BRINGING THE FIRM BACK IN:
FIRM-SPECIFIC CHARACTERISTICS AND THE RELATIONSHIP BETWEEN
NETWORK POSITION AND PERFORMANCE\textsuperscript{1}

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ABSTRACT:
This paper investigates factors that affect the relationship between a firm’s position in a network of inter-firm ties, and firm performance. Building upon the literature on inter-firm networks, I build a theoretical model that identifies mechanisms through which a firm’s position in an open network rich in structural holes could lead to improvements in its performance. I argue that whether or not individual firms can perform well in open networks depends upon several firm-level characteristics, such as specialization (scope), multimarket contact with partners and network centrality. I conduct empirical study examining networks formed among domestic and international investment banks advising their clients on merger and acquisition deals in the United Kingdom between 1992 and 2001. My results indicate that banks located in similarly structured open networks could obtain different performance results depending upon a) banks’ scope, which affects their ability to appropriate heterogeneous information transmitted by their network partners; b) banks’ level of multimarket contact with their partners, which affects capacity to prevent risks of partner non-cooperation; and c) banks’ network centrality, which affects their risks of isolation from other network members.
Studies in strategic management and organization theory suggest that a firm’s behaviors are affected by its location in an inter-firm network (e.g. Gulati & Gargiulo, 1999). While there is also some evidence that network positions have important implications for firms’ performance (Ahuja, 2000; Almeida, Dokko, & Rosenkopf, 2003; Powell, Koput, Smith-Doerr, & Owen-Smith, 1999; Stuart, 2000), there is no agreement among researchers on which network configurations are advantageous for firms. One of the key ideas currently dominating the literature is Burt’s (1992) “open network” or “structural holes” perspective, according to which a firm can obtain important performance advantages when exploiting brokerage opportunities created by the absence of ties between its partners. While there have been many findings in support of this idea (e.g. Baum, Calabrese & Silverman, 2000; Hargadon & Sutton, 1997; Finlay & Coverdill, 2000), some studies found quite the opposite, i.e. firms benefiting from the dense interconnections between their partners (e.g. Ahuja, 2000; Dyer & Nobeoka, 2000). As Burt’s (2000) review indicates, such seeming contradiction can be resolved by looking at the boundary conditions of the structural holes perspective, i.e. examining factors that determine whether or not a network member can extract performance benefits from exploiting the absence of direct ties amongst its partners.

Recently some researchers have started to look at environmental contingencies for the structural holes perspective. As Ahuja (2000) suggests, for example, benefits of open networks could be affected by the industry context in which a firm is competing. In some industries firms improve their performance by brokering information and resources amongst their partners (Hargadon & Sutton, 1997; Finlay & Coverdill, 2000; Pollock, Porac & Wade, 2004), while in other industries firms benefit from collaborating with their competitors (Ahuja, 2000; Dyer & Nobeoka, 2000). However, by primarily focusing on industry context, network scholars tend to overlook the possibility that whether a network position yields benefits to a firm may be a function of this firm’s characteristics.
Traditional strategy research has long recognized that firms are heterogeneous entities with individual resources and capabilities. Various firm-specific configurations of these resources and capabilities determine whether or not firms can benefit from embarking upon particular strategies, such as diversification (Hitt, Hoskisson, & Kim, 1997), cost reduction through parallel experimentation (Darr, Argote, & Epple, 1995) or establishing products as industry standards (Klepper & Simons, 2000). In addition to affecting strategies involving the focal firm and its affiliates, firm capabilities could also increase the benefits acquired from occupying positions in inter-firm networks. For example, by virtue of their exposure to heterogeneous markets, some firms may be more likely to appropriate heterogeneous information they receive across structural holes. Furthermore, in open networks some firms could be more capable than others in reducing the risks of partner non-cooperation or requiring greater flexibility in choosing their network partners. Lack of attention to these and similar factors could prevent strategy scholars from gaining a comprehensive understanding of linkages between firms’ network position and their performance.

In this paper, I explicitly focus on firm characteristics as boundary conditions for the “open” network view. My review of network literature suggests the existence of three main factors affecting a relationship between firm network position and performance, namely a) type of information exchanged in a network; b) risks of partner non-cooperation; c) risks of isolation from the rest of the network. First, I argue that in order to benefit from open networks, firms should have the capacity to absorb information and resources (Cohen & Levinthal, 1990) exchanged through structural holes. I propose that a firm’s scope experience, i.e. history of catering to different market segments, provides firms with such capacity. Second, firms face substantial challenges when they attempt to reduce the risks of partner opportunism within open networks (Burt, 1992). I propose that these risks are lowered when a firm meets its partners in multiple markets as such a position can facilitate
the development of cooperative norms among them (Jayachandran, Gimeno, & Varadarajan, 1999). Third, the absence of pressures to cooperate with familiar partners in open networks enables firms with low network centrality to build bridging ties to diverse partners and eventually increase their centrality whereby improving access to resources circulating within industry networks.

I test my ideas on a population of financial advisory firms acting as consultants to domestic and international companies participating in Merger and Acquisition (M&A) deals in the United Kingdom between 1992 and 2001. I collected data for this study from two principal sources. Archival information on the dynamics of financial advisors’ networks was downloaded from SDC Thompson Financial database “Worldwide Mergers & Acquisitions”. Furthermore, to gain first-hand insights into the underlying processes that shape inter-firm network structure, I conducted semi-structured interviews with senior investment bankers in Europe and North America.

THEORY DEVELOPMENT

Costs and Benefits of Open Networks

The “open network” perspective on a relationship between a firm’s network position and performance claims that firms can extract benefits from occupying positions among their network partners (Burt, 1992; Baum et al., 2000; Hargadon & Sutton, 1997). The more network partners, otherwise not connected to each other, are linked to the focal firm via “bridging ties” (Burt, 2002), the more structural holes this firm is spanning. Evidence in support of the positive effects of open networks typically comes from contexts in which the pursuit of goals requires timely access to novel ideas and brokerage opportunities (Hargadon & Sutton, 1997). The opposite of an “open” network is a “closed” network, in which firms’ partners are tied to each other (Walker, Kogut, & Shan, 1997). In closed networks firms benefit from social norms that facilitate large relationship-specific investments among
partners, which helps maximize the benefits of collaboration among them (Dyer & Nobeoka, 2000).

Open networks differ from closed ones in three key respects. These are: a) type of information exchanged through network ties; b) risks of partner non-cooperation; and c) risks of “overembeddedness” or isolation. First, firms surrounded by structural holes receive non-redundant or heterogeneous information about events taking place in different parts of their industry (McEvily & Zaheer, 1999). In closed networks, information is redundant because all members of this network have access to the same knowledge (Walker et al, 1997). Second, due to the absence of cooperative norms in open networks, firms embedded in such structures could fall prey to their partners’ non-cooperation, thus they have to make substantial investments in enforcing partner compliance. In closed networks, however, partner cooperation is secured by the mechanisms of collective sanctioning of deviant behavior (Walker et al, 1997). Finally, in closed networks, the pressures to reciprocate past favors and cooperate with the partners of partners could confine a firm to a small group of repeat allies, which could result in this firm’s overembeddedness and isolation (Uzzi, 1997; Gargiulo & Benassi, 2000). In contrast, positions in open networks allow brokers a considerable degree of flexibility in choosing their network partners (Baum, Shipilov & Rowley, 2003), which helps firms to avoid the risks of isolation and allows them to improve their network position by building bridging ties to otherwise disconnected network neighborhoods.

Can all firms similarly benefit from occupying network positions rich in structural holes? Strategy researchers have long recognized that the payoffs of following particular strategies depend upon the characteristics of individual firms: for example, their market presence or organizational size (e.g. Chandler, 1990; Darr, Argote & Epple, 1995; Klepper & Simons, 2000). However, there has been limited research done in the inter-firm networks literature about firm-level characteristics that could determine whether or not firms can reap
performance benefits from their network positions. Relatively few studies have looked at the relationships among firm’s network relationships and these firms’ performance (e.g. Almeida et al., 2003; Lee, Lee, & Pennings, 2001; Powell et al., 1999; Stuart, 2000); and none of these studies have explicitly looked at the effects that firm-level characteristics would have on a relationship between a firm’s position within open networks, and its performance. More theoretical and empirical development has been done in the literature on inter-personal networks and social capital (Burt, 2000; Emirbayer & Goodwin, 1994; Lin, 1999 provide reviews of this literature). There have been a number of studies exploring how different individuals have benefited from their network positions. People with higher levels of education or better socioeconomic standing have been shown to use their networks more efficiently in order to gain higher status (Lin, 1999), improve job performance (Mehra, Kilduff, & Brass, 2001; Burt, 1997), or achieve higher income (Meyerson, 1994). Even though studies of inter-personal networks have pointed at the importance of network members’ characteristics for the benefits that they can extract from a network position, studies in inter-firm networks have not explored this possibility.

In the sections that follow, I develop a theoretical model focusing on the relationships between a firm’s position in an open network, firm-specific characteristics and firm performance. Figure 1 provides a summary of my theoretical argument.

Insert Figure 1 about here

Information Heterogeneity and Firm Scope

The more markets a firm is present in, the wider the scope of this firm’s activities. As the vast strategy literature suggests, organizational scope materially affects the capabilities of firms (Chandler, 1990). For example, by offering products to different groups of customers, firms with wide scope can weather idiosyncratic risks associated with a specific market
segment, as losses in one market can be offset by gains in other markets. Furthermore, presence in several markets exposes firms to a wide spectrum of issues and problems, which improves their learning capabilities (Audia, Sorenson, & Hage, 2001). Narrow scope, or presence in a small number of markets, does not allow these benefits to firms.  

Prior research indicates that firms use their network partners to exchange information (Ahuja, 2000). The type of information exchanged, however, depends upon the configuration of networks in which these firms are embedded (Burt, 1992). If a firm is occupying multiple structural holes, as is the case within open networks, then all of its partners operate in different circles, and know of different opportunities to innovate and to develop unique competitive capabilities (McEvily & Zaheer, 1999). In order to benefit from diverse and non-redundant information circulating in open networks, firms need to have an absorptive capacity, defined as the ability to recognize the value of new information, assimilate it and apply to commercial ends (Cohen & Levinthal, 1990).

One of the key determinants of such capacity is the structure of a firm’s operations (Rosenberg, 1982). If firms have a wide scope of activities, then they are better equipped than their specialized counterparts to deal with heterogeneous information. When a firm embarks upon a strategy of expanding the scope of its operations, it becomes exposed to diverse heterogeneous information coming from its multiple markets. This information could relate to the events taking place in different market segments, changes in customer demands, behaviors of competitors or governmental regulatory agencies. To achieve an ability to deal with heterogeneous information, a firm needs to develop a set of routines. Organizational

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2 The concept of scope should not be confused with the concept of “diversification”. The general use of the term “diversification” encompasses firm’s presence in both related and unrelated markets (Nayyar & Kazanjian, 1993). For the purposes of a theoretical model developed in this paper, wide scope characterizes firms that established presence in multiple related markets.
routines are repeatedly invoked, socially constructed programs of action that embody the knowledge, capabilities, beliefs, values, and memory of the organization and its decision makers (Nelson & Winter, 1982). One example of such routines could be the development of procedures for analyzing and transferring heterogeneous information from one division of a wide scope firm to another. For instance, units selling different products have to share information between each other on the purchasing patterns and needs of their customers, which enables wide scope firms to capitalize on the information asymmetries of buyers and cross-sell their products (Nayyar & Kazanjian, 1993). Such information sharing also has to exist in firms that engage their units in parallel production or experimentation activities (Audia et al., 2001), as managers in one unit have to communicate with their peers in other units in order to exchange information on the successes or failures of their activities.

If routines for dealing with heterogeneous information are already in place as a result of a firm’s experience in a number of different markets (i.e. wide scope experience), then these routines can be used for dealing with heterogeneous information received from partners in open networks. The mere action of heterogeneous information provision, i.e. internal transfer of heterogeneous information between units responsible for serving different market segments (Lenox & King, 2004), is likely to increase the capacity of wide scope firms to exchange information between units that are responsible for dealing with different network partners. The presence of existing routines for dealing with heterogeneous information increases the capacity of a firm to absorb and appropriate information circulating across structural holes, ultimately leading to performance improvements for firms that possess wide scope experience. Thus, the following hypothesis can be advanced:

*Hypothesis 1: Network openness is positively related to performance for firms with wide scope experience.*
Ceteris paribus, this relationship is applicable to firms present in several related markets, in which case information and resources acquired from one market can be valuable in dealing with other markets. When the degree of unrelatedness in their markets increases, firms would no longer be able to effectively appropriate and transfer diverse information across unrelated markets or diverse partners, ultimately destroying the contribution that scope experience could make to their capacity of benefiting from a network position rich in structural holes.

**Risks of Partner Non-Cooperation and Multimarket Contact**

In the networks of competitors, the basic problem of coordinating inter-organizational relationships is worsened by the heightened threat of opportunistic behavior (Gulati & Singh, 1998). Opportunism can take the form of not fulfilling alliance obligations or attempting to appropriate the benefits from an alliance at the expense of other partners (Khanna, Gulati, & Nohria, 1998). From stealing partners’ technology and providing poorer quality investments, to not fulfilling ex ante commitments, inter-firm relationships could offer multiple opportunities for cheating, the consequences of which could lead to the deterioration of performance for the affected parties.

Prior studies suggest that social constraints associated with closed networks can facilitate large relationship-specific investments that help maximize the benefits of collaboration (Walker et al, 1997). Within such networks, firms can trust each other to honor obligations as information on deviant behavior is readily disseminated to all common partners and such behavior is collectively sanctioned (Walker et al., 1997). Within open networks, however, firms that have suffered from their partners’ misbehavior are not likely to be connected to the partners of the violators. Thus, in open networks, a misbehaving firm risks severing relationships with only a small fraction of its partners and doesn’t face risks of
collective action taken by the rest of the network. Consequently, in open networks, the burden of protecting itself against partner misbehavior lies upon the firm itself. This could be accomplished by erecting multiple contractual safeguards, by forming equity joint ventures with partners (Gulati, 1995a, b; Oxley, 1999) or by demanding exclusivity in the relationship (Gimeno, 2004). However, these governance options are costly, as they require substantial investments of managerial attention and financial resources (Oxley, 1997) as well as could force firms to develop capabilities that are not useful outside of their current alliance (Gimeno, 2004).

One of the possible ways a firm could protect itself against its partners’ opportunism could be to exploit the pressures to cooperate arising from the multimarket contact (MMC) with them. The basic assertion of multimarket contact research is that an increase in MMC between firms leads to an increase in mutual forbearance or cooperation among them (Jayachandran, Gimeno, & Varadarajan, 1999). If increase in the likelihood of cooperation is a consequence of MMC between the firms, then a firm maintaining multimarket contact with its network partners could use mutual forbearance as a defense against the prospects of partner opportunism.

Mutual cooperation and information exchange resulting from multimarket contact could compensate for the absence of cooperation-enforcing mechanisms in open networks. When a firm is being taken advantage of by its partner in one market, this firm not only can abrogate its existing relationships with the non-cooperating partner across all mutual markets, but can also engage in retaliatory behavior, by aggressively attacking its partners’ market positions. The threat of a firm’s retaliation across multiple markets could force its partners to behave cooperatively as short-term gains of non-cooperation in one market would have to be weighted against the long-term costs of severing relationships across multiple markets (Baum & Korn, 1999). For a firm located in an open network, lower risks of partner misbehavior
could translate into lower costs of maintaining its network position. Firms historically experiencing high levels of multimarket contact with partners would not need to expend as much resources on erecting safeguards against partner non-cooperation (i.e. developing complex contracts, building equity joint ventures or engaging in “hostage” exchange) as firms without multimarket contact. Firms with high levels of MMC to partners could divert the freed resources into more profitable uses - for example, into exploiting their core competencies, bridging more structural holes or expanding into new markets, which would ultimately lead to these firms’ improved performance. Furthermore, Greve and Baum (2001) suggest that firms maintaining multimarket contact are able not only to reduce competition amongst each other, but also command higher prices for their products. When a firm historically maintains high levels of MMC with its network partners both the firm and its allies learn how to cooperate (Stephan & Boeker, 2001), how to share their markets, how to avoid excessive competition for brokerage positions and how to collude on pricing issues, all of which would facilitate these firms’ performance in open networks. Therefore the following hypothesis can be advanced:

**Hypothesis 2: Network openness is positively related to performance for firms that historically have high levels of multimarket contact with their partners.**

**Risks of Isolation and Firm Centrality**

While governance mechanisms within open networks are not effective in preventing partner non-cooperation, firms still gain important advantages from maintaining positions rich in structural holes. One of such advantages is lower risk of “overembeddedness” (Uzzi, 1997; Gargiulo & Benassi, 2000). When a firm repeatedly builds ties with the same group of partners that are tied to one another, the ease of cooperation with familiar partners and collective pressures to reciprocate past favors, all raise the costs of making investments in
relationships with new partners outside the focal group (Gargiulo & Benassi, 2000). In such networks, the same strong bonds that ensure cooperation will also prevent novel ideas and perspectives from reaching the actors, isolating them from external environments (Grabner, 1993). As Uzzi (1997) argues, overembedded clusters face high risks of obsolescence and decline, which is detrimental to the performance of their individual members. When a firm is positioned in an open network, however, it usually does not confine itself to a small group of repeat partners, but rather seeks to expand its network reach by building bridging ties across different network sectors. The absence of strong bonds of cooperation and reciprocity in open networks allows firms to build and abrogate relationships with partners as business interests dictate (Baum et al., 2003), ultimately resulting in the development of flexible networks.

Such flexibility is particularly important when a firm occupies a disadvantageous position in the industry network. Studies of inter-organizational networks (e.g. Gulati & Gargiulo, 1999; Podolny, 1993) find that many industries exhibit the properties of core-periphery systems, i.e. they are dominated by a relatively small group of central firms (the core) with the bulk of the firms of low centrality located at the periphery. It is also a common finding in a network analysis that firms’ positions in a network core are associated with power and influence (Chung et al., 2000). Studies have shown that more powerful and resource-rich core firms can command higher prices for their output (Podolny, 1993), which results in their improved performance (Baum, Calabrese, & Silverman, 2000) as well as in increased growth rates and market share (Powell et al., 1996). The core-periphery industry structure is reinforced by homophilous pressures which push actors occupying similar network positions to partner amongst each other (McPherson & Smith-Lovin, 1987; McPherson et al., 2001; Podolny, 1993). As a result of these pressures, firms at the core of the industry are more likely to partner with other core firms, whereas firms at the periphery are likely to partner with peripheral firms. The homophily pressures pose an important
dilemma for peripheral firms. On the one hand, it is much easier to form ties with equally peripheral partners than it is with the core firms. On the other hand, repeat partnering with the same peripheral firms could embed it within a peripheral closed network, members of which have no access to the industry core and to the resource flows that circulate in that part of a network. A peripheral firm could attempt to improve its network position by building open networks rich in structural holes (Baum, Shipilov and Rowley, 2003). Lacking pressures to cooperate with the same network partners, such networks are likely to connect a peripheral firm to different network neighborhoods, expose it to novel deal-making opportunities, provide it with extra resources and possibly increase its centrality. Improved access to network resources would then lead to improved performance of a peripheral firm. Thus the following hypothesis can be advanced:

_Hypothesis 3: Network openness is positively related to performance for peripheral firms._

To summarize, whether or not a firm can improve its performance as a result of a position in an open network depends upon several firm-specific characteristics. Wide scope experience enables firms to appropriate heterogeneous information circulating in open networks and to translate this absorptive capacity to performance improvements (_Hypothesis 1_). Historically high levels of multimarket contact with network partners enable brokers to reduce the risks of partner non-cooperation, which leads to improved performance (_Hypothesis 2_). Finally, lack of collective norms of cooperation and reciprocity in open networks helps peripheral firms to build bridges to different network neighborhoods, which helps improve these firms’ network position and, consequently, performance (_Hypothesis 3_). In subsequent sections to this paper, I test these hypotheses on a population of investment

DATA AND METHODS

Data for this study was collected from two sources. Archival information on the dynamics of financial advisors’ networks was downloaded from the Securities Data Corporation (SDC) database “Worldwide Mergers & Acquisitions.” Several researchers have already relied on SDC databases when studying financial services industry (Eccles & Crane, 1988; Haunschild, 1994; Sorenson & Stuart, 2001); however, none of them have used this particular source for the study of networks formed among advisors on M&A transactions.

The “Mergers and Acquisitions” database includes comprehensive coverage of international transactions involving at least 5% of the ownership of the company. This private source is compiled using over 200 English and foreign language news sources, SEC filings and their international counterparts, trade publications, wires and proprietary surveys of investment banks, law firms and other advisors. For the analyses I chose to use the time frame between 1992 and 2001, as prior to 1992 my source excluded deals valued at less than 1 million dollars. Among over 1400 data elements in the SDC database, I was primarily interested in such variables as date of deal, value of deal, target and acquirer nation, target and acquirer industry sectors, names and parent company information of the advisors.

In order to better understand the functioning of the international financial advisory market and to construct variables that adequately capture the dynamics within this industry, I conducted interviews with senior bankers with experience in Merger & Acquisition advisory services. Altogether I interviewed managers working for 13 firms involved in M&A activities. My interviewees included bankers who worked in Canada, U.S., the United Kingdom, Switzerland and Germany. Usually I was able to interview managing directors or
vice-presidents of the banks as well as the heads of M&A departments for larger firms. When interviewing managers from small boutiques, I was usually able to speak to the firm’s owners. These interviews were semi-structured, lasted for about 45 minutes and in most cases were tape-recorded.

While the SDC database included information on M&A deals throughout the world, for this study I focused on transactions that involved a target company in the United Kingdom. The U.K. stands out in Western Europe as having the most permissive environment for M&A activity. Between 1992 and 2001 on average 36% of European M&A deals involved a target in the United Kingdom. When comparing merger and acquisition activity in the U.K. with that in Germany and France, two other economic superpowers in Europe, the value of deals involving U.K. targets in all but two years of my observation period exceeded the deal values involving German and French targets combined. Between 1992 and 2001, 385 investment banks advised on deals that involved a target in the United Kingdom. Advisors competing in the U.K. market included firms from over thirty countries in North America, Europe and Asia.

Network Definition

I defined inter-bank networks based on banks’ membership of advisory teams, i.e. groups of two or more banks retained by client companies to provide advice on their merger and acquisition activities. Banks participating in advisory teams together in a given year are also likely to interact in a range of ways with each other in periods proximate to the formal relations, i.e. negotiating the terms of cooperation or preparing the deal prior to the public announcement. To accommodate the likelihood of such ‘extra-team” interaction I adopt a two-year moving period approach to constructing the network over time (i.e., 1992-93, 1993-94, 1994-95, etc.). This approach also helps account for the fact that some acquisitions take over 20 months to complete. Consequently, constructing the network based on one-year
periods may represent the network inaccurately because advisory teams that have put together a deal may have been established in the prior year, but not measured in that year.

I organized my data into a series of sociomatrices. A particular matrix entry $X_{ij}$ corresponded to a sum for the two-year period of the number of times an investment bank in row “$i$” was working on a deal with a bank in column “$j$”. Thus, the value of $X_{ij}$ corresponded to the frequency of ties between banks $i$ and $j$. I used these networks to provide data on the characteristics of each bank’s network position in the second year of each two-year period. Thus, the 1992-93 network was used to measure investment advisors’ network positions for 1993, the 1993-94 network for positions in 1994, and so on.

**Dependent Variable**

I used *Market Share* of investment banks as an indicator of their performance, similar to previous studies of investment banking industry (Dunbar, 2000; Eccles & Crane, 1988). While there is no fixed rule for compensating a financial advisor, they are usually paid a percentage of the transaction value for their services, as all of my interviewees have pointed out. Thus, the higher the value of deals the investment bank facilitates, the higher its fees. Large market share also puts investment banks at the top of the league tables, the ranking device used by prospective clients and by the financial industry as a whole to evaluate reputation of an individual investment advisor. Supporting the insights contained in Eccles and Crane’s (1988) research, all of my interviewees have suggested that a bank’s position in the market share-based (or advised deal value-based) league tables is one the key devices that the financial industry uses to access relative performance of individual banks.

To measure market share at time $t$, I allocated the dollar value of each offering made during a year among the members of the syndicate that advised on the deal. For deals involving one investment bank only, this bank was assigned 100 percent of the offering’s dollar value. For deals involving multiple investment banks in an advisory team, I split the
value of the transaction equally among team members, which, as my interviewees have indicated, was a general rule for distributing advisory fees.

**Independent Variables**

My theoretical variables included specifications for the scope experience of an investment bank, history of multimarket contact with partners, network centrality, and a measure for a number of structural holes in an investment bank’s network. Almost all of my interviewees have pointed out that an investment advisor can specialize across two areas—sector of the economy and nationality of the companies it is working with. For example, Goldman Sachs specializes in advising on deals involving industrials, whereas Rothschild concentrates in utilities, telecommunication and financial services. Similarly, banks like Royal Bank of Canada and Bayerische Landesbank primarily advise on deals involving Canadian and German companies.

To compute scope specialization measures, I first defined categories that would describe a particular deal. In creating the economic sector component for *Specialization* variable I used the following industry categories: Agriculture, Forestry and Fishing (SIC Codes: 01-09); Mining (SIC Codes 10-14); Construction (SIC Codes 15-17); Manufacturing (SIC Codes 20-39); Transportation and Public Utilities (SIC Codes: 40-49); Wholesale Trade (SIC Codes 50-51); Retail Trade (SIC Codes 52-59); Finance, Insurance and Real Estate (SIC Codes 60-67); Services (SIC Codes 70-87) and Public Administration (SIC Codes 91-99). I also identified the following countries or geographic regions to indicate the nationality of acquirer: United Kingdom; North America (incl. US and Canada); Germany; Switzerland; France; the Netherlands; Other Continental Europe (e.g. Spain, Italy, Greece); Australia and Asia (e.g. Japan, Honk Kong). When conducting sensitivity analysis, I experimented with collapsing industrial and national categories in various ways (e.g. wholesale trade with retail
trade; or Germany with Switzerland, France and the Netherlands), however, the results were not substantively affected.

Based on the above categories, I computed a combined *Specialization* measure as a variant of the Herfindahl index:

\[
Specialization_{it} = \frac{1}{2} \left[ \sum_{j=1}^{n} \left( \frac{Sec_j}{k_{it}} \right)^2 + \sum_{jc=1}^{nc} \left( \frac{Cou_{jc}}{k_{it}} \right)^2 \right]
\]  

(1)

where \( k_{it} \) was the number of deals in which a bank \( i \) participated in a given period \( t \); \( n \) was a number of industry sectors in which these deals were made by all banks in a network, \( nc \) was a number of countries/regions from which acquirers made acquisitions in the U.K.; \( Sec_j \) was a number of deals in industry sector \( j \) that bank \( i \) participated in, \( Cou_{jc} \) was a number of deals facilitated by the bank from a country/region \( jc \) during the time period \( t \). When this index approached 1, then a particular bank had a narrow scope, whereas when this index approached 0, then this bank had a wide scope.

*Hypothesis 1* implies that over time banks develop routines for dealing with heterogeneous information. Thus measure of a scope needs to reflect not only bank’s current scope, but also incorporate information on its past experience. As Ingram and Baum (1997) suggest, variables reflecting organizational learning over time need to capture the decay of firm experiences, as usually more recent learning has a stronger impact on an organization than learning occurring some time in the past. The problem with the decay of experience, however, is that there is no a priori theoretical rationale for specifying a particular functional form of the decay. Therefore, following Ingram and Baum (1997), I have compared the results of different specifications for experience decay using the following basic indicator:

\[
Specialization \text{ Experience }_{it} = \sum_{t=1}^{t=n} \left( \frac{D_t}{\text{Discount}} \right)
\]

(2)
where $D_t$ was a market presence index computed in formula (1) above for each period $t$; $n$ was a number of periods a bank $i$ has been active on the U.K. market; Discount was one of the four different discount factors: a) set to 1, assuming no depreciation in the value of past experience; b) set to the square root of the age of the experience; c) set to the age of the experience assuming a linear depreciation; d) set to the age of the experience squared, which assumes that the value of past experience depreciates more rapidly than linear at first and then accelerates further with time. Sensitivity analysis, however, indicated that the results were not dependent on the choice of the discount rates. Below I discuss the results for the Specialization Experience variable with the discount factor set to the age of experience $^3$.

I modified Boeker et al’s (1997) measure to compute the indicator of a bank’s history of Multimarket Contact (MMC) with its network partners. First, I computed dyadic measures of multimarket contact between the focal bank $i$ and each other bank $j$ in an industry:

\[
MMC_{ij} = \frac{\left(\sum_{n=1}^{n} I_{in} * I_{jn}\right)}{\left(\sum_{n=1}^{n} I_{in}\right)}
\]

(3)

where $n$ was a total number of markets (defined the same way as economic and national sectors for Scope variable); $I_{in}$ was coded 1 if advisor $i$ was present at market $n$ and 0 otherwise; $I_{jn}$ was coded 1 if bank $j$ was present at market $n$ and 0 otherwise. Then individual measures of multimarket contact between the focal bank $i$ and all other investment advisors were aggregated into a measure of multimarket contact between the focal bank $i$ and all of its partners:

\[
MMC_{IP} = \frac{\left(\sum_{j=1}^{Nm} P_{ij} * MMC_{ij}\right)}{Nm}
\]

(4)

where $P_{ij}$ was set to 1 if bank $j$ was a partner of bank $i$ and 0 otherwise; $Nm$ was equal to the total number of investment advisor’s $i$’s partners. The higher $MMC_{IP}$ measure of multimarket

$^3$ I also computed a scaled version of this independent variable by dividing Specialization Experience by a bank’s Network Experience (count of periods between 1991 and 2001 that the bank was active in the U.K. M&A market). Results were very similar to those reported below, thus in this paper I use a simpler non-scaled version of this variable.
contact, at more markets bank $i$ was meeting its partners. Since I defined markets based upon both primary SIC codes of targets $MMC_{iP\_industry}$ and the nationality of acquirers $MMC_{iP\_country}$, I computed the following average measure of investment advisor $i$’s multimarket contact:

$$MMC_i = \frac{(MMC_{iP\_industry} + MMC_{iP\_country})}{2} \quad (5)$$

Ability of a firm to exploit its multimarket contact with partners does not appear overnight. As Stephan and Boeker (2001) point out, firms develop effective mechanisms for enforcing cooperation when they spend time observing each other’s behavior. Thus, a variable adequately reflecting firms’ ability to prevent partners’ non-cooperation needs to capture the history of a firm’s MMC with its network partners. Using equation (2) above, I computed *Historic MMC* of banks using single-year values of *MMC* from equation (5) and experimented with different discount factors. As with the *Specialization Experience* different discount factors provided similar results. Below I discuss results using *Historic MMC* variable with a discount set to the age of experience.

There are several measures available to compute an investment bank’s centrality in the industry network. For this analysis I chose Freeman’s *betweenness* measure (Freeman, 1979), capturing the degree to which a bank falls between the pairs of other banks on the shortest path connecting them. *Betweenness* has been used as a measure of an actor’s access to resources and information (Brass & Burkhardt, 1992; Freeman, 1979). An alternative specification for an investment advisor’s network position, namely its eigenvector centrality (Bonacich, 1987), yielded very similar results to the ones reported below. The distribution of *Betweenness Centrality* is highly skewed with very few banks with extremely high levels of centrality (*Maximum*=26.3) and most of the banks with very low levels of centrality (*Mean*=0.89, *Standard Deviation*=2.75) suggesting the existence of a core-periphery structure common to many industries (Gulati & Gargiulo, 1999; Podolny, 1994).
Finally, to capture the number of structural holes an investment bank’s network, I used Burt’s *Effective Size* (1992: 52) measure, which represents the difference between a number of bank’s partners and the average number of ties belonging to them, not counting partner ties to the investment advisor itself. High *Effective Size* means the bank’s partners have few ties to one another, thus the network of this bank contains multiple structural holes.

**Hypothesized Relationships**

I tested my hypotheses by entering into regression models interactions of *Effective Size* with *Specialization Experience*, *Historic MMC* and *Centrality*, respectively. A negative coefficient for the interaction of *Effective Size* and *Specialization Experience* would suggest support for Hypothesis 1 (as lower values of Herfindahl index are associated with wider scope of banks’ activities); positive coefficient for an interaction with *Historic MMC* would provide support for Hypothesis 2; and negative coefficient for an interaction with *Centrality* provides support for Hypothesis 3.

**Control Variables**

Many other factors may influence the performance of investment banks. Accordingly, my analysis controls for a baseline model that includes a range of additional characteristics of banks as well as industry-specific environmental factors. Following Silverman and Baum (2002), each variable was included for at least one of the following three reasons: 1) earlier research on the investment banking industry has shown the variable to have an effect on other dependent variables (Baum et al., 2003; Eccles & Crane, 1988); 2) a variable is well established in a network literature as influencing firm-level outcomes; 3) a variable measures some aspect of investment banking industry dynamics or the life-history of an investment advisor.

Among bank-level characteristics I controlled for its size, number of private deals, participation in advisory teams, specialization on advising targets of an M&A transaction,
number of years that a bank was not in the network during the observation window, number of a bank’s network partners and a bank’s network experience. Variable Size was computed by counting the number of deals in which a bank participated during each two-year period. Value for some deals in the SDC database was not reported, because they involved privately held targets and both the target and the acquirer agreed not to disclose these deal values. To control for the number of such deals in each bank’s portfolio, I included a count Number of Private Deals in my regression models. During my observation period, some banks did not participate in the advisory teams and acted as single advisors only. Controlling for systematic effects that networking activities of a bank could have on its performance, I created a variable Network. If during a given year a bank was not a part of a single advisory team, then a variable Network was set to zero, and when a bank participated in at least one deal as a part of an advisory team this variable was set to one. Controlling for the size of a bank’s network, I introduced a variable Number of Partners which reflected a count of a bank’s partners in every period. Furthermore, as Eccles and Crane (1988) point out, some banks prefer acting on the defensive side of the M&A transactions, by primarily acting as advisors to targets and very seldom acting as advisors to acquirers. To examine whether such orientation of banks systematically affected their performance, I introduced a control variable Target Advisor Specialization which was computed as a ratio of a number of deals in which a bank acted as an advisor to targets to the total number of deals in which a bank participated during a particular period of time. I also introduced a variable Missed Years which was a count of periods when a bank was not active in the U.K. market. Finally, I controlled for the number of years in which a bank has been active in the U.K. market by introducing a variable Network Experience. I calculated this variable as a sum of years during which a bank has been advising on M&A deals in the U.K.
Among environmental characteristics, I controlled for volatility affecting banks’ markets, density of industry network and industry concentration. Market share of investment banks can be affected by their exposure to those market segments that exhibit high volatility in demand for M&A deals. In any given year, the higher the volatility of demand for M&A deals within certain market segments, the more difficult it could be for investment banks exposed to these segments to maintain their performance (especially compared to banks not exposed to volatile sectors). To control for demand volatility in banks’ markets, I first used five-year moving windows to compute the standard deviations and means of the counts of offerings in all ten industry sectors and nine acquirer nationality sectors. Then I weighted banks’ exposure to these market segments by the ratio of standard deviation to the mean count of offerings they made in a particular segment:

\[
Deal Demand Variability_{sit} = \sum_{j=1}^{j=7} \left( \frac{\text{STD}_{sj}}{\text{Mean}_{sj}} \right) \times \left( \frac{S_{sj}}{k_{sit}} \right)
\]

where \(k_{sit}\) was the number of deals in which bank \(i\) participated during period \(t\), \(S_{sj}\) was the number of deals in sector \(j\) that bank \(i\) participated in, \(STD_{sj}\) was a standard deviation of the counts of offerings in a particular sector \((j)\) over the five-year period, and \(Mean_{sj}\) was the mean number of offerings in this segment over the same period. The higher the value of Deal Demand Variability (DDV), the larger the changes in demand market segments to which a bank was exposed. Having computed DDV in a bank’s industry sectors and acquirer nationality sectors separately, I then averaged them using the following formula:

\[
DDVi = \frac{(DDV_{sit industry} + DDV_{sit country})}{2}
\]

Furthermore, following Rowley, Behrens and Krackhard (2000), I introduced a variable Network Density which was computed as a ratio of all ties within the industry network in a particular period of time to the possible number of ties in the network, equal to \(N*(N-1)\)
where $N$ was a number of banks in the network. To control for the degree to which the industry was dominated by a few powerful banks, I calculated an *Industry Concentration* variable as a sum of market shares of 4 largest M&A advisors in the U.K.


**ANALYSIS AND RESULTS**

Standard descriptive statistics and correlations for all variables are given in Table 1a.

Although generally correlations are small in magnitude, quite a few of those is greater than 0.8, suggesting potential for multicollinearity. Of particular concern are high correlations between main effects of theoretical variables and their interactions (e.g. *Effective Size* and *Specialization Experience X Effective Size*). Such levels of correlation among theoretical variables could result in inflated standard errors. While some evidence indicates that multicollinearity is not likely to bias parameter estimates, and its effects are substantially reduced by large sample sizes (Kennedy, 1992), I still used checks to detect and avoid this problem. Such checks included building hierarchically nested models (Baum et al., 2000) and computing models’ Variance Inflation Factors (VIF). Average model’s VIF greater than 10 would create a cause for concern. To reduce the impact of multicollinearity on my results, for all theoretical interactions I centered main effects of *Specialization Experience*, *Historic MMC*, *Centrality* and *Effective Size* on their means within individual years prior to constructing all four interaction terms (Jaccard, Turrisi & Wan, 1990). This transformation reduced correlation between individual component terms and the interaction terms in most of
the cases. Table 1b reports descriptive statistics for all variables after centering main effects on their means prior to constructing interaction terms.

I estimated regression coefficients using a logarithmic growth model. This model can be formally defined as:

\[
\text{Ln(M.S.t+1)}_i = \alpha \times \text{Ln(M.S.t)}_i + \beta \times X_i(t-1) + \epsilon
\]  \hspace{1cm} (8)

where \( \text{M.S. (Market Share)} \) is a time-varying measure of performance. In the equation above \( \alpha \) is an adjustment parameter that indicates how current performance depends on prior performance and \( \beta \) is a vector of parameters for the effects of independent and control variables. Inclusion of past year’s performance (\( \text{Market share}_t \)) to predict the future year’s dependent variable helps account for the possibility that the empirical models of investment banks’ performance suffer from specification bias due to unobserved heterogeneity. My models were estimated on a pooled time-series dataset with each bank contributing a panel based on the number of years it was active on the market. For example, if a bank had four years of data, then it would contribute four observations to my analysis. Altogether I had 1257 bank-years after taking into account the lagged dependent variable.

Pooling repeated observations on the same banks, however, is likely to violate the assumption of independence from observation to observation and will result in the model’s residuals being autocorrelated. This renders OLS estimates inefficient, and for the model of interest with lagged dependent variable, autocorrelation would generate biased estimates (Judge, Griffiths, Hill, & Lee, 1985). To correct this problem, I relied upon fixed effects GLS models, which is equivalent to including dummy variables for each firm in the dataset. As an additional check for whether autocorrelation between performance measures materially
affects my results, I dropped lagged performance variable from my analysis\(^4\). As one could expect, the fit of the models was substantially reduced; however, the significance and direction of the coefficients was not affected. The results of this supplementary analysis are available upon request.

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Table 2 reports the estimates for the effects of theoretical and control variables on investment banks’ market share. Model 1 is a baseline that contains all the main effects of theoretical variables and controls and Model 2 is the same baseline model only using centered main effects of theoretical variables. In Models 3-5, I entered centered interactions of Effective Size with Specialization Experience, Historic MMC and Centrality respectively. By entering interactions in Models 3-5, I was able to achieve statistically significant improvements in the model fit in all cases. Model 6 contains the same variables as full Model 5, only without centering main effects of Specialization Experience, Historic MMC and Centrality. As one could expect, due to high correlation between main effects and their interactions, this model suffers from high levels of multicollinearity (average VIF=12.21). Perhaps due to these influences, a coefficient for Effective Size changes signs in this model as well as an interaction between Historic MMC and Effective Size looses its significance. Below I interpret results from Model 5, which contains all centered theoretical variables and interactions as well as has an acceptable average VIF (VIF=4.68).

\(^4\) To further check whether an inclusion of a lagged dependent variable results in the violation of homoskedasticity assumption in the regression models, I conducted a supplementary analysis using instrumental variables. In the two-stage regression model (Kennedy, 1992: 165). I first estimated a lagged market share with theoretical and control variables, and then included predicted values of market share into the second stage of regression. The results were identical to those presented below and are available upon request.
Coefficients in this model provide support for Hypotheses 1, 2 and 3. Banks with wide scope experience (low Specialization Experience) are able to benefit from a position in an open network due to their capacity to process and absorb heterogeneous information (Hypothesis 1 is supported $p>0.001$). Increases in the levels of historic multimarket contact between the bank and its partners result in performance improvements for banks positioned in open networks, since MMC serves as a governance mechanism preventing partner non-cooperation (Hypothesis 2 is supported $p>0.05$). Finally, investment banks that occupy peripheral network positions can avoid isolation and improve their performance by actively identifying and exploiting structural holes (Hypothesis 3 is supported $p>0.05$).

Coefficients of some other variables are worth noting. Effective Size appears to have a negative effect on market share of investment banks ($p>0.01$), suggesting that in the M&A advisory industry firms perform well when they form closed networks with their partners. This insight has been supported by most of my interviewees who suggested that it is vitally important for a success of an M&A transaction that members of advisory teams have good working relationships and trust among each other. Existence of a triadic relationship between advisors facilitates trust and cooperation among them. Furthermore, negative and significant coefficient of Specialization Experience ($p>0.001$) suggests that banks historically active in advising customers from only selected countries or industries are less likely to increase their market share than their wide scope counterparts are. Greater number of advisory deals was also associated with an increased market share of investment bank, as indicated by a significant and positive coefficient of Size ($p>0.001$). Growth in the historic levels of multimarket contact between the bank and its partners leads to improved performance ($p>0.1$), because it allows network members to learn how to avoid non-cooperative behaviors of other banks in a network. Increases in Betweenness Centrality lead to greater market share ($p>0.001$), suggesting that core firms in the investment banking industry outperform
peripheral firms. As one would expect, lagged market share was a very strong predictor of a future market share of a firm ($p > 0.001$). Finally, banks advising on deals in highly volatile market segments had a lower market share than banks advising on deals in stable market segments, as indicated by the negative coefficient of *Deal-Demand Variability* ($p > 0.001$).

**DISCUSSION**

Despite growing interest in studying inter-firm networks, the link between a firm’s network position and its performance still remains poorly understood and is subject to continuing debate in the literature (e.g. Ahuja, 2000; Walker et al, 1997; Hargadon & Sutton, 1997; Baum et al, 2000). Even though scholars have come to an agreement on the contingent nature of benefits that firms could obtain from occupying network positions, the question about specific contingencies that affect performance implications of a firm’s network position still remains unanswered. By analyzing the relationship between investment banks’ network position and performance, this study provides evidence that several bank-level characteristics, namely specialization experience, historic multimarket contact with partners, and network centrality, affect benefits that investment banks can reap from occupying network positions rich in structural holes.

While this study contributes to the understanding of a relationship between network position and performance in general, its findings also help illuminate the mechanisms affecting the performance of investment advisors on M&A deals. For example, my results indicate that just having access to open networks’ heterogeneous information about new deals or new partners is not sufficient to improve an investment banks performance. Just as earlier studies linking a firm’s prior experiences with its absorptive capacity (Cohen & Levinthal, 1990; Lane & Lubatkin, 1998; Lane, Salk, & Lyles, 2001; Lenox & King, 2004), this study also indicates that a bank needs to have experience in dealing with heterogeneous clients.
before it can take advantage of heterogeneous information circulating in open networks. If an investment bank is continuously advising on deals that include companies in different industries or countries, then this advisor will develop internal practices and routines for dealing with information coming from its diverse customers. As my interviewees pointed out, inside an investment bank’s organizational structure, units responsible for dealing with diverse clients eventually learn how to evaluate and exchange information amongst each other. Such procedural knowledge arising as a result of information sharing or information provision (Lenox & King, 2004), contributes to the development of investment banks’ capacity to absorb heterogeneous information. Internal information provision will also shape perceptual lenses of organizations’ decision makers who become trained in separating more relevant information signals from the less relevant ones (Cohen & Levinthal, 1990). Such changes in perceptual lenses increase the speed at which decision makers absorb information and act upon it. Ultimately, such experiences help investment advisors to effectively take advantage of heterogeneous information circulating in open networks and to convert their access to heterogeneous network information into tangible performance outcomes.

My interviews indicated that partner non-cooperation in the M&A advisory market could be a negative force that affects success of individual deals and performance of investment banks. This non-cooperation could take three main forms. First, it could be non-reciprocation of past favors: One investment bank can advance a favor to another when it makes recommendations to its clients on the inclusion of its former partner into an advisory team, which brings additional revenue to the recommended bank. It is generally expected that banks return such favors by making reciprocal introductions to their own clients; however, banks behaving non-cooperatively could repeatedly fail to do so. A second form of non-cooperation could occur when banks hire star professionals from their competition in order to build their own expertise in particular market sectors. By doing so, the non-cooperating bank
would be damaging both the human capital of the target bank as well as attacking its market positions. A third form of non-cooperative behavior could be exemplified by a bank inappropriately attacking its advisory team partners in front of the client and suggesting incompetence of its team members. By doing so, the bank would be damaging not only the rapport within the advisory team, but also the image of its partners in the industry. All these three forms of non-cooperation could be detrimental to the performance of investment banks.

In the absence of cooperative norms, investment banks need to rely on the threat of multimarket retaliation as a mechanism to prevent misbehavior. For example, if a bank’s partner attempts to hire its star specialists, the focal bank could retaliate by hiring specialists from its partner across several markets, ultimately destroying the capacity of the non-cooperating partner to provide investment advice. Alternatively, a bank could initiate a retaliatory attack by aggressively targeting customers in the markets occupied by the non-cooperating advisor. Furthermore, if as a result of their prolonged market contact a bank has observed behaviors of its partner and became aware that this partner is likely to misbehave, then the focal bank may disseminate information across all common markets about the non-cooperativeness of this particular partner. Threats of such retaliatory activities could reduce the risks of partners’ non-cooperation in the advisory networks.

Finally, both prior research (e.g. Eccles & Crane, 1988; Podonly, 1994; Gulati & Gargiulo, 1999) and my own data indicate the existence of a core-periphery structure in the investment banking industry. There are a few banks that enjoy advantageous positions at the industry core and there are many more banks that are located at the industry’s periphery. The most visible and lucrative deals go to the central banks, whereas peripheral advisors are forced to concentrate their business in niche markets. Banks of similar centrality tend to be included in the same deals, i.e. core banks advise on deals involving other core banks and
peripheral banks advise on deals involving other peripheral banks. For a peripheral bank, continuous participation in deals involving the same set of peripheral partners embeds it within a closed network. Membership in such networks helps banks to secure access to new deals through referrals of their repeat partners as well as improves cooperation among them. However, doing so could prevent banks from gaining access to deals beyond those available to its existing partners and could lead to a feeling of mutual obligation on the part of the group’s members who feel pressured to continue cooperating with each other. One way a bank could improve its network position is by participating in deals involving different advisors. Doing so would expose a peripheral bank to other sources of information on new deals and link it to different network neighborhoods. In so doing, peripheral banks could build flexible networks augmenting their centrality and performance.

Relative magnitudes of the effects for the theoretical variables on investment banks’ market share are particularly noteworthy. They are summarized in Table 3.

Using the coefficients from Model 5 (Table 2) and descriptive statistics (Table 1b) I computed the sizes of effects that differences in Specialization Experience, Historic MMC and Centrality would have on banks’ Market Share. If two banks (for simplicity denoted Bank 1 and Bank 2) are positioned in an open network (for example both with centered Effective Size = 3.91), Bank 2 with Specialization Experience of one standard deviation above the mean (indicating its narrow scope) would have a 3.44% lower Market Share than Bank 1 with a value of Specialization Experience one standard deviation below the mean (indicating its wide scope). When taking into account the impact of main effect of Specialization Experience on a banks’ market share ($\beta = -.025$), the narrow scope Bank 2 would have a
5.44% lower market share than a wide scope Bank 1. Furthermore, Bank 2 which is historically maintaining high levels of MMC with its partners (Historic MMC one standard deviation above the mean) would have a 0.54% greater market share than Bank 1 which is maintaining low levels of MMC with its partners (Historic MMC one standard deviation below the mean). When taking into account the impact of main effect of Historic MMC on banks’ market share ($\beta=0.005$), Bank 2 with a high level of Historic MMC would have a 1.03% greater market share than Bank 1 with a low level of Historic MMC. Finally, a peripheral Bank 1 (i.e. bank with value of Centrality one standard deviation below the mean) would be able to improve its market share by 0.4% with the use of bridging ties in an open network vis-à-vis a more central Bank 2 (i.e. a bank with value of Centrality one standard deviation above the mean). However, Bank 1 would still have a 2.66% lower market share than a more central Bank 2 due to a strong main effect ($\beta=0.006$) of Centrality on performance. Different magnitudes of these effects show that capacity to absorb heterogeneous information in an open network has a more profound effect on the ability of an investment bank to extract benefits from its structural holes than does either its ability to enforce partner cooperation or its core/periphery position. This analysis also implies that while building bridging ties could help peripheral banks improve their performance by avoiding overembeddedness, these ties are not likely to compensate for peripheral banks disadvantageous network position, which contradicts earlier research on bridging ties (e.g. Baum, Shipilov & Rowley, 2003).

Future Research Directions, Limitations and Conclusions

With its focus on firm-specific characteristics affecting payoffs received from maintaining network positions, this study contributes to the growing body of research linking a firm’s network position to its performance. Several lines of research could be explored
further. For example, one could extend the absorptive capacity argument advanced in this paper to explore how the overlap between information received through bridging ties and the past experiences of a firm affects the benefits this firm would obtain from spanning structural holes. One could speculate that if a firm’s bridging ties provide it with heterogeneous information that has absolutely no relevance to its past experiences, then this firm will not be able to commercialize this information, thus its investment in bridging ties will not pay off. In contrast, a firm may reap maximum benefits from its investment in structural holes when there is some overlap between the information it receives from its network partners and its own past experiences. Such a firm will be able to absorb new information and recombine it with existing knowledge, thus achieving maximum improvements in performance. However, when there is complete overlap between information received through structural holes and a firm’s own knowledge, then bridging ties would be providing a firm with something that the firm already knows. Such information redundancy may not be likely to provide a firm with competitive advantage, nor result in substantial performance improvements.

This study also doesn’t examine a possibility for reverse causality in relationships among a firm’s characteristics, its network position and performance. Just as a firm’s network position and firm-level characteristics could affect its future market share, so market share and firm-level characteristics could affect its network position. For example, a firm that is engaged in many deals simultaneously could enjoy access to multiple structural holes simply because it cooperates with many different network partners. A firm that has a wide scope of activities could also come to possess a lot of structural holes because its network partners operate in different market segments. Finally, an increase in a firm’s performance could make it an attractive ally to other firms and its number of structural holes could increase. Faced with a large choice of potential network partners, a firm could choose to partner with
otherwise disconnected alters in order to exploit structural holes among them to its own advantage.

In summary, this study is one of the first attempts to investigate how firm-level factors affect the likelihood that a firm will benefit from occupying network positions rich in structural holes. In so doing, this study suggests a fruitful avenue of research that would systematically examine boundary conditions of a “structural holes” perspective on a network-based competitive advantage. Such theory development is poised to improve our understanding of the links between a firm’s position within inter-organizational networks and its performance.
REFERENCES


| Variable                  | Mean  | StDev | Min  | Max  | 1          | 2          | 3          | 4          | 5          | 6          | 7          | 8          | 9          | 10         | 11         | 12         | 13         | 14         | 15         | 16         |
|---------------------------|-------|-------|------|------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| Market Share              | 0.03  | 0.07  | 0.00 | 0.70 | 1.00      |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |
| Lagged M. Share           | 0.02  | 0.07  | 0.00 | 0.70 | 0.76      | 1.00      |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |
| Effective Size            | 2.00  | 3.93  | 0.00 | 32.09 | 0.56      | 0.64      | 1.00      |           |           |           |           |           |           |           |           |           |           |           |           |           |           |
| Specialization Exp.       | 1.29  | 0.43  | 0.00 | 2.63  | -0.27     | -0.25     | -0.14     | 1.00      |           |           |           |           |           |           |           |           |           |           |           |           |           |
| Historic MMC              | 0.35  | 0.50  | 0.00 | 2.13  | 0.53      | 0.58      | -0.14     | 1.00      |           |           |           |           |           |           |           |           |           |           |           |           |           |
| Betweenness               | 0.89  | 2.75  | 0.00 | 26.28 | 0.48      | 0.50      | 0.82      | -0.18     | 0.45      | 1.00      |           |           |           |           |           |           |           |           |           |           |           |
| Size                      | 13.22 | 33.25 | 0.00 | 393   | 0.38      | 0.43      | 0.84      | -0.09     | 0.56      | 0.79      | 1.00      |           |           |           |           |           |           |           |           |           |           |
| Nr. Private Deals         | 2.80  | 11.13 | 0.00 | 152   | 0.14      | 0.15      | 0.62      | -0.02     | 0.34      | 0.65      | 0.90      | 1.00      |           |           |           |           |           |           |           |           |           |           |
| Target/Acquirer Spec.     | 0.79  | 0.23  | 0.50 | 1.00  | -0.33     | -0.34     | -0.44     | 0.13      | -0.59     | -0.33     | -0.37     | -0.22     | 1.00      |           |           |           |           |           |           |           |           |           |
| Missed Years              | 0.13  | 0.70  | 0.00 | 9.00  | -0.07     | -0.07     | -0.09     | 0.22      | -0.13     | -0.07     | -0.08     | -0.05     | 0.16      | 1.00      |           |           |           |           |           |           |           |           |
| Network Experience        | 2.41  | 2.43  | 0.00 | 9.00  | 0.21      | 0.27      | 0.45      | 0.53      | 0.66      | 0.20      | 0.36      | 0.24      | -0.44     | -0.02     | 1.00      |           |           |           |           |           |           |           |
| DDV                       | 0.15  | 0.07  | 0.03 | 0.87  | 0.00      | 0.04      | 0.07      | 0.23      | 0.10      | -0.03     | 0.03      | 0.02      | 0.07      | 0.12      | 0.23      | 1.00      |           |           |           |           |           |           |
| Density                   | 0.06  | 0.01  | 0.04 | 0.07  | 0.07      | 0.03      | -0.05     | -0.04     | -0.04     | -0.01     | -0.02     | -0.01     | -0.09     | -0.31     | -0.54     | 1.00      |           |           |           |           |           |           |
| Industry Concentration    | 0.38  | 0.03  | 0.35 | 0.43  | -0.02     | -0.07     | -0.05     | -0.11     | -0.06     | -0.02     | -0.02     | 0.00      | -0.01     | -0.09     | -0.31     | -0.54     | 1.00      |           |           |           |           |           |
| Spec. Exp. X Eff. Size    | 2.30  | 4.66  | 0.00 | 44.28 | 0.41      | 0.49      | 0.96      | 0.00      | 0.68      | 0.76      | 0.85      | 0.68      | -0.40     | -0.08     | 0.52      | 0.10      | -0.07     | -0.06     | 1.00      |           |           |           |
| Hist. MMC X Eff. Size     | 2.14  | 5.60  | 0.00 | 44.23 | 0.55      | 0.67      | 0.96      | -0.11     | 0.74      | 0.71      | 0.80      | 0.57      | -0.40     | -0.08     | 0.50      | 0.09      | -0.07     | -0.05     | 0.93      | 1.00      |           |           |
| Betweenness X Eff. Size   | 10.75 | 50.54 | 0.00 | 810   | 0.36      | 0.41      | 0.80      | -0.07     | 0.36      | 0.89      | 0.81      | 0.69      | -0.23     | -0.05     | 0.22      | 0.02      | 0.00      | -0.03     | 0.79      | 0.74      |           |           |

* all correlations above 0.05 are significant at p<0.05; N=1257; extremely high correlations (r>0.8) are highlighted in bold
TABLE 1b  
Descriptive Statistics and Correlations after Centering a

| Variable                      | Mean  | St. Dev | Min   | Max   | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   | 11   | 12   | 13   | 14   | 15   | 16   |
|-------------------------------|-------|---------|-------|-------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| 1 Market Share                | 0.03  | 0.07    | 0.00  | 0.70  | 1.00 |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| 2 Lagged M. Share             | 0.02  | 0.07    | 0.00  | 0.70  | 0.76 | 1.00|     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| 3 Effective Size              | 0.00  | 3.91    | -2.40 | 29.69 | 0.57 | 0.64| 1.00 |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| 4 Specialization Exp.         | 0.00  | 0.40    | -1.47 | 1.18  | -0.31 | -0.30 | -0.23 | 1.00 |     |     |     |     |     |     |     |     |     |     |     |     |     |
| 5 Historic MMC                | 0.00  | 0.49    | -0.50 | 1.83  | 0.08 | 0.04 | 0.04 | 0.04 | -0.03 | 1.00 |     |     |     |     |     |     |     |     |     |     |     |
| 6 Betweenness                 | 0.00  | 2.55    | -1.21 | 18.92 | 0.52 | 0.79 | -0.21 | 0.05 | 1.00 |     |     |     |     |     |     |     |     |     |     |     |     |
| 7 Size                        | 13.22 | 33.25   | 0.00  | 393   | 0.38 | 0.43 | 0.84 | -0.15 | 0.04 | 0.76 | 1.00 |     |     |     |     |     |     |     |     |     |     |
| 8 Nr. Private Deals           | 2.80  | 11.13   | 0.00  | 152   | 0.14 | 0.15 | 0.62 | -0.05 | 0.01 | 0.58 | 0.90 | 1.00 |     |     |     |     |     |     |     |     |     |
| 9 Target/Acquirer Spec.       | 0.79  | 0.23    | 0.50  | 1.00  | -0.33 | -0.34 | -0.44 | 0.16 | 0.00 | -0.35 | -0.37 | -0.22 | 1.00 |     |     |     |     |     |     |     |     |
| 10 Missed Years               | 0.13  | 0.70    | 0.00  | 9.00  | -0.07 | -0.07 | -0.11 | 0.19 | -0.03 | -0.07 | -0.08 | -0.05 | 0.16 | 1.00 |     |     |     |     |     |     |
| 11 Network Experience        | 2.41  | 2.43    | 0.00  | 9.00  | 0.21  | 0.27 | 0.41 | 0.33 | 0.00 | 0.25 | 0.36 | 0.24 | -0.44 | -0.02 | 1.00 |     |     |     |     |     |
| 12 DDV                        | 0.15  | 0.07    | 0.03  | 0.87  | 0.00  | 0.04 | 0.02 | -0.01 | 0.01 | -0.02 | 0.02 | 0.02 | 0.07 | 0.12 | 0.23 | 1.00 |     |     |     |     |
| 13 Density                    | 0.06  | 0.01    | 0.04  | 0.07  | 0.07  | 0.03 | -0.02 | 0.01 | 0.01 | 0.01 | -0.04 | -0.01 | 0.06 | -0.06 | 0.16 | 0.01 | 1.00 |     |     |     |
| 14 Industry Concentration     | 0.38  | 0.03    | 0.35  | 0.43  | -0.02 | -0.07 | -0.02 | 0.02 | 0.00 | -0.01 | -0.02 | -0.02 | 0.00 | -0.01 | -0.09 | -0.31 | -0.54 | 1.00 |     |     |
| 15 Spec. Exp. X Eff. Size     | -0.34 | 1.25    | -10.17| 4.39  | -0.62 | -0.69 | -0.61 | -0.03 | -0.04 | -0.52 | -0.37 | -0.12 | 0.28 | -0.04 | -0.38 | -0.02 | 0.02 | 0.03 | 1.00 |     |
| 16 Hist. MMC X Eff. Size      | 0.03  | 1.99    | -10.49| 29.95 | 0.14  | 0.06 | 0.10 | -0.02 | 0.16 | 0.14 | 0.10 | 0.03 | -0.03 | 0.00 | -0.01 | 0.00 | 0.03 | -0.01 | -0.10 | 1.00 |
| 17 Betweenness X Eff. Size    | 9.04  | 43.05   | -2.17 | 732   | 0.33  | 0.37 | 0.76 | -0.08 | 0.06 | 0.76 | 0.78 | 0.68 | -0.20 | -0.04 | 0.20 | 0.02 | 0.00 | -0.02 | -0.37 | 0.23 |

a all correlations above 0.05 are significant at p<0.05; N=1257; extremely high correlations (r>0.8) are highlighted in bold
### TABLE 2:
Fixed Effect Models of M&A Advisors’ Performance 1992-2001a

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1 Non-Centered Baseline</th>
<th>Model 2 Centered Baseline</th>
<th>Model 3</th>
<th>Model 4 Full Centered Model</th>
<th>Model 5 Full Centered Model</th>
<th>Model 6 Full Non-Centered Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effective Size</td>
<td>-0.0027* (0.001)</td>
<td>-0.002* (0.001)</td>
<td>-0.003** (0.001)</td>
<td>-0.003** (0.001)</td>
<td>-0.002+ (0.001)</td>
<td>0.009* (0.003)</td>
</tr>
<tr>
<td>Specialization Experience</td>
<td>-0.006 (0.01)</td>
<td>-0.014 (0.01)</td>
<td>-0.003** (0.001)</td>
<td>-0.03** (0.01)</td>
<td>-0.025** (0.004)</td>
<td>-0.005 (0.01)</td>
</tr>
<tr>
<td>Historic MMC</td>
<td>0.009 (0.01)</td>
<td>0.007* (0.003)</td>
<td>0.006* (0.003)</td>
<td>0.005+ (0.003)</td>
<td>0.005+ (0.003)</td>
<td>0.003 (0.01)</td>
</tr>
<tr>
<td>Betweenness Centrality</td>
<td>0.004** (0.001)</td>
<td>0.004** (0.0011)</td>
<td>0.005** (0.001)</td>
<td>0.0046** (0.001)</td>
<td>0.006** (0.001)</td>
<td>0.004* (0.019)</td>
</tr>
<tr>
<td>Specialization Experience X</td>
<td>--</td>
<td>--</td>
<td>-0.011** (0.002)</td>
<td>-0.01** (0.002)</td>
<td>-0.011** (0.002)</td>
<td>-0.007** (0.002)</td>
</tr>
<tr>
<td>Effective Size</td>
<td>--</td>
<td>--</td>
<td>0.001+ (0.0006)</td>
<td>0.0014* (0.000)</td>
<td>0.000* (0.000)</td>
<td>-0.0006 (0.000)</td>
</tr>
<tr>
<td>Historic MMC X</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>0.0002** (0.0001)</td>
<td>-0.0001+ (0.0001)</td>
<td>-0.0001 (0.0001)</td>
</tr>
<tr>
<td>Betweenness Centrality X</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>-0.0002** (0.0001)</td>
<td>-0.0011 (0.0001)</td>
</tr>
<tr>
<td>Lagged Market Share</td>
<td>0.23** (0.036)</td>
<td>0.24* (0.036)</td>
<td>0.172** (0.038)</td>
<td>0.179** (0.038)</td>
<td>0.166** (0.038)</td>
<td>0.170** (0.04)</td>
</tr>
<tr>
<td>Size</td>
<td>0.0007** (0.0002)</td>
<td>0.0007** (0.0002)</td>
<td>0.0005** (0.0002)</td>
<td>0.0005** (0.0002)</td>
<td>0.0006** (0.0002)</td>
<td>0.0007** (0.0002)</td>
</tr>
<tr>
<td>Number of Private Deals</td>
<td>-0.001** (0.0005)</td>
<td>-0.001** (0.0005)</td>
<td>-0.001+ (0.0005)</td>
<td>-0.0007 (0.0005)</td>
<td>-0.0007 (0.0005)</td>
<td>-0.0011* (0.0005)</td>
</tr>
<tr>
<td>Target/acquirer Specialization</td>
<td>-0.005 (0.01)</td>
<td>-0.005 (0.01)</td>
<td>-0.007 (0.0099)</td>
<td>-0.007 (0.009)</td>
<td>-0.005 (0.009)</td>
<td>-0.003 (0.010)</td>
</tr>
<tr>
<td>Missed Network Years</td>
<td>-0.001 (0.002)</td>
<td>-0.001 (0.002)</td>
<td>-0.002 (0.0027)</td>
<td>-0.002 (0.003)</td>
<td>-0.001 (0.003)</td>
<td>-0.0008 (0.0027)</td>
</tr>
</tbody>
</table>

Table 2 continued on the next page ...
<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network Experience</td>
<td>-0.004</td>
<td>-0.004</td>
<td>-0.003</td>
<td>-0.003</td>
<td>-0.003</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>DDV</td>
<td>-0.154**</td>
<td>-0.154**</td>
<td>-0.140**</td>
<td>-0.140**</td>
<td>-0.140**</td>
<td>-0.154**</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.044)</td>
<td>(0.043)</td>
<td>(0.04)</td>
<td>(0.043)</td>
<td>(0.043)</td>
</tr>
<tr>
<td>Network Density</td>
<td>-0.062</td>
<td>-0.125</td>
<td>-0.126</td>
<td>-0.139</td>
<td>-0.129</td>
<td>-0.035</td>
</tr>
<tr>
<td></td>
<td>(0.29)</td>
<td>(0.296)</td>
<td>(0.293)</td>
<td>(0.286)</td>
<td>(0.292)</td>
<td>(0.292)</td>
</tr>
<tr>
<td>Industry Concentration</td>
<td>0.035</td>
<td>-0.011</td>
<td>0.057</td>
<td>0.054</td>
<td>0.05</td>
<td>0.063</td>
</tr>
<tr>
<td></td>
<td>(0.132)</td>
<td>(0.132)</td>
<td>(0.131)</td>
<td>(0.13)</td>
<td>(0.13)</td>
<td>(0.131)</td>
</tr>
<tr>
<td>Deal in 1992-1993</td>
<td>-0.03</td>
<td>-0.027</td>
<td>-0.019</td>
<td>-0.02</td>
<td>-0.017</td>
<td>-0.025</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Deal in 1994-1995</td>
<td>0.009</td>
<td>-0.013</td>
<td>-0.019</td>
<td>-0.019</td>
<td>-0.021</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.015)</td>
<td>(0.015)</td>
<td>(0.015)</td>
<td>(0.015)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Deal in 1996-1997</td>
<td>0.016</td>
<td>-0.018</td>
<td>-0.018</td>
<td>-0.02+</td>
<td>-0.022+</td>
<td>-0.018+</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Deal in 1998-1999</td>
<td>-0.028**</td>
<td>-0.030**</td>
<td>-0.031**</td>
<td>-0.030**</td>
<td>-0.032**</td>
<td>0.029**</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.001)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.041</td>
<td>0.039</td>
<td>0.019</td>
<td>0.020</td>
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<tr>
<td></td>
<td>(0.06)</td>
<td>(0.060)</td>
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<td>(0.059)</td>
<td>(0.059)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.5073</td>
<td>0.4771</td>
<td>0.5268</td>
<td>0.5314</td>
<td>0.5478</td>
<td>0.5502</td>
</tr>
<tr>
<td>$\Delta R^2$ $^b$</td>
<td>--</td>
<td>--</td>
<td>0.0497**</td>
<td>0.0046**</td>
<td>0.0161**</td>
<td>--</td>
</tr>
<tr>
<td>$\Delta R^2$ $^c$</td>
<td>--</td>
<td>--</td>
<td>0.0497**</td>
<td>0.0543**</td>
<td>0.071**</td>
<td>0.043**</td>
</tr>
<tr>
<td>Model VIF</td>
<td>5.27</td>
<td>4.64</td>
<td>4.63</td>
<td>4.49</td>
<td>4.68</td>
<td>12.21</td>
</tr>
</tbody>
</table>

$^a$ p < 0.10; $^b$ p < 0.05; $^c$ p < 0.01; N=1257 ; $^b$ significance of $\Delta R^2$ as compared to previous nested model ; $^c$ significance of $\Delta R^2$ as compared to baseline model
<table>
<thead>
<tr>
<th>Banks' Characteristics</th>
<th>Value of Effective Size</th>
<th>Value of Specialization Experience, Historic MMC and Centrality for Bank 1</th>
<th>Value of Specialization Experience, Historic MMC and Centrality for Bank 2</th>
<th>Differences in market share of Bank 2 and Bank 1 due to main and interaction effects of theoretical variables&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Differences in market share of Bank 2 and Bank 1 due to interaction effects of theoretical variables&lt;sup&gt;b&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specialization Experience</td>
<td>3.91</td>
<td>-0.4</td>
<td>0.4</td>
<td>-5.44%</td>
<td>-3.44%</td>
</tr>
<tr>
<td>Historic MMC</td>
<td>3.91</td>
<td>-0.49</td>
<td>0.49</td>
<td>1.03%</td>
<td>0.54%</td>
</tr>
<tr>
<td>Centrality</td>
<td>3.91</td>
<td>-2.55</td>
<td>2.55</td>
<td>2.66%</td>
<td>-0.40%</td>
</tr>
</tbody>
</table>

<sup>a</sup>Differences in market shares between Bank 2 and Bank 1 were computed as follows:
\[
\text{exp}\left\{\beta_{\text{main}} \cdot B2 + \beta_{\text{interaction}} \cdot 3.91 \cdot B2\right\} - \text{exp}\left\{\beta_{\text{main}} \cdot B1 + \beta_{\text{interaction}} \cdot 3.91 \cdot B1\right\} - 1
\]
with \(\beta_{\text{main}}\) equal to a coefficient for main effects of Specialization Experience, Historic MMC or Centrality respectively from Table 2 and \(\beta_{\text{interaction}}\) equal to a coefficient for an interaction between Specialization Experience, Historic MMC or Centrality with Effective Size. B2 and B1 denote values of Specialization Experience, Historic MMC and Centrality for Bank 2 and Bank 1.

<sup>b</sup>Differences in market shares between Bank 2 and Bank 1 were computed as follows:
\[
\text{exp}\left\{\beta_{\text{interaction}} \cdot 3.91 \cdot B2\right\} - \text{exp}\left\{\beta_{\text{interaction}} \cdot 3.91 \cdot B1\right\} - 1
\]
with \(\beta_{\text{interaction}}\) equal to a coefficient for an interaction between Specialization Experience, Historic MMC or Centrality with Effective Size. B2 and B1 denote values of Specialization Experience, Historic MMC and Centrality for Bank 2 and Bank 1.