lehn (1985) and Pichler and Wilhelm (2001), we proxy the potential for moral hazard by a number of variables, namely, transaction size, target public listing status and opaqueness of target value from an acquirer's perspective, which are designed to capture variation in an acquiring firm's ability to monitor individual advisors in a syndicate across deals. Specifically, we expect free-riding to be more likely when monitoring is less effective since, in these situations, the level of information asymmetry between acquirer and advisors is higher, which makes it easier for advisors in a syndicate to conceal shirking. We use transaction size as the main proxy variable to measure the scope for moral hazard, reasoning that advisors' actions are more costly to observe and evaluate in a larger acquisition that contains greater external uncertainty and transaction complexity (e.g., Oxley, 1997; Prendergast, 2002; Kaplan and Stromberg, 2004).

We test our hypotheses on a sample of U.S. M&A transactions announced between 1990 and 2012. Consistent with the "service enhancement" hypothesis, we find that syndicates advise on more complex deals than do individual advisors. Specifically, both the probability of using a syndicate and syndicate size are positively affected by the absolute and relative transaction size, the number of competing bidders, whether the transaction is related to a foreign target, and whether it is a public (as opposed to non-public) acquisition. Acquirers are also more likely to hire a syndicate when they have a greater demand for external funds, as indicated by a larger shortfall in their internal cash reserves to fund the deal. This finding lends support to the idea that acquisition-related financing is an important determinant of syndicate use.

Next, we examine the relation between M&A syndicates and various transaction outcomes. We find that syndicates have a significant, nonlinear impact on the acquirer's three-day cumulative abnormal returns (CAR) depending on transaction size, our main proxy for the potential for moral hazard. In particular, for deals in the lowest quartile of the size distribution, acquiring firms experience 2.06% higher abnormal returns around the deal announcement if they use a syndicate rather than a single advisor. This translates into $116 million in enhanced shareholder value for an average-sized acquirer in our sample. In comparison, for transactions in the upper quartile of the size distribution, syndicates are associated with approximately 1% lower acquirer returns relative to individual advisors, all else being equal. This non-linear relationship is robust to controlling for the main effect of transaction size, the reputation of advisors participating in a syndicate and a wide array of other factors that are shown to be important determinants of acquirer abnormal returns in prior research. It continues to hold when we account for the endogeneity of syndicate choice and when alternative proxies for moral hazard, namely, target public listing status and opaqueness of target value, are used. Thus, consistent with the "service enhancement" and "moral hazard destruction" hypotheses, our results indicate that syndicates do have the ability to provide value-enhancing advice. However, the free-rider problem presents a key obstacle to the maximum value that a syndicate can create for its acquirer clients.

We explore several explanations for this conditional market response to the announcements of syndicate-advised deals. First, we investigate whether the lead advisor reputation explains our empirical findings. Reputation-based theories predict that because a lead banker suffers a lot more reputation loss than other syndicate members following poor performance, a more reputable lead advisor has a stronger incentive to: (i) provide high-standard service on its own part; and (ii) monitor others' behavior in a syndicate (e.g., Fang, 2005; Ljungqvist et al., 2006). If this is the case, the syndicate-acquirer CAR association we find may merely reflect variation in lead advisor reputation across syndicates. To explore this possibility, we hand-collect data on the identity of the lead advisor for each syndicated deal and control directly for the lead advisor reputation in our model. We find that our results are essentially unchanged. Further analysis reveals that syndicates led by a reputable lead advisor do not deliver higher acquirer CARs than those lead-managed by a non-reputable advisor in acquisitions within the top quartile of the size distribution, where we find syndicates are most susceptible to the free-rider problem. One interpretation of this finding is that because information on the identity of the lead financial advisor is not readily available to the public, the probability that a lead advisor will be punished by the market for bad performance is reduced. This potentially weakens a lead advisor's incentive to expend costly effort to regulate others in the syndicate. Our results therefore point to a potential limitation of lead investment bank reputation as a governance tool when market discipline is ineffective, at least in M&As.

Second, we examine whether the positive (negative) CAR emerges because syndicates provide relatively more (less) accurate deal pricing and/or a better (poorer) choice of target when they are less (more) susceptible to the free-rider problem. We find that the effect of syndicates on total synergy gains is decreasingly positive as transaction size increases. However, there is no significant difference between syndicate- and individual-advised deals in takeover premiums. Thus, syndicates appear to primarily affect acquirer returns through their superior advice on target selection, but not through deal pricing or negotiation.

Finally, we investigate whether the use of a syndicate leads to a higher probability of deal completion. We find that syndicates are positively associated with completion probability for a sample of deals where acquirers have insufficient internal cash funds to finance the deal. This finding supports the "acquisition-related financing" hypothesis, suggesting that syndicates are better able to complete a deal when financing is of critical importance to bid success.

The main contribution of this chapter is twofold. First, it contributes directly to the literature on the role of financial intermediation in M&As. The extant literature has focused almost exclusively on the traits of individual advisors (e.g., reputation, specialization and commonality) in explaining cross-sectional variation in acquirer announcement returns (e.g., Bowers and Miller, 1990; Servaes and Zenner, 1996; Rau, 2000; Rau and Rodgers, 2002; Kale et al., 2003; Walter et al., 2008; Kisgen, "Qj" Qian and Song, 2009; Bao and Edmans, 2011; Golubov et al., 2012; Agrawal et al., 2013; Song et al., 2013). We depart from this strand of literature and explore the economic value of investment banking syndicates. We show that syndicates play a very different role from individual advisors. Acquiring firms advised by a syndicate undertake more complex deals and have a greater need for external financing than individual-advised acquirers. The choice of syndicates versus individual advisors has important implications for acquisition outcomes. By facilitating the financing process, syndicates increase the probability of successfully closing a deal when external capital is required. They are able to create significantly greater shareholder value for acquirers, but this potential is constrained by the scope of moral hazard internal to a syndicate.

Song et al. (2013) examine the use and consequences of a boutique advisor (i.e., specialist in M&A) relative to a full-service advisor. In their supplementary analysis, they also explore advisory teams but in a specific form, that is, those teams containing only two types of advisors: boutique and full-service. They find that this type of mixed team is more likely to be used in large transactions and in cross-industry deals, but has no impact on acquisition outcomes measured by deal premium, completion probability and deal duration (acquirer CAR is not examined in the study). Kisgen et al. (2009) similarly investigate a multi-advisor structure constructed solely to provide fairness opinions (FO) for an M&A transaction. They find that the use of multiple FO advisors on the acquirer side is associated with lower deal premiums. However, there is no evidence that the multi-FO advisor structure provides better acquirer announcement returns or a higher completion probability when compared to transactions without an FO. The current work differs from these two studies in that we examine a general form of M&A syndicates, *without* imposing restrictions on the types of investment banks participating in a syndicate (e.g., boutique versus full-service) or the kind of services a syndicate provides (e.g., M&A advice or FO). Importantly, we show that syndicates do affect various acquisition outcomes and that this effect can be disguised if one fails to consider the moderating effect of free-riding in syndicates. To the best of our knowledge, this is the first study to present systematic evidence on the significant differences between the general form of syndicates and individual advisors in both acquirer clientele and performance consequence.

The chapter also complements the large body of literature on syndication in different financial markets such as venture capital, investment and commercial banking (e.g., Sahlman, 1990; Lerner, 1994; Chowdhry and Nanda, 1996; Lockett and Wright, 2001; Song, 2004; Corwin and Schultz, 2005; Sufi, 2007; Croce, Martí and Murtinu, 2013). It is the first study to examine the economic implications of investment banking syndicates in the context of M&As. In contrast to the compelling evidence on the benefits of syndication documented in these prior studies, however, we identify a neglected and yet nontrivial cost of forging a syndicate that emerges due to free-riding. Indeed, although the problem of moral hazard in teams has long been recognized, empirical evidence on this topic is sparse. Shivdasani and Song (2011) examine the negative effect of moral hazard on the performance of underwriting syndicates. However, their focus is on free-riding among *lead underwriters* only. The present chapter differs from theirs in that it examines free-riding among syndicate members and, therefore, provides broader implications for this moral hazard issue in a team production setting overall. Our results are consistent with the predictions of many theoretical models regarding the disastrous effect of moral hazard on team efficiency, such as Alchian and Demsetz (1972), Holmstrom (1982), Rayo (2007) and Pichler and Wilhelm (2001), when applied in the context of M&As.

The remainder of this chapter is organized as follows. Section 2 discusses the role of M&A advisors and related empirical hypotheses. Section 3 describes the econometric models, sample selection criteria and data employed in our empirical analysis. In Section 4, we present evidence on the determinants of syndicate formation and on the relation between syndication choice and acquisition performance. Section 5 verifies the robustness of our results, and Section 6 concludes the chapter.

2. Background and Hypotheses

This section begins with an overview of the potential roles that individual acquirer advisors and syndicates play in M&As. It then discusses the implications of the "service enhancement" hypothesis, the "acquisition-related financing" hypothesis and the "moral hazard destruction" hypothesis, for acquisition outcomes.

2.1. Functions of M&A Syndicates

Typically, the main services that a buy-side advisor provides include assessing a proposed acquisition and determining the competitive bid price (Agrawal et al., 2013). In certain cases, however, a firm may engage an investment bank to help identify strategic merger opportunities that can increase the firm's current scale or shareholder value.[16] The

[16] For example, Sandpiper Networks acquired Digital Island, Inc. in 1999, which was located by its financial advisor Credit Suisse First Boston. Similarly, in the 2000 merger of PSINet and Metamor Worldwide, Donaldson, Lufkin and Jenrette proposed five potential targets for PSINet, one of which was Metamor Worldwide (Agrawal et al., 2013).

quality of these M&A advisory services is, to a large extent, determined by a buy-side advisor's ability to produce information useful in locating a profitable target, understanding the target firm's stand-alone value and/or identifying the synergies resulting from the deal. Greater information on a target firm's growth opportunities, customer bases and labor relations, for example, usually permits an advisor to add more value to an acquirer as a result of the advisor's greater ability to select a synergistic target and price a deal. A buy-side advisor may also help an acquiring firm market the transaction to the target's shareholders, formulate bidding strategies, provide financing and negotiate deal terms (e.g., McLaughlin, 1990; McLaughlin, 1992; Kale et al., 2003).[17]

It is not until recent decades that investment banking syndicates have gained in popularity in M&As. For this reason, the extant literature conveys relatively little information about why and how acquiring firms establish a syndicate. In the security underwriting market, however, prior studies indicate that investment banking syndicates are frequently used to facilitate the distribution of issues, reduce risk, and increase aftermarket services such as analyst coverage and price stabilization (e.g., Chen and Ritter, 2000; Narayanan et al., 2004). Syndicate formation typically starts with the appointment of a lead investment bank by the issuing firm. When there are multiple underwriters competing for the lead position, the issuing firm may select some of them as co-managers after the lead manager is chosen (Corwin and Schultz, 2005). Occasionally, the lead investment bank may affect

[17] The SDC database classifies an investment bank as a financial advisor if it: (1) initiates the deal; (2) provides advisory service; (3) offers a fairness opinion; (4) arranges or provides financing; (5) represents the board, shareholders, major holders or creditors; and/or (6) acts as dealer manager or underwriter or an equity participant. An investment bank is not considered a financial advisor if it merely arranges or provides financing and/or acts as an equity participant (Rau, 2000).

the issuer's choice of co-managers by recommending banks with which it has had prior relationships (e.g., Corwin and Schultz, 2005; Ljungqvist et al., 2009).

To shed some light on the form and functions of M&A syndicates, we use the *Factiva* database to trace the news media coverage of the syndicated deals in our sample. We find that, like the formation of many underwriting syndicates, acquiring firms play a dominant role in deciding whether to form a syndicate and of what size. A syndicate is often observed in deals featured by greater challenges and uncertainties. In 1998, for instance, AlliedSignal Inc. hired the boutique investment bank Lazard Freres & Co to help it pursue the $9.6 billion friendly takeover bid for AMP Inc. Having received no response from AMP, AlliedSignal formally launched a hostile bid on August 10, 1998. However, the hostile takeover turned to be extremely hard to get through because AMP was incorporated in Pennsylvania that had some of the "toughest" U.S. Antitrust laws. Moreover, AMP had antitakeover defenses including a special "dead hand" provision which would grant only existing directors the veto power to redeem the poison bill. As a result of this increased complexity, AlliedSignal appointed Goldman Sachs & Co. as an additional advisor.[18]

Syndicates are also commonly used by acquiring firms to obtain additional target assessments from other advisors. In its acquisition of the financial services firm Westcorp in 2005, for example, Wachovia appointed Wachovia Securities as the firm's advisor and also Goldman Sachs to do its "*own independent analysis*". The management commented in its conference call that because everyone in the advisory team was able to "*triangulate*"

[18] See "Focus – AlliedSignal Launches AMP Bid, Hires Goldman", *Reuters News,* 11 August 1998. "Investors Seem Cautious On AlliedSignal-AMP Deal >ALD AMP", *Dow Jones Newswires*, 6 August 1998.

around a different set of financial assumptions on critical factors, such as economic shocks and the resulting increase in credit losses, the process yielded a more complete and accurate assessment of the expected synergies of the deal.[19]

Another frequently cited reason for acquirers using a syndicate is to obtain external financing. Acquirers do not always have sufficient internal funds to pay the cash component of the offer. In these circumstances, additional investment banks may be hired to provide incremental financing either through bank loan or security offerings. For instance, in the 1994 American Home Products Inc. ("AHP")'s acquisition of American Cyanamid Inc., AHP appointed Gleacher & Co. as its deal manager for the transaction and also Chemical Securities Inc., to help obtain a $9 billion bank loan.[20] Similarly, Goldman Sachs and LionTree Advisors were the lead advisors to Charter Communications on its giant $55 billion bid to buy Time Warner Cable in 2015. Credit Suisse and Bank of American Merrill Lynch were the co-advisors to Charter on that deal. They also acted as lead arrangers (along with Goldman Sachs and UBS) for the financing of the transaction.[21] In practice, this acquisition-related financing service is highly valued by acquiring firms since it not only saves the time that an acquirer would spend on "*wrangling together*" lenders, but also reduces the probability that a deal would fail to be consummated due to inadequate funding.[22]

[19] "Wachovia Corporation to Acquire Westcorp and WFS Financial Inc - Final", *Voxant FD Wire*, 12 September 2005.

[20] "American Home Pdts Secures $1.2B Loan From Chemical", *Dow Jones Newswires*, 10 August 1994.

[21] "Charter Communications To Buy Time Warner Cable For $55 Billion, Creating Cable Powerhouse", *The Forbes*, 26 May 2015.

[22] Many acquisitions fail to get through because the acquirers do not have a detailed plan for the required financing. One example is ArvinMeritor (ARM)'s tender offer for Dana Corporation in 2003, where Dana's management rejected the offer partially on the ground that ARM had not formed any agreements for the

2.2. Service Enhancement Hypothesis

Collaboration between investment banks creates some obvious advantages that a syndicate can leverage to enhance M&A advisory services (Berg and Friedman, 1981; Millon and Thakor, 1985; Itoh, 1991; Cooper and Kagel, 2005). First, investment banks have different, albeit overlapping, networks (Anand and Galetovic, 2000; Corwin and Schultz, 2005; Grullon et al., 2014). For instance, while bulge bracket banks commonly focus on large clients across the globe, "boutique" banks such as Houlihan Lokey, Jefferies & Co. and Piper Jaffray are often regionally focused, specializing in middle-market clients and transactions.[23] Investment banks also specialize along industry lines. Some firms like Goldman Sachs are known for their expeditious networks and expertise in the technology sector. Others such as Allen & Co. and Montgomery & Co are well regarded for their strong industry relationships in the media and internet sectors. Thus, to the extent that investment banks' networks differ from one another, the involvement of an additional investment bank extends the information sources, allowing greater information on target candidates to be drawn from a combined network.

Second, syndicates allow investment banks to perform separate assessments on a target firm based on their own expertise, knowledge and skills (Sah and Stiglitz, 1986; Anand and Galetovic, 2000; Brander et al., 2002; Cooper and Kagel, 2005; Casamatta and Haritchabalet, 2007; Cain and Denis, 2013). It has been widely recognized that individual assessments are almost always subject to some degree of imprecision because of either a

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financing required to complete its offer. See "Dana Corporation's Board of Directors Rejects Unsolicited Offer from ArvinMeritor", *Dow Jones Newswires*, 23 July 2003.

[23] For example, one factor affecting the strategic focus of different investment banks is administrative and regulatory expenses. In addition to significant administrative expense to manage, large investment banks are usually registered as fully licensed broker dealers with the SEC/FINRA, which causes a large amount of compliance expense. To recover these expenses, large banks will prefer larger deals/clients from which they can earn sufficiently high fee income.

lack of skill or unavailability of perfect information (Casamatta and Haritchabalet, 2007; Sah and Stiglitz, 1986; Cain and Denis, 2013). Consequently, an investment bank may commit "errors of judgment", that is, erroneously select bad targets while rejecting good ones, when assessing potential targets alone. Syndication potentially alleviates this adverse selection problem by permitting multiple investment banks to exchange independent information, opinion and assessments on the potential target with each other (Sah and Stiglitz, 1986; Anand and Galetovic, 2000; Brander et al., 2002; Cooper and Kagel, 2005). This interaction process increases the probability of detecting overlooked value killers of the target such as cost overruns, supply chain failures and anticipated industry-specific crises, thereby improving the estimates of deal price and takeover synergies. In addition, with the "second opinion" offered by other advisors, the risk that one of the advisors in a syndicate provides a biased valuation in order to push for deal completion is reduced (Kisgen et al., 2009; Agrawal et al., 2013).

The service enhancement hypothesis has several empirical predictions. First, by combining the information channels and expertise of multiple investment banks, a syndicate should most likely be observed in more complicated deals. We thus hypothesize that:

H1a: *Ceteris paribus,* acquirers are more likely to employ a syndicate when they face greater transaction complexity.

Second, the information advantage and separate assessments should enable syndicates to help acquiring firms make better acquisition decisions. All else being equal, this should translate into more favorable market reactions around the deal announcement. We therefore hypothesize that:

H1b: *Ceteris paribus*, syndicates have a positive effect on acquirer announcement abnormal returns.

2.3. Acquisition-related Financing Hypothesis

Another potential function of M&A advisory syndicates is to facilitate acquisition-related financing, which is important when an acquirer needs external funds to finance a cash or cash-equity offer. The common sources of financing include equity, debt and a combination of these two sources (Myers, 1984). When equity financing is utilized, an acquirer can exchange its shares directly from a seasoned equity offering for the shares of the target firms' shareholders (in an equity- or mixed-paid deal). Alternatively, the acquirer can offer cash generated by the proceeds from the sale of its new shares (Martynova and Renneboog, 2009). In debt-financing, an acquiring firm may either obtain cash by arranging a loan directly from one or more banks, or sell debt on an open market through a bond issue (Bharadwaj and Shivdasani, 2003). Adequate external financing is undoubtedly critical to the final success of an acquisition. However, the size/form of the required financing may jeopardize an acquiring firm's current financing condition, initiating a negative market reaction. In this case, syndication is valuable in that it offers a more flexible range of financing channels that would otherwise be unavailable to an acquirer if a single advisor was used. Specifically, most investment banks compete across all product lines. Some banks may have long-standing strength in bank credit/loans; others may possess unique investor clientele and demand channels that help them excel at underwriting security offerings (Corwin and Schultz, 2005; Grullon et al., 2014). By bringing together banks with strengths in different forms of financing, a syndicate broadens an acquiring firm's set of financing choices, thus increasing the likelihood of obtaining the required capital at the best possible terms. Furthermore, the participation of additional investment banks may provide incremental certification that helps reduce the information opacity of an acquiring firm (e.g., Song, 2004; Corwin and Schultz, 2005). For example, the fact that two or more investment banks are willing to lend money or certify the value of a firm's security issue used to finance a deal may communicate favorable information to the capital market, which lowers the transaction costs of financing. We thus hypothesize that:

H1c: *Ceteris paribus,* acquiring firms with a higher need for external financing are more likely to employ syndicates.

If deals backed by a syndicate are more likely to be adequately funded, we expect that:

H1d: *Ceteris paribus,* syndicated deals are more likely to be successfully completed compared to transactions advised by a single advisor.

It is noted that the "service enhancement" and "acquisition-related financing" hypotheses are not mutually exclusive; they may coexist if an acquirer needs both financing and M&A advisory services. If the sole motivation for establishing a syndicate is to obtain the funds needed to complete a deal, however, there should be no significant difference in acquirer abnormal gains between syndicate- and individual-advised transactions. [24]

[24] Agrawal et al. (2003) find that when both the acquirer and target hire the same investment bank as the financial advisor (i.e., common advisor), they are more likely to engage additional advisors than when they

2.4. Moral Hazard Destruction

As noted earlier, a potential problem with syndicates is that they are more vulnerable to moral hazard than individual advisors, which puts acquiring firms at a cost if there is a general lack of incentives for the investment banks of a syndicate to cooperate and supply effort. The problem of moral hazard has been comprehensively discussed in the economic literature (see e.g., Alchian and Demsetz, 1972; Groves, 1973; Holmstrom, 1982; Rayo, 2007). The standard model involves a setting where multiple agents jointly produce a monetary output that is to be shared among them. When individual inputs (e.g., effort) cannot be perfectly observed and directly contracted for, moral hazard arises. Each agent finds it optimal to shirk (i.e., supply a low level of input) since neither the principal nor other agents can observe and credibly verify his contribution *ex post.* Though such information asymmetry also exists in the classic principal-agent setting with one agent, the incentive problem can be relatively easily resolved since the agent is responsible for all of its actions. By tying the agent's rewards to the realized outcome, for example, the incentive to shirk is weakened because the agent knows that she has to bear the full cost of free-riding (e.g., a lower payoff and/or reputational loss) if a bad outcome occurs. In a multi-agent setup, however, the problem is complicated by the fact that the output serves only as an indicator for the joint inputs. That is, the output may allow the principal to infer whether or not the whole team slacks off, but it offers little information about the exact contribution made by each agent. As a result, moral hazard arises even if the output

are advised by separate advisors. They argue that the formation of a syndicate may, therefore, be driven by the concerns about litigation risks that are inherently higher in deals with common advisors. We do not formally consider this factor in our analysis because of the difficulty of obtaining data on common advisors. Nevertheless, Agrawal et al. (2003) show that during their sample period between1981 and 2005, only 98 deals were advised by a common advisor, among which 37 transactions involve an M&A syndicate. Given this small proportion of syndicated deals with common advisors, we believe that forming a syndicate out of litigation concerns is likely to be immaterial.

is linked to the team's payoff. It is in no individual team member's interests to work since each agent bears the full costs of supplying inputs, but the benefits are dispersed among the team. Indeed, Alchian and Demsetz (1972), Holmstrom (1982) and Rayo (2007) contend that moral hazard is inescapable in a team setting. The problem arises not solely because agent inputs are imperfectly observable, but equally because the profit-sharing rule makes shirking potentially profitable. In the absence of effective discipline tools, free-riding causes a lower supply of inputs and, consequently, inferior outcomes.

The above models generally relate to team production, but they are applicable to syndicates that share a similar structure to teams.[25] Pichler and Wilhelm (2001), for instance, relate the moral hazard problem to investment banking syndicates organized to underwrite security offerings. In their model, individual bankers are induced to free ride because their efforts in information production overlap with each other and are difficult to monitor.[26] Some of these insights are directly applicable to our case. In particular, achieving optimal acquisition outcomes requires individual banks in a syndicate to exert a high effort. Such effort is, however, non-contractible and imperfectly observable by the acquirer. Because lower bank effort entails a cost that is ultimately borne by the acquirer, the acquirer has the incentive to mitigate the internal free-riding problem by monitoring the activities of individual banks in the syndicate even at a cost.[27] However, most of the

[25] Holmstrom (1982), for example, notes that the team model can be generally applied to a syndicate.
[26] In contrast, activities that occur after the establishment of a syndicate are less likely subject to a free-rider problem because they involve bank efforts that are more visible. Negotiating or raising extra funds to finance the deal, for example, is more transaction-specific and readily comparable to outcomes. Furthermore, after the advisory syndicate is formed, syndicate managers can regularly monitor member banks' behavior and punish those who deviate from the explicit or implicit agreements among syndicate members (Benveniste, Ljungqvist, Wilhelm and Yu, 2003; Aggarwal, 2000; Pichler and Wilhelm, 2001).
[27] Alternatively, an acquirer may delegate the monitoring responsibility to a lead advisor (Corwin and Schultz, 2005). The monitoring activity, however, imposes an extra cost and burden on the lead advisor. Thus, a lead advisor would not voluntarily bear the costs of monitoring unless its reputation is tied to the

specific expertise, such as the techniques used in information production and evaluation, resides in individual advisors. Since acquirers typically do not have a comparable level of expertise in-house, they are likely to have difficulty in evaluating and rewarding advisors in a syndicate on an individual basis even if the efforts are separately observable. Furthermore, investment banking syndicates commonly share a joint fee. When an acquirer is unable to exclude the benefits of collective action from the advisors who did not contribute, this sharing rule encourages free-riding because a shirking advisor can enjoy the full benefits of shirking (e.g., greater leisure time) while sharing the associated costs with other team members.

It is noted that reputation concerns may help overcome investment banks' incentive problems given that, in a world of repeated interactions, the long-run costs of shirking in the form of forgone future revenues can more than offset the short-term gains (e.g., Chemmanur and Fulghieri, 1994; Pichler and Wilhelm, 2001). However, individual reputations may not be perfectly observable by outsiders in a team setting (Tirole, 1996; Shivdasani and Song, 2011). Thus, if all advisors in a syndicate have to share in the reputation loss following poor acquisition performance, the advisors are likely to have a lower incentive to maintain their respective reputations than when they advise a deal alone. This line of reasoning leads us to hypothesize that:

H1e: *Ceteris paribus*, the scope for free-riding moderates the positive influence of

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final acquisition performance. Consistent with this argument, reputation-based theories predict that a lead advisor will expend costly effort to monitor a syndicate only when poor acquisition performance hurts its reputation and causes a loss of future economic rents (e.g., Gopalan, Nanda and Yerramilli, 2011). As we show later in Section 4.2.4. of Chapter 3, however, this condition important for the reputation-based disciplining tool to work does not appear to hold in the market for M&As. This heightens the problem of free-riding, and hence, the need for acquirers to monitor the internal dynamics of syndicates even at a cost.

syndicate choice on acquisition performance, such that a syndicate creates more value for an acquirer when there is limited scope for free-riding and *vice versa*.

3. Data and Methodology

3.1. Sample and Data

We collect data on M&A transactions from the *Thomson Financials Securities Data Collection Platinum (SDC)* database. All the M&A transactions announced between January 1990 and December 2012 are considered unless: (i) the bid involved a non-U.S. acquirer; (ii) there was no investment bank hired by the acquirer; (iii) the transaction value was less than $1 million or less than 1% of bidder market value; [28] and (iv) the payment method was missing (e.g., Fuller, Netter and Stegemoller, 2002; Faccio, McConnell and Stolin, 2006; Bao and Edmans, 2011). We exclude deals that are classified as bankruptcy acquisitions, liquidations, self-tender, leveraged buyouts, privatizations, repurchases, restructurings, reverse takeovers and going private transactions, as per Golubov et al. (2012). Since acquirer returns are more likely to be affected in "completed control" acquisitions, we further require acquiring firms to have less than 10% of initial stake in the target and seek to own more than 50% of the target after the transaction, similar to Bao and Edmans (2011) and Faccio et al. (2006). Our final sample consists of 56,703 observations. Out of these, 8,175 involve an acquirer with sufficient data from the CRSP database to compute abnormal returns around the deal announcement.

[28] This criterion allows us to capture transactions that are economically important, and hence, likely to initiate non-negligible market reaction around the deal announcement.

3.2. Econometric Model and Variable Construction

3.2.1. Determinants of the Choice of Syndicate Formation

Our first objective is to investigate the determinants of the choice of syndicate use. The purpose of this analysis is twofold. First, it contributes to the literature by identifying factors that explain an acquirer's choice between a syndicate and a single advisor. Second, it helps us account for the potential endogenous relation between the choice of a syndicate and acquisition performance, as discussed in Section 3.2.2. The regression model takes the following form:

$$Syndicate_i = \varphi_0 + X_i\beta + W_i\gamma + \mu_i \qquad (1)$$

Where φ_0 is the intercept; μ_i is the disturbance term. The dependent variable, $Syndicate_i$, is measured in two ways: (i) a dummy variable which equals one if acquirer uses a syndicate for the i^{th} deal and zero otherwise; and (ii) syndicate size, which is the count of the number of investment banks hired by the acquirer for the i^{th} deal. We use Probit regression when $Syndicate_i$ is measured as a dummy variable; and Poisson regression if it is measured as a count variable.

X_i denotes a vector of explanatory variables that our theoretical framework suggests are important determinants of the choice of a syndicate. Specifically, the "service enhancement" hypothesis predicts that syndicates are more likely to be observed in more complicated deals. Following Servaes and Zenner (1996) and Song et al. (2013), 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.[29]

Deal size is perhaps one of the most important factors affecting the propensity of an acquiring firm to hire a syndicate. On the one hand, the participation of additional experts is more valuable to firms acquiring larger targets since these deals are more economically important and involve greater uncertainty about expected synergies (Alexandridis, Fuller, Terhaar and Travlos, 2013). On the other hand, investment banks may compete more vigorously for larger and more lucrative transactions, resulting in a larger syndicate size (Song, 2004; Corwin and Schultz, 2005; Shivdasani and Song, 2011). We thus expect that both the probability of forming a syndicate and syndicate size are positively related to transaction size.

When a takeover bid is hostile, acquiring firms are more likely to seek additional expertise to help with the potential antitakeover defense and solicitation of shareholder support. In a similar vein, public acquisitions demand more advisory skills than non-public deals since: (i) public targets are more widely held, making it harder for an acquirer to enforce post-deal indemnification when the target has hidden or undisclosed liabilities; (ii) public acquisitions are subject to more shareholder and regulatory approvals; and (iii) acquiring firms have greater difficulty in extracting synergy gains from a public firm that usually has greater bargaining power than an unlisted target (Golubov et al., 2012; Bhagwat, Dam and Harford, 2015).

Where multiple bidders are competing for the same target, establishing a syndicate is more likely because it is vital for the acquirer to react fast (Servaes and Zenner, 1996).

[29] We do not include the tender offer dummy in the syndication choice equation since the acquisition techniques are generally determined by the advisors and not vice versa (Golubov et al., 2012).

When the target firm operates in a different industry, an acquirer is likely to face greater difficulties in evaluating the target because of its unfamiliarity with the target's operating environment. In this case, a syndicate is more useful than a single advisor since it permits greater information about the target to be extracted from a more extensive network. Similarly, syndicates are more likely to be involved in a cross-border transaction, where potential synergies are difficult to value owing to differences in market conditions, accounting standards and regulations across countries (Rossi and Volpin, 2004).

In addition to transaction complexity, the "acquisition-related financing" hypothesis posits that syndicates are more likely to be hired when acquiring firms have a higher demand for external financing. According to the pecking order theory (Myers, 1984), acquiring firms with more financial slack are less likely to turn to external financing, which is relatively more expensive, because of the problems of adverse selection and asymmetric information. Other things being equal, this implies that outside capital is needed only when an acquirer's internal cash reserve is insufficient to fund the cash component of the acquisition. We therefore 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 capital.

We control for various factors that may render the formation of a syndicate unnecessary (denoted by W_i). Specifically, we expect a syndicate's joint bank certification and improved financing flexibility to be 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 capital at reasonable costs even on an "at arm's length" basis (Petersen and Rajan, 1994; Patrick and Xavier, 2000). We measure acquirer size by the firm's market capitalization 11 days before the announcement date. 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.[30]

Martynova and Renneboog (2009) report that when an acquiring firm experiences strong stock price performance before the deal announcement, the acquirer is more likely to use its own stock to finance a deal (i.e., make a stock offer). Given that external funding is unnecessary in these cases, the likelihood of hiring a syndicate should be lower, all else being equal. We measure an acquirer's pre-announcement stock price performance by stock price run-up, defined as the market-adjusted buy-and-hold returns of the bidder's stock over a 200-day window (-210, -11) (Masulis, Wang and Xie, 2007).

Compared with firms with little or no acquisition experience, better-experienced acquirers may possess stronger in-house M&A expertise. This reduces the value of a syndicate's enhanced expertise, lowering the probability of employing a syndicate. We measure an acquirer's experience by counting the number of acquisitions made by the acquirer over the last five years prior to the acquisition year (Servaes and Zenner, 1996; Kale et al., 2003).

[30] Smaller and riskier acquiring firms are more likely to hire multiple investment banks because syndicates provide these firms with an opportunity to build/maintain close relationships with multiple banks necessary for securing the availability of corporate financing particularly at times of financial distress (e.g., Petersen and Rajan, 1994; Patrick and Xavier, 2000).

When a reputable advisor is present, an acquirer is less likely 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). Moreover, many prestigious advisors, such as J.P. Morgan and Citibank, are also leading providers of corporate financing services. This potentially lessens the need to obtain additional financing services from other investment banks (Eccles, 1987; Anand and Galetovic, 2000). We follow Golubov et al. (2012) and define reputable advisors as the top eight investment banks ranked by the value of M&A transactions each bank has advised over our sample period.[31] When assigning this reputation measure to each deal, we take into account the mergers and acquisitions that took place among investment banks over the sample period. For instance, Merrill Lynch, a top-tier financial advisor, was merged with Banc of America Securities LLC in 2009 to form Bank of America Merrill Lynch. Thus, deals advised by Banc of America Securities LLC before its merger with Merrill Lynch are considered as non-top-tier advised, whereas deals advised by the merged firm Bank of America Merrill Lynch are considered as top-tier advised.[32]

Finally, we control for: (i) lagged syndicate size *(Syndicate size lag)*, defined as the number of advisors hired by an acquirer in its most recent deal; and (ii) an interaction term between lagged syndicate size and a ratio of the current and previous deal size *(Weighted size lag)*. These two variables are designed to control for unobservable variations in the propensity to use a syndicate across acquiring firms over time (Corwin

[31] A year-by-year rank of the top 8 advisors does not change our results given that these “top-tier” advisors, such as Goldman Sachs, Merrill Lynch and Morgan Stanley, maintain a fairly stable reputation over time (e.g., Fang, 2005; Bao and Edmans, 2011; Golubov et al., 2012).

[32] 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 accuracy, we combine the advisors’ names into one in such cases.

and Schultz, 2005).

3.2.2. The Effect of M&A Syndicate on Acquisition Outcomes

(i) General econometric model

In examining the effect of an M&A syndicate on deal outcomes, we recognize that whether to establish a syndicate and of what size are almost certainly endogenous. Both decisions are not random occurrences, but rather affected by certain acquirer-, deal- and advisor-specific characteristics, some of which are also determinants of acquisition outcomes. Thus, the primary concern here is that a stand-alone Ordinary Least Squares (OLS) or Probit regression may not estimate the acquisition outcome that individual-advised deals would have generated had they been advised by a syndicate (Heckman, 1978). To alleviate this concern, we employ a simple treatment effect model which considers the potential selection bias arising from a nonrandom treatment assignment (see e.g., Maddala, 1983; Terza, 1998; also see Kisgen et al., 2009 and Song et al., 2013 for the application of this methodology in investment banking studies). Formally, the general model takes the following form:

$$y_i = \alpha_0 + Syndicate_i\delta + MH_i\theta + Syndiate_i * MH_i\beta + X_i\omega + \varepsilon_i\ ; \tag{2a}$$

$$Syndicate_i^* = \varphi_0 + Z_i\gamma + \ \mu_i; \tag{2b}$$

$where$:

$$Syndicate_i = 1 \text{ if } Syndicate_i^* > 0\ , and\ Syndicate_i = 0 \text{ if } Syndicate_i^* \leq 0.$$ [33]

[33] One can view the decision of hiring a syndicate to be made based on a cost-benefit analysis. Thus, acquirers anticipating a negative or zero benefit from hiring a syndicate ($Syndicate_i^* \leq 0$) would choose to hire a single advisor, in which case $Syndicate_i$ is equal to zero. Otherwise, acquirers choose to hire a syndicate, in which case $Syndicate_i$ is equal to one.

Equation (2a) is the primary equation, where the dependent variable (y_i) is a deal outcome, such as the acquirer CAR and total synergy gains. $Syndicate_i$ is the main variable of interest, measured as either a dummy variable indicating whether a syndicate is used, or a count of the number of investment banks hired by an acquirer. MH_i denotes the scope for moral hazard in $Syndicate_i$ (discussed below). To allow the marginal effect (slope) of $Syndicate_i$ on y_i to vary with the scope for moral hazard, we include the interaction term, $Syndicate_i * MH_i$, in our model. The marginal effect for the syndicate measure can, therefore, be obtained by differentiating the conditional expected value of y_i with respect to the syndicate measure (i.e., syndicate dummy or syndicate size), shown as follows:

$$\frac{\partial y_i}{\partial Syndicate_i} = \delta + MH_i\beta \; ; \tag{3}$$

δ represents the effect of a one-unit (marginal) change in the syndicate measure on y_i when the conditional variable, MH_i, is zero; β indicates by how much a unit increase in MH_i changes the effect of $Syndicate_i$ on y_i. In light of the "moral hazard destruction" hypothesis, we expect β to be negative, that is, the dummy variable for syndicate choice would have higher conditional expected values of y_i when MH_i is low, whereas the reverse is true at higher values of MH_i. Similar interpretation can be made for the syndicate size variable. X_i contains a set of controls on advisor, deal and acquirer characteristics that have been shown to affect y_i in prior work (introduced in the following section). ε_i is the error term.

Equation (2b) is the treatment equation, where the left-hand variable ($Syndicate_i^*$) is a latent endogenous variable which determines whether or not an acquiring firm forms a syndicate ($Syndicate_i$). The treatment rule is that if $Syndicate_i^*$ exceeds zero, a syndicate is established (treated); otherwise, the acquirer hires a single advisor (untreated). Z_i denotes a set of explanatory variables affecting the choice of syndicate use, introduced in the previous subsection. μ_i represents the disturbance term.

We estimate the model in two steps. First, equation (2b) is estimated by Probit, from which we obtain the estimates for the probability of using a syndicate versus a single advisor:

$$Prob(Syndicate_i = 1|Z_i) = \Phi(Z_i\gamma); \tag{4}$$

$$Prob(Syndicate_i = 0|Z_i) = 1 - \Phi(Z_i\gamma); \tag{5}$$

$\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution. From these Probit estimates, we compute the hazard ratio h_i for each observation using the following formulas:

$$h_i = \begin{cases} \varphi(Z_i\gamma)/\Phi(Z_i\gamma) & if\ Syndicate_i = 1 \\ -\varphi(Z_i\gamma)/[1-\Phi(Z_i\gamma)] & if Syndicate_i = 0 \end{cases} \tag{6}$$

where $\varphi(\cdot)$ is the density function of the standard normal distribution. We then account for potential selection bias by inserting the hazard ratio h_i into equation (2a) as an additional regressor. Next, the augmented equation (7), shown below, is estimated by OLS:

$$y_i = \alpha_0 + Syndicate_i\delta + MH_i\theta + Syndicate_i * MH_i\delta + X_i\omega + h_i\lambda + \upsilon_i \tag{7}$$

It is advisable to have at least one exclusion restriction that affects selection ($Syndicate_i^*$)

but has no direct impact on the outcome of interest (y_i).[34] The two exclusive restrictions we employ are *Syndicate size lag* and *Weighted size lag*. As mentioned earlier, these two variables capture unobserved factors that influence the propensity to use a syndicate across acquiring firms over time. They are excluded on the basis that an acquirer's prior use of a syndicate should not directly affect the current deal's outcome, but operate *indirectly* through its impact on the acquirer's current decision to form a syndicate if there is any.[35]

(ii) Proxy for the severity of moral hazard

Another key factor complicating our empirical analysis is the measurement of the potential for moral hazard which is, by definition, difficult to observe and verify. Standard principal-agent theories suggest that although the principal cannot observe actions taken by the agents, he/she does observe the final outcome as a consequence of the realization of the agents' joint effort contingent on a random state of nature (Alchian and Demsetz, 1972; Fama and Jensen, 1983). Hence, when the outcome is a deterministic function of the effort exerted by team members, the principal can reduce the risk of free-riding by rewarding (punishing) the team if the realized outcome indicates that all the members have expended high- (low-) effort level. In reality, however, the outcome is often characterized by a degree of uncertainty and thus requires the principal to monitor and obtain additional information about the agents' efforts beyond that revealed through

[34] Strictly speaking, the identification of the treatment model does not require any exclusion restriction since the second-stage model is augmented with the hazard ratio, which is a nonlinear function of the variables (i.e., Z_i) included in the first-stage Probit model. It is this non-linearity that identifies the second-stage model, even if the two sets of independent variables included in the first- and second-stage equations ($X_i$and Z_i) are identical (Heckman, 1978; Wilde, 2000). It is advisable, however, to have at least one exclusion restriction.

[35] Corwin and Schultz (2005) employ similar instruments in examining the effect of underwriting syndicate size on IPO underpricing.

the outcome. All else being equal, this implies that the less effective the monitoring, the greater the degree of information asymmetry between the principal and the agents and generally, the higher is the risk of opportunistic behavior (e.g., Alchian and Demsetz, 1972; Holmstrom, 1979; Mirrlees, 1999).

This theoretical argument has provided the basis for many empirical studies examining the free-rider problem in firms. For example, in their study of the level of managerial ownership, Demsetz and Lehn (1985) argue that the scope for moral hazard is greater for managers of riskier firms. Firms can monitor managerial performance at a relatively low cost when they transact in a stable market. In less predictable environments, however, disentangling the impact of managerial behavior on firm performance from the effects of other exogenous factors (e.g., frequent changes in consumer taste, prices and technology) becomes costly. Managerial behavior is simultaneously more important in a firm's fortune and more difficult to monitor, thereby exacerbating the scope for managerial shirking. Accordingly, Demsetz and Lehn (1985) proxy the potential for moral hazard by firm-specific uncertainty, measured as the volatility of stock and accounting returns. Himmelberg, Hubbard and Palia (1999) extend Demsetz and Lehn’s (1985) work by arguing that firms with assets that are more difficult to monitor create a greater scope for managers to pursue their personal interests. They construct a number of proxies for moral hazard, such as firm size, R&D intensity and cash flow, which are designed to capture variation in the composition of assets across firms.

Armed with these insights, we seek to measure moral hazard by linking it to factors that are likely to affect an acquiring firm’s ability to monitor and, ultimately, control the actions of individual advisors in a syndicate. Transaction size is such a factor. On the one hand, monitoring is more costly in a larger transaction which typically covers a greater scope and scale of individual activities. For instance, larger deals often require more sophisticated financial due diligence for which an acquiring firm may not have the necessary competence to understand. This unavoidably increases the difficulty for the acquirer to verify the quality of the service delivered by each advisor. Moreover, the larger the target, the more are the divisions, lines of business and/or geographic regions. *Ceteris paribus*, this implies that each advisor working in a syndicate is likely to carry out more activities, some of which can be poorly observed (e.g., Holmstrom and Milgrom, 1991; Oxley, 1997; Prendergast, 2002; Kaplan and Stromberg, 2004).

On the other hand, larger deals typically involve a higher degree of external uncertainties. Alexandridis et al. (2013), for instance, show that market participants react negatively to large acquisitions due to the uncertainties about whether the acquiring firm can successfully assimilate a large business and deliver the synergy expected. Acquisitions of larger firms also attract more antitrust scrutiny, increasing the time to completion and the risk of failing to successfully complete a deal (Bhagwat et al., 2015). To the extent that these factors affecting the final acquisition outcomes are exogenous and beyond the control of individual advisors, an acquirer is likely to face greater challenges to discern how much variation in performance is attributable to advisors' incentive problems rather than others when the transaction size is large (Alchian and Demsetz, 1972; Oxley, 1997; Himmelberg, Hubbard and Palia, 1999; Maskin and Tirole, 1999; Hochberg and Lindsey, 2010). We therefore conjecture that the potential for free-riding is greater in syndicates advising on larger transactions.

To test the moderating effect of moral hazard on the syndicate-performance relationship, we interact the natural logarithm of $Deal\ size_i$ with each syndicate measure (i.e., the syndicate dummy variable and syndicate size). It is important to note that the main effect of transaction size is controlled for, so that the well-documented relationship between deal size and acquisition performance is held constant in all of our regression models. This helps us rule out the possibility that the interaction between the syndicate measure and transaction size captures the size effect driven by factors other than the varying effort levels of syndicates across deal size that we intend to measure.

Another potential proxy for free-riding is syndicate size. As the number of investment banks involved in a syndicate increases, an acquirer is arguably less able to monitor the behavior of every advisor in the syndicate, resulting in a higher risk of free-riding. While we do not employ syndicate size as a direct measure of moral hazard, we expect that the related free-riding effect, if there is any, is captured by the interaction term between the syndicate size and the natural logarithm of $Deal\ size_i$. A negative coefficient on this interaction term indicates a decrease in the slope of the syndicate size on an acquisition outcome (e.g., acquirer CAR), holding transaction size and other factors constant. There are certainly other proxies for moral hazard. We postpone a detailed discussion of these alternatives until later when we present our main results in this chapter.

3.3. Summary Statistics

Panel A, Table 3.1, provides information on the acquirers' use of syndicate versus individual advisors by announcement year. Of 8,175 M&A transactions announced over the sample period, 1,138 (13.92%) deals are advised by a syndicate, accounting for 41.68% of the total transaction value of our sample acquisitions. The market for M&A syndicates also grows rapidly, going from approximately US$ 8.57 billion in 1990 to over US$ 124 billion in 2012. Figure 3.1 depicts this trend in a graph. Panel B, Table 3.1, indicates that a mean (median) M&A syndicate comprises 2.23 (2) investment banks, with the largest size 9.[36]

[Insert Table 3.1 Here]

Table 3.2 summarizes the deal and acquirer characteristics associated with syndicates and individual advisors. The results in Panel A show that syndicates differ markedly from individual advisors in almost all deal characteristics. The mean (median) deal size for the full sample is $883.274 ($166.824) million, with a mean (median) relative size of 0.431 (0.187). Syndicates work on substantially larger transactions than individual advisors, both in absolute ($2644.377 million versus $598.475 million) and relative (0.662 versus 0.393) terms. Additionally, syndicates advise more on hostile bids, tender offers, public acquisitions, cash offers and deals involving more competing bidders.

Panel B, Table 3.2, indicates that acquirer clients of syndicates also exhibit significantly different traits from those of individual advisors. Syndicate-advised acquirers generally have a greater requirement for external financing, as indicated by the mean (median) cash *shortfall* of $67 ($9) million in funding for their transactions. In contrast, acquiring firms advised by individual advisors have a mean (median) cash *surplus* of $198 ($3) million, which suggests that these firms have more than enough internal funds to finance the cash component of their offers. The differences in mean and median between these two groups

[36] We note that the distribution of syndicate size is highly skewed (4.493). This could suggest that syndicate size (i.e., the number of investment banks hired by an acquirer) is less favorable than the dichotomous measure of syndicate, given that the non-normality may have an excessively strong effect on a model, resulting in potentially questionable results.

are both statistically significant at the 1% level. Moreover, syndicate-advised acquiring firms tend to be larger, have lower stock price volatility (sigma), higher leverage, and more acquisition experience than individual-advised acquirers. For instance, the mean (median) acquirer size in the full sample is $5645.994 ($918.459) million. Syndicate-advised acquiring firms have an average size of $9770.973 million, which is nearly twice as large as that of individual-advised acquirers ($4978.916 million). However, we find no significant difference in stock price run-up between syndicate- and individual-advised acquirer clients.

In Panel C, Table 3.2, we observe that, except for takeover premiums paid by acquiring firms, syndicate-advised deals are, on average, associated with poorer acquisition outcomes measured by acquirer three-day CAR and completion rate. For example, deals advised by a syndicate generate a mean (median) acquirer CAR of 0.20% (-0.30%). This is 0.3% (0.4%) lower than individual-advised deals, although the difference is not statistically significant.[37] However, given that univariate comparisons do not control for various firm and deal differences across the two groups, these results could be misleading. We therefore proceed to examine more closely the determinants of syndication choice and the performance consequence of this choice in a multivariate regression analysis setting. Table 3.3 presents the variance inflation factors (VIF) for all explanatory variables used in our empirical analysis. The results indicate that none of the VIF values exceeds the critical value of 10 (Gujarati, 2003). Hence, multicollinearity is unlikely to be a problem. All variables are defined in Appendix 3A.

[37] We winsorize the acquirer 3-day CAR at the 1% and 99% percentiles to account for the possibility of outliers.

[Insert Tables 2 & 3 Here]

4. Empirical Results

In Section 4.1, we investigate factors affecting the decisions whether to use a syndicate and of what size. Sections 4.2 and 4.3 test the "service enhancement" and "acquisition-related financing" hypotheses by examining the impact of M&A syndicates on the shareholder value of acquiring firms and completion probability, respectively.

4.1. Determinants of Syndication Choice

4.1.1. Syndicate Formation Regressions

Column (1), Table 3.4, presents the results from a Probit model for the probability that an acquirer hires a syndicate. To facilitate interpretation, the marginal effects (as opposed to Probit estimates) are reported.[38] We find that most of the variables intended to proxy for transaction complexity are important determinants of syndicate choice. Holding other factors constant, the probability of hiring a syndicate increases by 3.85% (ln(2)*0.0556) as the absolute deal size doubles. In addition, acquirers are 0.0256% more likely to form a syndicate for every 1% increase in the relative deal size. Furthermore, the likelihood of syndication use is 6.50% higher if it is a cross-border rather than a domestic transaction, and 2.77% higher if the target is a listed as opposed to an unlisted firm. The number of competing bidders also matters: for every one more bidder participating in the competition, the probability of using a syndicate increases by 4.33%, *ceteris paribus*. These findings support the "service enhancement" hypothesis (H1a), suggesting that syndicates handle more complicated deals in which combined information networks and

[38] The Probit regression model is estimated with a constant. Because Table 4 presents the marginal effects rather than Probit estimates, the constant whose marginal effect does not exist is not reported.

expertise are of greater value. Industry relatedness and hostility of target management, on the other hand, do not appear to influence the choice of syndication.

The next set of variables reflects acquirer characteristics. Consistent with the "acquisition-related financing" hypothesis (H1c), the coefficient on the *cash shortfall* variable is positive and significant at conventional levels. Thus, acquirers are indeed more likely to employ a syndicate when they require a greater amount of external funds to meet the shortfall in financing a deal. We also find that the propensity to employ a syndicate is significantly lower if an acquiring firm has a larger market capitalization, lower leverage ratio or smaller stock volatility (sigma). This is consistent with the argument that syndicates are less valuable for larger and safer firms, which have access to alternative forms of cheap financing options. However, there is little evidence that acquirer past acquisition experience or stock price run-up affects the choice of a syndicate.

As for other variables in column (1), Table 3.4, the coefficient on the syndicate size lag variable is positive and significant at the 1% level, indicating that acquirers' preferences over the syndicate size are time invariant. Contrary to our expectations, the participation of the top-8 advisor dummy variable is positive and significant at the 1% level, suggesting that prestigious investment banks are more likely to be involved in a syndicate. One possible explanation for this finding is that syndicated deals, which provide both higher fee income and a larger league table credit, increase the willingness of a top-tier advisor to participate.

Column (2), Table 3.4, reports the results from a Poisson regression of syndicate size, measured as the count of the number of investment banks hired by an acquirer. Similar to our earlier findings, syndicate size is significantly positively affected by the absolute and the relative size of the transaction, the number of competing bidders, whether the deal is cross-border and whether it relates to a public target firm. The size of a syndicate also increases when the acquiring firm's degree of cash shortfall, stock volatility and leverage ratio are higher, but decreases significantly if the acquirer has a larger market capitalization. The effects are all statistically significant at the 1% level. Lastly, the participation of the top-8 dummy and the syndicate size lag variable both generate a positive, significant impact on the number of investment banks hired by an acquirer. Overall, the results in Table 3.4 suggest that syndicates are more likely to be employed when acquiring firms undertake more complex deals and when they are in greater need for external financing.

[Insert Table 3.4 Here]

4.1.2. Additional Evidence on Acquisition-related Financing

A potential limitation of the above analysis is that we employ an *ex ante* measure (i.e., cash shortfall) to operationalize an acquirer's use of a syndicate to obtain acquisition-related financing. While the level of internal cash reserves certainly influences an acquiring firm's demand for outside funds and, consequently, the decision to hire a syndicate, it may be desirable to test directly whether acquiring firms that actually obtain external financing hire a syndicate. We address this question by collecting data on the financing of takeover bids in our sample from the SDC database. An acquisition is considered as externally funded if SDC reports that the deal is financed, either partially or entirely, by the proceeds from one of the following activities: bank loan, equity issue, debt issue or hybrid. Of 8,175 M&A transactions in our sample, 1,018 are funded by outside capital. We then construct a binary variable, *external financing*, to indicate whether external funds are obtained for a takeover bid. Appendix 3B, Table 3.I, re-estimates our models using the variable, *external financing* instead of *cash shortfall*. We find that the coefficient on *external financing* is positive and highly significant (at the 1% level) in both the Probit model for the probability of using a syndicate (column (1)) and the Poisson regression of syndicate size (column (2)). Thus, acquisition-related financing positively affects the probability of using a syndicate and syndicate size.

If syndicates are formed to help financing, we should also observe that some of the advisors in a syndicate are used to help raise the funds for the acquisition. Table 3.II, Appendix 3B, shows that this is indeed the case. Of the 1,018 externally financed deals, 995 transactions have non-missing information about the lead arrangers/book runners on the acquisition-related financing activities.[39] About 56.52% of the acquirers employ at least one financial advisor in the syndicate to lead-manage their bank loan, equity, debt or hybrid security offerings used to fund the deal. In contrast, only 26.15% of the individual-advised takeover bids have the acquirer advisor also providing help to arrange financing. When we split the sample by the source of financing, we find that approximately 94.44% (64.91%) of syndicate- (individual-) advised deals have at least one financial advisor also acting as a lead book-runner on the acquisition-related debt/equity issuance. For bank-loan funded deals, however, the ratio is relatively lower, specifically, 53.73% for syndicated deals and 23.56% for individual-advised transactions. Overall, these findings add to the evidence suggesting that financing is an important function of M&A syndicates.

[39] A book runner is usually the main underwriter or lead-manager/arranger/coordinator in equity, debt, or hybrid securities issuances.

4.2. Evidence of Service Enhancement

The previous subsection explored the determinants of syndicate formation in an attempt to discern the underlying motivation to hire a syndicate. In this subsection, we examine whether this motivation is value-creating from the acquirer shareholders' perspective. Specifically, we conduct a multivariate analysis of the acquirer three-day CAR using both the OLS and two-stage treatment model, as described in equations (2a) and (2b). The key variables of interest are: (i) the syndicate dummy and size variables; and (ii) their respective interactions with the logarithm of transaction size, constructed to capture the non-linear effect of the syndicate measure on acquirer abnormal returns according to the potential for moral hazard if any. We control for several variables that have been shown in the literature to affect acquirer abnormal returns. These include acquirer size, run-up, sigma, free cash flow, leverage, Tobin's Q, transaction size, relative size, industry relatedness, hostility of target management, number of competing bidders, tender offer and whether the deal is cross-border (e.g., Asquith, Bruner and Mullins Jr, 1983; Schwert, 2000; Fuller et al., 2002; Moeller, Schlingemann and Stulz, 2004; Moeller, Schlingemann and Stulz, 2007). In line with Golubov et al. (2012), we account for the interaction effects of target ownership status and M&A currency by creating six mutually exclusive indicators: *public target * all cash, private target * all cash, subsidiary target * all cash, public target * payment include stock, private target * payment include stock, subsidiary target * payment include stock*. To rule out the possibility that any positive association between the syndicate measure and acquirer CAR is driven by the involvement of a high-quality investment bank in a syndicate, we control for the reputation of participating advisors which is coded as one if one of the syndicate members is a top-8 investment bank; zero otherwise (*participation of top-8*). In each regression specification, year fixed effects are included but not reported.

4.2.1. Baseline Results

Panel A, Table 3.5, reports our baseline OLS results for acquirer abnormal returns. The t-statistics are adjusted for heteroskedasticity and acquirer clustering to account for any possible correlation in residual terms for acquiring firms advised by the same advisor (e.g., Masulis et al., 2007; Golubov et al., 2012). To validate our model design, we first estimate the acquirer three-day CAR as a function of the syndicate dummy and a set of controls listed above, without considering the moderating effect of moral hazard. The results are presented in column (1). The coefficient on the syndicate dummy is -0.0009 with a t-statistic of -0.2319, indicating that the average use of a syndicate has little impact on acquirer announcement returns.

Next, we augment the same regression model with the interaction term between *syndicate dummy* and *ln(deal size)*. If there are more opportunities for the advisors of a syndicate to behave opportunistically in a larger deal, the coefficient on this interaction term should be negative, representing a decrease in the slope of the *syndicate dummy* variable for every one unit increase in *ln(deal size).* As shown in column (2), the coefficient on the interaction term is indeed negative and highly significant at the 1% level. The first-order effect of the syndicate dummy is positive and significant at conventional levels. The magnitude of the coefficient estimates suggests that syndicates are, on average, associated with 4.14% higher acquirer CAR than individual advisors when the transaction is valued at $1 million (i.e., *ln(deal size)*=ln(1)=0). However, such improvement in acquirer abnormal returns decreases monotonically with transaction size. For every $10 million increase in deal size, for instance, the positive effect of the syndicate dummy on the acquirer's three-day CAR is offset by nearly two-fifths (ln(10)* (-0.0070)/0.0414). Thus, compared with the linear regression results shown in column (1), our analysis indicates that accounting for moral hazard in syndicates is statistically important and that ignoring this moderator can disguise the real effect of syndicate choice on acquirer CARs.

In columns (3) and (4), we replicate the analysis using syndicate size and find similar results, although the syndicate size variable and its interaction with *ln(deal size)* are only borderline significant in column (4). The negative coefficient on the interaction term adds to the evidence suggesting that at high values of transaction size, an acquiring firm experiences lower average abnormal returns around the announcement period if it is advised by a *larger syndicate*.

To get a better sense of the economic significance of syndicate choice, we break the sample into four groups based on the quartiles of transaction size, with each group comprising one-fourth of the data. We then compute the marginal effect of the syndicate dummy separately for each group. Panel B, Table 3.5, reports the results. In the quartile of deals with the lowest transaction size, syndicates deliver an average 2.06% higher acquirer abnormal returns than do individual advisors, a nontrivial improvement considering our sample mean CAR of 0.50%. The effect is statistically significant at the 5% level. Economically, it corresponds to a gain of $116 million in shareholder value for the average acquirer in our sample. Increasing transaction size attenuates the positive effect of syndicate use on acquirer CAR, in terms of both statistical significance and magnitude.[40] When the deal reaches a size beyond the 75th percentile in the sample, the average acquirer CAR is in fact approximately 1% lower if the deal is advised by a syndicate instead of a single advisor. Figure 3.2 graphically presents the trend of these conditional effects. The solid, downward sloping line highlights the decreasing positive effect of syndicate use on acquirer CARs as the deal size increases.

[Insert Figure 3.2 Here]

With respect to our control variables, most of the parameter estimates in Panel A, Table 3.5, are qualitatively similar to the findings of prior studies. For example, Golubov et al. (2012) document a positive association between advisor reputation and bidder returns in public acquisitions. We find that our top-8 advisor dummy is positive and significant in all specifications, irrespective of the target listing status. Alexandridis et al. (2013) find that larger targets destroy more value of the acquiring firms around the deal announcement. We show that this is not necessarily so. Although the interaction term between the logarithm of transaction size and each syndicate measure is negative, the main effect of the logarithm of transaction size is significantly positive (columns (2) and (4)). This suggests that large deals are in fact value-creating when they are advised by a single advisor (the base group), and that the value destruction primarily concentrates in

[40] It may be perplexing that syndicates add the greatest value to acquiring firms only in small deals which can be easily handled by a single or even no advisor. However, acquiring firms choose syndicates for different reasons. Some may employ syndicates for their enhanced M&A services, whereas others may choose syndicates for their superior ability to obtain financing (the acquisition-related financing hypothesis). The possibility that these two motivations could co-exist in reality creates a potential bias against finding empirical support for the service-enhancement hypothesis (Song, Wei and Zhou, 2013). For example, if certain acquiring firms select syndicates purely for their superior ability to obtain financing, then the positive effect of a syndicate on deal performance (derived from service enhancement) is diluted. This makes it harder to detect any statistical significance in a multivariate analysis. The problem is even more exacerbated in larger rather than small transactions, where the need for external financing is greater (e.g., Bharadwaj and Shivdasani, 2003). This may explain why we detect only a significantly positive effect of syndicates on acquirer CARs in the lower quartile of the size distribution but not in others.

large deals advised by a larger syndicate. This evidence, again, supports the argument that free-riding is more likely to occur in *larger syndicates* working on *large transactions*. Consistent with Asquith et al. (1983) and Schwert (2000), we find that acquiring firms experience higher abnormal returns if the target is relatively large, and lower abnormal returns when the deal is hostile as opposed to friendly. Among the six acquisition types based on target listing status and M&A currency, public acquisitions are associated with the lowest acquirer announcement returns irrespective of the payment type, confirming the evidence documented by Masulis et al. (2007). Finally, acquirer abnormal returns are negatively affected by acquirer size and free cash flow ratio, but significantly positively associated with acquirer leverage ratio and stock price volatility (sigma). These findings are in line with Moeller et al. (2004) and (2007).

[Insert Table 3.5 Here]

4.2.2. Endogenity in M&A Advisory Syndication

As is the case with many investment banking studies, the potential self-selection problem prevents us from concluding a causal relationship between syndicate and acquirer returns. Indeed, the analysis in Section 4.1 already reveals that the decisions whether to establish a syndicate and of what size are not random occurrences. Acquirers use syndicates more often when they face greater deal complexity and when they have a higher requirement for external financing. This endogenous selection process may, therefore, induce a bias in our OLS estimates. To alleviate this potential concern, we employ a two-step procedure as described in section 3.2.2. We rely on two exclusion restrictions, namely, *Syndicate* *size lag* and *Weighted size lag*, for identification.[41] Table 3.6 summarizes the results, with the z-statistics adjusted for both heteroskedasticity and acquirer clustering.

The first column relates to the selection model (Equation 2(b)), where the dependent variable is the probability of forming a syndicate and the explanatory variables are the same as those shown in Table 3.4 column (1). Despite the insignificance of the weighted size lag, the syndicate size lag variable is significant at the 1% level, implying that the identification problem is unlikely to be an issue here.

In the second-stage regression of the acquirer 3-day CAR, we estimate two specifications, one for each measure of the syndicate, shown in columns (2) and (3). The hazard ratio is insignificant in column (2). Thus, the choice of syndicates does not appear endogenous to the acquirer abnormal return determining process. Consistent with this interpretation, we find that the estimates for the syndicate dummy and its interaction with *ln(deal size)* are similar to those estimated by the OLS. In column (3), the hazard ratio is negative and significant at the 5% level. This indicates that the number of syndicate members is endogenously determined, so that certain unobservable factors resulting in a larger syndicate simultaneously reduce acquirer abnormal returns. By accounting for this negative selection bias, the syndicate size and the interaction term, *syndicate size*ln(deal size)*, both exhibit a stronger and more statistically significant (at the 1% level) effect on acquirer CAR, in comparison with the unadjusted OLS estimates. The parameter estimates for the control variables largely mirror those reported in Panel A, Table 3.5.

[41] We do not include the variable *acquirer experience* in the second-stage regressions, as it is neither significant in determining the choice of syndicate formation, nor does it have any significant impact on acquirer CARs. Including this variable, however, does not change our results.

Overall, the findings reported in Tables 5 and 6 provide strong support for the "service enhancement" and "moral hazard destruction" hypotheses (H1b and H1e). Compared to individual advisors, syndicates are better able to provide value-enhancing advice for their acquirer clients, but this ability is hampered in larger acquisitions where there is greater scope for the advisors in a syndicate to free ride. Our analysis indicates that market participants correctly value this and react negatively to a syndicate when the perceived risk of free-riding is high.

[Insert Table 3.6 Here]

4.2.3. Alternative Measures of Moral Hazard

We interpret the negative interaction effects of syndicate measures and transaction size as evidence of free-riding in syndicates. However, moral hazard can occur along many dimensions. If free-riding, which constrains the efficiency of a syndicate, is indeed present, one may expect the marginal effect of syndication to also differ along other dimensions. To provide further support for our interpretation, we re-estimate our CAR regressions using alternative measures of moral hazard.

The first measure is *Public target*, which is coded as one if the target is a listed firm and zero otherwise. We expect free-riding in a syndicate to be more likely in a public than a non-public acquisition for two reasons. First, monitoring a syndicate is more costly in a public transaction, in which individual advisors need to carry out a wider scope of (and potentially more complex) activities than they would do in a non-public deal. For example, investment banks advising on a public acquisition may need to help the acquirer solicit shareholder support, obtain regulatory approval, work on potential takeover defenses and mitigate the risk of post-deal indemnification for the target's hidden liabilities, all of which are typically not present in a private transaction (Golubov et al., 2012; Bhagwat et al., 2015). Second, the sale of a private firm is generally negotiated with a small number of known, identifiable bidders, whereas the sale of a public firm is typically auction-like in nature and associated with greater publicity (e.g., Fuller et al., 2002; Officer, 2007; Bargeron, Schlingemann, Stulz and Zutter, 2008; Harford, Humphery-Jenner and Powell, 2012). Consequently, the outcome of a public deal is susceptible to the influence of a greater variety of exogenous factors and, therefore, less informative about the advisors' joint effort. For instance, one may observe a negative or breakeven return to a bidder in a public takeover bid, but it is difficult to tell whether this is a consequence of advisors' free-riding or competitive bidding which increases the bidder's cost of acquisition (Boone and Harold Mulherin, 2008).

In a similar fashion, we expect free-riding to be more likely to occur when a firm acquires a high-tech target that falls outside of its core business. High-tech firms commonly have a significant proportion of intangible assets that are difficult to value and verify (Benou, Gleason and Madura, 2007). Thus, when an acquiring firm operates in a different industry, it may not have adequate knowledge about the activities that individual advisors carry out to evaluate the target firm's human capital, R&D projects, intellectual property rights and so forth. This, in turn, hampers the acquirer's ability to properly monitor and assess individual advisors' performance, aggravating the problem of moral hazard. By contrast, the incentive problem is less severe in acquisitions where the acquirer is either a high-tech firm and hence, knows better about the industry (i.e., a non-diversifying high-tech deal), or pursuing a target whose assets' value is less uncertain (e.g., a non-high-tech deal). Accordingly, we construct an alternative proxy for moral hazard, *diversifying high-tech deal*, which equals one if a target is a high-tech firm as defined in Loughran and Ritter (2004), and operates in a different industry from the acquirer; zero otherwise.[42]

Table 3.7 presents the results from the OLS regression of acquirer CAR using these two alternative measures. Columns (1) and (2) are based on the *public target* variable, whereas columns (3) and (4) are based on the *diversifying high-tech deal* variable. We control for the same set of variables as in Table 3.5, except that when the proxy measure *public target* is used, we control for the target listing status and whether the payment involves stock separately (as opposed to their interaction effects) to avoid any multicollinearity problems. We find that while the main effects of the syndicate dummy and syndicate size variable are positive, the interaction of these two measures with *public target* is negative and significant in both columns (1) and (2). The point estimates suggest that for non-public deals (Syndicate*Public Deal=0), syndicates are associated with 1.14% higher acquirer abnormal returns than individual advisors. The opposite is, however, true for acquisitions of public targets (Syndicate*Public Deal=1). The average CAR is about 1.19% (0.0114-0.0233x1) lower for acquirers hiring a syndicate, when compared to those acquirers hiring a single advisor (column (1)). In fact, for every one more advisor added to a syndicate, the return is reduced by 0.51% (0.0110-0.0161x1x1) in a public acquisition, holding other factors constant (column (2)). The results based on the *diversifying high-tech deal* variable are similar, though the *first-order* effects of the

[42] A target is classified as a high-tech firm if its SIC code is one of the following: 3571, 3572, 3575, 3577, 3578 (computer hardware), 3661, 3663, 3669 (communications equipment), 3671, 3672, 3674, 3675, 3677, 3678, 3679 (electronics), 3812 (navigation equipment), 3823, 3825, 3826, 3827, 3829 (measuring and controlling devices), 3841, 3845 (medical instruments), 4812, 4813 (telephone equipment), 4899 (communications services), and 7371, 7372, 7373, 7374, 7375, 7378, and 7379 (software) (Loughran and Ritter, 2004).

syndicate dummy and the syndicate size are not statistically significant (columns (3) and (4)). Overall, these findings lend additional support for the presence of free-riding in syndicates, suggesting that the performance effect of syndication does differ based on factors that are likely to exacerbate the problem of moral hazard.

[Insert Table 3.7 Here]

4.2.4. Does Lead Advisor Reputation Matter?

Thus far, we have not considered the role of the lead investment bank that often assumes the major responsibility of organizing and managing a syndicate (Corwin and Schultz, 2005). A large body of literature, both theoretical and empirical, attributes performance variation across investment banking syndicates to the lead bank reputation effect, reasoning that reputation concerns not only help align the lead bank's interests with those of clients (e.g., Carter and Manaster, 1990; Chemmanur and Fulghieri, 1994; Fang, 2005; Gopalan et al., 2011), but also encourage it to expend costly effort to monitor and regulate others in the syndicate (Alchian and Demsetz, 1972; Aggarwal, 2000; Pichler and Wilhelm, 2001; Benveniste et al., 2003; Corwin and Schultz, 2005). Thus, a natural concern is whether the nonlinear relationship between syndicates and acquirer CAR documented above is driven by the presence or absence of a reputable lead advisor in a syndicate. This could be a problem if our control for the involvement of a reputable advisor in a syndicate, i.e., *participation of top-8*, is inadequate or our syndicate measures and lead advisor reputation correlate positively. It is possible, for instance, that an acquiring firm appoints a prestigous lead investment bank when the syndicate is large and, hence, the anticipated level of free-riding is high. If the choice of a reputable lead advisor is also positively correlated with acquirer CAR, then the results in Table 3.5 would overstate the effect of syndicate size on acquirer abnormal returns. Conversely, the effect would be understated if the presence of a prestigious lead bank, which is arguably able to provide both high-standard M&A advice and financing services, is negatively related to the size of a syndicate. The important question here is whether syndication itself has an independent impact on acquirer returns, over and above the influence of lead advisor reputation, if there is any. We address this problem by directly controlling for the use of a reputable lead advisor in our CAR model.

We begin by collecting information on the identity of the lead investment bank for each M&A transaction from the *SDC* and the *Factiva* databases.[43] 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.[44] Where possible, we classify a lead advisor as the member bank in a syndicate that receives the largest share of advisory fee. 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 the lead advisor given that it is more likely to get involved in the strategic planning process and, hence, have a significant influence over the choice of other syndicate members. Where a syndicate involves only two advisors, we designate the member bank as co-advisor if it

[43] Data on the lead advisor for each M&A transaction are not directly available in the SDC database.
[44] 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.

advises a “minority shareholder” in a firm, given 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.[45] This process 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 data on the identity of 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 an investment bank plays a lead role in a transaction. It is noted that most news announcements provide a detailed description for the financial advisors participating in a syndicate. However, the information on who leads the syndicate is sparse in general. 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 for which the identity of the lead advisor is identified. We then combine the data with the individual-advised deals. The final sample consists of 7,384 observations (the lead sample hereafter).

To measure lead advisor reputation, we rank each investment bank on the basis of the aggregate transaction value it has advised. A lead advisor is classified as reputable if it is ranked among the top 8 and non-reputable otherwise (*top-8 lead*). Bank mergers are

[45] 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.

considered when assigning this reputation measure to each syndicate. The data suggest that the top-8 lead variable and the participation of a top-8 advisor are highly correlated in our sample (at the level of 68.3%). Thus, while top-8 investment banks do not always take a lead role in a syndicate, the *participation of top-8* variable does provide a close approximation for the presence of a reputable lead advisor.

In Panel A, Table 3.8, we re-perform the CAR analysis for the lead sample, with *participation of top-8* replaced by *top-8 lead*. Not surprisingly, controlling for the lead advisor reputation does not cause a material change to our results despite the significant decrease in sample size. The OLS regression results, shown in columns (1) and (3), indicate that both syndicate measures continue to exhibit a positive impact on acquirer abnormal returns, which decreases with transaction size. The effects are even stronger (all significant at the 1% level) when we take into account the endogeneity of syndication choice in columns (2) and (4). Thus, our previous findings do not appear to be driven by the presence of a reputable lead advisor.

The results in Panel A also indicate that a reputable lead advisor is associated with higher acquirer returns, although this is evident only when the syndicate is measured as a dummy rather than a count variable (columns (1) and (2)). As previously discussed, this positive effect could reflect either superior M&A advice provided by a top-8 lead advisor on its own part, or its ability to reduce free-riding in a syndicate, or both. Thus, a natural extension of the analysis is to investigate whether the lead advisor reputation improves acquirer CAR by mitigating the free-rider problem in a syndicate. We explore this possibility by examining whether the observed difference in acquirer three-day CAR between syndicate- and individual-advised deals varies according to the presence of a reputable lead bank.

Specifically, to allow the coefficients on our syndicate measures to differ for syndicates with and without a reputable lead advisor, we create two mutually exclusive variables for the syndicate dummy variable: (i) *syndicate led by top-8*, which equals one if the lead advisor is one of the top-8 investment banks, zero otherwise; and (ii) *syndicate led by non-top 8*, equal to one if the lead advisor is ranked below the top 8, zero otherwise. We similarly construct two continuous variables for syndicate size: (i) the number of investment banks for syndicates led by a top-8 advisor, zero otherwise; and (ii) the number of investment banks for syndicates led by a non-top 8 advisor, zero otherwise. If the fear of reputational damage induces a lead advisor to regulate the behavior of other syndicate members, we expect (larger) syndicates led by a reputable advisor to be less likely to shirk and, hence, more likely to help acquirers make value-creating deals. We test this conjecture on a sample of deals in the top quartile of the size distribution where our earlier findings indicate free-riding is most tempting and, hence, where the disciplinary effect, if any, of lead advisor reputation is most likely to be detected.

Panel B, Table 3.8, reports the results from the OLS regressions of acquirer three-day CAR for the large deal subsample. For both syndicate measures, the coefficient estimates for the top-8 and the non-top8 lead-managed syndicate variables are statistically insignificantly different from zero. Thus, compared with their individual-advised counterparts (the base group), acquiring firms are no better off using a reputable advisor to lead a syndicate when the scope for free-riding is large. This evidence contrasts sharply with the commonly held view that lead advisor reputation provides an internal governance mechanism against free-riding in a syndicate (e.g., Fang, 2005; Ljungqvist et al., 2006). One possible reason for this finding is that, unlike other financial markets such as security underwriting and venture capital, the information on the identity of the lead advisor is not readily available to the public. Indeed, our data collection process already reveals that for most syndicated acquisitions, the identity of the lead advisor is generally unknown through sources such as databases, media releases and business press. To the extent that this lack of public visibility impedes an outsider's ability to distinguish the reputation of a lead advisor from that of the syndicate, market discipline, i.e., punishing the lead advisor for poor performance in subsequent dealings, is likely to be ineffective in M&As. If the reputation loss following poor performance is shared by all advisors in the syndicate, the lead advisor would have little *ex ante* incentive to monitor others in a syndicate (e.g., Tirole, 1996; Shivdasani and Song, 2011). Our findings therefore point to a potential limitation of lead advisor reputation as a countervailing force against internal free-riding when there is information asymmetry between outsiders and the identity of the advisor lead-managing a syndicate in M&As.

[Insert Table 3.8 Here]

4.2.5. Sources of Value Creation

The body of evidence presented so far is consistent with the argument that syndicates that are less susceptible to free-rider problems generate higher acquirer abnormal returns and *vice versa*. However, this provides little insight into the exact channels through which a syndicate affects an acquiring firms' shareholder value. The "service enhancement" hypothesis predicts that by combining the networks of different investment banks and allowing for independent assessments of potential targets, syndicates improve target screening and evaluation processes. Ignoring any incentive problems, this implies that syndicates should help acquirers identify better targets and obtain more accurate deal pricing. On the other hand, the "moral hazard destruction" hypothesis posits that whether this service enhancement can be realized is conditional on the degree of moral hazard in a syndicate. When the potential for opportunistic behavior is significant, free-riding among advisors in a syndicate may lead to inferior advice on target choice and evaluation relative to that of individual advisors. To test these hypotheses, we examine the impact of syndication on total synergies and takeover premiums for a sample of public acquisitions for which we can obtain data on the target firms' stock price needed to compute synergy and takeover premiums.

Table 3.9 summarizes the results for total synergy gains, defined as the sum of the abnormal wealth gains to the acquirer and the target (Kale et al., 2003; Golubov et al., 2012). We control for the same set of advisor, deal and acquirer characteristics as in Table 3.5, except that the six interaction terms between target listing status and M&A currency are replaced by a dummy variable indicating whether the payment includes stock (*Pmt. incl. stock*).[46] The main variables of interest in the first two columns are the syndicate dummy and its interaction with *ln(deal size)*. The OLS regression results in column (1) suggest that the syndicate dummy has a marginally significantly positive impact on synergy gains, which decreases as transaction size grows. In column (2), we account for the endogeneity of syndicate choice by employing a two-stage treatment model with the first-stage regression results omitted here for the sake of brevity (refer to column (1), Appendix 3B, Table 3.III). The coefficient of the hazard ratio is significantly

[46] The restriction of public acquisitions renders the interaction of unlisted targets with payment types unnecessary.

negative (at the 1% level), indicating that endogeneity is present in the selection process, which potentially biases the OLS estimates downwards. Consistent with this interpretation, we find that the syndicate dummy and its interaction with *ln(deal size)* continue to be positive and negative, respectively, but both variables gain statistical significance to the 1% level. Thus, syndicates do contribute to the improvement of acquirer CAR by identifying more synergistic targets.

Columns (3) and (4) repeat the analysis using syndicate size. The OLS regression results indicate that neither the size of a syndicate nor its interaction term significantly affects synergy gains (column (3)). However, the two variables are statistically significant at the 5% and the 10% level, respectively, after accounting for the negative and highly significant selection bias (as indicated by the coefficient estimate for the hazard ratio in column (4)).

[Insert Table 3.9 Here]

In Table 3.10, we report the results for takeover premium, measured as the ratio of the offer price to the target stock price four weeks before the deal announcement minus one.[47] We control for several variables found in prior research to be important determinants of bid premiums. These include transaction size, relative size, the number of bidders, hostility of target management, all-cash offer, industry relatedness, tender offer, toehold, cross-border acquisition, target's market-to-book ratio, acquirer's Tobin's Q and acquirer market capitalization (e.g., Betton and Eckbo, 2000; Officer, 2003; Shleifer and Vishny, 2003; Goldman and Qian, 2005). We also take into account the fact that the acquirer and target advisors have opposite objectives in setting the sale price. Whereas

[47] We follow Officer (2003) and winsorize the percentage premium values beyond the range of [0, 200%].

acquirer advisors seek to buy the target "on the cheap", target advisors strive to sell the target at the highest possible price (Kisgen et al., 2009; Song et al., 2013). In these situations, it is important to control for target advisor characteristics that may positively affect takeover premium and, hence, disguise the effect of acquirer syndicates. We include the following variables in our regression model: (i) target syndicate, measured as either a dummy variable equal to one if target syndicate is present, zero otherwise; or a count of the number of target advisors; (ii) the interaction between the natural logarithm of deal size and each target syndicate measure, designed to account for the possibility that target syndicate efficiency is similarly constrained by the potential for moral hazard; and (iii) a dummy variable indicating whether a top-8 target advisor is employed.[48]

Columns (1) and (2), Table 3.10, estimate the OLS and the two-stage treatment model based on the syndicate dummy; columns (3) and (4) re-perform the analysis based on syndicate size. Again, we suppress the first-stage regression results for the syndication choice for the sake of brevity (refer to column (2), Appendix 3B, Table 3.III). We find that, for both measures of acquirer syndicate, the main and the interaction effects are statistically insignificant. This is true even after we take into account the endogeneity of syndication choice. Thus, syndicates do not seem to help reduce acquisition cost for their acquirer clients, at least in public transactions. We, however, note that many of our control variables are significant in explaining acquisition premiums. On average, larger deals are associated with lower takeover premiums, although the effect is highly significant in only specifications where syndicate is measured as a dummy variable

[48] In the case where the target firms hires a syndicate, this variable is equal to one if there is a top-8 advisor participating in the syndicate; zero otherwise.

(columns (1) and (2)). This confirms the findings of Alexandridis et al. (2013), indicating that acquiring firms pay less for larger targets which typically elicit greater integration complexity costs. Premiums are also significantly higher if the relative size of the target to the acquirer is larger, the bid is a tender offer, there are more competing bidders, and if the acquirer has greater market capitalization and higher Tobin's Q. These findings are generally consistent with the evidence documented in the literature (e.g., Smith Jr and Watts, 1992; Schwert, 2000; Officer, 2003). Other controls such as target syndicate measures, advisor reputation and toehold have either no or a marginally significant impact on deal premium.

[Insert Table 3.10 Here]

Taken together, the results from Tables 9 and 10 suggest that syndicates primarily create value by helping acquirers identify and construct deals that are more synergistic than those advised by individual advisors. This, however, occurs only when the potential for free-riding is limited.

4.3. Evidence of Acquisition-related Financing

In this section, we explore the implications of the "acquisition-related financing" hypothesis for the probability of deal completion (H1d). If syndicates are formed to facilitate financing, they should be better able to complete a deal than individual advisors when the key determinant of the bid success, external financing, is required. To test this hypothesis, we restrict our attention to a subset of deals where an acquirer has insufficient internal funds to finance the cash component of the deal, i.e., cash shortfall >0. The dependent variable is a dummy variable which takes the value of one if the deal is completed and zero otherwise (*completion*). We regress this variable on the syndicate dummy or syndicate size and several controls taken from prior studies, including Kale et al. (2003), Golubov et al. (2012) and Song et al. (2013).

The results are presented in columns (1) and (3), Table 3.11. In both specifications, we find that the probability of completing a deal is significantly lower in larger deals, hostile offers, public acquisitions, and deals involving more competing bidders. The reverse is true for acquirers having larger market capitalization, using a tender offer or making a same-industry acquisition. After controlling for these effects, we find that the completion probability is positively associated with each syndicate measure though the effect is only marginally significant.

To examine whether the effect of our syndicate measures on the probability of deal completion also varies with the scope for moral hazard, we include the interaction of each syndicate measure with the logarithm of transaction size in columns (2) and (4), respectively. We find that the interaction term does not add any explanatory power to the baseline regressions (the Pseudo R^2 is essentially the same). Moreover, the interaction in both columns is statistically insignificantly different from zero. Thus, advisors working in a syndicate do not appear to reduce their efforts in completing a deal even if there are sizable opportunities for them to act opportunistically. However, this is not surprising given that a large bulk of advisory fees is contingent on deal completion in a typical fee contract (McLaughlin, 1990; McLaughlin, 1992). It is not in individual advisor's interests to slacken effort in completing a deal because even with the collection of the upfront retainer fee, the lucrative payoffs each advisor get for advising (and even financing) are received after the deal is successfully closed.[49] Our findings therefore add to the existing evidence in the literature (e.g., Rau, 2000; Hunter and Jagtiani, 2003), suggesting that the contingent-fee structure encourages a syndicate to complete a deal but not necessarily improve deal quality.[50]

In Appendix 3B Table 3.IV, we verify the robustness of our results by employing a two-step procedure. We find that syndicates have a positive, highly significant (at the 1% level) impact on the likelihood of deal completion after accounting for the endogeneity of syndication choice. Overall, our findings support the idea that syndicates are better able than individual advisors to complete a deal in which financing is critical to bid success. This echoes our Probit model results (Table 3.4), which suggest that external financing is an important determinant of syndicate formation.

[Insert Table 3.11 Here]

5. Additional Robustness Checks

We conduct a number of additional tests to confirm the robustness of the non-linear effects of our syndicate measures on acquirer CARs. A first-order concern with our analysis is that lagged syndicate size and its transaction-valued weighted measure may be correlated with the error term in the second-stage regression of acquirer CAR and, thus, not be truly "exogenous", i.e., violate the exclusion restrictions. To alleviate this potential

[49] See "2015 Becomes the Biggest M&A Year Ever", *The Wall Street Journal*, 3 December 2015.
[50] As a robust test, we repeat our analysis for the full sample, with the cash shortfall variable included as an additional regressor. To test whether a syndicate indeed increases the probability of completing a deal by facilitating the acquisition-related financing process, we interact each of our syndicate measures with the cash shortfall variable. We find that the first-order effect of each of our syndicate measures is statistically insignificant, whereas the interaction effect with the cash shortfall variable is positive and significant at the 1% level. These results (unreported) are consistent with the findings reported in Table 3.11, suggesting that syndicates facilitate financing and lead to a higher probability of deal completion only when external financing is necessary.

concern, we follow Ljungqvist et al. (2009) and construct two alternative instruments, namely, the *largest debt* and the *largest equity market share prior year*, defined as the highest prior-year market share of the advisor in a syndicate in the debt and equity markets, respectively. [51] The data are obtained from the SDC New Security Issues database. These two instrumental variables are designed to capture the capacity of a single investment bank to provide an acquirer client with a one-stop service. The intuition is that if a syndicate is formed to facilitate other acquisition-related services such as financing, then the stronger is an advisor's capacity to offer a full range of services, all else being equal, the lower is the need for the acquirer to hire additional investment banks. These two variables are excluded on the basis that while a bank's capacity to provide financing, as reflected in its reputation in the equity/debt market, influences an acquirer's decisions about whether to use a syndicate and of what size, it is unlikely to have any *direct* impact on the acquirer's announcement abnormal returns. Table 3.V, Appendix 3B presents the results from the two-step treatment procedure with these alternative exclusive restrictions. The results are very similar to those reported in Table 3.6 of this chapter.

In principle, the exclusion restriction is not critical in a two-equation treatment model which is identified by the non-linearity of the hazard ratio. This is true even if the two sets of explanatory variables in the first- and second-stage equations are identical (Heckman, 1978; Wilde, 2000). This implies that our two-equation treatment model should be valid even without an instrument. We re-estimate the two-step treatment procedure for acquirer returns without an instrument; the results are reported in Table

[51] Where a single advisor is used, these two variables are equal to the debt/equity market share of the advisor.

3.VI, Appendix 3B. Our results remain unchanged.

We further perform the following robustness tests, including (i) using acquirer CAR computed over alternative event windows (-2,+2) and (-5,+5); (ii) employing the equally-weighted CRSP index (as opposed to value-weighted) as the market return; (iii) controlling for industry fixed effects; and (iv) controlling for the use and size of the target syndicate (reported in Appendix 3B, Tables 3.VII-3.IX). In all the tests, we find that our main results, namely, a non-linear effect of syndicate use or syndicate size on acquirer CAR conditional on specific values of the moderator variable, *ln(deal size)*, continue to hold.

6. Conclusion

In this chapter, we explore the economic rationale for the formation of M&A syndicates. We show that a syndicate, which combines the information channels, skills, expertise and fundraising capacity of different investment banks, is more likely to serve acquirer clients undertaking more complex transactions or having greater need for acquisition-related financing. The choice of a syndicate versus a single advisor has important implications for acquisition outcomes. Acquirers experience higher abnormal returns around the announcement period if they are advised by a syndicate with limited scope for free-riding. The reverse is, however, true when there is a wider window for the advisors in the syndicate to behave opportunistically. Contrary to common belief, we find no evidence that the lead advisor reputation helps mitigate this free-rider problem, possibly because the identity of the lead advisor is largely unknown to the public, resulting in lower incentives for a lead advisor to regulate others in the syndicate. We further show that, though acquiring firms advised by a syndicate do not pay lower takeover premiums, they make more synergistic deals if there is less scope for moral hazard. Finally, our results indicate that syndicates are better able to successfully close a deal in which external financing is important to acquisition success.

Overall, our findings highlight the collaborative efficiency that a syndicate can achieve to improve the M&A advisory services when the well-known team incentive problem is absent. The evidence of free-riding, however, points to the need for further investigation into governance mechanisms that can help acquirers resolve the incentive problems pertinent to M&A syndicates. In Chapter 4, we explore this issue by examining whether interbank networking serves as such a mechanism when M&A syndicates are used.

7. Figures

Figure 3.1
Advisory syndicates in the M&A Market

This figure presents acquirers' use of syndicates versus single advisor by year for a sample of 8,175 U.S. M&A transactions announced between January 1990 and December 2012. The analysis is based on the number and the value of the transactions.

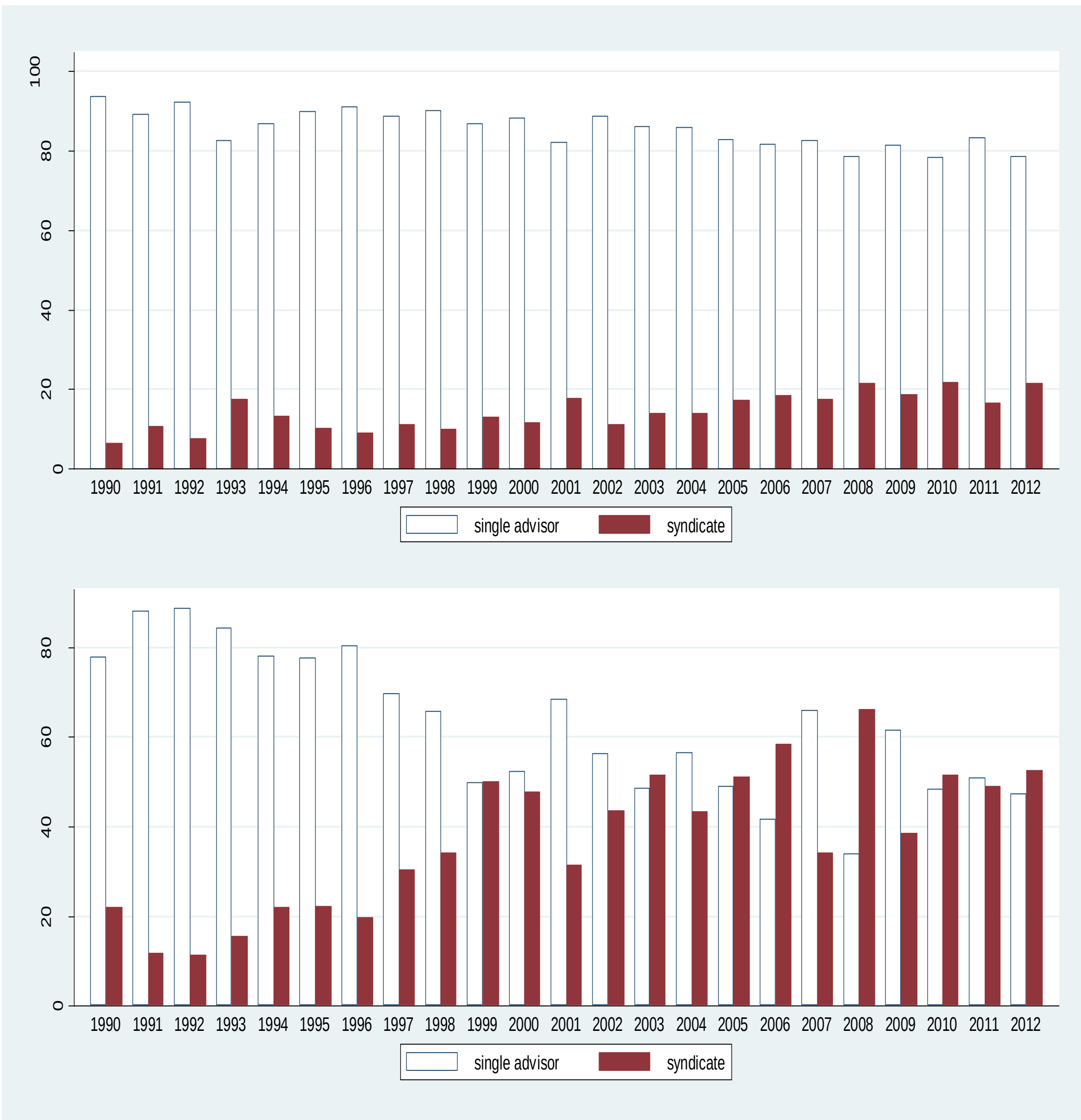
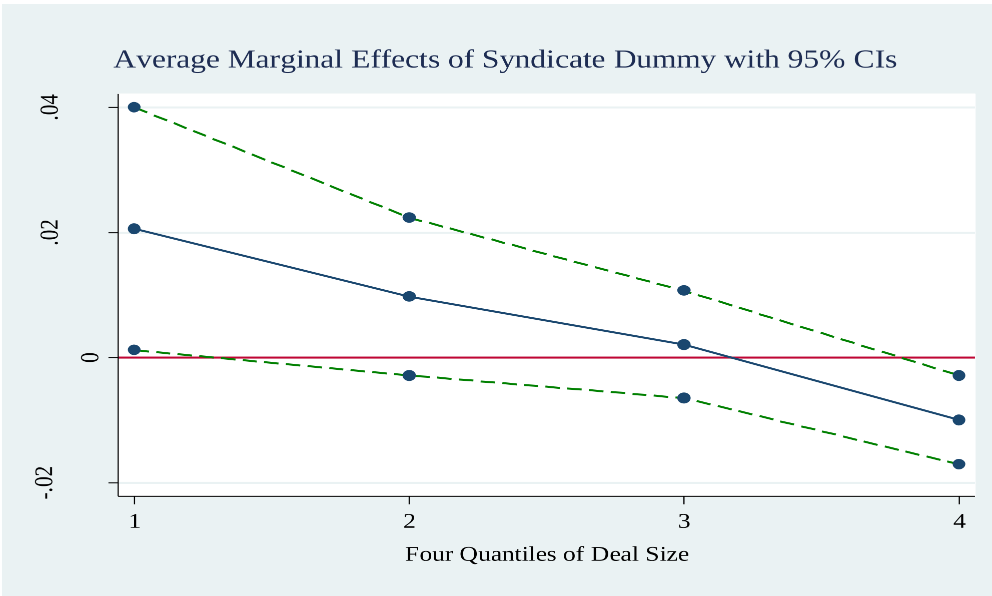


Figure 3.2
The Marginal Effects of Syndicate Choice on the Acquirer CAR

This figure displays the average effects of syndicate choice on the acquirer 3-day CAR estimated for each quartile of the deal size. The solid line shows how the average effect of the syndicate dummy changes with the transaction size, whereas the two surrounding dash lines indicate the 95% confidence intervals.



8. Tables

Table 3.1
Distribution of the Use of Syndicate

Panel A of this table shows acquirers' use of syndicates versus individual advisors by year for a sample of 8,175 U.S. M&A transactions announced between January 1990 and December 2012. Panel B presents the summary statistics for the number of investment banks in a syndicate. N denotes the number of observations.

Panel A: The frequency of using a syndicate versus individual advisor by year

	Number of deals			**Transaction value (in $Mil)**		
Ann. Year	Individual	Syndicate	Total	Individual	Syndicate	Total
1990	118	8	126	30366.12	8572.16	38938.28
	(93.65%)	(6.35%)		(77.99%)	(22.01%)	
1991	99	12	111	25367.49	3410.31	28777.80
	(89.19%)	(10.81%)		(88.15%)	(11.85%)	
1992	171	14	185	38050.97	4861.32	42912.29
	(92.43%)	(7.57%)		(88.67%)	(11.33%)	
1993	192	41	233	86015.27	15807.86	101823.10
	(82.4%)	(17.6%)		(84.48%)	(15.52%)	
1994	311	47	358	102977.30	28985.96	131963.30
	(86.87%)	(13.13%)		(78.03%)	(21.97%)	
1995	413	46	459	177085.30	50794.37	227879.70
	(89.98%)	(10.02%)		(77.71%)	(22.29%)	
1996	449	44	493	234393.80	57423.19	291817.00
	(91.08%)	(8.92%)		(80.32%)	(19.68%)	
1997	606	76	682	342192.40	148957.70	491150.10
	(88.86%)	(11.14%)		(69.67%)	(30.33%)	
1998	605	67	672	559427.20	290670.80	850098.00
	(90.03%)	(9.97%)		(65.81%)	(34.19%)	
1999	490	74	564	375945.20	377301.80	753247.00
	(86.88%)	(13.12%)		(49.91%)	(50.09%)	
2000	417	55	472	423516.40	(385448.30	808964.70
	(88.35%)	(11.65%)		(52.35%)	47.65%)	
2001	325	70	395	246933.30	113331.40	360264.70
	(82.28%)	(17.72%)		(68.54%)	(31.46%)	
2002	308	39	347	104225.80	80648.70	184874.50
	(88.76%)	(11.24%)		(56.38%)	(43.62%)	
2003	291	47	338	110995.60	117706.70	228702.30
	(86.09%)	(13.91%)		(48.53%)	(51.47%)	
2004	357	58	415	207388.00	159201.60	366589.60
	(86.02%)	(13.98%)		(56.57%)	(43.43%)	
2005	322	67	389	212942.10	222123.00	435065.10
	(82.78%)	(17.22%)		(48.94%)	(51.06%)	
2006	326	73	399	165789.80	232906.90	398696.70
	(81.7%)	(18.3%)		(41.58%)	(58.42%)	

2007	309	65	374	233276.50	120504.20	353780.70
	(82.62%)	(17.38%)		(65.94%)	(34.06%)	
2008	176	48	224	94854.03	185035.90	279889.90
	(78.57%)	(21.43%)		(33.89%)	(66.11%)	
2009	157	36	193	132789.90	82975.44	215765.30
	(81.35%)	(18.65%)		(61.54%)	(38.46%)	
2010	209	58	267	105035.80	111763.80	216799.60
	(78.28%)	(21.72%)		(48.45%)	(51.55%)	
2011	166	33	199	90008.03	86643.30	176651.30
	(83.42%)	(16.58%)		(50.95%)	(49.05%)	
2012	220	60	280	111890.60	124225.80	236116.40
	(78.57%)	(21.43%)		(47.39%)	(52.61%)	
Total	7037	1138	8,175	4211467.00	3009301.00	7220768.00
	(86.08%)	(13.92%)		(58.32%)	(41.68%)	

Panel B: The distribution of syndicate size for the full sample

	Mean	**Min.**	**Median**	**Max.**	**SD**	**Skewness**	**N**
Syndicate size	2.2302	2	2	9	0.6372	4.4930	1138

Table 3.2
Summary Statistics

This table presents the descriptive statistics for the sample of U.S. M&A transactions announced between 1/1/1990 and 31/12/2012. Panels A, B and C, respectively, report the mean, median and number of observations (*N*) for the deal, acquirer and main deal outcome characteristics for the full sample as well as the subsamples divided by syndicate use. A deal is syndicate-advised if the acquirer employs more than one investment bank; otherwise, it is individual-advised. 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 downloaded from Compustat. The symbols ***, ** and * denote significance of t-statistics at the 1%, 5% and 10%, respectively, for the test of difference in means and the Wilcoxon rank-sum test of difference in medians between the two subsamples divided by syndicate use.

	Full			**Syndicate-advised**			**Individual-advised**			**Diff. in**	**Diff. in**
	Mean	Median	N	Mean	Median	N	Mean	Median	N	**Mean**	**Median**
	(1)	(2)		(3)	(4)		(5)	(6)		(3) - (5)	(4) - (6)
Panel A: Deal characteristics											
Deal size ($mil)	883.274	166.824	8175	2644.377	547.061	1138	598.475	141.527	7037	2045.902***	405.534***
Relative size	0.431	0.187	8175	0.662	0.345	1138	0.393	0.172	7037	0.269***	0.173***
Related	0.640	-	8175	0.636	-	1138	0.641	-	7037	-0.005	-
Hostile	0.025	-	8175	0.061	-	1138	0.019	-	7037	0.041***	-
Tender	0.085	-	8175	0.155	-	1138	0.074	-	7037	0.081***	-
Cross border	0.153	-	8175	0.193	-	1138	0.147	-	7037	0.046	-
Pub. target	0.430	-	8175	0.551	-	1138	0.410	-	7037	0.141***	-
Priv. target	0.306	-	8175	0.184	-	1138	0.326	-	7037	-0.142***	-
Sub. target	0.264	-	8175	0.265	-	1138	0.264	-	7037	0.001	-
All cash	0.265	-	8175	0.293	-	1138	0.261	-	7037	0.032**	-
Num. of bidders	1.048	1.000	8175	1.117	1.000	1138	1.037	1.000	7037	0.080***	0.000***
Panel B: Acquirer characteristics											
Cash shortfall ($billion)	-0.163	-0.002	6944	0.067	0.009	925	-0.198	-0.003	6019	0.266***	0.012***

Acq. size ($mil)	5645.994	918.459	8175	9770.973	1660.162	1138	4978.916	823.980	7037	4792.057***	836.182***
Run-up	0.069	0.011	8175	0.085	0.029	1138	0.066	0.007	7037	0.018	0.022***
Sigma	0.027	0.022	8175	0.025	0.021	1138	0.027	0.023	7037	-0.003***	-0.002***
Leverage	0.150	0.110	7154	0.188	0.160	968	0.144	0.104	6186	0.044***	0.056***
Acq. experience	0.974	0.000	8175	1.153	1.000	1138	0.945	0.000	7037	0.208***	1.000***
Panel C: Deal outcomes											
CAR (-1, +1)	0.005	0.000	8175	0.002	-0.003	1138	0.005	0.001	7037	-0.003	-0.004*
Premium (%)	43.156	35.000	2966	39.832	32.920	557	43.924	35.430	2409	-4.092**	-2.510**
Completion	0.921	1.000	8175	0.888	1.000	1138	0.926	1.000	7037	-0.038***	0.000***
Deal duaration	1.029	0.830	7529	1.247	1.020	1011	0.995	0.790	6518	0.252***	0.230***

Table 3.3
VIF Diagnostics

This table reports the variance inflation factors (VIF) for all the explanatory variables used in our regression model. The sample consists of 8,175 deals announced between January 1990 and December 2012. The definition of each variable is provided in Appendix 3A.

Syndicate	Top-8 participated	Ln (Deal size)	Rel. size	Related
1.13	1.37	3.39	1.19	1.03
Hostile	Tender	Cross-border	Num. of bidders	Pub. * All cash
1.18	1.43	1.09	1.16	1.51
Priv. * All cash	Sub. * All cash	Pub. * Pmt. incl. stock	Priv. * Pmt. incl. stock	Ln (Acq. size)
1.21	1.22	1.62	1.41	3.5
Run-up	Sigma	FCF	Leverage	Tobin's Q
1.13	1.85	1.13	1.22	1.41

Table 3.4
Determinants of Syndicate Formation

This table reports the coefficient estimates from regressions of syndicate measures on various deal and acquirer characteristics. The sample consists of 8,175 deals announced between January 1990 and December 2012. Marginal effects are reported here. Syndicate is measured in two ways: (1) a dummy variable (*Syndicate dummy*) equal to 1 if more than one investment bank is hired by an acquirer, and 0 otherwise; and (2) a count variable (*Syndicate Size*) which equals the number of investment banks employed by an acquirer. Probit regression is run when the dependent variable is *Syndicate dummy* (column (1)); whereas a Poisson regression is estimated when the dependent variable is *Syndicate Size* (column (2)). Other variables are defined in Appendix 3A. The z-statistics listed in parentheses below the coefficients are generated using Huber White sandwich robust standard errors. N denotes number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Syndicate Dummy	**Syndicate Size**
	(1)	(2)
Ln (Deal size)	0.0556***	0.0849***
	(8.9200)	(10.1700)
Relative size	0.0256**	0.0288***
	(2.5400)	(2.9800)
Related	-0.0057	0.0143
	(-0.5500)	(1.0200)
Hostile	0.0465*	0.0604
	(1.7500)	(0.9800)
Cross-border	0.0650***	0.0805***
	(4.9200)	(3.7900)
Public target	0.0277**	0.0377**
	(2.5500)	(2.4900)
Num. of bidders	0.0433***	0.0873**
	(2.7600)	(2.2500)
Cash shortfall	0.0040**	0.0109***
	(2.3100)	(2.9100)
Ln (1+Acq. exp.)	0.0060	0.0080
	(0.6400)	(0.6100)
Run-up	0.0030	-0.0093
	(0.2500)	(-0.5800)
Ln (Acq. size)	-0.0231***	-0.0307***
	(-3.9300)	(-4.0900)
Sigma	1.1754**	1.7542***
	(2.5200)	(2.8600)
Leverage	0.1285***	0.1793***
	(3.5400)	(2.8900)
Participation of top-8	0.0683***	0.1031***
	(6.2900)	(6.7700)
Syndicate size lag	0.0633***	0.1086***

	(6.3300)	(5.2400)
Weighted size lag	-0.0002	0.0008
	(-0.3800)	(0.9500)
Year fixed effect	YES	YES
N	4383	4383
Pseudo R^2	0.164	0.014

Table 3.5
Baseline Results for Acquirer CAR

Panel A reports the results from the OLS regressions of the acquirer 3-day CAR on syndicate measures and other advisor-, deal- and acquirer- characteristics for the full sample. The dependent variable is the cumulative abnormal return (CAR) on the acquirer's stock over the event window (-1, +1), which is winsorized at the 1% and 99% percentiles. Syndicate in columns (1) and (2) is measured as a dummy variable (*Syndicate dummy*), which equals 1 if more than one investment bank is hired by an acquirer; and 0 otherwise. In columns (3) and (4), syndicate is measured as a count of the number of investment banks employed by an acquirer (*Syndicate Size*). Other variables are defined in Appendix 3A. Year fixed effects are controlled for in all models but the coefficients are suppressed. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. Panel B reports the marginal effect of the syndicate dummy and syndicate size on the acquirer 3-day CAR estimated for each quartile of the deal size. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: OLS regression

	Syndicate Dummy		**Syndicate Size**	
	(1)	(2)	(3)	(4)
Syndicate	-0.0009	0.0414**	0.0007	0.0219*
	(-0.2319)	(2.4500)	(0.2878)	(1.8160)
Ln (Deal size)	0.0010	0.0023**	0.0009	0.0045***
	(0.8046)	(2.0279)	(0.7266)	(2.5821)
Syndicate * Ln (Deal size)		-0.0070***		-0.0031*
		(-2.8559)		(-1.9472)
Participation of top-8	0.0065**	0.0063**	0.0064**	0.0061**
	(2.4856)	(2.4814)	(2.4121)	(2.3762)
Relative size	0.0042***	0.0042***	0.0042***	0.0042***
	(4.7440)	(4.7439)	(4.7473)	(4.7569)
Related	0.0004	0.0006	0.0004	0.0005
	(0.1818)	(0.2796)	(0.1816)	(0.2402)
Hostile	-0.0142**	-0.0123**	-0.0142**	-0.0133**
	(-2.2129)	(-2.0520)	(-2.2294)	(-2.1619)
Tender	0.0081	0.0069	0.0079	0.0072
	(1.3276)	(1.2618)	(1.2863)	(1.2507)
Cross-border	-0.0022	-0.0023	-0.0023	-0.0025
	(-0.8212)	(-0.8546)	(-0.8655)	(-0.9229)
Num. of bidders	-0.0016	-0.0015	-0.0018	-0.0017
	(-0.2696)	(-0.2698)	(-0.2936)	(-0.2821)
Pub. * All cash	-0.0093**	-0.0093***	-0.0092**	-0.0094***
	(-2.5188)	(-2.6226)	(-2.5117)	(-2.5807)
Priv. * All cash	0.0004	-0.0003	0.0003	-0.0001
	(0.0637)	(-0.0506)	(0.0519)	(-0.0195)
Sub. * All cash	0.0031	0.0024	0.0031	0.0027
	(0.9570)	(0.7423)	(0.9514)	(0.8161)
Pub. * Pmt. incl. stock	-0.0455***	-0.0453***	-0.0455***	-0.0455***

	(-16.4976)	(-16.4270)	(-16.4857)	(-16.4636)
Priv. * Pmt. incl. stock	-0.0037	-0.0035	-0.0038	-0.0036
	(-1.0444)	(-0.9630)	(-1.0541)	(-1.0131)
Ln (Acq. size)	-0.0048***	-0.0049***	-0.0048***	-0.0047***
	(-4.9853)	(-5.0847)	(-4.9519)	(-4.8782)
Run-up	-0.0055*	-0.0056*	-0.0055*	-0.0056*
	(-1.6800)	(-1.7285)	(-1.6863)	(-1.7433)
Sigma	0.3198***	0.3208***	0.3182***	0.3181***
	(2.8691)	(2.8725)	(2.8551)	(2.8496)
FCF	-0.0206*	-0.0209**	-0.0206*	-0.0208**
	(-1.9469)	(-1.9785)	(-1.9493)	(-1.9749)
Leverage	0.0315***	0.0307***	0.0313***	0.0306***
	(3.7094)	(3.6771)	(3.6741)	(3.6474)
Tobin's Q	-0.0010	-0.0010	-0.0010	-0.0010
	(-1.1160)	(-1.1408)	(-1.1147)	(-1.1303)
Intercept	0.0228**	0.0177*	0.0225**	-0.0014
	(2.3900)	(1.7889)	(2.2271)	(-0.0795)
Year fixed effect	YES	YES	YES	YES
N	6929	6929	6929	6929
R^2	0.105	0.108	0.105	0.106
Adj. R^2	0.099	0.102	0.099	0.100

Panel B: Marginal effect of the syndicate dummy on acquirer CAR across quartiles of deal size (in $Mil)

Deal Size	**Min**	**Max**	**N**	**Average Marginal Effect**	**z**	**p-value**
Q1	1.00	51.573	850	0.0206**	2.08	0.037
Q2	51.65	162.213	869	0.0098	1.52	0.128
Q3	162.25	499.000	941	0.0021	0.49	0.626
Q4	499.31	164746.900	941	-0.0099***	-2.74	0.006

Table 3.6
Two-step Treatment Procedure for Acquirer CAR

This table presents the estimation results from a two-step treatment procedure for the acquirer 3-day CAR for the full sample. Column (1) reports the Probit regression results, where the dependent variable is a dummy variable equal to 1 if an acquirer uses a syndicate; and 0 otherwise. The explanatory variables in the first-stage regression are the same as those in Table 3.4. The results from the second-stage regressions of the acquirer 3-day CAR are provided in columns (2) and (3), where syndicate is measured as a dummy variable (*Syndicate Dummy*) and a count of the number of investment banks employed by an acquirer (*Syndicate Size*), respectively. The variable *Hazard ratio*, which is estimated from the first-stage equation, is included in the second-stage regression as an additional regressor to adjust for the potential self-selection bias. Other variables are defined in Appendix 3A. The z-statistics statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes the number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Selection	**Outcome**	
		Syndicate Dummy	Syndicate Size
	(1)	(2)	(3)
Syndicate		0.0670***	0.0512***
		(3.7913)	(2.6487)
Ln (Deal size)	0.2814***	-0.0009	0.0036
	(8.8754)	(-0.6450)	(1.4531)
Syndicate * Ln (Deal size)		-0.0092***	-0.0056***
		(-5.1680)	(-2.5872)
Syndicate size lag	0.3238***		
	(6.0844)		
Weighted size lag	-0.0008		
	(-0.3537)		
Participation of top-8	0.3493***	0.0078***	0.0071**
	(6.1425)	(3.0191)	(2.4448)
Relative size	0.1319**	0.0038*	0.0033
	(2.4540)	(1.7197)	(0.7243)
Related	-0.0285	0.0004	0.0002
	(-0.5356)	(0.1850)	(0.0860)
Hostile	0.2388*	-0.0045	-0.0060
	(1.7590)	(-0.6395)	(-0.8460)
Tender		0.0054	0.0060
		(1.2681)	(0.9478)
Cross-border	0.3290***	-0.0028	-0.0033
	(4.9470)	(-0.9056)	(-1.0662)
Num. of bidders	0.2214***	-0.0052	-0.0057
	(2.7821)	(-1.2492)	(-0.8969)
Pub. * All cash		-0.0083**	-0.0082**
		(-2.0327)	(-2.0221)
Priv. * All cash		0.0073	0.0080

		(1.6299)	(1.1490)
Sub. * All cash		0.0022	0.0029
		(0.5819)	(0.7847)
Pub. * Pmt. incl. stock		-0.0372***	-0.0373***
		(-12.0422)	(-11.3748)
Priv. * Pmt. incl. stock		-0.0014	-0.0013
		(-0.3500)	(-0.2932)
Public target	0.1365**		
	(2.4377)		
Cash shortfall	0.0205**		
	(2.3646)		
Ln (1+Acq. exp.)	0.0309		
	(0.6601)		
Ln (Acq. size)	-0.1168***	-0.0021*	-0.0019
	(-3.8511)	(-1.7406)	(-1.2703)
Run-up	0.0147	0.0004	0.0004
	(0.2355)	(0.1306)	(0.0986)
Sigma	5.8032**	0.0995	0.0864
	(2.4207)	(0.9422)	(0.5150)
FCF		-0.0233***	-0.0232*
		(-3.0180)	(-1.7044)
Leverage	0.6515***	0.0417***	0.0408***
	(3.5398)	(4.9040)	(3.9373)
Tobin's Q		-0.0001	-0.0001
		(-0.1471)	(-0.0590)
Hazard ratio		-0.0043	-0.0093**
		(-0.7560)	(-2.3377)
Intercept	-3.8339***	0.0171	-0.0291
	(-7.5084)	(1.2572)	(-1.1528)
Year fixed effect	YES	YES	YES
N	4383	4383	4383

Table 3.7
Alternative Measure of Moral Hazard

This table provides the results from the OLS regressions of the acquirer 3-day CAR using alternative measures of moral hazard for the full sample. Syndicate is measured either as a dummy variable or a count of the number of investment banks employed by an acquirer. The proxy for the severity of moral hazard in the first two columns is public deal, which equals 1 if the target is a listed firm; 0 otherwise. In columns (3) and (4), we use diversifying high-tech deal as an alternative proxy, which equals 1 if the target is a high-tech firm, as defined in Loughran and Ritter (2004), and the acquirer is in a different industry from the target. Other variables are defined in Appendix 3A. 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.

	Proxy=Public Deal		**Proxy = Div. High-tech Deal**	
	Syndicate Dummy (1)	Syndicate Size (2)	Syndicate Dummy (3)	Syndicate Size (4)
Syndicate	0.0114*	0.0110**	0.0010	0.0017
	(1.7037)	(2.2888)	(0.2413)	(0.6666)
Proxy	-0.0319***	-0.0164**	0.0051	0.0336**
	(-11.1151)	(-2.5048)	(0.9626)	(2.0317)
Syndicate * Proxy	-0.0233***	-0.0161***	-0.0436***	-0.0296**
	(-2.9600)	(-2.9385)	(-2.8478)	(-2.0937)
Ln (Deal size)	0.0004	0.0001	0.0011	0.0010
	(0.3348)	(0.0830)	(0.8440)	(0.7622)
Participation of top-8	0.0062**	0.0059**	0.0066**	0.0065**
	(2.4501)	(2.3287)	(2.5279)	(2.4533)
Relative size	0.0043***	0.0043***	0.0042***	0.0042***
	(4.6844)	(4.6909)	(4.7871)	(4.7735)
Related	-0.0000	0.0000	0.0003	0.0003
	(-0.0054)	(0.0047)	(0.1389)	(0.1383)
Hostile	-0.0082	-0.0085	-0.0138**	-0.0139**
	(-1.3585)	(-1.3956)	(-2.1862)	(-2.1940)
Tender	0.0237***	0.0234***	0.0079	0.0077
	(4.6454)	(4.5379)	(1.2918)	(1.2429)
Cross-border	-0.0012	-0.0015	-0.0024	-0.0025
	(-0.4581)	(-0.5517)	(-0.8697)	(-0.9086)
Num. of bidders	-0.0015	-0.0017	-0.0020	-0.0020
	(-0.2686)	(-0.2934)	(-0.3289)	(-0.3336)
Pmt. incl. stock	-0.0114***	-0.0114***		
	(-4.7293)	(-4.7121)		
Priv. target	-0.0041	-0.0043		
	(-1.3985)	(-1.4542)		
Pub. * All cash			-0.0089**	-0.0089**

			(-2.4287)	(-2.4298)
Priv. * All cash			0.0004	0.0004
			(0.0722)	(0.0581)
Sub. * All cash			0.0029	0.0029
			(0.8744)	(0.8809)
Pub. * Pmt. incl. stock			-0.0454***	-0.0455***
			(-16.4790)	(-16.4647)
Priv. * Pmt. incl. stock			-0.0038	-0.0038
			(-1.0625)	(-1.0690)
Ln (Acq. size)	-0.0040***	-0.0039***	-0.0049***	-0.0048***
	(-4.1938)	(-4.0295)	(-5.0373)	(-4.9851)
Run-up	-0.0060*	-0.0060*	-0.0054*	-0.0055*
	(-1.8476)	(-1.8671)	(-1.6649)	(-1.6799)
Sigma	0.3481***	0.3453***	0.3142***	0.3148***
	(3.1367)	(3.1127)	(2.8119)	(2.8192)
FCF	-0.0202*	-0.0201*	-0.0205*	-0.0205*
	(-1.9031)	(-1.8991)	(-1.9398)	(-1.9372)
Leverage	0.0318***	0.0318***	0.0309***	0.0311***
	(3.8543)	(3.8299)	(3.6355)	(3.6365)
Tobin's Q	-0.0010	-0.0010	-0.0010	-0.0010
	(-1.1516)	(-1.1511)	(-1.1312)	(-1.1258)
Intercept	0.0259***	0.0157	0.0234**	0.0219**
	(2.6874)	(1.3364)	(2.4585)	(2.1711)
Year fixed effect	YES	YES	YES	YES
N	6929	6929	6918	6918
Adj. R^2	0.095	0.094	0.101	0.100

Table 3.8
Multivariate Analysis of the Lead Advisor Reputation Effect

Panel A of this table presents the OLS regressions and two-step treatment procedure for the acquirer 3-day CAR for a sample of individual-advised and lead-managed M&A deals announced between 1990 and 2012. The dependent variable in each column is the acquirer 3-day CAR which is winsorized at the 1% and 99% tails to account for the possibility of outliers. Syndicate in columns (1) and (2) is measured as a dummy variable equal to 1 if an acquirer uses a syndicate; and 0 otherwise. The first column reports the OLS regression results; the second column presents the estimates for the second-stage regression, with the first-stage regression results omitted for brevity. Columns (3) and (4) repeat the analysis for the alternative syndicate measure, *Syndicate Size*, which is a count of the number of investment banks employed by an acquirer. *Top-8 lead* is a binary variable equal to 1 if the lead investment bank in a syndicate is a top 8 investment bank ranked according to the value of transactions. In panel B, we examine the countervailing effect of lead advisor reputation on free-riding by running OLS regressions of the acquirer 3-day CAR for a sample of large deals, defined as those in the top quartile of size distribution. The main variables of interest in column (1) are *syndicate led by Top-8* and *syndicate led by non-top 8*. The former (the latter) is a dummy variable equal to 1 if the syndicate is lead-managed by a top-8 (non-top 8) advisor; 0 otherwise. Column (2) replicates the analysis using the number of investment banks lead-managed by top-8 and non-top 8 advisors, respectively. Other variables are defined in Appendix 3A. All models control for the year fixed effects whose coefficients are suppressed. The t- (z-) 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.

Panel A: Stand-alone effects

	Syndicate Dummy		**Syndicate Size**	
	OLS	Two-step	OLS	Two-step
	(1)	(2)	(3)	(4)
Syndicate	0.0523^{*}	0.1126^{***}	0.0239	0.1172^{***}
	(1.6980)	(4.0245)	(0.9686)	(2.8081)
Ln (Deal size)	0.0025^{**}	-0.0011	0.0056^{*}	0.0109^{**}
	(2.2712)	(-0.7406)	(1.7570)	(2.3314)
Syndicate * Ln (Deal size)	-0.0113^{**}	-0.0159^{***}	-0.0040	-0.0128^{***}
	(-2.4137)	(-5.8205)	(-1.2115)	(-2.8872)
Top-8 lead	0.0436^{**}	0.0273^{***}	0.0241	0.0233
	(2.4004)	(2.6386)	(1.3177)	(1.4197)
Relative size	0.0043^{***}	0.0071^{**}	0.0042^{***}	0.0052
	(4.8121)	(1.9754)	(4.8390)	(0.7508)
Related	0.0003	0.0004	0.0003	0.0002
	(0.1561)	(0.1780)	(0.1275)	(0.0923)
Hostile	-0.0164^{***}	-0.0062	-0.0178^{***}	-0.0076
	(-2.7536)	(-0.7817)	(-2.8247)	(-1.0599)
Tender	0.0093^{**}	0.0074	0.0107^{**}	0.0085
	(2.0093)	(1.5441)	(2.0146)	(1.6228)

Cross-border	-0.0024	-0.0025	-0.0027	-0.0026
	(-0.8757)	(-0.7941)	(-0.9594)	(-0.8194)
Num. of bidders	-0.0003	-0.0051	0.0003	-0.0053
	(-0.0651)	(-1.0671)	(0.0568)	(-0.8469)
Pub. * All cash	-0.0107***	-0.0108**	-0.0112***	-0.0115***
	(-3.0395)	(-2.4322)	(-2.9896)	(-2.7978)
Priv. * All cash	-0.0009	0.0060	-0.0002	0.0065
	(-0.1926)	(1.2717)	(-0.0449)	(1.1573)
Sub. * All cash	0.0026	0.0048	0.0029	0.0054
	(0.7759)	(1.2043)	(0.8737)	(1.4160)
Pub. * Pmt. incl. stock	-0.0450***	-0.0372***	-0.0458***	-0.0382***
	(-15.7606)	(-11.3627)	(-16.0012)	(-11.1013)
Priv. * Pmt. incl. stock	-0.0029	-0.0004	-0.0032	-0.0006
	(-0.7832)	(-0.0992)	(-0.8706)	(-0.1410)
Ln (Acq. size)	-0.0039***	-0.0004	-0.0037***	-0.0004
	(-3.9284)	(-0.3180)	(-3.6328)	(-0.2306)
Run-up	-0.0079**	-0.0026	-0.0078**	-0.0024
	(-2.4562)	(-0.8737)	(-2.4281)	(-0.5375)
Sigma	0.3679***	0.1711	0.3606***	0.1620
	(3.2245)	(1.5461)	(3.1548)	(0.9115)
FCF	-0.0247**	-0.0291***	-0.0246**	-0.0291**
	(-2.3450)	(-3.6477)	(-2.3371)	(-2.1714)
Leverage	0.0360***	0.0456***	0.0363***	0.0440***
	(4.2725)	(5.0550)	(4.2696)	(4.0744)
Tobin's Q	-0.0010	0.0001	-0.0009	0.0002
	(-0.9668)	(0.1766)	(-0.9287)	(0.1155)
Hazard ratio		-0.0059		-0.0204***
		(-0.8115)		(-2.6475)
Intercept	0.0079	0.0030	-0.0144	-0.1095**
	(0.7953)	(0.2163)	(-0.4800)	(-2.4506)
Year fixed effect	YES	YES	YES	YES
N	6283	3915	6283	3915
R^2	0.113	-	0.109	-
Adj. R^2	0.107	-	0.103	-

Panel B: The countervailing effect of lead advisor reputation for the top quartile deal size

	Large Deals	
	Syndicate Dummy	**Syndicate Size**
	(1)	(2)
Syndicates led by top-8	-0.0158	-0.0035
	(-1.5677)	(-0.9407)
Syndicates led by non-top8	-0.0092	-0.0015
	(-0.8570)	(-0.3757)
Ln (Deal size)	-0.0035	-0.0043

	(-1.1856)	(-1.4473)
Relative size	0.0046***	0.0046***
	(4.1760)	(4.1747)
Related	0.0060	0.0061
	(1.4762)	(1.4966)
Hostile	-0.0074	-0.0075
	(-0.9919)	(-0.9936)
Tender	-0.0055	-0.0058
	(-0.9468)	(-0.9796)
Cross-border	-0.0032	-0.0032
	(-0.5940)	(-0.5907)
Num. of bidders	-0.0025	-0.0026
	(-0.3885)	(-0.3935)
Pub. * All cash	-0.0123**	-0.0122**
	(-2.0985)	(-2.0779)
Priv. * All cash	-0.0002	-0.0001
	(-0.0170)	(-0.0127)
Sub. * All cash	-0.0034	-0.0034
	(-0.4991)	(-0.5001)
Pub. * Pmt. incl. stock	-0.0412***	-0.0419***
	(-7.2175)	(-7.3133)
Priv. * Pmt. incl. stock	0.0095	0.0093
	(0.7691)	(0.7572)
Ln (Acq. size)	0.0022	0.0024
	(1.1888)	(1.3004)
Run-up	-0.0036	-0.0035
	(-0.6398)	(-0.6338)
Sigma	-0.3382	-0.3453
	(-0.9834)	(-1.0000)
FCF	-0.0186	-0.0196
	(-0.5296)	(-0.5592)
Leverage	0.0391**	0.0386**
	(2.3815)	(2.3509)
Tobin's Q	0.0002	0.0002
	(0.1313)	(0.1492)
Intercept	-0.0113	-0.0076
	(-0.4411)	(-0.2929)
Year fixed effect	YES	YES
N	1430	1430
R^2	0.148	0.146
Adj. R^2	0.122	0.120

Table 3.9
Regression Analysis of Total Synergy Gains

This table provides estimation results for total synergy gain for the public subsample. The total synergy gain is computed as the combined dollar gain made by the acquirer and the target. Syndicate is measured in two ways: (1) a dummy variable (*Syndicate Dummy*) indicating whether more than one investment bank is hired by an acquirer; and (2) a count of the number of investment banks employed by an acquirer (*Syndicate Size*). For each syndicate measure, we first estimate the relation between syndicate and total synergy by OLS, and then implement a two-step treatment procedure to account for endogeneity. The first-stage regression estimates the probability of using a syndicate by Probit using the same explanatory variables as in Table 3.4. In the second stage, total synergy gain is regressed on the syndicate measures (*Syndicate Dummy* and *Syndicate Size*), hazard ratio, as well as other control variables. Other variables are defined in Appendix 3A. All models control for the year fixed effects whose coefficients are suppressed. The t- (z-) 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.

	Syndicate Dummy		**Syndicate Size**	
	OLS	Two-step	OLS	Two-step
	(1)	(2)	(3)	(4)
Syndicate	1367.8050*	4291.4475***	380.8363	2369.9885**
	(1.9016)	(8.3190)	(0.8238)	(2.1733)
Ln (Deal size)	55.3601	-183.4911***	46.8166	197.4319
	(0.9292)	(-2.6698)	(0.5079)	(1.4126)
Syndicate * Ln (Deal size)	-231.7182*	-296.8910***	-49.2710	-241.8189*
	(-1.8879)	(-3.9573)	(-0.7105)	(-1.9007)
Participation of top-8	63.4619	-66.3346	58.2338	10.4523
	(0.6640)	(-0.5223)	(0.6010)	(0.0759)
Relative size	15.4158	-74.4465	6.1907	-14.0582
	(0.5428)	(-0.9409)	(0.2365)	(-0.4717)
Pmt. incl. stock	-206.4338**	-290.1476**	-217.4039**	-261.8090*
	(-1.9940)	(-2.2919)	(-2.0900)	(-1.8497)
Related	-0.2334	48.7681	-0.3416	-4.1841
	(-0.0027)	(0.3995)	(-0.0040)	(-0.0343)
Hostile	5.0620	-132.9492	-19.8285	-86.9239
	(0.0234)	(-0.4877)	(-0.0894)	(-0.2747)
Tender	-31.2920	-90.8971	-29.4181	-39.2788
	(-0.2831)	(-0.6029)	(-0.2679)	(-0.2662)
Cross-border	253.5557	-253.0557	204.4462	111.7779
	(0.9593)	(-0.7347)	(0.8292)	(0.3222)
Num. of bidders	16.1495	-112.2223	3.8858	-43.0940
	(0.0895)	(-0.7159)	(0.0211)	(-0.1798)
Ln (Acq. size)	-11.7662	100.0490*	-3.2237	41.7774
	(-0.2270)	(1.6844)	(-0.0613)	(0.5285)
Run-up	-17.6404	50.7633	-7.7668	-3.2201

	(-0.1828)	(0.3689)	(-0.0823)	(-0.0197)
Sigma	4560.9154	-648.2329	4439.3795	2932.2728
	(1.1770)	(-0.1221)	(1.1410)	(0.4966)
FCF	37.2183	-56.3853	18.6550	-233.0896
	(0.1752)	(-0.1297)	(0.0911)	(-0.6696)
Leverage	494.5578	191.5639	406.2881	501.9405
	(1.4548)	(0.4226)	(1.2314)	(0.9621)
Tobin's Q	-35.6172	-36.6751	-36.9012	-33.9060
	(-1.0030)	(-1.5487)	(-1.0447)	(-0.5625)
Hazard ratio		-1554.343***		-689.1807***
		(-19.3283)		(-2.7869)
Intercept	-249.4080	546.9278	-386.7901	-2343.2812
	(-0.4145)	(0.5943)	(-0.4758)	(-1.5251)
Year fixed effect	YES	YES	YES	YES
N	2026	1393	2026	1393
R^2	0.036	-	0.026	-
Adj. R^2	0.017	-	0.007	-

Table 3.10
Regression Analysis of Takeover Premium

This table reports estimation results for the takeover premium for the public subsample. Takeover premium is a percentage premium of offer price over target market value four weeks before the deal announcement. Syndicate is measured in two ways: (1) a dummy variable (*Syndicate Dummy*) indicating whether more than one investment bank is hired by an acquirer; and (2) a count of the number of investment banks employed by an acquirer (*Syndicate Size*). For each syndicate measure, we first estimate the relationship between syndicate and total synergy by OLS, and then implement a two-step treatment procedure to account for endogeneity. The first-stage regression estimates the probability of using a syndicate by Probit, with explanatory variables the same as those shown in Table 3.4. In the second stage, takeover premium is regressed on the syndicate measures (*Syndicate Dummy* and *Syndicate Size*), hazard ratio, as well as other control variables. Other variables are defined in Appendix 3A. All models control for the year fixed effects whose coefficients are suppressed. The t-statistics listed in parentheses below the coefficients are generated using Huber White sandwich robust standard errors. N denotes number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Syndicate Dummy		**Syndicate Size**	
	OLS	Two-step	OLS	Two-step
	(1)	(2)	(3)	(4)
Syndicate	3.8579	10.1798	0.1899	-2.5508
	(0.3460)	(0.5941)	(0.0238)	(-0.2568)
Ln (Deal size)	-4.1182***	-4.4410***	-2.8907	-2.9851
	(-3.0515)	(-2.8008)	(-1.3968)	(-1.4000)
Syndicate * Ln (Deal size)	-0.4502	-0.7240	0.0090	0.3667
	(-0.3056)	(-0.4527)	(0.0089)	(0.3022)
Targ. Syndicate	15.4490*	17.2984*	11.0881	12.7457
	(1.7580)	(1.6642)	(1.1902)	(1.1005)
Targ. Syn. * Ln (Deal size)	-2.3139*	-2.4341*	-1.5359	-1.7416
	(-1.8667)	(-1.6491)	(-1.1052)	(-1.0133)
Participation of top-8	-1.2821	-2.2672	-1.1521	-1.8978
	(-0.6695)	(-1.0179)	(-0.6021)	(-0.8488)
Participation of targ. top-8	-1.2701	1.0004	-1.3311	1.0738
	(-0.6245)	(0.4444)	(-0.6546)	(0.4304)
Relative size	4.5681**	2.6933	4.6114**	3.0075**
	(2.0391)	(1.2798)	(2.0723)	(2.4721)
Num. of bidders	6.8485**	7.4557***	6.8973**	7.8590**
	(2.4715)	(2.6815)	(2.4824)	(2.5573)
Hostile	3.7292	-0.3789	3.6319	-0.1669
	(0.9949)	(-0.0814)	(0.9556)	(-0.0391)
Related	-1.0029	0.5190	-1.0676	0.2905
	(-0.5400)	(0.2467)	(-0.5734)	(0.1390)
Cross-border	3.5457	3.4959	3.7203	5.5789
	(0.5525)	(0.4353)	(0.5789)	(0.6684)

All cash	1.8366	0.7914	1.8615	0.8461
	(0.8128)	(0.2960)	(0.8228)	(0.3236)
Tender	7.4248***	8.5430***	7.4880***	8.5769***
	(2.8077)	(2.9999)	(2.8293)	(2.7171)
Toehold	-0.6633	2.7649	-0.8115	2.7587
	(-0.0904)	(0.4426)	(-0.1110)	(0.3196)
Ln (Target M/B)	-2.3873*	-2.7559**	-2.3214*	-2.7075*
	(-1.7632)	(-2.0025)	(-1.7048)	(-1.8212)
Tobin's Q	2.2600***	2.6821***	2.2680***	2.6623***
	(5.2652)	(7.0848)	(5.2952)	(4.5640)
Ln (Acq. size)	3.6072***	3.6231***	3.6210***	3.3708***
	(3.3570)	(3.0197)	(3.3788)	(3.1027)
Hazard ratio		-3.2721		-0.3772
		(-0.5758)		(-0.1581)
Intercept	45.7793***	55.7989***	36.1190**	46.8694***
	(4.8142)	(3.5913)	(2.5472)	(2.8377)
Year fixed effect	YES	YES	YES	YES
N	1662	1168	1662	1168
R^2	0.109	-	0.108	-
Adj. R^2	0.087	-	0.086	-

Table 3.11
Probit Analysis of Completion Rates

This table provides the results from Probit regressions of deal completion on syndicate measures and other advisor, deal and bidder characteristics for a subsample of deals in which acquirers have insufficient internal funds to finance the cash component of the offer, i.e., cash shortfall >0. In all specifications, the dependent variable is completion which is a dummy variable being 1 if the deal is completed and 0 otherwise. Syndicate in columns (1) and (2) is measured as a dummy variable (*Syndicate Dummy*), which equals 1 if more than one investment banks are hired by an acquirer; and 0 otherwise. In columns (3) and (4), syndicate is measured as a count of the number of investment banks employed by an acquirer (*Syndicate Size*). All the variables are defined in Appendix 3A. All regressions control for year fixed effects whose coefficients are suppressed. The z-statistics are in parentheses. N denotes number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Syndicate Dummy		**Syndicate Size**	
	(1)	(2)	(4)	(5)
Syndicate	0.2270*	-0.0034	0.1555*	0.0384
	(1.8069)	(-0.0078)	(1.7419)	(0.1182)
Syndicate * Ln (Deal size)		0.0365		0.0165
		(0.5498)		(0.3710)
Ln (Deal size)	-0.2406***	-0.2471***	-0.2415***	-0.2608***
	(-3.8698)	(-3.8931)	(-3.8570)	(-3.1932)
Participation of top-8	0.0480	0.0483	0.0525	0.0543
	(0.4632)	(0.4676)	(0.5083)	(0.5258)
Relative size	0.0330	0.0331	0.0346	0.0352
	(0.4918)	(0.4899)	(0.5080)	(0.5114)
Related	0.1819**	0.1829**	0.1812**	0.1815**
	(2.0398)	(2.0493)	(2.0323)	(2.0357)
Hostile	-2.0389***	-2.0455***	-2.0284***	-2.0302***
	(-11.4466)	(-11.4513)	(-11.3938)	(-11.3975)
Tender	0.5120***	0.5160***	0.5169***	0.5187***
	(3.2524)	(3.2743)	(3.2862)	(3.2962)
Cross-border	-0.1279	-0.1271	-0.1335	-0.1342
	(-0.9950)	(-0.9900)	(-1.0393)	(-1.0455)
Num. of bidders	-0.7928***	-0.7934***	-0.7966***	-0.7976***
	(-7.4463)	(-7.4540)	(-7.4616)	(-7.4690)
Pub. * All cash	-0.5644***	-0.5625***	-0.5611***	-0.5591***
	(-3.9503)	(-3.9351)	(-3.9257)	(-3.9087)
Priv. * All cash	-0.0260	-0.0266	-0.0256	-0.0260
	(-0.1274)	(-0.1304)	(-0.1255)	(-0.1276)
Sub. * All cash	0.2506	0.2545	0.2550	0.2575
	(1.3215)	(1.3405)	(1.3435)	(1.3561)
Pub. * Pmt. incl. stock	-0.3295***	-0.3319***	-0.3269***	-0.3282***
	(-2.6958)	(-2.7125)	(-2.6734)	(-2.6824)
Priv. * Pmt. incl. stock	0.1214	0.1180	0.1214	0.1201

	(0.7208)	(0.7000)	(0.7211)	(0.7125)
Ln (Acq. size)	0.2127***	0.2123***	0.2117***	0.2107***
	(3.5060)	(3.4918)	(3.4734)	(3.4461)
Run-up	-0.1054	-0.1038	-0.1044	-0.1031
	(-1.2536)	(-1.2321)	(-1.2420)	(-1.2248)
Sigma	-4.5049	-4.5648	-4.5472	-4.5909
	(-1.4852)	(-1.5012)	(-1.4975)	(-1.5092)
FCF	-0.1381	-0.1407	-0.1390	-0.1398
	(-0.5520)	(-0.5603)	(-0.5570)	(-0.5597)
Leverage	0.1156	0.1163	0.1199	0.1210
	(0.3358)	(0.3380)	(0.3477)	(0.3511)
Tobin's Q	-0.0186	-0.0181	-0.0185	-0.0182
	(-0.8507)	(-0.8263)	(-0.8492)	(-0.8329)
Intercept	1.8416***	1.8773***	1.6989***	1.8360***
	(4.6396)	(4.6618)	(4.2738)	(3.3911)
Year fixed effect	YES	YES	YES	YES
N	3295	3295	3295	3295
Pseudo R^2	0.328	0.328	0.328	0.328

9. Appendices

Appendix 3A Variable Definitions

Variable	Definition
Panel A: Dependent Variables	
CAR (-1, +1)	Cumulative abnormal returns of the acquiring firm stock over the event window (-1, +1) surrounding 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.
Completion	A dummy variable being 1 if the deal is completed and 0 otherwise.
Synergies (in $Mil)	The aggregate dollar gains made by the acquirer and the target, where dollar gain is a product of CAR (-1, +1) and the respective firms' market capitalization 11 days prior to the announcement date.
Premium Offered	A ratio of the offer price to the target market value four weeks before the announcement minus one, from the SDC.
Panel B: Deal Characteristics	
Deal Size	The value of the transaction in millions of $U.S. dollars (from the SDC)
Relative Size	The deal value divided by the market value of the bidding firm's equity one month prior to the announcement date (from CRSP)
Relatedness	A dummy variable being 1 if the bidder and the target are operating in the same industries with a common 3-digit SIC code and 0 otherwise (from the SDC).
Public Target	A dummy variable being 1 if the bid is for public target and 0 otherwise.
Private Target	A dummy variable being 1 if the bid is for private target and 0 otherwise.
Subsidiary Target	A dummy variable being 1 if the bid is for subsidiary target and 0 otherwise.
Foreign Target	A dummy variable being 1 if the bid is for foreign target and 0 otherwise.
All-Cash Deals	A dummy variable being 1 if the payment is pure cash and 0 otherwise.

Pmt. Incl. Stock	A dummy variable being 1 if the acquisition is either partially or fully financed with stock and 0 otherwise.
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 $U.S. dollars.
Tender Offer	A dummy variable being 1 if the deal is a tender and 0 otherwise.
Hostile	A dummy variable being 1 if the deal is hostile or unsolicited as reported by the SDC, and 0 otherwise.
Number of Competing Bidders	A dummy variable being 1 if there are multiple bidders and 0 otherwise.
Ln (Target M/B)	The natural logarithm of the ratio of the market value of equity relative to the book value of equity of the target for the prior fiscal year, similar to Song et al. (2012). The market value of target equity is calculated as 11 trading days before the announcement date.
Toehold	Dummy variable being 1 if acquirer holds 5% or more of the target stock before the announcement from the SDC.
Panel C: Acquirer Characteristics	
Bidder Size	The market value of the bidding firm's equity 11 days before the announcement date in millions of $U.S. dollars. The data are obtained from CRSP.
Tobin's Q	Market value of assets divided by book value of assets, where the market value of assets is equal to book value of assets plus market value of common stock minus book value of common stock minus balance sheet deferred taxes. The data are obtained from both CRSP and Compustat.
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. The data are obtained from

	both CRSP and Compustat.
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 Compustat.
Acquirer Experience	The total number of acquisitions made by the acquirer over the five years preceding the year of acquisition.
Panel D: Advisor Characteristics	
Participation of Top-8	A dummy variable being 1 if the deal involves a top-8 investment bank ranked according to the value of transactions it has advised over the sample period. The data are obtained from the league tables for financial advisors from the SDC.
Syndicate Size Lag	The number of advisors hired by the acquirer in its most recent deal.
Weighted Size Lag	An interaction term between syndicate size lag and a ratio of the current and previous deal size.

Appendix 3B Robustness Checks

Table 3.I
Alternative Proxy for Acquisition-related Financing

This table reports the coefficient estimates from regressions of syndicate measures on *External financing* and other deal and acquirer characteristics, for a sample of deals that are either partially or entirely financed by the proceeds from one of the following activities: bank loan, equity issue, debt issue or hybrid. *External financing* is a dummy variable which equals 1 if external funds are obtained for a takeover bid and 0 otherwise. The dependent variable in column (1) is *Syndicate Dummy*, measured as a dummy variable equal to 1 if more than one investment bank is hired by an acquirer and 0 otherwise. In column (2), the dependent variable is *Syndicate Size* which equals the number of investment banks employed by an acquirer. Probit regression is run when the dependent variable is *Syndicate Dummy*, whereas Poisson regression is estimated when the dependent variable is *Syndicate Size*. Other variables are defined in Appendix 3A. The z-statistics listed in parentheses below the coefficients are generated using Huber White sandwich robust standard errors. N denotes number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Syndicate Dummy (1)	**Syndicate Size** (2)
External financing	0.0469***	0.0903***
	(2.9900)	(2.9000)
Ln (Deal size)	0.0508***	0.0776***
	(8.0000)	(8.9400)
Relative size	0.0258**	0.0296***
	(2.5100)	(3.2000)
Related	-0.0047	0.0189
	(-0.4500)	(1.3500)
Hostile	0.0518**	0.0741
	(1.9700)	(1.2000)
Cross-border	0.0675***	0.0863***
	(5.1100)	(4.0300)
Public target	0.0301***	0.0368**
	(2.7500)	(2.5000)
Num. of bidders	0.0416***	0.0932**
	(2.5800)	(2.2300)
Ln (1+Acq. exp.)	0.0086	0.0087
	(0.9100)	(0.6700)
Run-up	0.0012	-0.0107
	(0.1000)	(-0.6800)
Ln (Acq. size)	-0.0224***	-0.0302***
	(-3.9100)	(-4.2200)
Sigma	1.1573**	1.6284***
	(2.4700)	(2.6500)

Leverage	0.1143***	0.1569***
	(3.1600)	(2.5900)
Participation of top-8	0.0636***	0.0907***
	(5.7900)	(5.9600)
Syndicate size lag	0.0640***	0.1115***
	(6.3700)	(5.2500)
Weighted size lag	0.0000	0.0009
	(-0.0200)	(1.0800)
Year fixed effect	YES	YES
N	4240	4240
Pseudo R^2	0.163	0.014

Table 3.II
The Use of Advisors in Acquisition-related Financing

This table reports the percentage of acquirers who employed their advisor(s) to help raise the funds for their acquisitions. The sample includes 995 externally financed transactions with non-missing information on the lead arrangers/book runners on the acquisition-related financing activities for the period 1990-2012. Column (1) reports the percentage of acquirers who hired at least one of the advisors in the syndicate to lead-manage their acquisition-related financing, particularly in debt/equity issuance and bank loan. Column (2) reports the summary statistics for individual advisors who also provided help to arrange financing.

	Syndicates	Individual Advisors
Acquisition-related financing	56.52%	26.15%
Source of financing:		
Debt/equity issuance	94.44%	64.91%
Bank-loan	53.73%	23.56%

Table 3.III
First-stage Regression of Syndicate Choice

This table provides the first-stage estimation results for the total synergy gain and takeover premium for the subsample of public acquisitions. The dependent variable in both columns is the probability of using a syndicate. The explanatory variables are the same as those in Table 3.4, except that *Public target* is omitted due to the restriction of the analysis to public deals only. Column (1) presents the first-stage regression results for total synergy gains; column (2) reports the results for takeover premium. All variables are defined in Appendix 3A. The year fixed effects are controlled for in both models but suppressed for brevity. The z-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.

	Synergy Gain	Premium
	Selection	**Selection**
	(1)	(2)
Syndicate size lag	0.1975***	0.3223***
	(2.7909)	(3.1129)
Weighted size lag	0.0020	-0.0016
	(0.8316)	(-0.4422)
Participation of top-8	0.2557***	0.2131*
	(2.7194)	(1.8797)
Ln (Deal size)	0.3446***	0.4778***
	(6.3480)	(7.1691)
Relative size	0.0758	0.1004
	(1.1197)	(1.1114)
Related	-0.1068	-0.2141**
	(-1.2064)	(-2.0059)
Hostile	0.1051	0.1225
	(0.5877)	(0.5644)
Cross-border	0.9132***	1.2444***
	(4.3704)	(3.9317)
Num. of bidders	0.0030	0.1779
	(0.0288)	(1.4684)
Cash shortfall	0.0983***	0.0471**
	(6.0213)	(2.3997)
Ln (Acq. size)	-0.1692***	-0.2116***
	(-3.4629)	(-3.3428)
Run-up	-0.1748**	-0.1889*
	(-2.0469)	(-1.8195)
Sigma	7.3286*	15.2519***
	(1.9008)	(3.2069)
Leverage	0.6648**	1.5936***
	(2.0909)	(4.0160)
Ln (1+Acq. exp.)	0.0178	0.1015
	(0.2788)	(1.1396)

Intercept	-2.8589*	-6.7789
	(-1.8065)	(-0.0810)
Year fixed effect	YES	YES
N	1393	1168

Table 3.IV
Two-step Treatment Procedure for Completion Probability

This table presents the estimation results from a two-step treatment procedure for deal completion probability for a subsample of deals in which acquirers have insufficient internal funds to finance the cash component of the offer, i.e., cash shortfall >0. Column (1) reports the Probit regression results of the first-stage selection equation, in which the dependent variable is a dummy variable equal to 1 if an acquirer uses a syndicate; and 0 otherwise. The explanatory variables in the first-stage regression are the same as those in Table 3.4. Column (2) of this table provides the results from the second-stage regressions of completion probability on syndicate dummy. Other variables are defined in Appendix 3A. All models control for the year fixed effects whose coefficients are suppressed. The z-statistics statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes the number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Selection	**Outcome**
	(1)	(2)
Syndicate		0.6117***
		(3.0195)
Ln (Deal size)	0.3244***	-0.2699***
	(6.2366)	(-4.6034)
Syndicate size lag	0.2000**	
	(2.4037)	
Weighted size lag	-0.0010	
	(-0.2835)	
Participation of top-8	0.4732***	0.0058
	(5.6069)	(0.0562)
Relative size	0.1099*	0.0255
	(1.8063)	(0.5024)
Related	-0.0674	0.1874**
	(-0.8528)	(2.1227)
Hostile	0.0457	-2.0108***
	(0.2426)	(-11.2217)
Tender		0.5106***
		(3.2819)
Cross-border	0.2733**	-0.1385
	(2.5420)	(-1.0845)
Num. of bidders	0.1710	-0.7996***
	(1.4359)	(-7.5933)
Public target	0.1568*	
	(1.9555)	
Cash shortfall	0.0337*	
	(1.7305)	
Ln (1+Acq. exp.)	0.1114	
	(1.5670)	
Pub. * All cash		-0.5707***

		(-4.0400)
Priv. * All cash		-0.0245
		(-0.1217)
Sub. * All cash		0.2338
		(1.2487)
Pub. * Pmt. incl. stock		-0.3440***
		(-2.8403)
Priv. * Pmt. incl. stock		0.1094
		(0.6548)
Ln (Acq. size)	-0.1673***	0.2153***
	(-3.4103)	(3.8576)
Run-up	-0.0286	-0.1052
	(-0.2861)	(-1.2582)
Sigma	9.7550***	-5.2635*
	(3.1920)	(-1.7394)
FCF		-0.1544
		(-0.5999)
Leverage	0.4083	0.0492
	(1.3979)	(0.1437)
Tobin's Q		-0.0176
		(-0.8195)
Rho		-0.3450**
		(-2.4000)
Intercept	-4.2008***	2.0178***
	(-3.3873)	(5.0237)
Year fixed effect	YES	YES
N	3295	3295

Table 3.V
Two-step Procedure for Acquirer CAR (-1, +1) using Alternative Instruments

This table reports the results from a two-step treatment procedure for the acquirer CARs for the full sample, using alternative exclusion restrictions. Specifically, column (1) presents the Probit regression results of the first-stage equation, where the dependent variable is a dummy variable equal to 1 if an acquirer uses a syndicate; and 0 otherwise. The explanatory variables in the first-stage regression are the same as those in Table 3.4, except that the two exclusion restrictions *Syndicate size lag* and *Weighted size lag* are replaced by the largest debt and equity market share (in U.S.$ billion) of the investment bank in an acquirer's syndicate in the calendar year before the announcement (*Largest debt/equity mkt. share prior year*). The results from the second-stage regressions of the acquirer 3-day CAR are provided in columns (2) and (3), where syndicate is measured as a dummy variable (*Syndicate Dummy*) and a count of the number of investment banks employed by an acquirer (*Syndicate Size*), respectively. The variable *Hazard ratio* is estimated from the first-stage regression, and included in the second-stage regression as an additional regressor to adjust for the potential self-selection bias. Other variables are defined in Appendix 3A. The year fixed effects are controlled for in all models with coefficients being suppressed. The z-statistics statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes the number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Selection	**Outcome**	
		Syndicate Dummy	Syndicate Size
	(1)	(2)	(3)
Syndicate		0.0516***	0.0481***
		(3.0188)	(2.9213)
Ln (Deal size)	0.3023***	0.0019*	0.0063***
	(13.8954)	(1.6810)	(3.3489)
Syndicate * Ln (Deal size)		-0.0075***	-0.0054***
		(-4.5231)	(-2.8831)
Largest debt mkt. share prior year	-0.0001		
	(-0.3739)		
Largest equity mkt. share prior year	0.0096***		
	(4.2350)		
Participation of top-8	0.2048***	0.0057**	0.0049*
	(3.8644)	(2.4586)	(1.8878)
Relative size	-0.0026	0.0041***	0.0042***
	(-0.2102)	(5.9322)	(4.7811)
Related	-0.0637	0.0007	0.0006
	(-1.4735)	(0.3459)	(0.2721)
Hostile	0.1210	-0.0126**	-0.0134**
	(1.0466)	(-1.9914)	(-2.2021)
Tender		0.0068*	0.0071
		(1.7371)	(1.2494)
Cross-border	0.3440***	-0.0027	-0.0034
	(6.2490)	(-1.0028)	(-1.2686)
Num. of bidders	0.2705***	-0.0022	-0.0030
	(3.9648)	(-0.5557)	(-0.5207)

Pub. * All cash		-0.0094**	-0.0095***
		(-2.5323)	(-2.6296)
Priv. * All cash		-0.0003	0.0002
		(-0.0706)	(0.0258)
Sub. * All cash		0.0024	0.0027
		(0.7049)	(0.8299)
Pub. * Pmt. incl. stock		-0.0454***	-0.0455***
		(-17.3269)	(-16.5127)
Priv. * Pmt. incl. stock		-0.0035	-0.0034
		(-1.1320)	(-0.9527)
Public target	0.0960**		
	(2.1088)		
Cash shortfall	0.0201**		
	(2.3907)		
Ln (1+Acq. exp.)	0.0687*		
	(1.8167)		
Ln (Acq. size)	-0.1479***	-0.0047***	-0.0043***
	(-7.1031)	(-4.9397)	(-4.3679)
Run-up	0.0604	-0.0057**	-0.0059*
	(1.3127)	(-2.5712)	(-1.8211)
Sigma	4.1184***	0.3152***	0.3071***
	(2.6629)	(4.2312)	(2.7526)
FCF		-0.0209***	-0.0209**
		(-3.3017)	(-1.9780)
Leverage	0.5048***	0.0299***	0.0291***
	(3.5636)	(4.2596)	(3.4760)
Tobin's Q		-0.0010**	-0.0010
		(-2.1192)	(-1.1285)
Hazard ratio		-0.0040	-0.0099***
		(-0.7175)	(-2.6125)
Intercept	-2.8897***	0.0189*	-0.0262
	(-10.6106)	(1.8533)	(-1.2322)
Year fixed effect	YES	YES	YES
N	6929	6929	6929

Table 3.VI
Two-step Procedure for Acquirer CAR (-1, +1) without Instruments

This table presents the estimation results from a two-step treatment procedure for the acquirer CARs for the full sample, without using any exclusion restrictions. Column (1) reports the Probit regression results of the first-stage equation, where the dependent variable is a dummy variable equal to 1 if an acquirer uses a syndicate; and 0 otherwise. The explanatory variables in the first-stage regression are the same as those in Table 3.4, except that the two exclusion restrictions *Syndicate size lag* and *Weighted size lag* are dropped. The results from the second-stage regressions of the acquirer 3-day CAR are provided in columns (2) and (3), where syndicate is measured as a dummy variable (*Syndicate Dummy*) and a count of the number of investment banks employed by an acquirer (*Syndicate Size*), respectively. The variable *Hazard ratio* is estimated from the first-stage regression, and included in the second-stage regression as an additional regressor to adjust for the potential self-selection bias. All the variables are defined in Appendix 3A. The z-statistics statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes the number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Selection	**Outcome**	
		Syndicate Dummy	Syndicate Size
	(1)	(2)	(3)
Syndicate		0.0443**	0.0466***
		(2.5648)	(2.8115)
Ln (Deal size)	0.3122***	0.0022*	0.0062***
	(14.4649)	(1.8881)	(3.2734)
Syndicate * Ln (Deal size)		-0.0071***	-0.0052***
		(-4.3261)	(-2.7939)
Participation of top-8	0.3506***	0.0061***	0.0049*
	(7.5146)	(2.6189)	(1.9057)
Relative size	-0.0038	0.0042***	0.0042***
	(-0.3028)	(5.9447)	(4.7796)
Related	-0.0634	0.0006	0.0006
	(-1.4732)	(0.3179)	(0.2697)
Hostile	0.1153	-0.0124**	-0.0135**
	(1.0078)	(-1.9606)	(-2.2047)
Tender		0.0069*	0.0071
		(1.7527)	(1.2486)
Cross-border	0.3280***	-0.0024	-0.0034
	(5.9824)	(-0.8865)	(-1.2551)
Num. of bidders	0.2775***	-0.0017	-0.0030
	(4.0987)	(-0.4361)	(-0.5101)
Pub. * All cash		-0.0094**	-0.0095***
		(-2.5179)	(-2.6273)
Priv. * All cash		-0.0003	0.0001
		(-0.0742)	(0.0150)
Sub. * All cash		0.0024	0.0027
		(0.7026)	(0.8257)
Pub. * Pmt. incl. stock		-0.0454***	-0.0455***
		(-17.2896)	(-16.5178)

Priv. * Pmt. incl. stock		-0.0035	-0.0035
		(-1.1329)	(-0.9656)
Public target	0.0969**		
	(2.1370)		
Cash shortfall	0.0192**		
	(2.3090)		
Ln (1+Acq. exp.)	0.0680*		
	(1.8077)		
Ln (Acq. size)	-0.1451***	-0.0048***	-0.0043***
	(-7.0139)	(-5.0770)	(-4.3761)
Run-up	0.0593	-0.0056**	-0.0059*
	(1.2881)	(-2.5402)	(-1.8174)
Sigma	4.2099***	0.3192***	0.3073***
	(2.7580)	(4.2841)	(2.7571)
FCF		-0.0209***	-0.0209**
		(-3.3049)	(-1.9788)
Leverage	0.5039***	0.0305***	0.0292***
	(3.5793)	(4.3362)	(3.4832)
Tobin's Q		-0.0010**	-0.0010
		(-2.1149)	(-1.1238)
Hazard ratio		-0.0011	-0.0093**
		(-0.1978)	(-2.4197)
Intercept	-2.9922***	0.0181*	-0.0246
	(-11.0006)	(1.7702)	(-1.1551)
Year fixed effect	YES	YES	YES
N	6929	6929	6929

Table 3.VII
Regression Results for Acquirer CAR over Alternative Windows

This table reports the results from the OLS regressions of acquirer CAR measured over alternative even windows and alternative market index for the full sample. In Panel A and B, the dependent variable is the cumulative abnormal return (CAR) on the acquirer's stock over the event window (-2, +2) and (-5, +5), respectively. The benchmark is the CRSP value-weighted index. The dependent variable in Panel C through E is acquirer CAR measured the event window (-1, +1), (-2, +2) and (-5, +5), respectively, where the benchmark is the CRSP equally-weighted index. In each panel, syndicate in columns (1) and (2) is measured as a dummy variable (*Syndicate Dummy*); and a count of the number of investment banks employed by an acquirer (*Syndicate Size*) in columns (3) and (4). We control the same set of control variables as in Table 3.5. To conserve space, however, the coefficients of these controls are suppressed here. Other variables are defined in Appendix 3A. 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.

Panel A: Acquirer CAR (-2, +2) using the value-weighted CRSP Index

	Syndicate Dummy		**Syndicate Size**	
	(1)	(2)	(3)	(4)
Syndicate	-0.0042	0.0399**	-0.0018	0.0204
	(-1.0012)	(2.1611)	(-0.6873)	(1.5832)
Syndicate * Ln (Deal size)		-0.0073***		-0.0032*
		(-2.7326)		(-1.9191)
Advisor reputation	YES	YES	YES	YES
Deal characteristics	YES	YES	YES	YES
Acquirer characteristics	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
N	6929	6929	6929	6929
R^2	0.094	0.096	0.094	0.095
Adj. R^2	0.088	0.091	0.088	0.089

Panel B: Acquirer CAR (-5, +5) using the value-weighted CRSP Index

	Syndicate Dummy		**Syndicate Size**	
	(1)	(2)	(3)	(4)
Syndicate	-0.0006	0.0389**	0.0016	0.0238*
	(-0.1260)	(2.0735)	(0.5229)	(1.7949)
Syndicate * Ln (Deal size)		-0.0065**		-0.0032*
		(-2.3887)		(-1.8776)
Advisor reputation	YES	YES	YES	YES
Deal characteristics	YES	YES	YES	YES
Acquirer characteristics	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
N	6929	6929	6929	6929
R^2	0.081	0.082	0.081	0.081

Adj. R^2	0.075	0.076	0.075	0.076

Panel C: Acquirer CAR (-1, +1) using the equally-weighted CRSP Index

	Syndicate Dummy		**Syndicate Size**	
	(1)	(2)	(3)	(4)
Syndicate	-0.0008	0.0400**	0.0007	0.0206*
	(-0.2126)	(2.3806)	(0.2824)	(1.7084)
Syndicate * Ln (Deal size)		-0.0067***		-0.0029*
		(-2.7697)		(-1.8309)
Advisor reputation	YES	YES	YES	YES
Deal characteristics	YES	YES	YES	YES
Acquirer characteristics	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
N	6929	6929	6929	6929
R^2	0.106	0.108	0.106	0.107
Adj. R^2	0.100	0.103	0.100	0.101

Panel D: Acquirer CAR (-2, +2) using the equally-weighted CRSP Index

	Syndicate Dummy		**Syndicate Size**	
	(1)	(2)	(3)	(4)
Syndicate	-0.0039	0.0390**	-0.0015	0.0195
	(-0.9313)	(2.1770)	(-0.6064)	(1.5517)
Syndicate * Ln (Deal size)		-0.0071***		-0.0031*
		(-2.7322)		(-1.8656)
Advisor reputation	YES	YES	YES	YES
Deal characteristics	YES	YES	YES	YES
Acquirer characteristics	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
N	6929	6929	6929	6929
R^2	0.095	0.097	0.095	0.096
Adj. R^2	0.089	0.092	0.089	0.090

Panel E: Acquirer CAR (-5, +5) using the equally-weighted CRSP Index

	Syndicate Dummy		**Syndicate Size**	
	(1)	(2)	(3)	(4)
Syndicate	-0.0008	0.0412**	0.0016	0.0255*
	(-0.1782)	(2.2644)	(0.5286)	(1.9484)
Syndicate * Ln (Deal size)		-0.0069***		-0.0035**
		(-2.6157)		(-2.0341)
Advisor reputation	YES	YES	YES	YES
Deal characteristics	YES	YES	YES	YES
Acquirer characteristics	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES

N	6929	6929	6929	6929
R^2	0.081	0.082	0.081	0.082
$Adj.\ R^2$	0.075	0.077	0.075	0.076

Table 3.VIII
Controlling for Industry Fixed Effects

This table reports the results from the OLS regressions of the acquirer 3-day CAR on syndicate measures and other advisor-, deal- and acquirer- characteristics for the full sample, controlling for industry fixed effects based on the Fama-French 48 industries classification. The dependent variable is the cumulative abnormal return (CAR) on the acquirer's stock over the event window (-1, +1), which is winsorized at the 1% and 99% percentiles. Syndicate in columns (1) and (2) is measured as a dummy variable (*Syndicate Dummy*), which equals 1 if more than one investment bank was hired by an acquirer; and 0 otherwise. In columns (3) and (4), syndicate is measured as a count of the number of investment banks employed by an acquirer (*Syndicate Size*). Other variables are defined in Appendix 3A. Year and industry fixed effects are controlled for in all models, with the coefficients 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.

	Syndicate Dummy		**Syndicate Size**	
	(1)	(2)	(3)	(4)
Syndicate	-0.0014	0.0399**	0.0003	0.0213*
	(-0.3806)	(2.4954)	(0.1259)	(1.8677)
Ln (Deal size)	0.0005	0.0017	0.0004	0.0040**
	(0.3631)	(1.4688)	(0.2804)	(2.2690)
Syndicate * Ln (Deal size)		-0.0068***		-0.0031**
		(-2.9346)		(-2.0361)
Participation of top-8	0.0059**	0.0057**	0.0058**	0.0055**
	(2.3196)	(2.3047)	(2.2474)	(2.1966)
Relative size	0.0041***	0.0040***	0.0041***	0.0041***
	(4.7347)	(4.7383)	(4.7382)	(4.7464)
Related	0.0029	0.0030	0.0029	0.0030
	(1.1929)	(1.2707)	(1.1959)	(1.2554)
Hostile	-0.0141**	-0.0122**	-0.0141**	-0.0131**
	(-2.2328)	(-2.0518)	(-2.2488)	(-2.1630)
Tender	0.0075	0.0064	0.0073	0.0066
	(1.2894)	(1.2124)	(1.2484)	(1.2041)
Cross-border	-0.0023	-0.0023	-0.0024	-0.0025
	(-0.8163)	(-0.8188)	(-0.8586)	(-0.8910)
Num. of bidders	-0.0032	-0.0031	-0.0034	-0.0032
	(-0.5501)	(-0.5645)	(-0.5718)	(-0.5651)
Pub. * All cash	-0.0081**	-0.0083**	-0.0080**	-0.0082**
	(-2.3081)	(-2.4095)	(-2.3051)	(-2.3774)
Priv. * All cash	0.0018	0.0011	0.0017	0.0013
	(0.2972)	(0.1997)	(0.2824)	(0.2204)
Sub. * All cash	0.0037	0.0031	0.0037	0.0033
	(1.1276)	(0.9309)	(1.1197)	(0.9930)
Pub. * Pmt. incl. stock	-0.0426***	-0.0426***	-0.0427***	-0.0427***
	(-14.6808)	(-14.6711)	(-14.6767)	(-14.6863)
Priv. * Pmt. incl. stock	-0.0011	-0.0008	-0.0011	-0.0010
	(-0.2928)	(-0.2349)	(-0.3050)	(-0.2761)
Ln (Acq. size)	-0.0045***	-0.0046***	-0.0045***	-0.0044***
	(-4.5704)	(-4.6756)	(-4.5297)	(-4.4685)

Run-up	-0.0055*	-0.0057*	-0.0055*	-0.0057*
	(-1.6785)	(-1.7363)	(-1.6855)	(-1.7476)
Sigma	0.3426***	0.3463***	0.3413***	0.3436***
	(2.8257)	(2.8516)	(2.8142)	(2.8324)
FCF	-0.0267**	-0.0268**	-0.0267**	-0.0268**
	(-2.4770)	(-2.4821)	(-2.4753)	(-2.4825)
Leverage	0.0271***	0.0262***	0.0269***	0.0262***
	(3.0909)	(3.0095)	(3.0708)	(3.0047)
Tobin's Q	-0.0007	-0.0007	-0.0007	-0.0007
	(-0.7651)	(-0.7864)	(-0.7646)	(-0.7760)
Intercept	0.0437***	0.0396***	0.0438***	0.0206
	(3.7516)	(3.3646)	(3.6341)	(1.1158)
Industry fixed effect	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
N	6921	6921	6921	6921
R^2	0.116	0.119	0.116	0.118
Adj. R^2	0.105	0.107	0.105	0.106

Table 3.IX
Controlling for Target Syndicate Characteristics

This table reports the results from the OLS regressions of the acquirer 3-day CAR on syndicate measures and other advisor-, deal- and acquirer- characteristics for the full sample, controlling for target syndicate characteristics. The dependent variable is the cumulative abnormal return (CAR) on the acquirer's stock over the event window (-1, +1), which is winsorized at the 1% and 99% percentiles. Syndicate in columns (1) and (2) is measured as a dummy variable (*Syndicate Dummy*), which equals 1 if more than one investment bank was hired by an acquirer; and 0 otherwise. In columns (3) and (4), syndicate is measured as a count of the number of investment banks employed by an acquirer (*Syndicate Size*). Other variables are defined in Appendix 3A. Year fixed effects are controlled for in all models, with the coefficients 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.

	Syndicate Dummy		**Syndicate Size**	
	(1)	(2)	(3)	(4)
Syndicate	-0.0015	0.0379**	0.0016	0.0196
	(-0.3648)	(2.0168)	(0.6305)	(1.6275)
Ln (Deal size)	-0.0023	-0.0013	0.0025*	0.0051***
	(-1.4688)	(-0.9302)	(1.8238)	(2.8016)
Syndicate * Ln (Deal size)		-0.0062**		-0.0027*
		(-2.3295)		(-1.6757)
Targ. Syndicate	0.0014	-0.0060	0.0055	0.0028
	(0.1227)	(-0.5105)	(1.0970)	(0.6024)
Targ. Syn.* Ln (Deal size)	-0.0003	0.0010	-0.0014*	-0.0009
	(-0.1589)	(0.5497)	(-1.7241)	(-1.1546)
Participation of top-8	0.0076***	0.0073***	0.0062**	0.0060**
	(2.6261)	(2.6085)	(2.3602)	(2.3428)
Relative size	0.0039***	0.0039***	0.0042***	0.0042***
	(5.1278)	(5.0708)	(4.7964)	(4.7953)
Related	-0.0002	-0.0000	0.0004	0.0005
	(-0.0879)	(-0.0086)	(0.1846)	(0.2365)
Hostile	-0.0108*	-0.0099*	-0.0129**	-0.0125**
	(-1.7700)	(-1.6782)	(-2.0603)	(-2.0401)
Tender	0.0093*	0.0084*	0.0080	0.0074
	(1.7552)	(1.7378)	(1.3328)	(1.3154)
Cross-border	-0.0034	-0.0037	-0.0023	-0.0025
	(-1.0537)	(-1.1474)	(-0.8650)	(-0.9110)
Num. of bidders	-0.0011	-0.0013	-0.0013	-0.0013
	(-0.2090)	(-0.2588)	(-0.2105)	(-0.2198)
Pub. * All cash	-0.0107***	-0.0107***	-0.0092**	-0.0092**
	(-2.8980)	(-2.9699)	(-2.4085)	(-2.4486)
Priv. * All cash	0.0072	0.0061	0.0003	-0.0001
	(0.8727)	(0.8179)	(0.0471)	(-0.0131)
Sub. * All cash	0.0039	0.0033	0.0031	0.0028
	(0.9797)	(0.8342)	(0.9431)	(0.8476)
Pub. * Pmt. incl. stock	-0.0435***	-0.0434***	-0.0452***	-0.0451***
	(-13.9541)	(-13.8679)	(-16.2946)	(-16.2127)
Priv. * Pmt. incl. stock	-0.0054	-0.0053	-0.0036	-0.0036

	(-1.1672)	(-1.1376)	(-1.0119)	(-0.9945)
Ln (Acq. size)	-0.0029***	-0.0030***	-0.0047***	-0.0047***
	(-2.7908)	(-2.8551)	(-4.8681)	(-4.8405)
Run-up	-0.0026	-0.0028	-0.0056*	-0.0057*
	(-0.6849)	(-0.7352)	(-1.7307)	(-1.7680)
Sigma	0.1066	0.1053	0.3251***	0.3212***
	(0.7536)	(0.7433)	(2.9167)	(2.8768)
FCF	-0.0148	-0.0154	-0.0210**	-0.0212**
	(-1.1243)	(-1.1685)	(-1.9836)	(-2.0052)
Leverage	0.0369***	0.0362***	0.0311***	0.0307***
	(3.8348)	(3.8141)	(3.6766)	(3.6600)
Tobin's Q	-0.0009	-0.0009	-0.0010	-0.0010
	(-1.1350)	(-1.1701)	(-1.1216)	(-1.1345)
Intercept	0.0216**	0.0175*	0.0144	-0.0033
	(2.1659)	(1.7087)	(1.2456)	(-0.1769)
Year fixed effect	YES	YES	YES	YES
N	5024	5024	6929	6929
R^2	0.113	0.115	0.106	0.106
$Adj. R^2$	0.105	0.107	0.100	0.101

CHAPTER 4: INTERBANK NETWORKING, PEER PRESSURE AND THE PERFORMANCE OF INVESTMENT BANKING SYNDICATES IN M&As

"*[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 et al., 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, however, is the role of interbank networks in counteracting the free-rider problem that is salient in peer cooperation, or more specifically, investment banking syndication. Indeed, many investment banking studies indicate 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 chapter, we explore the governance role of interbank relationships in the context of M&As. We ask whether the interconnections between the 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, though 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.[52] 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 efforts and punish those who free ride.

Peer pressure can take 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 make future cooperation contingent on whether a member bank free rides in the current deal.[53] Specifically, if any of the 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 share of fee (as in the standard one-shot game), but also by a loss of

[52] McLaughlin (1990, 1992) finds that in a typical fee contract, over 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.

[53] 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 of what size, the lead advisor and other syndicate members may influence its choice of co-advisors by recommending the banks with which they have had prior relationships.

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 will provide higher work effort when peer pressure is present than when 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 obvious costs which arise due to the activities of monitoring and sanctioning 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 related 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, interbank networks raise the power of mutual sanctioning (Fudenberg and Maskin, 1986; Kandori, 1992b). A notable phenomenon in investment banking 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 related investment banks in that it conveys greater potential for future cooperation. This benefit, however, must be balanced against more credible and rapid retaliation if one free rides on its immediate ties (Fudenberg and Maskin, 1986; Kandori, 1992a; Fehr et al., 1997; Hochberg et al., 2010). Moreover, reciprocity may encourage relationship investment banks to co-invest in certain assets such as information source 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 “break up” the relationship, they aggravate the peer penalty (Rauch, 2001; Brown et al., 2004; Rayo, 2007; Gilsing et al., 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 being equal, this should lead to greater effort provision and better acquisition performance measured by acquirer cumulative abnormal return (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 ties); 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 et al., 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 the non-syndicated deals, there is an additional problem of sample selection bias that 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 et al., 2012).

Using a sample of U.S. syndicated M&A transactions announced from 1/1/1990 to 31/12/2012, 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 the average-sized acquirer in our sample. We further conduct a difference-in-difference analysis on the repeal of the Glass-Steagall Act in 1999, which created an exogenous variation in network density characterizing each syndicate. The evidence from this test supports the causal relation between density and acquirer abnormal returns.

The value of interbank relationships may create differences in the observed peer behavior, depending on how frequently a pair of syndicate members interacted in the past. Consistent with this conjecture, we find that the positive effect of interbank networks on acquirer CAR accrues mainly to the ties that involve the most recent interaction between syndicate members over the last year, but not to those ties where the interaction has taken place over a relatively longer idle time period. Thus, an investment bank responds to behave cooperatively only if the value of the peer relationships, as reflected in the frequency of past interaction, is sufficiently high.

We explore various possible explanations for our findings regarding the positive association between network density and acquirer abnormal returns. First, the positive acquirer CARs may arise because related 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 who have demonstrated themselves as capable and honest partners can maintain their ties over time (Li and Rowley, 2002). Though 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 leads to better matching or a greater fraction of high-quality advisors to participate in a syndicate, then the positive density-acquirer CAR association 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 plays a key role in determining the value of interbank networks. In hot markets where syndication activities occur 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 et al., 2003). Thus, the positive association between interbank connections and acquirer returns we document may merely capture the governance effect of lead advisor reputation rather than that of interbank networks. 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. However, contrary to well-accepted economic wisdom, 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. In particular, 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 that 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 for unrelated bankers into a syndicate, which helps an acquirer preserve the quasi-rents provided to promote effort. We discriminate this alternative from the "peer-pressure" explanation by examining the level of fees paid to more densely networked syndicates. 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, thus, 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 networks lower the acquirer's cost of providing incentives through fees.

The present chapter 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 has largely focused on the single-advisor setting and explored various advisor characteristics in explaining cross-sectional differences in acquirer announcement returns, e.g., advisor reputation (Bowers and Miller, 1990; Servaes and Zenner, 1996; Rau, 2000; Rau and Rodgers, 2002; Kale et al., 2003; Walter et al., 2008; Bao and Edmans, 2011; Golubov et al., 2012), specialization in the M&A market (Song et al., 2013), dual agency (Agrawal et al., 2013), and the provision of fairness opinions (Kisgen et al., 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 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 are 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, the current chapter 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., Riordan and Williamson, 1985; Boot and Thakor, 2000; Asker and Ljungqvist, 2010; Ogura, 2010; Degryse et al., 2011; Engelberg et al., 2012; Hale, 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 it are weak, investment banks are induced to cooperate to prevent one another from free riding on costly information-gathering efforts. For this commitment to be self-enforcing, however, cooperation must be sufficiently profitable. This requires the aggregate market structure to be oligopolistic, with the entry into the market restricted. 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 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.

Our work is similar in its scope to the above papers in that it also 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's perspective. Moreover, our explicit attention to interbank networking as an endogenously emerged device that enhances the peer pressure effect is novel compared with the arguments adopted in the above papers. 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 present chapter differs from theirs in that we focus 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, the chapter links to a growing body of research which shows that peer pressure is highly effective in encouraging work effort in public good experiments (Fehr et al., 1997;

Carpenter et al., 2009), farms (Bandiera et al., 2005), contest between groups (Abbink et al., 2010), and firms (Mas and Moretti, 2009; Hochberg and Lindsey, 2010). We add to this strand of research by presenting the first empirical evidence on the effects of peer pressure in the investment banking context. More importantly, the present chapter yields a host of new insights that are absent in the extant literature. We show that peer effects are not uniform across different types of ties. Older, less frequently updated ties provide a weaker countervailing force against free-riding and *vice versa*. Peer effects are also more pronounced in hot markets where the power of peer punishment is strengthened through a higher level of expected payoffs. These findings indicate that even if investment banks in a syndicate are linked, they do not cooperate out of pure altruism, i.e., truly care about their friends' wellbeing and payoffs. Instead, they refrain from shirking only when the peer sanction is sufficiently harsh. Where future interactions are expected to be limited either because of market conditions or infrequent past interaction, investment banks are induced to capture the immediate rents through effort reduction. We further show that interbank networks can significantly influence 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, thereby enabling an acquirer to pay less to motivate optimal effort. The evidence echoes the predictions of many economic models that 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 chapter 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 other explanations for our results. Section 7 performs robustness check, and Section 8 concludes the chapter.

2. Theoretical Framework

2.1. Moral Hazard and Peer Pressure

The difficulty of observing individual agents' effort and the resulting moral hazard problem are 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 effort in networking with their respective investors, which overlaps with each another and is difficult to monitor. As a result, shirking is tempting because part of the cost of exerting low effort in information production is borne by the other investment banks in a syndicate rather than fully internalized by the free rider.

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 separately observable (Alchian and Demsetz, 1972). 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 such 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, which should allow 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. The complex, non-routine nature of M&As makes it possible that monitoring is 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).[54]

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 literature is that by 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 his own effort as well as that of his 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 from both the monetary penalty set under the compensation rule, and peer sanction that

[54] 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 of the chapter.

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 reputation 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; Fitzroy and Kraft, 1987).[55] 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 et al., 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, though the profit-

[55] There is a potential implicit collusion problem where connected banks may collude to work against the best interests of the acquirer. We, however, believe that reputation concerns reinforced through repeated dealings will serve as a mechanism that prevents this collusion problem.

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 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). Consequently, the question boils down to whether there exist certain devices that enhance the peer pressure function by easing mutual monitoring, while amplifying the severity of the sanction that one investment bank can impose on other syndicate members. We conjecture that interbank networks serve as such a device, 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). [56] One possible explanation for this phenomenon is that investment banks strategically network with each other to facilitate the operation of the peer pressure mechanism necessary for deterring free-riders (Persons and Warther, 1997; Anand and Galetovic, 2000; Benveniste et al., 2003; Morrison and Wilhelm, 2008).[57] Specifically, peer relationships permit investment banks to,

[56] 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).

[57] There are additional concerns that cooperation may create chances for partner 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 spill-over effect that causes their financial innovations to be easily reverse-engineered precludes perfect competition in the investment banking

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 the 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 inferences on expected outcomes (e.g., Holmstrom, 1982; Kandori, 1992b; Dixit, 2003). 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).

However, for syndicates in which members are relatively unrelated and thus unknown to one another, peer monitoring is likely to be imperfect. Absent mutual knowledge, the uncertainty concerning what performance each syndicate member shall achieve, increases (Prendergast, 2002). Thus, unless considerable time and effort are devoted to monitor individual actions, the lack of a proper "benchmark" on expected effort implies that it is more costly and challenging for unrelated member banks to accurately read on one another's effort level and, hence, detect who actually free rides (Kandel and Lazear, 1992; Mohnen et al., 2008). Accordingly, we expect mutual monitoring to be more effective in more densely linked syndicates 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, hence, can better read the member's effort signals).

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industry. This implies that investment banks would prefer to cooperate with and stick to those banks with which they are familiar (Persons and Warther, 1997; Anand and Galetovic, 2000; Benveniste et al., 2003).

In addition, peer relationships raise the *ex post* sanctioning capabilities of investment banks in a syndicate. The phenomenon of stable peer cooperation sketched above indicates that reciprocity is expected and that existing ties confer a greater probability 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. Furthermore, reciprocity may encourage relationship-specific investment, which further amplifies 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 a common language, specific communication channels and routines in order to increase efficiency gains from long-run cooperation (e.g., through reduced costs and complexities in streamlining decision making) (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 more costly when investment banks are cooperating with someone they know (Rauch, 2001; Brown et al., 2004; Rayo, 2007; Gilsing et al., 2008). We are thus led to expect that the more densely networked a syndicate, the more effective the peer pressure mechanism. All else being equal, this should translate into greater effort provision and better acquisition outcomes. Formally, we hypothesize that:

H1a: *Ceteris paribus*, the degree of connections between syndicate members positively affects acquirer abnormal returns.

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 pronounced in deals where the information asymmetry between acquirer and advisors is severe and, therefore, 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). Like 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 being 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 advisors' incentive to free ride because neither individual activities nor the joint outcome can be easily understood and related to advisors' effort provision with any precision (e.g., Oxley, 1997; Kaplan and Stromberg, 2004; Hochberg and Lindsey, 2010). We thus hypothesize that:

H1b: *Ceteris paribus,* the effect of interbank networks on acquisition performance is evident in deals in which the acquirer-advisor tie is absent.

H1c: *Ceteris paribus*, the effect of interbank networks on acquisition performance is evident in large transactions.

To test the conditional effects of interbank networks on acquisition performance, we perform regression analysis 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 fewer than two investment banks advising the acquirer; (ii) had the 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. Measurement 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 before the announcement. Panel C, Table 4.1, 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%. [58]

3.2.2. Measurement of Interbank Networks

As is standard in the literature (e.g., Hochberg et al., 2007, 2010), 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.[59] 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 have a tie, and zero otherwise.[60] 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

[58] The mean CAR is statistically insignificantly different from zero (with a p-value of 0.3199).

[59] 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 (refer to Appendix 4B Table 4.XI).

[60] 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 (see Appendix 4B Table 4.X).

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. Formally, the measure of network density can be written as follows:

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

Where:

D_S = symmetric density of syndicate S;

n = syndicate size;

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

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

To gain further intuition for density, Figure 4.2a depicts the networks for two hypothetical syndicates, "S_a" and "S_b". Each syndicate has four investment banks, 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 whereas the network of syndicate "S_b" is relatively sparse, with only one member being tied to another.

Figure 4.2b shows the matrix for each syndicate. For a syndicate comprising four investment banks, the maximum number of possible ties is 12 (4x3). Given that the sum of existing ties in syndicate "S_a" is 10, its relative degree of density is 10/12 (10 out of 12 possible ties). The degree of density in syndicate "S_b" is 2/12 (2 out of 12 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 2009. 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.[61] Panel A, Table 4.1, 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 research to be important determinants of acquirer CAR (e.g., Kale et al., 2003; Moeller et al., 2004; Masulis et al., 2007; Moeller et al., 2007; Golubov et al., 2012; Alexandridis et al., 2013; Song et al., 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.[62] Table 4.1, Panels B and C, report the sample summary statistics for these control variables. 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 approximately 8% (9.8%) and the mean (median) leverage ratio is around 18.8%

[61] 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.
[62] To avoid any multicollinearity problems, we do not control for acquirer stock price volatility (sigma), which is highly correlated with relative transaction size in our sample (at the level of 67.82%).

(16%). Tobin's Q is positively skewed, with a mean value of 2.070 versus a median of 1.507. The targets are relatively large for these syndicated deals, accounting for 66.2% of average acquirer size. Public and industry-related transactions make up 55.1% and 63.6% of the sample deals, respectively. 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 were 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. M&As 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, Table 4.1, indicates that roughly 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. In Chapter 3, we 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 syndicates in our sample is 2.23 (2) with a standard deviation of 63.7% (see Panel A, Table 4.1).

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 with 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 the interbank network 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 previously worked for the acquirer. 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, Table 4.1, indicates that the mean (median) vertical relationship density is 10.00% (0.00%) in our sample, with a standard deviation of 30.90%.

In Appendix 4A, we summarize all the variables used in our empirical analysis. The variance inflation factors (VIF) for these variables are presented in Table 4.2. None of the VIF values exceed the critical value of 10 (Gujarati, 2003), suggesting that multicollinearity is unlikely to be a concern.

[Insert Tables 4.1 & 4.2 Here]

4. An Empirical Framework for Analyzing 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 emerge exogenously. 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 effort (Himmelberg et al., 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 and 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 because of reputational concerns. If so, 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 the prior work and adopt a three-stage, selection-adjusted IV approach. In particular, we consider the model with the following form:

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

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

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

$where$:

$Syndicate_i = 1;$ $Density_i$ 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 that 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.[63] In Equation (4), we model the sample selection by specifying a selection rule based on whether a syndicate is observed. 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 equation 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, whereas 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 (see Chib, Greenberg and Jeliazkov, 2009).

[63] 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.

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 1990-2012, regardless of whether a syndicate is formed. The dependent variable is a binary variable equal to one if syndication is realized and zero otherwise. As in Chapter 3, we employ three categories of explanatory variables. The first category relates to transaction complexity which is measured by deal size, hostility of target management towards a deal, number of competing bidders, payment of stock, industry relatedness, target firm's listing status and whether the acquirer and the target are from different countries. The second set measures 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 flow. The last category controls for factors that may render the formation of a syndicate unnecessary, including acquirer size, stock return volatility, leverage ratio, stock price run-up, prior acquisition experience and the presence of a top-8 advisor in a syndicate. 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)*.[64] These two variables are constructed to capture unobserved factors that may affect the propensity to hire a syndicate across acquiring firms over time. 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}), whereas the generalized residual computed from the first step is

[64] Though the sample selection model, in principle, can be identified through the non-linearity of the general residuals (Heckman, 1978;Wilde, 2000), it is advisable to have at least one excluded variable to help with nonparametric identification (e.g., Maddala, 1983; Terza, 1998).

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 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 one other (e.g., through the participation of the same local associations, professional meetings and other similar events). This increases the probability for these bankers to establish ties (Hong, Kubik and Stein, 2005; 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.[65] 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 any. To account for the possibility that the degree of network density in an M&A syndicate is influenced by both the duration and

[65] 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).

strength of underwriting relationships in the debt market, we construct two variables. The first variable is an 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 an acquirer's 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 measure the density of interbank networks present in the acquirer's Federal State by the proportion of logically possible ties that exist among *all* the investment banks headquartered in the acquirer's State (*local network density*). Again, a tie exists if two investment banks have syndicated M&A deals one year before the announcement year.[66] 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 cause 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).[67] With this relatively large instrument set, we estimate our IV model (Equations (2) and (3)) by limited information maximum

[66] 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.
[67] 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.

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, 1974, 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, whereas the bias of 2SLS estimator increases with the size of the instrument set. In addition, the LIML estimator is more robust to weak instruments (i.e., instruments that are correlated with an endogenous regressor but only weakly) compared with 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 M&A performance. 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, 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 4.3. 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 by 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.

[Insert Table 4.3 Here]

5.2. Selection-adjusted Instrumental Variable Approach

We begin by estimating Equation by Probit (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), Table 4.4, 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. 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 the 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 the various resources of different investment banks, are more likely to get involved in complex deals. Consistent with our univariate 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 that 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), Table 4.4, 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 4.5. The dependent variable in each specification of Table 4.4 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), Table 4.4, presents the regression results for the full sample. Consistent with the intuition that an 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 being 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 60^{th} 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 of 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 4.4, we report the Hensen-J test statistics for our instruments for each specification. In all five columns, the p-value of the J statistic 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 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 only in the vertically unrelated subsample (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, 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 only in the vertically unrelated subsample (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 to involve a foreign advisor in a syndicate with 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 an only marginally significant effect on network density. Overall, the results presented in Table 4.4 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.

[Insert Table 4.4 Here]

In Table 4.5, 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 a 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 deals where acquirers are tied to one or more advisors in a syndicate. As seen in column (3), Table 4.5, 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 in the type of deals where the level of information asymmetry between acquirer and advisors is high and, hence, where peer pressure is likely to add value through a reduction in free-riding.

The parameter estimates of most control variables in Table 4.5 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 (2007), acquiring firms with higher Tobin's Q are related to lower CARs. The abnormal returns are, however, significantly higher when an acquirer experiencing greater stock price run-up undertakes a deal at or below the 60th percentile of the size distribution (column (5)), and when 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 but 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, hostility of target management and whether the deal is a tender 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.

[Insert Table 4.5 Here]

5.3. Variation in Cut-off Points of Transaction Size

Selection of the 60^{th} percentile of the transaction size as a cut-off point is obviously arbitrary. Thus, a natural concern about the above analysis is whether the relative strength of the density-acquirer CAR association varies if a different cut-off point of transaction size is used. 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 4.6, we test this conjecture by repeating our CAR analysis on the subsamples split at the 50^{th} and 75^{th} percentile. Again, Equations (2) and (3) are jointly estimated by LIML, conditional on the use of a syndicate. The instruments are the same as before. For the sake of brevity, we present only the estimates for the main equation of acquirer CAR with the estimates for the selection and reduced form equations reported in Appendix 4B Table 4.I. 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 4.5 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 economically sizable and 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 networking 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 4.5.

[Insert Table 4.6 Here]

5.4. A Quasi-natural Experiment with the 1999 Repeal of the Glass-Steagall Act

To further verify the causal relation between density and acquirer abnormal returns, we employ a simple experimental approach. Specifically, we exploit the repeal of the Glass-Steagall Act in 1999, which created an exogenous variation in network density characterizing each syndicate. Before the repeal of the Glass-Steagall Act, commercial banks were prohibited from underwriting corporate securities and, hence, primarily hired by acquiring firms in debt-financed deals for the purpose of obtaining access to bank loans (Allen, Jagtiani, Peristiani and Saunders, 2002). On November 12, 1999, the Gramm-Leach-Bliley Act repealed the Glass-Steagall restrictions on the ability of commercial banks to underwrite securities. This essentially permitted commercial banks to compete directly for stock-financed M&A deals that were predominantly advised by investment banks before the repeal. As a result, there was an increase in the number of financial advisors that could offer both acquisition advising and underwriting services, which reduced the average density of syndicates advising on stock offers after the repeal.[68] Accordingly, if the positive cross-sectional density-acquirer CAR association that we document is truly attributable to peer monitoring and sanction, we should observe that syndicates working on stock-financed deals generate lower acquirer abnormal returns following the "shock", given that lower density induces a weaker peer pressure effect.

We test this prediction by focusing on the sample period 1998-1999, which is right around the time of the legislative change.[69] The following specification is estimated by a difference-in-difference estimator:

$$y_i = \alpha_0 + \beta HighStockFinancing_i + \gamma Post + \delta HighStockFinancing_i * Post + \theta X_i + \varepsilon_i \, ; \qquad (5)$$

where y_i denotes the acquirer three-day CAR; $HighStockFinancing_i$ is an indicator variable equal to one if the value of stock financing is at or above the mean for the sample tested (the treated group) and zero otherwise (the control group).[70] *Post* is coded as one if an observation occurs in 1999 and zero otherwise. The main variable of interest is the interaction term between $HighStockFinancing_i$ and *Post*. The coefficient δ estimates the impact of the repeal of the Glass-Steagall Act on acquirer CAR for deals in which the value of stock financing is at or above the mean (the treated group). As noted earlier, we expect this coefficient to take a

[68] To illustrate, the measure *density* is defined as "the number of ties formed" over "the number of possible ties" among syndicate members. As the repeal of the Glass-Steagall Act removed the barrier for commercial banks to advising stock-financed deals, competition became fiercer for existing investment banks. There was a lot of talk, for example, about how commercial banks took away business from investment banks by successfully soliciting their banking clients to use them for M&A and associated underwriting work after the repeal. Consistent with this argument, empirical evidence shows that acquirers tend to select their relationship commercial banks as advisors in mergers (Allen et al., 2002). Thus, investment banks were forced to accept co-advisors that they would not have traditionally chosen (i.e., commercial banks that were previously restricted from underwriting due to their commercial banking activities by the Glass-Steagall Act). With these new entrants joining a syndicate, the numerator of *density* decreases and the denominator increases, giving a lower density at the syndicate level.

[69] It is worth noting that M&A transactions increased sharply in the 1990s, especially during the dot-com bubble. Thus, a drop in network density of a syndicate during booms might be driven by capacity constraints that have forced financial advisors to syndicate transactions with a wider group of peers that they would not traditionally choose. To alleviate this potential concern, we restrict the sample period to 1998-1999, during which M&A transactions peaked in both years.

[70] Our results broadly hold for alternative cut-off points such as the median.

negative sign if density has a causal effect on acquirer CAR. X_i is the same vector of covariates as in Table 4.5, except that we exclude the natural logarithm of deal size and the *All-cash* dummy variable given that *HighStockFinancing*$_i$ is a product of deal value and percentage of stock. [71] ε_i is the error term.

The estimation results are provided in Appendix 4B Table 4.II. As before, we run separate difference-in-difference cross-sectional regressions for the full sample, the vertically unrelated subsample and the subsample of large deals. For completeness, we report the results for large deals defined based on all cut-off points (i.e., the 50th, 60th and 75th percentile). We find that the results are similar across all five model specifications. The *Post* variable is statistically insignificant throughout the table, indicating that the repeal of the Glass-Steagall Act has no impact on acquirer abnormal returns for syndicated deals with below-mean stock-financing (the control group). The estimate for the *High Stock Financing* variable is similarly insignificant in all specifications. Thus, acquirer returns do not appear to change significantly for syndicated deals that involve at- or above-mean stock-financing before and after the repeal. The coefficient on the interaction term, *High Stock Financing * Post*, is negative and marginally significant in the full sample, but significant at the 5% level in each subsample of large deals defined based on different size cut-off points. For the analysis on the vertically unrelated subsample, however, the effect is statistically insignificant. Overall, the results indicate that the repeal of the Glass-Steagall Act, which in effect decreased network density for syndicates advising on at- or above-mean stock financed offers, resulted in lower average acquirer abnormal returns for these syndicates. This confirms our previous finding of the positive association between density and acquirer CAR around the deal announcement.

[71] Our results are robust to the inclusion of these two variables, as well as a full control of the six interaction effects between target status and payment method.

5.5. Time Decay of Peer Relationships

We have used a one-year rolling window to determine whether investment banks in a syndicate are tied to each other through past syndication. This allows us to capture interbank relationships that are most up-to-date. An interesting related question is whether the disciplinary value of peer relationships decays over time, such that less active ties provide a weaker countervailing force against free-riding and *vice versa*. Specifically, the threat of exclusion from relationships plays a key role in motivating an incumbent investment bank to work in our setting. For the threat to have “teeth”, however, the relationships must be sufficiently valuable or an incumbent investment bank would not care about losing them (Fudenberg and Maskin, 1986; Kandori, 1992b; Morrison and Wilhelm, 2007). This is easy if a pair of syndicate members has maintained active interaction over time, in which case the expected profit from the relationship is likely to outweigh the loss of the one-shot gain from shirking. It is harder, however, when the interaction occurs over a relatively longer idle period. All else being equal, the larger the time intervals between interactions, the lower the value of the relationship and, generally, the less powerful is the threat of exclusion from the relationship.

To explore this possibility, we divide interbank ties at the syndicate level into two types: (i) the ties that involve the most recent interaction between syndicate members during the last one year; and (ii) those involving relatively “older”, more outdated interactions over the last two to five years, but not in the recent one year before the announcement. Clearly, the second type of ties is less active and associated with lower interaction frequency than the first one. We then compute network density based on each type of the relationships (i.e., the *1-year-old* and *2-5-year-old relationship density*) and re-conducts our CAR analysis.

Table 4.7 presents the results for the acquirer CAR equation for the full sample, the vertically unrelated subsample, and the subsample of large deals above the 50^{th}, 60^{th} and 75^{th} percentile of the size distribution, with estimates for the reduced-form equations omitted here for the sake of brevity (refer to Appendix 4B Table 4.III). In each specification, the dependent variable is the acquirer three-day CAR, and the control variables are the same as those shown in Table 4.5. The main variables of interest are the one-year and two-to-five year interbank network density, both of which are considered as endogenously determined.

In a system with more than one endogenous regressor, strong model identification depends on cross-correlation of the instruments (Hochberg and Lindsey, 2010).; We thus add the following two variables to the instrument set employed in the previous analysis. The first instrument is the largest prior-year debt and equity market share of the advisor in a syndicate (*Largest debt/equity mkt. share prior year*), where the data are obtained from the SDC New Security Issues database. We expect advisors with a larger share in the debt or equity market to more easily renew their ties in the M&A market because they have more underwriting deals to share with other peers. This naturally makes them more valuable partners with whom other investment banks wish to reciprocate properly and strengthen the ties via the sharing of their businesses including M&As. On the other hand, there is no obvious reason to believe that an advisor's share in the equity or debt market would *directly* affect an acquirer's announcement abnormal returns.

The second instrument is *local network density over the past two to five years*, defined as the proportion of logically possible ties that have formed over the last two to five years among *all* the investment banks headquartered in the acquirer's State. Our logic for using this variable as an instrument is that an acquirer is likely to form a syndicate involving less active interbank ties if the average interaction among the local advisors is also lower. This variable is excluded on the basis that the population density of the pre-existing relationships among the local advisors should not have any direct impact on the acquirer's deal performance.

The regression diagnostics are provided at the bottom of Table 4.7. Again, we do not change the instrument set across samples to ensure that any observed difference in network effect is not driven by the selection of different instrumental variable combinations. The Hensen-J statistics fail to reject the null hypothesis that the set of instruments is valid. With multiple endogenous variables, the test statistic for weak identification no longer corresponds to the F-test of joint significance from the reduced-form model (Hochberg and Lindsey, 2010). We therefore report the Kleibergen-Paap rank Wald F-test statistic, which provides a test for instrument strength for models with more than one endogenous regressor and heteroskedasticity (Kleibergen and Paap, 2006). The test statistics exceed the Stock-Yogo 15% maximal LIML size distortion critical value of 2.83 only for the full sample and the vertically unrelated subsample (columns (1) and (2)), suggesting that our instruments are potentially weak in these two samples.[72] Further weak-instrument robust inference tests, such as the Anderson-Rubin (1949) Wald test and the Stock-Wright (2000) S test, yield insignificant statistics. Thus, the results presented in both columns (1) and (2) should be interpreted with some caution.[73]

For the large deal subsamples, the Kleibergen-Paap rank Wald F-test indicates that the instruments are collectively strong for the subsets based on above-50th and -60th percentiles,

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[72] Two primary features associated with weak instruments are: (i) the 2SLS is biased toward the OLS estimate, and alternative estimators such as LIML may not solve the problem; and (ii) the first-order asymptotic distribution does not give an accurate inference (Hahn and Hausman, 2003). Thus, when instruments are collectively weak, the LIML estimates are essentially biased toward OLS regression results. Consistent with this, we find the LIML estimation results are similar to the OLS regression estimates for the full sample and the vertically unrelated subsample.

[73] The Anderson-Rubin (1949) Wald test and the Stock-Wright (2000) S test both test the joint null hypothesis that the coefficients of the endogenous regressors are zero in the structural model and that the orthogonality conditions are valid (i.e., the instruments are uncorrelated with the error term). The Anderson-Rubin (1949) Wald and the Stock-Wright (2000) S statistic is 8.80 (*p*-value 0.27) and 7.49 (*p*-value 0.38), respectively, for the full sample; and 7.28 (*p*-value 0.40) and 6.38 (*p*-value 0.50), respectively, for the vertically unrelated sample, all of which fail to reject the null hypothesis.

but slightly problematic for deals above the 75th percentile. However, we note that the test statistics for weak-instrument robust inference are statistically significant for this subsample of deals above the 75th percentile, indicating valid inference even in the presence of weak identification.[74] We therefore focus our discussion on the estimation results for the subsamples of large deals only (columns (3) through (5)).

Consistent with our earlier findings, we find that the coefficients on both density measures are statistically indistinguishable from zero for deals above the 50th percentile (column (3)), but monotonically increasing as the transaction size moves from the 50th to the 75th percentile. Nevertheless, the peer effect we document in Tables 5 and 6 appears to reside mainly in the most updated rather than in those older, less active interbank ties within a syndicate. Specifically, the estimate for the one-year relationship density variable is positive and statistically significant at the 5% and 1% levels for deals above the 60th and the 75th percentile of the size distribution ((column (4) and (5)), respectively. In contrast, the two-to-five year relationship density variable exhibits no statistically significant association with the acquirer abnormal returns in both subsamples. The results thus support our argument that for the threat of terminating future cooperation to be a credible deterrent against shirking, the value of a peer relationship, as reflected in how frequently a pair of syndicate members interacts in the past, must be high enough to ensure that long-run cooperation is economically meaningful.

[Insert Table 4.7 Here]

Taken together, the results presented in this section indicate that network density improves acquirer CAR, but this occurs only when information asymmetry is so severe that acquirers cannot cheaply circumvent the moral hazard problem. This evidence lends support for our theoretical framework presented in Section 2, suggesting that network density facilitates the

[74] The Anderson-Rubin (1949) Wald test yields a statistic of 18.91 with a *p*-value of 0.009, and the Stock-Wright (2000) S test statistic is 12.85 with a *p*-value of 0.076.

operation of the peer pressure mechanism which, in turn, permits it to add value through reductions in free-riding. We also find that the quality of interbank ties matters. Other things being equal, fewer interacted interbank ties impose less peer pressure on an incumbent investment bank in a syndicate and *vice versa*. In the empirical analysis that follows, we explore other explanations for our main findings. We focus our attention on the full sample and the subsamples where the network effect is most evident, namely, the vertically unrelated and the large deal subsamples.

6. Alternative Explanations

6.1. Endogenous Matching and Selective Networking

We have argued that proximal relationships help investment banks gain better information about one another's unique skills 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 whom 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 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 type. The results presented in Tables 5 and 6 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 during market booms, there are more foreseeable syndication opportunities. 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). Of course, one may argue that in cold markets where many banks find it difficult to obtain business, an investment bank can have a stronger incentive to stay on good terms because this helps it to maximize the chance to be called in on the next deal. Moreover, even if the short-run profit from a relationship is low during market downturns, an investment bank may refrain from shirking due to concerns about the loss of future profits when the market bounces back. However, whether an incumbent bank chooses to shirk is influenced by the trade-off between the short-term gain from shirking and the *present value* of the long-run loss arising from the withdrawal of future cooperation with its peers. Conventional wisdom dictates that an investment bank would value more the profits realized in the near future than those realized in more distant future. This implies that cooperation occurring in the more distant future will be perceived to be less valuable and *vice versa*. Thus, any change in market conditions over time induces variation in the level of expected penalty arising from exclusion from a relationship. When a bank believes that repeated cooperation is sufficiently likely in the near future, it will have little incentive to free ride because the expected profit from cooperation is likely to be large enough to compensate for the loss of short-term gain from shirking. However, when there is little immediate prospect for repeat business, the bank will have a stronger incentive to maximize the short-term gain from the current deal rather than counting on the profits from future and less certain opportunities (e.g., profits received when the market rebounds). Accordingly, if the primary driver of the positive relation between density and acquirer returns is peer pressure, the relation should be more (less) evident during market peaks (downturns). Meanwhile, it will be 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 acquirer CAR concentrates only in the peak years of M&A cycles. Our sample encompasses two peak periods: (i) the dot-com bubble of 1998-2000; and (ii) the recent merger wave of 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. The selection model predicts the probability of using a syndicate. The reduced-form models predict the level of network density during the peak and non-peak years, respectively. The primary equation predicts the acquirer three-day CAR. As applied for the analysis of time decay of peer relationships, 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 better identification of the models with multiple endogenous regressors (Hochberg and Lindsey, 2010; Bun and Harrison, 2014). The control variables are the same as those shown in Table 4.5 except that the year dummies are excluded here, given that the *Peak Year* dummy is a time indicator itself. Table 4.8 presents our estimates for the primary equation for the full sample, the vertically unrelated subsample and the subsample of large deals above the 50th, 60th and 75th percentile for transaction size. The estimates for the selection and reduced-form models are reported in Appendix 4B Table 4.IV.

The regression diagnostics, reported at the bottom of Table 4.8, support 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 over-identifying 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 7.450, 6.088 and 4.972, respectively, for the subsample of deals above-50th, 60th and 75th percentile (columns (3) through (5)). 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 4.8, it is remarkable to observe that the network effect documented in Tables 5 and 6 comes almost entirely from the market peaks. The coefficient of the density variable during non-peak periods is insignificant or marginally significant throughout the table, indicating that interbank networks have little impact on acquirer abnormal returns when there are only 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 being equal, increasing density by one-standard-deviation during the peak years increases the acquirer three-day CAR by 2.69 (43.80%x0.0615)-3.49(43.80%x0.0797) percentage points, depending on the specification. This corresponds to a $263.20- to $341.09-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 difficult to explain through the "matching" and "selective networking" hypotheses.

[Insert Table 4.8 Here]

6.2. Lead Advisor Reputation

In practice, syndicates are often lead-managed by an investment bank that 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.[75] In this case, one may expect less free riding if a syndicate is led by a more reputable advisor

[75] 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.

who has a stronger incentive to exert effort monitoring. Thus, a natural question is whether the positive density-acquirer CAR association we document in Tables 5 and 6 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 in *mutually* exerting peer pressure. This difference makes it important to empirically distinguish these two alternative governance mechanisms and the associated effects on syndicate incentive structure.

To address this issue, we follow the procedure outlined in Chapter 3 and hand-collect data on the identity of lead investment banks from the *SDC* and *Factiva* databases. Of 1,138 syndicate-advised transactions, 347 acquisitions are identified as lead-managed (i.e., the lead sample). Appendix 4B, Table 4.V, provides summary statistics for this sample. Notably, the mean absolute (relative) deal size is around 1.65 (1.39) times larger than in the full sample. 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 arising from 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 indicate 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%.

Table 4.9 directly controls for lead advisor reputation and re-estimates our acquirer CAR models for the lead sample, the vertically unrelated subsample and the subsample of large deals above the 50th and 60th percentiles of the size distribution. The results for the subsample of deals above the 75th percentile are not reported here because its rather small sample size (76 observations) leads to unreliable estimates. 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 non-randomly determined (Fang, 2005; Golubov et al., 2012). We instrument for selection on a top-8 versus a non-top 8 lead advisor by the scope variable. This variable 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). It is equal to three if an acquirer has engaged a top-8 lead investment bank in all of the following three types of transaction: 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 transaction; one if it has hired a top-8 lead investment bank in one of the three types of transaction; 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 before 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. The degree of network density is instrumented by the same exogenous variables as those shown in Table 4.5.

Table 4.9 reports estimates for the primary CAR equation, with the estimates for the selection and the reduced-form equations reported in Table 4.VI, Appendix 4B for the sake of brevity. The Hensen-J statistics fail to reject the null hypothesis that our excluded instruments are valid at conventional levels. Due to the significant drop in sample size, the Kleibergen-Paap rank Wald F-test statistic for weak identification is problematic in all sets of models. We, however, note that the weak-instrument robust inference tests, such as the Anderson-Rubin (1949) Wald test, are significant at the 5% level in all specifications, suggesting 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 univariate 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 in Table 4.9, 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 most 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 4.5.

[Insert Table 4.9 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) offering an amount of fees exceeding individual member bank's 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 re-emerge. 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 preserve the quasi-rents provided to promote effort.

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" hypothesis 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 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 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 effort, 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 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 that can utilize contracts to efficiently align advisors' incentives. We explore this issue by estimating the impact of network density on advisory fees using the selection-corrected IV approach.

Table 4.10 presents the LIML estimation results for the full sample, the vertically unrelated subsample, and the subsample of large deals defined as those above the 50^{th}, 60^{th} and 75^{th} percentiles of the size distribution. The estimates for the reduced-form equations are provided in Appendix 4B, Table 4.VII. In each specification, the dependent variable is the advisory fee paid by an acquirer as a percentage of transaction value. We instrument network density by the same set of instruments shown in Table 4.5. As controls, we include syndicate size, the presence of a top-8 advisor in a syndicate, the level of vertical 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.[76]

The results reported in columns (1) and (2) indicate that density has a statistically insignificant impact on the percentage of advisory fee in the full sample and the vertically unrelated subsample. For large deals above the 60th and 75th percentile of the size distribution, however, the density variable is negative and significant at the 5% level (columns (4) and (5)). The magnitude of the coefficient estimates indicates that, holding other factors constant, increasing network density by one standard deviation (43.80%) reduces fees by around 0.14 percentage points (-0.0031x43.80%x100) This is approximately a \$3.71 (\$0.77)-million-reduction in advisory fee for a mean (median)-sized acquisition in our sample. As for our control variables, advisory fees are negatively 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. Consistent with Golubov et al. (2012), we find that fees are lower for deals financed with stock. Other variables such as industry relatedness

[76] 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.

and hostility of target management do not have any significant influence over the percentage fee.

Overall, the evidence does not 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 effort.

[Insert Table 4.10 Here]

6.4. Other Explanations

The main finding of this study 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 large. We interpret this result 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 positive density-performance association is peer pressure and not endogenous matching, selective networking, lead advisor reputation or incentive pay. A potential caveat to our study is that we do not observe which investment bank free rides in a syndicate. This prevents us from examining the actual means that syndicate members employ to punish free riders. Though exclusion from relationships is a natural enforcement device in a repeated setting, other forms of peer sanction may exist. For instance, with the mutual monitoring possibility, an acquiring firm may implement an information revelation scheme that encourages investment banks in 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 acquirer and 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 for IPO underwriting syndicates. They argue that co-managers may "whisper" the book manager's misconduct in the issuer's ear 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 solicit 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 chapter instead show that the level of interbank connections present in a syndicate positively and significantly affects acquirer abnormal returns, which provides clear evidence against this "private reporting" 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 with 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 in Table 4.8 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 because of 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 Checks

We perform a series 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 (as opposed to the value-weighted) CRSP index 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 before the announcement year; (v) employing an 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). The results are summarized in Appendix 4B, Tables 4.VIII-4.XII. None of these variations significantly changes the main results reported in this chapter.

8. Conclusion

Like 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 hypothesize 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 indeed enjoy higher abnormal returns at 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 networking occurs only when the acquirer-advisor tie is absent and when the transaction is large. This supports the notion that interbank networks improve effort provision when the free-rider problem is exacerbated due to information asymmetry between acquirer and advisors. The results are robust to endogeneity and a wide range of specifications.

We also provide evidence for several ancillary predictions of our hypothesis that is difficult to reconcile with other potential explanations. Specifically, we find that the value of interbank relationships decay over time, with more active ties having a stronger disciplinary effect and *vice versa*. In addition, the positive effect of interbank networking 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. They are inconsistent with other interpretations such as endogenous matching or selective networking since, 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 address the question of whether lead advisor reputation provides an alternative means to reduce free-riding. We find that acquirer announcement abnormal returns are unaffected by the presence of a reputable lead advisor and that they continue to be positively associated with network density after controlling for lead advisor reputation. This suggests that investment banking syndicates mostly rely on the collective effort of relationship investment banks in a syndicate rather than 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, which predicts that interbank networks elicit barriers to entry and allow more densely networked syndicates to capture a greater fraction of incentive rents, 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. In the next chapter, we summarize the main findings of this thesis and provide an outlook for future research.

9. Figures

Figure 4.1
Interbank Networks for the Year 2010

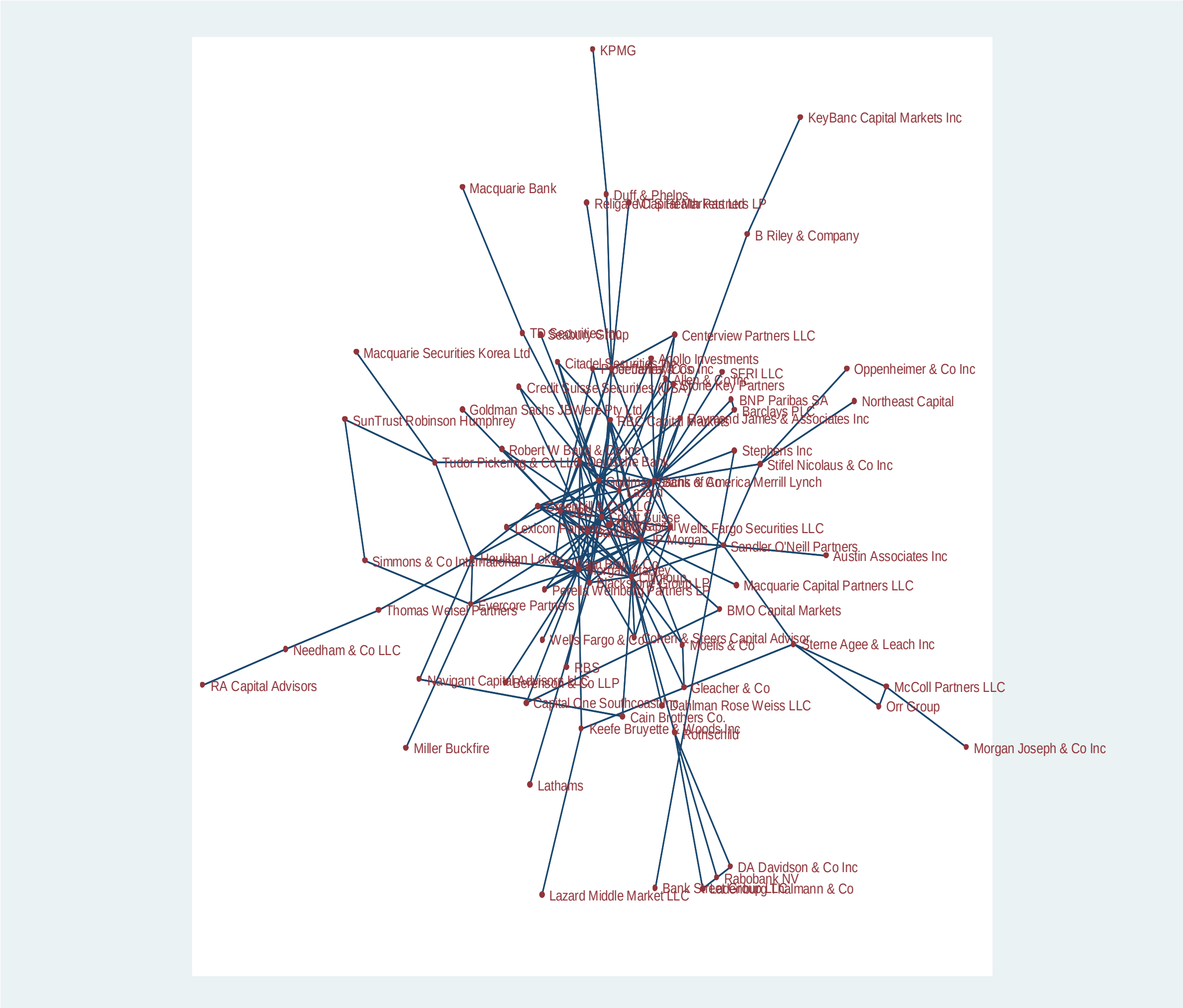

Figure 4.2
Examples of Density in Two Hypothetical Syndicates

Figure 4.2a 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 provided in Figure 4.2b. 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.

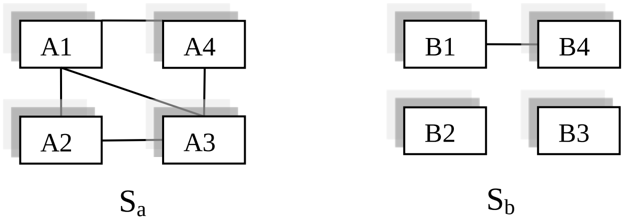

Figure 4.2a

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

Figure 4.2b

10. Tables

Table 4.1
Descriptive Sample Statistics

This table presents the descriptive statistics for the sample of U.S. M&A transactions involving two or more investment banks on the acquirer side 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 Compustat.

	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 4.2
VIF Diagnostics

This table reports the variance inflation factors (VIF) for the explanatory variables used in our main regression model of acquirer CAR. The sample consists of 1,138 syndicate-advised deals announced between January 1990 and December 2012. Each variable is defined in Appendix 4A.

Density	Syndicate size	Top-8 Participation	Vertical relationship density	Ln (Acq. size)	Run-up	FCF
1.25	1.12	1.36	1.08	3.84	1.27	1.11
Leverage	Tobin’s Q	Ln (Deal size)	Rel. size	Related	Tender	Hostile
1.27	1.42	4.37	1.52	1.09	1.57	1.29
All cash	Public deals	Private deals	Num. of bidders	Cross-border		
1.27	1.90	1.65	1.33	1.24		

Table 4.3
Network Density and Acquirer CAR: Ordinary Least Squares

This table reports the results from the OLS regressions of the 3-day acquirer CAR on syndicate density and other advisor-, deal- and acquirer-characteristics 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 computed as the cumulative abnormal return (CAR) on the acquirer's stock over the event window (-1, +1). Density at the syndicate level is calculated based on interbank syndication relationships 1 year prior to the announcement year. Other variables are defined in Appendix 4A. Year fixed effects are controlled for in all models, but the coefficients are suppressed for brevity. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. 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. R^2	0.170	0.172	0.168	0.112	0.178
N	923	791	132	356	567

Table 4.4
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. The syndication decision determines whether density at the syndicate level is observable. Columns (2) through (6) of the table estimate the reduced-form equation for the endogenous regressor, *density* (Equation (2)), 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 before the announcement date. The reduced-form and structural equations (Equations (3) and (2)) are jointly estimated by LIML. For space reasons, the results for the structural equation are reported separately in Table 4.5. 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 60^{th} percentile of the transaction size distribution. Other variables are defined in Appendix 4A. 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-1year 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-5 year debt underwriting relationship density weighted by		0.0006***	0.0005***	0.0014***	0.0003*	0.0008***

frequency						
		(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 4.5
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; columns (2) and (3) provide the results for the vertically unrelated (related) subsample of deals in which the acquirer-advisor tie is absent (present); columns (4) and (5) present the results for the subsample of deals above (at or below) the 60th percentile of the transaction size distribution. Other variables are defined in Appendix 4A. 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)	Vertically Related (3)	Large Deals (>60%) (4)	Ordinary Deals (<=60%) (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-5 year (weighted) debt underwriting relationship density.					
Diagnostics					
Centered R^2	0.224	0.079	0.219	0.141	0.045
Uncentered R^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 4.6
Network Density and Acquirer CAR: Selection-adjusted IV Approach

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 conditional on the syndication decision and with network density endogenized. The reduced-form estimation results are reported in Appendix 4B, Table 4.I. 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. Other variables are defined in Appendix 4A. 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.

	Large Deals (>50%)	Ordinary Deals (<=50%)	Large Deals (>75%)	Ordinary Deals (<=75%)
	(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-5 year (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	10% maximal LIML size	10% maximal LIML size	10% maximal LIML size
	5.44	5.44	5.44	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 4.7
Time Decay of Peer Relationships

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 the network density measured based on the existence of ties over the last one year (*1-year-old relationship density*) and the last two to four years (*2-5-year-old relationship density*) before announcement both of which are endogenized in each specification. Column (1) reports the estimates for the full sample; column (2) provides results for the vertically unrelated subsample; columns (3) through (5) present the results for the subsample of large deals defined as those above the 50th, 60th and 75th percentiles of the size distribution, respectively. In each specification, the selection model predicts the probability of using a syndicate; the reduced-form model predicts the level of the *1-year and 2-5-year-old relationship density*, respectively; and the primary equation predicts the acquirer three-day CAR. The estimates for the selection and reduced-form models are not reported here for brevity (refer to Appendix 4B Table 4.III). Other variables are defined in Appendix 4A. 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 (>50%) (3)	Large Deals (>60%) (4)	Large Deals (>75%) (5)
1-year-old relationship density	0.0398*	0.0485*	0.0358	0.0585**	0.0829***
	(1.7569)	(1.9110)	(1.5570)	(2.4680)	(2.9543)
2-5-year-old relationship density	0.0770*	0.0679	0.0257	0.0482	0.0773
	(1.7085)	(1.1287)	(0.5377)	(0.8816)	(0.9346)
Syndicate size	0.0087*	0.0083*	0.0114**	0.0139***	0.0195***
	(1.9399)	(1.7463)	(2.4222)	(2.7709)	(3.8908)
Participation of top 8	0.0167	0.0127	0.0086	-0.0073	-0.0368**
	(1.4321)	(0.9827)	(0.5656)	(-0.4340)	(-1.9670)
Vertical relationship density	-0.0128*		-0.0141**	-0.0185***	-0.0406***
	(-1.9148)		(-2.2081)	(-2.7312)	(-2.8245)
Ln (Acquirer size)	-0.0017	0.0006	0.0005	0.0038	0.0124
	(-0.3595)	(0.1184)	(0.0869)	(0.7017)	(1.4863)
Run-up	0.0257**	0.0238*	0.0301*	0.0277	0.0319*
	(2.1855)	(1.9463)	(1.9383)	(1.5403)	(1.8881)
FCF	0.0251	0.0276	0.0880	0.1123*	0.0707
	(0.9111)	(0.9526)	(1.5160)	(1.6668)	(0.9239)
Leverage	0.0025	0.0073	0.0386	0.0735	0.0084
	(0.0795)	(0.2013)	(0.9371)	(1.5491)	(0.1736)
Tobin's Q	-0.0032**	-0.0039***	-0.0037**	-0.0042**	-0.0055***

	(-2.3636)	(-2.9808)	(-2.4400)	(-2.3479)	(-3.3177)
Ln (Deal size)	-0.0109*	-0.0164**	-0.0070	-0.0083	-0.0232**
	(-1.7737)	(-2.5073)	(-0.9168)	(-0.9916)	(-2.3615)
Relative size	0.0020	0.0025	-0.0073	-0.0061	0.0007
	(0.2939)	(0.3589)	(-1.0640)	(-0.8023)	(0.0907)
Related	0.0007	0.0044	-0.0007	-0.0066	-0.0048
	(0.1003)	(0.5538)	(-0.0758)	(-0.7102)	(-0.4276)
Tender	0.0175*	0.0221*	0.0137	0.0102	0.0101
	(1.6688)	(1.8259)	(1.1609)	(0.8226)	(0.6365)
Hostile	0.0076	0.0007	0.0163	0.0097	0.0297*
	(0.6177)	(0.0492)	(1.1278)	(0.6709)	(1.7596)
Cross-border	0.0097	0.0028	0.0208	0.0172	0.0123
	(0.8571)	(0.2118)	(1.6196)	(1.2570)	(0.8488)
Num. of bidders	-0.0096	-0.0080	-0.0268**	-0.0327**	-0.0412***
	(-1.0369)	(-0.7304)	(-2.2704)	(-2.4969)	(-3.0984)
All cash	0.0073	0.0045	-0.0049	-0.0029	-0.0161
	(0.9396)	(0.4979)	(-0.4209)	(-0.2109)	(-1.0709)
Public deals	-0.0229**	-0.0188*	-0.0186	-0.0141	-0.0145
	(-2.4931)	(-1.8235)	(-1.6171)	(-1.0898)	(-0.7772)
Private deals	0.0120	0.0127	0.0228	0.0373	-0.0012
	(1.0576)	(0.9878)	(1.2993)	(1.2843)	(-0.0271)
General residuals	0.0069	-0.0029	0.0114	0.0042	-0.0210
	(0.3177)	(-0.1273)	(0.4407)	(0.1563)	(-0.7574)
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-5 year (weighted) debt underwriting relationship density; Local network density computed based on interbank ties over the last two to five years; Prior-year largest debt and equity market share.					
Diagnostics					
Hansen J Chi2	3.491	3.169	4.022	4.998	6.629
p-value	0.625	0.674	0.546	0.416	0.250
Instrument strength test *(KP rank Wald F-test)*	3.707	3.126	4.861	4.795	2.167
Stock-Yogo critical values:	10% maximal LIML size 3.90	10% maximal LIML size 3.90	10% maximal LIML size 3.90	10% maximal LIML size 3.90	10% maximal LIML size 3.90
Centered R^2	0.210	0.073	0.133	0.117	0.120

Uncentered R^2	0.211	0.073	0.133	0.117	0.120
F	3.601	4.827	3.178	3.051	2.269
N	665	533	367	294	200

Table 4.8
Network Density and Acquirer CAR in Hot Markets

This table presents the LIML estimation results for the structural model of the acquirer 3-day CAR. 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 of 2003-2007. Column (1) reports the estimates for the full sample; column (2) provides results for the vertically unrelated subsample; columns (3) through (5) report the results for the large deal subsample based on the 50th, 60th and 75th percentile size cut-off 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 4A. 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 (>50%) (3)	Large Deals (>60%) (4)	Large Deals (>75%) (5)
Density during peak years	0.0615**	0.0724**	0.0615**	0.0707**	0.0797**
	(2.2985)	(2.3818)	(2.0893)	(2.2454)	(2.0128)
Density during non-peak years	0.0386	0.0472*	0.0143	0.0183	0.0405
	(1.5700)	(1.8599)	(0.6150)	(0.7316)	(1.3500)
Syndicate size	0.0089**	0.0084*	0.0123***	0.0137***	0.0164***
	(2.1342)	(1.9054)	(2.8485)	(3.0079)	(3.7216)
Participation of Top 8	0.0100	0.0062	0.0074	-0.0083	-0.0219*
	(0.9417)	(0.4887)	(0.5182)	(-0.5978)	(-1.7076)
Vertical relationship density	-0.0259***		-0.0223***	-0.0257***	-0.0375**
	(-3.3083)		(-3.1546)	(-3.1442)	(-2.1982)
Ln (Acquirer size)	0.0036	0.0056	0.0073	0.0088*	0.0091
	(0.8221)	(1.2479)	(1.5864)	(1.9523)	(1.4062)
Run-up	0.0219*	0.0200	0.0268*	0.0233	0.0274
	(1.7828)	(1.5316)	(1.7578)	(1.3810)	(1.5043)
FCF	0.0451	0.0563*	0.0965	0.1432**	0.0977
	(1.5952)	(1.9422)	(1.4051)	(2.0048)	(1.4721)
Leverage	0.0133	0.0178	0.0488	0.1001**	0.0768
	(0.4504)	(0.5449)	(1.2210)	(2.2916)	(1.4635)
Tobin's Q	-0.0038***	-0.0042***	-0.0048***	-0.0046***	-0.0049***

	(-2.8830)	(-3.1161)	(-3.2005)	(-2.7994)	(-2.8672)
Ln (Deal size)	-0.0229***	-0.0281***	-0.0187***	-0.0170**	-0.0178**
	(-3.4282)	(-3.8343)	(-2.7801)	(-2.4721)	(-2.0753)
Relative size	0.0030	0.0030	0.0060	0.0067	0.0031
	(0.5253)	(0.5303)	(1.1997)	(1.5273)	(0.4080)
Related	-0.0014	0.0020	0.0019	-0.0043	0.0017
	(-0.1884)	(0.2349)	(0.2082)	(-0.4459)	(0.1566)
Tender	0.0197	0.0257*	0.0061	0.0024	-0.0004
	(1.5264)	(1.8435)	(0.4655)	(0.1858)	(-0.0290)
Hostile	-0.0002	-0.0095	0.0244	0.0163	0.0399**
	(-0.0148)	(-0.5555)	(1.4907)	(0.9723)	(2.4627)
Cross-border	-0.0049	-0.0126	0.0188	0.0156	0.0171
	(-0.4212)	(-1.0506)	(1.5767)	(1.3358)	(1.2063)
Num. of bidders	-0.0133	-0.0102	-0.0295***	-0.0348***	-0.0380***
	(-1.3331)	(-0.8821)	(-2.7013)	(-3.0395)	(-3.2397)
All cash	0.0097	0.0025	-0.0022	0.0008	-0.0028
	(1.2328)	(0.2710)	(-0.1880)	(0.0626)	(-0.2002)
Public deals	-0.0249***	-0.0220**	-0.0172	-0.0118	-0.0106
	(-2.7345)	(-2.1014)	(-1.3754)	(-0.8921)	(-0.5413)
Private deals	0.0194	0.0174	0.0231	0.0409	-0.0040
	(1.4076)	(1.1838)	(1.1770)	(1.3194)	(-0.1105)
General residuals	-0.0268	-0.0342	0.0119	0.0124	0.0273
	(-1.4437)	(-1.6230)	(0.6427)	(0.6705)	(1.2765)
"Excluded" Instruments: Local network density; Fraction of members from the same State; Prior-1 year (unweighted) and prior-5 year (weighted) debt underwriting relationship density; and Interactions of each of the above variables with the hot market dummy variable.					
Diagnostics					
Hansen J Chi2	6.360	4.606	5.747	5.269	4.358
p-value	0.384	0.595	0.452	0.510	0.628
Instrument strength test *(KP rank Wald F-test)*	10.107	8.362	7.450	6.088	4.972
Stock-Yogo critical values:	10% maximal LIML size 3.78	10% maximal LIML size 3.78	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	0.103	0.131	0.139
UncenteredR^2	0.139	0.138	0.152	0.217	0.278
F	4.127	4.678	4.034	3.546	3.662
N	665	533	367	294	200

Table 4.9
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 on the top-8 lead advisor and network density, conditional on the syndication decision modeled in Table 4. 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) through (4) present the results for the sample split according to whether the vertical tie is absent and whether the deal size is above the 50th and 60th percentile of the deal size distribution, respectively. The results for the subsample of deals above the 75th percentile are unreported here due to its rather small sample size (76 observations) which results in unreliable estimates. Network density is computed based on inter-bank syndicate relationships 1 year prior to the announcement year. Other variables are defined in Appendix 4A. 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	Large Deals (>50%)	Large Deals (>60%)
	(1)	(2)	(3)	(4)
Density	0.1628**	0.1860**	0.1639*	0.1433**
	(2.1269)	(2.0050)	(1.9063)	(2.0119)
Syndicate size	0.0180*	0.0198*	0.0216**	0.0204**
	(1.8509)	(1.8103)	(2.4085)	(2.2304)
Top-8 lead advisor	-0.0531	-0.0673	-0.0946	-0.0770*
	(-1.3486)	(-1.3780)	(-1.6262)	(-1.6800)
Vertical relationship density	-0.0291*		-0.0118	-0.0212
	(-1.7955)		(-0.6675)	(-1.1807)
Ln (Acquirer size)	0.0361**	0.0412**	0.0207	0.0213
	(2.2898)	(2.3644)	(1.3021)	(1.1643)
Run-up	-0.0004	-0.0275	0.0290	0.0217
	(-0.0140)	(-0.8248)	(0.8884)	(0.6270)
FCF	0.0180	-0.0024	0.2521**	0.3618***
	(0.2216)	(-0.0256)	(2.3346)	(3.0305)
Leverage	-0.1137	-0.1264	-0.0514	-0.0849
	(-1.5614)	(-1.5146)	(-0.6040)	(-0.9942)
Tobin's Q	-0.0091***	-0.0124***	-0.0099***	-0.0124***
	(-3.0803)	(-3.1899)	(-2.9827)	(-4.1584)
Ln (Deal size)	-0.0673***	-0.0713***	-0.0482*	-0.0503**
	(-2.7170)	(-2.6094)	(-1.9189)	(-2.0034)

Relative size	-0.0210	-0.0059	-0.0622**	-0.0562*
	(-0.9276)	(-0.2028)	(-2.0711)	(-1.8018)
Related	0.0055	0.0015	0.0092	0.0012
	(0.2892)	(0.0657)	(0.4075)	(0.0570)
Tender	-0.0013	-0.0078	0.0518	0.0640
	(-0.0535)	(-0.2909)	(1.3405)	(1.4139)
Hostile	0.0185	0.0344	-0.0024	-0.0195
	(0.5935)	(0.8650)	(-0.0750)	(-0.7021)
Cross-border	-0.0765***	-0.0766***	-0.0667	-0.0613
	(-2.6789)	(-2.7433)	(-1.1334)	(-1.3315)
Num. of bidders	-0.0740***	-0.0664**	-0.1225***	-0.1287***
	(-3.3976)	(-2.5700)	(-3.9580)	(-4.0706)
All cash	0.0015	0.0096	-0.0343	-0.0519
	(0.0527)	(0.3200)	(-0.7398)	(-1.1048)
Public deals	-0.1455***	-0.1312***	-0.1351*	-0.1242**
	(-3.6324)	(-3.2816)	(-1.8846)	(-2.1797)
Private deals	0.0344	0.0526	0.0817	0.1332***
	(0.6871)	(0.8987)	(1.2841)	(3.0319)
General residuals	-0.1447**	-0.1565**	-0.1820**	-0.1708**
	(-2.3171)	(-2.1762)	(-2.2685)	(-2.5001)
Year fixed effects	YES	YES	YES	YES
"Excluded" Instruments: Local network density; Fraction of members from the same State; Prior-1 year (unweighted) and prior-5 year (weighted) debt underwriting relationship density; Scope; Average use of a top 8 advisor by peers.				
Diagnostics				
Hansen J Chi2	5.713	6.965	5.009	9.277
p-value	0.222	0.138	0.286	0.055
Instrument strength test	3.382	3.082	2.145	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	10% maximal LIML size 4.06
Centered R^2	-0.023	-0.056	-0.037	0.231
UncenteredR^2	-0.023	-0.056	-0.037	0.231
F	3.968	3.341	2.045	4.596
N	170	141	108	94

Table 4.10
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 4. The results are presented in structural form, with the selection and reduced-form estimation results omitted for brevity (refer to Appendix 4B Table 4.VII). The dependent variable in each specification is advisory fee paid by acquirer as a percentage of transaction value. Column (1) reports the estimates for the lead sample; column (2) presents the results for the subsample of deals in which the vertical tie is absent; columns (3) through (5) provide results for the subsample of large deals defined as those above the 50^{th}, 60^{th} and 75^{th} percentiles of the size distribution, respectively. Network density is computed based on inter-bank syndicate relationships 1 year prior to the announcement year. Other variables are defined in Appendix 4A. 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	Large Deals (>50%)	Large Deals (>60%)	Large Deals (>75%)
	(1)	(2)	(3)	(4)	(5)
Density	-0.0020	-0.0031	-0.0026*	-0.0031**	-0.0032**
	(-0.9676)	(-1.1711)	(-1.7598)	(-2.0400)	(-2.1446)
Syndicate size	-0.0006	-0.0007	-0.0004	-0.0007*	-0.0006
	(-1.3891)	(-1.3585)	(-1.0730)	(-1.8327)	(-1.6199)
Participation of top8	0.0001	-0.0000	0.0010	0.0012	0.0005
	(0.0745)	(-0.0154)	(0.9500)	(1.0282)	(0.3796)
Vertical relationship density	0.0002		0.0001	0.0003	0.0002
	(0.2609)		(0.1038)	(0.3542)	(0.1419)
Ln (Deal size)	-0.0021***	-0.0022***	-0.0008***	-0.0010***	-0.0015***
	(-5.3906)	(-5.0656)	(-2.7939)	(-3.1492)	(-3.7122)
Relative size	-0.0012**	-0.0011*	-0.0002	-0.0000	0.0001
	(-2.1141)	(-1.7316)	(-0.4285)	(-0.1152)	(0.2466)
Related	-0.0009	-0.0020	0.0002	0.0001	0.0002
	(-0.8710)	(-1.5068)	(0.3365)	(0.1640)	(0.2576)
Payment incl. stock	-0.0050**	-0.0047*	-0.0046**	-0.0035*	-0.0012
	(-2.2834)	(-1.8263)	(-2.4866)	(-1.6669)	(-0.5045)
Hostile	-0.0001	0.0009	0.0009	0.0015	0.0022
	(-0.0585)	(0.3615)	(0.5320)	(0.7238)	(1.1268)
Tender	-0.0006	-0.0005	-0.0014	-0.0024	-0.0020
	(-0.3271)	(-0.2433)	(-1.0254)	(-1.5052)	(-1.0389)

General residuals	-0.0028	-0.0028	0.0033	0.0020	0.0022
	(-1.2723)	(-0.9589)	(1.5413)	(0.8402)	(0.8394)
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-5 year (weighted) debt underwriting relationship density.					
Diagnostics					
Hansen J Chi2	1.374	3.747	0.882	2.859	2.841
p-value	0.712	0.290	0.830	0.414	0.417
Instrument strength test (F-test)	5.243	5.624	7.498	8.268	7.804
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
Centered R^2	0.413	0.417	0.197	0.160	0.235
UncenteredR^2	0.413	0.417	0.197	0.160	0.235
F	6.388	5.662	3.736	2.276	2.536
N	135	110	96	83	70

11. Appendices

Appendix 4A Variable Definition

Variable	Definition
Panel A: Dependent Variables	
CAR (-1, +1)	Cumulative abnormal returns of the acquiring firm's 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 before the announcement.
Advisory Fee	The advisory fee paid by an acquirer as a percentage of transaction value, from SDC.
Panel B: Advisor Characteristics	
Density	The relative degree of adjacent (symmetric) ties within a syndicate, where a tie exists if two investment banks in the syndicate had syndicated one or more deals one year before the deal announcement.
Participation of Top 8	A dummy variable being 1 if one of the investment banks in a syndicate is ranked among the top 8 according to the value of transactions it has advised over the sample period; and 0 otherwise. The data are obtained from the league tables for financial advisors from SDC.
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 $U.S. dollars. The data are obtainedfrom CRSP.
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. The data are obtained from both CRSP and Compustat.
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. The data are obtained from both CRSP and Compustat.
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 Compustat.
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 $U.S. dollars (from Thomson Financial SDC).
Relative Size	The deal value divided by the market value of the bidding firm's equity 11 trading days before the announcement date (from CRSP).
Relatedness	A dummy variable being 1 if the bidder and the target are operating in the same industries with a common 3-digit SIC code and 0 otherwise (from Thomson Financial SDC).
Public Target	A dummy variable being 1 if the bid is for public target and 0 otherwise.
Private Target	A dummy variable being 1 if the bid is for private target and 0 otherwise.
Subsidiary Target	A dummy variable being 1 if the bid is for subsidiary target and 0 otherwise.
Foreign Target	A dummy variable being 1 if the bid is for foreign target and 0 otherwise.
All-Cash Deals	A dummy variable being 1 if the payment is pure cash and 0 otherwise.
Pmt. Incl. Stock	A dummy variable being 1 if the acquisition is either partially or fully financed with stock and 0 otherwise.
Cash Shortfall	The difference between the cash component of the payment in the takeover bid and the acquirer's free cash flows measured in billions of $U.S. dollars.
Tender Offer	A dummy variable being 1 if the deal is a tender offer and 0 otherwise.
Hostile	A dummy variable being 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 4B Robustness Check

Table 4.I
Network Density and Acquirer CAR for Alternatively-defined Large Deal Subsamples: Reduced-Form Models

This table presents the LIML estimates for the reduced-form equation (Equation (3)) for Table 4.6, for the sample split at the 50th and the 75th percentile size cut-off points, respectively. The dependent variable in each column is the endogenous regressor, *density*, 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. Column (1) ((2)) reports the results for the subsample of large (ordinary) deals above (below) the 50th percentile of the size distribution. Columns (3) and (4) repeat the analysis for the subsample of deals that lie above and at/below the 75th percentile of the size distribution. The "excluded" instruments are local network density, fraction of members from the same State, prior-1 year (unweighted), and prior-5year (weighted) debt underwriting relationship density. The variable, *general residuals*, is computed based on the Probit estimates from the syndication decision equation (Equation (3)), as shown in column (1) of Table 4. It is inserted here as an additional regressor to correct for sample selection bias. Other variables are defined in Appendix 4A. Year fixed effects are controlled for in all models, but the coefficients are suppressed for brevity. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Large Deals (>50%)	Ordinary Deals (<=50%)	Large Deals (>75%)	Ordinary Deals (<=75%)
	(1)	(2)	(3)	(4)
Instruments				
Local network density	0.3084***	0.8310***	0.3441***	0.6424***
	(3.6920)	(2.7959)	(3.4662)	(4.5039)
Fraction of members from the same State	0.2215***	0.0797	0.2527***	0.1070**
	(3.9969)	(1.5994)	(3.2320)	(2.3236)
Prior-1 year debt underwriting relationship density	0.2115***	0.0237	0.1912*	0.0522
	(2.7833)	(0.3643)	(1.7675)	(0.8645)
Prior-5 year debt underwriting relationship density weighted by frequency	0.0003*	0.0011***	0.0003	0.0008***
	(1.9665)	(4.5838)	(1.5166)	(5.3751)
Covariates from Third-Stage				
Syndicate size	-0.0046	-0.0054	0.0041	-0.0097
	(-0.2231)	(-0.1208)	(0.1421)	(-0.3471)
Participation of Top 8	0.1707**	-0.0439	0.0305	0.0325
	(2.5445)	(-0.6204)	(0.2602)	(0.5239)
Vertical relationship density	0.1252***	0.1329	0.1587*	0.0797
	(2.6490)	(1.5627)	(1.8101)	(1.5462)
Cash shortfall				
Ln (Acquirer size)	-0.0076	0.0229	-0.0187	0.0195
	(-0.2332)	(0.8618)	(-0.3354)	(0.8289)
Run-up	-0.1127*	-0.0060	-0.1161	-0.0362
	(-1.9445)	(-0.1043)	(-1.4733)	(-0.6965)
FCF	-0.0493	0.0170	-0.1660	0.0044
	(-0.1624)	(0.1102)	(-0.4208)	(0.0273)

Leverage	0.0069	-0.2183	0.0802	-0.2023
	(0.0344)	(-1.2615)	(0.2647)	(-1.3437)
Tobin's Q	0.0141**	-0.0137	0.0173**	-0.0107
	(2.3878)	(-1.0631)	(2.4333)	(-0.8123)
Ln (Deal size)	0.0193	-0.0130	0.0333	-0.0003
	(0.4069)	(-0.2813)	(0.4306)	(-0.0073)
Relative size	0.0453	-0.0456	0.0434	0.0020
	(1.6063)	(-1.1698)	(0.8489)	(0.0949)
Related	-0.0312	0.0529	0.0624	-0.0145
	(-0.6264)	(1.0654)	(0.8514)	(-0.3322)
Hostile	-0.0543	-0.1002	0.0313	-0.1266*
	(-0.6234)	(-1.3099)	(0.2929)	(-1.7214)
Cross-border	-0.1107	-0.1515**	-0.1184	-0.1353**
	(-1.4917)	(-2.1025)	(-1.1964)	(-2.1654)
Num. of bidders	-0.0015	-0.0683	-0.0195	-0.0408
	(-0.0253)	(-1.1390)	(-0.2134)	(-0.8690)
All cash	0.1106*	-0.0076	0.0448	0.0205
	(1.9085)	(-0.1718)	(0.4464)	(0.5306)
Tender	-0.0432	-0.0150	0.0043	-0.0604
	(-0.5743)	(-0.2246)	(0.0380)	(-1.0491)
Public deals	-0.1034	-0.0188	-0.2409*	-0.0086
	(-1.5581)	(-0.2937)	(-1.9708)	(-0.1610)
Private deals	-0.0669	-0.0234	-0.1577	0.0029
	(-0.6377)	(-0.3835)	(-0.8213)	(0.0538)
General residuals	0.0387	-0.2212	0.1340	-0.1834
	(0.2586)	(-1.2905)	(0.6060)	(-1.1917)
Intercept	-0.9652	0.5810	-0.3279	0.2427
	(-1.2354)	(0.9405)	(-0.4762)	(0.4085)
Year fixed effects	YES	YES	YES	YES
Diagnostics				
R^2	0.306	0.344	0.336	0.338
Adj. R^2	0.209	0.227	0.159	0.267
N	367	298	200	465

Table 4.II
Network Density and Acquirer CAR: Difference-in-Difference Approach

This table presents the results for the difference-in-difference cross-sectional regressions for the full sample, the vertically unrelated subsample as well as the subsamples of large deals above the 50th, 60th and 75th percentiles. The sample consists of deals announced during 1998-1999, which is around the time of the repeal of the Glass-Steagall Act. In each column, the dependent variable is acquirer three-day CAR. *Post* is a binary variable coded as one if an observation occurs in 1999 and zero otherwise. *High Stock Financing* is a dummy variable equal to one if the amount of stock financing is at or above the mean for the sample tested ($3268.049) and zero otherwise. The main variable of interest is the interaction term *High Stock Financing* x *Post*. Other variables are defined in Appendix 4A. 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 (1)	Vertically Unrelated (2)	Large Deals (>50%) (3)	Large Deals (>60%) (4)	Large Deals (>75%) (5)
Post	0.0093	-0.0024	0.0397	0.0424	0.0773
	(0.4022)	(-0.0893)	(1.2197)	(0.8826)	(1.5094)
High stock financing (above mean)	0.0214	0.0098	0.0234	0.0118	0.0552
	(0.5957)	(0.2532)	(0.5256)	(0.2343)	(0.9088)
High stock financing x Post	-0.0700*	-0.0596	-0.1023**	-0.1032**	-0.1239**
	(-1.7713)	(-1.2989)	(-2.0447)	(-2.0484)	(-2.1600)
Syndicate size	0.0135	0.0406	-0.0012	-0.0190	0.0007
	(0.6083)	(1.0361)	(-0.0463)	(-0.6903)	(0.0253)
Participation of top 8	0.0679***	0.0752***	0.0489	0.0861**	0.1432***
	(3.2058)	(2.8927)	(1.3562)	(2.4967)	(4.2233)
Vertical relationship density	-0.0170		-0.0319	-0.0180	-0.0140
	(-0.7925)		(-0.9687)	(-0.5697)	(-0.3949)
Ln (Acquirer size)	-0.0075	-0.0062	-0.0119	-0.0011	0.0015
	(-1.1269)	(-0.8588)	(-1.0703)	(-0.0670)	(0.0560)
Run-up	-0.0130	-0.0150	0.0091	-0.0047	0.0489
	(-0.4688)	(-0.4646)	(0.2699)	(-0.1249)	(1.2998)
FCF	0.0275	0.0298	-0.0071	0.0385	0.2015
	(0.5675)	(0.5743)	(-0.0379)	(0.1679)	(0.7503)
Leverage	-0.0347	-0.0356	-0.1754	-0.0587	0.0582
	(-0.3791)	(-0.3397)	(-1.2833)	(-0.5153)	(0.5420)
Tobin's Q	0.0036	0.0046	-0.0014	0.0038	-0.0006
	(0.7099)	(0.6918)	(-0.2273)	(0.5032)	(-0.1346)
Relative size	0.0045	0.0116	-0.0371	-0.0244	-0.0088
	(0.2024)	(0.4758)	(-1.4796)	(-0.7235)	(-0.1746)
Related	-0.0145	-0.0194	0.0006	-0.0281	-0.0127
	(-0.6543)	(-0.7766)	(0.0206)	(-1.1040)	(-0.3049)
Tender	0.0003	-0.0058	-0.0068	-0.0262	0.0399
	(0.0117)	(-0.2213)	(-0.2804)	(-0.7325)	(1.4232)
Hostile	-0.0267	-0.0295	-0.0514	-0.0701	-0.0500*
	(-0.9263)	(-0.8976)	(-1.2822)	(-1.5652)	(-1.8373)
Public deals	-0.0473*	-0.0415	-0.0158	0.0183	-0.0602
	(-1.7391)	(-1.3303)	(-0.4657)	(0.4727)	(-1.3804)

Private deals	0.0381	0.0578	0.0062	0.2264***	0.2058***
	(0.9312)	(1.3126)	(0.1026)	(4.1991)	(5.2277)
Cross-border	0.0197	0.0277	0.0162	0.0210	-0.0051
	(0.7718)	(0.8868)	(0.4694)	(0.6076)	(-0.1547)
Num. of bidders	-0.0159	-0.0171	0.0047	0.0047	-0.0158
	(-0.9035)	(-0.8185)	(0.2091)	(0.2285)	(-0.5313)
Intercept	0.0275	-0.0442	0.1198	-0.0293	-0.1522
	(0.3824)	(-0.4189)	(0.9454)	(-0.2145)	(-0.6372)
R^2	0.304	0.319	0.412	0.604	0.731
Adj. R^2	0.157	0.141	0.126	0.302	0.366
N	110	88	59	45	34

Table 4.III
Time Decay of Peer Relationships: Reduced-Form Models

This table presents the LIML estimates for the reduced-form equation (Equation (3)) for Table 4.7, for the full sample, the vertically unrelated and the large deal subsamples. For each sample, the first and the second column estimates the level of network density measured based on interbank ties that involve the most recent interaction over the last one year (*1-year-old relationship density*) and over the last two to five years but not in the recent one year (*2-5-year-old relationship density*) prior to announcement, respectively. The "excluded" instruments for the *1-year-old relationship density* are local network density, fraction of members from the same State, prior-1 year (unweighted), prior-5 year (weighted) debt underwriting relationship density. The "excluded" instruments for the *2-5-year-old relationship density* are local network density computed based on ties formed over the last two to five years, the largest debt and equity market share (in $U.S. trillion) of the investment bank in the syndicate in the calendar year prior to the announcement (*Largest debt/equity mkt. share prior year*). The variable, *general residuals*, is computed based on the Probit estimates for the syndication decision equation (Equation (4)), as shown in column (1), Table 4. It is inserted here as an additional regressor to correct for sample selection bias. Other variables are defined in Appendix 4A. Intercepts are not shown. 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		Large Deals (>50%)		Large Deals (>60%)		Large Deals (>75%)	
	1-year	*2- 5-year*	*1-year*	*2- 5-year*	*1-year*	*2- 5-year*	*1-year*	*2- 5-year*	*1-year*	*2- 5-year*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Instruments										
Local network density over the last year	0.4796***	-0.2870***	0.4907***	-0.2876***	0.4504***	-0.2964***	0.4477***	-0.2968***	0.4332***	-0.2431**
	(3.4176)	(-3.6538)	(2.7646)	(-2.8799)	(3.2523)	(-3.0443)	(3.2056)	(-2.7116)	(3.1695)	(-2.4704)
Fraction of members from the same State	0.1398***	0.0253	0.1564***	0.0041	0.2045***	0.0617	0.2023***	0.0688	0.2245***	0.0435
	(3.6580)	(0.7416)	(3.8130)	(0.1076)	(3.7668)	(1.3960)	(3.4564)	(1.4602)	(3.0231)	(0.7189)
Prior-year debt underwriting relationship density	0.0674	-0.0129	0.0986*	-0.0378	0.1592**	-0.0512	0.1393	-0.0151	0.1131	-0.0250
	(1.2555)	(-0.2871)	(1.7776)	(-0.7618)	(2.0462)	(-0.9112)	(1.5542)	(-0.2328)	(1.0803)	(-0.3337)
Prior-5 year debt underwriting relationship density weighted by frequency	0.0005***	-0.0000	0.0004***	0.0000	0.0002	0.0001	0.0002	0.0001	0.0002	0.0001
	(4.0771)	(-0.0565)	(3.2180)	(0.1159)	(1.5708)	(1.1035)	(1.3493)	(0.7996)	(0.9299)	(0.6393)
Local network density over the last 2-5 years	-0.0649	0.1503***	-0.0675*	0.1427***	-0.0952*	0.1628***	-0.0916*	0.1539***	-0.0800	0.1256***
	(-1.5951)	(3.9976)	(-1.6627)	(4.0044)	(-1.8966)	(4.0531)	(-1.8859)	(3.7823)	(-1.5767)	(2.7413)
Largest debt mkt. share	0.2925	0.3177*	0.4224*	0.1720	0.5365**	0.2638	0.7942**	-0.0181	1.0502***	-0.0089

prior year										
	(1.4404)	(1.8701)	(1.9495)	(0.9385)	(2.0124)	(1.2268)	(2.4708)	(-0.0826)	(2.6949)	(-0.0312)
Largest equity mkt. share prior year	0.9267	-3.6917***	0.6796	-3.0132*	-0.1249	-5.0449***	-0.8252	-3.8517**	-1.4235	-3.3327
	(0.5721)	(-2.5936)	(0.3741)	(-1.8973)	(-0.0595)	(-2.9293)	(-0.3327)	(-2.1072)	(-0.4777)	(-1.3931)
Covariates from Third-Stage										
Syndicate size	-0.0193	-0.0069	-0.0221	-0.0072	-0.0189	0.0078	-0.0271	0.0131	-0.0303	-0.0034
	(-1.0791)	(-0.4541)	(-1.1534)	(-0.4428)	(-0.8910)	(0.4534)	(-1.1684)	(0.7445)	(-1.0402)	(-0.1663)
Participation of Top 8	0.0257	0.0235	0.0575	0.0281	0.1313*	0.0056	0.1090	0.0095	0.0152	0.0844
	(0.5012)	(0.5098)	(1.0481)	(0.5583)	(1.8920)	(0.0911)	(1.3460)	(0.1361)	(0.1355)	(1.3062)
Vertical relationship density	0.1254***	-0.0170			0.1176**	-0.0320	0.1191**	-0.0389	0.1141	-0.0473
	(3.1664)	(-0.5831)			(2.4408)	(-1.0379)	(2.2937)	(-1.3305)	(1.1978)	(-0.7259)
Ln (Acquirer size)	0.0022	0.0133	-0.0150	0.0231	-0.0143	0.0383	-0.0318	0.0364	-0.0263	0.0602
	(0.1050)	(0.7117)	(-0.6796)	(1.1007)	(-0.4515)	(1.5330)	(-0.8975)	(1.3734)	(-0.4898)	(1.6030)
Run-up	-0.0575	-0.0675**	-0.0466	-0.0693*	-0.1203**	-0.0584	-0.0815	-0.0707	-0.0980	-0.0470
	(-1.3794)	(-2.0697)	(-1.0355)	(-1.6613)	(-2.1116)	(-1.0931)	(-1.2363)	(-1.1771)	(-1.2859)	(-0.8198)
FCF	-0.0437	0.0684	-0.1036	0.0771	-0.1587	0.3637	-0.2541	0.5016*	-0.3015	0.5335**
	(-0.3164)	(0.6300)	(-0.7300)	(0.6880)	(-0.5355)	(1.5861)	(-0.7999)	(1.8962)	(-0.8146)	(2.1645)
Leverage	-0.0412	0.1006	-0.0364	0.1273	0.0750	0.0762	0.0637	0.0812	0.1930	0.0402
	(-0.3401)	(0.9717)	(-0.2861)	(1.0550)	(0.3908)	(0.6440)	(0.2880)	(0.6632)	(0.6886)	(0.2272)
Tobin’s Q	0.0099**	0.0018	0.0108**	0.0034	0.0155***	0.0045	0.0128**	0.0062	0.0159**	0.0015
	(2.0001)	(0.4014)	(2.1242)	(0.6547)	(2.7339)	(0.7352)	(2.0274)	(0.9467)	(2.3677)	(0.2257)
Ln (Deal size)	0.0163	-0.0091	0.0564*	-0.0222	0.0299	-0.0514	0.0802	-0.0638	0.0643	-0.0461
	(0.5050)	(-0.3391)	(1.6739)	(-0.7307)	(0.6428)	(-1.3619)	(1.5465)	(-1.5427)	(0.8342)	(-0.9300)
Relative size	0.0137	0.0028	0.0240	0.0003	0.0414	0.0032	0.0356	0.0083	0.0631	0.0037
	(0.8124)	(0.2944)	(1.4782)	(0.0296)	(1.4871)	(0.1930)	(1.1330)	(0.4685)	(1.2314)	(0.1098)
Related	0.0121	0.0137	0.0191	0.0137	-0.0205	0.0340	0.0114	0.0119	0.0603	-0.0188
	(0.3443)	(0.4636)	(0.4991)	(0.4104)	(-0.4142)	(0.8655)	(0.2058)	(0.2912)	(0.8229)	(-0.3845)
Tender	-0.0241	-0.0236	-0.0331	-0.0228	-0.0415	-0.0028	-0.0437	0.0158	0.0026	-0.0145
	(-0.4978)	(-0.5796)	(-0.5952)	(-0.4868)	(-0.5684)	(-0.0516)	(-0.5359)	(0.2651)	(0.0255)	(-0.2053)
Hostile	-0.0781	-0.0156	-0.0790	0.0201	-0.0482	-0.0281	-0.0070	-0.0113	0.0430	-0.0837
	(-1.2505)	(-0.3195)	(-1.1510)	(0.3547)	(-0.6211)	(-0.5368)	(-0.0872)	(-0.2015)	(0.4492)	(-1.6096)
Cross-border	-0.0987*	-0.0595	-0.0192	-0.1140**	-0.1045	-0.0481	-0.0523	-0.0976	-0.0957	-0.0579
	(-1.9558)	(-1.3933)	(-0.3418)	(-2.3788)	(-1.4320)	(-0.8225)	(-0.6503)	(-1.6001)	(-1.0149)	(-0.7833)

Num. of bidders	-0.0367	-0.0232	-0.0272	-0.0308	-0.0055	-0.0267	0.0203	-0.0480	-0.0046	-0.0637
	(-0.8428)	(-0.7713)	(-0.5139)	(-0.8984)	(-0.0865)	(-0.7109)	(0.3074)	(-1.1629)	(-0.0477)	(-1.3223)
All cash	0.0334	0.0039	0.0604	-0.0194	0.1273**	-0.0035	0.1811***	-0.0340	0.0852	0.0463
	(0.9518)	(0.1302)	(1.4656)	(-0.5594)	(2.2451)	(-0.0837)	(2.6378)	(-0.6793)	(0.8826)	(0.7123)
Public deals	-0.0463	0.0063	-0.0314	0.0024	-0.0792	0.0314	-0.0988	0.0375	-0.1901	0.1089
	(-0.9897)	(0.1645)	(-0.6192)	(0.0576)	(-1.1954)	(0.5956)	(-1.2067)	(0.6501)	(-1.5898)	(1.4424)
Private deals	-0.0098	-0.0101	-0.0073	-0.0536	0.0090	0.0432	-0.1059	0.1439	-0.0726	-0.0398
	(-0.1937)	(-0.2056)	(-0.1324)	(-0.9827)	(0.0830)	(0.4757)	(-1.0188)	(1.1101)	(-0.3859)	(-0.3678)
General residuals	-0.0648	-0.0018	0.1139	-0.0399	0.0509	-0.0340	0.1190	-0.0428	0.2033	-0.1093
	(-0.5829)	(-0.0194)	(0.9683)	(-0.3908)	(0.3500)	(-0.2685)	(0.7740)	(-0.3319)	(0.9555)	(-0.6832)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Diagnostics										
Centered R^2	0.210	0.210	0.073	0.073	0.133	0.133	0.117	0.117	0.120	0.120
Uncentered R^2	0.211	0.211	0.073	0.073	0.133	0.133	0.117	0.117	0.120	0.120
F	3.601	3.601	4.827	4.827	3.178	3.178	3.051	3.051	2.269	2.269
N	665	665	533	533	367	367	294	294	200	200

Table 4.IV
Network Density and Acquirer CAR in Hot Markets: Reduced-Form Models

This table presents the LIML estimates for the reduced-form equation (Equation (3)) for Table 4.8, for the full sample as well as the vertically unrelated and the large deal (defined as those above the 50th, 60th and 75th percentile) subsamples. For each sample, the first and the second columns estimate the level of network density during peak and non-peak years, respectively, where peak years include the dot-come bubble of 1998-2000, and the recent merger wave 2003-2007. The "excluded" instruments are local network density, fraction of members from the same State, prior-1 year (unweighted), prior-5 year (weighted) debt underwriting relationship density, and the interactions of the above variables with the peak year dummy variable. The variable, *general residuals*, is computed based on the Probit estimates from the syndication decision equation (Equation (4)), as shown in column (1), Table 4. It is inserted here as an additional regressor to correct for sample selection bias. Other variables are defined in Appendix 4A. 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		Large Deals (>50%)		Large Deals (>60%)		Large Deals (>75%)	
	Density during peak years (1)	Density during non-peak years (2)	Density during peak years (3)	Density during non-peak years (4)	Density during peak years (5)	Density during non-peak years (6)	Density during peak years (7)	Density during non-peak years (8)	Density during peak years (9)	Density during non-peak years (10)
Instruments										
Local network density	-0.1214***	0.6801***	-0.1109***	0.6519***	-0.1174**	0.4686***	-0.1062*	0.4566***	-0.0805	0.4510***
	(-3.5093)	(5.5234)	(-3.1494)	(4.7558)	(-2.1429)	(3.9962)	(-1.8994)	(4.0737)	(-1.2173)	(3.1586)
*Peak year	0.4874***	-0.7379***	0.4404***	-0.6711***	0.4625***	-0.5263***	0.4133***	-0.4998***	0.3873**	-0.4543***
	(3.1469)	(-4.7426)	(2.6322)	(-4.1340)	(2.8496)	(-3.6878)	(2.7480)	(-3.5667)	(2.5136)	(-2.8064)
Fraction of members from the same State	-0.0807***	0.2344***	-0.0635***	0.2209***	-0.1224***	0.4273***	-0.1231***	0.4067***	-0.1384**	0.4418***
	(-4.1647)	(5.0002)	(-3.1849)	(4.4044)	(-3.9843)	(6.9337)	(-3.3413)	(5.6784)	(-2.5925)	(5.1144)
*Peak year	0.2642***	-0.3345***	0.2596***	-0.3049***	0.3138***	-0.4841***	0.3188***	-0.4666***	0.3379***	-0.4805***
	(6.3166)	(-7.3662)	(5.1481)	(-6.0833)	(6.2312)	(-8.1764)	(5.6154)	(-6.8682)	(4.1101)	(-5.8609)
Prior-year debt underwriting relationship density	-0.0437*	0.1083	-0.0117	0.1727**	-0.1009***	0.3258***	-0.1027***	0.3320***	-0.0963*	0.2946**
	(-1.6758)	(1.3752)	(-0.4326)	(2.0858)	(-3.1539)	(3.3669)	(-2.6485)	(2.7855)	(-1.7725)	(2.1068)
*Peak year	0.1244	-0.1804**	0.0838	-0.2389***	0.2063**	-0.3532***	0.1917*	-0.3678***	0.2159*	-0.3075**
	(1.6413)	(-2.2604)	(1.0286)	(-2.8223)	(2.1349)	(-3.6105)	(1.8592)	(-3.0051)	(1.7311)	(-2.1577)
Prior-5 year debt	-0.0001**	0.0006***	-0.0001**	0.0005***	-0.0000	0.0002	-0.0001	0.0002	-0.0001	0.0002

underwriting relationship density weighted by frequency										
	(-2.2555)	(4.3364)	(-2.4991)	(3.7117)	(-0.7630)	(1.0808)	(-0.9076)	(1.1184)	(-0.6266)	(1.0158)
*Peak year	0.0012***	-0.0006***	0.0011***	-0.0005***	0.0009***	-0.0003	0.0010***	-0.0002	0.0008*	-0.0002
	(5.3001)	(-4.3675)	(4.7254)	(-3.4629)	(3.4158)	(-1.4156)	(2.8443)	(-0.8034)	(1.8455)	(-0.9450)
Covariates from Third-Stage										
Syndicate size	-0.0045	-0.0072	-0.0060	-0.0045	-0.0004	-0.0161	-0.0013	-0.0165	-0.0012	-0.0166
	(-0.3960)	(-0.5933)	(-0.5195)	(-0.3621)	(-0.0286)	(-1.3734)	(-0.0937)	(-1.2564)	(-0.0718)	(-1.1002)
Participation of Top 8	0.0619**	0.0491	0.0642*	0.0739**	0.1113**	0.0564	0.1135*	0.0628	0.0650	0.0572
	(2.0184)	(1.6447)	(1.9099)	(2.1618)	(2.2700)	(1.4366)	(1.9602)	(1.3871)	(0.8222)	(1.0682)
Vertical relationship density	0.0383	0.1076***			0.0456	0.0855**	0.0558	0.0831*	0.1632**	0.0581*
	(1.2883)	(2.9579)			(1.2587)	(2.1562)	(1.3804)	(1.8405)	(2.0871)	(1.7496)
Ln (Acquirer size)	-0.0079	-0.0079	-0.0124	-0.0092	-0.0246	-0.0027	-0.0356	-0.0146	-0.0290	-0.0144
	(-0.5238)	(-0.6167)	(-0.7868)	(-0.6745)	(-1.1613)	(-0.1830)	(-1.5411)	(-0.9003)	(-0.7620)	(-0.5938)
Run-up	0.0056	-0.0742**	-0.0028	-0.0688**	-0.0448	-0.0976*	-0.0590	-0.0505	-0.1087*	-0.0348
	(0.1918)	(-2.3088)	(-0.0936)	(-1.9981)	(-1.0111)	(-1.9370)	(-1.1643)	(-1.0616)	(-1.7970)	(-0.7202)
FCF	-0.1136	0.0823	-0.1464	-0.0004	-0.2333	0.2123	-0.1647	0.0769	-0.0172	0.0487
	(-0.9879)	(1.1095)	(-1.1881)	(-0.0061)	(-1.0564)	(1.0582)	(-0.7104)	(0.3727)	(-0.0612)	(0.2702)
Leverage	0.0816	-0.0814	0.0940	-0.0859	0.1412	-0.0473	0.0261	0.0126	0.0552	-0.0647
	(1.0187)	(-0.9224)	(1.1065)	(-0.9331)	(1.0481)	(-0.3635)	(0.1671)	(0.0944)	(0.2301)	(-0.4022)
Tobin's Q	0.0076**	0.0018	0.0085**	0.0026	0.0116**	0.0068	0.0120**	0.0043	0.0162***	0.0028
	(2.1159)	(0.4151)	(2.2761)	(0.6781)	(2.5809)	(1.3557)	(2.3442)	(0.9855)	(2.7826)	(0.6460)
Ln (Deal size)	0.0362*	0.0287	0.0471**	0.0413**	0.0638*	-0.0166	0.0806**	0.0091	0.0636	0.0030
	(1.8095)	(1.4247)	(2.2879)	(1.9952)	(1.9636)	(-0.8196)	(2.0797)	(0.4127)	(1.2036)	(0.1128)
Relative size	0.0047	0.0015	0.0064	0.0099	0.0084	-0.0009	0.0061	0.0002	0.0442	-0.0464*
	(0.7441)	(0.1198)	(1.0563)	(0.7475)	(1.0020)	(-0.0762)	(0.7342)	(0.0171)	(1.2907)	(-1.7912)
Related	-0.0135	0.0414	-0.0170	0.0589**	-0.0123	-0.0291	-0.0106	-0.0079	-0.0035	0.0397
	(-0.5490)	(1.5944)	(-0.6093)	(2.0426)	(-0.3425)	(-0.9155)	(-0.2546)	(-0.2258)	(-0.0616)	(0.8812)
Tender	-0.0341	-0.0170	-0.0230	-0.0579	-0.0669	0.0349	-0.0777	0.0600	-0.0395	0.0497

	(-1.0130)	(-0.3970)	(-0.5580)	(-1.3669)	(-1.2394)	(0.6274)	(-1.3282)	(0.9138)	(-0.4757)	(0.6031)
Hostile	-0.0334	-0.0004	-0.0351	0.0198	-0.0207	-0.0571	-0.0025	-0.0221	-0.0205	-0.0080
	(-0.6618)	(-0.0079)	(-0.5816)	(0.3455)	(-0.3374)	(-0.8281)	(-0.0367)	(-0.2976)	(-0.3146)	(-0.0896)
Cross-border	-0.0246	-0.0252	0.0016	0.0072	-0.0286	-0.0506	-0.0231	-0.0304	-0.0734	-0.0010
	(-0.7389)	(-0.6739)	(0.0410)	(0.1818)	(-0.5746)	(-1.0914)	(-0.4397)	(-0.5484)	(-1.0669)	(-0.0144)
Num. of bidders	0.0272	-0.0557*	0.0396	-0.0764**	0.0328	0.0006	0.0448	0.0050	-0.0098	0.0191
	(0.8258)	(-1.9351)	(0.9740)	(-2.4249)	(0.7480)	(0.0173)	(0.9903)	(0.1279)	(-0.1415)	(0.3684)
All cash	0.0438	-0.0109	0.0531*	0.0172	0.0970**	0.0176	0.1075**	0.0466	0.1075	-0.0327
	(1.5962)	(-0.3989)	(1.7734)	(0.5738)	(2.1994)	(0.4663)	(2.1348)	(1.0019)	(1.3921)	(-0.5324)
Public deals	0.0352	-0.0738**	0.0314	-0.0636*	0.0606	-0.1462***	0.0445	-0.1407**	-0.0119	-0.1577**
	(1.1455)	(-2.0393)	(0.9112)	(-1.6605)	(1.4165)	(-2.9090)	(0.8775)	(-2.4808)	(-0.1512)	(-2.1357)
Private deals	0.0316	-0.0933**	0.0026	-0.0606	0.0462	-0.1268*	-0.0333	-0.2303***	0.0227	-0.2309**
	(0.9304)	(-2.1827)	(0.0738)	(-1.2782)	(0.6339)	(-1.6884)	(-0.5288)	(-3.2003)	(0.1833)	(-2.2673)
General residuals	0.0562	0.0074	0.1119**	0.0621	0.1422	-0.0705	0.1481	0.0360	0.1253	0.0376
	(1.0475)	(0.1169)	(1.9667)	(0.9141)	(1.6111)	(-1.0468)	(1.3747)	(0.5234)	(0.9314)	(0.5390)
Intercept	-0.2471	0.0435	-0.3818**	-0.1344	-0.4806*	0.4104*	-0.5119	0.1616	-0.3089	0.2253
	(-1.6353)	(0.2429)	(-2.3577)	(-0.7055)	(-1.7378)	(1.8521)	(-1.5294)	(0.6948)	(-0.6280)	(0.7980)
Diagnostics										
Centered R^2	0.137	0.137	0.138	0.138	0.103	0.103	0.131	0.131	0.139	0.139
UncenteredR^2	0.139	0.139	0.138	0.138	0.152	0.152	0.217	0.217	0.278	0.278
F	4.127	4.127	4.678	4.678	4.034	4.034	3.546	3.546	3.662	3.662
N	665	665	533	533	367	367	294	294	200	200

Table 4.V
Descriptive Statistics of the Lead Subsample

This table presents the descriptive statistics for the sample of U.S. syndicated M&A transactions in which a lead advisor can be identified based on the information from the SDC and Factiva databases. The sample covers 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 advisor-, 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 Compustat.

	N	Mean	Median	Std. Dev.
Panel A: Advisor characteristics				
Syndicate density	347	0.281	0.000	0.425
Top-8 lead advisor	347	0.478	0.000	0.500
Syndicate size	347	2.251	2.000	0.751
Panel B: Acquirer characteristics				
Acquirer ties with syn. members	347	0.090	0.000	0.330
Acquirer size (in $mil)	347	11899.648	1478.083	41538.373
Run-up	347	0.080	0.014	0.411
FCF	279	0.081	0.094	0.118
Leverage	292	0.212	0.194	0.166
Tobin's Q	293	1.947	1.368	2.021
Acquirer experience	347	1.014	1.000	1.374
Panel C: Deal characteristics				
Deal size	347	4367.430	826.042	12870.416
Relative size	347	0.917	0.639	1.850
Num. of bidders	347	1.144	1.000	0.405
Public target	347	0.758	-	0.429
Private target	347	0.130	-	0.336
Subsidiary target	347	0.112	-	0.316
Cross border	347	0.110	-	0.313
All cash	347	0.176	-	0.381
Pmt. incl. stock	347	0.703	-	0.458
Related	347	0.640	-	0.481

Tender	347	0.184	-	0.388
Hostile	347	0.063	-	0.244
CAR (-1, +1)	347	-0.008	-0.016	0.119

Table 4.VI
Top-8 Lead, Density and Acquirer CAR: Selection and Reduced-Form Models

This table presents the results of the LIML estimation from an IV-style regression of acquirer 3-day CAR on the top-8 lead advisor and network density, conditional on the syndication decision. The sample consists of deals with hand-collected data on the identity of the lead advisor. Column (1) estimates the determinants of the syndication decision (Equation (4)) by Probit, where the dependent variable is a dummy variable equal to 1 if a syndicate is used; and 0 otherwise. The syndication decision determines whether density at the syndicate level is observable. Columns (2) and (3) estimate the reduced-form equation for the endogenous regressor, *density* and *top-8 lead advisor*, respectively, for the full sample; columns (4) and (5) repeat the analysis for the vertically unrelated subsample; and columns (6) and (7) present the results for the subsample of deals in the top-two size quintiles. Other variables are defined in Appendix 4A. Year fixed effects are controlled for in all models, but the coefficients are suppressed for brevity. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Selection	Full		Vertically Unrelated		Large Deals (>50%)		Large Deals (>60%)	
		Density	Top-8 lead	Density	Top-8 lead	Density	Top-8 lead	Density	Top-8 lead
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(6)	(7)
Instruments									
Lagged syndicate size	0.2746***								
	(3.8254)								
Weighted lagged syndicate size	0.0044								
	(1.6289)								
Local network density over the last year		0.3228	0.1232	0.2410	0.0230	0.2292	0.2035	0.0390	0.1460
		(1.3415)	(0.5230)	(0.8625)	(0.0940)	(0.6822)	(0.5097)	(0.0984)	(0.4496)
Fraction of members from the same State		0.1668**	0.0064	0.1889**	-0.0435	0.2150	0.0474	0.3167**	0.0802
		(1.9822)	(0.1615)	(2.1292)	(-0.8380)	(1.5597)	(0.7287)	(2.1718)	(1.1652)
Prior-year debt underwriting relationship density		0.2104*	0.0318	0.2294**	-0.0072	0.3537**	0.0705	0.5181**	0.1713**
		(1.8967)	(0.5420)	(2.0358)	(-0.1240)	(2.5284)	(1.0202)	(2.5381)	(2.4613)
Prior-5 year debt underwriting relationship density weighted by frequency		0.0003	0.0002	0.0002	0.0001	0.0001	0.0002	-0.0001	-0.0001
		(1.2700)	(0.9614)	(0.9107)	(0.3803)	(0.2162)	(0.8007)	(-0.2479)	(-0.2379)
Scope		0.1565***	0.5645***	0.1772***	0.5811***	0.2592***	0.5594***	0.2949**	0.6679***
		(2.6881)	(12.5281)	(2.6978)	(12.8043)	(3.4933)	(10.3655)	(2.5525)	(9.7253)

Near-firm mean use of top-8 lead advisor		-0.1918	0.0003	-0.2344*	-0.0230	-0.2865**	0.0195	-0.3753**	0.0645
		(-1.6376)	(0.0046)	(-1.7800)	(-0.3163)	(-1.9925)	(0.2305)	(-2.0439)	(0.6847)
Covariates from Third-Stage									
Syndicate size		-0.0299	0.0245	-0.0343	0.0089	-0.0406	0.0404	-0.0337	0.0223
		(-0.8574)	(0.9944)	(-0.8328)	(0.3410)	(-0.8619)	(1.2422)	(-0.6730)	(0.6203)
Participation of Top 8	0.4170***								
	(4.6657)								
Vertical relationship density		0.0624	-0.0586			0.0420	-0.0850	0.0832	-0.1431**
		(0.7488)	(-1.2887)			(0.3737)	(-1.4496)	(0.6373)	(-2.4539)
Cash shortfall	0.0189								
	(1.6018)								
Ln (Acquirer size)	-0.1380***	-0.0988*	0.0614*	-0.0996	0.0379	-0.0666	0.0205	-0.0574	0.0920
	(-2.6144)	(-1.7736)	(1.7471)	(-1.5417)	(1.0118)	(-0.8280)	(0.4056)	(-0.5350)	(1.6407)
Run-up	-0.0178	-0.0297	0.1051	0.1489	0.0956	-0.1743	0.1209	-0.2042	0.1608
	(-0.2154)	(-0.2220)	(1.4752)	(1.0750)	(1.3008)	(-0.8705)	(0.9263)	(-0.8377)	(1.1568)
Sigma	0.8870								
	(0.2245)								
FCF		-0.2714	0.1279	-0.1252	0.0405	-0.0973	-0.2265	-0.3695	-0.2030
		(-0.8381)	(0.9561)	(-0.3215)	(0.2618)	(-0.1536)	(-0.5817)	(-0.5226)	(-0.4301)
Leverage	1.1765***	0.2024	-0.5067***	0.2309	-0.4217**	0.1228	-0.4021	0.4119	-0.5236*
	(4.2564)	(0.7780)	(-2.8532)	(0.7677)	(-2.3322)	(0.2883)	(-1.4921)	(0.8791)	(-1.7862)
Tobin's Q		0.0122	-0.0072	0.0242*	-0.0061	0.0098	-0.0064	0.0173	-0.0155
		(0.9602)	(-0.8547)	(1.7785)	(-0.6023)	(0.6318)	(-0.5984)	(1.0824)	(-1.3986)
Ln (1+Acquirer experience)	-0.0237								
	(-0.3178)								
Ln (Deal size)	0.3198***	0.1741**	-0.1348***	0.1701*	-0.0976*	0.1060	-0.0752	0.1050	-0.1331*
	(5.7120)	(2.1433)	(-2.9153)	(1.7734)	(-1.8754)	(0.8367)	(-1.0836)	(0.6665)	(-1.7214)
Relative size	0.1492*	0.0412	-0.0414	0.0139	-0.1062**	0.0394	-0.0399	0.0177	0.0508
	(1.7141)	(0.4625)	(-0.7648)	(0.1255)	(-2.1274)	(0.3432)	(-0.4474)	(0.1129)	(0.4744)
Related	-0.0776	-0.0618	-0.0923	-0.0615	-0.1430**	-0.0840	-0.0824	-0.1284	-0.0605
	(-0.9621)	(-0.6742)	(-1.5743)	(-0.5965)	(-2.3604)	(-0.6443)	(-0.8742)	(-0.9248)	(-0.6611)
Hostile	-0.0084	-0.1268	0.0238	-0.2372	0.0570	-0.0798	0.0697	0.0699	0.0450
	(-0.0408)	(-0.8136)	(0.2762)	(-1.5286)	(0.5953)	(-0.3474)	(0.5857)	(0.3126)	(0.4410)
Cross-border	0.1274	0.0564	-0.0548	0.0415	-0.0863	0.1666	-0.1265	0.1863	-0.0476
	(1.0349)	(0.4783)	(-0.7367)	(0.3624)	(-1.1074)	(0.6034)	(-0.7338)	(0.6622)	(-0.2983)

Num. of bidders	0.2808***	0.0797	-0.1656***	0.0295	-0.1399***	0.1508	-0.1963***	0.2314	-0.1904**
	(2.8841)	(0.9257)	(-3.5888)	(0.3194)	(-2.9591)	(1.1495)	(-2.7299)	(1.6364)	(-2.2325)
All cash		-0.0117	-0.1040	-0.0394	-0.1517	0.1917	0.0984	0.2618	0.1159
		(-0.0876)	(-1.0926)	(-0.2847)	(-1.5575)	(0.5983)	(0.6786)	(0.7595)	(0.8513)
Tender		0.0995	0.0242	0.1005	0.0954	-0.0538	-0.0056	-0.2733	0.0141
		(0.7147)	(0.2866)	(0.7040)	(1.0928)	(-0.2058)	(-0.0392)	(-1.1349)	(0.0902)
Public deals	0.4947***	0.1345	-0.2641***	0.0117	-0.2458***	0.1341	-0.2527	0.1200	-0.1791
	(5.4372)	(0.9238)	(-3.1061)	(0.0751)	(-2.7160)	(0.4303)	(-1.6183)	(0.4143)	(-1.0942)
Private deals		-0.0689	0.1168	-0.2246	0.1266	0.0562	0.0652	0.0991	0.5332**
		(-0.3893)	(1.3853)	(-1.2613)	(1.2670)	(0.1757)	(0.3320)	(0.3148)	(2.4719)
General residuals		0.3173	-0.5455***	0.3668	-0.5215***	0.1395	-0.4221**	0.0610	-0.4479**
		(1.5793)	(-4.3727)	(1.5283)	(-3.7900)	(0.4132)	(-2.4720)	(0.1635)	(-2.1342)
Intercept	-4.0870***	-1.3816*	2.1594***	-1.2803	2.1523***	-0.6356	1.1377*	-0.9513	0.9160
	(-8.5300)	(-1.7592)	(4.1830)	(-1.4206)	(3.9277)	(-0.5470)	(1.7207)	(-0.7458)	(1.1171)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Diagnostics									
R^2	-	0.453	0.847	0.501	0.866	0.465	0.822	0.520	0.864
Adj. R^2 (Pseudo R^2)	0.270	0.261	0.793	0.279	0.806	0.119	0.708	0.126	0.752
N	3878	170	170	141	141	108	108	94	94

Table 4.VII
Network Density and Advisory Fee: Reduced-Form Models

This table presents the LIML estimates for the reduced-form equation (Equation (3)) for Table 4.9, for the full sample, the vertically unrelated subsample and the subsamples of large deals above the 50th, 60th and 75th percentiles of the size distribution. The dependent variable in each column is the endogenous regressor, *density*, computed as the relative degree of interbank relationships within a syndicate that formed through M&A syndication over the last one year prior to the announcement date. The "excluded" instruments are local network density, fraction of members from the same State, and prior-1 year debt underwriting relationship density. The variable, *general residuals*, is computed based on the Probit estimates for the syndication decision equation (Equation (4)), as shown in column (1), Table 4. It is inserted here as an additional regressor to correct for sample selection bias. Other variables are defined in Appendix 4A. Year fixed effects are controlled for in all models, but the coefficients are suppressed for brevity. The t-statistics in parentheses are adjusted for heteroskedasticity and acquirer clustering. N denotes number of observations. The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Full	Vertically Unrelated	Large Deals (>50%)	Large Deals (>60%)	Large Deals (>75%)
	(1)	(2)	(3)	(4)	(5)
Instruments					
Local network density	0.5865*	0.3650	0.8766**	0.9531***	1.0935***
	(1.7715)	(1.0043)	(2.6016)	(2.7666)	(3.5320)
Fraction of members from the same State	0.2228**	0.2604**	0.3821**	0.4110***	0.4722***
	(2.1618)	(2.3590)	(2.5681)	(2.6802)	(2.8634)
Prior-year debt underwriting relationship density	0.3284***	0.3818***	0.5306***	0.5004***	0.5816***
	(2.7333)	(3.0484)	(3.9022)	(2.8678)	(3.0014)
Prior-5 year debt underwriting relationship density weighted by frequency	0.0002	0.0002	0.0001	0.0001	-0.0003
	(0.7786)	(0.5374)	(0.1617)	(0.2659)	(-0.6243)
Covariates from Third-Stage					
Syndicate size	0.0270	0.0375	0.0443	0.0367	0.0039
	(0.6762)	(0.8222)	(0.8891)	(0.6441)	(0.0592)
Participation of top8	-0.0228	-0.0021	-0.0702	-0.0757	-0.0341
	(-0.2107)	(-0.0156)	(-0.4789)	(-0.4198)	(-0.1651)
Vertical relationship density	0.0325		0.0410	0.1632	0.2002
	(0.2457)		(0.2951)	(1.0445)	(1.0812)
Ln (Deal size)	0.0425	0.0497	0.0369	0.0486	0.0508
	(1.0931)	(1.1793)	(0.7067)	(0.8100)	(0.6910)
Relative size	0.0471	0.0697	0.0561	0.0246	0.0082
	(1.0011)	(1.2966)	(0.9951)	(0.4674)	(0.1606)

Related	-0.0214	-0.0818	-0.0646	-0.0449	-0.0151
	(-0.2309)	(-0.7429)	(-0.4907)	(-0.2900)	(-0.0867)
Payment incl. stock	-0.5846***	-0.5053***	-1.0708***	-0.9820***	-0.8448*
	(-3.1362)	(-2.7005)	(-3.6807)	(-2.8230)	(-1.9019)
Hostile	-0.0106	-0.0913	-0.2342	-0.1852	-0.2334
	(-0.0724)	(-0.6862)	(-1.2942)	(-0.8789)	(-0.8276)
Tender	-0.3648**	-0.3631**	-0.1872	-0.1358	0.0685
	(-2.4013)	(-2.4926)	(-0.8526)	(-0.5298)	(0.2024)
General residuals	0.1211	0.3036	-0.0688	-0.2383	-0.3387
	(0.5875)	(1.3254)	(-0.2042)	(-0.6566)	(-0.7901)
Year fixed effects	YES	YES	YES	YES	YES
Diagnostics					
Centered R^2	0.413	0.417	0.197	0.160	0.235
UncenteredR^2	0.413	0.417	0.197	0.160	0.235
F	6.388	5.662	3.736	2.276	2.536
N	135	110	96	83	70

Table 4.VIII
Network Density and Alternative Measures of Acquirer CAR

This table presents the LIML estimation results for the structural equation (Equation (2)), conditional on the syndication decision and with network density endogenized. The selection and reduced-form estimation results are omitted for brevity. Panels A and B report the results for acquirer value-weighted CAR measured over an alternative event window (-2, +2) and (-5, +5), respectively. Panels C, D and E repeat the analysis for acquirer equally-weighted CAR measured over the event window (-1, +1), (-2, +2) and (-5, +5), respectively. The "excluded" instruments and control variables are the same as those shown in Table 4.5. In each panel, we report the coefficients on network density only for space reasons. The estimates for the full sample are presented in column (1); results for the vertically unrelated (related) subsample of deals are provided in column (2) ((3)); columns (4) through (5) report results for the sample split at the 50%, 60% and 75% size cut-off points, respectively. The Stock-Yogo critical value for a 10% maximal LIML size is 5.44 throughout the table. Other variables are defined in Appendix 4A. 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.

Panel A: Value-weighted acquirer CAR (-2, +2)

	Full (1)	Vertically Unrelated (2)	Vertically Related (3)	Large Deals (>50%) (4)	Ordinary Deals (<=50%) (5)	Large Deals (>60%) (6)	Ordinary Deals (<=60%) (7)	Large Deals (>75%) (8)	Ordinary Deals (<=75%) (9)
Density	0.0363	0.0443*	-0.0081	0.0357	0.0508	0.0473**	0.0576	0.0684**	0.0182
	(1.6043)	(1.8361)	(-0.1845)	(1.5578)	(1.2422)	(2.0460)	(1.5447)	(2.4323)	(0.5690)
Diagnostics									
Hansen J Chi2	1.397	0.707	1.620	0.716	0.453	0.133	0.674	4.595	1.562
p-value	0.706	0.872	0.655	0.869	0.929	0.988	0.879	0.204	0.668
Instrument Strength test (F-test)	18.251	18.606	4.018	13.424	10.823	11.399	14.275	9.772	16.675
Centered R^2	0.211	0.111	0.218	0.166	0.104	0.177	0.095	0.196	0.118
Uncentered R^2	0.214	0.111	0.218	0.166	0.104	0.177	0.095	0.196	0.118
N	665	533	132	367	298	294	371	200	465

Panel B: Value-weighted acquirer CAR (-5, +5)

	Full (1)	Vertically Unrelated (2)	Vertically Related (3)	Large Deals (>50%) (4)	Ordinary Deals (<=50%) (5)	Large Deals (>60%) (6)	Ordinary Deals (<=60%) (7)	Large Deals (>75%) (8)	Ordinary Deals (<=75%) (9)
Density	0.0256	0.0331	0.0085	0.0211	0.0385	0.0363	0.0375	0.0627*	-0.0041

	(0.9427)	(1.1921)	(0.1355)	(0.7224)	(0.8357)	(1.1609)	(0.8991)	(1.7530)	(-0.1107)
Diagnostics									
Hansen J Chi2	3.200	2.214	3.375	3.870	0.122	2.351	0.184	6.994	1.221
p-value	0.362	0.529	0.337	0.276	0.989	0.503	0.980	0.072	0.748
Instrument Strength test (F-test)	18.251	18.606	4.018	13.424	10.823	11.399	14.275	9.772	16.675
Centered R^2	0.184	0.135	0.175	0.125	0.107	0.127	0.099	0.141	0.123
Uncentered R^2	0.185	0.135	0.175	0.125	0.107	0.127	0.099	0.141	0.123
N	665	533	132	367	298	294	371	200	465

Panel C: Equally-weighted acquirer CAR (-1, +1)

	Full	Vertically Unrelated	Vertically Related	Large Deals (>50%)	Ordinary Deals (<=50%)	Large Deals (>60%)	Ordinary Deals (<=60%)	Large Deals (>75%)	Ordinary Deals (<=75%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Density	0.0300	0.0385	-0.0060	0.0309	0.0437	0.0432*	0.0521	0.0626**	0.0138
	(1.3286)	(1.6021)	(-0.1317)	(1.3465)	(1.0566)	(1.9118)	(1.3858)	(2.2951)	(0.4339)
Diagnostics									
Hansen J Chi2	1.375	0.576	2.935	0.800	0.302	0.198	0.581	3.990	1.411
p-value	0.711	0.902	0.402	0.850	0.960	0.978	0.901	0.263	0.703
Instrument Strength test (F-test)	18.251	18.606	4.018	13.424	10.823	11.399	14.275	9.772	16.675
Centered R^2	0.213	0.109	0.251	0.173	0.112	0.194	0.098	0.211	0.124
Uncentered R^2	0.215	0.109	0.251	0.173	0.112	0.194	0.098	0.211	0.124
N	665	533	132	367	298	294	371	200	465

Panel D: Equally-weighted acquirer CAR (-2, +2)

	Full	Vertically Unrelated	Vertically Related	Large Deals (>50%)	Ordinary Deals (<=50%)	Large Deals (>60%)	Ordinary Deals (<=60%)	Large Deals (>75%)	Ordinary Deals (<=75%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Density	0.0307	0.0414*	0.0090	0.0235	0.0578	0.0364	0.0556	0.0535**	0.0236
	(1.4377)	(1.8571)	(0.2206)	(1.0345)	(1.5008)	(1.5912)	(1.6037)	(1.9631)	(0.8564)
Diagnostics									

Hansen J Chi2	2.874	1.890	2.043	1.166	0.125	1.001	0.246	2.880	0.882
p-value	0.411	0.596	0.564	0.761	0.989	0.801	0.970	0.411	0.830
Instrument Strength test (F-test)	18.251	18.606	4.018	13.424	10.823	11.399	14.275	9.772	16.675
Centered R^2	0.254	0.113	0.299	0.192	0.089	0.205	0.089	0.219	0.113
Uncentered R^2	0.255	0.113	0.299	0.192	0.089	0.205	0.089	0.219	0.113
N	665	533	132	367	298	294	371	200	465

Panel E: Equally-weighted acquirer CAR (-5, +5)

	Full (1)	Vertically Unrelated (2)	Vertically Related (3)	Large Deals (>50%) (4)	Ordinary Deals (<=50%) (5)	Large Deals (>60%) (6)	Ordinary Deals (<=60%) (7)	Large Deals (>75%) (8)	Ordinary Deals (<=75%) (9)
Density	0.0260	0.0347	0.0207	0.0151	0.0488	0.0301	0.0470	0.0549	0.0001
	(0.9756)	(1.2635)	(0.3015)	(0.5215)	(1.0449)	(1.0005)	(1.0959)	(1.6275)	(0.0019)
Diagnostics									
Hansen J Chi2	2.131	0.962	4.525	3.774	0.066	1.930	0.231	5.683	0.650
p-value	0.546	0.810	0.210	0.287	0.996	0.587	0.972	0.128	0.885
Instrument Strength test (F-test)	18.251	18.606	4.018	13.424	10.823	11.399	14.275	9.772	16.675
Centered R^2	0.186	0.134	0.217	0.152	0.082	0.175	0.075	0.183	0.116
Uncentered R^2	0.187	0.134	0.217	0.152	0.082	0.175	0.075	0.183	0.116
N	665	533	132	367	298	294	371	200	465

Table 4.IX
Alternative Measures of Network Density and Acquirer CAR

Panel A reports the Pearson correlations of the alternative syndicate density measures; Panels B through F present the LIML estimation results for the structural model of acquirer three-day CAR (Equation (2)), with the selection and reduced-form estimation results suppressed for brevity. Panels B and C report the results for network density measured over alternative 3 and 5 years prior to the announcement year, respectively. In Panels D, E and F, we repeat the analysis for network density measured as the proportion of all logically possible ties that are present among investment banks in the syndicate, where each tie is weighted by the number of times that two banks had syndicated M&A deals over 1, 3 and 5 years prior to the announcement year, respectively. The "excluded" instruments and control variables are the same as those shown in Table 4.5. In each panel, we report the coefficients on network density only for space reasons. The estimates for the full sample are presented in column (1); results for the vertically unrelated (related) subsample of deals are provided in column (2) ((3)); columns (4) through (5) report results for the sample split at the 50^{th}, 60^{th} and 75^{th} percentiles of the size distribution, respectively. The Stock-Yogo critical value for a 10% maximal LIML size is 5.44 throughout the table. Other variables are defined in Appendix 4A. 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.

Panel A: Pearson correlations of different syndicate density measures

		1	**2**	**3**	**4**	**5**	**6**
1	Syndicate density	1.0000					
2	Unweighted Syndicate density measured over 3 year	0.7964*	1.0000				
3	Unweighted Syndicate density measured over 5 year	0.7479*	0.9399*	1.0000			
4	Weighted Syndicate density measured over 1 year	0.6812*	0.5463*	0.5128*	1.0000		
5	Weighted Syndicate density measured over 3 year	0.5771*	0.5403*	0.5081*	0.9129*	1.0000	
6	Weighted Syndicate density measured over 5 year	0.5301*	0.5052*	0.4889*	0.8451*	0.9658*	1.0000

Panel B: prior-3 year unweighted density of syndicate

	Full (1)	Vertically Unrelated (2)	Vertically Related (3)	Large Deals (>50%) (4)	Ordinary Deals (<=50%) (5)	Large Deals (>60%) (6)	Ordinary Deals (<=60%) (7)	Large Deals (>75%) (8)	Ordinary Deals (<=75%) (9)
Density	0.0368*	0.0468**	0.0081	0.0315	0.0498	0.0409*	0.0481	0.0673**	0.0321
	(1.7817)	(2.0909)	(0.2146)	(1.4358)	(1.5186)	(1.8205)	(1.6032)	(2.2501)	(1.2830)
Diagnostics									
Hansen J Chi2	1.594	2.185	0.382	1.161	0.389	0.804	0.189	4.157	0.559
p-value	0.661	0.535	0.944	0.762	0.943	0.848	0.979	0.245	0.906
Instrument	23.149	19.491	4.040	20.816	13.311	17.845	16.190	12.573	19.885

Strength test (F-test)									
Centered R^2	0.261	0.127	0.282	0.197	0.105	0.191	0.132	0.170	0.129
Uncentered R^2	0.262	0.127	0.282	0.197	0.105	0.191	0.132	0.170	0.129
N	665	533	132	367	298	294	371	200	465

Panel C: prior-5 year unweighted density of syndicate

	Full	Vertically Unrelated	Vertically Related	Large Deals (>50%)	Ordinary Deals (<=50%)	Large Deals (>60%)	Ordinary Deals (<=60%)	Large Deals (>75%)	Ordinary Deals (<=75%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Density	0.0408*	0.0544**	-0.0063	0.0330	0.0443	0.0398*	0.0534	0.0608*	0.0399
	(1.7762)	(2.0823)	(-0.1558)	(1.3425)	(1.2436)	(1.6726)	(1.5130)	(1.9271)	(1.4997)
Diagnostics									
Hansen J Chi2	1.068	1.492	0.064	1.450	0.410	1.070	0.311	3.837	0.088
p-value	0.785	0.684	0.996	0.694	0.938	0.784	0.958	0.280	0.993
Instrument Strength test (F-test)	19.814	14.960	4.866	17.886	10.402	15.781	10.153	11.609	10.751
Centered R^2	0.257	0.112	0.276	0.191	0.123	0.190	0.131	0.205	0.119
Uncentered R^2	0.258	0.112	0.276	0.191	0.123	0.190	0.131	0.205	0.119
N	665	533	132	367	298	294	371	200	465

Panel D: prior-1 year weighted density of syndicate

	Full	Vertically Unrelated	Vertically Related	Large Deals (>50%)	Ordinary Deals (<=50%)	Large Deals (>60%)	Ordinary Deals (<=60%)	Large Deals (>75%)	Ordinary Deals (<=75%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Density	0.0060	0.0098	-0.0021	0.0064	0.0131	0.0084	0.0122	0.0110	0.0064
	(1.1586)	(1.5743)	(-0.1783)	(1.0438)	(1.3078)	(1.3496)	(1.4599)	(1.0407)	(1.0532)
Diagnostics									
Hansen J Chi2	2.950	2.945	0.197	1.716	0.048	1.708	0.030	5.750	0.246
p-value	0.399	0.400	0.978	0.633	0.997	0.635	0.999	0.124	0.970
Instrument	14.497	11.897	3.327	11.315	6.842	9.110	10.534	4.822	17.081

Strength test (F-test)									
Centered R^2	0.251	0.090	0.284	0.169	0.059	0.169	0.072	0.186	0.101
Uncentered R^2	0.253	0.090	0.284	0.169	0.059	0.169	0.072	0.186	0.101
N	665	533	132	367	298	294	371	200	465

Panel E: prior-3 year weighted density of syndicate

	Full (1)	Vertically Unrelated (2)	Vertically Related (3)	Large Deals (>50%) (4)	Ordinary Deals (<=50%) (5)	Large Deals (>60%) (6)	Ordinary Deals (<=60%) (7)	Large Deals (>75%) (8)	Ordinary Deals (<=75%) (9)
Density	0.0023	0.0036	0.0003	0.0024	0.0047	0.0030	0.0048	0.0045	0.0030
	(1.2297)	(1.5725)	(0.0696)	(1.1260)	(1.3316)	(1.3896)	(1.4699)	(1.4127)	(1.3038)
Diagnostics									
Hansen J Chi2	2.748	3.253	0.229	1.936	0.609	2.018	0.433	6.946	0.178
p-value	0.432	0.354	0.973	0.586	0.894	0.569	0.933	0.074	0.981
Instrument Strength test (F-test)	20.780	17.052	5.040	18.160	4.499	14.609	7.394	11.354	12.866
Centered R^2	0.253	0.096	0.277	0.173	0.065	0.174	0.068	0.186	0.090
Uncentered R^2	0.254	0.096	0.277	0.173	0.065	0.174	0.068	0.186	0.090
N	665	533	132	367	298	294	371	200	465

Panel F: prior-5 year weighted density of syndicate

	Full (1)	Vertically Unrelated (2)	Vertically Related (3)	Large Deals (>50%) (4)	Ordinary Deals (<=50%) (5)	Large Deals (>60%) (6)	Ordinary Deals (<=60%) (7)	Large Deals (>75%) (8)	Ordinary Deals (<=75%) (9)
Density	0.0015	0.0022	-0.0000	0.0015	0.0031	0.0019	0.0032	0.0035*	0.0020
	(1.1340)	(1.3584)	(-0.0124)	(1.0743)	(1.3126)	(1.2480)	(1.4467)	(1.6650)	(1.3039)
Diagnostics									
Hansen J Chi2	3.764	3.709	0.567	1.710	1.152	2.369	1.123	6.819	1.102
p-value	0.288	0.295	0.904	0.635	0.765	0.499	0.772	0.078	0.777

Instrument Strength test (F-test)	18.031	14.479	3.962	14.956	3.535	12.004	6.105	10.886	9.468
Centered R^2	0.255	0.110	0.280	0.173	0.078	0.175	0.079	0.165	0.092
Uncentered R^2	0.256	0.110	0.280	0.173	0.078	0.175	0.079	0.165	0.092
N	665	533	132	367	298	294	371	200	465

Table 4.X
Asymmetric Network Density and Acquirer CAR for the Lead Sample: Selection-adjusted IV Approach

This table presents the results of the LIML estimation from an IV-style regression of acquirer 3-day CAR on the top-8 lead advisor and network density measured based on directed ties, conditional on the syndication decision. The sample consists of deals with hand-collected data on the identity of lead advisor. Asymmetric density is computed based on inter-bank syndication relationships which arise only if one of the two investment banks lead-managed a syndicate with another 1 year prior to the announcement year. Panel A reports the estimates for the selection and the reduced form equations. Column (1) estimates the determinants of syndicate choice (Equation (4)) by Probit, where the dependent variable is a dummy variable equal to 1 if a syndicate is used; and 0 otherwise. The syndication decision determines whether density at the syndicate level is observable or not. Columns (2) and (3) estimate the reduced-form equation for the endogenous regressor, *asymmetric density* and *top-8 lead advisor* respectively, for the full sample; columns (4) and (5) repeat the analysis for the vertically unrelated subsample; and columns (6) and (7) present the results for the subsample of deals in the top-two size quintiles. Panel B presents the results for the main model of acquirer 3-day CAR, with both the *asymmetric density* variable and the *top-8 lead advisor* variable endogenized. Column (1) reports the estimates for the lead sample; columns (2) and (3) present the results for the sample split according to whether the vertical tie is absent and whether the deal size is above the 60th percentile, respectively. Given the small sample size, we note that the results presented here are tentative due to weak identification problems, i.e., the Kleibergen-Paap rank Wald F-test statistics for weak identification are below the Stock-Yogo critical value of 4.72 for a 10% maximal size distortion. Other variables are defined in Appendix 4A. Year fixed effects are controlled for in all models, but the coefficients are suppressed for brevity. The t-(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.

Panel A: Estimates for the selection and reduced form equations

	Selection	Full		Vertically Unrelated		Large Deals (>60%)	
		Asymmetric Density	Top-8 Lead	Asymmetric Density	Top-8 Lead	Asymmetric Density	Top-8 Lead
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Instruments							
Lagged syndicate size	0.3105***						
	(4.2986)						
Weighted lagged syndicate size	0.0047*						
	(1.7311)						
Fraction of members from the same State		0.1022***	0.0199	0.1025***	-0.0343	0.1102**	0.0710
		(2.8039)	(0.4813)	(2.6579)	(-0.7006)	(2.1272)	(1.0391)
Prior-year debt underwriting		0.0551	-0.0396	0.0559	-0.0653	0.1342	0.0565

relationship density							
		(1.0147)	(-0.7005)	(1.0344)	(-1.1183)	(1.6392)	(0.7384)
Prior-5 year debt underwriting relationship density weighted by frequency		-0.0001	0.0002	-0.0000	0.0001	-0.0002	0.0002
		(-0.4933)	(1.3086)	(-0.0281)	(0.6844)	(-0.9967)	(0.8245)
Scope		0.0381	0.5758***	0.0333	0.5910***	0.0895**	0.5912***
		(1.4289)	(15.9810)	(1.0682)	(15.6301)	(2.3073)	(9.4543)
Covariates from Third-Stage							
Syndicate size		0.0042	0.0160	0.0219	-0.0008	0.0010	0.0131
		(0.3709)	(0.7276)	(1.4503)	(-0.0327)	(0.0574)	(0.5413)
Participation of Top 8	0.4170***						
	(4.6098)						
Vertical relationship density		0.0763**	-0.0296			0.0619	-0.0926
		(2.3641)	(-0.5561)			(1.3842)	(-1.4545)
Ln (Acquirer size)	-0.0990*	-0.0342**	-0.0266	-0.0356**	-0.0461	-0.0355	-0.0354
	(-1.8650)	(-2.0904)	(-0.9277)	(-2.2919)	(-1.6522)	(-1.2595)	(-0.7271)
Run-up	-0.0379	-0.0082	0.0207	0.0585	0.0266	0.0216	0.0726
	(-0.4148)	(-0.1577)	(0.3048)	(1.0885)	(0.3635)	(0.2369)	(0.6951)
Sigma	-0.1560	-1.8817	-2.0151	-2.3970	-2.0182	-2.2275	-0.0235
	(-0.0390)	(-1.2759)	(-0.8450)	(-1.4788)	(-0.8697)	(-0.8963)	(-0.0073)
FCF	-0.1042	-0.0038	-0.1253	0.0770	-0.1550	-0.4048	-0.6730
	(-0.3277)	(-0.0328)	(-0.8036)	(0.6431)	(-0.9450)	(-1.4410)	(-1.3302)
Leverage	1.1567***	0.0093	-0.3145*	0.0672	-0.2377	0.0707	-0.3085
	(3.9549)	(0.0695)	(-1.9424)	(0.4491)	(-1.3866)	(0.3142)	(-1.1530)
Tobin's Q	-0.0173	0.0065	0.0023	0.0092	-0.0023	0.0100	-0.0013
	(-0.7427)	(0.7983)	(0.2394)	(1.0213)	(-0.2225)	(1.1544)	(-0.0941)
Ln (1+Acquirer experience)	-0.0549						
	(-0.7346)						
Ln (Deal size)	0.2729***	0.0366	0.0133	0.0439	0.0569	0.0128	0.0254
	(4.8531)	(1.4350)	(0.3230)	(1.5122)	(1.2905)	(0.2625)	(0.3760)
Relative size	0.1724*	-0.0178	-0.0288	-0.0219	-0.0406*	-0.0161	-0.0093
	(1.8690)	(-0.9124)	(-1.3650)	(-1.1321)	(-1.8615)	(-0.5630)	(-0.2324)
Related	-0.1199	-0.0452	-0.0886	-0.0788**	-0.1271**	-0.0275	-0.0785
	(-1.4813)	(-1.2939)	(-1.5787)	(-2.0643)	(-2.2557)	(-0.5049)	(-0.9650)
Hostile	0.1254	0.0335	-0.0249	0.0282	0.0343	0.1030	-0.0188

	(0.5938)	(0.3204)	(-0.2940)	(0.2572)	(0.3815)	(0.8393)	(-0.1687)
Cross-border	0.2352*	-0.0240	0.0197	0.0036	0.0138	-0.1251	-0.0548
	(1.8995)	(-0.4617)	(0.2552)	(0.0601)	(0.1916)	(-1.5598)	(-0.4649)
Num. of bidders	0.3214***	0.0481	-0.1392***	0.0157	-0.1587***	0.1148	-0.1000
	(3.2070)	(0.9691)	(-3.1156)	(0.2873)	(-3.1429)	(1.5274)	(-1.3256)
Pmt. incl. stock	0.4390***						
	(4.8443)						
Tender		-0.0547	0.0487	-0.0925	0.1343*	-0.1703	0.0508
		(-0.6881)	(0.6813)	(-1.0608)	(1.7720)	(-1.4287)	(0.4286)
Public deals	0.3602***						
	(3.7206)						
Public deals * All cash		0.0967	-0.2065*	0.0868	-0.2024*	0.2533	0.0059
		(0.9907)	(-1.7575)	(0.8657)	(-1.6693)	(1.3328)	(0.0296)
Private deals * All cash		-0.0272	0.4666***	0.0264	0.5751***		
		(-0.2182)	(3.0745)	(0.1975)	(3.2890)		
Subsidiary deals * All cash		-0.0110	0.1014	-0.0445	0.1565	0.1220	0.1334
		(-0.1922)	(0.6930)	(-0.7335)	(1.2666)	(1.2743)	(0.9296)
Public deals * Pmt. incl. stock		0.0556	-0.1660*	0.0804	-0.0505	0.0549	-0.1398
		(0.9072)	(-1.8406)	(1.1468)	(-0.5181)	(0.6722)	(-1.0925)
Private deals * Pmt. incl. stock		0.0308	0.0501	0.0326	0.1645	0.0697	0.2032
		(0.3664)	(0.5163)	(0.3583)	(1.4365)	(0.5698)	(1.1332)
General residuals		0.0241	-0.2307**	0.0681	-0.1685	-0.0589	-0.0979
		(0.3217)	(-2.1140)	(0.7954)	(-1.5377)	(-0.5237)	(-0.6201)
Intercept	-4.3543***	-0.1951	1.1830***	-0.2920	0.9881**	0.1465	0.5994
	(-8.6758)	(-0.5583)	(2.7815)	(-0.7222)	(2.1895)	(0.3095)	(1.0894)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES
Diagnostics							
R^2	-	0.335	0.832	0.356	0.859	0.441	0.825
Adj. R^2 (Pseudo R^2)	0.281	0.131	0.781	0.106	0.805	0.088	0.714
N	3878	197	197	162	162	112	112

Panel B: Estimates for the structural form equation

	Full	Vertically Unrelated	Large Deals (>60%)
	(1)	(2)	(3)
Asymmetric density	0.0289	0.0034	-0.0334
	(0.1972)	(0.0136)	(-0.1796)
Top-8 lead advisor	-0.0149	-0.0135	-0.0087
	(-0.6853)	(-0.5014)	(-0.2406)
Syndicate size	0.0100	0.0095	0.0109
	(1.3738)	(1.1251)	(1.6221)
Vertical relationship density	-0.0080		0.0013
	(-0.5419)		(0.0642)
Ln (Acquirer size)	0.0087	0.0110	-0.0059
	(0.9463)	(0.9283)	(-0.6342)
Run-up	-0.0013	-0.0046	0.0084
	(-0.0572)	(-0.1748)	(0.2068)
Sigma	-0.5562	-1.0953	-1.2942
	(-0.6133)	(-0.9972)	(-1.0157)
FCF	-0.0517	-0.0585	0.0800
	(-1.1456)	(-1.0908)	(0.6669)
Leverage	-0.0573	-0.0491	-0.0763
	(-1.0194)	(-0.7156)	(-1.0876)
Tobin's Q	-0.0032	-0.0043	-0.0052*
	(-1.2416)	(-1.3916)	(-1.6790)
Ln (Deal size)	-0.0203*	-0.0239	-0.0002
	(-1.6462)	(-1.2928)	(-0.0158)
Relative size	-0.0065	0.0032	-0.0161
	(-0.7269)	(0.4154)	(-1.2996)
Related	0.0137	0.0128	0.0096
	(0.9393)	(0.5949)	(0.6197)
Hostile	-0.0247	-0.0407	-0.0197
	(-0.9492)	(-1.3747)	(-0.6855)
Cross-border	-0.0343	-0.0340	-0.0033
	(-1.3322)	(-1.2182)	(-0.1053)
Num. of bidders	-0.0572***	-0.0481***	-0.0717**
	(-3.6336)	(-3.0997)	(-2.1250)
Pub. * All cash	-0.0358	-0.0351	-0.0330
	(-1.2091)	(-1.0622)	(-0.5972)
Priv. * All cash	0.1571***	0.1590***	
	(3.2617)	(2.6068)	
Sub. * All cash	-0.0049	-0.0255	-0.0385
	(-0.1421)	(-0.5567)	(-0.8606)
Pub. * Pmt. incl. stock	-0.0807***	-0.0966***	-0.0452
	(-3.2582)	(-3.1831)	(-1.5909)
Priv.* Pmt. incl. stock	0.0843*	0.0220	0.1494***
	(1.7115)	(0.4224)	(2.6326)
Tender	-0.0038	-0.0259	0.0090
	(-0.1751)	(-0.7522)	(0.2192)
General residuals	-0.0583*	-0.0605	-0.0305
	(-1.8531)	(-1.4409)	(-0.9464)

Year fixed effects	YES	YES	YES
"Excluded" Instruments: Fraction of members from the same State, Prior-1 year (unweighted) and prior-5 year (weighted) debt underwriting relationship density; Scope.			
Diagnostics			
Hansen J Chi2	1.596	3.892	1.992
p-value	0.450	0.143	0.369
Instrument Strength test *(KP rank Wald F-test)*	2.216	2.182	1.331
Stock-Yogo critical values:	10% maximal LIML size 4.72	10% maximal LIML size 4.72	10% maximal LIML size 4.72
Centered R^2	0.350	0.365	0.311
Uncentered R^2	0.350	0.365	0.311
F	5.814	6.785	2.016
N	197	162	112

Table 4.XI
Network Density and Acquirer CAR without Adjusting for Selection

This table presents the results from a simple IV-style regression of acquirer 3-day CAR without considering sample selection bias. Panel A reports the estimates for the reduced form equation, where the dependent variable is the endogenous regressor, *density*, 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. Column (1) through (5) present the estimates for the full sample, the vertically unrelated subsample and the subsamples of large deals above the 50th, 60th and 75th percentiles of the size distribution, respectively. Panel B reports the results for the main model of acquirer 3-day CAR, with *density* endogenized. Other variables are defined in Appendix 4A. Year fixed effects are controlled for in all models, but the coefficients are suppressed for brevity. The t-(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.

Panel A: Estimates for the reduced form equation

	Full (1)	Vertically Unrelated (2)	Large Deals (>50%) (3)	Large Deals (>60%) (4)	Large Deals (>75%) (5)
Instruments					
Local network density	0.3870***	0.3790***	0.2942***	0.2944***	0.3202***
	(3.7010)	(3.0182)	(3.6651)	(3.7020)	(3.5477)
Fraction of members from the same State	0.1560***	0.1681***	0.2176***	0.2235***	0.2517***
	(3.9382)	(3.9483)	(3.8810)	(3.6167)	(3.1847)
Prior-year debt underwriting relationship density	0.1078**	0.1364**	0.2107***	0.1916**	0.1913*
	(2.0444)	(2.4400)	(2.7012)	(2.0659)	(1.7484)
Prior-5 year debt underwriting relationship density weighted by frequency	0.0006***	0.0005***	0.0003*	0.0003*	0.0003
	(4.6782)	(3.9469)	(1.9298)	(1.7848)	(1.2388)
Covariates from Third-Stage					
Syndicate size	-0.0078	-0.0073	-0.0065	-0.0094	-0.0021
	(-0.4608)	(-0.4150)	(-0.3141)	(-0.4257)	(-0.0733)
Participation of Top 8	0.0929**	0.0923**	0.1626***	0.1246	0.0009
	(2.5191)	(2.2313)	(2.6837)	(1.5965)	(0.0078)
Vertical relationship density	0.1244***		0.1158**	0.1272***	0.1444*

	(3.0081)		(2.4653)	(2.6478)	(1.6826)
Ln (Acquirer size)	0.0052	0.0104	0.0017	-0.0208	-0.0008
	(0.3055)	(0.6041)	(0.0566)	(-0.6188)	(-0.0149)
Run-up	-0.0572	-0.0473	-0.1091*	-0.0775	-0.1217
	(-1.3360)	(-0.9851)	(-1.9239)	(-1.1778)	(-1.6041)
Sigma	1.5361	1.0457	-1.7925	-3.4219	-2.9027
	(0.8861)	(0.5474)	(-0.6320)	(-1.0343)	(-0.5737)
FCF	-0.0119	-0.0432	-0.0511	-0.2323	-0.2698
	(-0.0873)	(-0.3196)	(-0.1685)	(-0.7100)	(-0.6531)
Leverage	0.0025	-0.0642	-0.0107	-0.0672	-0.0061
	(0.0220)	(-0.5164)	(-0.0578)	(-0.3178)	(-0.0194)
Tobin's Q	0.0084	0.0094*	0.0148**	0.0140**	0.0192***
	(1.6054)	(1.8161)	(2.5300)	(2.2322)	(2.7378)
Ln (Deal size)	0.0287*	0.0236	-0.0042	0.0333	-0.0094
	(1.6797)	(1.3220)	(-0.1242)	(0.8345)	(-0.1584)
Relative size	0.0193	0.0202	0.0445*	0.0235	0.0388
	(1.1752)	(1.2775)	(1.6863)	(0.7976)	(0.7353)
Related	0.0089	0.0215	-0.0261	0.0145	0.0593
	(0.2507)	(0.5428)	(-0.5272)	(0.2592)	(0.8044)
Hostile	-0.0765	-0.1056	-0.0601	-0.0307	0.0077
	(-1.1753)	(-1.4337)	(-0.7221)	(-0.3487)	(0.0754)
Cross-border	-0.0864**	-0.0493	-0.1138*	-0.0897	-0.1238
	(-2.0230)	(-1.0605)	(-1.6563)	(-1.1628)	(-1.2994)
Num. of bidders	-0.0246	-0.0459	-0.0028	0.0086	-0.0279
	(-0.6715)	(-0.9933)	(-0.0496)	(0.1441)	(-0.3403)
Tender	-0.0277	-0.0481	-0.0553	-0.0577	-0.0326
	(-0.5619)	(-0.8453)	(-0.7253)	(-0.6501)	(-0.2821)
Public deals * All cash	0.0330	0.0659	0.0526	0.0718	-0.0821
	(0.5987)	(1.0606)	(0.6245)	(0.7215)	(-0.5779)
Private deals * All cash	-0.0042	0.0240	0.0257	-0.1600	
	(-0.0672)	(0.3592)	(0.1264)	(-1.3890)	
Subsidiary deals * All cash	0.0710	0.1002	0.2274***	0.2402**	0.2206

	(1.1688)	(1.4290)	(2.6628)	(2.4696)	(1.6367)
Public deals * Pmt. incl. stock	-0.0006	0.0162	-0.0091	-0.0519	-0.0864
	(-0.0151)	(0.3382)	(-0.1526)	(-0.6906)	(-0.8006)
Private deals * Pmt. incl. stock	0.0264	0.0429	0.0221	-0.1505	-0.0876
	(0.3702)	(0.5254)	(0.1675)	(-1.2585)	(-0.4661)
Intercept	-0.5205*	-0.4612*	-0.8076	-0.4274	-0.0404
	(-1.9301)	(-1.6606)	(-1.2212)	(-0.5395)	(-0.0715)
Year fixed effects	YES	YES	YES	YES	YES
Diagnostics					
R^2	0.330	0.347	0.308	0.332	0.327
Adj. R^2 (Pseudo R^2)	0.279	0.286	0.206	0.205	0.141
N	665	533	367	294	200

Panel B: Estimates for the structural form equation

	Full	Vertically Unrelated	Large Deals (>50%)	Large Deals (>60%)	Large Deals (>75%)
	(1)	(2)	(3)	(4)	(5)
Density	0.0344	0.0457**	0.0274	0.0376*	0.0586**
	(1.6306)	(2.0341)	(1.2390)	(1.7146)	(2.1320)
Syndicate size	0.0072*	0.0063	0.0103**	0.0127***	0.0174***
	(1.7054)	(1.3903)	(2.2609)	(2.6496)	(4.1450)
Participation of Top 8	0.0156*	0.0132	0.0034	-0.0045	-0.0220
	(1.7783)	(1.3331)	(0.2744)	(-0.3390)	(-1.5304)
Vertical relationship density	-0.0123		-0.0157**	-0.0189***	-0.0381**
	(-1.6369)		(-2.1801)	(-2.6915)	(-2.5066)
Ln (Acquirer size)	-0.0045	-0.0035	-0.0017	0.0007	0.0091
	(-1.1948)	(-0.8887)	(-0.4126)	(0.1701)	(1.3736)
Run-up	0.0191*	0.0165	0.0263*	0.0258	0.0298*
	(1.6715)	(1.4424)	(1.6607)	(1.4709)	(1.7534)
Sigma	-0.5856*	-0.5589	-1.1247***	-0.7664	-1.1777
	(-1.6749)	(-1.3432)	(-2.5967)	(-1.5211)	(-1.5691)
FCF	0.0109	0.0073	0.0838	0.1203**	0.0801
	(0.3880)	(0.2380)	(1.6322)	(2.1468)	(1.3100)
Leverage	0.0002	0.0097	0.0311	0.0716	0.0197
	(0.0078)	(0.3111)	(0.7988)	(1.6222)	(0.3798)
Tobin’s Q	-0.0023*	-0.0030**	-0.0025	-0.0033*	-0.0044**
	(-1.6823)	(-2.4926)	(-1.6245)	(-1.9135)	(-2.5166)
Ln (Deal size)	-0.0098**	-0.0125***	-0.0086	-0.0073	-0.0169**
	(-2.3851)	(-2.8289)	(-1.5673)	(-1.1287)	(-2.0969)
Relative size	0.0001	0.0012	-0.0099	-0.0073	0.0019
	(0.0102)	(0.1675)	(-1.4798)	(-1.0975)	(0.2083)
Related	0.0033	0.0065	0.0010	-0.0039	-0.0045
	(0.4895)	(0.8811)	(0.1131)	(-0.4410)	(-0.4339)
Tender	0.0011	0.0075	-0.0051	-0.0043	0.0002
	(0.1216)	(0.7049)	(-0.4488)	(-0.3545)	(0.0114)
Hostile	0.0049	0.0006	0.0109	0.0068	0.0260*

	(0.3992)	(0.0381)	(0.7703)	(0.4678)	(1.6553)
Cross-border	0.0006	-0.0056	0.0145	0.0105	0.0124
	(0.0678)	(-0.6204)	(1.3137)	(0.9303)	(0.9683)
Num. of bidders	-0.0127	-0.0078	-0.0234**	-0.0305***	-0.0393***
	(-1.6203)	(-0.8514)	(-2.2305)	(-2.6395)	(-3.8118)
Public deals * All cash	-0.0094	-0.0136	-0.0181	-0.0128	-0.0142
	(-0.8867)	(-1.1393)	(-1.1768)	(-0.7529)	(-0.7680)
Private deals * All cash	0.0272*	0.0219	-0.0198	0.0389**	
	(1.8134)	(1.3109)	(-1.0803)	(2.2094)	
Subsidiary deals * All cash	-0.0176	-0.0277**	-0.0320**	-0.0268	-0.0261
	(-1.4754)	(-2.0051)	(-2.0208)	(-1.4932)	(-1.0643)
Public deals * Pmt. incl. stock	-0.0402***	-0.0416***	-0.0393***	-0.0307**	-0.0161
	(-4.5625)	(-4.0880)	(-3.6231)	(-2.5022)	(-0.9383)
Private deals * Pmt. incl. stock	0.0042	-0.0069	0.0447	0.0539	0.0010
	(0.2258)	(-0.3463)	(1.3991)	(1.2921)	(0.0213)
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-5 year (weighted) debt underwriting relationship density.					
Diagnostics					
Hansen J Chi2	2.615	1.797	1.044	0.842	3.731
p-value	0.455	0.616	0.791	0.839	0.292
Instrument Strength test *(KP rank Wald F-test)*	18.269	17.297	12.984	10.875	9.347
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
Centered R^2	0.251	0.112	0.184	0.186	0.185
Uncentered R^2	0.252	0.112	0.184	0.186	0.185
F	4.756	4.807	3.288	3.495	2.239
N	665	533	367	294	200

CHAPTER 5: CONCLUSION

1. Summary of Findings

It remains an open question whether financial advisors create value for acquirer clients. In this thesis, we explore two dimensions of advisor traits that have been largely ignored in the literature, namely, syndication and interbank networking.

Conventional economic wisdom suggests that the unique organizational structure of investment banking syndicates should allow them to perform a different role from which individual advisors perform in M&As. We conjecture that by pooling information networks, expertise, lending and underwriting capacity of different investment banks, syndicates enhance the services provided to an acquirer, primarily in target screening, deal pricing and financing. An unavoidable consequence of joint production is, however, that fees must be shared across syndicate members. This creates incentives for the advisors in a syndicate to free ride on one another's costly effort. Consequently, whether service enhancement can be translated into superior acquisition outcomes is conditional on the scope for free riding pertinent to a syndicate.

The data on M&A transactions announced from 1990 to 2012 provide evidence supporting our conjectures. We find that, compared with individual advisors, syndicates advise more on cross-border deals, public acquisitions, deals that are absolutely or relatively larger, and deals involving more competing bidders. They also serve more acquiring firms that have a larger shortfall of internal cash to finance the cash component of their offer. These findings suggest that syndicates, which expand the scale and scope of resources available to an acquiring firm, are perceived to be more valuable in situations where the deal is more complex and where there is a higher need for acquisition-related financing.

As expected, the choice of syndicates versus individual advisors has a pronounced and non-linear effect on various acquisition outcomes. Syndicates are, on average, associated with a marked increase in acquirer announcement abnormal returns and total synergy gains, but this occurs only when there is limited scope for internal free-riding. Where advisors of a syndicate have sizable opportunities to behave opportunistically, syndicates are associated with lower acquirer returns and total synergy gains relative to individual advisors. These non-linear associations persist after we account for the endogenous nature of syndicate choice and other likely determinants such as industry fixed effects and target syndicate characteristics. We further find that the use of a reputable lead advisor does not necessarily limit free-riding. We argue that because the information on the identity of the lead financial advisor is not publically available for most M&A transactions, a lead advisor has little incentive to expend costly effort to regulate others in a typical M&A syndicate. Finally, we observe that syndicates are more likely to complete a deal when external financing is required. This finding is consistent with syndicates facilitating acquisition-related financing, leading to a greater probability of bid success.

In the light of the above results, we analyze for the first time in the extant literature whether interbank networking overcomes the free-rider problem that plagues M&A syndicates. We argue that more densely networked syndicates display stronger incentives to cooperate (as opposed to free ride on one another) on two accounts. First, information accumulated through past interaction eases mutual monitoring. Second, termination of future cooperation represents a more credible and powerful threat of punishment against members when they are tied to each other. Using a novel selection-adjusted IV approach, we show that syndicates characterized by a higher degree of interbank connections are indeed associated with better acquirer announcement abnormal returns when free-riding is likely to occur, as indicated by the absence of acquirer-advisor tie and large transaction size. However, peer relationships do not always induce investment banks to behave cooperatively. Rather, banks internalize the externality only when peer sanctions are harsh enough, as applies when bank interaction takes place over a shorter idle time period and when the market is hot and thus has ample opportunities for future cooperation. These findings suggest that the positive network effects are primarily driven by peer pressure and not by altruism, endogenous matching or selective networking, in which case one may expect the network structure of a syndicate (i.e., densely or loosely linked) to be indifferent in any case. Additional analysis reveals that more densely networked syndicates do not receive higher advisory fees. This helps to rule out the possibility that interbank networking creates a barrier to entry for unrelated advisors into a syndicate and, therefore, improves acquisition performance by preserving the quasi rents offered by an acquirer to motivate best efforts.

Overall, our findings suggest that investment banking syndication and the resulting networks are important to our understanding of the cross-sectional variation in M&A transaction outcomes.

2. Contribution

This thesis contributes to the literature in a number of distinct ways. First, it provides fresh insights into the role of investment banks in M&As. By considering only financial advisors who act alone, prior research offers an incomplete picture of the value that investment banks add to an acquiring firm in the M&A process. This thesis fills the gap by identifying the fundamental differences between syndicates and individual advisors in terms of both acquirer clientele and value creation. We show that, compared with individual advisors, syndicates are more likely to serve acquirers undertaking more complex deals and with a greater demand for external financing. By expediting financing, syndicates increase the probability of successfully closing a deal that demands external capital. They are also able to create significantly greater shareholder value for acquirers, although this potential is constrained by the scope for moral hazard internal to a syndicate. These findings underscore the “two-faces” of an investment banking syndicate in M&As.

Second, this thesis adds a number of new dimensions to the literature on the form and functions of investment banking syndicates. Previous work has explored these issues mainly in the context of security offering markets (see e.g., Chowdhry and Nanda, 1996; Chen and Ritter, 2000; Song, 2004; Corwin and Schultz, 2005; Ljungqvist et al., 2009; Shivdasani and Song, 2011). However, we show that, although less frequently employed, investment banking syndicates are equally important in the market for takeovers and mergers. Importantly, unlike most prior studies that examine a specific form of syndicate structure and its impact on a performance outcome (e.g., Song, 2004; Corwin and Schultz, 2005; Shivdasani and Song, 2011), we show that the value of syndicates, irrespective of their structure, varies according to contingencies that are likely to exacerbate internal free-riding. Our results provide significant empirical support for the theories of free-riding in teams. To the best of our knowledge, this is the first study to uncover systematic evidence on the moderating effect of free-riding on the relationship between the choice of an investment banking syndicate and deal outcomes. Though research by Shivdasani and Song (2011) shows that syndicates *led* by multiple underwriters are associated with poorer bond issuing firms’ quality, our study offers broad implications for how the moral hazard problem affects the performance of a syndicate in general.

Third, this thesis is the first to investigate the implications of networks of relationships that investment banks maintain with each other for the performance of M&As. The results of this thesis suggest that, all else being equal, acquiring firms benefit when there is a higher degree of interbank connections and that these benefits are more evident when the free-rider problem is an important concern. Our results also demonstrate the complex nature of interbank relationships. Investment banks have stronger (weaker) incentive to stay on good terms with their relationship partners when the expected penalty for shirking is more (less) severe, as in the case where past interaction is relatively more (less) active and where the market is experiencing a boom (downswing).

In addition, our emphasis on interbank networking as a potential disciplinary tool in a repeated setting marks an important departure from many existing investment banking studies. Indeed, Pichler and Wilhelm (2001) focus on a short-term relationship among underwriters and advocate the use of an incentive-pay scheme that allows an issuer to mitigate the problem of moral hazard by sharing the surplus with the underwriters in a syndicate. Corwin and Schultz (2005), on the other hand, argue that syndication itself is an efficient mechanism to reduce the lead underwriter's incentive to free ride because co-managers are rewarded for reporting the lead underwriter's misconduct to the issuing firm. Other studies hypothesize a positive relation between syndicates led by a reputable investment bank and performance outcomes, implicitly viewing lead bank reputation as a prominent countervailing force against free-riding (see e.g., Fang, 2005; Ljungqvist et al., 2006). We contribute to this literature by identifying interbank relationships that raise mutual dependence and the ability to penalize dishonest peers, as an additional mechanism by which the free-rider problem can be alleviated.

Fourth, this thesis provides evidence suggesting that interbank networks can have a significant impact on the size of advisory fees. We show that network density creates implicit incentives that potentially lower the cost of providing incentives through explicit fee contracts. This result runs counter to common economic wisdom that horizontal (i.e., peer) networking is detrimental to clients and can induce "counter-productive" behavior leading to negative consequences such as restricted effort or higher fees. Instead, we show that close relationships among investment banks encourage coordination and keep investment banks doing the "right" job through peer pressure.

This thesis also has important implications for practitioners undertaking takeovers and mergers. The results of this thesis suggest that an acquiring firm should take into account the agent costs when making the choice between a syndicate and a single advisor. For instance, when there is limited scope for free-riding, hiring a syndicate is beneficial because it allows a wide variety of sources of value to be created through collaboration across investment banks. Where the anticipated risk of free-riding is high, the traditional strategy of hiring a reputable lead banker may not help reduce the agent costs in the market for M&As. Since the identity of the lead advisor is not disclosed to the public in most circumstances, the market is unable to penalize lead advisors with poor performance as in other markets such as IPOs. Rather, forming a syndicate that has a higher degree of interbank relationships appears to be the better choice.

3. Future Research

Like other studies, our work provides a fruitful avenue for future research in the investment banking area. For example, while we have considered the major cost of syndication that arises from internal free-riding, there may be other potential costs preventing acquirers or investment banks from establishing a syndicate. For instance, it could be the case that the group decision-making process increases coordination and timing difficulties, reducing the attractiveness of a syndicate. Additionally, we have shown that interbank networking motivates additional advisor effort through peer pressure, which lowers the level of fees paid by an acquirer. An interesting and unanswered question is whether networks provide certain benefits to relationship banks. For example, networking may allow investment banks to compete more efficiently in other capital markets such as IPOs, equity and debt issuance markets. We hope that future research will shed light on these important issues.

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