POPULAR, TALENTED AND NICE: HOW FIRMS EVALUATE AND SELECT INTERORGANIZATIONAL PARTNERS

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ABSTRACT

Prior research on interorganizational relationships suggests that firms tend to choose past partners for future alliances, because they have access to information on these partners that reduces selection uncertainty. However, the types of information utilized have not been articulated. Applying a social network framework, we model how firms evaluate and differentiate among past partners for future alliance opportunities, and find that reciprocity and success in past ties influence the alliance selection process.

Information availability is a pertinent issue in interorganizational relationships as firms search for intelligence to reduce uncertainties inherent in the partner selection process (Gulati, 1999). Selecting an alliance partner is non-trivial because it is difficult to predict whether a potential partner "comes from one part of the opportunism distribution rather than another" (Williamson, 1985: 58) or is capable of making a worthwhile contribution to the alliance (Larson, 1992; Uzzi, 1996). As a result, firms show a propensity toward past partners in alliance selection decisions because the information gained from these past experiences helps reduce uncertainty regarding potential partners' capabilities (talent) as effective contributors to the relationship and reliability as trustworthy and cooperative allies (nice) (Balakrishnan & Koza, 1993; Gulati & Gargiulo, 1999). Thus, in partner selection decisions firms "consider first those potential exchange partners about whom they have the greatest knowledge (prior partners) and then choose the best among them" (Podolny, 1994: 458).

The types of information and knowledge used in selecting the "best" past partners, however, have not yet been articulated. Researchers have not specified what types of *experiential* information from a firm's history of ties are used to discriminate among its past partners when selecting allies for new collaborative opportunities. Without further analysis into the types of experiential information used in evaluating past partners, prior studies implicitly assume that all past partners are equally likely to be selected for future alliances. In this study, we argue that firms discriminate among past alliance partners based on information accumulated from previous partnership interactions.

To contribute to the growing stream of literature surrounding "with whom firms form alliances" (Gulati, 1995: 619), we use data characterizing relationships among U.S. investment banks over a five-year period in order to model how firms discriminate among their partners in order to choose the "best" among them for future alliances. We set the partnership formed between the lead and co-lead managers of an initial public offering (IPO) syndicate as the unit of analysis and ask the question: With respect to its set of past ties, why do lead manager firms choose some partners but not others for IPO events? Our results support the notion that the network of past ties is an important information repository regarding potential interorganizational partners (Gulati & Gargiulo, 1999). Moreover, we find that in addition to an actor's relative status (popular), the intelligence extracted (and evaluated) from the information cache of past interorganizational interactions includes partners' past successes (talent) and reciprocity behavior (nice). Investment banks choose past partners (to be co-lead managers for an IPO deal) that have reciprocated in kind past invitations to participate in underwriting IPOs; and they attempt to re-create past underwriting successes by selecting the co-lead managers from those experiences for new IPO deals. Thus, firms identify their best partners as those that are popular (status consideration), talented (associated with successful past alliances) and cooperative (willing to reciprocate).

INFORMATION AVAILABILITY IN ALLIANCE PARTNER SELECTION

The key task in the alliance selection process is reducing uncertainty regarding potential partners' capabilities/skills (Kogut, 1988) and reliability as trustworthy, cooperative partners (Gulati, 1995). Given the paucity and ambiguity of information available for reducing this uncertainty (Gulati, & Gargiulo, 1999), partners may not be able to adequately evaluate each other prior to forming an alliance. Through experiences with specific partners, however, firms gain information regarding their partners' skills and willingness to cooperate. In addition, alliance partners solicit and share information from their other interfirm relationships, endorsing particular actors as quality exchange partners (Uzzi, 1996). Gulati and Gargiulo (1999: 1440) argue that "over time, these 'embedded' relationships (Granovetter, 1985) accumulate into a network that becomes a growing repository of information on the availability, competencies, and reliability of prospective partners (Gulati, 1995; Kogut, Shan & Walker, 1992; Powell, Koput & Smith, 1994)."

Many aspects of a firm's network have been recognized as providing information useful for assessing potential partners. Podolny (Larson, 1992; Oliver, 1990; Ring & Van de Ven, 1992) suggests when firms are unable to easily appraise a potential partner, status is used as a surrogate. While status is an indicator of a partner's quality, this assessment is based not only on the actor's actual behavior or performance, but also the status of its exchange partners (Stuart, Hoang & Hybels, 1999): Ties to high-status partners increase esteem bestowed on the actor, because such affiliations are perceived to be associated with actual quality, which might not be readily discernible. In this way, links to high-status others act as endorsements of the actor's character as an exchange partner. Because associations with lower-status actors negatively impact one's own status, firms tend to form alliances with similar-status actors. Podolny (1994) finds empirical support for a status homophily effect: Firms tend to form alliances with similar-status actors because forming an alliance with a lower-status actor has an negative effect on their own status rating.

As well, Podolny (1994: 479) suggests that status - an assessment of a firm's relative position in the network - is a second-best approach to evaluating potential partners and is a more salient proxy of an actor's value as an ally when prior alliance experience (experiential information) is not available. That is, firms prefer firsthand knowledge of potential partner abilities and behavior (Granovetter, 1985). It is because prior ties provide information which can reduce partner selection uncertainty (capabilities and trustworthiness), that firms favor past partners in alliance selection decisions (Balakrishnan & Koza, 1993; Gulati, 1998). Gulati (1995) provides empirical support for the notion that firms tend to choose past partners for future alliance opportunities. In addition, Uzzi's (1996) study of relationships in the

New York apparel industry illustrates that third-party endorsements play a role in alliance formations - firms solicit partner nominations from their existing partners, who make suggestions based on their own alliance experiences. As firms become embedded in the surrounding structure of interorganizational ties, information regarding the actors in their immediate network (past partners and partners' partners) becomes available, and, as a result, firms tend to limit their selection set to these players. Therefore, by establishing stable, enduring relationships firms have access to information that reduces the search costs and risks inherent in the alliance selection process (Gulati & Gargiulo, 1999).

The question remains, however, what types of information from a firm's past experience with partners are utilized (and how) in the alliance selection process? As mentioned above, without considering the types of experiential information firms gather from past relationships, our alliance selection models do not discriminate among a firm's past partners, assuming that all past partners are equally likely to be chosen for future opportunities. Moreover, empirical evidence of firms favoring past partners does not unambiguously support the notion that firms rely on the information from these ties to make future alliance selection decisions.

Based on the work of researchers examining organizational change and routines, this propensity to select past partners might alternatively be explained by path dependence: Firm behavior could be driven (partly) by the inertia of previous decisions rather than the information advantage gained from experiencing past partners' behaviors. From this perspective, firms tend to engage in local searches - in the "neighborhood" of their experience and knowledge - when confronting uncertain problems (Cyert & March, 1963). The search for a solution is focused on options that are easily accessible or have been incorporated in the past to address similar issues (Huber, 1991). From this perspective, organizations develop routines, which produce continuity in how they respond to frequently occurring stimuli (Nelson

& Winter, 1982; Stuart & Podolny, 1996). Amburgey and Miner (1992: 336) argue that "as an organization takes actions over time, it develops routines and competencies which then become independent engines for further actions (Burgelman, 1983; Levitt & March, 1988)." In other words, firms develop routines for dealing with certain strategic issues such that decision outcomes form a repetitive momentum pattern (Amburgey & Miner, 1992). Our examination of experiential information from past ties provides a means for more closely assessing whether firms use information from past ties in the alliance selection process after controlling for a repetitive momentum tendency: Do firms indiscriminately choose past partners based on previous decisions (inertia) or do they evaluate information from past ties to distinguish among their past partners and identify their best past allies? In the next section, we examine the influence of reciprocity and success - two information aspects from past ties - on how firms select allies from among their past partners.

EXPERIENTIAL INFORMATION FACTORS

Reciprocity

One type of information from past ties that is utilized in the alliance selection process is the partner's willingness to engage in cooperative exchanges. We argue that the record of past contributions a firm's partner makes represents valuable information used to evaluate (and possibly select) this partner for future alliances. This information provides evidence of the partner's reliability in terms of its trustworthiness and willingness to cooperate.

Because cooperation is viewed as a critical element for achieving successful interorganizational alliances (Mohr & Spekman, 1994), several researchers argue that reciprocal exchanges – the act of receiving a benefit from a partner in return for a benefit given previously to that partner (Gouldner, 1960; Powell, 1990; Kranton, 1996) – facilitate alliance objectives and longevity (Axelrod, 1984; Larson, 1992; Ring & Ven de Van, 1994; Ikkink and van Tilburg; 1999). "By following the principle of reciprocity, a firm shows the partner its willingness both to share the benefits of good economic opportunities in the uncertain future and to bear the possible risks and costs involved in collaboration" (Chung, Singh, & Lee, 2000: 6). As a result, a partner engaging in reciprocal exchanges is the practical evidence of its reliability. In other words, cooperation, in the interorganizational exchange context, is embodied in reciprocal behavior.

Generally, reciprocity has been defined as the act of receiving a benefit from a partner in return for a benefit given previously to that partner (Gouldner, 1960; Powell, 1990). Time plays a role in reciprocal exchanges, as the "give-and-take" does not occur simultaneously: One partner provides to another with the shared understanding of receiving compensation at a future time (Kranton, 1996). Time between giving to a partner and receiving from that partner provides an opportunity for the receiving partner to prove its reliability as a cooperative partner or *defect* by not returning the giving partner's contribution to the alliance (Axelrod, 1984).

Moreover, Powell (1990) illustrates that there is some debate regarding whether reciprocity requires exchanges of equivalent value or not. Several economists argue that equity (or balance) is an important element in gauging reciprocity, and partners make rational calculations of their allies' contributions relative to their own (Chung et al., 2000; Keohane, 1986; Ikkink and van Tilburg; 1999). In this view, rational actors, who are driven by self-interested goals, assess whether (and/or to what degree) a partner has matched (or exceeded) its own contributions; and actors are likely to terminate relationships from which they receive fewer benefits than they provide (Ikkink & van Tilburg, 1999). From a sociological perspective, reciprocity involves more of a sense of indebtedness and fair dealing, which allows for a great range of imbalance in the relationship. "In fair dealing, reciprocity is sufficient (Gouldner, 1959), but equivalence in quid pro quo is not necessary. Fair rates of exchange are between costs and benefits are sufficient, but equality is not necessary" (Ring & Van de Ven, 1994: 94). This indebtedness is the glue that holds actors together and "calling attention to the need for equivalence might well undermine and devalue the relationship" (Powell, 1990: 304). In our study, we do not suggest that partners must maintain balance in the relationship in order to be chosen in the future. Nevertheless, reciprocity involves both the receiving as well as the giving of benefits in the relationship, and therefore assessing a partner's reciprocal behavior is conditional: how a firm evaluates a partner's contributions depends on the level of its own contribution, but equivalence is not necessary. Thus, whether a partner's past contribution is judge to be significant or not depends one's own level of contribution, which involves a less strict definition of reciprocity than equal exchanges.

As mentioned above, we argue that information regarding partners' cooperative, reciprocal behavior in past ties is used to evaluate them for future alliance opportunities. This argument is supported by existing research on alliance formation and governance. Cooperation, in the form of reciprocity, plays a primary role in alliance formation. The initial stages of a partnership are characterized by a process of incremental trust-building, which is contingent on a series of reciprocal exchanges. Larson's (1992) rich description of seven interorganizational relationships reveals the importance of a back-and-forth reciprocating pattern in the early stages of the partnership: "If one side extended itself in a special effort to deliver on a promise, the other side responded in kind at the next opportunity. The results were perceived by both as beneficial (even if gains were small)." A reciprocal pattern of exchange in the early stages of a relationship is the mechanism by which trust and norms of cooperation are incrementally established (Dyer, 1996; Larson, 1992). By estimating a partner's reciprocity behavior, a firm determines the partner's willingness to cooperate and how much to trust this partner.

Reciprocity is important also in the governance – monitoring and control – of interorganizational alliances. In discussions of how economic exchanges are organized, relational contracting (e.g., interfirm alliances) represents either a hybrid organizing form on the continuum between markets and hierarchies (Williamson, 1991) or a distinct exchange and governance arrangement that is different in kind rather than degree (Powell, 1990). From either perspective, interfirm alliances address the inadequacies of markets and hierarchies for organizing and governing certain types of exchanges, such as those involving tacit, knowledge-based skills (Powell, 1990).

Just as price and fiat are the governance mechanisms found in markets and hierarchies, respectively, trust and norms of cooperation, which are fostered through reciprocal exchanges, are the control devices in interfirm alliances (Larson, 1992; Ring & van de Ven, 1992). In addition to fostering cooperation in the initial stage of the partnership, reciprocity provides a means for monitoring and evaluating a partner's behavior throughout the relationship (Khanna, Gulati, & Nohria, 1998; Rowley, Behrens & Krackhardt, 2000). From a sociological perspective, social norms/customs produce a perceived duty to repay the giver (Gouldner, 1960; Ring & Van de Ven, 1992) and those actors that comply with this norm are considered to be trustworthy, cooperative and reliable (Chung et al., 2000). On the other hand, economists suggest that a partner's willingness to reciprocate indicates its belief that the future benefits from maintaining a long-term relationship outweigh the short-term gains from cheating (Axelrod, 1984; Chung et al., 2000; Zucker, 1986) given both partners are likely to punish non-cooperative behavior by terminating the alliance (Keohane, 1986a; Kranton, 1996). From this perspective, reciprocity is not an indicator of a partner's innate character, but rather resource interdependencies between the partners (Levine & White, 1961). From either viewpoint, reciprocity is a signal of a partner's willingness to be a reliable exchange ally, and is therefore valuable information concerning whether it will be a cooperative partner in the future.

> Hypothesis 1 (H1): Within *i*'s set of past partners, the likelihood of *i* forming an alliance with *j* increases as the degree of reciprocal behavior between *i* and *j* increases.

Success

While alliances are commonplace in many industries, the failure rates for such organizational forms are rather high (Harrigan, 1985), as the outcomes of many alliances do not achieve the goals constituting their formation (Mohr and Speckman, 1994). The tasks of selecting a competent partner and structuring an appropriate alliance are plagued with uncertainty. From the resource-based view perspective, alliances represent socially complex resources (Barney, 1986) as they are founded on unique interpersonal relationships and experiences that are difficult to quantify or re-create. As a result, determining the reasons a particular alliance was successful or producing subsequent successful alliances with new partners are not well understood tasks.

Researchers explain the propensity of firms to select past partners by suggesting this behavior provides a means for dealing with the inherent uncertainty. We argue that firms consider the performance outcomes of ties with these partners in past relationships when pursuing new alliance opportunities. There are two elements comprising the logic underlying our contention that past tie successes are used to determine partners' capabilities and select allies for new alliances. First, firms attribute (in part) alliance outcomes to their partners' contributions and capabilities. Even if their capabilities cannot be identified or the means-ends relationship is unclear, successful outcomes reinforce partnership selection decisions (Lawler & Yoon, 1996).

Second, based on organizational learning research, organization actions are driven by routines and past experiences/outcomes. Organizational decisions are based on historical observations and experiences more than anticipations of future conditions (Levitt & March, 1988), and searches for solutions to problems are highly localized and strongly path dependent (Cyert & March, 1963; Levinthal & March, 1993; March & Simon, 1958). After exploring the local environment for solutions (through trial and error learning), firms select among their available options by "adopting those routines, procedures, or strategies that lead to favorable outcomes" (Levitt & March, 1988: 322). That is, firms develop and choose routines and strategies that were successful in similar past endeavors. Viewing alliance selection decisions within an organizational learning framework suggests that firms rely on past partners, develop (routines) preferences for certain allies and incrementally adjust their choices towards its most successful past partners. Moreover, given the need for accountability in managerial decision-making (Cyert & March, 1963), selecting partners from past successful alliances provides a clear rationale and legitimacy for selecting particular past partners rather than others.

Because firms base decisions on past experiences and attribute alliance success (or failures) to partner choice, firms not only choose past partners (due to the information advantage in reducing alliance selection uncertainty), but also fine-tune their choice by selecting those past partners that are associated with prior alliance success. While firm decisions change incrementally based on past experiences and performance outcomes, previous success with a given partner produces a bias toward this partner when evaluating new alliance opportunities (Levitt & March, 1988; March, 1991).

> Hypothesis 2 (H2): Within *i*'s set of past partners, as the success of past ties with *j* increases, the more likely *i* will form an alliance with *j*.

METHODOLOGY

Interorganizational Ties Among U.S. Investment Banks

In this study, the central question involves determining how firms use information from past relationships to discriminate among its past allies when selecting a partner for an alliance opportunity. In other words, we examine how firms identify the best among their past partners. The history of relationships between lead and co-lead managers among U.S. investment banks facilitating initial public offerings (IPO) provides a meaningful operational setting for this analysis. Investment banks act as financial intermediaries for organizations (issuers) that are raising funds on stock exchanges through IPOs. Lead managers – investments banks that are awarded the right to underwrite issuers' IPO securities – often attempt to spread risk and access a larger customer base by inviting fellow investment banks (co-lead managers) to participate in selling IPOs. Several researchers characterize this industry as "relationship-oriented" (Eccles & Crane, 1988), because the common practice of working in concert with other investment banks to sell shares – in underwriting syndicates – has created a network of alliances among these players.

Data Description

We compiled information for IPOs of common stocks on all stock exchanges in the U.S. between January 1, 1994 and April 24, 1998. During this interval, no major market crises – market crashes or substantial new securities regulations – perturbed the transaction activities among banks. The activities of these exchanges are comprehensively recorded longitudinally in accordance with Securities and Exchange Commission (SEC) requirements. Most of our data on specific aspects of IPO events (e.g., IPO date, size and filing prices, names of lead managers and co-lead managers) were collected from a data reseller called *IPO Maven,* which sources its data from the *Edgar* database of the SEC. We compared these data with information publicly available on numerous Web sites to ensure that no IPOs were omitted. Our database contains information on 1,525 IPO events.

Analysis Model and Dependent Variables

Partner Selection. Using a logistic regression model, we assessed the probability of a lead manager bank (Bank *i*) selecting each of its past partners to be a co-lead manager (Bank *j*) for a future IPO event. The dependent variable, *Partner Selection,* was a dichotomous measure recording whether Bank *i* entered into an alliance with Bank *j* for an IPO event. In studies examining how firms choose interorganizational partners, the risk set of possible partners has usually included all organizations in the sample (Chung et al., 2000; Gulati, 1995; Podolny, 1994). Given our motivating question was specific to how firms discriminate among its *past* partners when choosing allies for future interorganizational relationships, Bank *i's* risk set was limited to only those banks with which it was affiliated (either as a lead or co-lead manager) to underwrite previous IPO deals.

Although this approach better captured our analytical question, limiting the risk set of possible partners created a potential sample selection bias (see Vella, 1998 for a review), because Bank *i* could choose a past partner or a new partner (not in the specified risk set). To address this issue, we followed Heckman's (1974) prescribed method for dealing with this potential bias. We performed a sample selection logistic regression as the first step in our analysis in order to generate a predicted likelihood of an observation (the selected Bank *j)* being a member of our risk set (Heckman, 1974). This variable, *Predicted Likelihood,* was included in the logistic regression analysis of the hypothesized relationship to control for the potential sample selection bias. Appendix One provides a detailed introduction to the sample selection analysis.

Left-Censored Data. Because the IPO events in our data began at 1/1/94, we considered the possibility of left-censored data effects. Specifically, Guo (1993) argued that left-censored cases sampled at the beginning of the observation period tended to over represent low-risk cases among any given cohort. Although Guo (1993) provided solutions for some left-censored data, his method was not useful for our analysis, because it required *a priori* determination of the risk set. The underlying question related to this issue was the size of the observation window: at what point did past IPO deals no longer influence a bank's selection of co-lead managers?

Unfortunately, there was no *a priori* way of deciding how long to set the observation window, because we simply do not know how soon Bank *i* would "forget" past IPO deals. To address the potential bias associated with the choice of observation window, we created and compared two approaches. In the first method, we divided our whole time axis into two periods: 1/1/94-12/31/94 and 1/1/95-4/24/98 (mm/dd/yy). IPO events in the period 1/1/94-12/31/94 were omitted from the logistic regression analysis, because data from the period 1/1/94-12/31/94 was needed to calculate variables related to partners' behaviors in past alliances (e.g., all the independent variables). In other words, we only analyzed IPO events that took place during 1/1/95-4/28/98. We set the reciprocity window from 1/1/94 to one day before the IPO event under observation. For instance, when an IPO event took place on 7/20/97, we set the *reciprocity window* to 1/1/94-7/19/97. In the second method, we ran sensitivity analyses by setting the *reciprocity window* to one year, one and a half years, two years and two and a half years prior to the event. To illustrate, for an IPO event on 7/20/97, reciprocity windows were set to 7/19/96-7/19/97, 1/19/96-7/19/97, 7/19/95-7/19/97 and 1/19/95-7/19/97, respectively. All the independent and control variables were constructed using both methods, but the logistic regression results from each approach did not produce substantially different results. As a result of this sensitivity analysis, we concluded that left-censored data is not a serious concern for our analysis and we reported results from the former method only.

Independent Variables

Reciprocity. Although $N_{j \rightarrow i}$ – the number of times in the past Bank *j* was the lead manager for an IPO for which Bank *i* was a co-lead manager -- provides some indication of Bank *j*'s willingness to cooperation, our definition of reciprocity demands that we acknowledge the conditional nature of cooperation in interorganizational exchanges. Whether $N_{j \rightarrow i}$ is viewed to be significant or not depends on how much Bank *i* has contributed to Bank *j* in the past (($N_{i \rightarrow j}$).

Chung et al. (2000), who emphasize the notion of equity (balance) incorporate the ratio $[(N_{j \rightarrow i})+1]/[(N_{i \rightarrow j}) +1]$ to capture reciprocity. We could not employ this measure because, in our sample, the addition of 1 to the numerator and denominator, which is used to avoid values of infinity, distorts the relationship between ($N_{i \rightarrow j}$) and ($N_{j \rightarrow i}$). This ratio measure is an artifact of the operationalization when either $N_{j \rightarrow i}$ and/or $N_{i \rightarrow j}$ is 0. In our full sample (the set of all possible future ties not restricted to only Bank *i*'s past partner), there is a significant number of the 181,863 observations in which $N_{j \rightarrow i}$ and/or $N_{i \rightarrow j}$ equal 0. Even in the restricted sample of Bank *i*'s past partners, there are many dyads in which either $N_{j \rightarrow i}$ or $N_{i \rightarrow j}$ equals 0. Therefore, Chung et al's (2000) measure produces an artificial and potentially skewed measure when applied to our data.

As well, the ratio measure is motivated by the notion of balance, which is uncommon in our data. In many cases, balance in the exchange is not possible because the lead bank, on average lead 30.0 IPO deals in our sample, while the potential co-lead banks lead 3.5 IPO deals (the difference is significant at $p < .0001$, paired-samples t-test). Our t-test analysis indicates that the possibility of balance in the exchange of IPO deals is rare due to the division of labor in this industry.

Instead, to capture the degree to which bank *j* reciprocated in past relationships we employ the interaction between $N_{i \to j}$ and $N_{j \to i}$, because Bank *i*'s assessment of Bank *j*'s contribution is conditional on its own contributions. That is, how Bank *i* perceives a given level of contribution from Bank *j* in past ties is conditional on how much it has given to Bank *j*. Therefore, if Bank *j* contributes only a small amount to Bank *i*, Bank *i* is less likely to hold this against bank *j* (in selecting a partner for a future alliance), if Bank *i*'s contribution is also small. However, as Bank *i*'s contribution increases, it is more important for Bank *j*'s to have contributed a significant level in past ties in order to be perceived as a cooperative partner willing to engage in reciprocal exchanges. The interaction between $N_{i \to j}$ and $N_{j \to i}$ captures this relationship, and the effect of this measure is projected to be positive with respect to the likelihood of Bank *i* and Bank *j* forming an alliance.

Success. Partnership success consists of several dimensions that have been operationalized in multiple ways. One fundamental measure is based on the notion that alliances are formed to achieve particular goals, and partnership success should capture the degree to which the goals are achieved (Mohr and Speckman, 1994). In the investment banking industry, banks form partnerships with one another to achieve their primary goal: to enhance their revenues from underwriting fees (at the lowest possible risk) by creating demand for the issue and increasing the price of the shares at the IPO launch. How well the underwriting syndicate of banks achieves this objective is captured in the relative price of the IPO shares, because the underwriting fee is a relatively stable percentage (usually 7%) of the IPO price (Chen & Ritter, 2000).

Thus, relationship success was considered to be a function of how well the underwriting syndicate (of investment banks) distributes the IPO issue in terms of the share price. The success of Bank *i*'s past ties with Bank *j* was operationalized using an approach employed by researchers in the finance field, which compared the filing price range with the actual price at the launch of the IPO (Hanley, 1993). The SEC required that the issuer and lead manager filed a prospectus in which the intended price range for the IPO was indicated. Immediately before the IPO was launched on a stock exchange (usually one day before), the lead manager and issuer informed the SEC of the actual IPO price (*IPO Price*). To measure the success of the IPO, we compared the price range to the actual price. For example, if the IPO price range was set at $13-$15, then $14 was the average filing price and indicated the expected issuing price for the IPO (Hanley, 1993). This average filing price was denoted as *AvFilingPrice*, and *Success* was calculated as (*IPO Price – AvFilingPrice*) divided by *AvFilingPrice*.

One of the reasons this measure was deemed appropriate was that the underwriters' goal was to increase demand for the issue. Issues that were "over subscribed" by investors, because the underwriting syndicate was able to increase demand from investors, were sold at a higher price than anticipated when the filing range was established; and the lead and co-lead managers received higher revenues as their underwriting fees were set at a percentage of the actual price. Before the actual price was determined, the lead and co-lead banks solicited potential buyers (i.e., individual and institutional investor clients), attempting to increase demand for the issue and estimate an appropriate price. In short, underwriting syndicates were successful when a high share price was achieved through the efforts of the participating banks.

As well, there are strong sanctions inhibiting investment banks from manipulating the filing price range – above or below their actual estimate – in an effort to achieve higher commissions or build a reputation for an ability to capture a higher than average share price. Finance researchers argue that a lead manager's task in pricing an IPO is to strike a balance between pleasing the issuer and the investors (Benveniste & Spindt, 1989; Ritter, 1991), which mollifies the fear of possible IPO price manipulation on the part of the lead manager. One might reason that investment banks set the filing price range above their estimates in an attempt to increase the initial share price and capture higher commissions. However, this is a risky strategy as the underwriters are responsible for any unsold shares, which they purchased from the issuer (often using eighty or ninety per-cent short-term financing) and would need to carry unclaimed shares or sell them at a discount (Teweles, Bradley, & Teweles, 1992). During the period between the filing of the initial prospectus and the actual launch of the IPO, investors, especially institutional investors, use the midpoint of the IPO price range to judge the investment value of this IPO (Hanley, 1993). An overly high (midpoint) price discourages interest from the investment community, and institutional investors may decline to register purchase interest with the lead and co-lead managers before the actual launch of the IPO. A tepid response caused by a high midpoint price leads not only to undersubscription, but also poor after-launch performance of the IPO shares, which negatively impacts the lead manager's reputation (Carter, Park, & Singh, 1998).

In addition, it is not in the lead manager's best interest to set a low price in order to create demand so as to easily unload the entire issue. Investment banks are evaluated based partly on their ability to accurately forecast share price and capture the highest possible price. A low filing price relative to the actual price signals to prospective issuers that the investment bank did not have the capacity accurate to accurately estimate the demand and perhaps obtained a price well below the sought-after maximum.

Given the incentive to file a true estimate of the price range, a high actual price (relative to the filing range) suggests that the underwriting syndicate successfully distributed the issue. On the other hand, a relatively low actual price signaled that the IPO was not well received, which negatively affected perceptions of the banks' reputations and the value of their alliance: Prospective issuers would be suspect of the investment banks' abilities to distribute their IPOs and institutional investors would question their capability of bringing them "hot" IPOs.

In our logistic regression analysis, we calculate two *Success* indexes. The first, denoted $Success_{i \rightarrow j}$, was the average success of all the IPO deals in which Bank *i* was the lead manager and Bank *j* was a co-lead manager. The second, denoted $Success_{j \rightarrow i}$, was the average success of the IPO deal in which Bank *j* was the lead manager and Bank *i* was a co-lead manager.[1]

Control Variables

Several control variables were included because they were known through previous studies or expected to affect firms' alliance selection behavior. In addition to the control variable used to address the potential sample selection bias (*Predicted Likelihood*), we included *Status Dissimilarity*, which equaled the absolute value of the difference between the status of a lead manager and that of a co-lead manager in an IPO event.[2] Bank status was derived using Bonacich's (1987) measure, which has been commonly used (cf Podolny, 1994). Bonacich's method suggested that a bank's status increases positively by connections to high status others, and its status also increased by transacting with many other banks. Appendix Two introduces detailed information on the calculation. Prior research

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[1] We also used $Last\ Success_{i®j}$, which was the success indexes for the most recent IPO deal in which Bank *i* invited Bank *j*, and $Last\ Success_{j®i}$, which was the success indexes for the most recent IPO deal in which Bank *j* invited Bank *i*. No significant differences were found in our analysis. Therefore, we only reported the results of $Success_{i®j}$ and $Success_{j®i}$.

[2] Podolny (1994) argued that the use of the absolute value of the difference between the lead manager's and potential co-manager's status would result in an identification problem: "One could not be sure whether or not the positive effect for this coefficient was due to the difference between the two variables or simply to changes in the levels of one or both of the variables." He used a dual spline formulation to overcome this identification problem. We suggest that a dual spline formulation is unnecessary due to the fact that we only want to control for the possibility that *on average* banks transact with other banks with similar status, and the question of whether the homophily phenomenon is more pronounced at a certain level of status is not of concern here.

consistently found that *Status Dissimilarity* is negatively related to the possibility that a potential co-lead bank was chosen (Podolny, 1993, 1994).

Because several researchers find evidence that past ties between Bank *i* and Bank *j* influence the likelihood of future alliance activity between these actors (Chung et al., 2000; Gulati, 1995; Gulati & Gargiulo, 1999), we included several variables to control for this effect. Consistent with Chung et. al (2000), we included *Co-Participation* which indicates the number of deals led by a third bank in which the lead and potential co-lead both served as co-lead managers. We also included the squared term of *Co-Participation*, to control for the saturating impact of *Co-Participation*. In addition, for all IPO events, the number of past IPO events in which the lead manager invited each potential co-lead manager ($N_{i \to j}$) and the number of past IPO events in which the potential co-lead manager invited the lead manager ($N_{j \to i}$) were included in the analysis. These two variables were included to control for the tendency of repetitive momentum (Amburgey & Miner, 1992) and organizational routine (Cyert & March, 1963). However, it is commonly argued that as the number of ties between a pair of firms increased beyond a threshold, the likelihood of future ties begins to diminish due to carrying-capacity constraints (Baum & Oliver, 1992) or concerns of becoming overly dependent on one partner (Gulati, 1995). Therefore, we controlled for this proposed n-shaped relationship by including the squared terms for $N_{i \to j}$ and $N_{j \to i}$. Prior research found that *Co-Participation*, $N_{i \to j}$ and $N_{j \to i}$ have positive impacts, and the squared terms for *Co-Participation*, $N_{i \to j}$ and $N_{j \to i}$ had negative impacts on the possibility that Bank *j* was chosen.

It was possible for certain banks to build a strategic position or reputation as either predominantly a lead or co-lead manager. If a bank developed a reputation for usually serving as a lead bank, it may have received fewer offers from other banks to play a co-lead manager role. We used four variables to capture the potential influence of a firm's traditional role in the industry. For each potential Bank *j* in the risk set, the number and volume (aggregate size of the issues) of the IPO events it served as a lead and as a co-lead manager (denoted as *No. j As Lead*, *No. j As CoLead, Volume j As Lead* and *Volume j as CoLead*) were included in the analysis.

We controlled for the size of each IPO event, because lead managers may be more likely to form alliances with multiple co-lead managers for larger IPO deals in order to reach a wider investor base and spread the higher risk associated with underwriting substantial issues (Chung et al., 2000). Two variables are employed. We included *Syndication Size* – the number of co-lead managers in the IPO deal – because larger IPOs often involve a greater number of co-lead managers, which increases the likelihood that Bank *i* will choose each potential Bank *j*. *Offer Size* – the product of the actual price, *IPO Price*, and the number of shares – provided another control for any effect due to the size of the issue.

It was important to consider the role time played in alliance selection decisions. Gulati (1995) found a n-shaped relationship between a pair of actors forming an interorganizational alliance and the time lapse since the formation of their last tie. For each IPO event involving a particular dyad (Bank *i* and Bank *j*), we used the variable *Time Lapse* (and its squared term) to measure the time (in days) since the most recent previous IPO event for which these two banks were both affiliated.

Observation Dependency

There are two dependency issues commonly discussed for this type of study, which could affect regression analysis. First, one concern was the presence of a common-actor effect (Lincoln, 1984) – the lead bank's decisions across multiple IPO deals may not have been independent. Because some banks were in the data as lead managers more than once (the lead manager on multiple IPO events), we needed to address the possibility that its decisions in one IPO deal were influenced by preceding alliance decisions. Some researchers argue that this type of dependence is not an issue because the nature of financing required by each issuer, which was unique for most issuers, drove alliance decisions (Chung et al., 2000). Moreover, we followed Podolny's (1994) approach, directly controlling for this type of dependence: The relationship variables – number of past ties, co-participation and status dissimilarity – address many of the effects related to this type of non-independence.

Another method we used to control for dependency across IPO deals involving a single lead manager was to treat it as a sampling issue (Barnett, 1993). In each year, banks that were the lead managers for multiple IPOs were "oversampled," and could have had a greater impact on the results than other banks. This problem was corrected in the model estimation using a standard weighting method to discount over-sampled cases in proportion to their degree of over sampling (Hoem, 1985). Each of the *n* IPO deals for which a particular bank was the lead manager was given a weight of *1/n* in the likelihood calculation. Although this approach did not eliminate the potential problem of non-independence, it did address the problem of overrepresentation.

The second non-independence issue related to a lead manager's decisions within a *single* IPO deal involving the selection of multiple co-lead managers. For example, if Bank *i* chose two co-lead managers, there would be concern if its selection of the "second" co-lead manager depended on the choice of the first co-lead manager, because certain pairs of co-lead managers work better together. Technically, however, this type of non-independence is not problematic: "Because the lead bank may form alliances with no partners, one partner, or multiple partners, there is no strict dependence problem among observations" (Chung et al., 2000).

RESULTS

Table 1 displays descriptive statistics and correlations for all variables in the analysis. In Table 2, we report the models explaining alliance formation among past partners. Model I contains all the control variables, including the *Predicted Likelihood* variable (probability that Bank *j* is in the risk set) to address a potential sample selection bias. This variable is negative and significant at the $p < 0.001$ level. Generally, the control variables have the predicted sign. The number of past IPO events for which Bank *i and j* was a lead manager (i.e. $N_{i \to j}$ and $N_{j \to i}$), the number of co-lead managers (*Syndication Size*), the status difference between Bank *i* and *j* (Status Dissimilarity), the number of IPO events for which they were both co-lead managers (*Co-Participation and its squared terms*) and Bank *j*'s volume as lead and co-lead manager in the past (*Volume j As Lead* and *Volume j As CoLead*) are consistently significant across the six models as variables are added to the analysis. The squared terms for the number of past IPO events for which Bank *i* was the lead manager and Bank *j* was a co-lead managers ($N_{i \to j}$ *Squared*) and the squared term for the number of past IPO events for which Bank *j* was the lead manager and Bank *i* was a co-lead managers ($N_{j \to i}$ *Squared*) are negative and significant. Consistent with past studies (Chung et al., 2000; Gulati, 1995), these results suggest a diminishing increase in alliance formation between Bank *i* and *j* as the number of relationships between them increases.

Insert Table 1 about here

Both the time lapse since the last IPO event involving Bank *i* and *j*, and the squared term are strong and significant. The results suggest that as time passes, the likelihood of forming an alliance with a past partner decreases, but only to a point – the squared term is positive – suggesting a U-shaped relationship. After a certain time passes, the likelihood of a tie between these two actors diminishes. Interestingly, these findings are seemingly opposite to those in Gulati's (1995) study in which he examines alliance formation decisions when selecting an ally from among the set of *new as well as past* partners. He argues that in the first few years after an initial alliance is formed between two actors, they are more likely to form an alliance because of the mutual awareness. However, this effect diminishes over time as new information is no longer gained from the partnership. In contrast, in our study of selection decisions involving *past* partners only, firms tend to not choose those partners with whom they have recently formed a tie. Resource dependency theory provides one plausible explanation of this behavior (Pfeffer & Salancik, 1978). These actors attempt to manage a stable of multiple past partners in order to gain the unique expertise offered by different partners and avoid becoming overly dependent on a small number of partners. Thus, to some degree, they must rotate their selection of allies through a set of their "best" partners rather than simply choose the very highest-ranked partner. Therefore, firms are less likely to choose its most recent past partners, because part of the selection decision is a consideration of maintaining multiple partnerships. Based on this reasoning, firms offer alliance opportunities to those past partners with whom they have not recently been affiliated in order to preserve the relationship and their network of valuable partners. As a result, because firms worry that valuable partnerships might be in jeopardy as the absence of a new tie grows, they favor these partners over others with whom they have recently formed an alliance.

Insert Table 2 about here

We emphasize that, although on the surface our results seem to contradict those of Gulati's (1995) study, we are examining different types of selection decisions. We investigated a firm's choices among its *past* partners and found that firms rotate through their set of preferred past partners. In contrast, Gulati (1995) examined a different scenario in which the selection group included *new and past* partners, and found support for the notion that inertia played an important role (but decreasingly so over time).

In Model II, we introduce the *Reciprocity* variable, which is positive and significant (p <.05). Hypothesis 1 predicts that the likelihood that Bank *i* will select Bank *j* increases as the degree of reciprocal behaviors between Bank *i* and Bank *j* increases. Thus, the results provide evidence that firms use information from previous ties to evaluate past partners' willingness to form a relationship based on reciprocal exchanges. This finding suggests that the selection of past partners for future ties is not simply due to inertia – a standardized response to an uncertain decision based on local search (Amburgey & Miner, 1992) – because inertia and momentum have been accounted for by including $N_{i \to j}$ and $N_{j \to i}$ and their squared terms. This finding supports Gulati and Gargiulo's (1999) theoretical argument that past partners are favored because of an information advantage gained through relational experience and used to evaluate their capabilities and reliability.

Model III adds success of past ties with Bank *j*, denoted as $Success_{i \to j}$ and $Success_{j \to i}$, respectively. Success of past ties is argued (Hypothesis 2) to be another factor from previous relationships used to assess partners for future alliance opportunities. The average success of past ties with Bank *j* for which Bank *i* was the lead manager is significant and positive (p < .05). However, the average success of past ties involving Bank *j* as the lead manager is not significant. These results suggest that past success is an important criterion in selecting an alliance partner from the set of past allies, but firms do not indiscriminately choose past partners that are associated with successful IPO events. Instead, these data suggest that firms attempt to re-create past success by structuring the alliances in the same pattern: they choose co-lead managers who were successful co-lead managers in the past. However, according to the findings, a potential partner's success as a lead manager in past ties with Bank *i* does not influence Bank i's decision whether to select it to be a co-lead manager for a future alliance.

DISCUSSION AND CONCLUSION

This study takes the next step in comprehending alliance formation behavior. Researchers concerned with understanding how firms choose interorganizational partners – "with whom are firms likely to ally" (Gulati, 1995: 619) – find empirical evidence that the social context and network of existing relationships plays a paramount role in the selection process. Firms form ties with past partners, their partners' partners and other actors in close relational proximity to themselves (Gulati & Gargiulo, 1999). In addition, firms form ties with similar status others as defined by their (and their partners') positions in the network (Podolny, 1994). The rationale for this behavior is that firms source their networks for information in order to reduce the uncertainty inherent in alliance decisions. Because assessing a potential partner's capability to perform the required tasks and reliability as a trustworthy partner is difficult before the alliance is initiated, firms seek information from their network to alleviate these concerns. While the social network serves as a repository for information on partner characteristics, the types of information available and used to evaluate partners have remained, for the most part, unexplored: If firms favor past partners for future alliance opportunities, because they have knowledge of their past partners' capability and reliability, then how do firms decide which of these partners are the best options for new alliance opportunities?

By concentrating on the alliance selection process *among past partners*, our study identifies types of information utilized in evaluating partners for future alliances and how firms discriminate among its past partners. This stream of research is necessary to assess the theories offered to explain why firms rely on their networks of past partners. While firms may have a propensity for selecting past partners because of the information advantage in the social network, as suggested by several researchers (Chung et al., 2000; Gulati, 1995; Gulati & Gargiulo, 1999), alternatively this behavior could be the result of a repetitive momentum pattern – firms develop routines over time that become standardized response to certain managerial issues (Amburgey & Miner, 1992).

Our study furnishes empirical support for the argument that firms rely on their social networks because of the information stored within these relationships. As indicated by the interaction terms between $N_{i \rightarrow j}$ and $N_{j \rightarrow i}$, our findings suggest that reciprocity matters. That is, firms choose those past partners that have contributed to the relationship in the past and show a willingness to build a cooperative, long-term partnership. Thus, this study supports the claim made by several researchers arguing that relationships thrive on cooperative, back-and-forth exchanges between trustworthy/reliable partners (Larson, 1992; Ring & Van de Ven, 1992; Uzzi, 1996).

Our results provide support for the notion that success is an important information factor gathered from past ties. The different results for our two measures of past alliance success ($Success_{i®j}$ and $Success_{j®i}$) provide an interesting contrast. The information pertaining to $Success_{i®j}$ is more directly useful than the information regarding $Sucess_{j®i}$, when Bank i is considering a new affiliation with Bank j. The empirical finding that $Success_{i®j}$ is significant while $Success_{j®i}$ is non-significant suggests that firms utilize information on a partner's past successes as a co-lead manager, but not its achievements as a lead manager. This result is consistent with the notion that firms attempt to use information from past ties that best approximates (or can be extrapolated to) the current situation. That is, firms attempt to re-create past success (by choosing past successful partners) and are conscious of the different roles/expertise required to fulfill alliance objectives. As a result, when choosing a co-lead manager, a potential partner's successes as a lead manager in past ties is not as relevant as its performance as a co-lead manager.

Moreover, status remains a significant factor after adding past reciprocity and success into the model. In our data, an actor's popularity or prominence as measured by its relative status remains significant. Holding all else constant, this finding suggests that when two firms receive equal reciprocity and success evaluations, a firm will form an alliance with the one having the most similar status to its own.

Therefore, past partners are assessed and prioritized for new alliance opportunities based on their prominence (status), capabilities (success) and reliability (reciprocity), which suggests sought-after partners are popular, talented and nice (respectively). One future research opportunity involves systematically comparing the magnitude of these influences on the alliance selection process. Consider the influence of status dissimilarity one standard deviation below the mean in our data. Under this condition, Bank i is 15.1 percent more likely to choose Bank j. In comparison, one standard deviation above the mean value of success for past ties with Bank j increases the likelihood that Bank j will be chosen by 8.7 percent; and one standard deviation above the mean value for reciprocity in our data leads to a 33.5 percent increase in the likelihood of selecting Bank j.

Our research has important implications for policy-making. Stock market are acclaimed as one of the most efficient market systems in human history and the regulators of stock markets, such as the Securities and Exchange Commission (SEC), strive to maintain efficiency and transparency. Our analysis clearly indicates that U.S. investment banks are not choosing transactional partners on the basis of price and service quality alone. Their exchange relationships are to some extent based on reciprocation of former favors. The reciprocation consideration restricts transactions to closely linked circles of investment banks. Thus, the investment banking industry is not a purely efficient market in the neoclassical economics sense (Powell & Smith-Doerr, 1994). Instead, the industry is segmented into enduring cliques, possibly with business information (e.g., potential IPO issuers) circulating among groups of close-linked banks. How these enduring cliques impact IPO pricing, and consequently, on the investors in the stock market, warrants serious attention from policy-makers.

Overall, the results of this study suggest that firms employ specific types of information from their past ties and social networks when evaluating potential interorganizational partners. In addition, firms discriminate among their past partners, using information such as a partner's record of reciprocity and success, to identify the best partners among its stable of past allies. The network of past ties among an organizational field of actors represents a valuable repository of information, which is influential in single alliance selection decisions, and, as a result, the overall evolution of the network.

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Table 1. Descriptive statistics (N = 7,229)

Variables	Mean	s.d.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1 *Reciprocity*	0.10	0.29																			
2 *Predicted Likelihood*	0.43	0.36	0.08																		
3 *No. j As Lead*	29.24	25.06	0.06	0.63																	
4 *No. j As CoLead (/10)*	2.81	2.10	0.05	0.58	0.80																
5 *Volume j As Lead (/1000,000)*	3.34	4.93	0.01	0.43	0.73	0.33															
6 *Volume j As CoLead (/1000,000)*	5.78	6.50	0.02	0.48	0.52	0.39	0.71														
7 *Offer Size (/1000)*	0.07	0.05	-0.01	-0.09	0.01	0.02	0.00	0.00													
8 *Syndication Size*	1.67	0.47	0.05	0.18	0.04	0.01	0.03	0.03	-0.13												
9 *Status Dissimilarity*	4.63	3.15	-0.06	-0.17	-0.11	-0.19	0.06	-0.01	-0.05	0.13											
10 *Co-Participation*	1.20	1.63	0.08	0.51	0.35	0.30	0.20	0.17	0.00	0.08	-0.19										
11 *Co-Participation Squared*	4.09	9.49	0.06	0.42	0.31	0.23	0.18	0.12	0.00	0.06	-0.19	0.91									
12 *Nij*	2.63	3.20	0.11	0.57	0.40	0.36	0.15	0.11	-0.05	0.18	-0.16	0.51	0.45								
13 *Nji*	2.78	2.75	0.06	0.75	0.52	0.28	0.60	0.45	0.01	0.02	-0.19	0.49	0.44	0.39							
14 *Nij Squared*	17.11	35.98	0.08	0.48	0.37	0.31	0.17	0.11	-0.05	0.15	-0.16	0.43	0.41	0.92	0.35						
15 *Nji Squared*	15.26	33.31	0.04	0.58	0.45	0.21	0.55	0.38	0.00	0.02	-0.16	0.42	0.40	0.34	0.94	0.31					
16 *Time Lapse (/1000)*	0.26	0.26	-0.10	-0.10	-0.01	-0.03	0.10	0.04	0.04	-0.10	0.08	-0.20	-0.15	-0.41	-0.02	-0.29	-0.03				
17 *Time Lapse Squared (/1000)*	0.14	0.28	-0.07	-0.07	0.01	-0.01	0.12	0.06	0.03	-0.08	0.08	-0.17	-0.12	-0.29	-0.01	-0.20	-0.01	0.91			
18 *Nij ´ Nji*	10.68	22.87	0.09	0.57	0.40	0.24	0.35	0.25	-0.03	0.10	-0.22	0.56	0.56	0.74	0.74	0.77	0.75	-0.23	-0.17		
19 *Successij*	0.01	0.13	0.04	-0.03	-0.02	0.02	-0.09	-0.10	-0.01	0.03	-0.02	-0.03	-0.03	0.17	-0.07	0.15	-0.03	-0.16	-0.11	0.06	
20 *Successji*	-0.01	0.17	-0.01	0.16	0.07	0.04	0.13	0.12	0.01	-0.01	-0.05	0.00	-0.02	-0.04	0.20	-0.01	0.14	-0.01	-0.03	0.07	0.04

Note: $p < .05$ if the absolute value of bivariate correlation is larger than .024.

Table 2: Results of Logistic Regression Models (N = 7,229).

	Model I	**Model II**	**Model III**
	Beta (s.e.)	beta (s.e.)	beta (s.e.)
Intercept	-2.860 (0.246)***	-2.814 (0.246)***	-2.855 (0.246)***
Predicted Likelihood	-0.619 (0.353)	-0.418 (0.359)	-0.380 (0.360)
No. j As Lead	0.013 (0.005)**	0.013 (0.005)**	0.012 (0.005)**
No. j As CoLead	-0.047 (0.044)	-0.046 (0.044)	-0.042 (0.044)
Volume j As Lead	-0.057 (0.023)**	-0.052 (0.023)*	-0.049 (0.023)*
Volume j As CoLead	0.016 (0.010)	0.013 (0.010)	0.013 (0.010)
Offer Size	-0.698 (0.853)	-0.594 (0.854)	-0.572 (0.854)
Syndication Size	0.349 (0.099)***	0.334 (0.099)***	0.335 (0.099)***
Status Dissimilarity	-0.050 (0.015)***	-0.049 (0.015)***	-0.049 (0.015)***
Co-Participation	0.194 (0.064)***	0.213 (0.065)***	0.214 (0.065)***
Co-Participation Squared	-0.029 (0.010)***	-0.034 (0.010)***	-0.035 (0.010)***
N_{ij}	0.094 (0.042)*	0.089 (0.042)*	0.072 (0.043)
N_{ji}	0.195 (0.079)**	0.141 (0.081)†	0.160 (0.082)*
N_{ij} *Squared*	-0.006 (0.003)	-0.010 (0.004)***	-0.010 (0.004)**
N_{ji} *Squared*	-0.011 (0.005)*	-0.013 (0.005)**	-0.014 (0.005)***
Time Lapse	-2.127 (0.416)***	-2.067 (0.415)***	-2.015 (0.415)***
Time Lapse Squared	1.117 (0.360)***	1.105 (0.358)***	1.049 (0.356)***
N_{ij} ´ N_{ji}		0.013 (0.006)*	0.014 (0.006)*
$Success_{ij}$			0.707 (0.368)*
$Success_{ji}$			-0.378 (0.248)
Log likelihood	-4386.27	-4380.91	-4375.46
d.f.	16	17	19
Dc^2		5.36*	5.45†

Note: † $p < .1$; * $p < .05$; ** $p < .01$; *** $p < .001$ (Two-tailed Test)

APPENDIX ONE: SAMPLE SELECTION EQUATION

We used a logistic regression to model the likelihood of an observation to be included in our selected sample. Our sample selection equation included the same independent and control variables as those in our logistic regression analysis for our selected sample, except for the following variables: $\textit{Success}_{i \rightarrow j}$, $\textit{Success}_{j \rightarrow i}$, *Time Lapse* and its squared term. These excluded variables *must* be excluded because they are not defined for those lead and potential co-lead dyad in which either $N_{i \rightarrow j}$ or $N_{j \rightarrow i}$ (or both) is zero. These excluded variables are defined for all our selected observations due to the definition of our risk set. That the analyses for the full sample and the selected sample must include at least one different variable is a necessary condition for model identification for the selected sample model (cf Vella, 1998).

The dependent variable for our sample selection analysis is a dichotomous variable, which is coded 1 when $N_{j \rightarrow i}$ is larger than zero, and 0 otherwise. This dependent variable allows our sample selection analysis to investigate the factors that influence Bank *j*'s likelihood of inviting Bank *i* into an IPO deal(s).

APPENDIX TWO: CALCULATING INVESTMENT BANK STATUS RANKINGS

To calculate status rankings we followed Podolny (1994) and Chung et al. (2000) by first creating a matrix (185 x 185), denoted as **R**, to record the relative positions of banks in all the IPO's occurring in a particular year. The elements of the matrix are derived by the equation:

$$r_{ij} = \sum_{k=1}^{n} (A_k + B_k + C_k)$$

where n is the total number of IPO's that investment banks i and j both participated in for a given year. For example, in the kth IPO in a given year, if investment bank i was the lead manager, then $A_k = 4$; if investment bank i was the first co-lead manager, then $B_k = 2$; if investment bank i is the second co-lead manager then $C_k = 2$ (cf. Carter et al., 1998). After completing the data analysis, we performed a sensitivity test by assigning the values 4, 2, and 1, and then the values 6, 2, and 1. Our results are robust and no significant changes in the results were found.

We standardized **R** so that all matrices have column sums of unity (Taylor, 1969) and used Bonacich's (1987) method to calculate each bank's status:

$$\mathbf{c} = \alpha\,(\mathbf{I} - \beta\mathbf{R})^{-1}\,\mathbf{R}\,\mathbf{1}$$

where **c** is the vector of bank rankings, **I** is the identity matrix, and **1** is a column vector of ones.

It should be noted that there is no *a priori* way to determine the value of β. Thus, consistent with the suggestions of Bonacich (1987; cf Podolny, 1993), we used three values of β to calculate different **R's**. We set β to 75, 50 and 25 percent of the reciprocal of **R**'s largest eigenvalue. Because this sensitivity analyses yielded similar results, we only reported the results for the analyses in which β was set to 75 percent.