SOCIAL NETWORK ANALYSIS:
FOUNDATIONS AND FRONTIERS ON ADVANTAGE

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ABSTRACT

We provide an overview of social network analysis focusing on network advantage as a lens that touches on much of the area. For reasons of good data and abundant research, we draw heavily on studies of people in organizations. Advantage is traced to network structure as a proxy for the distribution of variably sticky information in a population. The network around a person indicates the person's access and control in the distribution. Advantage is a function of information breadth, timing, and arbitrage. Advantage is manifest in higher odds of proposing good ideas, more positive evaluations and recognition, higher compensation, and faster promotions. We discuss frontiers of advantage contingent on personality, cognition, embeddedness, and dynamics.

INTRODUCTION

Through the last decade, social network analysis (SNA) has experienced a golden age of rapid growth in participants, significant developments, and productive expansion into new substantive areas. Another such age occurred in the 1970s, still another in the 1950s, during the broader golden age of social psychology. In fact, much of contemporary SNA builds on foundations established in that golden age of social psychology. Recent academic growth in SNA can be attributed in part to expanded computing and communication technology that creates detailed network data and machines with which to process the data. Growth is also a function of contemporary participation in social networks, though conclusions vary on practical implications: People accumulate hundreds of friends and acquaintances through social media (Rainie et al. 2011), but social and community engagement seems to be declining outside the ranks of affluent young white people (Putnam 2000) and people report

fewer friends in whom they can confide than was the case even a decade earlier (McPherson et al. 2006). Before the advent of social network media, people were able to connect with complete strangers through about five intermediaries (Travers & Milgram 1969, Watts 1999), but it seems that email users still require five to seven intermediaries to reach target persons by forwarding messages through acquaintances (Dodds et al. 2003).

One chapter is insufficient to cover the many developments in SNA; in fact, we know of no textbook treatment that provides general coverage. We focus on an area of SNA in which there has been significant progress related to social psychology, bringing in as we have space related developments in argument, methodology, and evidence. We cover a wide diversity of topics, but our focus is network advantage.[1] We draw extensively from research on people in organizations because of the abundant data and results available. Our setting is a person, ego, surrounded by a network of contacts, typically within a broader market or organization (i.e. the "ego-network" -- Wellman 1993). This structure was initially described by Jacob Moreno, the father of American network analysis, as the "social atom," the smallest unit of social structure in a community (Moreno 1934, pp. 141ff.). Our focus in this chapter is how ego gains advantage from the network around her. Network forms associated with advantage constitute social capital (Coleman 1988, Burt 1992, Portes 1998, Putnam 2000, Lin 2002, Burt 2005), but we put aside the social capital abstraction to speak simply in terms of advantage. The gist of our story is that network structure can be studied as a proxy for the distribution of variably sticky information in a population, the network around ego indicates her advantaged or disadvantaged access and control in the distribution, and ego acting on her advantage is rewarded with recognition, compensation, and promotion for her work moving otherwise unknown or misunderstood information to places where it has value. We begin with information foundations; turn to argument and evidence on advantage, then close with research frontiers.

FOUNDATIONS

Network models of advantage use structure as an indicator of how information is distributed in a system of people. The models build on two facts established in social psychology during the 1940s and 1950s (e.g., Festinger et al. 1950, Katz & Lazarsfeld 1955): (1) people cluster into groups as a result of interaction opportunities defined by the places where people meet; and (2) communication is more frequent and influential within than between groups such that people in the same group develop similar views. People tire of repeating arguments and stories explaining why they believe and behave the way they do. Within a group, people create systems of phrasing, opinions, symbols and behaviors defining what it means to be a member. Beneath the familiar arguments and experiences are new, emerging arguments and experiences awaiting labeling, the emerging items more understood than said within the group. What was once explicit knowledge interpretable by anyone becomes tacit knowledge meaningful only to insiders. With continued time together, information in the group becomes "sticky" – difficult to move to other groups (Von Hippel 1994). Much of what we know is not easily understood beyond the colleagues around us. Explicit knowledge converted into local, tacit knowledge makes information sticky such that holes tear open in the flow of information between groups. These holes in the social structure of communication, or more simply "structural holes" (Burt 1992), are missing relations that inhibit information flow between people.

Figure 1 illustrates the resulting network image as a "sociogram" (Moreno 1934) of individuals variably connected as a function of prior contact, exchange, and attendant emotions. Lines indicate where information flows more routinely, or more clearly, between people represented by the dots. Solid (dashed) lines indicate strong (weak) flow. Figure 1 is adapted from (Burt 2005, p. 14) where discussion of the figure can be found in more breadth and detail. The defining feature in Figure 1 is clusters demarked by line density greater within clusters than between clusters. Within a cluster, people share certain explicit and implicit understandings, which constitute the knowledge sticky to their cluster. Empty space between clusters in Figure 1 indicates a structural hole. The structural hole between two groups need not mean that people

in the groups are unaware of one another. It means only that the people focus on their own activities over the activities of people in the other group. A structural hole is a buffer, like an insulator in an electric circuit. People on either side of the hole circulate in different flows of information. When significant differences in understanding occur, they are more likely between people in separate clusters than between people in the same cluster. The value-potential of the structural holes is that they define nonredundant sources of information, sources that are more additive than overlapping.

——— Figure 1 About Here ———

An attractive feature of the network-information link is that network models of advantage are easy to move across levels of analysis. The people in Figure 1 cluster into groups, but the clusters themselves cluster into three macro clusters — one to the northwest, one to the northeast, and one to the southeast. The three macro clusters could be organizations, each containing groups of people coordinated around a central cluster of senior people (indicated by dense areas toward the center of Figure 1). Or, the dots in Figure 1 could be organizations. The three macro clusters then would be markets, or "institutional fields" in which individual organizations cluster in market niches around a central cluster of typical organizations (Powell et al. 2012). The dots in Figure 1 could just as well be communities. The three broad clusters then would be geographic regions in which individual cities are variably linked as satellites around three hub cities (e.g., Eagle et al. 2010). Our focus is on individual people but the network mechanisms to be described generalize across levels of analysis.

BROKERAGE, CREATIVITY, AND ACHIEVEMENT

People can play either of two roles in Figure 1: specialize within a cluster (closure) or build bridges between clusters (brokerage). Closure is about strengthening connections to gain advantage by getting better at what we already know. Brokerage is about connecting across clusters to engage diverse information. Several network concepts emerged in the 1970s on the advantages of bridges: Granovetter on weak ties (when they are bridges across clusters), Freeman on network centrality as a

function of being the connection between otherwise disconnected people, Cook and Emerson on the advantage of having alternative exchange partners, Burt on the advantage of disconnected contacts, later discussed as access to structural holes, and Lin on the advantage of distant, prestigious contacts, later elaborated in terms of having contacts in statuses diverse and prominent. Application of these models to predict performance differences in representative cross-sections of managers began in earnest in the 1980s and 1990s, encouraged by earlier images of boundary-spanning personnel (reviews in footnote 1).

Robert and James in Figure 1 illustrate the difference provided by connections across clusters. The two men have the same number of contacts, six strong ties and one weak tie, but different structures surround them. James is connected to people within group B, and through them to friends of friends all within group B. Like James, Robert is tied through friends of friends to everyone within group B. In addition, Robert's link with contact 7 is a network bridge connection for information from group A, and his link with 6 is a bridge for information from group C.

Relative to James, Robert is advantaged three ways by his network: information breadth, timing, and arbitrage. With respect to breadth, Robert's bridge relations give him access to less redundant information. With respect to timing, Robert is positioned at a crossroads in the flow of information between groups, so he will be early to learn about activities in the three groups, and often be the person introducing to one group information on another. Robert is what early diffusion research identified as an opinion leader, a person responsible for the spread of new ideas and behaviors (Katz & Lazarsfeld 1955, on opinion leaders; Burt 1999, on opinion-leaders as network brokers). Third, Robert is more likely to know when it would be rewarding to bring together separate groups, which gives him disproportionate say in whose interests are served when the contacts come together. More, the structural holes between his contacts mean that he can broker communication while displaying different beliefs and identities to each contact. Robert's connections across social clusters give him an advantage in translating opinion and behavior familiar in one group into the dialect of a target group. People who connect across structural holes are presented with

opportunities to coordinate people otherwise disconnected, which puts them in a position to derive ideas or resources from exposure to contacts who differ in opinion or practice. Thus, a structural hole is a potentially valuable context for action, brokerage is the action of coordinating across the hole with bridge connections between people on opposite sides of the hole, and network entrepreneurs, or more simply, brokers, are the people who build the bridges. Network brokers operate somewhere between the force of corporate authority and the dexterity of markets, building bridges between disconnected parts of markets and organizations where it is valuable to do so. Relations with contacts in otherwise disconnected groups provide a competitive advantage in detecting and developing rewarding opportunities.

Distinguishing Network Brokers

Figure 2 illustrates metrics that distinguish the brokers in a network. The computations are simple, typically described in introductory works, and SNA software is readily available (see footnote 1). Ego's contacts are indicated by grey circles in Figure 2. Lines indicate connections between contacts (here a simple 0,1 binary measure, but the measures all easily handle continuous measures of connection strength). To keep the sociograms simple, ego's relations with each contact are not presented.

——— Figure 2 About Here ———

A network is closed to the extent it is small (providing few contacts that could be separated by a structural hole) and the contacts in it are interconnected (indicating that the contacts are already coordinating with each other). In Figure 2, network size (also discussed as "degree" in graph theory) increases down the figure, from networks of three contacts at the top to networks of ten at the bottom. Connectivity between contacts increases from left to right, from networks at the left in which none of ego's contacts are connected (labeled "broker networks"), to the networks on the right in which all of ego's contacts are connected (labeled "clique networks"). Network density is the average strength of connection between ego's contacts, which in Figure 2 is the number of connections divided by the number possible. Density is zero for all

networks in the left column, where no contact is connected with others, and 100 for all networks in the right column, where every contact is connected with every other.

A second way contacts can be connected so as to close the network around ego, is by mutual connection with a central figure other than ego. This is illustrated by the "partner networks" in the middle column of Figure 2. Partner networks are a substantively significant kind of closure useful in detecting diversity problems in a population (discussed below). The middle column networks in Figure 2 are characterized by no connections between contacts except for all being connected with contact A. The networks are centralized around A, making contact A ego's "partner" in the network. This kind of network is detected with an inequality measure, such as the Coleman-Theil disorder measure in the third row of each panel in Figure 2 (Burt 1992, pp. 70-71). Hierarchy varies with the extent to which connections among ego's contacts are all with one contact. There is zero hierarchy when contacts are all disconnected from one another (first column in Figure 2) or all connected with each other (third column). Hierarchy scores are only non-zero in the middle column. As ego's network gets larger, the partner's central role in the network becomes more obvious and hierarchy scores increase (from 7 for the three-person network, to 25 for the five-person network, and 50 for the ten-person network).

The graph in Figure 2 provides a sense of the population distributions from which manager networks are sampled. The graph plots hierarchy scores by density scores for two thousand manager networks in six management populations. The populations, analyzed in detail elsewhere (Burt 2010), include stock analysts, investment bankers, and managers across functions in Asia, Europe, and North America. The large, open networks of brokers are in the lower left of the graph, low in density and low in hierarchy. Closure can involve simultaneous hierarchy and density, but the extremes of either exclude the other. To the lower right are clique networks, in which there is no hierarchy because all contacts are strongly connected with each other. To the upper left are partner networks, in which density is below 50% because there are no connections between contacts other than their mutual strong connection with ego's partner.

Network constraint is a summary index of closure around ego. Intuitively the percent of ego's network time and energy consumed by one group, constraint decreases with extent to which ego has many contacts (size), increases with the extent to which ego's network is closed by strong connections among ego's contacts (density), and increases with the extent to which ego's network is closed by a partner strongly connected with all of ego's contacts (hierarchy). The equation for network constraint is displayed and illustrated in the Robert-James insert box in Figure 1.[2] A maximum constraint score of 100 indicates no access to structural holes (ego had no friends, or all of ego's friends were friends with one another). Across the networks in Figure 2, network constraint increases from left to right with closure by hierarchy or density (e.g., 20 points for the five-person disconnected network versus 65 points for the five-person clique network), and decreases from top to bottom with increasing network size (e.g., 93 points for the three-person clique network versus 10 points for the ten-person clique network).

Figure 2 includes two additional metrics often used to distinguish network brokers. "Nonredundant contacts" is a count of ego's contacts discounting contacts redundant with ego's other contacts — in essence a count of the clusters to which ego is attached (Burt 1992, p. 52). For the networks of disconnected contacts in the first column of Figure 2, nonredundant contacts equal network size. Every contact is nonredundant with the others. For the clique networks in the third column of Figure 2, ego has only one nonredundant contact regardless of increasing network size, because every contact is redundant with the others. The final metric in Figure 2 is Freeman's (1977) betweenness index that measures the structural holes to which ego has monopoly access. Two disconnected contacts give you one opportunity to broker a connection. Four contacts disconnected from one another gives you six opportunities to broker connections. For the networks of disconnected contacts in the first column of Figure 2, betweenness equals the number of possible connections between contacts because all are disconnected (e.g., betweenness is 10.0 for the broker network of five contacts because none of the 10 possible connections between ego's five contacts exist). For the clique networks in the third column of Figure 2,

betweenness is zero because there are no holes between ego's contacts. In the middle column of Figure 2, ego shares access to structural holes with her partner. For example, ego has access to a disconnect between contacts B and C in the three-person network, but so does contact A, so ego's betweenness score is .5, half of one structural hole. Ego has access to six holes between contacts in the five-person partner network, but access is shared with the partner, so ego's betweenness score is 3.0, half the number of holes to which ego has access.[3]

Evidence of Broker Advantage

Figure 3 presents three graphical illustrations of broker advantage (network constraint measured on the horizontal axis). Figure 3a derives from an analysis of the social origins of good ideas in a supply-chain company (Burt 2004). Two senior executives evaluated each manager's idea for improving the value of the supply chain. Average evaluations vary up the vertical axis. There is a strong negative, nonlinear association in the graph. Brokers (relative to managers in closed networks) are likely to have their ideas evaluated as good and worth pursuing. These results are attractive for displaying a continuous quantitative association between a person's access to structural holes and the acknowledged value of their ideas, but more depth to the association is available from ethnographic network studies of creativity (Obstfeld 2005, Lingo & O'Mahony 2010, Leonardi & Bailey 2011).

——— Figure 3 About Here ———

The data in Figure 3b illustrates the fact that network brokers are compensated for their work decoding and encoding information to move it between clusters. The performance association with networks in Figure 3b is similar to the association in Figure 3a with idea quality. Figure 3b contains stock analysts, investment bankers, and managers from diverse functions in Asia, Europe, and North America (Burt 2010, p. 26, provides more detail). The vertical axis is adjusted so that zero is performance typical for a manager's peers, with respect to which an individual manager can be performing higher (positive z-scores) or lower (negative z-scores). Performance is measured for the investment bankers as bonus compensation, for the stock analysts

as industry recognition (election to the <u>Institutional Investor</u>'s All America Research Team), and for the managers as compensation, annual evaluations, or early promotion to higher job rank. As in the first graph, the second shows a nonlinear, downward sloping association in which network brokers (relative to their peers) are paid more, receive more positive evaluations and recognition, and get promoted more quickly to senior positions. The performance association in Figure 3b is replicated by numerous studies reporting performance metrics higher for network brokers (reviews in Burt 2005, 2010). More recently, analyses of email traffic between people in a small headhunter organization show that network brokers engage in diverse information exchanges and, in addition, headhunters in closed networks who exchange diverse information with contacts also have high performance (Aral & Van Alstyne 2011). Information diversity is the key factor predicting performance, not the network. Holes in ego's network are merely an indicator of ego's access to diverse information.

RESEARCH FRONTIERS

Social network analysis illustrates the general point that argument and debate drive theory and research forward (Lakatos 1970). Currently, SNA is less a paradigmatic orthodoxy than it is a set of evolving ideas about behavioral and cognitive implications of network structure (Kilduff et al. 2006). With respect to network advantage, we note a few frontiers in the ongoing debate.

Agency and Personality

Our discussion of network advantage thus far could be read as though achievement springs directly from a network. But everyone knows that networks do not act – people act. Networks can facilitate or inhibit action, but people are the source of action. Thus the agency question in network analysis: How much does the psychology of the individual at the center of ego's network matter? Even controlling for relevant individual differences such as those held constant in Figure 3 (rank, gender, age, etc.) we are likely to find that different kinds of people are better at bridging structural holes, and those kinds of people may be prone to high achievement. The lack of attention to

human agency in network models has been noted from diverse perspectives (Emirbayer & Goodwin 1994, Kilduff & Krackhardt 1994, Baum & Rowley 2008, Kilduff & Brass 2010, pp. 335-336, Sasovova et al. 2010, Singh et al. 2010) but two recent discoveries bring the agency question back into focus.

The first is the lack of advantage spillover between adjacent networks. If the network advantage of brokers results from broader, earlier access to diverse information, then there should be an advantage to connections with other brokers. But across varied management populations, Burt (2010) shows that ego gains no increased benefit from contact with brokers versus contacts in closed networks. The advantage of access to structural holes is defined entirely by the diversity of ego's own contacts, not the diversity of her friends' contacts. The argued implication is that the advantage does not result from access to diverse information, it is a by-product of processing diverse information. Advantage results from intellectual and emotional skills developed in the process of encoding and decoding information to communicate between diverse contacts. Even a little network training can produce substantial improvements in learning to see and benefit from structural holes (Janicik & Larrick 2005, Burt & Ronchi 2007).

And we know that performance differs widely between network brokers. This is the second empirical fact that demands attention to human agency — people often perform below their level of network advantage. The suspicion has long existed (Burt 1992, p. 37), but the fact is illustrated in Figure 3c, which plots the raw data averaged to define the data in Figure 3b. Vertical performance differences between network brokers (low constraint) are wider than the differences between people in closed networks (high constraint). This is evident from Figure 3c's triangular data distribution and its statistically significant heteroscedasticity, both in the context of wider performance differences in the raw data (vertical axis goes from -3.0 to 7.0 in Figure 3c, from -2.0 to 2.5 in Figure 3b).

The two empirical facts have implications for research on network advantage. Work with formal models of network advantage often involves assuming agency away. Formal models have been used to explore theoretical questions such as what would

happen if everyone focused on bridging structural holes (Goyal & Vega-Redondo 2007, Ryall & Sorenson 2007, Buskens & van de Rijt 2008), or if contacts exercised power to erode ego's returns to bridging structural holes (Reagans & Zuckerman 2008). In these models, the agency question is resolved by assuming that people act on all opportunities their network provides (subject to a budget constraint of limited time or resources). Agency can be ignored because it is coincident with opportunity. To know who acts on network advantage, you only need to know who has advantage.

Contrary to this agency-free depiction, the empirical research just summarized shows that performance differences among network brokers are substantial, with many brokers showing no higher performance than people in the most closed networks. The primary characteristic of the data display in Figure 3c is not the absence of low performers in broker networks; it is the absence of high performers in closed networks. A formal-model strategy more suited to the empirical facts would be to shift focus from the advantages of brokerage to the disadvantages of closed networks (e.g., Burt 2010, pp. 244-247 on network fear).

Second, the two empirical facts are a call for close study of broker behavior to distinguish high-performing brokers from low-performers. Emerging work emphasizes the importance of behavior appropriate to the situation. Depending on the situation, it can be advantageous to play contacts against one another (Fernandez-Mateo 2007), facilitate exchange otherwise at risk of misunderstanding (Obstfeld 2005, Leonardi & Bailey 2011), connect contacts as a translation buffer to protect each side from the other's irritating specialist jargon (Kellogg 2012), or facilitate the development of broker skills in colleagues (Powell et al. 2012). More, occupations have characteristic behaviors (it would be unseemly for a nun to behave like a salesman, or a banker to behave like a construction worker) whereas organizational selection and socialization create company differences in characteristic employee personalities. For a large population of managers, Schneider et al. (1998) show similar Myers-Briggs personality scores for managers employed in the same organization. Burt et al. (2000) study network advantage among managers in a French engineering firm and an American engineering firm. The French networks are based on long-standing friendships that

rarely span the boundary of the firm. The Americans build from work relations that often reach outside the firm. Differences notwithstanding, the French managers benefit from access to structural holes just as the Americans do. Xiao & Tsui (2007) argue that brokering connections across structural holes is inconsistent with Chinese social norms, and show no network advantage in the job ranks on which they have data. On the other hand, Merluzzi (2011) finds higher performance evaluations for Chinese and other Asian managers with access to structural holes, so perhaps the key variable is not being Chinese but working in a Chinese company.

Third, the two empirical facts encourage a deeper recognition of personality in network analysis. What kinds of people are prone to brokerage, with higher odds of success? Despite the occasional voice lamenting the possible contamination of structural research through consideration of the attributes of individuals (e.g., Mayhew 1980, Burt 1992, Chp. 5), there is a history of research relating personality to networks (see Kilduff & Tsai 2003, Chp. 4 for review) and to interpersonal engagement more generally (see Snyder & Deaux 2012 for overview).

These exchanges notwithstanding, there is a sharp contradiction in the way sociologists and psychologists understand personality. A basic assumption of personality psychology is that there are stable individual traits that affect outcomes. The big five personality dimensions, for example, exhibit substantial heritability (Jang et al. 1996) as does the self-monitoring personality orientation (Snyder & Gangestad 1986). Thus, personality psychologists investigate the effects of personality on social relationships and report, for example, that extroverts tend to have numerous peer relations but that social relationships do not affect personality (Asendorpf & Wilpers 1998). Stable individual differences include distinctive patterns of behavioral variability across situations, that is, distinctive individual behavioral signatures (Mischel & Shoda 1995). In contrast, social network analysis derives much of its intellectual capital from sociology where the prevailing assumption is that the dispositions of individuals reflect the structural positions that they occupy. In its early years, for example, the Social Science Research Council funded research that investigated the ways in which social settings affected personality formation; and the ways in which individuals' personalities

adapted to their cultural environments (Bryson 2009). Carrying the sociological perspective into network analysis, Burt (1992, pp. 251-264) analyzed personality as structure's "emotional residue."

The return of personality to the social network agenda has coincided with an interest in self-monitoring, a personality variable especially relevant to network advantage. In establishing theory, evidence and measurement concerning individual differences in the control of self-presentations for situational appropriateness, self-monitoring research (see Gangestad & Snyder 2000 for a review) offers a personality analogue to the brokerage versus closure distinction in network research. Without implying causality one way or the other, network brokers should have higher scores on self-monitoring, and they do (Mehra et al. 2001). Further, a study of ethnic entrepreneurs shows that the effects of self-monitoring ripple across social structure. Entrepreneurs high in self-monitoring tend to have acquaintances who are unconnected with each other, and high self-monitors also tend to occupy positions such that the acquaintances of their acquaintances are unconnected with each other (Oh & Kilduff 2008). The above studies are cross-sectional. Panel analysis of personality and network connections in a Dutch hospital show that high self-monitors are more likely than low self-monitors to attract new friends and to occupy new bridging positions over time; and the new friends the high self-monitors attract tend to be unconnected with previous friends — thereby increasing the number of structural holes in the high self-monitors' networks (Sasovova et al. 2010).

Given the correlation between achievement and structural holes, and correlation between self-monitoring and structural holes, achievement should be correlated with self-monitoring. It is. Kilduff & Day (1994) show for a cohort of MBA students that high self-monitors were more likely to receive promotions within and between companies in the five years after graduation. Holding constant network differences between employees in a small technology company, Mehra et al. (2001) show that employees with high self-monitoring scores received more positive evaluations from their supervisors, but the network association with performance remains: self-monitoring neither moderates nor mediates the network association with work

performance. Virtual worlds provide more behavioral detail. In a network analysis of people playing multiple roles in a virtual world game, Burt (2012) shows that about a third of the variance in network advantage is consistent across the roles a person plays. For example, people who build a closed network in one role tend to build closed networks in their other roles. However, the consistent variation in a person's networks contributes almost nothing to predicting achievement. Achievement in a role is predicted by role-specific factors: the experience a person accumulates in the role and the broker network built up in the role.

Empirical success with measures of self-monitoring should encourage research with related measures. A recent study with cross-sectional and panel data showed that leader charisma (a personality dimension evaluated by the reports of subordinates) did not predict leaders being central in team advice networks (Balkundi et al. 2011). Rather, formal leaders who were central in team advice networks tended to be seen as charismatic by subordinates. This suggests that a leadership-relevant aspect of personality — charisma — may derive from network centrality, compatible with a sociological approach to leadership emergence and compatible with the social network emphasis on the ways in which "a person's social environment elicits a specific personality" (Burt 1992, p. 262). Of course these results are also compatible with personality psychology's emphasis on the ways in which appropriate situations allow personality traits to be exhibited and channeled (Winter et al. 1998). Beyond charisma, people differ in the extent to which they believe their actions affect events which is likely to explain why certain people act on their brokerage opportunities. To answer this question, example personality measures would include Rotter's locus of control in which high internal control refers to a belief that your actions have a causal effect on events (e.g., Hansemark 2003 on internal-control men more likely to be entrepreneurs, Rotter 1966 for the initial statement, Hodgkinson 1992 for a scale adapted to business settings), or Bandura's concept of self-efficacy in which stronger belief in one's capabilities is associated with greater and more persistent effort (Wood & Bandura 1989, Bandura 2001 for review). People also differ in the extent to which they look for network advantages on which they can act. McClelland (1961) argues

that early formation of a need to achieve is a personality factor significant for later entrepreneurial behavior. People raised insecure in their childhood should have a need to achieve that would predispose them to act on network advantage, resulting in them achieving more than peers. Anderson (2008) shows that managers with a high "need for cognition" (Cacioppo et al. 1996), are more likely to take advantage of the information advantages of the network around them.

In sum, research on network advantage is rapidly expanding to include individual differences associated with how people play the role of network broker, and their psychological fit to the role. The practical note to take away from the work is that access to structural holes does not guarantee achievement, it enhances the risk of productive accident — the risk of encountering a new opinion or practice not yet familiar to colleagues, the risk of envisioning a new synthesis of existing opinion or practice, the risk of finding a course of action through conflicting interests, the risk of discovering a new source for needed resources.

Cognition

Network structure is by no means obvious to the person at the center of the network. Individuals are often mistaken about patterns of relationships that include themselves and their colleagues. They tend to perceive themselves as more central in their friendship networks than they really are (Kumbasar et al. 1994). They forget casual attendees at meetings, tending to recall the meetings as attended by the habitual members of their social groups (Freeman et al. 1987). They are attentive to different qualities of their network depending on experience (Janicik & Larrick 2005) and situational stimuli (Smith et al. 2012).

Social network analysis from its beginnings has shown a creative tension between approaches that treat networks as cognitions in the minds of perceivers (e.g., Heider 1958) and approaches that treat networks as concrete patterns of interpersonal interactions (e.g., Cartwright & Harary 1956). To the extent that the theoretical basis of research is psychological, it is the perceptions in the minds of social network participants that constitute the relevant phenomena (Krackhardt 1987). Perhaps the

most firmly established body of work examining cognitive perceptions of social networks has flowed from De Soto's early experiments (e.g., De Soto 1960). Recent examples have examined how the experience of low power leads to more controlled cognition and therefore more accurate perceptions of social networks (Simpson et al. 2011a) and the paradox that more accurate knowledge about ties between others in the network can be collectively disadvantageous for low-power actors (Simpson et al. 2011b). Such results could result from powerless individuals processing more peripheral and detailed information, treating all information as equally important (Guinote 2007), or from socially peripheral, and therefore powerless, individuals focusing on information from people too similar to themselves (Singh et al. 2010). Relatedly, we know that people of low status who encounter a job threat (such as the likelihood of getting laid off) tend to call to mind smaller and tighter subsections of their networks. By contrast, people of high status activate larger and less constrained subsections of their networks (Smith et al. 2012). In sum, people's cognitive representations of their networks shift in response to situational pressures and threats.

Even if there are discrepancies, it would seem evident that patterns in the mind are derived from experience with real-world social networks. For example, people who have a network rich in structural holes find it easier to learn new network structures that contain structural holes (Janicik & Larrick 2005). A range of features that are present in actual networks (such as clustering, structural holes, and actors more central than others) are exhibited in perceptions — but in simplified and exaggerated fashion (Freeman 1992). People tend to economize on cognitive demands and they also exhibit biased perceptions of social networks through their use of default expectations such as the expectation that friendship ties are likely to be reciprocated, and the expectation that if two individuals have a mutual friend then the two individuals themselves will be friends (Krackhardt & Kilduff 1999). There are a range of more complex biases as well. For example, the small worlds described in co-citation analyses and elsewhere (Dorogovtsev & Mendes 2003) are more apparent in individuals' perceptions than in their actual social interactions (Kilduff et al. 2008).

The ongoing creative tension between networks as social interaction and networks as cognitive structures has been updated in terms of the distinction between networks as pipes versus prisms (Podolny 2001). Social networks are considered as pipes through which resources (such as affection or money) flow; or as prisms through which individuals attempt to evaluate others. If social networks are considered as prisms then there is the potential for such lenses to distort the true nature of the individuals being focused on. The old adage "we are known by the company we keep" is represented by the prisms view, although little work so far has addressed the ways in which perceived social network connections distort the evaluation of individuals (but see Kilduff & Krackhardt 1994 for preliminary work on this theme).

Future research on networks as prisms will depend on assumptions that are basic to the cognitive perspective: first that the monitoring and recall of relationships among even relatively small numbers of people (e.g., 20 people) pose cognitive challenges given that the number of potential relationships increases exponentially with the size of the network (Krackhardt & Kilduff 1999, Kilduff et al. 2008); and second that the accurate mapping of relationships is of importance to individuals trying to form project teams and build alliances (Janicik & Larrick 2005). Intriguingly, research on the actual group structures of interconnected individuals also suggests cognitive constraints on the size of social networks (Dunbar 2008). The argument with respect to actual interactions is not so much about the recall and learning of relationships, but more about the cognitive limitations on how many people the individual can be expected to know on a personal basis so that the individual can discern qualities such as trustworthiness and potential cooperation. Thus, the evidence suggests that individuals' social worlds are limited in size to about 150 people and these people are cognitively structured around the individual so that those people with whom we have intense relationships are closer and those with whom we have less intense relationships are further away. The human brain, it is suggested, is limited in the number of people it can acquire knowledge about in order to predict others' behavior; and is also limited in terms of the number of relationships that can be serviced at a given level of emotional intensity (Roberts & Dunbar 2011).

To summarize this section, we can say that the biggest avenue for further research on cognitive networks concerns outcomes such as performance in organizations. Although there has been impressive work detailing the various biases that afflict people's perceptions of social networks, there is much less attention to how these biases affect outcomes at the individual, team, or organizational level. There is speculation concerning how cognitions in the minds of leaders concerning the flow of social capital within and across organizational boundaries and the presence and meaning of social divides contribute to leader effectiveness (Balkundi & Kilduff 2005). But this speculation has not been matched as yet by empirical work detailing important outcomes. The pipes versus prisms contrast is likely to feature prominently in future work on network cognition.

Embeddedness

It could seem as though nothing but disadvantage accrues to people like James in Figure 1, people who live inside one of a network's dense clusters. To the contrary, dense clusters produce trust and reputation, which constitute the governance mechanism in social networks. Network theory and research on this topic is voluminous (for review, see Burt 2005, Chps. 3-4, 2010, Chp. 6). Within our focus for this chapter, we discuss the work as it bears on network advantage.

Work in this area was energized by Granovetter's (1985) argument for the importance of understanding economic relations in social context because context has implications for behavior in a relationship. "Relational" embedding refers to a relationship in which the two connected people have deep history and investment with each other. "Structural" embedding refers to people who have many mutual contacts.

The more embedded a relationship, the more likely bad behavior by either party will become known, thereby creating a reputation cost for bad behavior, which facilitates trust and collaboration. With bad behavior likely to be detected, people are expected to be more careful about their behavior. Thus, trust is facilitated between people in a closed network, making collaborations possible that would otherwise be difficult or unwise. Examples abound on the internet such as eBay's reputation

system, oyster.com, or dontdatehimgirl.com. The same logic can be found in significant contemporaneous work such as sociologist Coleman (1988) arguing that closed networks are social capital, and economist Grief (1989) arguing that trust within closed networks facilitated medieval trade in the Mediterranean.

Empirical research has shown that closed networks increase trust and preserve reputations (for review and illustrative results, see Burt 2005, pp. 196-213; 2010, pp. 161-179). For example, in a large population of investment bankers and analysts, bridge relations decay at a rate of 92% a year after formation, while relations embedded in closed networks decay at a lower 53% rate (Burt 2010, p. 182, cf. Rivera et al. 2010). The higher decay rates in bridge relations make sense in that bridge relations are more subject to short-term cost-benefit analysis since bridge relations are not protected by obligations ensured by mutual friends, and so are more open to suspicions about the person on the other side (Stovel et al. 2011). Aggregating to banker reputations, reputation is autocorrelated from year to year about .73 for bankers evaluated by colleagues in closed networks. In contrast, the reputations of bankers evaluated by colleagues separated by structural holes show almost no stability. The year-to-year autocorrelation is a negligible .09 (Burt 2010, p. 164). As Coleman (1988:S107–S108) summarizes: "Reputation cannot arise in an open structure, and collective sanctions that would ensure trustworthiness cannot be applied."

To the point of this chapter, embedding is a critical contingency factor for returns to network brokerage. First, understanding, trust and collaboration are more likely across strong bridges relative to weak bridges (relational embedding). Example studies are Uzzi (1996) on garment manufacturers less likely to go bankrupt if they concentrate their business in a small number of suppliers, Reagans & McEvily (2003) on strong bridges facilitating knowledge transfer, Centola & Macy (2007) on complex ideas more likely to diffuse through "wide" bridges, Tortoriello & Krackhardt 2010 on innovation associated with strong bridges, termed "Simmelian ties," and Sosa 2011 on creativity associated with strong rather than weak bridges. Second, returns to brokerage depend on being known as trustworthy (structural embedding). Burt &

Merluzzi (2013) describe high returns to brokerage for investment bankers, salesmen, and managers who have above-average social standing in their organizations. For people in the same populations with below-average social standing, returns to brokerage cannot be distinguished from random noise, even for a person rich in access to structural holes.

Dynamics

Network analysis developed in sociology against a backdrop of functional theory in which the imprimatur of "social structure" was reserved for the stable features of networks. Networks that persist in time have meaning, serve some purpose, are real in their consequences. Much like human capital is anchored in enduring education credentials acquired as a person moves up through a stable stratification of grade levels, network advantage was studied and taught as a level to be developed and preserved. As Laumann & Pappi (1976, p. 213) expressed the sentiment during the 1970s resurgence of network images in sociology: "Despite differences in nuance associated with 'structure,' the root meaning refers to a persisting order or pattern of relations among units." And well after network images were again mainstream in sociology, Sewell (1992, p. 2) broadened the observation as criticism: "structural language lends itself readily to explanations of how social life is shaped into consistent patterns, but not to explanations of how these patterns change over time. In structural discourse, change is commonly located outside of structures."

The focus on stability was reinforced by empirical research. The most-replicated fact we know about network dynamics is that the more closed a network, the more stable the relations in it and the more stable the reputations emergent from it. And patterns of relations such as friendship seem to stabilize relatively quickly within a bounded social system (such as a student living group, Newcomb 1961). Under the surface one suspects movement in that some actors form stable relations while others "dance between friends throughout the observation period" (Moody et al. 2005, p.1229). However, despite contemporary technology offering people many opportunities to expand their networks, to meet new people, and so to pursue new

opportunities, it seems that people fail to take advantage of social occasions to forge new relationships (Ingram & Morris 2007).

Broker networks are less stable than closed, but they too exhibit surprising stability. In theory, they should not. Theoretical models describe how advantage should be distributed in stable "equilibrium" networks (Goyal & Vega-Redondo 2007, Ryall & Sorenson 2007, Buskens & van de Rijt 2008, Kleinberg et al. 2008, Reagans & Zuckerman 2008, Dogan et al. 2009). The models imply pessimistic conclusions about the feasibility of stable access to structural holes, though people seem able to muddle through (Burger & Buskens 2009), and the people who have advantaged access to holes today are often the people who had network advantage yesterday. For example, among the bankers analyzed by Burt & Burrows (2011), relative access to structural holes is correlated .64 from year to year. Zaheer & Soda (2009) report that Italian TV production teams rich in access to structural holes tend to be composed of people who were rich in access several years ago. Sasovova et al. (2010) report that continuing access to structural holes in their Dutch hospital includes access to many of the same structural holes along with expanding access to new ones.

More recently, network dynamics have become less a question of orthodoxy and more an empirical question — in part because of more available detailed network data, and in part because of improved time-sensitive statistical models (Snijders 2011, Rivera et al. 2010). Quintane et al. (2012) is an exemplary study. Network data were collected on eight months of email traffic among employees in the US and European offices of a digital advertising company. The network data were analyzed in continuous time using Butts' (2008) relational event model. Each message is predicted by the history of message events before it, and becomes a defining element in the social context for the next message event. The analysis describes decay in structural holes. Brokers connect across certain holes, those holes close, then the brokers move to new places in the network. The Quintane et al. results are consistent with a less sophisticated analysis of a broader population. Studying network advantage for bankers observed in four annual panels, Burt & Burrows (2011) show that advantage is enhanced by a certain amount of volatility. Too much volatility can

erode advantage, but too little erases advantage. Banker bonus compensation is strongly associated with network advantage for bankers who have some churn in their network contacts, but not at all associated with network advantage for bankers whose network metrics are stable over time.

CONCLUSION

Social network analysis (SNA) continues to develop many themes enunciated by pioneering social psychologists. At its best, SNA draws from traditions of research and theory in psychology, sociology, and other areas to describe how patterns of interpersonal relations are associated with diverse behavioral, cognitive, and emotional outcomes. Looking to the future, we see deepening interest in the psychological underpinnings of why some people more than others engage and benefit from the network of contacts within which they are embedded.

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ENDNOTES

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[1]Even within our focus on network advantage, there is a burgeoning literature (see reviews by Lin 2002, Burt 2005, 2010; Podolny 2005; Smith-Doerr & Powell 2005;

Stovel & Shaw 2012). Here are leads into SNA more generally: There are general and specialist introductions (Cross & Parker 2004, Borgatti et al. 2009, Kilduff & Brass 2010, Kashushin 2012, Rainie & Wellman 2012, Prell 2012), Freeman's (2004) history of SNA development through the 20th century, introductions to network computations (Scott 2000, Hanneman & Riddle 2005, Hansen et al. 2011), data strategies (Marsden 2011), advanced introductions to computations (Wasserman & Faust, 1994, de Nooy et al. 2005, Carrington et al. 2005), textbooks providing an integrative view for people at the rich interface between computer science and the social sciences (Jackson 2008, Easley & Kleinberg 2010, Newman 2010), and encyclopedic handbooks covering topics introductory through sophisticated reviews(Scott & Carrington 2011). Software is readily available. UCINET (Borgatti et al. 2002) and Pajek (de Nooy et al. 2005) are widely used, but many useful software options can be found at the INSNA website (see "related resources" at end of the chapter). Social contagion is the most glaring omission from this chapter. The topic is substantively important and well established in research. Relative to the topics we cover, however, contagion is most distant from our focus on network advantage. Christakis & Fowler (2009, 2012) offer thorough introduction, with Aral et al. (2009) a sophisticated search for evidence. It is worth noting that these contagion works focus on a "pipes" image of networks in which influence flows through communication channels. Neglected is the broader image of networks in which influence also flows between structurally equivalent peers who communicate by social comparison (see Burt, 2010, pp. 329-365, for historical review and illustrative evidence).

[2]More detailed discussion is available elsewhere (Burt, 1992, pp. 54 ff., 2010, pp. 293 ff.). Caution: the index was designed to describe networks of connected managers. Scores can exceed one if ego has only two strongly-connected contacts (Burt, 1992, pp. 58-59). We convert constraint scores greater than one to equal one. Also, constraint is undefined for social isolates because proportional ties have no meaning (zero divided by zero). Some software outputs constraint scores of zero for isolates, which implies that isolates have unlimited access to structural holes when in fact they have no access (apparent from the low performance scores observed for managers who are social isolates). For social isolates, network constraint equals one.

[3]Two cautions: (a) If Freeman's betweenness index is used as a measure of access to structural holes, a control has to be added for network size. Freeman (1977) proposed dividing by number of possible contacts that ego could broker, which is a function of network size. (b) Betweenness scores in Figure 2 are computed from ego's direct access to structural holes, as Freeman (1977) initially proposed the index for small group research. When scores are computed across contacts beyond ego's network, as they often are, the index measures ego's direct and indirect access to structural holes and the index is better interpreted as a measure of network centrality or status.

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RELATED RESOURCES

http://www.insna.org

A

B

1
2
3
James

Robert

7

5
4

6

C & D

Density Table

85				Group A
5	25			Group B
0	1	100		Group C
0	0	29	0	Group D

Network Constraint
$(C = \Sigma_j c_{ij} = \Sigma_j [p_{ij} + \Sigma_q p_{iq}p_{qj}]^2, i,j \neq q)$

person 3: $.402 = [.25+0]^2 + [.25+.084]^2 + [.25+.091]^2 + [.25+.084]^2$

Robert: $.148 = [.077+0]^2 + [.154+0]^2 + [.154+0]^2 + [.154+0]^2 + [.154+0]^2 + [.154+0]^2 + [.154+0]^2$

Network indicates distribution of sticky information, which defines advantage.
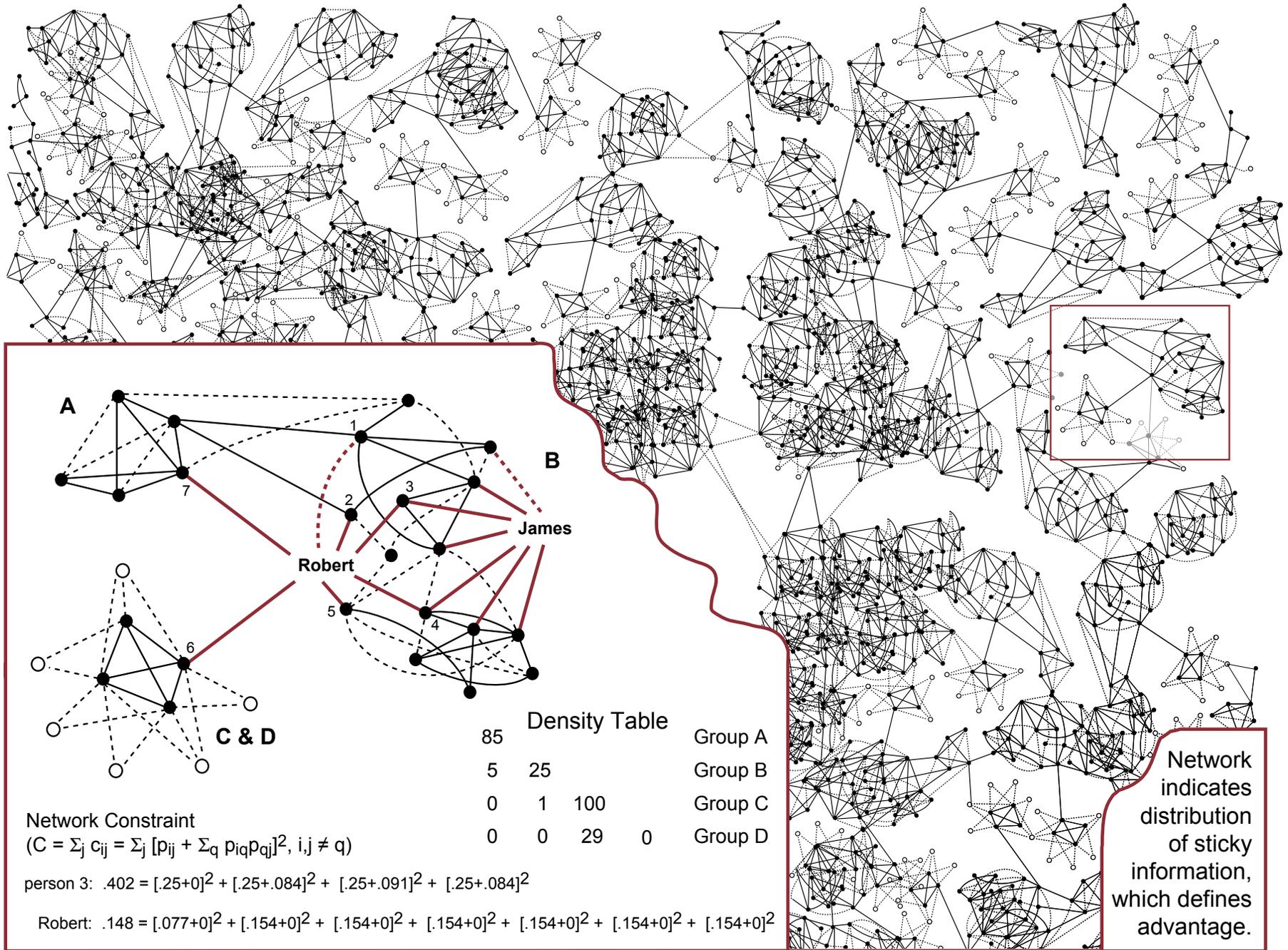
Figure 1. Network Bridge and Cluster Structure
Adapted from Burt (2005:14).

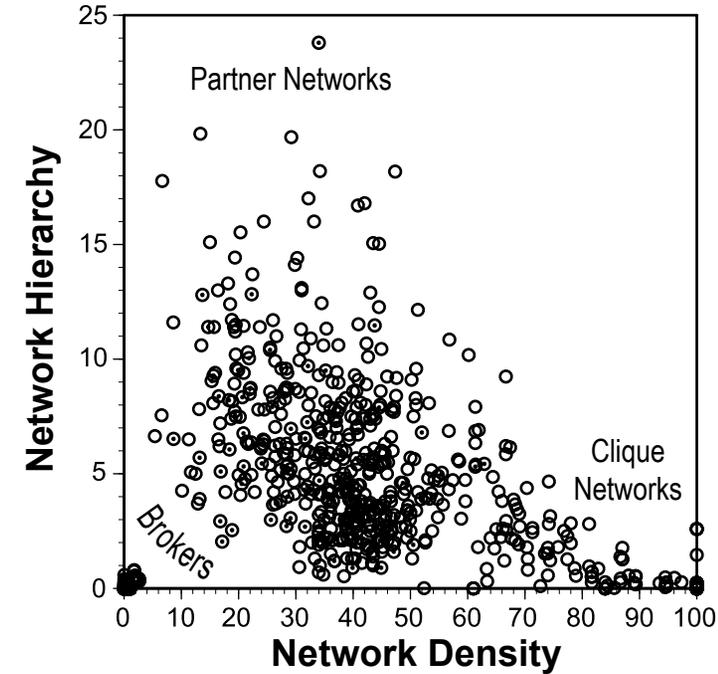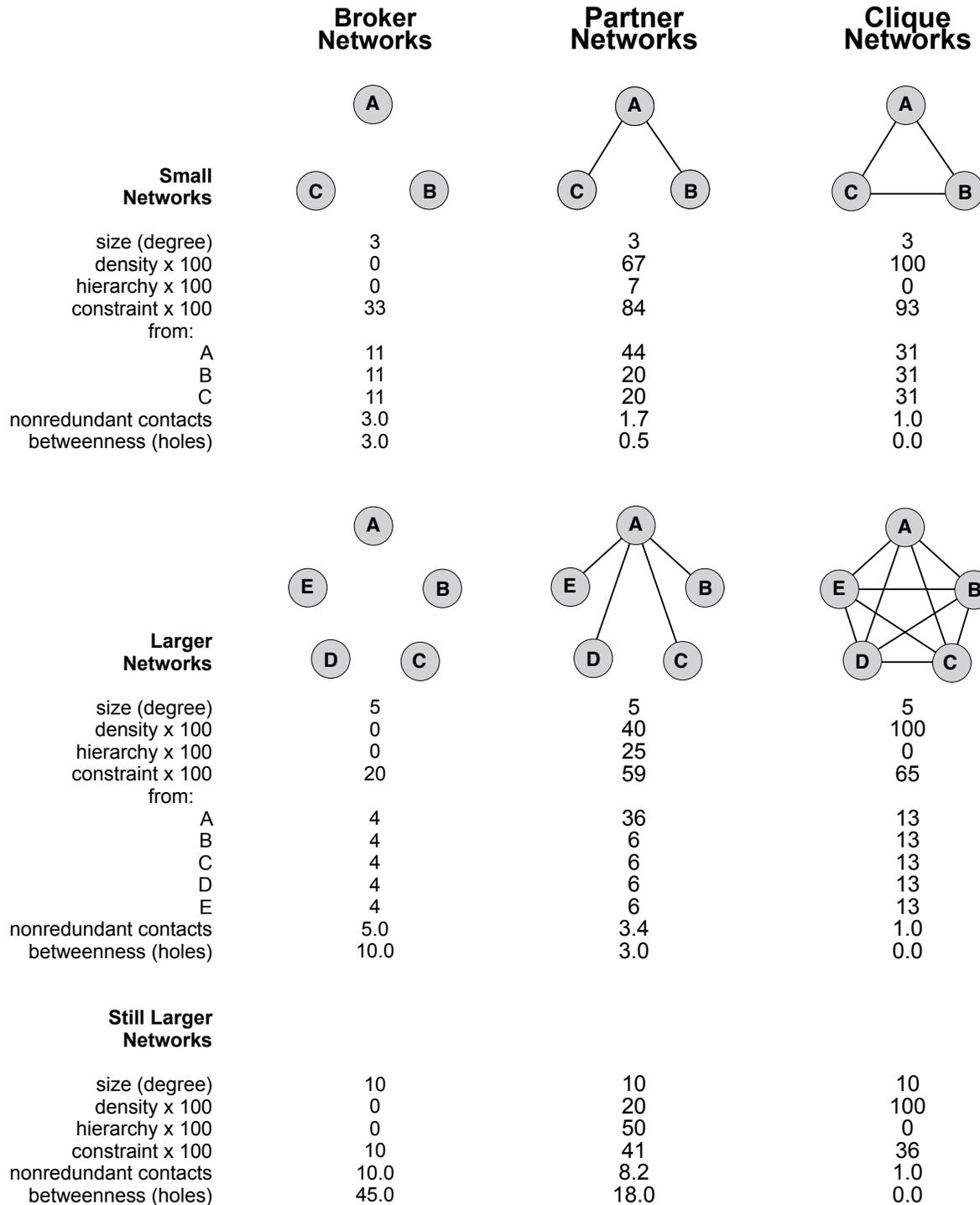|	Broker Networks	Partner Networks	Clique Networks
Small Networks			
size (degree)	3	3	3
density x 100	0	67	100
hierarchy x 100	0	7	0
constraint x 100	33	84	93
from:			
A	11	44	31
B	11	20	31
C	11	20	31
nonredundant contacts	3.0	1.7	1.0
betweenness (holes)	3.0	0.5	0.0
Larger Networks			
size (degree)	5	5	5
density x 100	0	40	100
hierarchy x 100	0	25	0
constraint x 100	20	59	65
from:			
A	4	36	13
B	4	6	13
C	4	6	13
D	4	6	13
E	4	6	13
nonredundant contacts	5.0	3.4	1.0
betweenness (holes)	10.0	3.0	0.0
Still Larger Networks			
size (degree)	10	10	10
density x 100	0	20	100
hierarchy x 100	0	50	0
constraint x 100	10	41	36
nonredundant contacts	10.0	8.2	1.0
betweenness (holes)	45.0	18.0	0.0

Figure 2. Network Metrics

Adapted from Burt (2010:298). To keep the sociograms simple, relations with ego are not presented. Graph above plots density and hierarchy for 1,989 networks observed in six populations (analysts, bankers, and managers in Asia, Europe, and North America; aggregated in Figure 3 to illustrate returns to brokerage). Dot-circles are executives (MD or more in finance, VP or more otherwise). Hollow circles are lower ranks. Executives have significantly larger, less dense, and less hierarchical networks.
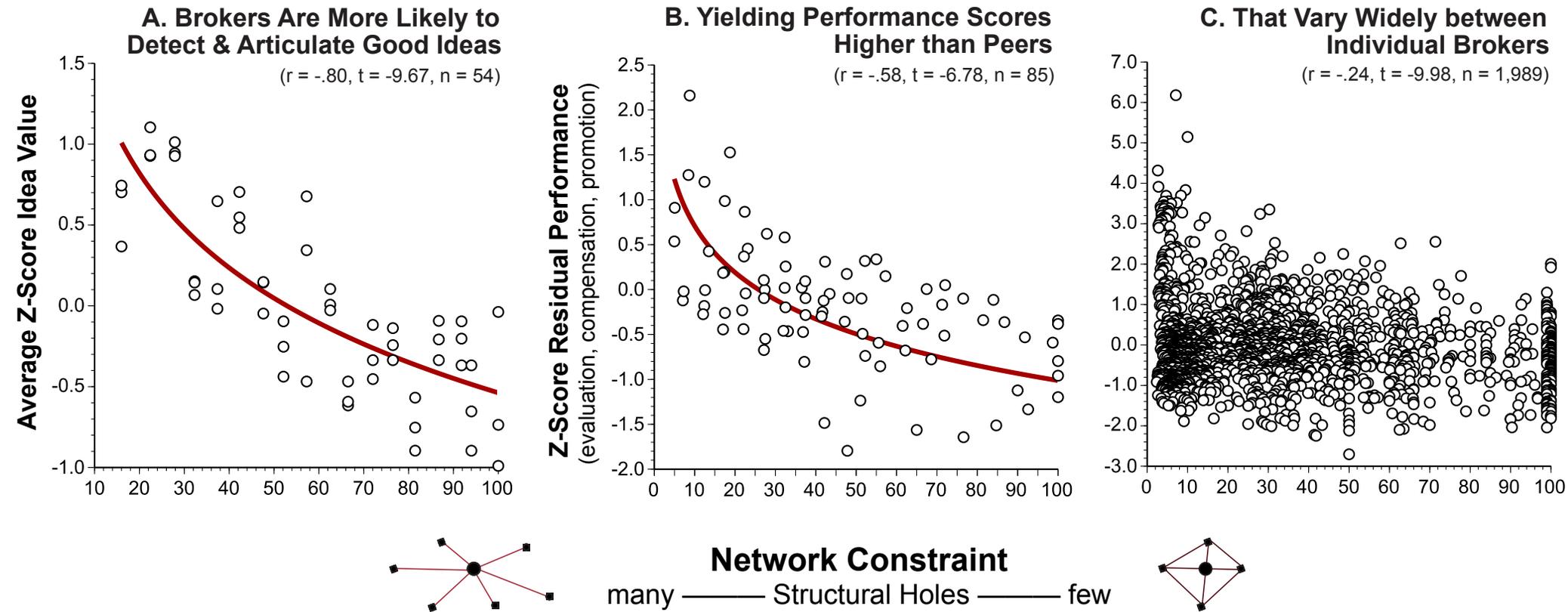
A. Brokers Are More Likely to Detect & Articulate Good Ideas

(r = -.80, t = -9.67, n = 54)

Average Z-Score Idea Value

B. Yielding Performance Scores Higher than Peers

(r = -.58, t = -6.78, n = 85)

Z-Score Residual Performance (evaluation, compensation, promotion)

C. That Vary Widely between Individual Brokers

(r = -.24, t = -9.98, n = 1,989)

Network Constraint

many ——— Structural Holes ——— few

Figure 3.
Brokerage for Detecting & Developing Opportunities

Graph A shows idea quality increasing with more access to structural holes. Circles are average scores on the vertical axis for a five-point interval of network constraint among supply-chain managers in a large electronics firm (Burt, 2004:382, 2005:92). Bold line is the vertical axis predicted by the natural logarithm of network constraint. Graph B shows performance increasing with more access to structural holes. Circles are average scores on the vertical axis for a five-point interval of network constraint within each of six populations (analysts, bankers, and managers in Asia, Europe, and North America; heteroscedasticity is minor, χ^2 = 2.97, 1 d.f., P ~ .08; Burt, 2010:26, cf. Burt, 2005:56). Graph C shows the raw data averaged in Graph B (Burt 2012). Vertical axis is wider to accommodate wider range of performance scores. Heteroscedasticity is high because of wide performance differences between individual brokers (χ^2 = 269.5, 1 d.f., P < .001), but returns to brokerage remains statistically significant when adjusted for heteroscedasticity (Huber-White, t = -8.49).