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Structural holes and managerial performance: Identifying the underlying mechanisms☆

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ABSTRACT

Structural holes theory suggests a variety of possible explanations for the empirically observed relationship between structural holes and individual managerial performance. However, little has been done to disentangle one mechanism from another. This paper empirically tests a mediated moderation model that distinguishes between the five different theoretical mechanisms: autonomy, competition, information brokering, opportunity recognition and innovativeness. The findings suggest that of these five theoretical causal motors, innovativeness plays a key role in linking network structure and network content to performance.

1. Introduction

Empirical work in the area of structural holes theory has shown a robust relationship between social network structure and individual managerial performance. A manager whose network has a high proportion of structural holes is generally promoted faster, paid more and assessed as higher performing than one whose contacts are densely interconnected (Burt, 1992; Burt, 2000). Structural holes theory suggests five distinct mechanisms that might account for this finding: autonomy, competition, opportunity recognition, information arbitrage, and innovativeness.[1] However, as yet we have no empirical evidence as to which are actually responsible for the structure–performance relationship. Although Rodan and Galunic (2004) have taken a tentative step in this direction, describing the independent effects of knowledge heterogeneity and network structure, their study showed only that knowledge mattered, particularly for managerial innovativeness. While this could be interpreted as suggestive of different mechanisms, their paper does not make this claim, nor does their empirical analysis distinguish explicitly between mechanisms. And while Reagans and McEvily (2003) have looked at the relationship between network structure and knowledge transfer, knowledge is not implicated all of the possible mechanisms connecting structural holes to high performance, thus the broader question of which mechanism gives structural holes their potency is not yet completely answered. A better understanding of the underlying causal mechanisms is important because each could well have different implication at higher levels of analysis; depending on the mechanism at work, what is good for the individual may or may not be good for the collective.[2]

While the social network literature is large, there is relatively little that deals with questions of mediation and moderation, some notable exceptions aside (e.g., moderation in Westphal et al., 1997; Sorenson and Stuart, 2001; Tsai, 2001; Brass et al., 1998; mediation in Brass, 1981; Brass and Burkhardt, 1993; Yli-Renko et al., 2001; moderation and mediation in Mehra et al., 1998). In this paper I employ a mediated moderation model using ego-network data collected at European Telecommunications Company to try to disentangle the different mechanisms.

2. Linking network structure to managerial performance

A structural hole is the absence of a tie between two alters. Burt originally proposed two broad categories of mechanism to account for the association between structural holes and managerial performance (1992, 2000): the first, under the heading of control benefits, includes autonomy and competition; the second, labeled

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[1] It might be argued that there is nothing that distinguishes opportunity recognition from innovativeness. Opportunity recognition is treated here as the process of realizing that an existing product or service meets an existing need. Innovation I conceive of as more cognitively demanding and complex, the imagining of a completely new concept; this is a more stochastic cognitive process (Amabile, 1990, 1996; Arieti, 1976; Turner and Fauconnier, 1999). Prior literature (Burt, 2004; Rodan and Galunic, 2004) makes the case that they are separate, though there is a relatively fine line separating the two constructs.

[2] Indeed whether structural holes are beneficial at all at higher levels of analysis remains an unanswered empirical question, though not one addressed here.

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Table 1
Summary of structural holes theory mechanisms.

Mechanism	Constructs	Description
Autonomy	Network structure	Depends only on the lack of a tie between ego's contacts, and does not depend on the heterogeneity of information among contacts.
Opportunity recognition	Knowledge heterogeneity	Depends only on the diversity of information to which ego has access, and does not depend on ties or lack of between ego's contacts.
Competition	Knowledge heterogeneity and Network structure	Requires disconnected contacts to prevent their collusion against ego, and substitutability which requires a lack of knowledge heterogeneity.
Information arbitrage	Knowledge heterogeneity and Network structure	Requires both a hole between contacts across which to broker the information and heterogeneity of information across contacts to motivate the transfer.
Innovativeness	Knowledge heterogeneity	Stimulated by interaction with contacts with heterogeneous knowledge.

information benefits, covers opportunity recognition and information arbitrage. Reagans and Zuckerman (2008) have sharpened this account by carefully distinguishing between competition, which requires that contacts are structurally disconnected and alike, and thus substitutable, and information arbitrage which depends on disconnected contacts being different and therefore having information to trade. A fifth mechanism has been proposed (Rodan and Galunic, 2004; Burt, 2004) suggesting that creativity and innovation stemming from knowledge recombination (Galunic and Rodan, 1998) might provide yet another explanation for the relationship between structural holes and performance.

Each mechanism depends on a particular combination of three constructs: the presence of structural holes in a manager's network, the heterogeneity of his contacts in terms of what they know, possibly mediated by a third, managerial innovativeness. Building on earlier work (Rodan and Galunic, 2004) which argued that knowledge heterogeneity and network structure were theoretically distinct and showed them to be empirically separable constructs, I next show how the five mechanisms may be represented in reduced form using these three constructs. I then develop testable propositions to identify the presence of the different mechanisms. Table 1 summarizes the mechanisms discussed below.

2.1. Autonomy

An individual, *i*, who has ties to two people (*j* and *k*) who are not themselves connected[3] is thought to have an advantageous position in the network by virtue of the absence of the *j*–*k* tie, the structural hole between *j* and *k*. The autonomy afforded by structural holes reduces the degree to which *i* is constrained by his contacts. If *i* reveals only snippets of information about his activities to *j* and *k*, each may not have enough information to perceive a pattern and deduce what *i* is up to. However, if *j* and *k* confer, they may jointly have enough pieces of the puzzle to work out what *i* is trying to do. For example, in garnering resources for a new project, an R&D manager might not volunteer that he has already secured funding from another part of the company when trying to solicit additional financial support. A structural hole between the two department managers from whom he is seeking support reduces the likelihood that this duplication of funding will be discovered by either department.

Managers with structural holes in their networks also have greater freedom to dissemble: "Structural holes are the setting for tertius strategies. . .ambiguous, or distorted information is moved strategically between contacts by the tertius" (Burt, 2000:11). In securing backing for his project, our R&D manager might go further than simply being economical with the truth. He might tell one sponsor that her department's requirements are of paramount importance and that they will take precedence over all others, and yet say exactly the same thing to a manager of another sponsoring department. Both cannot be true, but unless the two sponsoring department managers share information, neither manager is any the wiser. A structural hole between them greatly reduces the likelihood that this deception will be discovered. An important point here is that the benefit autonomy provides arises purely from the structure of the network and does not depend on the properties of the network nodes around ego. Autonomy is also about power; as Emerson noted, if *j* and *k* depend on *i* while *i* may choose between *j* and *k*, *j* and *k*'s dependence on *i* gives *i* power over them (Emerson, 1962). *i*'s power disappears when *j* and *k* form a coalition, in other words when there exists a tie between *j* and *k* and the structural hole disappears. In terms of the reduced from representation, autonomy depends only on network structure (top path in Fig. 1).

This suggests the first hypothesis:

Hypothesis 1. If performance depends only on the structure of ego's immediate network and not on the knowledge heterogeneity of her contacts, autonomy is the most likely mechanism responsible for the structural holes–performance association.

2.2. Opportunity recognition

The second mechanism linking structure to performance in structural holes theory, opportunity recognition, depends on the variety of information to which the tertius has access through her network (bottom path in Fig. 1). People separated by a structural

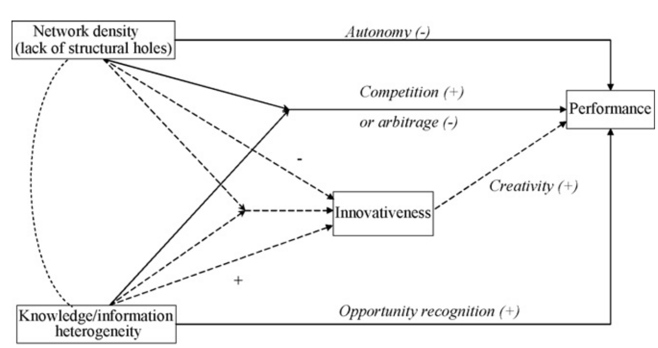

Fig. 1. Influence diagram of the possible mechanisms linking knowledge heterogeneity, network structure and performance.

[3] Structural Holes Theory uses the term 'tertius' to refer to an actor spanning a structural hole. In this paper, *i* typically refers to the focal manager, sometimes called the ego, while *i*'s contacts, *j* and *k* are referred to as his alters.

hole tend to know different things. If *i* knows *j* and k, but *j* and *k* do not know one another, *j* and *k* are likely to possess non-redundant information (Burt, 1992). Thus *i* has access to a greater variety of knowledge and information than if *j* and *k* were connected. Ties are more likely to form between people who share common attributes, knowledge or ideas (Homans, 1950; Mark, 1998). Moreover, where ties exist, knowledge tends to become more widely shared and thinking increasingly similar (Carley, 1986). Common interests and overlapping knowledge may lead to association at common focii, such as chess clubs and choirs (Feld, 1981), increased frequency of interaction and a higher probability of tie formation.

If dense networks are associated with homogeneity, sparse ones should be relatively heterogeneous. Granovetter's (1973) weak ties bridged disconnected social worlds and led to very different pools of information; opportunity recognition was the mechanism that helped his job seekers find employment more effectively. In structural holes theory, opportunity recognition connects structure to performance though an intermediary construct, the diversity of information and knowledge in *i*'s network. Where the heterogeneity information and knowledge is not measured, a measure of structural holes will act as a proxy for contact heterogeneity, a point noted by Reagans and McEvily (2003).

To the extent that information distribution in a network is related to its structure, one would expect to see an association between opportunity recognition and structural holes, but it is important to note that what really drives opportunity recognition is not the structure of the network per se but the variety of knowledge with which sparse structures are usually thought to be associated. Thus my second hypothesis:

Hypothesis 2. If performance depends only on the heterogeneity of knowledge in ego's immediate network and not on the structure of her network, opportunity recognition is the most likely mechanism responsible for the structural holes–performance association.

2.3. Competition

The third mechanism in structure holes theory relies on the creation and exploitation of competition. This has close parallels in industrial organization economics: a firm dealing with fragmented buyer- or supplier-markets is likely to be able to exploit the structural holes that are assumed to increase with falling up- or down-steam market concentration. Porter (1980) discusses this under the heading of bargaining power of buyers and suppliers. Indeed, Burt begins his detailed exposition of structural holes theory in the context of market competition between firms (1992:83–114).

Competition requires that contacts are substitutable (Reagans and Zuckerman, 2008). A firm cannot play one supplier off against another to bargain down prices if their products are different. Similarly, when a manager's contacts each have unique knowledge, creating a competitive situation between them is more difficult. Thus a second condition for this mechanism is not only the existence of structural holes but homogeneity of knowledge among contacts. In the context of the stylized example used earlier, if *j* and *k* have the same information, knowledge and skills, *i* can instigate competition between the two for his time and attention by indicating to both that they are replaceable, just as Emerson's children did (Emerson, 1962:35). Once *j* and *k* begin to compete for *i*'s attention, *i* acquires power over *j* and k. *i* would find this difficult if *j* and *k* had different knowledge and were thus both uniquely useful to *i* (the heterogeneity condition), or if *j* and *k* were tied to one another and were thus able to present a united front in the face of *i*'s attempts to divide them (the structural condition). Competition is shown in solid lines as an interaction in Fig. 1; the coefficients associated with this mechanism are explained in Appendix A.

Hypothesis 3. If performance is contingent on the similarity of alters knowledge and the presence of structural holes competition is the most probable mechanism driving individual managerial performance.

2.4. Information arbitrage

A fourth way in which sparse networks can be of use arises when contacts are sources of non-redundant knowledge or information and the network structure affords ego the opportunity to exploit it through arbitrage. As Burt notes: "Structural Holes are the setting for tertius strategies. Information is the substance." (Burt, 1992:48)[4] Given the same simple three person network *j*–*i*–*k*, *i* can take information learned from *j* and knowing what *k* might find useful, selectively pass that information to *k*, possibly in exchange for some other piece of information that *k* has which *i* thinks may be of value to *j*; *i* benefits by amassing more information than those with less diverse contacts. In so doing she acquires a reputation as a source of knowledge and might emerge as a 'market-maker' of information, a process of positive feedback similar to that described by Gould (2002) in the emergence of high status individuals. The exchange need not be reciprocal; *i*, by passing *k* some piece of useful information, may create in *k* a sense of social obligation to be drawn on at a later date (Blau, 1964). Information arbitrage benefits *i* in several ways; she acquires more information than others in the organization becoming a focal point for information exchange, she generates social obligations and debts in her favor, and gains a reputation as a knowledgeable individual, as Blau noted in his description of the tax office (Blau, 1955). All are likely to enhance *i*'s perceived performance, and the likelihood of early promotion and higher pay.

Absent the structural hole, *i*'s opportunity to create such debts is reduced even when *j* and *k* have non-redundant information, since *j* and *k* would likely exchange the information directly cutting *i* out of the exchange (Obstfeld, 2004). Information brokering therefore depends on the heterogeneity of information or knowledge across contacts and on the holes themselves that enable this heterogeneity to be exploited to the broker's advantage (Reagans and Zuckerman, 2008). This is the antithesis of competition, at least with respect to the heterogeneity of contact knowledge; while competition requires structural holes and homogeneity of contacts, information brokering depends on holes and heterogeneity among contacts.[5]

Hypothesis 4. If information arbitrage is the mechanisms in use, the extent to which ego-network sparseness increases managerial performance will be contingent on the dissimilarity of alters knowledge.

[4] Exchange is not restricted to information; exchange can include tangible resources, time and effort, or even relatively fungible social obligations.

[5] Prior work (Reagans and Zuckerman, 2008) suggests that *i* will pursue arbitrage when contacts are dissimilar and a competitive strategy when they are alike. Could *i* do both? Could she convince dissimilar alters that they were substitutable while at the same time brokering information between them? There is another symmetric possibility: that *i* might play the role of a broker between similar alters who in fact have nothing of value to exchange by manipulating the information in such a way as to make it appear sufficiently different as to be of value in a dyadic exchange. While both are theoretically possible, I suggest neither are likely to be very common because of the difficulty of maintaining the fiction in each case. Although holes clearly support both of these strategies, the degree of deception involved is considerably greater than that involved in simply protecting the identity of ones sources (which would be all that brokering would require) or maintaining a state of competition that hinders the formation of alliances and bonds between the tertius' contacts. Thus if competition generally requires homogeneity and arbitrage heterogeneity, the two mechanisms are likely to be mutually exclusive.

Table 2
Network survey questions.

Name generator questions	
Advice contacts	"Getting your job done on a daily basis as a manager often requires advice and information from others. Who are the key people who you regularly turn to for information and work-related advice to enhance your ability to do your daily job?"
Innovation contacts	"Some contacts are particularly useful in helping you to be creative in your job, such as helping you to generate new ideas. Who are the key people that help you the most to formulate new ideas?"
Buy-in contacts	"New ideas often require support from others without which you cannot proceed. Who are the key people that provide essential support to new initiatives?"
Social support contacts	"Most people rely on a few select others to discuss sensitive matters of personal importance - i.e., 'confidants' on whom they rely for personal support. Who are the key people in your work environment that you regard as your most important source of personal support?"
Name interpreter question for knowledge similarity	
Ego–alter knowledge distance (4 point Likert scale) 1 – "Very little" 4 – "A great deal"	"How much information or knowledge does each of your contacts normally bring to your discussions, over and above what you already know?"
Ego-network questions	
Alter–alter tie strength (3-point Likert scale)	**How well do your contacts know one another?** The next set of questions deals with the relations BETWEEN each of your contacts. Chose 'Especially close' if there is a close relationship between the person named in the question and the person you are considering from the list underneath. Chose 'Distant' if the person named in the question and person you are considering from the list underneath rarely work together or are total strangers as far as you know.
Alter–alter knowledge distance (4 point Likert scale)	**How similar is your contacts' knowledge?** The next set of questions deals with relative similarity or difference in knowledge between your contacts. Chose 'Very similar' if the knowledge of the person named in the question and person you are considering from the list underneath is very similar, for example a football player and the football-team coach. Here the two people should have a great deal of work related knowledge in common. Chose 'Very different' if the knowledge of the person named in the question and person you are considering from the list underneath is very different, for example an airline pilot and a computer scientist. In this case, the two people should have almost no work related knowledge in common.

2.5. Innovativeness

The final mechanism is innovativeness, defined here as the conceiving of something that is thought likely to be both novel and useful (Amabile, 1996). Innovative ideas rarely appear out of thin air; they are usually new combinations of existing knowledge, the coming together of two or more disparate concepts (Aldrich and Fiol, 1994; Zaleznick, 1985). People tend to be more creative when their cognitive frameworks are disturbed (Amabile, 1988:152). Interaction with people all of whom have different knowledge and perspectives can lead to a modification of one's cognitive framework; each encounter with a concept that does not fit into one's current schema presents an opportunity for cognitive 'reconstruction.' When cognitive frameworks are dismantled and rearranged to accommodate new knowledge, novelty may result as current links are broken and new ones established. Interaction with a variety of people each with different knowledge is therefore likely to enhance creativity. The more contacts whose knowledge differs from ego's and from that of ego's other contacts, the more ego's creativity will be stimulated. A number of empirical studies (Pelled et al., 1999; Pelz, 1956; Reagans and Zuckerman, 2001; see also Milliken and Martins, 1996 for a review of other studies) suggest that heterogeneity among one's contacts contributes to creativity and innovativeness. If performance depends on innovativeness and innovativeness on knowledge heterogeneity which itself is correlated with structural holes, holes should be correlated with performance.

The question arises as to whether innovativeness mediates the relationship between heterogeneous contact knowledge and performance described in the earlier discussion of opportunity recognition. Moreover, since there is some evidence that innovation depends also on autonomy and thus on network structure (Burgelman, 1991; Rodan and Galunic, 2004), it is possible that innovativeness also mediates the relationship between network structure and performance. Finally, to the extent that innovativeness depends jointly on autonomy and knowledge heterogeneity, the effect of their interaction on performance, which was previously suggested as an indicator of information arbitrage, might be mediated by innovativeness. Thus the final hypothesis is:

Hypothesis 5. Innovativeness will mediate the interaction of knowledge heterogeneity and network structure on performance.

In summary, structural holes theory suggests five possible mechanisms that might account for the association between structural holes and managerial performance. By looking for the patterns of coefficients for the three 'primitives', knowledge heterogeneity, ego-network density and their interaction and their possible mediation by innovativeness, I attempt to isolate the mechanism or mechanisms that underpin the well-known structure–performance relationship.

3. Methods

The data for this study were collected from a Scandinavian telecommunications service provider with approximately eighteen thousand employees. It operates both wire-line and wireless services principally in its domestic market, though it has built and operated wireless networks in Eastern Europe. Privatization and the loss of its position as a regulated monopoly in the mid-1990s meant that the company was looking increasingly to innovation to defend itself against new entrants.

Middle managers, identified as those having managerial responsibility for people or projects from two departments, Project and Product Management and Product Marketing in the Residential Services Division were selected as the target sample for the study by the company's top management team. Twenty-two interviews were conducted prior to deploying the survey to gain a deeper understanding of the firm. Information from these interviews was used to tailor survey questions to the particular context, replacing general or academic terminology with more familiar wording. For example, 'high school' was replaced by 'gymnasium', a term more familiar in Scandinavian countries. As many of the interviewees indicated that they had regular contact with people outside the departments in which the company had originally elected to conduct the survey, it became clear that a snowball sampling approach would be needed (Wasserman and Faust, 1994).

Each manager in the sample was sent a package containing a letter from the company's senior management encouraging the recipient to participate, one from the research team with a general overview of the research program of which the survey was a part and assurances of confidentiality, instructions for completing the survey, a diskette with a computer program for administering the survey and collecting the responses, and a pre-addressed envelope with which to return the completed survey diskette directly to the researchers. The survey packages were sent by the research team to the company's project liaison who then distributed them to those in the initial sample and later to the snowball sample.

The survey comprised three sections. The first included general demographic questions (age, organizational tenure, job tenure, job title, sex, highest level of education completed, college major or area of concentration). Section two dealt with the respondent's social network. Four commonly used name generators were used to solicit contacts for advice, task execution, idea generating exchange and friendship networks (top panel, Table 2). The name generators were accompanied by a list of the people in the target sample to aid recall. However, any contact not in the list could be added by the respondent if necessary. To avoid right censorship of large networks, no limit was stipulated as to the number of contacts respondents could cite.

Next came a number of name interpreter questions for each dyadic (ego–alter) tie dealing with relationship strength and relative knowledge contribution from each alter in ego's network. Although several questions relating to knowledge similarity between ego and her alters were included, only one produced meaningful results; that question is shown in the middle panel Table 2.[6] Finally, respondents were asked to complete two ego-network questions, one relating to the structure of their immediate networks and the other, the heterogeneity of knowledge among their contacts (bottom panel, Table 2). Ego-network questions ask the respondent to make an assessment of each possible pair of contacts in his network. Typically this is used to elicit information about alter–alter tie strength from which network structure is inferred. The same approach was used here to gather ego's assessment of the similarity, in terms of what ego thought they knew, of each contact to each of her other contacts.

Respondents who had not completed the survey were contacted by email after a month and again after 6 weeks encouraging them to respond. Based on the data collected from the 48 respondents in the initial sample, a further 80 potential respondents who had been cited as contacts were identified. A single snowball round was administered to these 80 additional managers who worked in five other departments; Network Administration (responsible for the technical operation of the company's network) Research and Development, Information Technology, Finance, and Human Resources. The snowball sample was contacted after a month and again after 6 weeks by email and after 8 weeks by telephone encouraging them to respond.

Snowball sampling typically has some potentially serious limitations (Heckathorn, 1997; Salganik and Heckathorn, 2004): the initial sample is seldom random; respondents in the snowball round are biased towards more cooperative individuals; respondents may specifically not refer friends when there is some stigma associated with the population; and snowball participants with larger networks are likely to be oversampled. In this case the initial sample was not found to be statistically different from the population, suggesting that the first problem associated with the snowball method does not apply. Heckathorn also notes that the number of snowball responses is typically much larger than the initial sample, which was not the case here. Second, since primary incentives were used (a letter from the director of the division was sent to all potential participants asking them to respond) the response rate in both the initial and snowball rounds depended on cooperation to the same degree. Snowball respondents were not identified by personal referral but by a more impersonal process of citation; the snowball respondents did not know by whom they have been referred. Thirdly, there is (one would hope) no stigma involved in working for the company at which the data were collected.

The fourth potential problem, that the snowball approach oversamples people with large networks who would not be representative of the population, could well apply here. The snowball sample was therefore checked for significant differences from the initial sample. No significant differences were found in sent relations, degree, ego-network density, seniority, intrinsic motivation, extrinsic motivation (measured by incentive strength), knowledge heterogeneity or innovativeness. Particularly striking was the similarity in size and dispersion of outdegree: the mean of 11.94 (std. dev. = 7.3) for the snowball is only fractionally higher than that for the initial sample (11.5, std. dev. = 5.9).

However some differences between the initial sample and the snowball round are important to note; first the response rate from the snowball round was far higher than that of the initial round. 58 out of the 80 snowball round surveys were completed, compared to 48 out of an initial sample of 158. This difference might be attributable in part to a higher level of encouragement from the research team to respond; it had been assumed that the likely response rate from the snowball round would be lower since participants were not in departments initially selected by the company for participation. Secondly, there were five dimensions on which the snowball sample differed significantly from the initial sample. Snowball respondents were about 5 years older (44 vs. 39), had been with the company longer (13.8 years vs. 8.3 years), had been longer in their current jobs (2.4 years vs. 2 years), were more likely to have a bachelors degree or equivalent (67% vs. 48%) and were much more likely to have an engineering or scientific background (88% vs. 53%). While these differences may seem strange, for the most part this is probably a function of the departments from which the snowball sample was drawn. The initial sampling was done in the Residential Services division in two departments; Product and Project Management, and Product Marketing. The snowball round sampled people from Network Administration, R&D, I.T., Finance and H.R. The first three departments, from which 54 of the 58 snowball responses came, require highly technical skills requiring either long apprenticeships or more recently an engineering degree.[7] This

[6] A corollary question to that of Table 1 dealing with ego's knowledge contribution to each alter was also asked but there was no correlation between the two. In hindsight this was a poorly worded question.

[7] The company had historically recruited its engineers from high school and trained them itself; more recently the trend had been towards hiring engineering graduates.

Table 3
Performance assessment questionnaire.

"Please write the number from the 7-point scale that best corresponds to your assessment of **this manager's performance** over the **last 12 months**.
Managerial performance
Overall, to what extent is the manager performing his/her job the way you would like it to be performed.
To what extent has she/he met your expectations in his/her roles and responsibilities?
If you had your way, to what extent would you change the manner in which he/she is doing the job?
To what extent are you satisfied with the total contribution made by this person?
Managerial innovativeness
To what extent is this person particularly creative: someone able to come up with novel and useful ideas?
To what extent is this person good at implementing novel ideas?"

helps explain both the average age difference and the difference in both the type of educational background and the level of education. Finally, while the snowball sample was not significantly different at the 0.1 level from the initial sample on overall performance and innovativeness, the probability that the two groups were the same was 0.11 and 0.13, respectively. In order to account for this difference between the groups, the regressions were run with both a control for membership in the snowball sample and without this control.

Managerial performance was assessed independently from the main survey by two senior managers. They jointly assessed respondents on six dimensions (Table 3) approximately 6 months after the administration of the main survey.

3.1. Measures

The independent variables used in the models were ego-network measures. However, unlike many ego-network based studies, the measures were not derived directly from the respondents' reporting of their networks. Instead, because respondents and the alters they cited were identified by their full names, the responses were used to recover a partial picture of the complete network. Two kinds of information were collected; basic structural information, who ego knows and which of ego's alters knew one another, and information about similarity in knowledge, how similar was each alter's knowledge to egos (middle panel, Table 2) and how similar was each alter's knowledge relative to each of ego's other alters (second question in the bottom panel, Table 2). The aggregation rules by which the ego-network tie data were used to construct a single network matrix are summarized in Table 4. In the case of the knowledge distance (or dissimilarity) matrix, responses were made using a four point Likert scale and a simple averaging approach was used when either two people reported on the same alter–alter distance or when an ego–alter distance was combined with an alter–alter distance from another respondent. Two full network matrices were constructed. One was a binary choice adjacency matrix indicating the existence of absence of a tie; the other was a matrix of knowledge distances, an indicator of how similar each person's knowledge was to that of each other person in the sample. Using data from multiple respondents generates a slightly more accurate representation of the network than would be the case using only each respondent's responses; the approach is very similar to that suggested by Adams and Moody (2007). As they note: "If multiple reports of the same relationship are found to be in agreement, the use of these data collection approaches should continue and greater confidence can be placed in similarly collected singly reported network data." (2007:46). In the second part of Appendix A I report some testing for consistency across multiple respondent reporting of dyads. Generally the results suggest the ego reporting of alter–alter ties was not altogether too shabby; only about 10% of alter–alter ties that could be cross-checked were incorrectly reported.

Table 4
Adjacency matrix aggregation rules.

Rule 1	A tie from i to j exists if i cites j.
Rule 2	A tie exists from j to k if the average j–k tie strength reported by $i_1 \ldots i_n$ is greater or equal to 0.5, where a response of 0 indicates "I believes j and k have no relationship or a distant one", 0.5 that "they are neither close nor distant" and 1 that "they are especially close". (The 3-point Likert responses from upper section, middle panel, Table 2 are coded 0, 0.5 and 1.)
Rule 3	A j–k reported by $i_1 \ldots i_n$ (Rule 2) does not exist if j is a respondent and does not cite k and k is also a respondent and does not cite j.

Ego-network measures of local density and knowledge heterogeneity were then derived from these aggregated matrices rather than from the individual respondents' ego-network data. The specific formulation of the measures is described below.

3.1.1. Ego-network density

The density of an individual's immediate network provides a simple and intuitive indication of the absence of structural holes. I use density rather than constraint because the latter measure, by construction, embodies some assumptions about mechanisms. The constraint measure (Burt, 1992:54–61) moderates the influence of ties between alters by the extent to which alters are themselves widely connected to ego's contacts. As Burt's discussion of alternative formulations suggests, this relies on some assumptions about behaviors of the nodes and the way they interact. In this sense is it not a completely neutral measure of structure. Density, Δ_i, was calculated as the number of ties between alters divided by the number of all possible alter–alter ties (Wasserman and Faust, 1994)[8]:

$$\Delta_i = \frac{\sum_{j=1, j \neq i}^{N} \sum_{k=1, k \neq i}^{N} x_{i,j} x_{i.k} x_{j,k}}{\sum_{i=1}^{N} x_{i,j} \left(\sum_{i=1}^{N} x_{i,j} - 1 \right)} \quad (1)$$

3.1.2. Alter knowledge heterogeneity

The knowledge heterogeneity measure is an Eigen equation based measure. It is derived from respondents' perceptions of the similarity or dissimilarity of their own knowledge with respect to each of their alters and the perceived similarity or dissimilarity of each alters knowledge relative to each of the respondents' other alters. The dissimilarity of each node relative to each other node was assembled into a single knowledge distance matrix. From this full knowledge distance matrix an ego knowledge distance matrix was extracted, using only ego's cited contacts. This ego knowledge distance matrix was used to derive a measure of alter knowledge heterogeneity – the contribution in terms of non-redundant knowledge to ego of each of his alters – using the approach described by Rodan and Galunic (2004). The measure takes into account not only how different each alter's knowledge is from ego's but also how different each alter is from each of ego's other alters: a set of alters

[8] Density was calculated on the full ego-network matrix which was extracted from the reconstructed full matrix; none of the matrices were symmetrized and so the information on the direction of ties was incorporated in the calculation. Where tie information came exclusively from respondents reporting of their assessment of alter–alter ties, these ties had to be treated as symmetric. I considered symmetrizing all ties, but this would mean recording as undirected ties that, according to the survey responses I had, were un-reciprocated. Ultimately I decided that it was better to have this mix of directed (based on ego–alter data) and undirected (from alter–alter data) rather than discard the more fine grained information in the ego–alter data.

who are only moderately dissimilar from ego but quite different from one another may bring as much non-redundant knowledge to ego as a set of alters who are all very different from ego but identical to one another. The uniqueness, u_j, of each contact is found in the solution of the Eigen equation:

$$\lambda U = DU \tag{2}$$

The vector U is an Eigenvector whose elements are the uniqueness values of each of the ego's key contacts and D is ego's key contact knowledge distance matrix. The knowledge heterogeneity measure, h, uses the uniqueness values from the first solution to Eq. (1) (sorted by size of Eigenvalue) and the ego–alter knowledge distances to calculate the total contribution of non-redundant knowledge from all of ego's key contacts and is defined as:

$$h_i = \frac{\lambda}{N} \sum_{j=1, j \neq i}^{N} d_{ij} u_j \tag{3}$$

where N is the number of cited contacts in i's network, λ largest Eigenvalue in the solution of Eq. (1), d_{ij} is the knowledge distance between i and j, and u_j is the uniqueness of contact j. The measure has relatively intuitive properties; it is an increasing function of the distance between alters, the distance between ego and any of her contacts and of network size.[9]

3.1.3. Performance

A measure of individual job performance was based on data collected in a separate performance assessment questionnaire completed jointly by two senior managers in the company approximately 9 months after the main survey had been conducted. The time lag was designed to reduce the likelihood that mechanisms that worked in the opposite direction would be detected (Davis, 1985). The performance assessment involved rating all those who had responded to the survey on four items (Tsui, 1984), shown in Table 1. A principal component factor analysis yielded a single factor with an Eigenvalue greater than one and a strong Cronbach alpha (0.93). This factor was used as the measure of job performance.

3.1.4. Innovativeness

Two items relating to innovativeness were included in the same senior management assessment of the respondents. These questions were designed to focus on innovation, specifically, new idea creation, implementation and execution. Since they tap two quite different but jointly required aspects of innovation, a formative index is appropriate (Bollen and Lenox, 1991; Diamantopoulos and Winklhofer, 2001). The measure of managerial innovation was formed as the square root of the product of managerial creativity and implementation/execution, modeling the necessity of the joint presence of creativity and implementation skills likely needed for successful innovation.

3.1.5. Controls

In the modeling exercise, I ran the estimations with and without controls; while there were some small changes to the standard errors of the independent variables, the signs are the same and the levels of significance almost identical[10] and the arguments made from the findings are unchanged; I therefore chose to present the results of the estimations without controls principally because it makes the tables simpler to interpret. In this section I explain the controls that were tested.

I controlled for tenure in case the structural properties of managers' networks changed systematically with the length of time they had been at the company. Longer-tenured managers may retain contacts they made in prior jobs in other parts of the company (Gargiulo and Benassi, 2000), leading to an association between tenure and the presence of holes in their networks. At the same time tenure may be related to experience and greater experience may lead to higher performance. By controlling for tenure I distinguish between the direct effects of experience and effects that are structural in origin. I controlled for level of education in case people with differing levels of education developed different kinds of network, since education and performance might be directly related. For the same reason, I also controlled for gender and seniority. I included dummy variables for departmental affiliation to control for differences in performance that were principally a function of departmental affiliation rather than network structure. For example, Research and Development works with people from a variety of other departments and respondents from R&D are therefore likely to have relatively sparse networks; they may also be evaluated differently in a systematic way because of the different job requirements and evaluation criteria in that department. A control for network size was included since the density of a network decreases with its size and I wanted to ensure that the density measure was picking up the structure of the network rather than its size. For the same reason, the number of key contacts was included since the knowledge heterogeneity of key contacts measure is highly correlated with the number of key contacts. I also controlled for differences between the initial sample and the snowball round. Finally, as suggested by Doreian (1981), I tested for spatial autocorrelation in both the dependant variables using the Moran measure of spatial autocorrelation (Cliff and Ord, 1973; Moran, 1950). The autocorrelations were relatively low (0.122 for performance and 0.138 for innovativeness) and autocorrelation was not considered sufficiently problematic to render the ordinary least squares assumption of independence inapplicable. While several of the control variables were significant, their inclusion did not affect the findings.

4. Results

Of the 238 surveys sent out, 108 were returned; two were incomplete leaving 106 usable responses. Sample selection bias was tested using limited available data on respondents and non-respondents; although company policy at the data collection site precluded the disclosure of any personal information including performance data, the company did provide aggregate data for age, tenure and gender for the company as a whole. No significant difference was found in terms of gender, though there was a significant difference between respondents and non-respondents in terms of tenure (respondents had been with the company three and a half years less than the company average, $p < 0.005$) and age (respondents[11] were on average 4 years younger than the average age for the company, $p < 0.05$). However, there was no significant relationship between either tenure or age and ego-network density or knowledge heterogeneity in the sample, suggesting that while the sample may differ from the population in terms of age and tenure (the two are strongly correlated), there is no reason to believe that they differ in terms of the two independent variables of interest in the study. While I would have preferred to be able to have done some more rigorous testing for sample

[9] An alternative formulation, $h_i = \sum_{j=1}^{N} d_{ij} u_j$, has similar properties but is much less sensitive to network size.

[10] The significance levels were slightly better with the inclusion of controls – that the findings hold absent the inclusion of controls is a more conservative test.

[11] We have age data for only 88 of the 108 respondents.

Table 5
Means, standard deviations, and pair-wise correlations.

		Mean	Std. dev.	1	2	3	4
1	Job performance	0.00	1.00				
2	Innovativeness	0.00	1.00	0.70***			
3	Ego-network density	0.54	0.16	−0.38***	−0.41***		
4	Knowledge heterogeneity	0.30	0.17	0.24*	0.27**	−0.23*	
5	Ego-net. Den. X Know. het.	0.16	0.09	0.01	0.00	0.27**	0.82***

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 6
Regression models.

	1 Job performance	2 Knowledge heterogeneity	3 Job performance	4 Job performance	5 Innovativeness	6 Job performance
Constant	0.9853***	0.3971***	0.4712	−0.4931	−0.4506	−0.0562
	(0.285)	(0.056)	(0.339)	(0.415)	(0.556)	(0.257)
Ego-network density	−1.9151***	−0.2044*	−1.5179**	0.1514	0.0354	0.1458
	(0.507)	(0.1)	(0.497)	(0.723)	(0.968)	(0.449)
Knowledge heterogeneity			0.9334*	3.0536**	4.3081**	−0.4933
			(0.471)	(1.142)	(1.531)	(0.722)
Ego-net. Den. X Know. het.				−4.147†	−6.0587*	0.2036
				(2.175)	(2.914)	(1.361)
Innovativeness						0.7205***
						(0.047)
R squared	0.1418	0.0522	0.1651	0.1549	0.2084	0.4643
P [*F* > Fcrit]	0.0003	0.0444	0.0004	0.0005	0.0001	0.0000
Adj. *R* sq.	0.1335	0.0431	0.1489	0.1301	0.1851	0.4431

$N = 106$. Standard errors in parentheses.
† $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

selection bias this was all that I was able to do with the data available.

Table 5 shows the correlations between the variables. Performance is positively associated with knowledge heterogeneity and negatively related to network density. Innovativeness shows the same pattern of associations. There is a negative relationship between density and knowledge heterogeneity.

Table 6 shows the results of the regression model estimations.[12] Because there was some heteroscedasticity in the data, and multicollinearity between the knowledge–ego-network density interaction term and the main knowledge heterogeneity term (variance inflation factors of about 9), I used the Stata robust regression 'rreg' procedure for estimating the models. Two data points had considerable impact on the models and the rreg weighting procedure reduces this problem. While one solution to the issue of multicollinearity would be to mean center the variables, interpretation of mean centered interaction terms in which one has a positive and the other a negative influence on the dependant variable is much less straightforward than when the variables are bounded in the range [0,1].

The first step in the analysis was to verify that if structure was influencing performance, it was not doing so through its influence on knowledge heterogeneity and the latter's impact on performance. I tested for the potential mediating effect of knowledge heterogeneity in the structure–performance relationship (Baron and Kenny, 1986) by first testing the relationship that will be mediated (Model 1). There is a significant negative relationship between ego-network density and job performance. There is also a significant relationship between knowledge heterogeneity, the potential mediator, and the independent variable whose effect may be being mediated, ego-network density (Model 2). With the addition of knowledge heterogeneity to the ego-network density job performance estimation the coefficient for job performance declines in magnitude by 20% but remains significant. This suggests that while structure has been acting as a proxy for knowledge effects when used in absent any variable that captures knowledge distribution in the network, knowledge heterogeneity does not completely mediate the structure–performance relationship; there remains a significant independent effect of structure, controlling for knowledge heterogeneity.

Next the interaction term was added to test for the two contingent mechanisms, arbitrage and competition. The lack of a significant coefficient for density in Model 4 and the fact that the coefficients for knowledge heterogeneity and the density-knowledge heterogeneity interaction are both significant, of about the same magnitude and positive and negative respectively, is consistent with information arbitrage. Thus far, the analysis suggests that of the four original mechanisms in structural holes theory, autonomy, opportunity recognition, competition and information arbitrage, only the last is present. There is no direct effect of density outside of the interaction which suggests competition is not playing a role. Knowledge heterogeneity is only beneficial when density is low (the interaction term effectively cancels out its contribution when density is high) which suggests that opportunity recognition, which should be independent of structure, is not contributing while arbitrage, which depends on heterogeneity and sparseness is. Were competition to be active, density would matter but only when

[12] I also ran all the models with a control for potential autocorrelation, ρWy, where ρ is the autocorrelation coefficient, W is the weights matrix, in this case the row standardized adjacency matrix, and y is the dependant variable. Except for Model 3, in which density is now significant and knowledge hterogeneity is no longer significant, the results for all other models are unchanged when this control is included.

heterogeneity was low; this would show as negative coefficients for density and knowledge heterogeneity balanced by a positive interaction term (see Appendix A). Thus H1, H2, H3 are not supported; H4 may be as long as the mechanism is not mediated by innovativeness.

Model 5 tests the second potential mediating variable, innovativeness for a relationship with all the independent variables, density and knowledge heterogeneity and their interaction; all are significant and have the same signs as in the prior model, suggesting that innovativeness may mediate the relationship between some or all of these variables and performance. The final model introduces the potential mediating variable, innovativeness, into the performance–density–knowledge estimation. Both the independent variables from Model 4 are no longer significant suggesting that innovativeness is the mechanism that connects structure and knowledge heterogeneity to performance, rather than arbitrage. H4 is therefore not supported while H5 is.

5. Discussion

The findings here are in essence twofold; first, while structure has been acting as a proxy for knowledge heterogeneity in prior work which does not measure both, structure still matters. Secondly, these results suggest that managerial innovativeness mediates the relationship between network structure, knowledge heterogeneity, their interaction, and managerial performance. Information arbitrage, which seemed to be present when managerial performance and the network variables were regressed against job performance without innovativeness to mediate the relationship, appears not to be directly responsible for higher performance; density, knowledge heterogeneity and their interaction are driving performance through the innovativeness of these managers, which in turn is related to their assessed job performance. It is also interesting that sparseness matters for innovativeness.

The principal conclusion is that structural holes, at least at the company where these data were collected, are not used to exploit individual autonomy, to create competition between contacts, to broker information, nor even to gain an advantage through earlier and more frequent recognition of opportunities. Rather, it seems that the heterogeneity of knowledge to which managers are exposed leads to greater creativity and innovativeness, and it is this that leads to managers being judged to be higher performers. That structure also matters for innovativeness suggests that innovativeness is not only a matter of generating new ideas, but also of having sufficient autonomy to act on them. Neither knowledge heterogeneity not autonomy on its own is enough; innovativeness seems to need both.

Several caveats are in order. First, the results may be an artifact of a form of common method bias. Although the performance and innovativeness measures were not provided by the survey respondents (thus avoiding a common method bias problem between the performance and network variables), the performance and innovativeness measures were both derived from the same senior managers' assessments and in one model, Model 6, innovation appears on the right-hand side of the equation while performance is on the left. The greater the extent to which these senior managers saw innovativeness as synonymous with performance, the more closely the two outcome measures would be correlated which could artificially inflate the mediating effect of innovativeness. It is also unfortunate (though understandable) that given the task of assessing 106 managers our two senior managers who provided the performance ratings split the task and then compared notes before returning a single set of ratings, since it precluded any assessment of inter-rater reliability. That being said, only 48% of the variance in their assessment of overall performance is accounted for by their assessment of innovativeness. This suggests firstly that they do not see the two constructs as one and the same and second, that there is plenty of unexplained variance for any direct causal link, not mediated by innovativeness, to be exploited in the estimation. Moreover, any bias arising from the confounding of performance and innovativeness in the minds of the managers who carried out the performance evaluations may in fact reflect an organizational reality. The managers who provided the performance data were also those who made promotion decisions and shaped the organization. If they considered innovativeness an important part of individual performance, this would likely be communicated within the organization and become part of the organizational culture. This shaping of the organizational context will likely lead to more innovative activity; thus what appears to be a methodological bias may reflect factors that have created exactly the phenomenon that the findings have uncovered.

Second, the lack of any finding for control or arbitrage may be context dependent. The data were collected from a Scandinavian company; since Scandinavian culture tends to downplay individual competitiveness, the tertius strategies Burt describes, particularly those relying on competition and arbitrage, may have been curtailed by societal norms. Although Burt does not explicitly test the relative magnitudes of the mechanisms discussed in structural holes theory, it is possible that the control and information benefits he described, although not found here, may have been present in the settings from which his data were collected. Since this study was carried out in one company, caution must be used in generalizing too broadly from the results.

Thirdly, the finding that innovation trumps the other mechanisms of structural holes theory might be attributable to bias in the sample. Because the respondents were younger on average than the company as a whole, the study may have oversampled people who were less set in their ways and more willing to suggest innovative solutions to problems. These people may have turned to innovation first before thinking about the other ways that their holes might be exploited. However, dropping observations with the 20 shortest tenures, which brings the sample mean up to the mean for the company as a whole, actually strengthens the findings slightly.

Finally, because there was no restriction on the number of contacts respondents could cite, and because the length of the ego-network question grows with the square of the number of cited contacts, the time needed to complete the survey can be somewhat onerous for people who cite a large number of contacts. It is possible that people with large networks failed to complete the survey and did not return the diskette. If so, the sample would be biased towards those with smaller networks. I tested the models dropping the bottom quartile in terms of ego network size and the results were unchanged. Symmetrically I also re-ran the models dropping the largest quartile in network size and again the results remained unchanged. Although this is obviously not a definitive test, and though it is possible that those with large networks gave up on the survey, it does not seem as though this would prevent generalizing the overall conclusions from the sample to the population.

While the level of analysis in this work is the individual manager, the results may also have implications for levels of analysis such as departments within firms or firms within an industry. However, considerable caution should be exercised generalizing from one level to another; while the mechanisms may be the same, their relative importance may be quite different. Competition between departments within a firm may apply when those departments are assigned the same task or goal; for example, large firms often have several R&D departments competing with each other to solve a particular problem. Moreover, while all managers are treated in a broadly similar way, at the firm level of analysis whether network nodes are competitors, buyers or suppliers will have a significant impact on the dominant mechanisms in any dyad or triad. For example, autonomy may be useful to firms trying to benchmark their competitors; when a firm has at least some information regarding many of its competitors while they have a more restricted set of reference firms, the focal firm may have an advantage. Competition is also likely to be the dominant mechanism when considering both a firm's relationships with its buyers and suppliers. Large firms very often engage many suppliers of the same part to enable them to play one off against another, and prefer not to be beholden to a single buyer for their outputs. Firms often benefit from arbitrage; for example consulting companies gain insights into problems in one client which are helpful in providing advice to other clients in the same industry.[13] Innovation may occur when companies see how certain products and services available from its suppliers may be combined to solve client problems; the greater the variety of supplier technologies the firm deals with and the wider its array of customers – and potential problems to be solved – the more likely innovation will be. While the mechanisms associated with structural holes theory may be found at many levels of analysis, it is unlikely that the results regarding their relative contribution will be generally applicable to other levels.

5.1. Implications for research

A reasonable question remains: why do these findings matter? If all roads lead to Rome (higher individual performance) should we care about which mechanism is responsible? I believe the answer is 'yes' because each causal mechanism is likely to have a different effect at a more aggregate level. As DiMaggio notes (1991), aggregation across levels of analysis requires care and higher level outcomes cannot simply be extrapolated as the sum of lower level ones. Whether structural holes between managers benefit the department, division or firm will likely depend on the way in which they are exploited and thus on the mechanism in use.

When sparse networks are exploited for the autonomy they provide, there will likely be variance in activities across an organization. By reducing autonomy dense networks should increase the extent to which actions are congruent with the firm's strategic context (Bower, 1970) reducing the variety of avenues being pursued. Variation is important to successful exploration (March, 1991) and the less dense organizational networks are, the more exploration one would expect. To the extent that exploration and learning are drivers of firm performance, autonomy should therefore be beneficial at the firm level.

Creating competition might benefit the organization as a whole when it leads to greater effort. However, competition depends on low knowledge heterogeneity and therefore is likely to be associated with low creativity and innovation. Thus while increased competition and effort may be helpful at the collective level in stable environments, in dynamic environments this may come at the cost of innovation and adaptability. Moreover, if control is exercised by passing ambiguous or distorted information, managers will on occasion be misinformed which will impede decision making and the exploitation of their organization's collective knowledge (Conner and Prahalad, 1996). Furthermore, should those who receive distorted information discover they have been misled, trust and extra role behavior (Kim and Mauborgne, 1996) – doing more than is required by the organizations rules and standard operating procedures, often vital to collective performance (Barnard, 1938; Crozier, 1964; Crozier and Friedberg, 1980) – may decline.

Opportunity recognition is at the heart of entrepreneurship (Kaish and Gilad, 1991) and much has been written that attests to the importance of entrepreneurial activity inside the firm (e.g., Burgelman, 1984; Kogut and Zander, 1992). Opportunity recognition also encompasses the recognition of usefulness of internal information in the pursuit of the development of a new product, market or firm capability (Doz et al., 2001; Stuart and Podolny, 1996) and is therefore likely to be beneficial to the organization.

However, when information is bartered, some is likely to be held back until it can be exchanged to best advantage. As Reagans and McEvily (2003) argue, absent cohesion, a desire to remain useful and non-substitutable will reduce information sharing. Thus while information flow occurs as a result of arbitrage, less transfer occurs, and in a less timely manner, than would have been the case had the broker simply closed the hole between his two contacts (Obstfeld, 2004).

Finally, innovation is important for survival in turbulent environments, and generates opportunities for economic value creation and appropriation (Dougherty, 1992; Dougherty and Heller, 1994; Henderson and Clark, 1990; Kanter, 1988; Moran and Ghoshal, 1999; Nonaka and Takeuchi, 1995); individual innovativeness is therefore likely to be positively related to organizational performance. The finding that innovativeness seems to be the dominant mechanism, at least in the context of the firm studied here, might therefore be construed as encouraging for managers and strategy scholars alike.

Much work remains to be done however. Since the relative strengths of mechanisms reported here may not be found in other cultural settings, it would be worthwhile to undertake a similar study in a cultural context that is more individualistic and individually competitive, perhaps the UK or the US. Another useful extension would be to test the effect of different kinds of formal organizational structure. Podolny and Baron (1997) found that the use of networks for buy-in requires cohesion rather than structural holes and it is clear that the general results presented here for aggregated networks comprising task, friendship, buy-in and advice ties, will apply only for some activities and within certain kinds of network. A useful line of empirical inquiry would be to investigate the contingent relationships between each mechanism, and types of network, elements of context, such as structure, and shared norms and values. Further work on the linkages between structure and individual performance, perhaps using more qualitative methods, would also be useful.

Finally, and perhaps most importantly, data is needed to assess the aggregate level effects of these mechanisms. While I have speculated briefly as to their possible implications, and isolated them in the context of one firm, further work is clearly needed here. It is almost two decades since "Structural Holes" was published; an answer to the question "how do individual structural holes influence business unit or firm performance?" seems somewhat overdue.

6. Conclusion

This paper shows how the different mechanisms by which network structure has been linked to individual performance may be represented in reduced form using three underlying constructs: network density, knowledge heterogeneity and innovativeness. Using this framework, it fills a gap in the literature by answering the question: which of the five mechanisms in structural holes theory actually drives managerial performance? The findings suggest that innovation mediates the relationships found in earlier work between knowledge heterogeneity and performance (Rodan and Galunic, 2004), and between network structure and performance (Burt, 1992, 2000). Of the different mechanisms suggested in structural holes the-

[13] Although the specifics of a client's operations are typically protected by confidentiality agreements, general principles and a sense of the problems an industry faces are transferable between one client and another.

ory, in the company from which the data were collected innovativeness seems to be the principal operative mechanism.

Appendix A.

A.1. Sign of interaction coefficients

Suppose the dependent variable, y exhibits an interaction with x_1 and x_2 such that it increases fast with x_1 when x_2 is small and more slowly when x_2 is large and does not change at all when x_2 reached its maximum value. This would be the case for information arbitrage, which rises with an increase heterogeneity of contacts when ego-network density is low (i.e. there are holes in the network) but is zero when density is high since there are no arbitrage opportunities in a completely closed network. Thus one could write:

$$y = b_{arb}k(1-d)+\varepsilon \quad (4)$$

Here y might represent performance, k knowledge heterogeneity and d density; b_{arb} is a scaling factor. When density is 1, knowledge heterogeneity has no effect on performance; when it is 0, performance increases by b_{arb} for a unit increase in knowledge heterogeneity. Expanding this gives:

$$y = b_{arb}k - b_{arb}kd + \varepsilon \quad (5)$$

If the following regression model is estimated:

$$y = \beta_0 + \beta_1 k + \beta_2 d + \beta_3 kd + \varepsilon \quad (6)$$

The coefficient for the main effect of knowledge, β_1, will be positive while that for the interaction term, β_3, will be the same size but negative. The density coefficient, β_2, will be zero (or small) and not significant.

Next, consider the case in which k and d jointly cause a reduction in y. This would be the case of competition. When density is low, the structural opportunity exists for creating and exploiting competition. When knowledge heterogeneity is high, competition cannot be created because individuals are not substitutable. Given a sparse network structure, competition is thought to increase with substitutability and thus decline with knowledge heterogeneity. When density is high, few if any structural opportunities exist for competition and the effect of increasing heterogeneity will be negligible. In dense networks ($d=1$), heterogeneity does not matter; similarly, in networks with maximum heterogeneity ($k=1$) substitution is not possible changes in density will also have no effect. Performance will be maximized by the joint absence of heterogeneity and density:

$$y = b_{comp}(1-k)\times(1-d)+\varepsilon \quad (7)$$

Expanding this gives:

$$\begin{aligned} y &= b_{comp}(1-k-d+kd) \\ &= a + b_{comp} - b_{comp}k - b_{comp}d + b_{comp}kd + \varepsilon \end{aligned} \quad (8)$$

If the following regression model is estimated:

$$y = \beta_0 + \beta_1 k + \beta_2 d + \beta_3 kd + \varepsilon \quad (9)$$

Here the coefficient for both main effects, β_1 and β_2, will be negative, while interaction term, β_3, and the intercept β_0 will be positive. All coefficients should have about the same absolute value.

Although I have argued that is unlikely that one individual would simultaneously employ both arbitrage and competition strategies it is certainly possible that some people would be exploiting their holes by information arbitrage while others are using competition. To assess the implications for the modeling strategy used here I

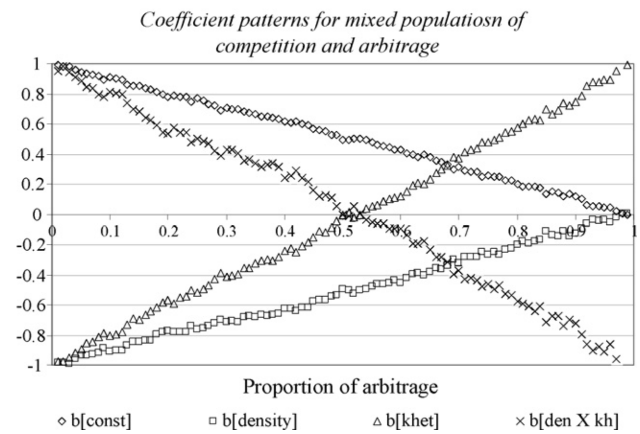

Fig. 2. Coefficient patterns for mixed population of competition and arbitrage.

generated some Monte Carlo data with varying proportions of the two mechanisms where α observations had y defined as in Eq. (4) and $\alpha - 1$ where y was defined by Eq. (7). α was varied from 0 to 1 in steps of 0.01. The results are shown in Fig. 2.

With mostly competition and little arbitrage operating, the main effects of both density and knowledge heterogeneity are negative while their interaction is positive. When there are equal proportions of both mechanisms the interaction term and the knowledge heterogeneity term are both zero and not significant; this pattern of coefficients could be seen as evidence for either autonomy (only a structural effect) or equal proportions of arbitrage and competition. As arbitrage increases and competition declines the pattern becomes clearer again with no main effect from density, a positive main effect from knowledge heterogeneity balanced by a negative interaction term.

A.2. Dyad confirmation

Adams and Moody (2007) suggest checking where possible to see whether reporting of ties is corroborated. I checked each alter–alter dyad reported by respondents against all other respondents' reports for that tie, and against any reports in which either end of the dyad was also a respondent. Of the 14,772 alter–alter ties which were reported on by two different respondents, 20.5% were reported inconsistently. Of course this does not mean that 79% of ties identified in the ego-network data collection question were accurate, only that there is a high level of agreement. Since only 19% of ego-network dyads were reported as missing, there may be a tendency to over-attribute alter–alter ties. The higher this over-attribution the greater the level of agreement will be, so this relatively low error rate may be misleading.

Some insight into the actual error rate rather than the extent of reporting agreement can be gleaned from comparing the cases in which: either an ego reports an alter–alter tie as present and neither alter, both themselves being respondents, mentions this tie; or ego reports as absent an alter–alter tie and one of the ends of that tie is a respondent. Of the 1473 cases in which alter–alter reports could be verified in this way, all were case in which ties were reported by one respondent and missed by a third party; none were reported ties that were confirmed as absent. Of these, 160 (10.85%) were misidentified. If this figure represents a 'true' error rate, then correct assessments were made in about 89% of cases. The joint likelihood of a correct prediction in two people making assessments of alter–alter ties is the square of this, or 79%. This is about the same as the measured alter–alter to alter–alter comparison error rate of 20%. Taken together, these findings seem to suggest a fairly high level of reporting consistency.

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