Chapter 6

On Firmer Ground: The Collaborative Team as Strategic Research Site for Verifying Network-Based Social-Capital Hypotheses

Ray E. Reagans, Ezra Zuckerman, and Bill McEvily

Social networks command the interest of scholars and others because these relational patterns are assumed to have causal force. In particular, network theories typically adopt the premise that such patterns often lead to individual or collective outcomes that cannot be fully ascribed to the exogenous forces that determined such configurations. When this premise of network exogeneity is undermined, network analysis may be a useful tool for viewing the operation of other forces, but it cannot fulfill the network analyst's ambition of demonstrating how social networks shape important outcomes. Moreover, network analysts must concede that network structures are always subject to manipulation by actors and can thus never be considered exogenous to the same degree as are, say, a person's natural endowments and fixed characteristics, such as age, gender, or innate ability. Thus, to place network theories on firmer ground, there must be strong theoretical and empirical reasons for adopting the premise of network exogeneity with confidence.

In this chapter we focus on a key class of network hypotheses that is particularly vulnerable to the criticism that networks do not have causal force: claims that differential success or performance
may be attributed to an actor’s position in a social network. Such hypotheses have gained considerable popularity in recent years and may be summarized as hypotheses regarding social capital. Examples of such hypotheses include the claim that individuals whose networks are better (or more poorly) constructed are more (or less) likely to achieve their goals—say, obtaining a job (Granovetter 1974/1995) or advancing through a corporate hierarchy (Burt 1992). The general difficulty that such analyses face is that, to the extent that certain network positions are more advantageous than others, all actors should be expected to strive for them. And to the extent that such efforts are made by all actors but that only some succeed, this suggests that occupancy of differentially valuable network positions reflects prior differences among actors that are responsible both for observed differences in performance and for network position. In short, the premise of network exogeneity can be undermined by “unobserved heterogeneity,” or the possibility that the variation in social capital reflects differences in intrinsic attributes; and by “reverse causality,” or the possibility that prior performance differences (or even the prior anticipation of future performance differences) are responsible for the social capital attained.

It is crucial to note that the fact that hypothesized network effects might be endogenous in a particular case does not mean that they always are. Indeed, we shall argue that there are ample theoretical reasons to expect network exogeneity in many cases. The challenge is to find nonexperimental research contexts that may serve as “strategic research sites” (Merton 1987) for testing social-capital hypotheses. The primary objective of this chapter is to make progress in meeting this challenge.

In particular, we argue that contexts that include sets of overlapping collaborative teams represent such a strategic research site under certain conditions. Such teams, which may be defined as collective actors that comprise multiple individuals who are responsible for a joint product, include film projects, academic or scientific collaborations, and work groups in organizations—even organizations themselves. The hypothesis that a given team—like an individual—outperforms others because of how it is positioned in a wider social network is weakened by the possibility that the team’s network is not causally responsible for the outcome. For instance, the observed performance differences could be due to differences in composition—for example, a team with more highly skilled members both succeeds at its task and attracts many useful ties, but the latter does not actually cause the former. Alternatively, it could be that teams that either have a history of past success or who experience success at the beginning of a project develop effective networks as a result.

How can these quite reasonable objections be countered? We show below that teams can have two features that make them useful for countering such objections and thereby serving as strategic research sites for testing hypotheses about social capital. Such teams have relatively short lives and contain members with multiple and overlapping team memberships. The team’s having a short life means that it will not have a prior performance record and its members will not be able to anticipate its future success and thus shape their social networks in light of the outcome. This means that one can collect social network data regarding the team members well before the team comes into existence. Multiple and overlapping team membership is important because it means that we can identify each person’s average contribution to team performance. That is, we can recover baseline fixed effects for each of the team members (and even subsets of these members) and thereby deal with the problem of unobserved heterogeneity. Put simply, this strategy helps determine whether a team is really more than the sum of its parts.

Validating Network Exogeneity: Ideal and Reality

Before considering the difficulties of validating the premise of network exogeneity, it bears reminding why it may make sense to invoke this premise. Network analysts are rarely explicit in stating their rationale, but there appear to be two main justifications for the premise. The first is based on the recognition that actors typically are involved in multiple arenas and roles and that the network observed for one arena is, at least in part, a by-product of relations in other arenas. This notion of network-as-by-product is at the heart of Mark Granovetter’s (1985) discussion of embeddedness in market interactions. Granovetter argues that the social-network overlay on
economic exchange may often have functional (and also dysfunctional) consequences. However, the origins of such networks often reside in more "primordial" affiliations (as in the archetypical example of the Hasidic diamond traders; see also Coleman 1988), which are essentially exogenous (but see Zuckerman 2003, 558). In this example, the social network observed in the economic sphere is a by-product of activity in an exogenous sphere. And the reverse may occur as well. For example, a common theme in the "embeddedness" literature is that once actors become members of an economic network, they acquire a commitment to the relationships that can no longer be reduced to self-interest (see Sgourev and Zuckerman 2006 for a test of this argument; see also Granovetter 1974/1995, 463–5; Lawler 2001; Uzzi 1997, 55). In such cases then, a social network develops as a by-product of economic interests.

Another possibility is a situation where networks in each of multiple arenas may arise endogenously, but, since each privileges a different type of network and networks cannot be adjusted quickly, it is effectively impossible for the actor to design a network that works for both arenas. For example, Ezra W. Zuckerman (1999, 2000) argues that firms suffer a price penalty when their egocentric network of coverage by securities analysts implies a mismatch between the firm’s industrial participation and the way it has been classified by analysts. Why would a firm not endeavor to eliminate such a penalty by realigning its corporate strategy in a way that induces a more favorable position in the coverage network? The answer may be that such a change would require the firm to realign its corporate strategy in a way that hurts profits in the long term, even if it removes the financial-market penalty in the short-term. Thus, if firms optimize for profits, their position in the analyst coverage network will be at least somewhat exogenous.

A second rationale for treating networks as exogenous relies on principles of path dependence similar to those familiar from studies of technological networks. Although prior forces may be responsible for "seeding" a network, the initial configuration unleashes a dynamic that reinforces such initial conditions, thereby imputing causal force to the resulting network. Such models are prominent in the literature on status hierarchies, which can be considered social networks where the links are relations of deference from one party to another. For example, Joel M. Podolny (2005) argues that, whereas the initial status hierarchy results from initial differences in quality, the "loose linkage" between the two implies that over time, initial quality differences are solidified as substantial differences in status that are then relatively insensitive to changes in quality. Roger V. Gould's (2002) model of status hierarchy implies a similar decoupling of status from quality. Key to both models is a rationale for why low-status actors remain in their positions even though they suffer from lower performance. In both cases, the rationale relies on the paradox that a high-status actor risks losing status if he competes with low-status actors because he will thereby become affiliated with them. So a network structure with greater returns accruing to particular positions may exist in a steady state. And this means that the resulting network can be treated as exogenous.

**How Exogenous?**

Thus, the primary challenge to the premise of network exogeneity is not theoretical but empirical. Since in virtually all cases, it is possible to derive both a social network-based and a network-free explanation for the observed association between network position and performance, the challenge is to find research contexts in which network position may indeed be treated as at least partly exogenous.

In attempting to meet this challenge, it is useful to consider the experimental design necessary to demonstrate the causal impact of social-network position on performance. Such an experiment must satisfy two straightforward conditions. First, the experimenter should assign network positions to individual subjects (collectivities) rather than allowing networks to emerge from interaction. Second, such assignments should be conducted in a manner that is random with respect to underlying differences in quality or ability or any other factor that might be correlated with performance. If an experiment that is designed in such a manner (see, for example, Cook et al. 1983; Willer 1999) finds that network position affects performance, such results provide unambiguous evidence that network position is causal.

Researchers who analyze processes outside the laboratory are
rarely able to engineer social networks (but see Karlan 2004; Rubineau 2007; Sacerdote 2001 for exceptions). The challenge that confronts most analysts, then, is to analyze observational data using methods that help them to isolate the causal impact of network position. In particular, the experimental conditions given may be translated into two directives for analysis of observational data. First, one must measure social networks prior to the measurement of performance. Second, one must demonstrate that the observed association between network position at time $t$ and performance (at time $t + 1$) could not have been spuriously produced by one or more prior variables that affect both network position and performance (see Davis 1985). Such prior variables may be classified into three types: measures of underlying differences in ability or quality; past performance; and expectations of future performance. Elimination of the first type of variable solves the problem of unobserved heterogeneity; elimination of the second and third solves the problem of reverse causality. In general, to the extent that the analysis establishes the temporal priority of network position and succeeds either in controlling for the three types of spurious effects or in eliminating them via experimental design, we may be confident that the observed association between network position and performance indeed reflects causation. Yet these directives are extremely hard to fulfill in practice, as we show next in a review of how past research has struggled to justify the premise of network exogeneity.

Eliminating Reverse Causality

The difficulty of eliminating the problem of reverse causality is perhaps best illustrated by the fact that researchers have been hard-pressed even to meet the basic directive that network data be collected before the observation of performance. Indeed, the challenge of collecting data over time has forced many studies (for example, Burt 1992; McEvily and Zaheer 1999; Reagans and Zuckerman 2001; Uzzi 1996) to analyze cross-sectional data and to make the unverified assumption that the causal arrow runs from network position to success rather than vice versa. Yet gathering network data prior to the observation of performance is not enough to rule out the possibility that the network position resulted from past performance or the anticipation of future performance. For example, to support his assumption that the positive association between "structural autonomy" and organizational success reflects a causal effect of the former on the latter, Burt (1997, 349; see also Burt 1992, 173–80) replicates the result with data from a study for which the network data were collected six months prior to the observation of performance. However, it is quite possible that either (unobserved) performance at or prior to the collection of the network data affect both network position and future performance or that performance six months hence may be anticipated by actors with some accuracy and therefore may affect how they manage their relationships. Thus, it is insufficient to verify network exogeneity simply by measuring networks prior to that of performance.

A related study that makes progress in solving the reverse causality problem is Podolny and James N. Baron (1997). Podolny and Baron observe performance (mobility in a corporate hierarchy) over a period that begins prior to and includes their survey window, but they are also careful to include in their analysis only relationships that were reported to have begun one year prior to the survey. In addition, Podolny and Baron report that they conducted robustness tests that showed that the observed associations between egocentric network patterns and performance did not become stronger when more recent ties are included. Since the performance effects are more salient with network data from the more distant past, this suggests to Podolny and Baron that the networks must be causal. This creative strategy weakens but does not eliminate the possibility that the observed relationship is produced by past performance differences or the anticipation of future ones. In particular, Podolny and Baron did not obtain the respondent’s full network one year prior to the survey, but only a selection based on the criteria presented to the respondent at the time of the survey. As a result, their network data are a subset of the respondent’s network from the prior year that could have been selected in a way that is related to past or in anticipation of future performance. Indeed, it is not unreasonable to expect older ties to be more strongly associated with performance
because they have proved themselves to be more valuable (and were therefore selected by the respondent), whereas newer ties may be generated by more temporary, short-lived needs.

The possibility that the anticipation of future performance drives observed relationships between network position and future performance is particularly problematic where the network data can be construed as patterns of endorsement or certification. For example, several studies have shown that endorsement by the state or a prominent firm may increase the survival or valuation of a firm (Singh, Tucker, and House 1986; Baum and Oliver 1991, 1992). Other studies posit effects of network position on performance where the network is interpreted alternatively as involving the transfer of resources (for example, Powell, Koput, and Smith-Doerr 1996; Ahuja 2000) or as conferring implicit endorsements (for example, Stuart, Hoang, and Hybels 1999). All such studies face the possibility that the certification of an actor has no independent effect on her performance but merely reflects the anticipation on the part of the certifier that the actor will perform at a high level. And, unless one is willing to entertain the possibility that endorsements are handed out randomly, it is a reasonable working hypothesis that they are at least correlated with forecasts of future performance. A similar difficulty confronts studies that examine the positive impact of organizational status on profits or returns (Podolny 1993; Benjamin and Podolny 1999) in that one may receive greater deference when one performs (or is expected to perform) at a higher level. The challenge faced by all such research involves demonstrating that the positive relationship between certification, or deference, and performance is not spuriously produced by that between interpretations of performance on the part of the observer, and performance itself.

Paul Ingram and Peter Robert’s (2000) analysis of the effect on hotel performance (yield) by friendship ties among hotel managers deserves attention for its creative attempt to eliminate the possibility that prior performance is responsible for the observed effects. In particular, they endogenize the network by regressing the existence of a friendship from manager i to j on a series of covariates that are presumed to be unrelated to performance. This then allows them to use an instrumental-variables (IV) regression technique (see for ex-

ample, Hanushek and Jackson 1977; Greene 1997) to identify the portion of the relationship between the network variables and performance that is not due to performance differences. This analytic strategy should be widely emulated in future research. However, one must recognize that IV regression techniques are only as good as the identifying assumptions. In particular, one must be willing to believe that the covariates used to explain network position are truly unrelated to performance. For example, one might wonder whether hotel managers who have shown themselves to be (or display indications that they will be) high performers are also more likely to have more friends, a variable Ingram and Roberts (2000, 414) use to identify network exogeneity. In general, it is extremely difficult to find covariates that are clearly responsible for the development of the network but are unrelated to performance (but see Munshi 2001), which limits the cases for which IV techniques will be applicable.

### Eliminating Unobserved Heterogeneity

Clearly, eliminating reverse causality is difficult. However, the challenge of eliminating unobserved heterogeneity may be even more daunting. Short of random assignment (for example, Karlan 2004; Rubineau 2007; Sacerdote 2001), which is obviously not feasible in most research contexts and can rarely generate substantial variation in network structure, how can we be sure that network structure is independent of the actors’ underlying characteristics? Most researchers have tried to solve this problem by controlling for human-capital variables that might be responsible for the observed relationship between network position and performance (for example, Burt 1992, 1997; Podolny and Baron 1997). But the observable indicators of human capital are typically general variables such as years of education and age rather than the specific forms of human capital (for example, knowledge of organizational routines or managerial ability), which are more likely to affect performance in a local context. An alternative strategy to using observable indicators of human capital, often applied to panel data, involves using fixed effects or the inclusion of a dummy variable for each of the actors (see, for example, Burt 1992, 283–84; Zuckerman 1999). This strategy helps eliminate underlying differences between actors in both perfor-
hypotheses that we wish to consider. In this section, we discuss a strategy for validating such hypotheses.

Our strategy applies to social units that are collections of individuals. Two distinctive features of collectivities are useful for the purpose at hand. First, many collectivities are short-lived relative to the time frame of performance. In particular, the collectivity itself may be formed to carry out a defined task within a particular time frame. Such groups' performance may be affected by their members' internal and external networks of relations, but prior performance of the group per se cannot be responsible for observed effects for the simple reason that the group did not exist previously. In addition, it is feasible to eliminate the possibility that expectations of future performance (by the actors themselves as well as others, such as their managers) are responsible for such a group's success by measuring networks that were formed prior to any expectation that the group will be constituted.

Of course, all collectivities have at least an initial endowment of resources that predates their existence and could be responsible for their relative success. For example, an observed association between an organization's network structure and its subsequent success could reflect the fact that the organization has employees who are particularly skilled, and such skills facilitate the formation of the observed networks. Furthermore, expectations that certain employees, who may have more effective preexisting networks, will be more successful could lead to their inclusion in the group, thereby generating a spurious association between the members' networks and its performance. In sum, unobserved heterogeneity remains an issue even if analysis of collectivities helps resolve the problem of reverse causality.

Yet this brings us to a second distinguishing feature of certain collectivities. In various contexts, substantial overlap in human-resource elements may be found in numerous collectivities. Examples include academic collaborations, short-term project organizations such as films (Soda, Usai, and Zaheer 2004) or conventions, professional service firms (for example, consulting, legal, accounting) and even organizations themselves, when viewed over a longer period
of time. Imagine an organization where each individual is a member of a unique set of teams and whose memberships partially overlap with many other individuals. Such a population aids in the identification of person-level and even higher-order (dyadic, triadic) effects that are distinct from those at the level of the collectivity.

Hedonic models in econometrics (for example Griliches 1961; Rosen 1974), which specify a product's quality as a weighted average of the product's underlying attributes, provide a useful analogy for such identification. Since the same attributes are observed in different combinations across multiple products, it is possible to recover baseline effects for each characteristic and specify the extent to which outcomes for the products exceed or fall short of a level that is expected, given the characteristics included in the product. Although we do not know of a precedent for applying this logic to human collectivities, such an extension seems compelling. If individuals in a population (for example, an organization) are each members of multiple collectivities (such as work groups), it is possible to produce an expected level of performance on the basis of such human-capital endowments and then to observe deviations from such a level. In particular, such a strategy allows one to make good on the conceptual distinction between individual and position that is basic to structural sociology (Gould 2002; Sørensen 1977; Podolny 1993). Analytically separating associations with individual attributes from positional effects is notoriously difficult at the individual level (see Zuckerman et al. 2003). Yet assuming that the social-capital hypothesis applies at the collective level, it affords such a separation at the collective level—and thereby helps address the problem of unobserved heterogeneity for analyses of such collectivities.

We illustrate this approach with the hypothetical population of teams presented in tables 6.1 to 6.3. In table 6.1, we present ten five-person teams and their performance on tasks of equal difficulty. In table 6.2 we present the mean performance score for a given actor, taken over the teams in which she participates. To what extent can the differences in team performance be explained by differences in the skills that their members bring to the table? This can be estimated by trying to compute estimated team performance from the individual-level means. In this case, the correlation between expected and actual performance is considerable, though there is much variance that remains to be explained. And this residual performance could be due to the way that the social-capital available to each individual team member aggregates to become a team-level characteristic that is greater or less than the sum of its parts. That is, if we find that team social capital (measured according to our hypothesis) explains performance beyond the person-level fixed effects, this would imply strong, if not conclusive, validation of the social-capital hypothesis. In the language of the counterfactual model of causality (see, for example, Winship and Morgan 1999; Stuart,

<table>
<thead>
<tr>
<th>Table 6.1</th>
<th>Hypothetical Projects: Membership and Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Members</td>
<td>Abe</td>
</tr>
<tr>
<td></td>
<td>Chris</td>
</tr>
<tr>
<td></td>
<td>Jane</td>
</tr>
<tr>
<td></td>
<td>Ike</td>
</tr>
<tr>
<td>Observed</td>
<td>1</td>
</tr>
<tr>
<td>Performance</td>
<td></td>
</tr>
</tbody>
</table>

Source: Authors' compilation.
individuals, individual-level effects can be distinguished from collectivity-level effects, thereby helping to address the concern of unobserved heterogeneity.

**Team Social Capital: Internal Density and External Range**

Our hedonic approach promises to test whether team social capital is causally responsible for performance; this raises the question of the specific mechanisms by which a team's social network affects its performance. Following our earlier work (Reagans and Zuckerman 2001; Reagans, Zuckerman, and McEvily 2004), we focus on two key variables: the extent to which the team has a high degree of internal network density, and the extent to which the team has a high degree of external network range.

The first of these variables is often cited in the social-capital literature as well as in research on organizational work teams. In this work, density is often measured in terms of the demographic homogeneity of a team owing to the common assumption that homophily (or the tendency of people with similar attributes to form ties more easily than those who are dissimilar) operates. A common metaphor in both literatures is the mutual support and coordination often found in cohesive ethnic communities (for example, Aldrich and Zimmer 1986; Portes and Sensenbrenner 1993). Network density, or "closure," in such communities is thought to facilitate mutual identification among members of a collectivity (for example, Portes and Sensenbrenner 1993) and to promote a degree of trust sufficient to support social exchange and collective action (Coleman 1988). To the extent that closure promotes the development and enforcement of norms and insofar as these norms emphasize high performance, increasing network closure can be expected to have a positive effect on performance (Homans 1950).

The absence of network closure—or the presence of "structural holes" (Cross and Cummings 2004; Oh, Chung, and Labianca 2004)—is problematic within a team. Meanwhile, a second strand of the social-capital literature focuses on the advantages of structural holes between external contacts or external range. Cohesion and range are thought by many scholars to be in tension (for example,
Podolny and Baron 1997, pp. 674; Adler and Kwon 2000; Ahuja 2000; Bae and Gargulio 2003). Yet Ray Reagans and Ezra W. Zuckerman (2001) clarify that each applies at different locations in the social network (see also Burt 2001; Gabbay and Zuckerman 1998, 195–96; Ingram and Roberts 2000, 395–96; Reagans and McEvily 2003, 263; see also Burt 1980; Burt 1982, chapter 7; Burt 1992, chapter 3). Figure 6.1 reproduces these researchers’ distinction between internal (or local) and external (or global) structural holes. Although local structural holes may hinder internal coordination and the team’s capacity for collective action, ties that bridge holes outside the team generate “information benefits” because they represent points of contact into different network clusters, each of which tends to represent a relatively nonredundant concentration of information and resources (Burt 1992, 13–16). Therefore, the most productive teams are characterized by both high internal density and high external range.

Two notes are in order here. First, Rauch and Watson’s chapter in this volume could be interpreted as assuming that a team that is high on internal density must necessarily be low on structural holes. In particular, if all founders of an entrepreneurial venture originate from the same organization, they can be expected to have preexisting relationships that facilitate coordination but to lack wide-reaching links to the environment that are crucial for securing resources and information. This tension can be reconciled when we recognize that the internal density hypothesis focuses on direct relationships between team members. Insofar as the members of a team have such direct relationships, they should be able to coordinate more easily. The problem arises when the team members also have high overlap in their indirect relationships— with people who are not on the team. Insofar as such overlap is significant, the team members will be limited in the resources and information they can access. However, it is possible for an organization’s founders to have good working relationships from their past experiences together but not to overlap greatly in their indirect relationships (perhaps because each worked in a different function or region of their parent organization).

Second, there is a subtle difference between the internal-density hypothesis and the external-range hypothesis as they relate to our strategy for testing social-capital hypotheses. In particular, while the external range hypothesis can be and has been applied to both individual and collective units of analysis, the internal-density hypothesis only applies to collective units. Thus, for the latter hypothesis the value of our approach lies in exploiting certain aspects of team organization (short lives, and overlap in membership across teams) to identify when internal density allows a team to achieve a level of performance beyond what they would achieve if the members had no prior relationships. And for the former hypothesis, the value of our approach lies in identifying a strategic research site for testing the hypothesis because it is difficult to test in other contexts (as reviewed earlier).
“Proof of Concept”: The Social Capital of Project Teams at Malibu Research

We now turn to an empirical application that illustrates the approach we have developed. The empirical context provides us with a good opportunity to examine how much of a team’s performance can be traced to unobserved individual differences and how much to the team’s social capital. That is, the context provides us with a unique opportunity to apply the hedonic approach that we propose and therefore to examine the network exogeneity assumption.

Research Context

We present a concise summary of the data and analytic approach here and refer the reader to our prior work (Reagans, Zuckerman, and McEvily 2004; see Reagans and McEvily 2003) for more details. Briefly, the firm we call Malibu Research is a midwestern contract research and development firm that specializes in material sciences and undertakes projects for two types of clients: its parent organization and outside firms in its local market. Projects fall into six categories, for six basic types of services provided by Malibu: “scientific analyses” such as analyzing material properties or assessing product reliability; conceptualization, or analyzing the potential and feasibility for new product ideas; product and material development, which involves either developing a new product or assisting the client in developing a new product more efficiently; “process development,” whereby Malibu helps the client to improve its process designs and flows; “manufacturing,” which involves either performing material compounding for the client or assisting the client in manufacturing in-house or with a third firm; and “cost and quality initiatives,” which includes an array of services whereby Malibu assists clients in improving the cost or quality of a product subsequent to its initial launch.

Data collection followed the procedures described for dealing with reverse causality and unobserved heterogeneity. First, since the projects are short-lived and network data were collected before the commencement of the projects whose performance we model, the challenge of reverse causality is minimized. In particular, sur-

veys were completed in the summer of 2001 by 104 out of the 113 Malibu employees who had worked on project teams during a one-year period subsequent to the survey. We then obtained detailed data on the several hundred projects that were initiated by the firm in the year subsequent to our survey. Thus, although the networks of team members may change once the team is constructed, and such networks may be shaped by the team’s level of success in reaching its goal, the network structures we observe cannot be subject to such endogeneity because these networks antedate the team’s formation. Insofar as a team’s position in such networks affects its performance, this would imply a path-dependent process of network formation such that a team’s network may be treated, at least in part, as exogenous.

The second key aspect of this data set is that, just as with the hypothetical teams in table 6.1, each individual participated in a unique set of projects but with significant overlap with others. As a result, we can apply the hedonic approach described earlier, whereby we calculate baseline expectations for a team’s performance on the basis of the composition of the team, and then examine the extent to which the team’s social capital explains residual differences in team performance. In particular, our baseline model expects a significant amount of variation in team performance to be explained by dummy variables, or “fixed effects,” for each of the individuals (who worked on at least two projects) who make up the team.

Data and Methods

In the analysis that follows, our performance metric is project duration (see Hansen 1999). There are of course many ways of measuring team performance and it would be ideal to model multiple such measures. Yet project duration, which is the only metric available, is widely regarded at Malibu as a reliable indicator of team performance (see Reagans, Zuckerman, and McEvily 2004, 33–35). Indeed, although Malibu bills clients on a cost-plus basis and thus could be said to benefit from longer projects, the reputational costs from project delays loom large. As one of our main Malibu informants explained, “If you overstay your welcome, there’s a perception
that you don’t deliver. Everybody wants it done yesterday. Deliver quickly and they will always invite you back.” Thus, we model the amount of time until a project’s completion starting with the day it was initiated as a function of network variables and a variety of control variables, including individual fixed effects and labor input.

As detailed by Reagans, Zuckerman, and McEvily (2004; see also Reagans and McEvily 2003), social network data were collected using a combination of sociometric and egocentric techniques (Wasserman and Faust 1994, 45–50). Each respondent was first presented with a roster composed of a random sample of fifteen potential contacts from among the set of coworkers who had billed hours to the same projects as the respondent in the prior year. Respondents were asked to eliminate the names of individuals with whom he or she did not “share knowledge” during that year and copy up to ten of the remaining names onto a contact list. Respondents copied a mean of nine names onto this list. Next, each respondent was asked two free-recall questions. The respondent was first asked to list the names of colleagues who had been a significant source of knowledge during the previous year and then was asked to list the names of colleagues for whom he or she had been a significant source of knowledge. A respondent could list up to five colleagues in response to each name-generator question, for a total of ten additional contacts. Respondents provided a mean of six additional names, with three unique names for each free-recall question. Reagans, Zuckerman, and McEvily (2004, 24–33) discuss the advantages and disadvantages of this network survey methodology. They show that the data do not appear to suffer from appreciable bias in relation to data collected from a purely sociometric instrument.

Internal Density and External Range
We measure internal density as the mean strength of ties between project members:

\[ ND_k = \frac{\sum_{i=1}^{N_k} \sum_{j=1}^{N_k} \frac{z_{ij}}{\max(z_{ij})}}{N_k(N_k - 1)}, \]

where \( z_{ij} \) is the strength of the tie from team member \( i \) to member \( j \), \( \max(z_{ij}) \) is the strongest of \( i \)'s reported ties to anyone in the firm, \( N_k \) is the number of members in team \( k \), and \( N_k(N_k - 1) \) is the maximum number of ties among members of team \( k \). Scaling by \( \max(z_{ij}) \) removes individual differences in the tendency to report high tie strength to others. Network density varies from zero (no relations between team members) to 1 (maximum-strength relations between all team members).

Our measure of external range is the reverse of network constraint:

\[ ER_k = 1 - C_k, \]

where constraint is measured as in Burt (1992, chapter 2) and averaged over all team members:

\[ C_k = \frac{\sum_{i=1}^{N_k} \sum_{j=1}^{N_k} \left( p_{ij} + \sum_{q=1}^{N} p_{iq}p_{qj} \right)^2 / N_k}{N_k}, \]

where \( N \) is the number of contacts external to the team. Constraint has two components. The first is the proportion of total tie strength that person \( i \) allocates to contact \( j \) directly:

\[ p_{ij} = \frac{(z_{ij} + z_{ji})}{\sum_{q=1}^{N}(z_{iq} + z_{qj})}. \]

The second component is the proportion of total tie strength \( i \) spends with contact \( j \) indirectly through mutual contacts \( q \), where \( p_{iq} \) is the proportion of network time that person \( i \) indirectly through mutual contacts \( q \), where \( p_{iq} \) is the proportion of network time that person \( i \) allocates to contact \( q \) and \( p_{qj} \) is the proportion of network time that contact \( j \) allocates to contact \( q \).
constraint is decreasing as $i$ spreads his tie strength among more contacts. The second component captures the possibility that some of these contacts may have strong ties with each other and thus make $i$'s network more concentrated than is implied solely by inspecting her direct ties. And the lower the mean constraint of a team, the higher is its external range.  

**Control Variables**

In addition to the social-capital variables, the models to be presented include seven control variables included in the prior analysis. Three such variables concern the allocation of labor hours by team members to current and past projects. First, although our analysis focuses on projects that were initiated after the administration of the network survey, projects prior to the network survey were used to define the sampling frame for formal contacts. Thus, it is important to identify the aspect of network structure that is due solely to the construction of the survey and the aspect that reflects "true" network patterns. To that end, we use data on the number of hours each person allocated to projects in the prior year to calculate the tendency for each pair of team members in the current year to have worked together in the prior year, which is the team members' shared prior-year experience:

$$PYE_k = \sum_{i=1}^{N_k} \sum_{j=1}^{N_k} (s_i + s_j) / (total_i + total_j) / N_k (N_k - 1),$$

where $s_i$ is the number of hours that person $i$ allocated to projects that included $j$, $s_j$ is the number of hours that person $j$ bills to the same projects, and total$_i$ and total$_j$ are total hours they each billed in the previous year. Using the same billing data, we calculate the tendency for project members to overlap in their billable hours on other, concurrent projects. The equation for team members' shared concurrent experience is identical to the equation for shared prior-year experience, except we consider only projects that are ongoing as of day $d$ rather than those from the final year. Finally, we include the cumulative labor hours devoted to the project, which reflects the total resources dedicated to the project to date. This variable is logged to adjust for skewness.

The remaining control variables measure aspects of the team's size and composition. Team size is simply the number of people on the team. We log this variable to adjust for skewness. We also include two indicators of demographic diversity, function-based and tenure-based diversity. Function-based diversity is defined as

$$DV_k = 1 - \sum_{c=1}^{C} p_c^2,$$

where $C$ is the number of functional areas (six) and $p_c$ is the proportion of team members from area $c$. Tenure-based diversity is measured as the average difference in tenure between project members,

$$CMD_k = \frac{1}{N_k (N_k - 1)} \sum_{i=1}^{N_k} \sum_{j=1}^{N_k} |t_i - t_j|, i \neq j,$$

where $t_i$ and $t_j$ are the tenure of person $i$ and person $j$, respectively (Kendall and Stuart 1977, 48). We also include a measure of mean tenure, which is the average organizational tenure of project members. And as discussed above, we control for unobserved differences between teams stemming from their composition by including individual fixed effects.

**Results**

In table 6.4, we present descriptive statistics and a correlation matrix for the variables used in the models in table 6.5. As in Reagans, Zuckerman, and McEvily (2004), we model the failure time (or time to completion) for the 1,518 projects initiated in the year subsequent to the administration of our survey, 785 of which were completed by the close of our observation window. The models are continuous-time models estimated using the streg procedure with the Stata statistical package. The error terms in the models are assumed to have a log-logistic distribution, though results are not sensitive to this assumption. For example, we get the same pattern of results if we assume a Weibull or lognormal distribution. Our models also include robust standard errors to account for clustering of the errors among the multiple observations for the same project.

To illustrate how much the different predictors contribute to team
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>3.744</td>
<td>.630</td>
<td>.514</td>
<td>.312</td>
<td>.493</td>
<td>.762</td>
<td>.335</td>
<td>.198</td>
<td>1.557</td>
<td>2.972</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>1.349</td>
<td>.630</td>
<td>.514</td>
<td>.312</td>
<td>.493</td>
<td>.762</td>
<td>.335</td>
<td>.198</td>
<td>1.557</td>
<td>2.972</td>
</tr>
</tbody>
</table>

* Logged values.

Table 6.5 Log-Logistic Continuous Failure-Time Models of Project Duration with Robust Standard Errors

<table>
<thead>
<tr>
<th>Predictor</th>
<th>I Individual Dummies</th>
<th>II Controls</th>
<th>III Internal Density</th>
<th>IV External Range</th>
<th>V Network Structure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>2.953*</td>
<td>1.938*</td>
<td>1.753*</td>
<td>2.934*</td>
<td>2.574*</td>
</tr>
<tr>
<td></td>
<td>(.091)</td>
<td>(.341)</td>
<td>(.346)</td>
<td>(.400)</td>
<td>(.417)</td>
</tr>
<tr>
<td>Number of previous completions</td>
<td>.103*</td>
<td>.102*</td>
<td>.103*</td>
<td>.102*</td>
<td>.102*</td>
</tr>
<tr>
<td></td>
<td>(.029)</td>
<td>(.028)</td>
<td>(.028)</td>
<td>(.028)</td>
<td>(.027)</td>
</tr>
<tr>
<td>Cumulative labor hours devoted to project</td>
<td>.010</td>
<td>.012</td>
<td>.021</td>
<td>.020</td>
<td>.020</td>
</tr>
<tr>
<td></td>
<td>(.039)</td>
<td>(.039)</td>
<td>(.039)</td>
<td>(.039)</td>
<td>(.039)</td>
</tr>
<tr>
<td>Team members’ shared prior-year experience</td>
<td>.928*</td>
<td>1.847*</td>
<td>1.264*</td>
<td>1.978*</td>
<td>.928*</td>
</tr>
<tr>
<td></td>
<td>(.407)</td>
<td>(.528)</td>
<td>(.425)</td>
<td>(.529)</td>
<td>(.407)</td>
</tr>
<tr>
<td>Team members’ shared concurrent experience</td>
<td>.429</td>
<td>.394</td>
<td>.388</td>
<td>.362</td>
<td>.429</td>
</tr>
<tr>
<td></td>
<td>(.710)</td>
<td>(.695)</td>
<td>(.694)</td>
<td>(.684)</td>
<td>(.710)</td>
</tr>
<tr>
<td>Logged team size</td>
<td>.450*</td>
<td>.477*</td>
<td>.444*</td>
<td>.467*</td>
<td>.450*</td>
</tr>
<tr>
<td></td>
<td>(.170)</td>
<td>(.170)</td>
<td>(.168)</td>
<td>(.168)</td>
<td>(.170)</td>
</tr>
<tr>
<td>Diversity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Function based</td>
<td>.327</td>
<td>.117</td>
<td>.258</td>
<td>.090</td>
<td>.327</td>
</tr>
<tr>
<td></td>
<td>(.261)</td>
<td>(.265)</td>
<td>(.261)</td>
<td>(.265)</td>
<td>(.261)</td>
</tr>
<tr>
<td>Tenure based</td>
<td>.014</td>
<td>.010</td>
<td>.017</td>
<td>.013</td>
<td>.014</td>
</tr>
<tr>
<td></td>
<td>(.018)</td>
<td>(.018)</td>
<td>(.018)</td>
<td>(.018)</td>
<td>(.018)</td>
</tr>
<tr>
<td>Mean tenure</td>
<td>.006</td>
<td>.004</td>
<td>.007</td>
<td>.005</td>
<td>.006</td>
</tr>
<tr>
<td></td>
<td>(.009)</td>
<td>(.009)</td>
<td>(.009)</td>
<td>(.009)</td>
<td>(.009)</td>
</tr>
<tr>
<td>Network structure</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Logged internal density</td>
<td>-1.052*</td>
<td>-1.889*</td>
<td>-1.052*</td>
<td>-1.889*</td>
<td>-1.052*</td>
</tr>
<tr>
<td></td>
<td>(.347)</td>
<td>(.348)</td>
<td>(.347)</td>
<td>(.348)</td>
<td>(.347)</td>
</tr>
<tr>
<td>Logged external range</td>
<td>-4.572*</td>
<td>-3.625*</td>
<td>-4.572*</td>
<td>-3.625*</td>
<td>-4.572*</td>
</tr>
<tr>
<td></td>
<td>(1.285)</td>
<td>(1.255)</td>
<td>(1.285)</td>
<td>(1.255)</td>
<td>(1.285)</td>
</tr>
</tbody>
</table>

Model fit

| N of projects      | 1,518                  | 1,518       | 1,518                | 1,518             | 1,518             |
| N of completions   | 785                    | 785         | 785                  | 785               | 785               |
| N of project days  | 10,554                 | 10,554      | 10,554               | 10,554            | 10,554            |
| Log likelihood     | -980.32                | -957.98     | -951.62              | -953.34           | -948.85           |
| pseudo R-square    | .187                   | .206        | .211                 | .209              | .213              |

* Robust standard errors are in parentheses.
* p < .05
performance, variables of interest are entered sequentially across table 6.5. Model 1 contains the individual fixed effects. Model 2 contains the control variables. The social-capital variables are entered individually in models 3 and 4. All of the variables are entered in model 5. As with the hypothetical teams in table 6.3, a large part of the reason that some teams outperform others is that the faster teams have members who typically finish faster (and thus have lower mean duration, which is captured in the fixed effect) than others. Note that the unobserved heterogeneity captured here is not due only to differences in the average skill levels of the teams. Another likely reason is that different types of projects (which vary in their typical duration) require different personnel. Thus, the fixed effects capture unobserved differences between teams due both to any advantage in human capital that one may have over another and to differences in the tasks that different teams are asked to perform. The question then is whether differences in social capital can explain residual differences in team performance beyond the hedonic baselines.9

The social-capital variables make significant contributions beyond the hedonic baselines. In model 5 we see that the coefficient for internal density is negative and significant. This reflects the idea that structural holes that are internal to a group or collectivity hinder effective collaboration. Also in model 5, we see that the coefficient for external range is negative and significant as well. Where internal holes are detrimental to performance, holes in the external network are beneficial. The results, therefore, provide support for the social-capital hypotheses. Moreover, by controlling for unobserved individual differences, we can conclude that the effects of the network variables are exogenous, which provides support for the premise of network exogeneity. At the same time, although social capital matters, it would be incorrect to say that team social capital is the factor that matters the most. The bottom row in table 6.5 contains a pseudo R-square and provides a sense for the “variance explained” by each kind of factor. The jump in variance explained occurs after the fixed effects are introduced. The scale, demographic, and social-capital variables contribute to the variance explained, but the vast majority of the variance explained is accounted for by the individual fixed effects. This is not surprising. There are a large number of fixed effects in the model, so the individual fixed effects should explain more variance. The social-capital effects indicate that our teams are clearly more than the sum of their individual parts, but the amount of variance explained by the individual fixed effects reminds us not to forget the human capital contributed by individual team members.

We have also conducted two sets of additional analyses to check the robustness of these results. First, we tested the possibility that unobserved individual differences are better captured by the amount that individuals contribute to a team. That is, instead of simply including the individual fixed effects and the total number of labor hours contributed to the project, it seems appropriate to control for the number of labor hours contributed by each individual team member. Indeed, hours contributed by more able or skilled individuals could have more of an effect on the likelihood that the project will be completed. There is no guarantee, however, that hours contributed by more able or knowledgeable individuals will have a positive effect on completion times. More able individuals could be assigned to more complex and difficult projects. When we replace the individual fixed effects and the total number of labor hours contributed to the project with the individual labor hour variables, the coefficient for internal density is −.88 (p < .001) and the coefficient for external range is −2.33 (p < .05).

A related issue concerns the possibility that team performance is driven by the presence of particular combinations of actors on a team. That is, as previously discussed, certain dyads may have complementary skills such that they make their teams more productive, quite apart from the social capital they bring to the team. This issue is particularly salient because, although we have assumed that pairs of individuals are randomly assigned to projects (and our Malibu informant assures us that teams are staffed solely on the basis of availability), it is possible that particular sets of people end up on the same teams because they are particularly productive when they work together (and are recognized as such by those with influence over team staffing). As discussed above, resolving this issue requires the inclusion of dyadic (or even higher order) fixed effects in our models.
Across the 785 projects, there are 2,877 distinct pairs of individuals. The vast majority of people work with each other on a small number of projects. On average, members of each pair worked with each other on approximately five projects and more than 90 percent of the individuals worked with each other on less than ten projects. There is, however, a small subset of individuals who did work with each other on a large number of projects. Models will not converge if we include all of the dyadic fixed effects in the duration equation and we are concerned with particular pairs of individuals who appear to be interdependent. Pairs of individuals who worked on twenty-three or more projects during the observation year are one standard deviation above the mean, so it seems unlikely that these two individuals are randomly assigned to those projects. When we replace the individual fixed effects with the dyadic fixed effects for team members who worked on twenty-three or more projects, the coefficient for internal density is −.63 (p < .05) and the coefficient for external range is −4.50 (p < .001). In other words, the coefficient for internal density is weaker but is still significant.

Summary and Discussion

To recap, we have introduced and validated a general-purpose research strategy for validating network exogeneity in naturally occurring human collectivities. Results from our study of Malibu Research project teams suggest that the hedonic approach should increase our confidence that observed network effects are truly causal. That is, we have seen evidence for substantial effects of a team’s position in the organizational social network above and beyond a baseline hedonic expectation that is caused by variation in human-capital endowments.

This conclusion relates to the other contributions in this volume and the larger theme of network formation and decay on two interlocking levels. First, a concern with network dynamics puts a spotlight on the premise of network exogeneity. As network analysis has matured and as economists (and natural scientists) have joined sociologists and anthropologists in the study of networks, sensitivity has grown to issues of endogeneity. The working assumption that long guided network analysis, whereby the network is treated as a given and the observed associations with outcomes of interest as causal, cannot be taken on faith. Indeed, although there are certainly cases where networks are exogenously given (for example, Munshi 2001) and social experiments sometimes occur whereby networks are randomly assigned (for example, Karlan 2004; Rubineau 2007; Sacerdote 2001), these cases are rare. Moreover, most of the interesting network-based theories apply precisely to situations where the networks are at least partially endogenous. For instance, the network-based theories in economic sociology reviewed above apply almost exclusively to such classes of network structures. In many cases, the premise of network exogeneity can be defended in these cases with some mix of the two rationales presented above—that the observed networks are by-products of networks constructed in other arenas and thus are only partially endogenous to the arena under analysis; and that path-dependent processes render networks at least somewhat exogenous for processes within a restricted temporal time frame. The premise of network exogeneity can be defended in the abstract, but it is quite another matter to defend it in a given analysis. The hedonic approach developed in this chapter helps in this regard, by providing a tool for setting up a baseline expectation above which we may have greater confidence that the observed association between network position and performance reflects a causal relationship.

At the same time, it is worth reflecting on the limitations of this approach. The most obvious is that it applies only to cases of short-lived collectivities with unique but highly overlapping membership. We think that there are many instances of such collectivities—for example, academic collaborations, short-term project organizations such as films (Soda, Usai, and Zaheer 2004) and events such as conventions, professional service firms (for example, consulting, legal, accounting) and even organizations themselves, when viewed over a longer period of time. At the same time, this approach clearly cannot be applied to individuals. Thus, additional approaches are needed to help validate network exogeneity.

Another limitation relates to the thematic issue of this volume, whose theme is the formation and decay of economic networks.
Because we anticipate that networks change as a result of past and expected performance, our hedonic approach focuses on short-lived collectivities for which one may collect social-network data from a period that predates the existence of the collectivities. And insofar as we observe effects of network variables applied to the teams that eventually form, this reflects the importance of path-dependence in network formation. But note that although our results suggest the importance of such path dependence, we have had to "black-box" the nature and extent of path dependence and, more generally, the social networks that are formed subsequent to the formation of the team. The ideal data set would include social network data both from the period before the formation of the teams and throughout the teams' life spans. Such data would allow the analyst to answer key questions on network formation and decay. For instance, what is the degree of path dependence in the network? That is, to what extent are the networks that are enacted and used by team members in the course of a project shaped by prior networks or constructed in the course of the team's work? And, is team performance determined more by the preexisting exogenous networks or the networks that emerge endogenously? In particular, do teams pool the networks of different members, which would work to dampen path dependence by building new connections between people who were not previously tied, and do such new ties endure to become part of the individuals' networks? As sensitivity grows to issues of network formation and decay, and as our capacity to collect temporal network data grows, we hope and expect that significant progress will be made on these questions.

Notes

1. There is already a substantial literature on the challenges of verifying a second type of hypothesis—that which expects social or spatial autocorrelation in the attitude or behavior of linked actors (see, for example, Frank and Fahrbach 1999; Leenders 1995; Moun 2003; see also Manski 1993).

2. The term "social capital" is notorious for being imprecise even while (or perhaps because) it has become very popular throughout the social sciences and popular discourse more generally. In this chapter we use "social capital" as an umbrella term to cover a family of social network-based processes that have been hypothesized (primarily by sociologists) to explain differential success or performance.

3. This is a weaker criterion than that suggested by James A. Davis (1985), whose rule of thumb is that, "when estimating a direct effect of $x_1$ on $x_p$, [one should] control all prior and intervening variables" (68). In this discussion we ignore variables that intervene between network position and performance because it is uncontroversial that social-network effects must operate through processes that are more proximate to performance. For example, structural autonomy is thought to raise the likelihood of success because such structural positions increase the information available to an actor and the control that she may exert over others (Burt 1992; but see Reagans and Zuckerman 2006). Similarly, status increases a firm's profitability because it reduces the costs of placing securities (Podolny 1993). Such hypotheses may be challenged not on the basis of assuming direct effects when the impact is in fact indirect, but in providing insufficient evidence for the posited intervening causal pathways. See Christopher Winship and David J. Harding (2005) for related discussion concerning the identification of age, period, and cohort effects through intervening mechanisms.

4. A study that attempts directly to control for an indicator of both past performance and expectations of future performance is Zuckerman's (1999) analysis of the impact of coverage mismatch on a firm's stock price.

5. This response rate of 92 percent compares extremely well with past research in this vein (for example, Burt 1992; Podolny and Baron 1997). See Reagans, Zuckerman, and McEvily (2004, 19) for more detail on the handling of missing data as well as how attrition and the arrival of new employees were handled in the analysis.

6. Our measure of external range is based on the tendency for contacts outside the team to be disconnected because such alters are more likely to provide access to nonredundant information (Burt 1992). Even if two contacts are disconnected, however, they may have very similar sets of ties to third parties—that is, they may be structurally equivalent—and therefore provide highly redundant information. Accordingly, we have reanalyzed the results presented here with an alternative measure of external range that considers the extent to which external contacts are both disconnected and structurally nonequivalent. This variable has an even more powerful effect on team performance than the conventional measure of range. We have chosen to present results based on direct ties because this measurement strategy is closest to past practice and a full discussion of the issue exceeds the scope of this chapter.
7. Taking the (inverse of the) mean constraint reflects a model whereby a team that is composed of members who each have ties to nonredundant actors beyond the team provide a wide array of information and resources to complement that accessed teammates. It is also interesting to consider an alternative model of aggregation, whereby the team pools the members’ networks rather than pooling the information and resources. According to the latter model, a team that is composed of a set of individuals who each have low external range but who have ties to different people off the team could be considered to have high external range. Analysis using such an alternative measure generated weaker results than those presented below.

8. As discussed by Reagans, Zuckerman, and McEvily (2004), functional heterogeneity is also a useful control in this regard because it should reflect the complexity of the project. Reagans, Zuckerman, and McEvily (2004, 38) discuss additional models designed to address the issue of unobserved heterogeneity.

9. From the other control variables, we see that project scale seems important as well. Larger projects take longer to complete. It is not clear whether projects in trouble attract more labor input or whether larger teams find it more difficult to coordinate their behavior. We also see that demographic diversity (in terms of functional area and tenure) does not seem to have much of an effect on project performance. Reagans, Zuckerman, and McEvily (2004) describe how the effect for demographic diversity is mediated by the network variables.

References


Stuart, Toby E., Ha Hoang, and Ralph C. Hybels. 1999. "Interorganizational..."


