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Abstract

We argue that the debate regarding the performance implications of demographic diversity can be usefully reframed in terms of the network variables that reflect distinct forms of social capital. Scholars who are pessimistic about the performance of diverse teams base their view on the hypothesis that decreased network density—the average strength of the relationship among team members—lowers a team's capacity for coordination. The optimistic view is founded on the hypothesis that teams that are characterized by high network heterogeneity, whereby relationships on the team cut across salient demographic boundaries, enjoy an enhanced learning capability. We test each of these hypotheses directly and thereby avoid the problematic assumption that they contradict one another. Our analysis of data on the social networks, organizational tenure, and productivity of 224 corporate R&D teams indicates that both network variables help account for team productivity. These findings support a recasting of the diversity-performance debate in terms of the network processes that are more proximate to outcomes of interest.

(*Social Capital*; *Social Network Analysis*; *Diversity*; *Performance*; *Research and Development*; *Sociology*)

Introduction

Research on how the demographic diversity of a team affects its performance is marked by a sharp debate between two views. According to what might be called the "pessimistic" view, demographic diversity is problematic because it introduces social divisions that hinder effective teamwork. In his classic statement on organizational demography, Pfeffer (1983) illustrates this view with the example of tensions between members of different organizational cohorts. Pfeffer argues that informal social networks and a sense of shared identity take root among individuals who enter the organization at the same time. This leads to an increased capacity for intracohort communication but a potential for strain in intercohort relations. Homogeneous groups are thus expected to perform at a higher level because such groups coordinate their actions more easily than diverse teams (cf., McCain et al. 1983, O'Reilly et al. 1989, Zenger and Lawrence 1989).

The second view contends that having a diverse membership actually improves a team's performance. Proponents of this "optimistic" view also invoke organizational tenure to illustrate their thinking. For example, Ancona and Caldwell (1992, p. 355) write that teams which draw their members from different cohorts achieve higher performance because "Members who have entered the organization at different times know a different set of people and often have different technical skills and different perspectives on the organization's history." That is, while homogeneous groups may in fact be more harmonious, the performance of such teams is limited by the relative redundancy of members' perspectives, information, and resources (e.g., Ancona and Caldwell 1992, Bantel and Jackson 1989, Pelled et al. 1999). Because greater demographic diversity entails relationships among people with different sets of contacts, skills, information, and experiences, heterogeneous teams enjoy an enhanced capacity for creative problem solving.

Thus, it appears that sharp lines have been drawn between pessimists, who worry about the coordination problems introduced by demographic diversity, and optimists, who focus on the learning benefits it provides. But, observe that pessimists see demographic diversity as problematic because they believe that it introduces difficulties that generally *outweigh* the benefits that it provides, but not because such advantages do not potentially exist. Accordingly, while Pfeffer has been taken as asserting that demographic diversity lowers performance, he has also suggested that it promotes learning. For instance, he describes the benefits of employee turnover in terms of the

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different outlook "new blood" often brings to an organization (Pfeffer 1983, pp. 325–330, Staw 1980).[1] Conversely, such optimists as Ancona and Caldwell (1992, p. 323) recognize that diverse teams are likely to face significant difficulties because of a lessened capacity for coordination.

If each side of the debate concedes the merits of the other, then why has the issue been framed as involving stark opposition? We argue that the primary basis for such disagreement lies in the typical research strategy critiqued by Lawrence (1997), one in which demographic diversity is used as a proxy for network patterns on a team. As we discuss below, each side of the diversity debate involves a hypothesis about how one of two network variables affects performance. Pessimists expect homogeneous teams to achieve higher performance because such teams are characterized by a higher level of network density. Network density is the average strength of the relationship between team members. Network density is minimized when no relationships exist between team members and maximized when all team members are connected by strong relationships. For example, network density is maximized when all team members communicate with each other frequently. Because increases in network density reflect an increase in the number of team members who are connected to one another and the strength of those connections, increases in network density are thought to indicate the enhanced capacity for a team to coordinate its actions, thereby enhancing performance. By contrast, optimists argue that diverse teams should perform at a higher level because demographic diversity increases the links that cut across demographic categories. This implies that as demographic diversity increases, team members allocate more of their network time to cross-category or "boundary-spanning" interactions. We call this more diverse distribution of network time network heterogeneity. Increases in network heterogeneity are thought to facilitate learning and creativity, resulting in a higher level of team performance.

When the two views on demographic diversity are thus framed in network terms, the apparent contradiction between them dissolves. After all, it is possible for a team to be characterized by dense relations and for such relations to cross demographic boundaries. According to both views, such a team should perform at a higher level than teams that have sparse networks in which interaction occurs only between members of similar demographic categories. However, the fact that both variables may independently predict performance is masked by existing research because it generally does not analyze these network variables directly (see Williams and O'Reilly 1998 for a review). As a result, researchers are compelled to make the problematic assumption that observed relationships between demographic diversity and performance reflect one but not the other network variable (Lawrence 1997, Carroll and Harrison 1998).

Our objective in this research is to move beyond the debate regarding the overall effect of demographic diversity by directly analyzing how the two network variables which underlie this debate affect team performance. We exploit survey data on 224 R&D teams, which include information on the communication network within each team, on team productivity, and on organizational tenure—a key demographic variable in diversity research. These data allow for the calculation of network density and heterogeneity and for a direct analysis of how they affect team productivity without compelling us to take a stance—pessimistic or optimistic—regarding the overall performance implications of demographic diversity.

We proceed as follows. First, we discuss the relationship between the diversity-performance debate and the network-based literature on social capital, and submit the hypotheses that we test in our analysis. Next, we describe our research setting: corporate R&D labs in the mid-1980s. In the subsequent sections, we describe the methods used and then present our results. We conclude by discussing the implications of these results for research on the interaction of demographic diversity and network structure in the generation of performance differences.

Theory

The two views in the diversity-performance debate have striking parallels in the literature on social capital. While work falling under the rubric of social capital is quite varied (see e.g., Portes 1998, Adler and Kwon 1999, Gabbay and Leenders 1999), what is most relevant to the diversity-performance debate are the two conceptions of social capital that emerge from social-network theory. In particular, thinking consistent with the "closure" perspective (Coleman 1988, 1990) underlies the pessimistic view of demographic diversity, and the "structural holes" approach (Burt 1992) is the basis for the optimistic view.

Network density or social "closure" inside a group indicates the likely absence of "structural holes," and is thought to foster identification with the group (Portes and Sensenbrenner 1993) and a level of mutual trust, which facilitates exchange and collective action (Coleman 1988). Density thus enables the joining of individual interests for the pursuit of common initiatives. And, this is precisely the argument made by those who are pessimistic about demographic diversity. Just as discussions of social closure focus on the collective trust found in cohesive, ethnic communities (e.g., Aldrich and Zimmer 1986, Portes and Sensenbrenner 1993), the pessimistic view regards diverse teams as unlikely to assume cohesive, community-like characteristics. Pessimists base their view on the closure perspective, which expects network density to lead team members to identify with one another and thereby facilitate mutual coordination (e.g., Pfeffer 1983, McCain et al. 1983, O'Reilly et al. 1989, Zenger and Lawrence 1989).

The second network-based approach to social capital understands it as value derived from bridging "structural holes" or gaps between nodes in a social network (Burt 1992, 1982). Such boundary spanning generates "information benefits," because information tends to be relatively "redundant" within a given group (Burt 1992, p. 13–16). As a result, actors who develop ties with disconnected groups gain access to a broader array of ideas and opportunities than those who are restricted to a single one (Granovetter 1973). This idea motivates the optimistic view on demographic diversity as well. According to optimists, teams which draw members from diverse demographic categories benefit because such teams generate links between people with different skills, information, and experience. Such ties within the team bridge structural holes in the larger organization, and thereby enhance its capacity for creative action (e.g., Ancona and Caldwell 1992, Bantel and Jackson 1989, Pelled et al. 1999, 1991, pp. 74–81).

Note that we have not simply replaced the debate between optimists and pessimists with an opposition between closure and structural holes. Rather, these two perspectives on social capital do not conflict with one another. While the closure perspective focuses on the presence or absence of relations in *local* interaction, the structural holes responsible for information benefits are those that divide a social system *globally*.[2] The network of the team depicted in Figure 1 illustrates this distinction. Local structural holes, such as that which divides the Actors 1 and 2, are instances in which little or no relationship exists among members of *the same group* or collectivity. The proliferation of such holes is thought to reduce the group's capacity for collective action. Global structural holes, such as that which separate Groups A and B, reflect an absence of relations between *different groups* or collectivities. Such gaps are thought to limit the transfer of information and experience between groups. Figure 1 also shows how relations on a team may bridge such global structural holes. In particular, the relationship between Actors 1 and 3 indirectly links Groups B and C. To the extent that many such relationships exist on a team, the team bridges otherwise disconnected pools of information. Note that Figure 1 illustrates another difference between the two views on diversity. Pessimists focus internally and examine how demographic diversity affects *local* interactions. Optimists focus externally and examine how demographic diversity on a team provides the team with an opportunity to act as a bridge between groups generally disconnected from each other. Optimists focus on *global* structural holes and the information benefits that bridging such holes provide. So, for example, a cross-functional team is expected to bridge holes between different functional areas in the larger organization, and as a result a cross-functional team is expected to outperform a team that draws its membership from a single function.

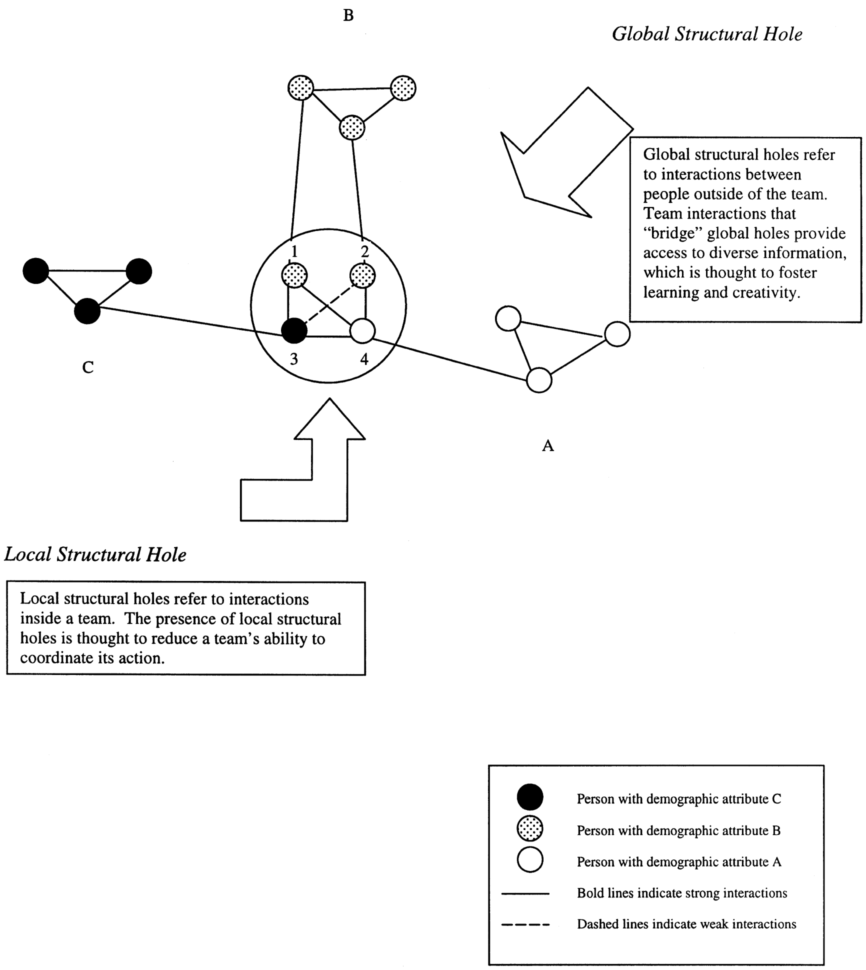
Thus, the social processes captured by each of the two perspectives on social capital are logically distinct. As such, we may delineate hypotheses that focus on the network variables that underlie the diversity debate but do not contradict one another. Below, we calculate a team's network density as the average frequency of communication among the scientists on an R&D team. The more dense a team's network, the more it resembles a clique in which all members communicate and interact with each other frequently. In addition, we define a team's *network heterogeneity* as the extent to which interaction on the team cuts across salient demographic categories. We focus on a key demographic variable that has been the subject of much research on demographic diversity: organizational tenure. As we calculate it, a high level of network heterogeneity on a given team indicates that the fact that a given pair of team members entered the organization many years apart does not reduce their level of interaction. Using these definitions, the following hypotheses will be tested:

HYPOTHESIS 1. *The greater the density of a team's internal network, the higher its productivity.*

HYPOTHESIS 2. *The greater the network heterogeneity of a team, the higher its productivity.*

Figure 2 illustrates how network density and heterogeneity vary in the context of demographic diversity. Following Lawrence (1997), teams of the same demographic composition may differ in the extent to which demographic boundaries hinder or promote interaction.[3] Thus, while the two scenarios show no change in the degree of demographic diversity, the network patterns are different. In addition, we have held network density constant across the two scenarios to show how network density and heterogeneity may vary independently of one another. Although each actor has the same amount of strong and weak ties in each network, the two scenarios differ greatly in the degree of network heterogeneity achieved. Demographic boundaries are highly salient in the first scenario in that they prevent the formation of relations between highly dissimilar actors. For example, Individuals 1 and

Figure 1 Structural Holes in the Team Context



5 do not communicate with Individuals 3 and 4. By contrast, actors in Scenario 2 form ties with dissimilar team members rather than with those who are like themselves. In this situation, Individuals 1 and 5 do not communicate with each other but instead communicate with Individuals 3 and 4. This team is thus hypothesized to benefit because it succeeds at building links among individuals who represent groups separated by global structural holes.

Recasting the diversity-performance debate in network terms helps undermine the very basis of this debate. Figure 3 presents the causal pathways that link demographic diversity, the network variables, and team performance in a manner that is consistent with *both* the optimistic and the pessimistic views on diversity. As depicted, increasing demographic diversity raises network heterogeneity ($\beta_1 > 0$) and lowers network density ($\beta_2 < 0$), and each of these network variables is positively associated with performance ($\lambda_1 > 0$ and $\lambda_2 > 0$). The observed relationship between demographic diversity and performance (δ) is the difference between the two causal pathways ($\beta_1\lambda_1 - \beta_2\lambda_2$). Depending on the value of β_1 and β_2, the association between demographic diversity and performance (δ) could be positive, negative, or zero *even where* λ_1 *and* λ_2 *are both positive*. Analyses which test the relationship between demographic diversity and performance (δ) thus do not test the social capital arguments implicit in the diversity-performance debate. Furthermore, a focus on the overall demographic-diversity effect obscures the fact the two views of demographic diversity do not differ on the social processes that improve and impede team performance. Rather, optimists differ from pessimists only in the weight they assign to the paths in Figure 3.

In sum, the stark opposition in the diversity-performance debate has been based on two problematic assumptions. First, it has been presumed that network

Figure 2 **Demographic Diversity is an Opportunity for Interactions Inside the Team to Bridge Global Structural Holes Outside the Team**

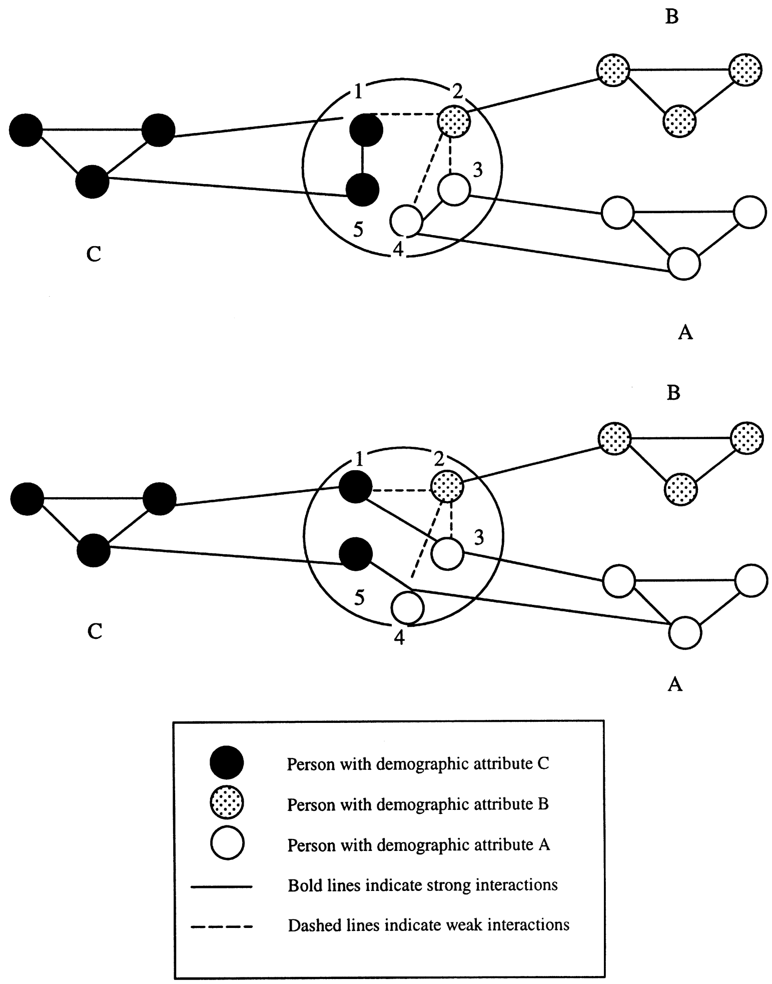
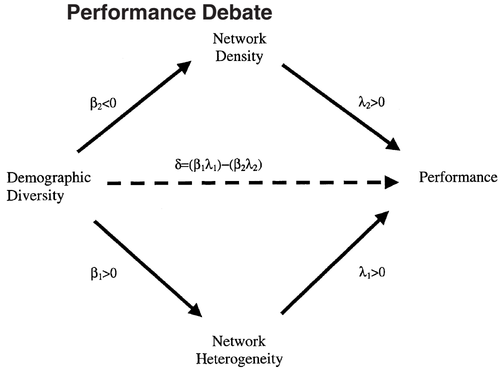


Figure 3 **The Causal Model Underlying the Diversity-Performance Debate**



density and heterogeneity are opposed network principles, which are the basis for opposed processes. But, because density is based on success in bridging local structural holes and heterogeneity depends on links across global structural holes, the two principles and corresponding processes are distinct. Second, in the absence of direct measures of network density and heterogeneity, researchers have assumed that one of the two variables will have a stronger effect, thus producing the observed effect of demographic composition. However, this framing of the debate has helped obscure the fact that the two views agree that both dense and heterogeneous networks may improve team performance. Thus, we proceed to test directly for the hypothesized effects of these two network variables because this represents a more direct and straightforward way of uncovering the social processes at work.

The Setting: Corporate R&D Teams

A consistent theme sounded by studies of corporate R&D over the past 30 years highlights the importance of informal communication networks as a critical means by which scientists keep up with technological and scientific developments as well as organizational directives (e.g., Allen 1977, Katz and Tushman 1979, Katz 1982, Zenger and Lawrence 1989, Hansen 1999). Furthermore, while much research focuses on the communication links that bind R&D teams to one another, within-team interaction has been shown to be important as well (Allen and Cohen 1969, Tushman 1977). Thus, to the degree that the network patterns posited by the opposing perspectives on demographic diversity have greater effects on productivity in contexts where networks are more salient, such effects should be evident in a study of corporate R&D teams.

The survey data we use in our analysis are suited to shed light on the issues at hand. The survey, administered in 1985–1986, covered 224 R&D teams in 29 corporations from seven industries: automotive, chemicals, electronics, aerospace, pharmaceuticals, biotechnology, and oil (see Cohen and Zhou 1991, Shenhav 1991). The sample included a wide variety of R&D teams, ranging from those focused on basic research to those working on more applied projects, such as product and process development and improvement. Two separate questionnaires were administered. Team leaders or managers were asked a series of questions regarding their team, including its productivity. Team members were asked a wide variety of questions on their work and how it relates to that of other members. Overall, 2,077 of the 2,285 of the R&D team members completed the questionnaires, a response rate of 91% (Shenhav 1991, p. 56). Most relevant to the issues at hand, the data include information on the scientists' tenure in the organization as well as their level of contact with fellow team members. Organizational tenure is a useful demographic variable in this context because its meaning is largely invariant across organizations and teams and because it allows us to link our research with a large number of previous studies on the correlates of demographic diversity, in which organizational tenure has figured quite prominently (e.g., Ancona and Caldwell 1992, O'Reilly et al. 1989, Pfeffer 1983, Wagner et al. 1983, Zenger and Lawrence 1989).[4] The network data were collected through a sociometric instrument. Each team member—including both scientists and managers—was given a list of all team members. They were then asked to indicate how frequently they communicate with the other members *of the same R&D team* (0 = "never", 1 = "less than once a month", 2 = "1 to 3 times a month", 3 = "1 to 3 times a week", 4 = "daily"). Together with data on organizational tenure, these network data allow us to look at how the two network variables of interest—density and heterogeneity—affect team productivity.

Method

Analytic Framework

We test these hypotheses with a set of regression analyses, which assess the effects on team productivity of the demographic-diversity variables and other factors discussed below. Because our data set has a nested structure in that multiple teams within the same organization are considered, we estimate the models as fixed-effects regression analyses, whereby a dummy variable for each organization is included in each model. Coefficients in these equations reflect how a covariate affects within-firm variation in productivity (e.g., Hannan and Young 1977).

Measures

Dependent Variable—Team Productivity. Team productivity is constructed from the answers to the following question, asked of team managers regarding the 11 items listed in Table 1:

> Consider each of the following written products and/or prototypes that could have resulted from the work of this team during the last three years. How many of each has this team produced? For each product, choose one of the listed alternatives, and enter its number in the space provided.

Details on the construction of a summary-productivity score from this question are given in the technical appendix. Briefly, we factor analyzed the matrix of correlations

Table 1 Team Productivity

Item	Mean	SD	Factor Loading
Positions Papers.	1.5	1.2	0.47
Project proposals.	2.0	1.1	0.53
Published scientific/technical articles.	1.4	1.3	0.18
Patents or patent applications.	1.5	1.2	0.65
Books (including editorship).	0.13	0.47	0.15
Algorithms, blueprints, drawings, etc.	1.4	1.4	0.16
Reports which remained within the unit.	2.0	1.3	0.50
Reports which circulated outside the unit.	2.5	0.93	0.60
Experimental prototypes of devices, instruments, components of devices, etc.	1.4	1.3	0.26
Experimental materials, e.g., fibers glass, plastics, metals, drugs, chemicals, etc.	1.2	1.3	0.51
Prototype computer programs.	1.1	1.3	0.04

among the 11 items, and we extracted three factors using the unweighted least-squares method (Harman 1976). The three factors explain 44% of covariance among the 11 items. The first factor explains 24% of the covariance. Table 1 gives summary statistics for the 11 items and their loadings on the first factor, which we treat as our summary-productivity measure (Harman 1976, Bollen 1989, Jobson 1992). High scores on the variable indicate the extent to which a team has generated many papers, proposals, patents, and reports. While all 11 items load positively on this factor, those which have low factor loadings, such as books and computer programs, tend to load higher on the second two factors, and the correlations between the first and next two factors are negative. The pattern of correlations indicate that being a generalist comes at the expense of being productive at more specialized tasks. So, while our measure taps a general dimension of productivity, other aspects of productivity are not represented. In addition, because managers were asked only about the amount of work a team has produced in various areas, our measure cannot speak to other dimensions of performance.

Because the productivity variable is constructed using responses from a single source, common-methods variance is a potential problem (Podsakoff and Organ 1986, Aviolo et al. 1991, Doty and Glick 1998). Common-methods variance would be an issue, for example, if one part of the observed correlation between any two of the items in Table 1 is "true," and another part is attributable to survey response bias (Berman and Kenny 1976, Salancik and Pfeffer 1977, Arnold and Feldman 1981). For the current study, the predictors of common methods variance are mixed (see Doty and Glick 1998, pp. 379–381). An important mitigating factor is that the data come from two sources—a survey of managers and a survey of scientists—and the independent variables are aggregated across responses to the latter. However, common-methods variance cannot be ruled out completely because the data were collected at a single point in time, and each manager belongs to the team he or she evaluates. Thus, common methods variance can neither be completely ruled out nor is it clearly present as a problem.

Main Independent Variables

Network Density. The two network variables of interest are both constructed using the sociometric data on communication frequency to indicate relational strength.[5] Tie strength has two components: communication frequency and emotional closeness (Granovetter 1973, Marsden and Campbell 1984, Burt 1990). Communication frequency is how frequently individuals speak with each other, and emotional closeness is the level of emotional affect associated with the interaction. Unfortunately, emotional-closeness network data was not available. Thus, we follow other network researchers in using communication or interaction frequency as a measure of relational strength (e.g., Uzzi 1996, 1999), though we encourage future researchers to consider emotional closeness as well (see Burt 1992).

Network density is the average level of communication between any two members of team *k,*

$$Density_k = \frac{\sum_{i=1}^{N_k} \sum_{j=1}^{N_k} z_{ijk}/\max(z_{ijk})}{N_k(N_k - 1)}, \; j \neq i, \qquad (1)$$

where z_{ijk} ($\ni\{0,1,2,3,4\}$) is the frequency at which team member i reports communicating with team member j, $\max(z_{ik})$ is the largest of is reported ties to anyone on the team, and N_k is the number of members in team k. Density varies from zero (no communication between team members) to one (maximum strength communication between all team members).[6]

Network Heterogeneity. Network heterogeneity measures the extent that scientists allocate a large proportion of their network time to colleagues far removed in the team's tenure distribution. Network heterogeneity is calculated based on two dyadic components, which we discuss in greater detail in the technical appendix: p_{ijk}, the proportion of scientist is interaction that she allocates to colleague j on team k; and w_{ijk}, the degree of tenure similarity between scientist i and colleague j. For each scientist on team *k,* network heterogeneity is defined as:

$$nh_{ik} = 1 - \sum_{j=1}^{N_k} w_{ijk} * p_{ijk}, \; j \neq i. \qquad (2a)$$

For the team, network heterogeneity is the mean of these individual-level scores:

$$NH_k = \frac{\left(\sum_{i=1}^{n_k} nh_{ik}\right)}{N_k}. \qquad (2b)$$

A high score on network heterogeneity indicates that the team has achieved a high level of contact among individuals who are distant from one another in the team's organizational-tenure distribution. Network heterogeneity is high when interactions span the team's tenure distribution.

It might be conjectured that, rather than employ network heterogeneity, Hypothesis 2 could be tested with an interaction effect between organizational tenure diversity (defined below) and network density. That is, if relations between similar team members raise (lower) productivity, then there should be a positive (negative) interaction effect between network density and organizational tenure diversity. However, while such an interaction effect is broadly consistent with the hypotheses, it suffers from a version of the ecological fallacy (Robinson 1950). For instance, a positive-interaction effect implies dense relations between individuals of dissimilar organizational tenure; such dense relations could in fact be between members with similar tenure in the organization. By contrast, network heterogeneity captures the desired interaction effect directly in Equation (2b) ($w_{ij} * p_{ij}$) by measuring it at the level of the *relationship*, rather than the team.

Control Variables

Organizational Tenure Diversity. While the present analysis approaches the performance implications of demographic diversity by examining the relationship between relevant network structures and productivity, it is important to also include a measure of a team's demographic diversity. Two principal considerations motivate the addition of such a variable. First, the organizational tenure diversity of a team necessarily conditions the level of network heterogeneity it displays: At the limit, when all members are of the same tenure, team networks will be completely homogeneous.[7] Following Lawrence (1997), we have posited that the network structure of a team is not reducible to its composition. Accordingly, our measure of network heterogeneity is conditioned on a scientist's opportunity for interacting with team members, depending on their relative locations in the team's organizational tenure distribution. In addition, the inclusion of organizational-tenure diversity as a control variable provides an additional check to see whether our results are actually because of network features, rather than demographic composition per se.

The second consideration relates to more substantive concerns. Although we have framed the debate on demographic diversity and productivity in terms of a team's social network, it might be objected that it is inappropriate to reduce the effect of demographic diversity to network variables alone. For example, following social categorization theory (cf., Tajfel 1981, Turner 1987), one variant of the perspective that sees demographic diversity as problematic expects individuals to attribute positive characteristics to members of their own demographic category and negative traits to other categories. As a result, greater demographic diversity may heighten social tensions via an increase in negative sentiment but not necessarily through a change in interaction levels or patterns (e.g., Ely 1994, Pelled 1996, Riordan and Shore 1997). Alternatively, it may be that the *benefits* of demographic diversity arise not through changes in interaction among individuals with different perspectives but by creatively resolving conflict between such actors in a team context (Eisenhardt et al. 1997). That is, whether demographic diversity promotes or erodes team productivity, such an effect may not occur through its social network.

Unfortunately, the data set we use does not allow us to measure social-categorization processes or the level of conflict in the team. However, to the extent that such processes and others affect productivity independent of a team's social network, a relationship between organizational-tenure diversity and productivity should be observed independent of the network structure of the team. By contrast, the absence of an effect for organizational-tenure diversity would indicate that the relevant processes occur largely through the network variables.

We measure diversity in organizational tenure with the Gini coefficient of mean difference (CMD, Kendall and Stuart 1977, p. 48):[8]

$$CMD_k = \frac{1}{N_k(N_k - 1)} \sum_{i=1}^{N_k} \sum_{j=1}^{N_k} |t_{ik} - t_{jk}|,\ j \neq i, \quad (3)$$

where t_{ik} and t_{jk} indicate individual i's and j's tenure in the organization, and N_k is the number of individuals in R&D team k.

The CMD differs from the more familiar Gini index in that the latter divides the CMD by twice the group mean. The typical motivation for scaling a measure of inequality such as the Gini index—or its near equivalent, the coefficient of variation—by a function of the mean is to tap the intuition that, holding constant the dispersion on some resource, an increase in the level on that resource lowers the degree of felt inequality (Allison 1978, p. 867). For instance, as the average level of income in a population increases, absolute differences in income become less important. However, while this rationale for scaling by the mean makes sense for inequality, it is not clear whether it applies to the case of demographic diversity. For instance, with respect to organizational tenure, this would imply that work groups with higher mean tenure are less diverse than those with lower mean tenure, independent of the dispersion in tenure. It is possible that differences in tenure become less salient as average tenure increases; however, it is equally reasonable to think that tenure differences are less salient when most team members are recent arrivals. Thus, rather than assume a particular relationship between mean organizational tenure and the experience of tenure diversity, we consider the CMD and mean tenure as separate variables so that we may disentangle the effects of each empirically. Note that similar issues apply to the coefficient of variation (see Sorensen 1999). We discuss measurement of demographic diversity in greater detail in the technical appendix.

Task. The R&D teams under study vary in the type of research they perform. It is particularly important to control for the type of team because the productivity measure we use may vary in salience across such types. Following Cohen et al. (1986), we classify the teams as devoted to basic research (17% of all teams), product development (42%), product improvement (6%), process improvement (24%), and research targeted toward fixing a specific problem with a product or process (11%). Teams are classified in one of these categories based on the mean response by team members to a question that asked them to choose which of these types best describes their team.

Competition. Prior research has indicated that competition in the surrounding market affects team productivity (Ancona and Caldwell 1992). We measure the competitiveness of the market context with the manager's or team leader's response to the follow question: What is the competitive pressure in this product area? The manager or team leader could respond to the question on a four-point scale ranging from "Not keen (uncontested market available)" to "Prohibitive (any sales increase highly contested)."

Size. Finally, team size represents an important control variable. The teams vary considerably in size, ranging from one team, which contains three members to one that contains 34 scientists. Because the dependent variable is a function of the volume of work produced by group members, it should be significantly related to size. In addition, because the density of a group's network—as well as its degree of network heterogeneity—is generally a negative function of its size, it is important to include size as a control in our analysis.

Results

Table 2 contains summary statistics and Table 3 produces a correlation matrix for the covariates in the analysis. Several relationships in the latter table are noteworthy. First, we see confirmation of the importance of size as a covariate: Large teams have significantly less dense and less homogenous networks than do small teams. Second, note the insignificant correlation between organizational-tenure diversity and network heterogeneity ($r = -0.07$). This reflects the construction of the network heterogeneity measure in that it is conditioned on each actor's opportunity for interaction with scientists of varying similarity in organizational tenure.[9] Third, the correlation between network density and network heterogeneity is negative ($r = -0.44$). However, the correlation does not reflect an inherent trade-off between network density and network heterogeneity. The observed correlation is largely a function of size. Controlling for network size, the correlation declines in magnitude ($r = -0.25$). In addition, results from simulations discussed in the technical appendix indicate that the observed relationship reflects the fact that, in the R&D units in our study, those units composed of small cohorts tend to have more dense communication networks.

Table 2 Descriptive Statistics

Variable	Mean	SD	Min	Max
Productivity	0	0.86	−2.0	1.5
Basic Research	0.17	0.37	0	1
Applied Research	0.11	0.31	0	1
Product Development	0.42	0.49	0	1
Product Improvement	0.06	0.23	0	1
Process Improvement	0.24	0.43	0	1
Market Competition	2.1	1.1	0	4
Average Organizational Tenure	10.6	4.9	1.9	24.9
Organizational Tenure Diversity	8.2	3.8	1	18
Size	10.2	4.9	3	34
Network Density	0.54	0.18	0.18	1
Network Heterogeneity	0.89	0.03	0.77	1

Table 4 presents the fixed-effects regression results in stepwise fashion. Control variables are included in the first model. We see that teams which are more senior in their membership achieve a higher degree of productivity, which suggests the importance of experience for productivity. In models not shown, we also checked for a nonlinear association between average organizational tenure and productivity (cf., Katz 1982). There is evidence for such nonlinearity but it is not statistically significant. We see, however, no effect for organizational-tenure diversity. Diversity in organizational tenure appears neither to enhance nor to degrade team productivity. We estimated the demographic effect using a variety of diversity measures, and in each instance, the estimate is not significantly different from zero. The insignificant effect for organizational-tenure diversity provides further support for our research strategy, which is not to focus on the aggregate demographic effect but instead to examine the social-capital variables underlying the debate directly.

The network hypotheses are tested in the second and third models. Network density is introduced in the second model and provides a test for the closure view of social capital (e.g., Coleman 1988, Portes and Sensenbrenner 1993). We find support for the hypothesis. The estimate for network density is positive and significant. Teams that

Table 3 Correlations

	1	2	3	4	5	6	7	8	9	10	11	12
1. Productivity	1											
2. Basic Research	−.03	1										
3. Applied Research	−0.07	−.15**	1									
4. Product Development	0.004	−0.38***	−0.30***	1								
5. Product Improvement	−0.09	−0.11*	−0.09	−0.21**	1							
6. Process Improvement	0.12*	−0.26***	−0.20**	−0.49***	−0.14**	1						
7. Market Competition	0.23	−0.09	−0.04	0.07	0.02	0.02	1					
8. Average Organizational Tenure	0.16**	−0.08	−0.02	0.03	0.07	−0.002	0.02	1				
9. Organizational Tenure Diversity	0.07	−0.13**	0.02	0.04	0.12*	−0.02	0.07	0.72***	1			
10. Size	0.33***	−0.14**	0.05	−0.005	−0.09	−0.13**	0.10	0.02	−0.01	1		
11. Network Density	0.001	0.16**	−0.09	0.03	−0.09	−0.05	−0.05	−0.08	0.004	−0.51***	1	
12. Network Heterogeneity	0.33***	−0.11	0.07	−0.09	−0.05	0.17**	0.05	0.04	−0.07	0.71***	−0.44***	1

Note. These are zero-order correlations. * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.001$.

Table 4 Networks and Productivity

Predictors	Controls	H1: Network Density	H2: Network Heterogeneity	Network Density and Heterogeneity
Control Variables				
Constant	−0.88	−1.6	−0.97	−6.05
Basic Research	−0.04	−0.02	−0.01	0.05
Applied Research	−0.40**	−0.34*	−0.31*	−0.34*
Product Development	0.02	0.04	0.07	0.09
Product Improvement	−0.19	−0.09	−0.24	−0.23
Market Competition	0.09**	0.10**	0.10**	0.10**
Size	0.04**	0.06***	0.03*	0.04*
Organizational Tenure Diversity	−0.001	−0.004	−0.002	0.004
Average Organizational Tenure	0.03*	0.04**	0.03*	0.03*
Network Variables				
Network Density		0.88**	0.89**	1.3**
Network Heterogeneity			5.5**	5.0**
× Network Density				22.9**
Firm Differences				
F-statistic	2.47	2.19	2.23	2.48
degrees of freedom	28, 174	28, 173	28, 172	28, 171
p-value	<.001	<.001	<.001	<.001
Model Fit				
N	211	211	211	211
R-squared	0.42	0.44	0.46	0.47
Adj R-squared	0.30	0.31	0.34	0.35

Note. Estimates based on ordinary least squares with team performance as the dependent variable. The units are clustered within firms and models are estimated using the AREG procedure in STATA. AREG controls for mean differences across firms, for predictors and the dependent variable.
* = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.001$.

average more frequent communication among their members achieve higher productivity. Better communication links among members of a group enable its members to achieve a greater degree of coordination, and hence a level of productivity that is unattainable by teams that are less well connected. To the extent that diversity reduces network density, the result provides support for the position taken by pessimists who view diversity as problematic because it reduces effective teamwork.

Network heterogeneity is introduced in the third model and provides a test for the structural hole view of social capital (Burt 1992). As predicted, the estimate is positive and significant. Teams that experience more extensive links among members of different organizational tenure achieve a higher level of productivity than teams with highly homogeneous networks. The estimate indicates that communication ties which cut across demographic boundaries—and the different sets of information, experiences, and outlooks that such boundaries divide—enriches the research process and promotes greater productivity.[10] To the extent that diversity increases network heterogeneity, the result provides support for the position taken by optimists who view diversity as beneficial because it promotes learning.[11]

The final model in Table 4 explores whether network density and network heterogeneity interact in their affects on productivity. It would seem to follow from the present discussion that network density should be particularly advantageous when the network is heterogeneous. And, indeed, we see in the results from this model that there is a significant negative-interaction effect between the two network measures. That is, communication across demographic boundaries appears to be more valuable when such relations are relatively strong than when they are weak. At the same time, this result should be interpreted with caution. While greater density in the overall network of relations on a team gives a reduced boost to productivity when the overall network on the team tends to be confined to similar individuals, it is unclear which relations are responsible for this affect—i.e., whether or not it is the linkages that span the greatest demographic distances that are, in fact, the most dense. A more precise analysis would examine productivity at the dyadic or individual level, which we cannot perform with the data at our disposal.[12]

Summary and Discussion

In evaluating the contribution of the present effort, it is useful to begin with what we *did not* find. In particular, it is worth underlining the fact that we found significant affects for the two network variables but no affect for diversity in organizational tenure. This confirms our strategy of exploring the impact of the network processes that underlie theories of the diversity-productivity relationship. A direct examination of the frequency of interaction across the organizational-tenure distribution on a team sheds light on this relationship in a way that would have been unattainable had we focused on measures of demographic composition alone. Indeed, our results confirm Lawrence's (1997) words of caution regarding the difficulty of treating demographic diversity and interaction patterns as "congruent" and do so from a reversed perspective: Whereas many analysts find affects for diversity and interpret these results as consistent with a particular network of relationships on the team, we find affects for such network variables which are independent of demographic composition.

Thus, we regard the preceding results as an important first step in gaining a better understanding of the social processes that link the demographic composition of teams and their productivity. As argued above, existing theory on this relationship may be usefully classified in terms of two views on how social structure affects a team's capacity for effective action, i.e., its social capital. Corresponding to those who see social capital as emerging from the dense networks emblematic of close-knit communities, one view worries that demographic diversity introduces potential bases for social cleavage, which prevent such cohesion from developing. We have found support for such a view of social capital in our finding that R&D teams that have more dense networks of interaction achieve a higher level of productivity than do those with sparse networks. However, we also find that teams that display greater levels of contact between individuals of the same organizational tenure are *less* productive than do teams that are characterized by links between members who entered the organization at different points in time. The latter results reflects the orientation of a second view on diversity, corresponding to a second perspective on social capital, which emphasizes the importance of interchange among individuals with a wide range of skills, information, and experiences, for maximizing a group's capacity for creativity and effective action.

That we find some support for both network perspectives on social capital should not be surprising. As argued above, the structural principles that underlie each of these principles are quite distinct. One focuses on dense patterns of local interaction as the basis for coordination and collective action, and the other focuses on bridges across global divisions as the basis for information transfer and learning. Moreover, both principles capture important elements of what it takes for a task group to achieve success in reaching its goals. A team that does not develop the connections among their members, which enable it to coordinate effectively, faces an uphill battle. However, when such networks remain concentrated among homogeneous sets of individuals, the team fails to generate the learning that can only come from interaction among different individuals. Thus, whereas the diversity-performance debate sees two opposed processes, our recasting of the issue, in terms of the network forms of social capital, highlights the fact that the processes are logically and behaviorally distinct and that diversity is not inherently an either-or phenomenon.

We hope that these results set the stage for future research on the performance of organizational teams, which may vary both in their demographic composition and network structure. In particular, a consideration of five important limitations in the current study suggests directions that future studies might make their focus. First, we focus on network affects, but we do not explain the origins of those affects. This strategy is useful because it allows us to avoid assuming that demographic diversity is congruent with the network patterns on a team. But, it begs the question of just how changes in the demographic composition of a group affect its network structure. Future research on this relationship is necessary for a complete model of the relationship between diversity, networks, and performance as depicted in Figure 3. Such research should be especially valuable to managers because a team's demography is subject to greater manipulation than is its informal network, even if the latter is a more proximate determinant of performance.

Second, while we do not assume that demographic composition is congruent with interaction patterns at the local or team level, we do assume a particular relationship between the two at the global or organizational level. In particular, our analysis of network heterogeneity relies on the assumption that individuals who occupy different points on the organizational-tenure distribution tend to have different information and experiences, and that they generally do not interact as much with each other as with others who are of similar tenure. This assumption is the basis for our argument that teams will benefit from cultivating links between scientists who are dissimilar in organizational tenure. While we believe that this assumption is reasonable, it should be tested in future research.

A third concern is that the patterns we find pertain to organizational tenure but may not be as relevant for other demographic variables. In particular, while organizational tenure is often a salient characteristic because of the way it relates to hiring practices and organizational-seniority systems (Pfeffer 1983), it is likely that the relationship between diversity, networks, and productivity is somewhat different in the context of such traits as gender and race that are salient on a societal scale. For instance, it may be that the learning that results from bringing members with different organizational tenure into communication with one another does not emerge when the boundaries between the different demographic categories are so great as to preclude effective communication.

Fourth, the findings presented here may be limited to R&D teams. As discussed above, research and development is an area where having communication links with others, who are engaged in similar or related research, is critical for achieving success. As such, it may be that both network density and network heterogeneity may be less important in other types of organizational teams.[13] Thus, only with similar analyses of other settings may we build a general theory of the relevant processes.

Finally, while we find that network heterogeneity increases productivity, it may be that extensive intercategory links have negative implications for other outcomes. In particular, those who see diversity as problematic stress the conflict that arises from the introduction of social divisions into a group (e.g., Pelled et al. 1999). Thus, greater network heterogeneity may increase the level of conflict among members and thereby reduce its performance on outcomes other than productivity. As Williams and O'Reilly (1998, p. 98) emphasize, the key question is whether the enrichment in information and skill which derives from diversity outweighs the negative consequences which result from possible increases in conflict. Following the strategy we have proposed and adopted here, we suggest that our understanding of the social mechanisms involved in such processes must begin with a focus on the social networks which occur within and across demographic categories.[14]

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Appendix

Measuring Productivity. Managers were asked to indicate how many of the 11 items in Table 1 the team had produced over the last three years. The manager could indicate that the team had produced 0, 1, 2–5, or more than 5 of an item. The items represent an unobserved productivity variable. For example, Cronbach's alpha between the 11 items is 0.72. The items are aggregated into a productivity variable using standard exploratory factor-analysis techniques (Harman 1976). To construct the productivity variable, the correlation matrix between the 11 items was factor analyzed using unweighted least squares. Factors with an eigenvalue >1 were rotated using an oblique rotation, which allows factors in the final solution to be correlated (Harman 1976, Bollen 1989, Jobson 1992). The resulting productivity variable is a factor score, and each team's score was computed using the regression method (Harman 1976, Chapter 16). Productivity is defined as $\Sigma_{k=1}^{11}\, n_k s_{ik}$, where n_k is a weight resulting from the factor analysis for item k, and s_{ik} is the score that team i has on item k. The productivity variable is a weighted average of the 11 productivity items. The productivity variable could be constructed using other techniques. For example, productivity could be defined as the sum of the 11 items, $\Sigma_{k=1}^{11}\, s_{ik}$, or it could be defined as the average of the 11 items, $\Sigma_{k=1}^{11}\, s_{ik}/11$. Both approaches assume that the each productivity item makes an equal contribution to the unobserved productivity variable. However, instead of assuming equal weighting for the items, we estimate the weights from the observed correlations between the 11 items.

Measuring Network Heterogeneity. Network heterogeneity measures how scientists allocate their network time across the team's tenure distribution. Network heterogeneity is a function of p_{ijk} and w_{ijk}. The former reflects the proportion of scientist i's interaction that is devoted to colleague j:

$$p_{ijk} = z_{ijk} \Big/ \sum_{q=1}^{N_k} z_{iqk} \quad i \neq q,$$

where z_{ijk} is the level of communication from scientist i to colleague j, and $\Sigma_{q=1}^{N_k}\, z_{iqk}$ is the amount of network time that scientist i allocates to his or her team. By conditioning z_{ijk} on $\Sigma_{q=1}^{N_k}\, z_{iqk}$, differences in mean interaction frequency are removed from the network-heterogeneity measure. The second component of network heterogeneity, w_{ijk}, is the degree of tenure similarity between two scientists:

$$w_{ijk} = (d \max_{ik} - d_{ijk}) \Big/ \sum_{q=1}^{N_k} (d \max_{ik} - d_{iqk}),$$

where d_{ijk} is the difference in tenure between actor i and actor j, and $d \max_{ik}$ is the maximum distance between actor i and any other individual on the team. The equation transforms tenure differences into similarity in two steps (cf., Burt 1982, pp. 176–177). First, the difference in tenure from individual i to each team member j is subtracted from the maximum difference, resulting in a similarity measure. Second, the similarity from individual i to individual j is normalized by the extent to which individual i is similar to all team members. This normalization reflects the fact that i's similarity to j must be understood in the context of the overall tenure distribution of the team, and i's position along that distribution. For example, if a team is composed of a large subset of scientists who are more senior than a smaller subset, members of the latter have more opportunity for contact with individuals of dissimilar tenure.

The tenure-similarity variable (and organizational-tenure diversity) scales time in linear fashion, a scaling that does not capture the full meaning of what is meant by the "cohort" concept. Cohorts emerge from categories not of calendar time but of social time; a cohort groups together individuals who have moved through social structure in parallel (e.g., Ryder 1965, Elder 1974). In the present context, identifying such cohorts would require isolating those tenure ranges that are socially similar. Unfortunately, while an effort was made to follow the method of Burt (1991) in isolating such cohorts through the network of interyear relations, the data under study do not lend themselves to such a strategy. In particular, each organization included in the study provides insufficient network and tenure data to render reliable cohort categories. Thus, our analysis proceeds under the caveat that calendar time is only a rough proxy for social time. Network heterogeneity measures the extent that team members allocate a large proportion of network time to colleagues who are close in the team's tenure distribution.

Measuring Diversity. We measure demographic diversity using the coefficient of mean difference (CMD), which in the current context is the average difference in tenure between scientists. In our data, demographic diversity does not have a significant effect on productivity. We checked whether the nonsignificant effect is a function of how diversity is measured. For example, demographic diversity is often measured with either the Gini index or the coefficient of variation. But, when the effect for demographic diversity is estimated using these variables, the estimates are not significant. This should not be surprising. The CMD, the Gini index and the coefficient of variation are all related. The following equation illustrates how (see Allison 1978 p. 870)

$$\left| \frac{1}{2N_k(N_k - 1)} \sum_{i=1}^{N_k} \sum_{j=1}^{N_k} |t_{ik} - t_{jk}|^r \right|^{1/r} j \neq i.$$

When $r = 1$, the equation equals the CMD. Dividing the CMD by twice the mean yields the Gini index. When $r = 2$, the equation is the standard deviation of tenure on the team. Dividing the standard deviation by the average tenure on the team results in the coefficient of variation. So, results using one of these measures will typically reflect the others as well. This is true as well for the "relational-demography" approach that has been used in diversity research (Tsui et al. 1992). In this line of research, the following is a measure commonly used at the individual level of analysis to describe how similar an individual is to his or her colleagues:

$$\frac{1}{N_k} \sum_{j=1}^{N_k} |t_{ik} - t_{jk}|^2$$

In the current context, the measure is the average squared difference in tenure between a scientist and his or her colleagues. Aggregated to the team level, the measure would indicate the average squared difference in tenure between team members. Note that the CMD is the average difference in tenure between team members. The measures are highly related mathematically. One examines the average difference in tenure, and the other focuses on the average squared difference in tenure.

Association Between Network Heterogeneity and Density. As we emphasize above, network density and network heterogeneity are logically distinct variables: The former reflects the overall frequency of interaction within a group, and the latter captures the extent to which interaction occurs within or across demographic boundaries. Nevertheless, the network variables are likely to be correlated in a given empirical setting and, indeed, we find that the zero-order correlation between the two variables in the present context is -0.44 . The partial correlation, controlling for team size is -0.25. To obtain a better understanding of the relationship between the two variables, we ran simulations where we studied the partial correlation between them under two types of conditions. In the first set of simulations, we treated w_{ijk} and z_{ijk} as random variables. The mean partial correlation of 100 simulations under these conditions was 0.001. In the second set of simulations, w_{ijk} was fixed as observed for a given dyad, and z_{ijk} was randomly assigned to pairs of scientists, under the constraint that the distribution of the random z_{ijk} had to match the observed distribution of z_{ijk} on a given team. The mean partial correlation of the 100 simulations run under these conditions was -0.08, with the observed correlation of -0.25 lying in the second quartile of the distribution. We conclude that the observed correlation between network density and network heterogeneity is not because of anything inherent in how the network variables are measured. Instead, the observed correlation reflects a substantive association: It indicates that, in the R&D units in our study, those units composed of small cohorts tend to have more dense communication networks, and moreover, scientists on those teams allocate a larger proportion of their interaction to colleagues inside their cohort than to colleagues outside of their cohort. However, in other contexts, other relationships between network heterogeneity and density are possible.

Endnotes

[1]Pfeffer also counsels managers to defy the homophily principle by selecting assistants from different cohorts, thereby improving the manager's access to parts of the organization to which he or she might otherwise be cut off (Pfeffer 1985, pp. 75–76).

[2]The second element in structural holes theory, which concerns the control benefits that derive from brokerage positions, is also frequently misinterpreted as contradicting the closure perspective. In fact, both theories hold that actors gain from dense relations among structurally equivalent peers and sparse relations among exchange partners (see Gabbay and Zuckerman 1998, p.195).

[3]This excludes the extreme case (unobserved in our data) in which there is no demographic diversity. Network heterogeneity would be undefined for such teams.

[4]While a focus on organizational tenure has advantages, a more complete account of the relationship between networks, diversity, and productivity would involve a consideration of other demographic characteristics—particularly those that are relevant to major social divisions, such as race and gender. Unfortunately, the R&D teams under study are too homogeneous with respect to these variables to lend themselves to useful study. In addition, respondent age was collected in 10-year intervals, making any analysis based on age suspect. Thus, as we emphasize in the discussion below, future research would do well to analyze populations in which such demographic characteristics, and their interaction with networks and productivity, may be examined.

[5]Results based on friendship networks generated substantially the same results as those we report for the communication networks.

[6]Nonresponse poses a potential problem for the measurement of network density and network heterogeneity, because these variables require information on all members of a team. For example, each nonresponse produces $N - 1$ missing relations in a network. Fortunately, the response rate for the present study was excellent: There is full information on 83.8% of all possible network relations, and at least one response on another 14.6%. Relations are not forced to be symmetric in the analysis, but the individuals generally agree about the frequency of their communication. For example, in dyads where full information exists, 45% of the reported interaction frequencies matched exactly and 74% differed by no more than one level. Following Gabbay and Zuckerman (1997, p. 201), we conducted a series of sensitivity analyses to assess the reliability of the results presented below in the face of different assumptions about the pattern of missing responses to both the network items and organizational tenure. We also compared the results using raw network data with networks that were scaled using a loglinear model (see Gabbay and Zuckerman 1997, p. 200). We found our results to be highly robust to all such transformations of the data. Details of these tests are available upon request.

[7]Thus, it is appropriate to view demographic diversity as antecedent to any affect found for network heterogeneity, which is reflected in Figure 3. That is, there must be some variance on the former for the latter to be meaningful and consequential. At the same time, within the observational range of this and most data sets, there is sufficient variance such that it is possible to treat diversity and network heterogeneity as independent variables.

[8]In the original formulation, the denominator is N^2. We use $N(N - 1)$ here because the latter is the true number of dyads in a group.

[9]Alternative measures which do not control for this opportunity set correlate very highly with tenure diversity, as one would expect.

[10]Following the suggestion of a reviewer, we investigated the possibility that these results do not reflect a general tendency for relations to occur between individuals of dissimilar organizational tenure, but for the presence of improved relations between lab managers and scientists, who would generally be distant from one another in the organizational-tenure distribution. To test this, we broke up the network heterogeneity into two components, one that reflects the level of network heterogeneity in manager-scientist dyads (*NH-M*) and another, which reflects such heterogeneity in scientist-scientist dyads (NH-S). In models that replaced network heterogeneity in Model 4, only NH-S had a significant effect, which suggests that the observed effect is not because of better relations with managers.

[11]In results not shown, we replaced the network heterogeneity measure used here with one based on *team tenure* (*NH-TT*), rather than the measure based on organizational tenure (*NH*-organizational tenure), which we discuss here. These results were substantially the same as those reported in Table 4. However, when both NH-TT and NH-organizational tenure are included, only the latter is significant. For that reason, and so as to provide a closer link with the large literature on organizational tenure, we present and discuss the results for NH-organizational tenure.

[12]Multicollinearity does not appear to be affecting these results. A rule of thumb is that multicollinearity is an issue when a predictor has a variance-inflation factor (VIF) larger than 10 (Belsley et al. 1980). In the final model of Table 4, VIF is 2.63 for network heterogeneity and 2.58 for network density. The largest values occur for team size and organizational-tenure diversity, with VIF equal to 3.46 and 3.07, respectively. We also checked for potential outliers using robust regression. The estimate for average organizational tenure is 0.03 (with 1.9 *t*-statistic). The estimate for network density is 1.2 (with 2.9 *t*-statistic). The estimate for network heterogeneity is 6.2 (with 2.9 *t*-statistic) and the estimate for the interaction between the two network variables is 21.5 (with a 2.4 *t*-statistic).

[13]The inclusion of several different types of R&D in the present data set might seem to lend itself to an analysis of how the affects for network density and network heterogeneity vary by task type. Some tasks are more dependent upon the exchange of information and others

are more dependent upon diverse information. We added slope adjustments for network density and network heterogeneity for each task type. None of the adjustments were significant. Indeed, it would seem that, when considered in light of the full range of possible work tasks, all types of R&D involve roughly similar issues.

[14]The observed pattern of effects is not a function of the amount of time scientists dedicate to their teams. Teams where scientists dedicate more time could be more productive and have better communication patterns. Respondents were asked to indicate the proportion of time they spend working on team-related activities and could select one of four responses: 100%, 50–99%, 25–49%, or less than 25%. Across individual scientists, 21.6% responded less than 25%. 9.6% selected 25–49%. 22.2% selected 50–99% and 46.6% allocate 100% of their time. The broad categories used to collect time data makes any analysis based on time suspect. When the mean response for a team is entered into the final mode in Table 4, it does not have a significant effect on performance, and the network effects remain the same.

References

Adler, Paul S., Seok-Woo Kwon. 1999. Social capital: The good, the bad, and the ugly. Unpublished manuscript, Marshall School of Business, University of Southern California, Los Angeles, CA.

Allen, Thomas J. 1977. *Managing the Flow of Technology: Technology Transfer and the Dissemination of Technological Information within the R&D Organization.* MIT Press, Cambridge, MA.

——, Stephen I. Cohen. 1969, Information flow in research and development laboratories. *Admin. Sci. Quart.* **14** 12–19.

Allison, Paul D. 1978. Measures of inequality. *Amer. Sociological Rev.* **43** 865–880.

Aldrich, Howard E., Catherine Zimmer. 1986. Entrepreneurship through social networks. D. L. Sexton, R. W. Smilor, eds. *The Art and Science of Entrepreneurship.* Ballinger, Cambridge, MA 3–24.

Ancona, Deborah G., David F. Caldwell. 1992. Demography and design: Predictors of new product team productivity. *Organ. Sci.* **3** 321–341.

Arnold, H. J., D. C. Feldman. 1981. Social desirability response bias in self-report choice situations. *Acad. Management J.* **24** 377–385.

Avolio, Bruce J., Francis J. Yammarino, Bernard M. Bass. 1991. Identifying common methods variance with data collected from a single source: An unresolved sticky issue. *J. Management* **17** 571–587.

Bantel, Karen A., Susan E. Jackson. 1989. Top management and innovations in banking: Does the composition of the top team make a difference? *Strategic Management J.* **10** 107–124.

Belsley, David A., Edwin Kuh, Roy E. Welsch. 1980. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity.* Wiley, New York.

Berman, J. S., D. A. Kenny. 1976. Correlational bias in observer ratings. *J. Personality Soc. Psych.* **34** 263–273.

Burt, Ronald S. 1982. *Toward a Structural Theory of Action: Network Models of Social Structure, Perception and Action.* Academic Press, New York.

——. 1990. Kinds of relations in American discussion networks. Craig Calhoun, Marshall W. Meyer, W. Richard Scott, eds. *Structures of Power and constraint: Papers in honor of Peter M. Blau.* Cambridge University Press, Cambridge, MA.

——. 1991. Measuring age as a structural concept. *Soc. Networks* **13** 1–34.

——. 1992. *Structural Holes: The Social Structure of Competition.* Harvard University Press, Cambridge, MA.

Carroll, Glenn R., J. Richard Harrison. 1998. Organizational demography and culture: Insights from a formal model and simulation. *Admin. Sci. Quart.* **43** 637–667.

Cohen, Bernard P., Xueguang Zhou. 1990. Status processes in enduring work groups. *Amer. Sociological Rev.* **51** 179–188.

Coleman, James S. 1988. Social capital in the creation of human capital. *Amer. J. Sociology* **94** S95–S120.

——. 1991. *Foundations of Social Theory.* Harvard University Press, Cambridge, MA.

Cook, Karen S., Richard M. Emerson, Mary R. Gillmore, Toshio Yamagishi. 1983. The distribution of power in exchange networks: Theory and experimental results. *Amer. J. Sociology* **89** 275–305.

Doty, D. Harold, William H. Glick. 1998. Common methods bias: Does common methods variance really bias results. *Organ. Res. Methods* **1** 374–406.

Elder, Glenn H., Jr. 1974. *Children of the Great Depression.* University of Chicago Press, Chicago, IL.

Eisenhardt, Kathleen M., Jean L. Kahwajy, L. J. Bourgeois III. 1997. How management teams can have a good fight. *Harvard Bus. Rev.* **75** 77–85.

Ely, Robin J. 1994. The effects of organizational demographics and social identity on relationships among professional women. *Admin. Sci. Quart.* **39** 203–238.

Evans, D. R., K. L. Dion. 1991. Group cohesion and productivity: A meta-analysis. *Small Group Res.* **22** 175–186.

Gabbay, Shaul M., Roger Th. A. J. Leenders. 1999. CSC: The structure of advantage and disadvantage. Roger Th.A.J. Leenders, Shaul M. Gabbay, eds. *Corporate Social Capital and Liability.* Kluwer Academic Publishers, Boston, MA 1–14.

——, Ezra W. Zuckerman. 1998. Social capital and opportunity in corporate R&D: The contingent effect of contact density on mobility expectations. *Soc. Sci. Res.* **27** 189–217.

Granovetter, Mark S. 1973. The strength of weak ties. *Amer. J. Sociology* **78** 1360–1380.

——. 1985. Economic action and social structure: The problem of embeddedness. *Amer. J. Sociology* **91** 481–510.

Hannan, Michael T., Alice A. Young. 1977 Estimation in panel models: Results on pooling cross-sections and time series. David Heise, ed. *Sociological Methodology 1977.* Jossey-Bass, San Francisco, CA, 53–87

Hansen, Morten T. 1999. The search-transfer problem: The role of weak ties in sharing knowledge across organization subteams. *Admin. Sci. Quart.* **44** 82–111.

Jobson, J. D. 1992. *Applied Multivariate Data Analysis: Volume II: Categorical and Multivariate Methods.* Springer-Verlag, New York.

Katz, Ralph. 1982. Project communication and performance: An investigation into the effects of group longevity. *Admin. Sci. Quart.* **29** 81–104.

——, Robert Tushman. 1979. Communication patterns, project productivity, and task characteristics: An empirical evaluation and integration in an R&D setting. *Organ. Behavior Human Productivity* **23** 139–162.

Kendall, Maurice, Alan Stuart. 1977. *The Advanced Theory of Statistics. Vol. 1. 4th ed.* Macmillan, New York.

Lawrence, Barbara S. 1997. The black box of organizational demography. *Organ. Sci.* **8** 1–22.

Leavitt, Harold J. 1951. Some effects of certain communication patterns on group performance. *J. Abnormal Soc. Psych.* **46** 31–50.

March, James G. 1991. Exploration and exploitation in organizational learning. *Organ. Sci.* **1** 71–87

Marsden, Peter V., Karen E. Campbell. 1984. Measuring tie strength. *Soc. Forces* **63** 482–501.

McCain, Bruce E., Charles O'Reilly, Jeffrey Pfeffer. 1983. The effects of departmental demography on turnover: The case of a university. *Acad. Management J.* **26** 626–641.

O'Reilly, Charles A. III, David F. Caldwell, William P. Barnett. 1989. Work group demography, social integration, and turnover. *Admin. Sci. Quart.* **34** 21–37.

Pelled, Lisa Hope. 1996. Demographic diversity, conflict, and work group outcomes: An intervening process theory. *Organ. Sci.* **7** 615–631.

——, Kathleen M. Eisenhardt, Katherine R. Xin. 1999. Exploring the black box: An analysis of work group diversity, conflict, and productivity. *Admin. Sci. Quart.* **44** 1–28.

Pfeffer, Jeffrey. 1982. Organizational demography. L. L. Cummings, Barry M. Staw, eds. *Research in Organizational Behavior* **5** JAI Press, Greenwich, CT, 299–357.

——. 1983. Organizational demography: Implications for management. *California Management Rev.* **28** 67–81.

——, Gerald R. Salancik. 1978. The external control of organizations. Harper and Row, New York.

Podsakoff, Philip, Dennis Organ. 1986. Self-reports in organizational research: Problems and prospects. *J. Management* **12** 531–543.

Portes, Alejandro. 1998. Social capital: Its origins and applications in modern sociology. *Ann. Rev. Sociology* **24** 1–24.

——, Julia Sensenbrenner. 1993. Embeddedness and immigration: Notes on the social determinants of economic action. *Amer. J. Sociology* **98** 1320–1350.

Riordan, Christine M., Lynn McFarlane Shore. 1997. Demographic diversity and employee attitudes: An empirical examination of relational demography within work teams. *J. Appl. Psych.* **82** 342–358.

Robinson, W. S. 1950. Ecological correlations and the behavior of individuals. *Amer. Sociological Rev.* **15** 351–357.

Accepted by Barbara Lawrence.

Ryder, Norman B. 1965. The cohort as a concept in the study of social change. *Amer. Sociological Rev.* **30** 843–861.

Salancik, Gerry R., Jeffrey Pfeffer. 1977. An examination of need-satisfaction models of job attitudes. *Admin. Sci. Quart.* **22** 427–456.

Shenhav, Yehouda A. 1992. Expected managerial careers with growing and declining R&D establishments. *Work and Occupations* **18** 46–71.

Simmel, Georg. 1955. *Conflict and The Web of Group Affiliations.* Kurt H. Wolff, trans. Reinhard Bendix, Free Press, New York.

Sorensen, Jesper B. 1999. The use and misuse of the coefficient of variation in organizational demography research. Working paper, University of Chicago Graduate School of Business, Chicago, IL.

——. 2000. Organizational heterogeneity and job turnover. *Amer. Sociological Rev.* **65** 298–310.

Staw, Barry M. 1980. The consequences of turnover. *J. Occupational Behavior* **1** 253–273.

Tajfel, Henri. 1981. *Human Groups and Social Categories: Studies in Social Psychology.* Cambridge University Press, Cambridge, England.

——, John Turner. 1986. The social identity of intergroup behavior. Stephen Worchel, William G. Austin, eds. *Psychology and Intergroup Relations.* Nelson-Hall, Chicago, IL, 7–24.

Turner, John. 1987. *Rediscovering the Social Group: A Social Categorization Theory.* B. Blackwell, Oxford, England.

Tushman, Michael L. 1977. Technical communication in R&D laboratories: The impact of project work characteristics. *Acad. Management J.* **20** 624–645.

Uzzi, Brian. 1996. The sources and consequences of embeddedness for the economic performance of organizations: The network effect. *Amer. Sociological Rev.* **61** 674–698.

——. 1999. Embeddedness in the making of financial capital: How social relations and networks benefit firms seeking financing. *Amer. Sociological Rev.* **64** 481–505.

Wagner, Gary W., Jeffrey Pfeffer, Charles A. O'Reilly, III. 1983. Organizational demography and turnover in top-management groups. *Admin. Sci. Quart.* **29** 74–92.

Williams, Katherine Y., Charles A. O'Reilly, III. 1998. Demography and diversity in organizations: A review of 40 years of research. *Res. Organ. Res.* **20** 77–140.

Zenger, Todd R., Barbara S. Lawrence. 1989. Organizational demography: The differential effects of age and tenure distributions on technical communication. *Acad. Management J.* **32** 353–376.