SECOND-HAND BROKERAGE:
EVIDENCE ON THE IMPORTANCE OF LOCAL STRUCTURE
FOR MANAGERS, BANKERS, AND ANALYSTS

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Abstract

The social capital of brokerage is evident from higher compensation, more positive recognition, and broader responsibility given to people who coordinate across the structural holes in a network. This paper is about brokerage among direct versus indirect contacts. Information moved between direct contacts I discuss as direct brokerage, to distinguish it from information moved between friends of friends — people to whom one is only connected indirectly — which I discuss as second-hand brokerage. Analyzing network associations with performance in three study populations, I find that second-hand brokerage has little or no value in a wide variety of circumstances. Brokerage benefits are dramatically concentrated in the immediate network around a person. Why that is so, and conditions under which it is more or less so, are the subjects of this paper. The implication for research design is that brokerage can be measured using designs in which data are limited to the immediate network around an individual. The theory implication is that the social capital of brokerage is a local phenomenon as in the Austrian market metaphor with its emphasis on tacit knowledge about local norms and practice.

Figure 1 displays the network of colleagues around an investment banker working in New York in the late 1990s. The network data come from annual peer evaluations the company conducted to develop employees and monitor employee reputation with colleagues. The dots are employees and lines connect employees where one cited the other in the annual evaluation process as a colleague with whom substantial business was done last year. The banker's direct contacts are displayed in Figure 1A. It is a simple picture, but it is the actual network around an actual banker, and it is the picture captured by the network size and density measures so often used to predict opinion, behavior, and performance: Figure 1A shows a banker connected to eight colleagues (network size), most of whom do not cite one another as colleagues (network density, as the average connection between contacts, is four observed connections over 28 possible, or .14).

There is reason to expect the banker to be successful. The colleague network around him is full of structural holes. A structural hole refers to missing relationships that inhibit information flow between people. A hole "is a buffer, like an insulator in an electric circuit" (Burt, 1992:18). The lack of relations between the banker's colleagues in Figure 1A implies that they are separated by structural holes. Numerous studies show that managers whose social networks bridge structural holes have a competitive advantage over peers confined to a single group of interconnected people. Information, opinion, and practice are more homogenous within than between groups, so a manager whose network spans structure holes (call him a network broker, connector, or entrepreneur) has a vision advantage in early exposure to diverse information and a political advantage as a hub in the information flow. The competitive advantage is manifest in more positive job evaluations, higher compensation, faster promotion, good ideas — a host of performance indicators. Recent research review, opinion, speculation, and practical advice can be found in Adler and Kwon (2002), Baker (2000), Brass, Galaskiewicz, Greve and Tsai (2004), Burt (2005), Cohen and Prusak (2001), Cross and Cummings (2004), Cross and Parker (2004), Lin (2002),

Monge and Contractor (2003), Oh, Chung and Labianca (2004), Pollock, Porac and Wade (2004), Soda, Usai and Zaheer (2004). As in other studies, results discussed below on the study population containing the banker in Figure 1 show that bankers connected to otherwise disconnected colleagues are better paid than peers surrounded by a dense network of colleagues.

However, the banker in Figure 1 was not particularly successful. On average, the colleague evaluations he received were slightly below what others in his job rank received (-.32 z-score). His compensation for the year was similarly undistinguished. He received about a million dollars in salary and bonus that year, which was below the average for peers at his rank with his background (-.49 z-score).

Insert Figure 1 about here

The exception should not to be blown out of proportion: First, there is a strong association on average between brokerage and compensation in the banker population (as I will show later). Second, the banker in Figure 1 is one datum and individual variation from the average is to be expected. Some people with networks rich in structural holes will not do as well as others. The prediction is only that the people with networks rich in structural holes are at higher risk of success; bumping into ideas with which they can create value, seeing ways to develop their ideas, and so on.

Nevertheless, a broader view of the network makes the banker's undistinguished performance less surprising. Beyond the eight colleagues with whom the banker was directly connected were 45 employees connected to one or more of the banker's eight colleagues. The additional 45 employees are displayed as a sociogram in Figure 1B. Dots are people and lines connect people where one cited the other in the annual evaluation process as a colleague with whom substantial business was done last year. Here, as in the sociograms to be presented, two people are close together to the extent that they are connected directly and indirectly through mutual colleagues (based on a "spring-embedding" heuristic multidimensional scaling algorithm, Borgatti, 2002). The primary cluster, at the top of Figure 1B, is composed of other investment bankers. Most of the banker's direct contacts are in the cluster. These contacts are not often connected directly, but they are frequently connected indirectly through mutual ties to other bankers in the cluster. Further, the banker's one

contact disconnected from everyone in Figure 1B is in another banker cluster, but newly hired to a junior rank so no one in the banker's primary cluster cited her as a colleague (see the direct contact to the southeast of the banker). That leaves one contact to a senior person outside the banker's own cluster: The contact to the southwest of the banker in Figure 1A is in the cluster at the bottom of Figure 1B, which is a group of people who specialize in a kind of financial instrument. Three of the instrument specialists are connected to bankers. The instrument specialist connected to the banker in Figure 1A is central among the specialists, directly connected with everyone in the specialist cluster.

In contrast to the Figure 1A image of the banker spanning many structural holes, Figure 1B shows the banker bridging one hole, between the bankers and the instrument specialists. Freeman's (1977) betweenness index puts an intuitive metric on the difference between the two sociograms. In Figure 1A, the banker is in a position to broker 82% of possible connections between his colleagues (23 of 28 possible). In Figure 1B, there are more connections possible in the larger network, most of which do not involve the banker. He is in a position to broker 15% of the possible connections (207 of 1378 possible). The much-lower score in Figure 1B indicates a much less-central position for the banker, making his undistinguished performance less surprising.

This paper is about the performance implications of the difference illustrated in Figure 1. Specifically, this paper is about the extent to which predicting performance from the simple network in Figure 1A is strengthened by including the additional data in Figure 1B. The network in Figure 1A defines opportunities to move information between direct contacts. I discuss such activity as direct brokerage, to distinguish it from information moved between friends of friends — between people to whom one is only connected indirectly — which I discuss as second-hand brokerage. In the example, apparent opportunities for direct brokerage largely disappear with the inclusion of indirect contacts that link the banker's direct contacts. Looking past the connections involving the direct contacts, opportunities for second-hand brokerage are diminished by the dense connections among the indirect contacts themselves. Note that I am making no distinction between opportunities to broker and acts of brokerage.

The assumption is that more opportunities to broker increase the probability of brokerage. This is a common assumption in network research on brokerage, but it is worth noting that opportunities to broker do not automatically trigger acts of brokerage (e.g., Burt, 2005:240-244). The empirical question for this paper is whether known performance correlates of direct brokerage extend to second-hand brokerage.

Despite abundant evidence on the returns to direct brokerage, we know virtually nothing about returns to second-hand brokerage (Owen-Smith and Powell, 2004, is an exception noted below). Figure 1A illustrates the extent of data obtained in the survey network research design so often used to estimate network brokerage effects on performance. The respondent cites contacts, then describes relations with and among the cited contacts. To the extent that the additional data in Figure 1B better predict performance, much of the available evidence on returns to brokerage is wrong, and wrong in an unknown way. The network of direct contacts in Figure 1A overstates competitive advantage relative to the network of indirect contacts in Figure 1B. Understatement is equally possible. There were bankers in the same study population who worked in teams of densely interconnected colleagues led by someone with diverse contacts beyond the team. For such bankers, the closed network of direct contacts understates the abundant indirect access they had to structural holes among the contacts of their team leader. Does indirect access to structural holes through the team leader improve performance despite the lack of direct access?

I begin with the implications of second-hand brokerage for social capital theory and the way we study social capital, describe my research design, then present results from three study populations. I find that the complexity in Figure 1B offers little or no improvement to predicting performance from the simple network in Figure 1A. Why that is so, and the network conditions under which it is more or less so, are the subjects of this paper.

IMPLICATIONS OF SECOND-HAND BROKERAGE

Second-hand brokerage is consequential because it lies at the decision point between two ways of understanding, and two ways of studying, social capital.

Implications for Research Design

Beginning with the more concrete decision point, consider the research design issue discussed in the introduction. The usual survey-network research design involves gathering data on relations with and among direct contacts to define the immediate network around the survey respondent. This yields the network in Figure 1A. Measures of network structure among the direct contacts, such as network size and density, are then added to traditional stratification variables predicting achievement and rewards. In an early report on returns to brokerage, for example, Burt (1992:Chap. 4) drew a probability sample of managers and measured brokerage within the network among each respondent's direct contacts. The same measurement strategy was used in Podolny and Baron's (1997) analysis of returns to brokerage for managers drawn from a broader range of job grades, Hansen, Podolny and Pfeffer's (2001) analysis of brokerage and team performance, Mizruchi and Sterns' (2001) analysis of brokerage, risk, and success in securing loan authorization, and Seibert, Kraimer, and Liden's (2001) report on alumni career correlates of bridging structural holes.

Structure beyond the respondent's immediate network (illustrated in Figure 1B) is ignored in these research efforts, as in other studies based on the same survey-network research design. If there are returns to second-hand brokerage, the above research is wrong in its assumption, the reported estimates of returns to brokerage are inconsistent, and much of what has been taken as evidence is called into question.

That is, unless either of two conditions is true: the structure of direct contacts is redundant with the broader structure of indirect contacts, or the structure beyond direct contacts is irrelevant to performance.

If the network structure of direct contacts is correlated with the broader structure of indirect contacts, then it could be argued that the broader structure will not improve predictions from the structure of direct contacts. Everett and Borgatti (2005) provide one of the few, if not the only, study of structural holes among direct contacts relative to holes in the broader network (cf. Reagans and Zuckerman, 2006, for related analysis). Using Freeman's betweenness measure, they report high correlations

between direct and indirect access to structural holes. The more important question for social capital research is the association with performance. Regardless of correlation between the network structure of direct contacts and the network structure of indirect contacts, what is the relative association of each network with performance? Among the bankers and analysts described below, for example, the network structure of direct contacts is strongly correlated with the structure of indirect contacts — but only the structural of direct contacts is significant for performance.

Performance irrelevance is a second justification for ignoring indirect contacts. There is precedent for ignoring indirect contacts. Early network analysis focused on direct contacts. America's pioneer in this was Moreno, who focused on the network of direct contacts as a "social atom." The social atom around an individual consists of people sought by the individual and people who seek out the individual, and beyond the social atom lies a broad "acquaintance volume" of contacts "without emotional meaning for the subject." (Moreno, 1936:289). The social atom is the focus of emotional life around the person, the "first tangible structure empirically discernable in the formation of a human society. It is its smallest unit." (Moreno, 1941:25)

Moreno had a psychiatric interest in the emotional state of an individual, so it made sense to focus on the immediate network surrounding the physical site of the emotions to be understood.

In contrast, the social capital of brokerage concerns information arbitrage. Knowing how information varies between friends of friends could be valuable. For example, building on Brass's (1984) early report of promotion correlated with information control measured by Freeman's betweenness centrality, Cross and Cummings (2004:932) show positive returns to brokerage measured by betweenness, a measure they use because of "its ability to account for direct and indirect ties and to thereby potentially capture greater access to expertise." Their cited precedent is Mehra, Kilduff and Brass (2001:130) who include in their network measures "all the actors in the organization rather than just the actors mentioned by the focal individual" and justify their decision with the claim that "ego network data used to assess structural holes are potentially distorted by perceptual biases."

However, such studies do not clarify the value of indirect access to structural holes so much as they assume it. Betweenness combines direct with indirect contacts, so either direct or indirect access to holes could be responsible for betweenness associations with performance. Data quality is a red herring here. Whatever the method by which network data are obtained, the question remains of whether to measure brokerage with respect to the immediate network around a manager or the broader network — and we have no evidence on which to base the decision. Providing the missing evidence is the purpose at hand.

Implications for Social Capital Theory

Choice between research designs is a choice between assumptions about information flow. Information arbitrage is essential to the idea that network brokerage provides social capital. There is no competitive advantage to brokering interpersonal connections if full information is readily available. If information flow is difficult beyond direct contacts, or more valuable when facilitated between direct contacts, then it makes sense to limit brokerage models to direct contacts, as in Figure 1A. If, on the other hand, information flows easily between friends of friends, or distant bits of information can be locally valuable, then it makes sense to model brokerage into the network beyond direct contacts, as in Figure 1B.

Viewed in terms of information-flow assumptions in network models, second-hand brokerage takes on theoretical significance redirecting future research because it lies at a decision point between two long-debated market metaphors on information flow: Austrian versus neoclassical. The neoclassical metaphor is currently dominant, and taken for granted in claims that chains of indirect connection are valuable for brokerage. However, network models of brokerage have much in common with the Austrian market metaphor, most notably as found in the work of Schumpeter and Hayek (see Birner, 1996, 1999; Burt, 2005: Chap. 5).

With respect to network brokerage, the two market metaphors can be contrasted on three points. First, they both assume a small world of variably segregated groups where knowledge is more homogeneous within than between groups. Second, they both assume there is a premium available for the integrative work of moving

knowledge between groups. Third, the benefits received for successfully moving knowledge make visible the price for integrative work. To my understanding, the third point is the juncture at which the Austrian metaphor is most distinct from the neoclassical. The neoclassical metaphor posits a central mechanism, an invisible hand, by which price is determined (Rosen, 1997:140): ". . . the methods of neoclassical economics mainly are concerned with the establishment of economic equilibrium under fully known or (in Marshallian terminology) given conditions of resource availability, technology and preferences." In contrast, the Austrian metaphor holds that commercial activities (Rosen, 1997:140-141; cf. Ferrier and Smith, 1999:373-374): ". . . evolve as the amalgamation and interactions of trials and errors among economic agents. Entrepreneurial ventures and experiments, arbitrage activities, and survival of the fittest play crucial roles in this process. . . .This approach begins with the premise that there is an enormous amount of ignorance in the system. No one knows or can ever know what is being maximized overall. Decentralization is fundamental because specialization is extreme." Where the neoclassical metaphor focuses on the balance of market factors at equilibrium, the Austrian focuses on the process by which markets move toward equilibrium. Taking information diffusion as the central market problem, Hayek (1945:527) refers to the market as "a system of telecommunications." If a market were to clear as if it contained a central pricing mechanism, it would be because there are sufficient intermediaries to carry local prices across otherwise segregated locations (Hayek, 1945:524-526; cf. Baker, 1984).

Returns to second-hand brokerage are an empirical fulcrum for deciding between the two market metaphors as foundation for social capital theory.

Within the neoclassical metaphor, social capital is a system-wide phenomenon in which brokers find advantage in the flow of information among people who are known to the broker as well as people beyond the broker's immediate circle of contacts. In a mature capital market, for example, returns to second-hand brokerage are to be expected. Information on the cost of yen can be an advantage in decisions about dollar investments. The more concrete information is in a neoclassical market, the more easily it can move across the market. So, value lies not in knowing specific groups in detail so much as to knowing how groups differ – which means higher

returns to second-hand brokerage because of the diversity of groups it can reach. In short, the more performance-relevant the network structure of indirect contacts, the more theory-relevant the neoclassical metaphor with its emphasis on system-wide mechanisms. Substantial returns to second-hand brokerage support a neoclassical perspective on social capital.

Within the Austrian metaphor, social capital is a local phenomenon in which brokers find advantage in the flow of information familiar to the broker. The less performance-relevant the structure of indirect contacts, the more theory-relevant the Austrian metaphor with its emphasis on tacit knowledge about local norms and practice. Negligible returns to second-hand brokerage support an Austrian perspective on social capital. Relative to a mature capital market for example, most markets (certainly resource markets within organizations) are less fluid, more sticky, more shaped by the politics of who supports an idea and who rises in opposition. Even in a relatively mature capital market, investors know they can benefit from insider information on the organizations coming together in a deal. This emphasis on the local is the heart of the Austrian market metaphor and can be found in diverse network studies. For example, Friedkin (1983) describes a limited "horizon of observability" in networks. The probability that two directly connected professors know something about one another's current work drops to 28% as likely if their connection is only indirect through a mutual colleague, then to a near-zero 3% as likely if their connection is less direct. Killworth and Bernard (1978) found in their "reverse small world" experiments that people searched for an unfamiliar target person in a distant location by jumping to someone they knew in the target's region from whom a local search could begin. Drawing more general comparison, Stuart and Podolny (1996) infer "local search" from the tendency for organizations to file patents drawing on technology similar to the technology on which they drew for previous patents (despite the fact that such "crowding" is likely to produce a "dead end" patent, Podolny and Stuart, 1995), Sorenson and Stuart (2001) describe the concentration of venture capital investments in companies that are within a few-mile radius around the investor, and Owen-Smith and Powell (2004) describe how successful patenting in biotechnology is predicted by brokerage within the local network more than brokerage in the extra-local network.

Against a backdrop of patent co-author networks in Boston and the Silicon Valley (two inventors are connected if they have co-authored a patent within a five-year window), Fleming, Colfer, Marin and McPhie (2004) tell a story about segregated groups in Silicon Valley becoming connected via people who had insider connections with one another from their time as post-docs at IBM's Almaden Valley Labs. As Sorenson and Stuart (2001:1584) conclude: "Whenever personal and professional networks play a central role in economic activity, we will likely observe spatial patterns in the unfolding of that activity."

I draw two hypotheses about second-hand brokerage from the discussion. The more closed the group network, the more likely that people in the group work with tacit knowledge in the form of mutually understood, unwritten language and routines to coordinate with one another. Distinct tacit knowledge familiar within groups is prone to being ignored or misunderstood between groups, which creates a premium to people who can coordinate it across the groups. The more tacit the information to be moved between groups, the more likely there will be misunderstandings in moving the information, so the more valuable it will be to anticipate and manage the misunderstandings by knowing the two groups through personal contacts in the groups – which calls for direct brokerage. People who have close contacts in two groups will be better able to translate tacit knowledge between the groups. Imagine an economist and a psychologist trying to explain to economists the value of research on a psychological mechanism. Whatever the psychologist's advantage from knowing the mechanism, the economist has an advantage in knowing the economic vernacular so she is more likely to find an attractive way to frame and communicate the mechanism to the target audience (e.g., consider the development of behavioral economics as an area). So it is in organizations more generally. A manager familiar with the tacit knowledge in a group has an advantage over outsiders in finding a way to frame and communicate a new idea to make attractive to the group. Since there is always some element of tacit knowledge underlying the social capital of brokerage — else information would move easily between groups so brokerage would offer no competitive advantage — and direct contact facilitates moving tacit knowledge, direct brokerage should be more rewarding on average than second-hand brokerage:

> *Hypothesis 1. Returns to brokerage are greater for direct contacts than indirect contacts.*

How much greater is an empirical question. The extreme case would be the complete absence of returns to second-hand brokerage. Even if the extreme case is true in a population, however, it can be missed using current data-collection methods. The line between direct and indirect contacts varies with research method. The fewer relations recorded as direct contacts, the more likely that some direct contacts will be coded as indirect contacts. Brokerage among such "indirect" contacts would in fact be brokerage among direct contacts erroneously coded as indirect contacts. Assuming that closer contacts are more likely to be recorded as direct contacts in any research design, however, average returns to brokerage among direct contacts should be higher than average returns to brokerage among indirect contacts. Therefore, the hypothesis is stated in terms of variable proximity: the more proximate the contacts, the higher the returns to brokering connection between the contacts.

The idea that brokerage among direct contacts is a variable amount more valuable than brokerage among indirect contacts is segue to a second hypothesis. The more segregated the groups in an organization or market, the more likely their operations involve distinct tacit knowledge, so the more that brokerage involves moving tacit knowledge and the more valuable it is to have direct contact with people steeped in the tacit knowledge:

> *Hypothesis 2. Returns to brokerage are more concentrated in direct contacts where groups are more segregated from one another.*

The extreme case would be the complete absence of returns to second-hand brokerage where groups are segregated, but here again, segregation is a variable condition so the hypothesis is stated in terms of more versus less segregation.

Both hypotheses are assertions that the social capital of brokerage is more consistent with an Austrian than a neoclassical market metaphor. Tacit knowledge accumulates in groups and is difficult to move across groups, so I expect brokerage to be more valuable when it involves contacts unlikely to understand one another (H2) but well-known to the broker (H1).

DATA AND METHOD

My research design is to test hypothesis one by predicting performance from network measures of direct and second-hand brokerage for a cross-section of managers in a large organization, then test hypothesis two by replicating the analysis in two less-segregated study populations.

Network Constraint

I measure brokerage opportunities with a summary index, network constraint, that has been found associated with performance and varies with three network dimensions: size, density, and hierarchy. Network constraint measures the lack of brokerage opportunities. Constraint on a person is high if the person's contacts are strongly connected to one another directly (dense network) or through a central, mutual contact (hierarchical network). The constraint index begins with the extent to which manager i's network is directly or indirectly invested in the manager's relationship with contact j (Burt 1992: Chap. 2): $c_{ij} = (p_{ij} + \Sigma_q p_{iq} p_{qj})^2$, for $q \neq i,j$, where p_{ij} is the proportion of i's network time and energy invested in contact j, $p_{ij} = z_{ij} / \Sigma_q z_{iq}$, and variable z_{ij} measures the strength of connection between contacts i and j. Connection z_{ij} measures the lack of a structural hole so it is made symmetric before computing p_{ij} in that a hole between i and j is unlikely to the extent that either i or j feels that they spend a lot of time in the relationship (strength of connection "between" i and j versus strength of connection "from" i to j; see Burt, 1992:51). The total in parentheses is the proportion of i's relations that are directly or indirectly invested in connection with contact j. The sum of squared proportions, $\Sigma_j c_{ij}$, is the network constraint index C. I multiply scores by 100 to discuss integer levels of constraint.

Insert Figure 2 about here

The example in Figure 2 illustrates network constraint and my use of it to distinguish direct from second-hand brokerage. There are six groups in Figure 2, each containing two roles: Persons 11 through 28 are "group members" in the sense that they are only connected to other people inside their own group (e.g., 11 is connected

to 12, 13, and 5). The other role, "group leader," refers to people connected to someone outside their own group (persons 5 to 10). Persons 1 through 4 play a third role. They are positioned to be "brokers" in the sense that they connect people across groups. The first column of the table in Figure 2 reports network constraint scores for the three roles. Constraint is lowest for the brokers who link across groups (33.3), higher for the group leaders who have at least the brokerage opportunity of linking their group to an outside person (58.3), and highest for the group members who only know people within their own group (86.8).

Indirect Network Constraint

My corresponding measure of limited opportunities for second-hand brokerage is the average network constraint on a person's direct contacts. I tried more sophisticated aggregations, but the results are strongly correlated with the arithmetic average (see Appendix A). A network surrounds each direct contact. The more connected the network around each contact, the more the contact is constrained in his or her brokerage opportunities. Constraint on a person's contacts is indirect constraint on the person. I discuss the average network constraint on a person's direct contacts as "indirect" network constraint to distinguish it from the "direct" constraint on the person in their immediate network of direct contacts. There are degrees to second-hand brokerage: Indirect contacts could be friends of friends as in this paper, or more distant contacts such as friends of friends of friends, and so on. For the purposes of this paper, I only use the broad distinction between direct and indirect contacts.

The second column of the table in Figure 2 shows indirect constraint scores for the illustrative network. Person 1 is connected to persons 2, 3, and 4, all of whom have constraint scores of 33.3, so the indirect constraint on person 1 is reported in Figure 2 as 33.3. Persons 2, 3, and 4 are each connected to person 1 and two people who are embedded in a group, so the indirect constraint on them is higher; 50.0 in Figure 2. Group leaders are each connected to a broker and three group members, so indirect constraint on them is higher still (73.3). Finally, group members face the highest indirect network constraint (77.2) because their friends of friends are primarily other members of the group.

The third column of the table is included to illustrate how direct and indirect constraint are associated with Freeman's (1977) betweenness index. Betweenness measures access to structural holes anywhere in the network. Person 1, the broker of brokers, has the highest score. She brokers connections between 243 pairs of other people in the network, which is 69.2% of all 351 pairs possible. Persons 2, 3, and 4 broker fewer connections (168 of 351, or 47.9% betweenness). The group leaders broker connections with their team members (72 of 351 connections, or 20.5% betweenness). Team members are connected only to people already connected, so the team members broker no connections between direct or indirect contacts.

Returns to Brokerage

The broad prediction from previous research is that brokers (people in low-constraint networks such as persons 1 to 4 in Figure 2) have a social capital advantage over people in closed, high-constraint networks (e.g., team members 11 to 28 in Figure 2). The social capital advantage is visible as higher performance scores for the brokers.

This paper is about variation around the broad prediction from previous research. I argued in the previous section that there is always some element of tacit knowledge underlying returns to brokerage, that direct contact offers better comprehension of tacit knowledge, and concluded in hypothesis one that direct access to structural holes should be more valuable than indirect access. If the argument against second-hand brokerage is correct, performance scores should be highest for the three brokers in Figure 2 who have direct contacts in the groups, that is, persons 2, 3, and 4. Their personal connections in separate groups give them an advantage in translating opinion and behavior between the groups.[1]

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[1]The network in Figure 2 is similar to the laboratory network Cook and her colleagues use to study power in exchange networks (Cook and Emerson, 1978:726; Cook, Emerson and Gillmore, 1983:280). My hypothesis about returns to brokers 2, 3, 4 higher than to broker 1 is similar to Cook's conclusion about who is most powerful in the network. There is an important difference at the periphery of the network. Figure 2 would replicate Cook's experimental network if the group members (person 11 to 28) had no relations with one another, whereupon they would depend entirely on their team leader for information on the outside world. Instead, Figure 2 has complete connections within each group, whereupon group members can turn to one another within their separate social worlds for exchange and support. The image in Figure 2 of dense groups connected by bridges through brokers

On the other hand, where information is more easily moved between groups (as in a mature capital market), the value of brokerage lies not in knowing specific groups in detail so much as to knowing how groups differ. Second-hand brokerage could be a competitive advantage because of the diversity of groups reached. In this situation, performance scores should be highest for brokers like person 1 in Figure 2. Through her connections to persons 2 and 4, for example, she can select and synthesize among bits of knowledge in the four groups at the top of Figure 2. Of the four brokers in the network, person 1 is exposed to the greatest diversity of opinion and behavior via her indirect connections to all six groups (person 1 has the highest betweenness score in the network).

Job rank is important to hold constant in these considerations so that returns to bureaucratic authority do not get confounded with returns to brokerage. Other things constant, brokerage opportunities increase with job rank. For example, direct network constraint decreases for the managers described below from a mean of 74 points for junior managers down to 30 for the average executive (-11.38 z-score test for ordinal association with five levels of job rank), and indirect network constraint decreases from 59 points for the average junior manager down to 37 for executives (-8.82 z-score). Senior people have separate work groups or divisions reporting to them, which gives them direct access to the structural holes between their subordinates and indirect access to the structural holes among the subordinates of their subordinates. In this light, the illustrative network in Figure 2 resembles a traditional corporate hierarchy with six teams reporting to three middle managers and the middle managers reporting to a senior executive.

I use regression models of the following form: $P = b_1 C + b_2 (IC) + BX$, where P is a measure of individual performance, C is network constraint on the individual from direct contacts (first column of the table in Figure 2), and IC is the indirect network constraint on the individual from connections among indirect contacts (second column in the table in Figure 2). The final term, X, is a matrix containing a regression intercept and various control variables, including job rank, for a specific study population. My

corresponds to the information arbitrage of brokerage in a small-world image of markets and organizations (Burt, 2005:Chap. 1; Ahuja, 2000:449-450).

performance data come from institutional sources beyond the individuals whose performance is predicted: annual compensation and evaluations from company personnel records, and published records of individuals winning industry awards. My network data come from surveys as explained for each study population. More constrained networks span fewer structural holes, which means fewer opportunities for brokerage, so returns to brokerage are indicated by the strength of negative association between performance and network constraint: Coefficient b_1 measures returns to direct brokerage and b_2 measures returns to second-hand brokerage.

SUPPLY-CHAIN MANAGERS

I begin with supply-chain leadership in a large American electronics company. Supply-chain managers worked in legacy organizations that had been acquired by the parent company, but retained substantial freedom to purchase supplies where they wished. In each product line, managers knew the products for which they ordered supplies and vendors from whom they had ordered supplies. There was little incentive to know the supply chain in other product lines. With people segregated by product and geography in separate groups, local supply-chain operations are likely to involve quite a bit of tacit knowledge and performance is likely to depend on coordinating people with whom managers had direct personal contact. Of the three populations to be analyzed, this is the one in which second-hand brokerage is least likely to enhance performance.

Network Structure

Survey network data were collected by the standard method of name generators and interpreters (e.g., Marsden 1990, 2005). The survey contained two name generators. Managers were asked to describe their best idea for improving supply-chain operations, and then asked if they had discussed the idea with anyone. If yes, they were asked to name the person. Next, they were asked, "More generally, who are the people with whom you most often discuss supply-chain issues?" The respondent was then guided through a matrix in which the respondent's perceived relation between

each pair of contacts was coded as "often," "sometimes," or "rarely" in regards to how often the two contacts discussed supply-chain issues. The 455 survey respondents are representative of all 673 managers in the population in the sense that there are no significant differences between respondents and non-respondents in geographic region, business unit, job rank, age, race, gender, or education (Burt, 2004:360-365). Perceived relations are used to fill in the network around non-responding managers. There are two precedents for handling perceived relations elicited by survey name interpreters: assume equal intervals between response categories (e.g., Podolny and Baron, 1997: 683; Mizruchi and Sterns, 2001: 655-656) or derive quantitative scores from the response-category pattern of association with reported relations (e.g., Burt and Guilarte, 1986; Burt, 1992: 287-288). Scaling the supply-chain manager perceived relations shows that the managers make a deep distinction between relations perceived as "often" versus the less-strong relations perceived as "sometimes" or "rarely" in that contacts perceived to meet "often" are much more likely to cite one another as discussion partners (Burt, 2004: 361n). I therefore connect two managers when they are perceived by a colleague to meet "often," or, of course, when one cites the other directly as a discussion partner. Figure 3 is a sociogram of the network across managers. The discussion network around individual managers varies from one to 25 contacts around a median of seven contacts. For this analysis, I focus on discussion partners, and their partners, around each of the 455 managers who responded to the survey.[2]

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[2]I have complete network data on direct contacts for the 455 respondent managers, and respondent reports on relations among their contacts provide network data on indirect contacts for each contact cited by a survey respondent. However, the network data on indirect contacts are probably incomplete. Suppose a manager cites Joe who has four key contacts, two of whom were cited by the manager. I know Joe's relations with the two key contacts cited by the manager. I do not know Joe's relations with the two uncited key contacts. Fortunately, the survey respondents cited many connected contacts, so another manager can cite Joe and the two key contacts not cited by the first manager, thereby filling in Joe's relations with the other two key contacts. I only use perceived relations with the supply-chain managers. There is ample precedent cited in the text for using perceived relations in analyses of survey network data, but I am primarily reassured in using perceived relations with the supply-chain managers by the fact that the manager results are the same as the banker results in the next section where I have complete network data on the direct and indirect contacts of the bankers.

Insert Figure 3 about here

Figure 3 shows the managers working in company divisions segregated by geography and products. The density table to the lower right in Figure 3 shows high percentages of discussion citations among managers in the same division and low percentages to anyone outside the division. There is a clear separation in the sociogram between managers in the largest division (triangles in the bottom half of the sociogram) and other managers. Within the largest division, there is a visible separation between (solid triangle) managers in a subdivision geographically segregated from the rest of the division (white triangles). In the top half of the sociogram, managers in the second-largest division (white circles) are separate from managers in the smaller divisions (solid circles). The location of squares in the sociogram show some headquarters managers working in division offices, but most headquarters managers are at the center of the sociogram because of their connections to multiple divisions. Another way to describe the segregation is to compare the number of citations observed in the cells of the Figure 3 table to the number expected if group source and target of a citation were independent. Citations within the five groups, on average, are six times the number expected if source and target were independent (572%). Citations in the twenty cells between groups are, on average, a fraction of the number expected if source and target were independent (24%).[3]

Results

Figure 4 displays two measures of manager performance, each showing returns to direct and second-hand brokerage. I am predicting performance evaluations and salary figures defined about six months after the network survey was conducted, but network and performance should be considered coterminous since salary is strongly

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[3]The count of relations expected under independence is computed here in the usual way (row marginal times column marginal divided by table total), so ratios of observed to expected are not exact. Exact counts require correction for relations cited by the same respondent (the 3,804 relations tabulated in Figure 3 come from 455 survey respondents). For the purposes here, the reported ratios of observed to expected relations are heuristics to put a familiar metric on the tendency for managers to talk primarily with colleagues in their own division.

correlated between adjacent years (.98 correlation between salary in the predicted year and salary the year before) and performance evaluations, though more subject to change than salary, are also strongly correlated between adjacent years (.82 correlation).

Relative compensation is dollars of salary measured as a z-score on the vertical axis of Figure 4A. In round numbers, salaries varied across the managers from $50,000 to $200,000. A score of zero on the z-score salary variable in Figure 4A indicates a manager paid an average salary. Variables predicting salary are listed in Table 1, with means, standard deviations, and correlations in Table 2. Salary and the manager-background variables in the tables are taken from company personnel records. "Job Rank" is a five-category distinction between vice presidents, senior directors, directors, senior managers, and managers. "Age" is measured in years. The two education variables refer to college graduation or completing a post-graduate program. "Minority" is a dummy variable distinguishing women, African-Americans, Asians, and Hispanics. "Hightech Organization" and "Lowtech Organization" are dummy variables respectively distinguishing divisions in which supply-chain managers had to have some technical expertise or no technical expertise. "Regional HQ" distinguishes managers who worked in the headquarters of the largest division in the company. "Corporate HQ" distinguishes managers who worked in corporate headquarters (squares in Figure 3). Returns to direct brokerage are shown in Figure 4A by the solid line describing a strong association between salaries and direct network constraint (-14.9 t-test for the regression line in the graph). Returns to second-hand brokerage are shown by the dashed line, which describes a strong salary association with indirect network constraint (-9.1 t-test).

Insert Figure 4, Table 1, and Table 2 about here

Relative performance evaluation is the criterion in Figure 4B. Managers were assigned in their annual performance evaluation to one of three categories: outstanding, average, or poor (synonyms for the words actually used). For comparison with the salary metric, I computed from integer values and the distribution of managers a z-score for each level of evaluation (1.88 for outstanding, .06 for average, and –1.58 for poor). The solid line in Figure 4B shows that managers with

diverse contacts were likely to receive an outstanding evaluation and managers with inter-connected contacts were likely to receive a poor evaluation. Returns to direct brokerage are statistically significant (-6.7 t-test for the bold regression line in Figure 4B). The dashed line shows detectable, but weaker, returns to second-hand brokerage (-2.5 t-test).

Regression equations in Table 1 show what happens when the network variables are combined with job rank and the other background variables to predict performance: Returns to direct brokerage are strong. There are no returns attributed to second-hand brokerage. The ordinal logit regression in the third column shows the same results as the second-column model predicting the z-score evaluation metric in Figure 4B.

Job rank is the key control variable. Managers in more senior positions had more direct and second-hand brokerage in the sense that their direct personal contacts were people in separate groups who managed work across groups of lower-rank people (-.58 and -.41 correlations in Table 2 for job rank with direct network constraint and indirect network constraint). Holding only job rank constant eliminates the Figure 4 returns to second-hand brokerage for compensation (-9.1 t-test in Figure 4A drops to -1.2) and performance evaluation (-2.5 t-test in Figure 4B drops to 0.6).

INVESTMENT BANKERS

Segregation by product and geography made it likely that the managers relied on local tacit knowledge. They provided a relatively weak test of the second-hand brokerage hypothesis. The next study population is a strong test in that it involves a global network integrated through a single center operating in a mature capital market. In this population, information can be expected to move quickly, across far distances, free of local interpretations. The second population is a group of senior people in a large American financial organization during the late 1990s (before the dot.com bubble bulged and burst). The people craft investments and offer advice on investments. I

will call them bankers.[4] Work in this population requires flexible cooperation. It is impossible to monitor banker cooperation through bureaucratic chains of command because so much of their interpersonal behavior is unknown to their immediate supervisor. The firm is typical of the industry in using peer evaluations to monitor employee cooperation. Each year, bonus-eligible people identify colleagues with whom they worked during the preceding year and indicate how productive it was to work with the person (poor, adequate, good, or outstanding; these are my synonyms for the words actually used). The ratings are considered in promotion and bonus decisions, so virtually all eligible employees respond.

Network Structure

From three years of peer evaluations, I identified contacts cited by each banker and contacts who cited the banker, then looked at each contact's evaluations to see how the contacts were connected with one another. The network around individual bankers contained a median of 20 senior contacts in and beyond the banking division. Figure 5 displays relations among 154 bankers in the third year. A line connects bankers where one cited the other as a colleague with whom he or she did frequent or substantial work during the year.

Insert Figure 5 about here

In contrast to the managers, the bankers live in a center-periphery structure. They are connected through a single center indicated by the dense conjunction of lines in Figure 5. If second-hand brokerage has value, it is more likely among the bankers than the managers because the bankers are less segregated into groups, reflecting the advantages of being close to the vortex of the "deal stream." Individual bankers shift position in the network from one year to the next, but the same center-periphery structure characterizes the network in the preceding two years. Annual sociograms of the bankers show the center-periphery structure is stable across years, though

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[4]There is nothing awkward revealed about the organization in this paper, but to honor management's wish for anonymity, I am vague on job ranks in the study population, and vague on the number of people in lower ranks with whom study-population people cited relations. The people I discuss as "bankers" and "analysts" could be described with other job labels. I use "banker" and "analyst" because the labels are short and not inappropriate.

relations between individual bankers change from year to year. The organization has two headquarter offices, one in the United States and one in Europe (EU HQ in Figure 5). In addition, there are senior people scattered across the globe in offices of one to a dozen individuals in select cities. Cells in the table to the lower right of the sociogram show the percent of citations made by the bankers in the row that go to the bankers in the column (tabulating only citations between bankers in Figure 5). For example, 24% of the citations from bankers in the European headquarters were to bankers in the US headquarters. The primary feature of the network is the central role played by the US headquarters, with some segregation between operations in the US and operations outside the US (recall that the data describe operations before September, 2001). Bankers at the US headquarters are at the center of the sociogram with dense ties to other bankers. The banker sociogram in Figure 5 is so densely connected it looks like a cloud of gnats more than the globally dispersed network it is.

Results

I use annual compensation as a performance metric for the bankers (see Eccles and Crane, 1988: Chap. 8, on deliberations over banker compensation). Compensation is from the organization's personnel records. Total annual compensation — which includes salary, bonus, and the cash value of other compensation — varied from several hundred thousand dollars to several million. To obscure exact dollar amounts and remove year-to-year fluctuation, I standardized compensation for each year. A score of zero on the z-score compensation variable indicates a banker who received an average level of compensation for that year. A score of 1.0 indicates a banker with compensation one standard deviation higher than average, and so on. With people entering and leaving over the three years, there are a total of 467 banker observations (156 in the first year, 157 in the second year, and the 154 in Figure 5 in the third year). For each year, I know the banker's compensation and background from company personnel records, and have data on the banker's network constructed from citations with and beyond senior colleagues in the banking division.

Insert Table 3 and Table 4 about here

The regression models in Table 3 show returns to both direct and second-hand brokerage with key background factors held constant (means, standard deviations, and correlations in Table 4). I do not repeat for the bankers the zero-order associations presented in Figure 3 for the managers. The regression results in Table 3 should now be sufficient to tell the story. Compensation next year is predicted from the row variables this year. Compensation is higher for bankers currently in the senior rank, who work in the US headquarters, and especially those who receive more positive evaluations from other employees. "Peer Evaluation" is the average evaluation reported for the banker in that year's annual peer evaluations. Some bankers in senior rank by the third year were not in senior rank two years earlier. "Senior Job Rank" is a dummy variable distinguishing bankers in the senior rank from those who will reach but have not yet reached the senior rank. "Years with Firm" is the years that the banker has been with the firm. "Minority" is a dummy variable distinguishing females, African-Americans, Asians, and Hispanics. "US Headquarters" is a dummy variable distinguishing bankers working that year in the US headquarters office.

Model A shows returns to direct brokerage. There is a strong negative association between compensation and direct network constraint (-4.51 t-test). In other words, higher compensation went to bankers whose contacts in separate groups gave them opportunities to broker connections between groups.[5]

Model B shows returns to second-hand brokerage. There is a strong negative association between compensation and indirect network constraint (-3.70 t-test). In

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[5]I want the statistical power of re-observing people over time, but outcome correlation between adjacent years means that standard errors have to be increased for autocorrelation. Salary does not change much between years, but salary is a small portion of total compensation to the bankers (14% on average) so total compensation, in theory, could vary between years. However, gossip ensures stable reputations, which in turn ensure high correlation between compensation in adjacent years (see Burt, 2005:Chap. 4, for detailed evidence of reputation stability increasing with network closure): Total compensation is correlated .93 between the first and second years, .94 between the second and third years. Even if I hold constant the predictors in Table 3 (job rank, tenure, minority, US headquarters, and average peer evaluation), the partial correlations between compensation in adjacent years are .88 for the first and second years, .91 for the second and third years. Test statistics in Table 3 are adjusted down for autocorrelation in compensation across years (using the "cluster" option in STATA).

other words, higher compensation went to bankers whose contacts' contacts were in a position to broker connections between groups.[6]

However, bankers with many, disconnected contacts often had contacts who themselves had many, disconnected contacts, which means strong correlation between the measures of direct and indirect network constraint (.74 correlation). The results in Model C show what happens when the two network measures are tested against one another. Returns to direct brokerage remain strong. Returns to second-hand brokerage are negligible. In other words, association between second-hand brokerage and compensation is due to disconnected direct contacts, through whom the banker reaches diverse indirect contacts.

ANALYSTS

Given the lack of returns to second-hand brokerage among the bankers, I move to a kind of work even more likely to benefit from second-brokerage. The third study population is composed of senior people, in another division of the financial organization from which the bankers were drawn, who make recommendations about the market value of investments. I will discuss them as analysts. They work in a center-periphery structure broadly similar to the one in which the bankers work, though more segregated by geography. Greater segregation can be expected to erode the value of second-hand brokerage, but analysts do a kind of work especially likely to benefit from second-hand brokerage. Information arbitrage is the substance of their work — speeding a bit of information found here to a customer over there — so

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[6]The peer-evaluation data distinguish positive from negative relationships. I do not discuss the distinction in the text for two reasons: It cannot be replicated with the usual network data used to measure communication intensity or frequency. Second, positive and negative relations have the same association with performance, so they need not be distinguished in this paper. For each banker, each year, I computed two average levels of indirect network constraint: average constraint on the colleagues with whom the banker had a negative relationship (banker or colleague evaluated the relationship as adequate or poor), and average constraint on the colleagues with whom the banker had a positive relationship (banker or colleague evaluated the relationship as good or outstanding). If I re-estimate Model B in Table 3 with indirect constraint through positive relations, I get a -3.84 t-test for indirect constraint. I get a similarly strong -3.36 for indirect constraint through negative relations. Model C in Table 3 re-estimated with indirect constraint through positive relations yields a -1.10 t-test for indirect constraint and a similarly negligible -1.16 for indirect constraint through negative relations.

analysts are especially likely to benefit from the access to diverse information that second-hand brokerage can provide.

Network Structure

My data on the analysts describe them during a transition in the definition of their work. Beginning in the 1970s, market pressure on commissions for buying and selling stocks led to analyst work becoming increasingly tied to investment banking. Especially through the 1990s, analysts became a prominent and powerful factor in investment business. The trend intensified a conflict of interest between analyst accuracy and analyst support of employer-sponsored investments. The conflict of interest drew public attention when the dot.com bubble burst in 2000 and it became apparent that analyst opinions expressed in emails with colleagues sometimes contradicted their opinions expressed in published reports.

Insert Figure 6 about here

The point significant for this analysis is that as analysts rose above their traditional back-room staff role to become contenders in the bonus pool, they were included in peer evaluations like bankers and other people with leadership responsibilities in financial organizations. Their inclusion in the peer evaluations provides the network data for this analysis. I have peer evaluations from and of senior analysts for the last two years of the three on which I have banker peer evaluations. The study population contained 197 analysts during the two years, 157 of whom were present in both years, for a total of 354 annual observations. As was done for the bankers, I identified for each year contacts cited by each analyst and contacts who cited the analyst, then looked at each contact's evaluations to see how the contacts were connected with one another. Analysts had a median annual network of 10 colleagues (versus 20 for the bankers).

Figure 6 displays relations among the 182 analysts present in the second year. A line connects analysts where one cited the other as a colleague with whom he or she did frequent or substantial work during the year. The distribution of analysts in Figure 6 resembles the distribution of bankers in Figure 5, but the analysts are more segregated by geography. Cells in the table to the lower-right of the sociogram show

the percent of citations made by analysts in the row that go to analysts in the column (tabulating only citations between analysts in the sociogram). For example, two percent of citations from analysts in the European headquarters were to analysts in the US headquarters. Analysts in the US focused on analysts at the US headquarters, largely disregarding analysts outside the US. Analysts in the European headquarters focused on one another. Analysts elsewhere outside the US focused on office colleagues and headquarters' analysts. Each analyst in the network is connected directly or through intermediaries to every other analyst. It is a connected network. Relative to the bankers, however, there is more obvious geographic segregation between the analysts.

Results

The substantial impact of analyst opinion on corporate finance has been an incentive to study and rate analysts for the quality of their opinions (see Hayward and Boeker, 1998; Zuckerman, 1999; Phillips and Zuckerman, 2001; Fang and Yasuda, 2005, for complementary illustration and research review). With the growing celebrity of analysts in the 1990s, rating services multiplied. The "All-America Research Team," begun in 1972, is one of the longest-running and often-noted ratings. The October issue of the trade magazine, Institutional Investor, names a first, second, third, and runner-up analyst in each of several industries. Election to the All-America Research Team involves votes from a few thousand institutional investors in several hundred financial organizations. Polling for the 1999 ratings was explained as follows (Institutional Investor, October 1999, pp. 105-106): "To select the members of this year's All-America Research Team, Institutional Investor sent questionnaires covering 90 industry groups and investment specialties to the directors of research and chief investment officers of major money management institutions. Included were those managers on our rankings of the largest institutions in the U.S., as well as other key U.S., European and Asian institutions. . . . The opinions of more than 2,300 individuals — representing approximately 90 percent of the 100 largest U.S. equity managers, as well as more than 300 other key money management firms — were tapped." Analysts are rated for their stock selection, earnings forecasts, written reports, and service. The

highest-rated analyst in an industry is named to the first team, the next highest to the second team, and so on. Election to the All-America Research Team is a coveted award associated with professional status and financial reward (Eccles and Crane, 1988: 153-154; Hayward and Boeker, 1998). In fact, the award is so much coveted that the election process is deliberately kept vague, as illustrated by the following excerpt from the 2005 Institutional Investor website: "To mitigate the likelihood of extraordinary, vote-generating activities on the part of firms or analysts during the fieldwork, it is the policy of Institutional Investor not to reveal the details relating to certain aspects of the survey execution process."

Let election recognition be the highest level of recognition that an analyst achieves in the Institutional Investor election: 0 for not recognized, 1 for runner-up, 2 for third team, 3 for second team, 4 for first team. I give analysts with non-zero scores in more than one industry the score for the highest recognition they achieved in any industry. I get the same associations with the network variables if I predict an analyst's aggregate recognition across industries (because study-population analysts recognized across industries tend to be extremely good in at least one industry; half of the study-population analysts with non-zero scores in multiple industries were elected to the first team in at least one industry).

I will also express election recognition as a z-score (0 to 4 raw score minus the mean for the year across analysts, quantity divided by the standard deviation for the year). There is no reason to believe that election to the first versus second team is the same difference in recognition as election to the third team versus runner-up. I include predictions of z-score recognition together with logit models predicting ordinal levels of recognition to show that both provide the same results, so I can use z-score recognition in a summary graph across populations at the end of the paper.

Table 5 contains the results of predicting election recognition this year from forecast activity during the year and company variables as of last year.[7] To preserve

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[7]I use network structure one year to predict election recognition next year, but I do not make too much of the time order because election recognition is so stable over time. For the two years in which I tracked the study-population analysts, 84% of analysts elected in the first year were re-elected in the second year, and there is a .91 correlation between z-score recognition in the two years (the dependent

confidentiality, intercepts are not reported for the logit models. Means, standard deviations, and correlations are given in Table 6.

Model A in Table 5 shows returns to direct brokerage. There is a strong negative association between election recognition and direct network constraint (-3.90 test statistic). Analysts connected across groups last year are more likely to be elected to the All-America Research Team this year.

Model B shows returns to second-hand brokerage. Election recognition has a negative association with indirect network constraint (-2.68 test statistic). Analysts who worked with colleagues who were connected across groups last year are more likely to be recognized in the election this year.

Models D and E show the lack of returns to second-hand brokerage. The two equations, respectively ordinal and interval predictions, show that election recognition of an analyst has a strong association with direct brokerage (test statistics of -3.30 and -4.05 for direct network constraint) and no association with second-hand brokerage (test statistics of -1.62 and -1.63 for indirect network constraint).

It is not the control for direct brokerage that eliminates the analyst evidence of returns to second-hand brokerage. Among the bankers, holding constant direct brokerage eliminated returns to second-hand brokerage (model C in Table 3). Bankers connected to brokers were themselves brokers. The banker explanation does not explain the analysts. Model C in Table 5 is for the analysts what model C was for the bankers in Table 3. Model C shows returns to second-hand brokerage for the analysts even when their immediate network is held constant. Election recognition of an analyst decreases with direct network constraint from immediate contacts (-3.40 test statistic) and the indirect network constraint to which the analyst is exposed through those contacts (-2.28 test statistic).

What eliminates the analyst evidence of returns to second-hand brokerage is the control for analyst differences in the accuracy of their forecasts. There are two sets of control variables in Table 5: six variables holding constant differences in analyst backgrounds and two variables controlling for analyst accuracy. The background

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variable in model E in Table 5). Test statistics in Table 5 are adjusted down for autocorrelation within analysts across years (using the "cluster" option in STATA).

variables are defined as they were in Table 3 for the bankers, and are taken similarly from company personnel files. The one additional background variable is "Office in the US," which equals one for analysts working in the US at the time the network was measured, zero for analysts outside the US. I added the US control variable to test for effects from a US focus in the election or the segregation between US and non-US analysts evident in the Figure 6 sociogram. When both network constraint variables are in the prediction, the US control variable has no association with election outcomes, from which I infer that being in the US is not as consequential for election recognition as brokering the flow of market information, which happens to be anchored in the US for this study population. Of the six background variables in Table 5, positive peer evaluations is the only one associated with election recognition across the models: positive reputation inside the company is a robust correlate of positive reputation in the broader market outside the company.[8]

Insert Table 5 and Table 6 about here

I follow Phillips and Zuckerman (2001) in measuring analyst accuracy relative to competitors. "Forecast Accuracy" in Table 5 is the extent to which an analyst's earnings forecasts were more accurate than forecasts by other analysts covering the same companies (see Appendix B). Accuracy is an oft-discussed aspect of analyst work and there is evidence of more accurate analysts being more likely to get elected to the All-America Research Team (Stickel, 1992, for 1981-85; Fang and Yasuda, 2005, for 1983-2002). Model D in Table 5 is model C with a control for differences in analyst accuracy. Model C shows that analysts who make more accurate forecasts are more recognized in the All-America election (2.62 test statistic), but holding accuracy constant eliminates the evidence of returns to second-hand brokerage (-2.28 test statistic for indirect network constraint in model C is -1.62 in model D).

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[8]I suspect that job rank would be associated with election recognition if the population were expanded to lower ranks. However, estimating job-rank effects on election recognition is not the goal here. To better distinguish components in the election association with network structure, I focus on senior people, the people most at risk of recognition across institutional investors, and so most at risk of election to the All-America Research Team. "Senior Job Rank" in Table 5 distinguishes analysts in senior rank for both years from those promoted into senior rank during the first year. It is included in the table to control for the minimal job-rank differences between the analysts.

I have to go one step deeper to explain the lack of returns to second-hand brokerage among the analysts. Accuracy is not the key variable. Many people with an "analyst" job title in the study population cannot be found in the two years of I/B/E/S data. Specifically, 74 of the 197 analysts could not be matched to forecasts. All 197 analysts are senior people in a large financial organization, so they are not peripheral people. In fact, three of the 74 unlisted analysts were elected to the All-America Research Team during the two years under study. One explanation for the unlisted analysts is that analysts can choose not to have their name listed with their forecasts in the I/B/E/S data. Another explanation is that the "analyst" job category includes people, a great many people judging from this study population, who do not make earnings forecasts about individual companies. For example, the three unlisted analysts elected to the All-America Research Team each managed a team of analysts.

Whatever the reason for the unlisted analysts, they create a problem for holding accuracy constant when comparing people within the "analyst" job category. The problem does not arise when a study population is defined by available archival data, because analysts for whom there are no forecast records do not appear in the data (e.g., Stickel, 1992; Phillips and Zuckerman, 2001; Fang and Yasuda, 2005).

For models A, B, D, and E in Table 5, I resolved the problem in an ad hoc way by giving the unlisted analysts a z-score accuracy of zero — i.e., average — in as much as I had "found no forecasts more or less accurate than forecasts from other analysts."

I tried alternative solutions to the problem, all of which led to the same conclusion, so I present the simplest of the alternatives as model F in Table 5. Model F is an ordinal logit model identical to model D except that model F contains in the bottom row a dummy variable, "In the I/B/E/S Data," that distinguishes analysts for whom I found forecasts in the two years of I/B/E/S data.

Three things happen when I add the control for unlisted analysts. First, the negligible association between election recognition and second-hand brokerage drops to near zero (0.24 test statistic for indirect network constraint in model F versus -1.62 in model D).

Second, unlisted analysts were unlikely to be elected. Publishing forecasts so as to appear in the I/B/E/S data is strongly associated with election recognition (and the

same strong association occurs in predicting z-score election recognition, 4.62 test statistic). I computed a more sophisticated measure that increased with the visibility of the companies an analyst covered, but covering more visible companies added nothing to the prediction by the simple dummy variable "In the I/B/E/S Data" (see the last paragraph in Appendix B).

Third, analyst accuracy is no longer associated with election recognition. I also obtain this result if I predict z-score election recognition, or estimate models D and E using only observations on the analysts for whom I found forecasts in the I/B/E/S data (reducing the 351 observations in Table 5 to 211 observations). For these analysts, publishing accurate forecasts was less important for election recognition than the publishing itself. Phillips and Zuckerman (2001:410-411) report a similarly near-zero correlation across all analysts between forecast accuracy and election recognition.

In sum, an analyst's chances of being elected to the All-America Research Team increased with publishing forecasts (so as to appear in the I/B/E/S data) and having good contacts in diverse groups (direct brokerage and positive peer evaluations). Chances were not improved directly by working with people who had good contacts in diverse groups (second-hand brokerage). Having one's own direct, personal contacts in diverse groups mattered for the analysts, as it did for the managers and bankers.

Insert Table 7 about here

ACROSS THE THREE POPULATIONS

The managers are a productive contrast to the bankers and analysts because the groups work in structures with such different implications for brokerage. The bankers and analysts work in a global center-periphery structure anchored in the US headquarters. A large, sparse colleague network surrounded the average banker. The median number of contacts is 20 with 14 points of network constraint. Analyst contacts were fewer in number but drawn from more diverse groups so average network constraint was about the same as it was on bankers (10 contacts for the median analyst with 13 points of network constraint). Given a mature capital market and strong connections across groups, information should move easily across groups, which would make more valuable the broad diversity of information provided by

second-hand brokerage. The most efficient way to stay in touch with developments across the network would to be to work with colleagues who are broadly connected across the network. It would not be surprising to find returns to second-hand brokerage among the bankers and analysts.

In contrast, the segregation of supply-chain managers by geography and products makes it likely that returns to brokerage are concentrated in direct rather than second-hand brokerage. The average manager was surrounded by a small, dense discussion network. The median number of contacts is seven with 60 points of network constraint. Belief and practice are likely to differ between people segregated in separate groups, so coordination across groups is likely to involve moving tacit knowledge between groups, which is facilitated by direct, personal contact to people in the groups. It would not be surprising to see meager returns to second-hand brokerage among the managers.

All the more striking to see the lack of returns to second-hand brokerage along side substantial returns to direct brokerage in all three study populations. Consider the summary comparisons in Table 7. Rows distinguish combinations of high and low levels of direct and indirect network constraint (high is above median for a study population, noted in Figure 4 for the managers), and performance is a z-score residual holding constant all but the two network variables in Tables 1, 3, and 5.

Performance is most clear in the extreme networks. Performance is highest for managers, bankers and analysts rich in direct and second-hand brokerage (top row in Table 7). Performance is lowest in closed networks ("No Brokerage" rows at the bottom of Table 7).

The key results are in the middle of Table 7, for compound networks in which direct and second-hand brokerage contradict one another. Direct brokerage alone is associated with performance while second-hand brokerage is not ("Direct Only" versus "Second-Hand Only" rows in Table 7). Emphasize the qualifier "alone." It is not the case that people connected to brokers do poorly. Quite the contrary; they do well. The zero-order association between performance and second-hand brokerage is strong in all three study populations. However, people who do well and are affiliated with brokers, are people who are themselves brokers. The most telling evidence

against second-hand brokerage comes from the negligible returns to networks that provide little direct access to structural holes but high indirect access ("Second-Hand Only" rows) — people who are not brokers themselves get no performance benefit from affiliation with a broker.[9]

CONCLUSIONS AND DISCUSSION

Direct brokerage involves a person moving information from one group to another, relying on his or her own contacts in the groups. Previous research has documented various returns to direct brokerage, including good ideas, more positive job evaluations, higher compensation, and faster promotion. Second-hand brokerage refers to moving information between groups to which the broker is only indirectly connected through other brokers. Judging from the results in Tables 1, 3, and 5, performance in all three populations is more associated with direct than indirect brokerage — as predicted in hypothesis one. More striking is the complete irrelevance of indirect contacts, which goes beyond the hypothesis to say that social capital in circumstances as diverse as the managers, bankers and analysts is concentrated in a person's network of direct contacts. There is no evidence of the contingency predicted by hypothesis two. To be sure, there is evidence of returns to second-hand brokerage among the analysts when the key variables of direct constraint and job rank are held constant (model C in Table 5), and the analysts can be argued to be more likely than the managers or bankers to benefit from information arbitrage through indirect contacts. However, the evidence of analyst returns to second-hand brokerage disappears when forecast accuracy is held constant (models D, E, and F in Table 5).

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[9]The categories of direct and indirect network constraint in Table 7 might trigger thoughts about interaction between the categories affecting performance. I multiplied log direct constraint (adjusted for its average within a population) times log indirect constraint (adjusted for its average within a population) and entered the interaction term to the predictions. Performance has no association with the interaction term: 0.36 and -.75 test statistics for the managers in the first two models in Table 1, 0.40 for the bankers in model C in Table 3, and -.12 for the analysts in model F in Table 5.

Implications for Research Design

The results are consequential for the two reasons discussed at the beginning of the paper. With respect to research design, the lack of returns to second-hand brokerage supports the validity of designs in which brokerage is measured with network data limited to each respondent's direct contacts. This does not mean that designs including the broader network of indirect contacts are incorrect. The point is only that network data on direct contacts are sufficient to measure brokerage, which is an extremely attractive conclusion for scholars wishing to include network variables in area probability surveys.

Ignoring structure beyond the immediate network simplifies research design in other ways. For example, one need not worry about how to aggregate links in indirect connections. How strong is a two-step friend-of-a-friend connection relative to a direct connection, or relative to a three-step friend-of-a-friend-of-a-friend connection? There is no definitive answer. Katz (1953) proposes fractional links so that indirect connections decrease as a function of the number of steps involved (e.g., .5 for two-step, .25 for three-step, .125 for three-step, etc.). Burt (1976) proposes a frequency measure in which strength decreases as a function of the volume of contacts at each step (the more people reached, the less strong the connection with each person). Freeman (1977) gives equal weight to connections of any length in his popular betweenness index (the probability that a message passes along any particular geodesic is equal to one over the number of alternatives). These measures all assume simultaneous relations. Moody (2002) discusses the further complication of indirect connections in discontinuous relations ordered in time. If a connection between persons A and B happens today, and a connection between persons B and C happens tomorrow, then A's news can travel to C through the A-B-C indirect connection, but C's news will not travel to A through the C-B-A connection because the A-B discussion is finished by the time C's news reaches B. Sequence is an obvious issue in the sexual relations that Moody (2002) describes. In a discussion network, on the other hand, B can remember C's news and relay it in B's next conversation with A. Coordination is still an issue: How much time will elapse before B has another conversation with A? Will B remember to transmit C's news in

subsequent conversations? With these complexities in mind, analysis is greatly simplified by the knowledge that returns to brokerage are concentrated in direct contacts. Weighting links in indirect connections to friends of contacts is not an issue for brokerage measures because measurement can stop with the network of direct contacts. The timing of component links in indirect connections beyond direct contacts is similarly unproblematic – though time remains an interesting puzzle: Observed returns to brokerage might depend on the tension of contradictory simultaneous relations with direct contacts (see Merton, 1957, on role strain alleviated by segregating in time relations that conflict with one another), and sequence disorder beyond direct contacts could be responsible for the observed lack of returns to second-hand brokerage.

Implications for Social Capital Theory

With respect to theory, I contrasted the neoclassical market metaphor implicit in network measures of information moving through long, indirect connections versus the Austrian metaphor emphasizing tacit knowledge about local norms and practice. The lack of returns to second-hand brokerage in the three study populations highlights the relevance of the Austrian market metaphor to social capital theories of brokerage.

More interesting than a choice between the two market metaphors is the possibility of characterizing an organization by the degree to which it corresponds in operation to either metaphor. Consider the graph in Figure 7. The horizontal axis is the number of network steps between broker and contact. Direct contacts are one step, friends of friends are two steps, and so on. The vertical axis is the magnitude of the test statistic reported here for association between performance and brokerage among contacts at each remove. From an initial level of three and a half times the standard error for returns to direct brokerage, returns drop below statistical significance for second-hand brokerage — for the managers, the bankers, and the analysts.

<div align="center">Insert Figure 7 about here</div>

The lines in the graph are the reason for presenting Figure 7. The lines are extrapolated from returns to direct and second-hand brokerage using a power function

to capture decreasing returns from brokering connections between more distant contacts, $t = a(PD^\gamma)$, in which t is the test statistic on the vertical axis of Figure 7, PD is the path distance from broker to contact on the horizontal axis, a is an intercept, and gamma (γ) describes the extent to which returns to brokerage are concentrated in direct contacts. For example, t-tests for the bankers in model C, Table 3, are -3.43 for direct constraint and -1.50 for indirect constraint, which implies a value of -1.19 for gamma describing the bold line in Figure 7. Some other functional form could be more appropriate. I use a power function here because it is simple and often describes network effects.

The gamma coefficients in Figure 7 describe the extent to which structural holes in an organization are difficult to bridge so the organization corresponds in operation to the Austrian market metaphor with its emphasis on tacit knowledge about local norms and practice. A gamma coefficient of zero indicates an organization in which information moves easily across groups such that the organization can be described by a neoclassical market metaphor and brokerage opportunities should be measured by indirect connections across the organization. The more negative the gamma coefficient, the more that brokerage value is concentrated in the immediate network around individuals. The minimum gamma in Figure 7 is –2.00 for manager job evaluations, which means that their job evaluations are the criterion performance variable in this paper that is most improved with local, tacit knowledge.

Let the lines described by a gamma coefficient in Figure 7 be "gamma lines." A question for future research is how gamma lines vary across organizations. The three study populations analyzed here are quite different, but the gamma lines for them in Figure 7 are quite similar. Is it usual for gamma lines to be so similar for such different organizations? How rare are flat gamma lines? If flat gamma lines do not occur, network models of brokerage need not take into account long indirect connections since such connections do not affect direct brokerage. Are there organizations in which returns to brokerage are even more concentrated in direct contacts, which would mean steeper gamma lines than the one in Figure 7? The more steep the gamma lines, the more exclusively brokerage is about local connections and tacit knowledge.

There are implications for policy informed by social capital theory: the flatter the gamma line for an organization, the more efficient it is to centralize services. Consider a leadership team launching a process initiative such as Six Sigma. The organization operates multiple business units in multiple cities. Some companies develop Six Sigma experts within the businesses. Other companies develop experts at a central location and send them as needed to the businesses. The virtue to developing experts within the businesses is that the experts know the local business so they can more readily explain how Six Sigma can help in the business. The virtue to developing experts in a central location is a uniform level of expertise at lower cost. Choosing between the two alternatives can be a political struggle. Gamma lines have diagnostic value. The steeper the gamma line for the business units affected by the new initiative, the more that brokerage depends on direct connections, so change agents should be located in the businesses. The flatter the gamma line, the more that brokerage is productive across long indirect connections, so the more efficient it would be to centralize change agents in one location.

Turning from whole organizations to the individuals within them, the concentration of brokerage value in direct connections raises questions about micro mechanisms that could be success factors in brokerage. Motivation is an example. Why would anyone want to be connected to a broker? The answer is clear in the neoclassical market model: Being close to brokers is an efficient way to get early access to diverse information traveling over long, indirect connections. The answer is not clear when returns are concentrated in direct contacts. Brass (2006) describes a variety of ways that brokers profit more from contacts than contacts profit from brokers. He also describes unique benefits of being connected to a broker. The balance between benefits and costs remains a question. The results summarized in Table 7 show no returns to being connected to a broker without being a broker one's self.

<div align="center">Insert Table 8 about here</div>

However, there is a learning function not explored here. Second-hand brokerage this year could be valuable as a way to learn to broker next year. Rauch and Watson (2006) explore a game-theoretic model in which the probability of someone becoming

an entrepreneur is increased by having a colleague who became an entrepreneur. The results summarized in Table 7 would seem to reject the Rauch and Watson model since there are no returns to the second-hand brokerage of being connected to a broker. In fact, the benefit is indirect, as assumed in Rauch and Watson's model. Using the network constraint data in this paper, Table 8 shows two regression models predicting the network structure of direct contacts next year from the structure of direct and indirect contacts this year, one for bankers and the other for analysts. The analyst model in Table 8 shows that direct brokerage next year increases with direct and second-hand brokerage this year. Being connected to a broker this year increases direct access to structural holes next year. The same is not true for the bankers. I have three annual observations on the bankers so each banker is observed through two transitions: year one to two, and year two to three. Direct brokerage next year has no association with second-hand brokerage this year.

These results are consistent with the idea that second-hand brokerage provides future competitive advantage where people learn to broker through direct contact with existing brokers. Second-hand brokerage offers some advantage to the analysts, and they are the people for whom second-hand brokerage last year enhances direct brokerage this year.

Other familiar micro mechanisms come quickly to mind for future research. With respect to cognitive ability, for example, returns to second-hand brokerage might be available to anyone who can think strategically about indirect contacts, but returns end up concentrated in direct contacts because most people cannot, or do not have the energy to, think through the complexity of brokerage in the broader network. The research question for this possibility would ask how returns to second-hand brokerage vary with broker intelligence. With respect to face-to-face mechanisms, the value of brokerage could be concentrated in direct contacts because successful brokerage requires emotional connection as lubricant, which works best with direct contact — the proverbial value of beginning with a face-to-face meeting. The research question for this possibility would ask about the emotions that attend brokerage and whether returns to brokerage are eroded or enhanced by emotional correlates. From emotion, it is a short step to trust. Perhaps the trust required for brokerage is concentrated

between friends, fading quickly between friends of friends. Research questions for this possibility would ask how returns to brokerage vary with the history between broker and contact, or how returns vary with enforceable reputation cost for poor behavior between broker and contact. There is argument and initial evidence for all of these possibilities. The summary conclusion from this paper is that returns to brokerage are concentrated in direct connections. That concentration in the immediate network around a person gives micro mechanisms of cognition and emotion new significance as success factors in brokerage.

APPENDIX A: MEASURING INDIRECT CONSTRAINT

Let ego be the focal person whose performance is to be predicted. Let alter be one of ego's direct contacts. I measure ego's opportunities for second-hand brokerage in terms of average network constraint on alters, but more sophisticated measures could be productive in other study populations. The arithmetic average is strongly correlated with more sophisticated measures in this paper's study populations. For example, I computed indirect constraint as the weighted average of constraint with weights proportional to the constraint posed by each contact. The 1/n weight for alter j in the arithmetic mean is replaced with c_{ij}/C, where c_{ij} is the level of constraint posed on ego i by alter j and C is the total constraint on ego (see the text under the heading "Network Constraint"). This weighting emphasizes the networks around the direct contacts who most constrain ego. The weighted measure of indirect network constraint is correlated with the arithmetic mean .84, .78, and .97 respectively for the analysts, bankers, and managers. I also tried weighting inverse to c_{ij} to emphasize networks around the contacts most likely to be bridges. Again the weighted measure is strongly correlated with the arithmetic mean and yields the same associations with performance. Another approach, pursued by Reagans and Zuckerman (2006), is to aggregate direct and indirect constraint to better measure access to structural holes. The gist of their argument is that two connected contacts from different groups are less redundant than two connected contacts from the same group. The Reagans and Zuckerman co-memberships are defined by structural equivalence and cohesion, and so introduce an element of structure beyond the direct contacts used to define direct constraint. For the purposes of this paper, I want to test for independent effects of direct and indirect constraint so I do not combine them in a summary measure.

Indirect constraint on ego measured by average constraint on alters has three properties to note for future research. First, it does not measure total indirect constraint. The total has two components: a component defined by connections within the network around each alter, and a component defined by connections across the networks around each alter. Averaging constraint scores across alters captures the first component plus some unknown portion of the second component (larger portion to the extent that the contacts for one alter are the same for other alters). I am

comfortable focusing on the first component in this paper because returns to brokerage are so concentrated in direct contacts for the managers, bankers, and analysts.

<div align="center">Insert Table A1 about here</div>

A second property to note for future research is that the average-alter measure can be unproductive in describing distant alters. Specifically, where each person in a population can reach every other person by some number of intermediaries, each person is indirectly constrained by N-1 alters (everyone else in the population) and indirect constraint averaged across all alters equals the population average excluding ego. In such a population, as alters further removed are included in alter averages, variance in indirect constraint decreases and the correlation between direct and indirect constraint approaches negative one.

Illustrative results are given in Table A1 for the investment bankers discussed in the text. The first column is the length of the path distance from ego to alters included in the network around ego, the second column is the standard deviation of indirect constraint measured as the average network constraint on ego's alters, and the third column is the correlation between direct and indirect network constraint. The first row is the measure used in the text: Indirect constraint is the average network constraint on ego's direct contacts (alters one step distant from ego). The bottom row corresponds to the longest path distance, which in this population is 5 steps. As the network around ego expands to include more distant alters (down the rows), the indirect-constraint standard deviation decreases and the correlation between direct and indirect constraint approaches negative one. I am comfortable in this paper with alter averaging because indirect constraint is limited to direct contacts and direct contacts are few relative to the number of people in each study population. In other populations, convergence could be an issue to consider. Ceteris paribus, the convergence to negative one will be faster in smaller, more-connected populations.

Third, the average-alter measure of indirect constraint used in this paper should not be confused with counts of indirect contacts. For example, the lack of returns to second-hand brokerage in this paper does not contradict Ahuja's (2000) widely-cited demonstration that innovation is associated with direct and indirect contacts. Ahuja

uses the collaboration network among 107 chemicals firms to predict the number of successful patents filed by each firm annually over a ten-year period. Two firms are connected when they have a collaborative tie such as a joint venture, a technology-sharing agreement, etc. Ahuja (2000:437-439) characterizes each firm's position in the network by three measures: a count of direct contacts (firms with which the focal firm has a collaborative tie), a count of indirect contacts (collaborators with the focal firm's direct contacts; weighted counts of indirect ties are correlated .92 with the simple count), and efficiency (the proportion of a firm's contacts that are nonredundant). Table A2 contains correlations among the criterion patent count, the three network predictors, an interaction between direct and indirect contacts, and firm size measured as the log number of employees (Ahuja, 2000:444). The correlation pattern shows that filing patents is associated with large firms in numerous collaborations (many direct contacts), direct contacts are the dominant component in the interaction term (.99 correlation), and the count of indirect contacts is strongly correlated with efficiency (.86 correlation, firms with disconnected direct contacts have numerous indirect contacts).

<center>Insert Table A2 about here</center>

Conclusions from the Table A2 correlation pattern are twice unaffected by the results reported here on the managers, bankers, and analysts. First, counts of direct and indirect contacts are distinct from network constraint. Counts of direct and indirect contacts measure centrality: Table A2 shows that firms central in the industry collaboration network are more involved in patents. Network constraint is about direct and indirect access to disconnected contacts. On that note, Ahuja uses network efficiency as a measure of access to structural holes among direct contacts. However, my second point here is that efficiency, akin to network density, is one of the three components in network constraint (size, density, and hierarchy). Efficiency is the ratio of nonredundant contacts to total contacts. Efficiency equals 1.0 for a firm with three disconnected contacts. It equals 1.0 for a firm with thirty disconnected contacts. Surely, the second firm has more access to structural holes. Network constraint increases with density and decreases with network size to capture access to structural

holes (constraint on the three-contact firm would be 32.7 points as discussed in the text and constraint on the thirty-contact firm would be a much-lower 3.3 points).

APPENDIX B: MEASURING ANALYST ACCURACY

I follow Phillips and Zuckerman (2001) in measuring the relative accuracy of analysts: the extent to which an analyst's earnings forecasts were more accurate than forecasts by other analysts covering the same company. I use data from the I/B/E/S Detailed History File for each of the two years concluded with an <u>Institutional Investor</u> election, dating each forecast by the point at which its accuracy would be known (e.g., a forecast published in December 1997 about annual earnings as of June 1998 would be assigned to 1998). Analyst forecasts of company earnings per share (EPS) are listed in the I/B/E/S data with actual earnings so the magnitude by which an analyst forecast was wrong for company f can be measured as (cf. Phillips and Zuckerman, 2001:410): $ABSDIF_{ift}$ = | Actual EPS_{ft} – Forecast EPS_{ift} |, which is the absolute difference between the actual annual ESP for firm f in year t and analyst i's forecast of the company's annual ESP. To hold constant differences between the companies covered by different analysts, the following z-score measures accuracy relative to other forecasts on the same company: Z_{ift} = $(MABSDIF_{ft}$ - $ABSDIF_{ift})/SDABSDIF_{ft}$, where $MABSDIF_{ft}$ is the average $ABSDIF_{jft}$ for analysts j forecasting firm f's EPS in year t, and $SDABSDIF_{ft}$ is the standard deviation of their forecasts. To measure analyst i's accuracy during year t, I averaged the Z_{ift} across firms f during year t for analyst i's annual earnings forecasts made within six months of the company announcing its actual earnings. An accuracy z-score of zero indicates an analyst for whom I found no forecasts more or less accurate than forecasts from other analysts covering the same companies. Positive z-scores indicate an analyst for whom I found forecasts closer to actual earnings than the forecasts from other analysts covering the same companies.

I have three notes on the accuracy measure. The first concerns the time interval in which accuracy is measured. Table B1 shows the rate at which forecasts became more accurate closer to a company announcing its actual earnings. The I/B/E/S data

list an average of 141,773 annual-earnings forecasts per year from 1996 through 1999. For each forecast made by any analyst in the two years of the I/B/E/S data under study here, I computed the Z_{ift} accuracy measure described in the text for analyst i forecasting the annual earnings of firm f during year t. I divided the number of days between forecast date and the date of announced earnings by 30 to assign forecasts to a month, distinguished by the rows in Table B1. Forecasts made less than 30 days before announced earnings are in the "Same Month" row at the top of the table. Forecasts made more than 360 days before announced earnings are in the "Eleven or More" row at the bottom of the table. Variation in forecasts (last column) is consistent across the rows, but the center of the distribution, the average analyst forecast, becomes more accurate closer to announced earnings (middle column). Accuracy is highest for forecasts made during the month in which earnings were announced (.65 mean z-score). Accuracy decreases with length of time in longer-range forecasts to a minimum in forecasts made a year before earnings were announced (-.53 mean z-score). The pattern is the same for both of the two years under study here, it is the same for US companies versus companies elsewhere, and there is no tendency for forecasts on US firms to occur earlier or later than forecasts on companies outside the US. Note the shift from below-average to above-average accuracy during the sixth month before announced earnings — which encourages following Phillips and Zuckerman (2001) in measuring analyst accuracy with forecasts made six months before announced earnings, and is the reason for the non-zero mean accuracy in Table 6 (accuracy in the text is based on forecasts six months before announced earnings and the above table shows that forecasts in that interval are above-average accurate). Some analysts tended to make forecasts closer to announced earnings, so they were on average more accurate in their forecasts, which could affect the accuracy association with election recognition. I computed the average time interval between forecast and announced earnings for each analyst, each year (mean is 3.77 months before announced earnings with a standard deviation of 3.29 months), and re-estimated models D and F in Table 5 with average time interval held constant. Election associations with network constraint in models D and F are not affected: Test statistics for election recognition eroded by direct network

constraint are -2.97 and –2.89 in models D and F respectively, and indirect network constraint continues to have no association with election recognition (-0.14 and –0.90 test statistics).

<div align="center">Insert Table B1 about here</div>

A second note concerns averaging across forecasts to characterize an analyst's accuracy. The measure in the text gives equal weight to each company on which an analyst makes forecasts. To consider a more sophisticated alternative, I computed accuracy as an average weighted by company prominence — on the intuition that investors are more likely to notice analyst accuracy in forecasts about more prominent companies. Instead of the simple average in the text ($\Sigma_M Z_{ift}[1/M]$, where M is the number of forecasts being averaged), I computed a weighted average ($\Sigma_M Z_{ift}[RF/RI]$, where RF is the number of forecasts made by any analysts on firm f during year t, and RI is the total number of forecasts made by any analysts on the firms in the M forecasts). For example, imagine an analyst who made two forecasts, one about company A and one about company B, where there were 44 forecasts from other analysts about company A and 4 forecasts from other analysts about company B. The accuracy measure in the text would give equal weight to the analyst's two forecasts (M = 2). The weighted average would give nine times more weight to the analyst's forecast about company A (RF = 45 for company A, RF = 5 for company B, RI = 50 for the analyst). I suspect that analysts make more forecasts about prominent companies, whereupon an unweighted average is self-weighting for company prominence, because the weighted and unweighted measures are correlated .96 for the analysts in this paper, and I obtain the same predictions in Table 5 with either measure. I only report the simpler unweighted measure in the text.

A third note concerns analysts unlisted in the I/B/E/S data. I tried a measure more sophisticated than the simple dummy variable used in the text. The more sophisticated measure treated unlisted analysts as the low end of a continuum that increases with the visibility of the companies on which an analyst made forecasts. Let N_{ft} be the number of forecasts in the I/B/E/S data predicting the annual earnings of firm f during year t. Let N(i) be the average of N_{ft} for firms f on which there was a record in the I/B/E/S data of a forecast on firm f from analyst i during year t. N(i) equals zero for

unlisted analysts. It increases above zero as analyst i covers companies on which many analysts publish many forecasts. The more forecasts made about the companies an analyst covers, the more visible the analyst's companies in the sense of warranting the attention that went into the many forecasts. I added $N(i)$ to model F in place of the dummy variable at the bottom of Table 5 and obtained exactly the same results reported in Table 5: analysts who covered more visible companies were more likely to be elected to the All-America Research Team and there were no election associations with accuracy or indirect network constraint. However, if I re-estimate the models for only the analysts located in the I/B/E/S data, or if I return the dummy variable distinguishing unlisted analysts, there is no election association with analyst differences in the visibility of the companies they covered. Test statistics for model F in Table 5 are 0.95 for $N(i)$ and 2.73 for the dummy variable at the bottom of the table distinguishing unlisted analysts, versus 2.69 for $N(i)$ when the dummy variable is not included in the model. In short, the aspect of the more sophisticated measure that is associated with election recognition is the aspect captured by the dummy variable in the text distinguishing analysts who could not be matched to forecasts in the I/B/E/S data.

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AUTHOR BIOGRAPHICAL SKETCH

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TABLE 1. Predicting Manager Performance[a]

	Annual Salary	Annual Evaluation	
		A	B
Intercept	-.589	1.582	-5.084
			-2.637
Direct Network Constraint	-.170 (.049) **	-.331 (.113) *	-.709 (.246) *
Indirect Network Constraint	-.083 (.052)	.087 (.120)	.216 (.254)
Job Rank	.549 (.020) **	.193 (.046) **	.369 (.102) **
Age	.009 (.003) **	-.022 (.006) **	-.041 (.013) *
College Degree	.019 (.049)	.139 (.113)	.087 (.239)
Graduate Degree	.010 (.047)	-.063 (.108)	.119 (.235)
Minority	-.048 (.042)	.234 (.096) *	.455 (.208) *
High-Tech Businesses	.092 (.045) *	-.052 (.102)	-.158 (.222)
Low-Tech Business	-.218 (.075) *	-.205 (.173)	-.459 (.374)
Regional HQ	.198 (.061) *	.193 (.141)	.355 (.302)
Corporate HQ	.300 (.056) **	-.105 (.127)	-.101 (.279)

[a]The two performance variables are measured as z-scores and plotted in Figure 4. For 455 supply-chain managers, the first two models respectively predict annual salary and annual performance evaluation (.85 and .19 squared multiple correlations). The third column is an ordinal logit model predicting the three categories of annual evaluation and the two intercepts are the cut points between the three categories (74.8 chi-square with 11 d.f., P < .001). Network constraint is the log of constraint. Standard errors are given in parentheses.

* p < .05

** p ≤ .001

TABLE 2.
Correlations for Supply-Chain Managers[a]

	Mean	Standard Deviation													
Direct Network Constraint	4.03	.47	—												
Indirect Network Constraint	3.89	.40	.23	—											
Salary	.00	1.00	-.57	-.39	—										
Annual Evaluation	.00	1.00	-.30	-.11	.34	—									
Job Rank	1.95	1.42	-.58	-.41	.90	.34	—								
Age	49.17	7.33	-.06	-.08	.15	-.14	.10	—							
College Degree	.67	.47	-.25	-.22	.42	.18	.46	.00	—						
Graduate Degree	.31	.46	-.20	-.19	.32	.09	.35	-.10	.09	—					
Minority	.36	.48	.12	.01	-.17	.07	-.17	-.10	-.22	-.10	—				
High-Tech Businesses	.32	.47	.03	-.04	.09	.02	.01	.00	.06	-.03	.06	—			
Low-Tech Business	.07	.26	.03	.03	-.13	-.08	-.07	.02	-.03	.08	.06	-.19	—		
Regional HQ	.15	.36	-.11	-.10	.18	.15	.13	.03	-.03	-.02	.25	.36	-.09	—	
Corporate HQ	.17	.37	-.11	-.03	.34	.05	.30	-.06	.18	.08	-.13	.07	.02	-.19	—

[a]Correlations are computed across 455 survey respondents. Network constraint is the log of constraint. The two performance variables are measured as z-scores.

TABLE 3.
Predicting Banker Compensation[a]

	A	B	C
Intercept	-1.63	-1.92	-1.41
Direct Network Constraint	-.38 (.09) **	—	-.32 (.09) **
Indirect Network Constraint	—	-.39 (.106) **	-.18 (.12)
Senior Job Rank	.73 (.08) **	.79 (.086) **	.73 (.08) **
Peer Evaluation	.51 (.09) **	.58 (.100) **	.51 (.09) **
Years with Firm	.02 (.01)	.03 (.012) *	.02 (.01)
Minority	-.05 (.19)	-.14 (.187)	-.07 (.19)
US Headquarters	.28 (.11) *	.23 (.106) *	.27 (.11) *

[a]Regression coefficients are presented for bankers observed in three annual panels (469 observations). Compensation next year is predicted from row variables this year. Network constraint is the log of constraint. Annual compensation includes salary and bonus. Compensation is measured as a z-score within each year to indicate a banker's relative annual compensation. Squared multiple correlations for the three equations are .31, .28, and .31. Standard errors, given in parentheses, are adjusted for autocorrelation within individuals across years.

* $p < .05$

** $p \leq .001$

TABLE 4.
Correlations for Bankers[a]

	Mean	Standard Deviation								
Direct Network Constraint	2.18	.63	—							
Indirect Network Constraint	2.06	.43	.46	—						
Annual Compensation	.00	1.00	-.35	-.20	—					
Senior Job Rank	.81	.40	-.14	-.04	.32	—				
Peer Evaluation	3.05	.52	-.19	-.07	.29	-.12	—			
Seniority	8.67	6.56	-.19	-.03	.26	.17	.07	—		
Minority	.14	.34	.13	-.04	-.05	-.07	.02	-.06	—	
US Headquarters	.58	.49	.07	-.02	.16	.06	.01	.16	.16	—

[a]Correlations are computed across bankers observed in three annual panels (469 observations). Network constraint is the log of constraint. Annual compensation includes salary and bonus. Compensation is measured as a z-score within each year to indicate a banker's relative annual compensation.

TABLE 5. Predicting Analyst Election to the Institutional Investor All-America Research Team[a]

	A	B	C	D	E	F
Intercept	—	—	—	—	-.67	—
Direct Network Constraint	-1.70 (.44) **	—	-1.54 (.45) **	-1.50 (.45) **	-.30 (.07) **	-1.42 (.45) **
Indirect Network Constraint	—	-1.96 (.73) *	-2.37 (1.04) *	-1.66 (1.03)	-.18 (.11)	.17 (.71)
Senior Job Rank	-.15 (.96)	-.00 (.90)	-.26 (.88)	-.36 (.94)	-.06 (.21)	-.90 (1.04)
Peer Evaluation	2.42 (.92) *	3.00 (.87) **	1.85 (.86) *	2.49 (.94) *	.45 (.18) *	2.55 (.98) *
Years with Firm	-.01 (.03)	-.01 (.03)	-.02 (.03)	-.02 (.03)	-.01 (.01)	.01 (.03)
Minority	.46 (.49)	.18 (.52)	.32 (.50)	.33 (.52)	.14 (.19)	.25 (.58)
US Headquarters	-.14 (.56)	.05 (.64)	.00 (.56)	.01 (.57)	-.07 (.34)	.48 (.68)
Office in the US	3.11 (1.15) *	2.84 (1.24) *	2.02 (1.24)	2.31 (1.26)	.44 (.33)	2.99 (1.25)
Forecast Accuracy	2.01 (.64) *	1.75 (.58) *	—	1.60 (.61) *	.32 (.13) *	-.15 (.63)
In the I/B/E/S Data	—	—	—	—	—	2.96 (.77) **

[a]Regression coefficients are presented for annual data pooled across two years (351 observations). Election this year is predicted from the two forecast variables for this year (bottom two rows) and the other row variables for last year. Network constraint is the log of constraint. Models A, B, C, D, and F are ordinal logit regressions predicting an analyst's highest rating for the year (4 for first team, 3 for second, 2 for third, 1 for runner-up, 0 for not being named; chi-square statistics of 45.76, 45.72, 39.80, 40.52, and 46.28 with 8, 8, 8, 9, and 10 d.f.). Model E is a least-squares regression predicting the numerical value of the five rating categories expressed as a z-score for the year (.23 squared multiple correlation; zero-order correlations in Table 6). Standard errors, given in parentheses, are adjusted for autocorrelation within individuals across years.

* p < .05

** p ≤ .001

TABLE 6.
Correlations for Analysts[a]

	Mean	Standard Deviation											
Direct Network Constraint	2.11	.70	—										
Indirect Network Constraint	1.75	.48	.55	—									
All-America Team	.00	1.00	-.35	-.30	—								
Senior Job Rank	.90	.31	-.21	-.17	.05	—							
Peer Evaluation	3.06	.35	-.27	-.13	.30	.07	—						
Seniority	7.31	6.69	-.21	-.17	.08	.01	.07	—					
Minority	.20	.40	-.02	-.13	.10	.08	-.04	-.02	—				
US Headquarters	.57	.50	-.21	-.25	.27	-.09	.34	.33	.16	—			
Office in the US	.61	.49	-.26	-.30	.33	-.06	.45	.32	.18	.89	—		
Forecast Accuracy	.25	.39	-.13	-.21	.16	.06	-.05	-.03	.04	-.05	-.02	—	
In I/B/E/S Data	.60	.49	-.20	-.24	.26	.14	-.17	-.17	.06	-.29	-.24	.53	—

[a]Correlations are computed across analysts observed in two annual panels (351 observations). Network constraint is the log of constraint. The performance variable, election to the All-America Research Team, is for each year an analyst's highest rating from Institutional Investor (4 for election to first team, 3 for second team, 2 for third team, 1 for runner-up, 0 for not being named). To preserve confidentiality and relative performance during each year, the performance variable is here measured as a z-score for each year (criterion variable for model E in Table 5).
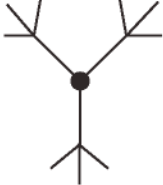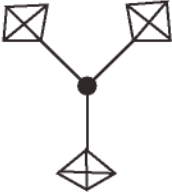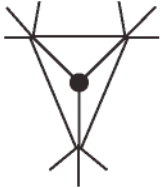
TABLE 7. Average Returns to Direct and Second-Hand Brokerage

Network Brokerage Category	Constraint[a] Direct, Indirect	Study Population	Mean Z-Score Performance[b]	Test Statistic[c]
Direct and Second-Hand	Low, Low	Managers	.52	8.02 **
		Bankers	.38	4.31 **
		Analysts	.39	3.76 **
Direct Only	Low, High	Managers	.09	3.95 **
		Bankers	.25	3.68 **
		Analysts	.01	2.53 *
Second-Hand Only	High, Low	Managers	-.28	.96
		Bankers	-.23	1.22
		Analysts	-.21	1.38
Closed Network	High, High	Managers	-.40	-4.90 **
		Bankers	-.34	-5.01 **
		Analysts	-.40	-3.35 *

[a]Network constraint is dichotomized at its median level within each study population.

[b]This is z-score residual performance after holding constant all but the two network predictors in Tables 1, 3, and 5.

[c]Results from z-score residual performance regressed across rows. "Closed Network" is the reference category.

* $p < .05$ ** $p \le .001$

TABLE 8.
Brokerage Next Year Can Develop
from Second-Hand Brokerage This Year[a]

	Analysts	**Bankers**
Intercept	.21	.67
Direct Network Constraint this Year	.63 (.05) **	.76 (.08) **
Indirect Network Constraint this Year	.34 (.10) **	-.02 (.12)

[a]Direct network constraint next year is predicted by row measures of this year's network. Variables are log scores as in Tables 3 and 5. There is one observation per analyst, two per banker. Squared multiple correlation is .61 for the analysts, .42 for the bankers. Standard errors, given in parentheses, are adjusted for repeated observations of each banker.

 * $p < .05$

 ** $p \leq .001$

TABLE A1.
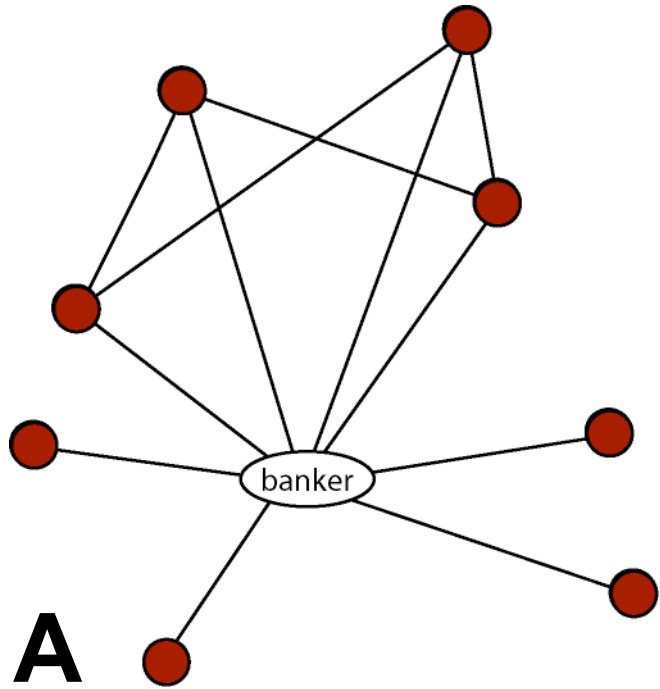## Average Constraint on Increasingly Distant Alters

Maximum Path Distance to Averaged Alters	Standard Deviation in Indirect Constraint	Correlation between Direct and Indirect Constraint
1	4.68	.31
2	1.51	-.09
3	.92	-.52
4	.25	-.76
5	.11	-1.00

TABLE A2.
Patent Correlations with Direct and Indirect Contacts

Patents	—					
Direct Contacts	.30	—				
Indirect Contacts	.11	.28	—			
Direct x Indirect	.31	.99	.35	—		
Efficiency	.14	.31	.86	.33	—	
Firm Size	.66	.39	.18	.23	.10	—

TABLE B1.
Analyst Accuracy by Time between Forecast and Announced Earnings

Months Between Earnings Forecast and Announced	Z-Score Accuracy (mean Z_{ift})	Z-Score Accuracy (sd Z_{ift})
Same Month	.65	1.00
One	.54	.94
Two	.47	.88
Three	.40	.82
Four	.28	.83
Five	.12	.82
Six	.05	.82
Seven	-.08	.86
Eight	-.23	.89
Nine	-.34	.90
Ten	-.43	.95
Eleven or More	-.53	.99

A

direct contacts 8
indirect contacts ignored
network constraint 23
network betweenness 82

B
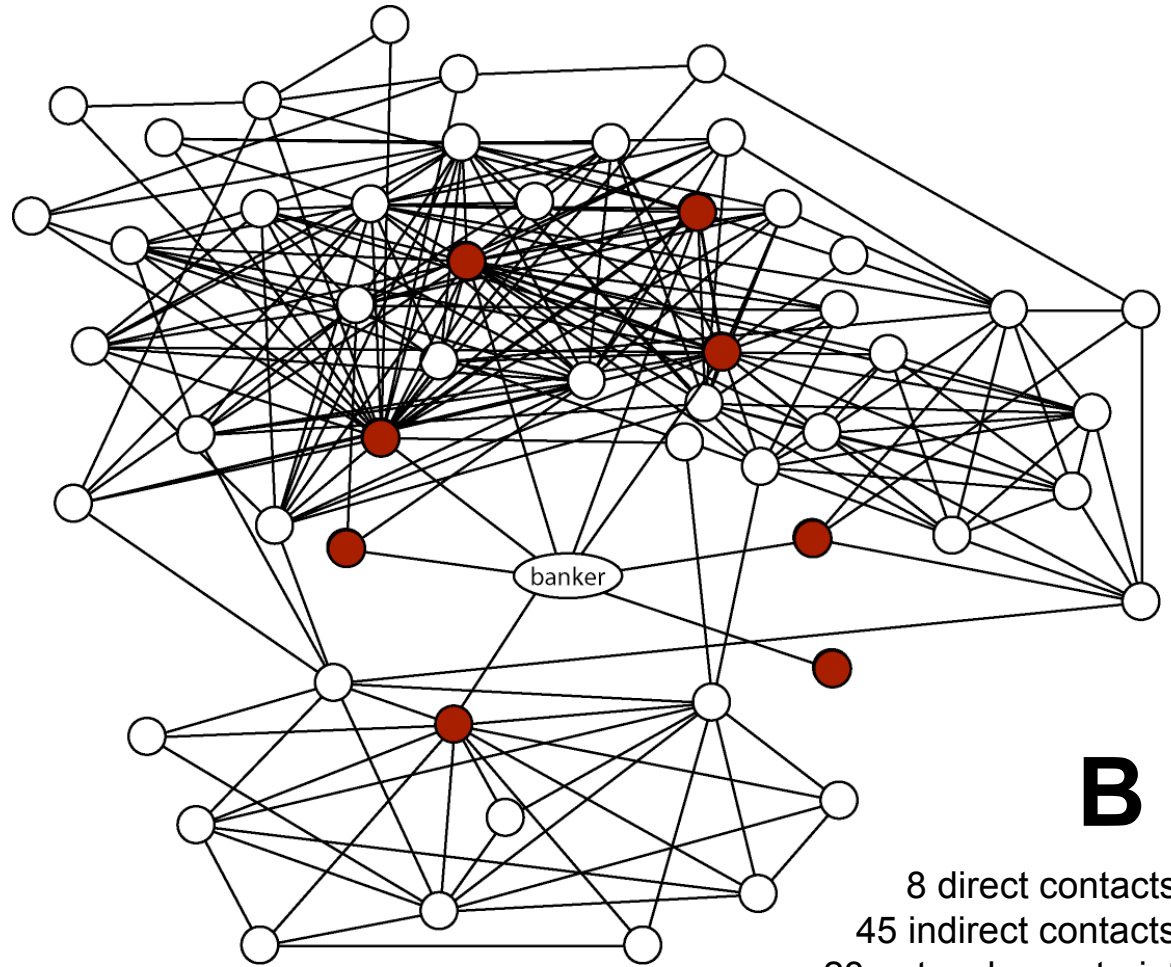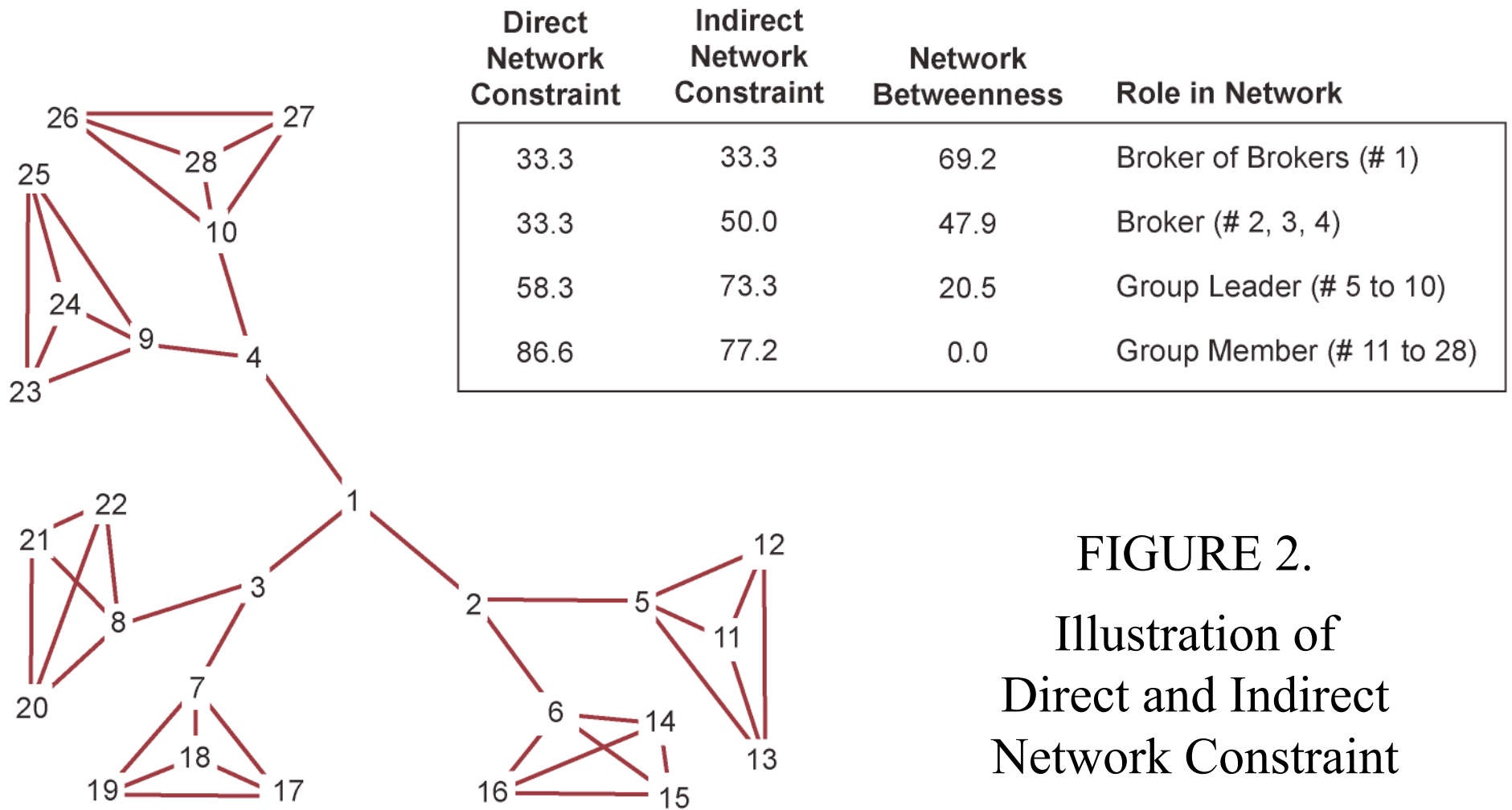
8 direct contacts
45 indirect contacts
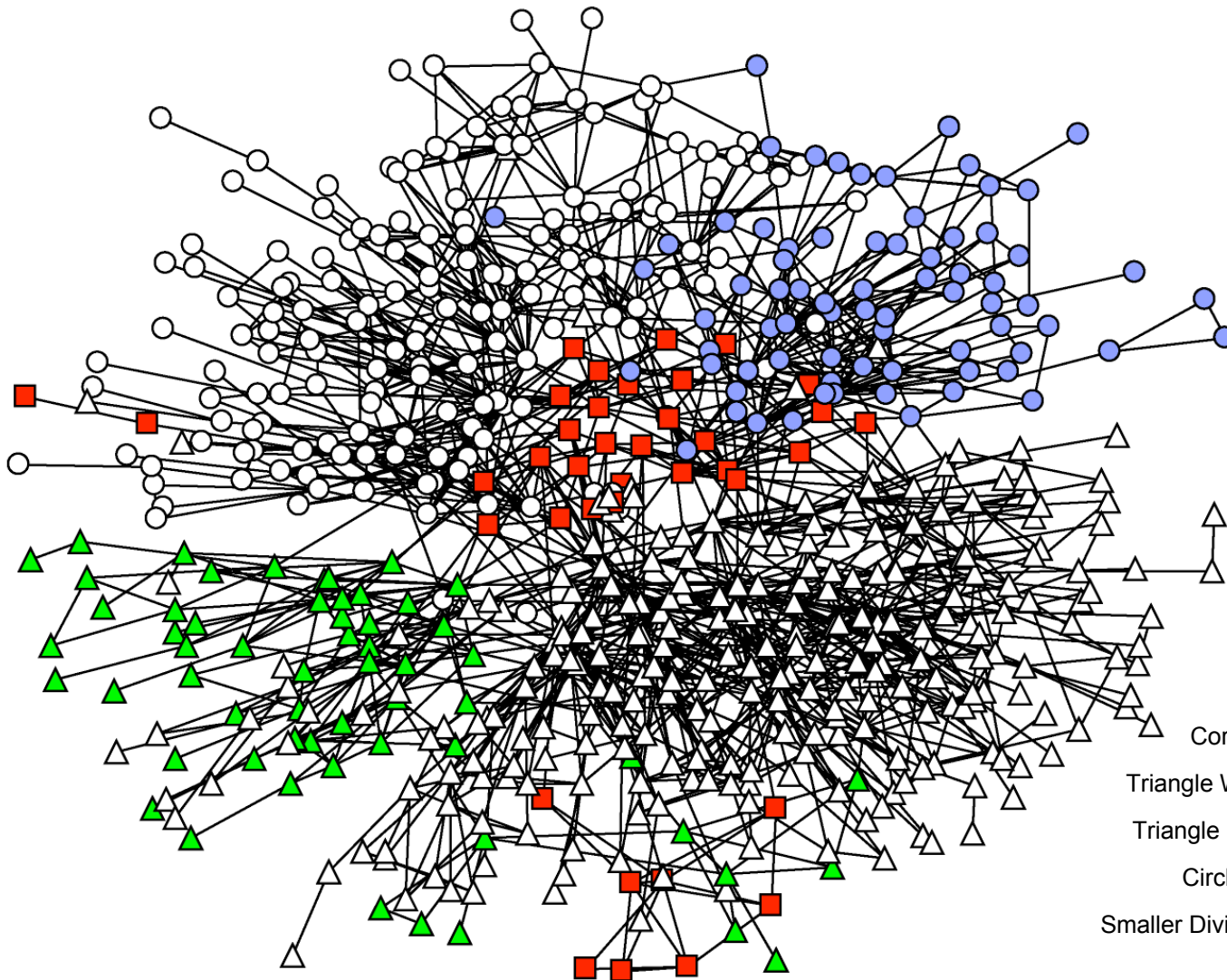23 network constraint
15 network betweenness

FIGURE 1.

Direct and Indirect Contacts around an Investment Banker

Solid dots are direct contacts. Hollow dots are indirect contacts.

Direct Network Constraint	Indirect Network Constraint	Network Betweenness	Role in Network
33.3	33.3	69.2	Broker of Brokers (# 1)
33.3	50.0	47.9	Broker (# 2, 3, 4)
58.3	73.3	20.5	Group Leader (# 5 to 10)
86.6	77.2	0.0	Group Member (# 11 to 28)

FIGURE 2.

Illustration of Direct and Indirect Network Constraint

Lines connect managers who often discuss their work with one another.

Triangles indicate managers in the largest division. Solid ones indicate individuals working in a geographically segregated subdivsion.

White circles are managers in the second largest division. Solid ones indicate managers working in two smaller divisions.

Squares indicate managers at corporate headquarters.

Corp HQ	55%	18%	3%	13%	11%
Triangle W-Div	3%	92%	1%	2%	2%
Triangle S-Div	2%	6%	91%	1%	0%
Circle Div	5%	3%	1%	89%	2%
Smaller Divisions	5%	4%	0%	3%	88%

FIGURE 3. Sociogram of Manager Discussion Network

Table shows percent of sociometric citations from people in the row that go to people in the column.
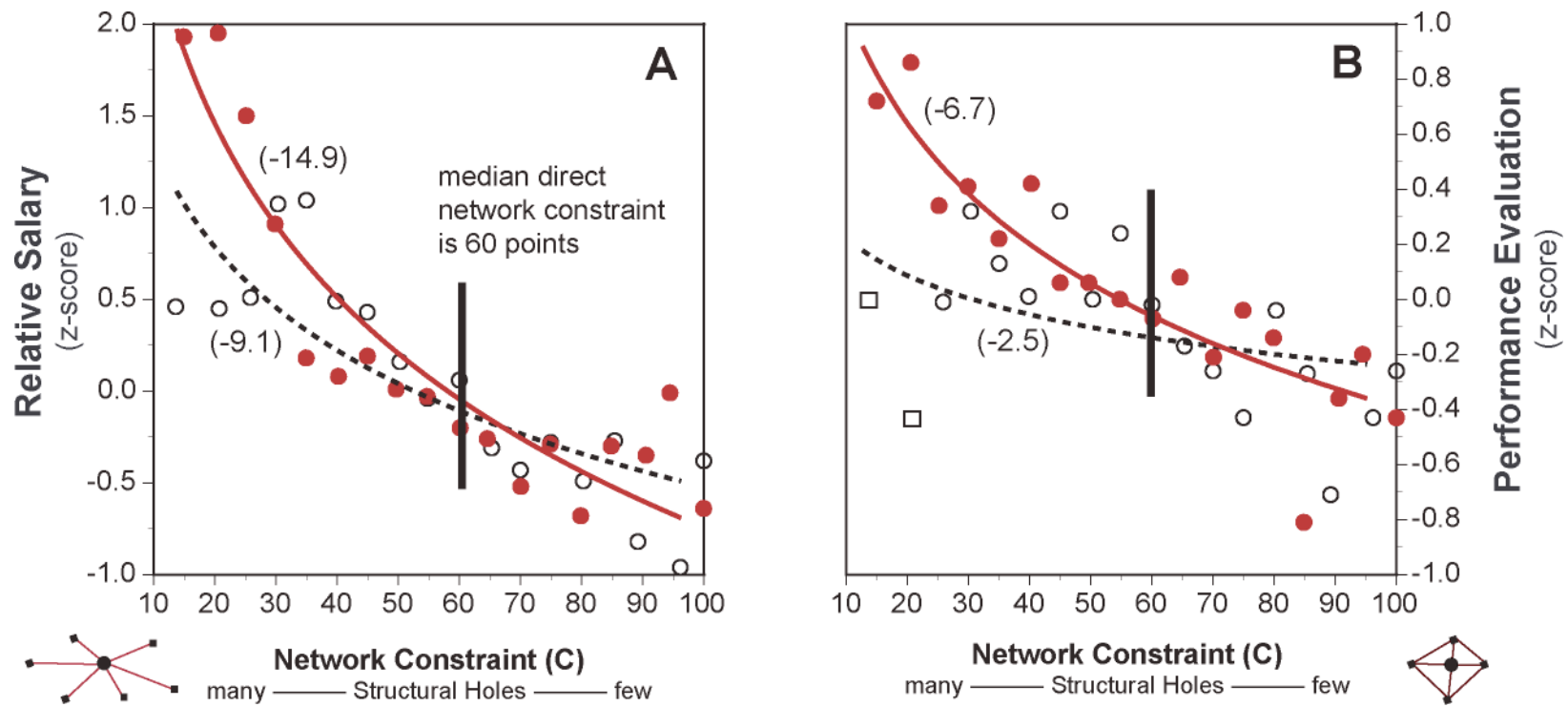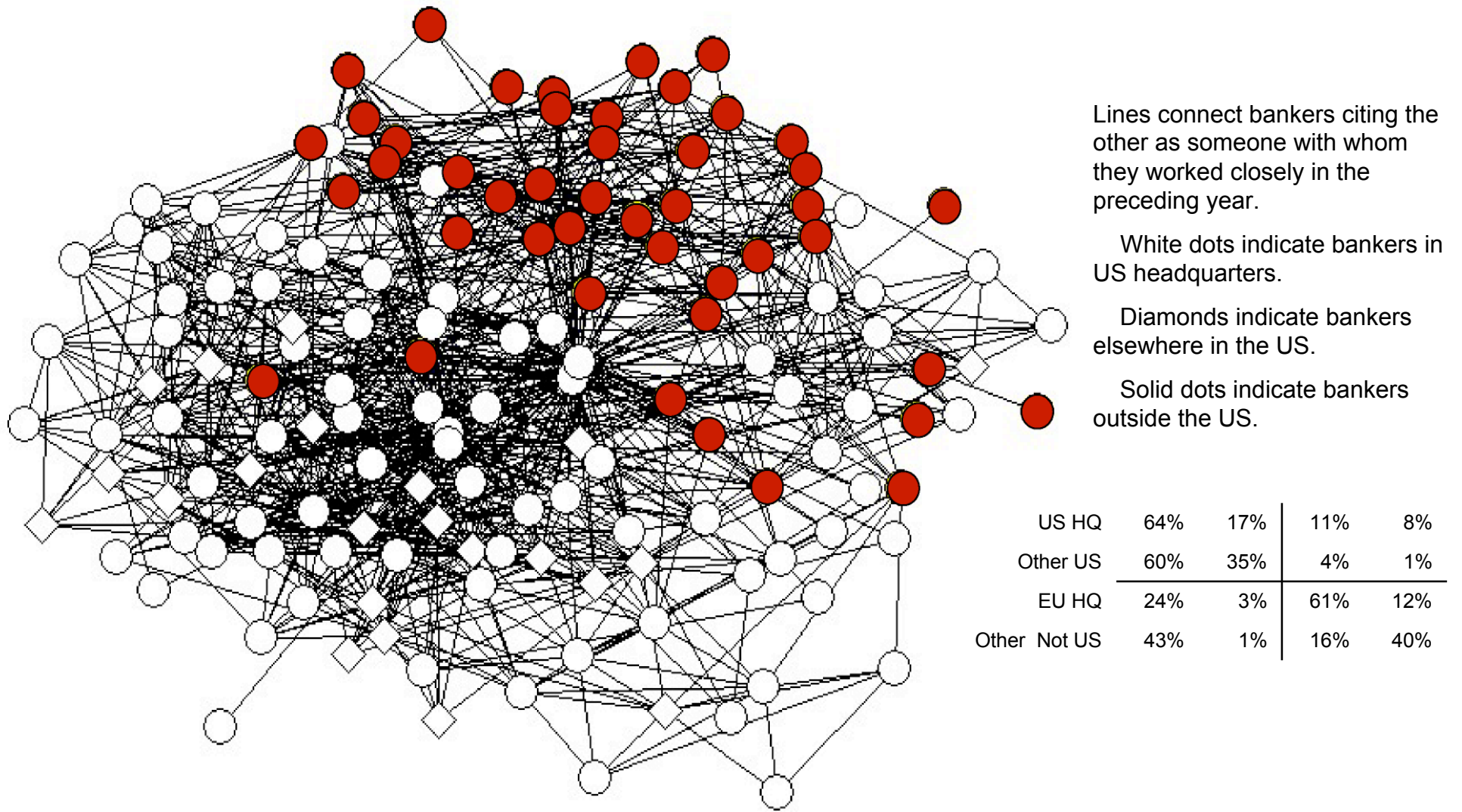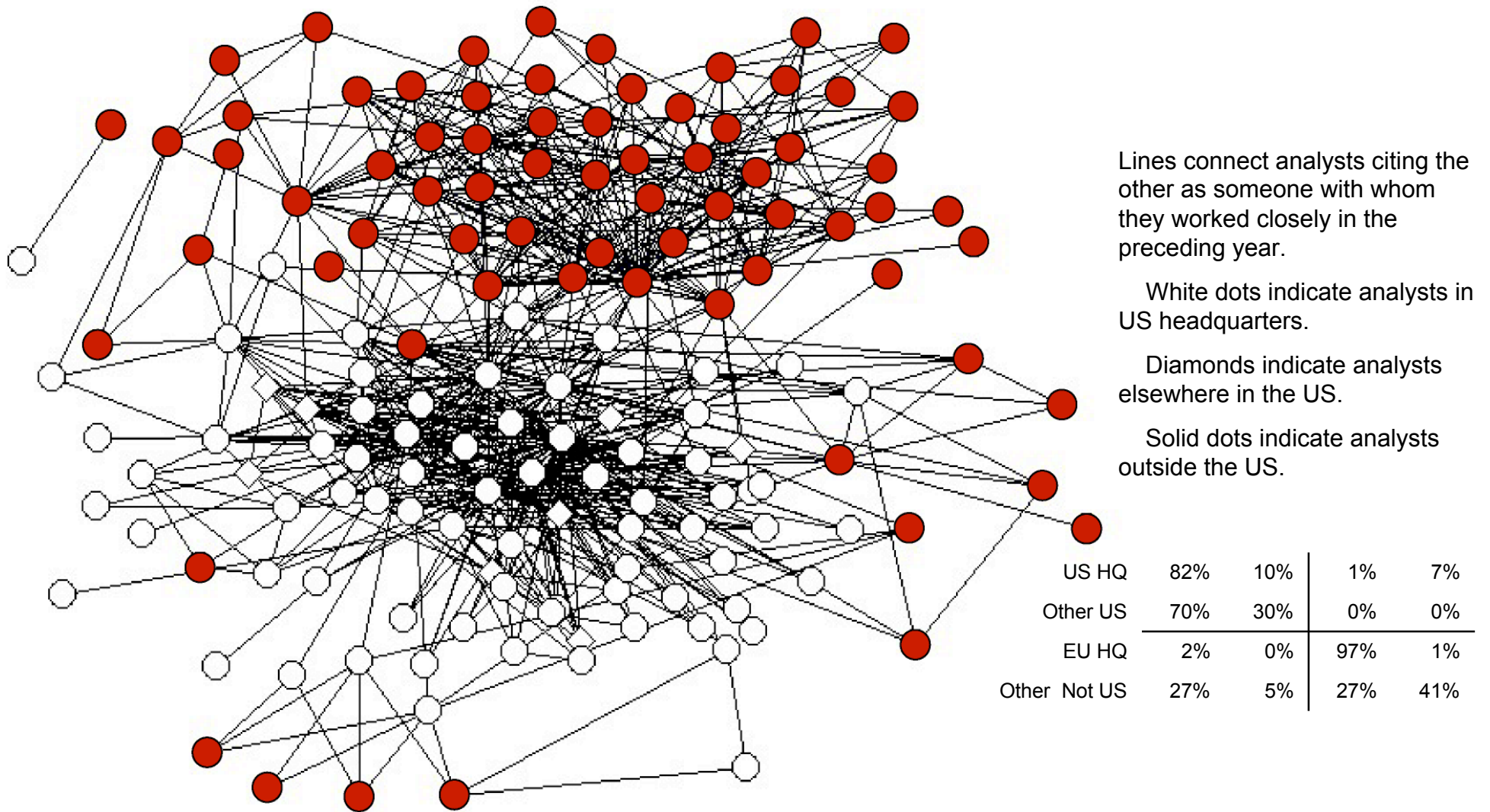
FIGURE 4.

Manager Performance and Network Constraint

Constraint scores are pooled for 5-point intervals on horizontal axis. Solid symbols and line indicate performance at levels of direct constraint. Hollow symbols and dashed line indicate performance at levels of indirect constraint. Parentheses contain t-test statistics for association across 455 managers.

Lines connect bankers citing the other as someone with whom they worked closely in the preceding year.

White dots indicate bankers in US headquarters.

Diamonds indicate bankers elsewhere in the US.

Solid dots indicate bankers outside the US.

US HQ	64%	17%	11%	8%
Other US	60%	35%	4%	1%
EU HQ	24%	3%	61%	12%
Other Not US	43%	1%	16%	40%

FIGURE 5. Sociogram of Banker Colleague Network

Tables show percent of sociometric citations from people in the row that go to people in the column.

Lines connect analysts citing the other as someone with whom they worked closely in the preceding year.

White dots indicate analysts in US headquarters.

Diamonds indicate analysts elsewhere in the US.

Solid dots indicate analysts outside the US.

US HQ	82%	10%	1%	7%
Other US	70%	30%	0%	0%
EU HQ	2%	0%	97%	1%
Other Not US	27%	5%	27%	41%

FIGURE 6. Sociogram of Analyst Colleague Network

Tables show percent of sociometric citations from people in the row that go to people in the column.

FIGURE 7.
Gamma Lines for Decreasing Returns to Brokerage