NEIGHBORHOODS: A TACIT SOCIAL STRUCTURE CONNECTING INDIVIDUALS AND ORGANIZATIONS

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ABSTRACT

We propose and inductively explore neighborhoods, a tacit social structure connecting individuals and organizations. Neighborhoods are clusters of individuals' organizational reference groups, in which the people each individual knows are demographically-similar to the people other individuals know. Because of their internal similarity, neighborhoods circumscribe the social information individuals receive and thus plausibly generate shared perceptions and meaning. Using latent class cluster analysis on data from a large organization, we induce five neighborhoods. While individuals' own attributes are related to those of others in their neighborhood, their attributes frequently differ from those in their neighborhood. Neighborhoods discriminate between individuals' career-related perceptions and social network attributes.

And so when anthropologists claim to 'take the native's point of view,' we have been in the habit of asking, 'Which native?' (Hannerz, 1992, p. 12)

Organizational scholars have struggled for many years to explicate the mechanisms that connect individuals and organizations. These mechanisms typically involve the creation of intersubjective meanings, shared perceptions and common cognitive schema that guide individuals' generation and use of culture (DiMaggio, 1997). The raw material for this process is social information, the cognitive and affective knowledge individuals acquire about and from others, which represents a fundamental conduit through which shared understandings develop (cf. Giddens, 1984; Hannerz, 1992; Salancik & Pfeffer, 1978). While scholars pay considerable attention to collecting and interpreting such information, they pay less attention to the people from whom individuals receive it (cf. Fortado, 1992; Mohr, 1998). Organizational research generally pre-defines these people using formal structures, such as work groups or divisions, or by asking individuals to identify several salient work relationships. Yet, these approaches are decreasingly representative. Individuals receive social information from a wide variety of others through different media, over large geographic distances, and through telecommuting or boundaryless careers. Thus, we need a more inductive approach to the question of where shared perceptions come from.

This paper presents an exploratory study of a large utility that examines such an approach. A large organization was used because, unlike small organizations where everyone obtains social information from everyone else, large organizations provide individuals the opportunity to develop broad, idiosyncratic organizational reference groups (Lawrence, 2006). These reference groups, including everyone from whom individuals obtain social information, from salient relationships to recognized names on an email, represent an example of social

context in which individuals are not confined by geography or formal structures. Thus, the analysis induces social structure from individuals' perceptions of social context in a setting where these perceptions may differ. This contrasts with many studies that first define group boundaries, such as workgroups or divisions, and then establish shared perceptions, meanings or values using a direct consensus model (Chan, 1998). Moreover, it differs from many demography studies that focus on individuals as the level-of-analysis. Here, the level-of-analysis is the organizational reference group and the question is whether these groups are organized in ways that define distinct social contexts.

Specifically, we examine whether organizational reference groups are organized into neighborhoods, where each neighborhood represents a mutually-exclusive cluster of reference groups whose members share common attributes. In an individual-level study, individuals typically associate with other similar individuals. In this case, two individuals are similar when they share attributes, such as a common age, gender, ethnicity or education. In a neighborhood study, individuals associate with similar organizational reference groups. Here, two individuals are similar when the people they know share attributes. Figure 1 provides an example loosely-based on actual data. The three individuals whose organizational reference groups fall into the first neighborhood are more likely than the two in the second to be aware of older Asian women. This does not mean that the individuals themselves are older Asian women; it means that the social context they each perceive tends to include such women.

An important question is whether such neighborhoods merely index individuals' attributes, suggesting that similar individuals hold similar perceptions of social context, or whether neighborhoods define distinct social contexts. If neighborhoods merely index individuals' attributes, they provide no additional value beyond a clustering of similar

individuals, a type of analysis currently accomplished with relational similarity measures (Riordan & Wayne, 2008) and social network measures such as structural or regular equivalence (Doreian, Batagelj, & Ferligoj, 2005). However, if neighborhoods characterize distinct social contexts, they represent a social structure that is a level-of-analysis higher than individuals' social networks. The key question, then, is whether neighborhoods facilitate the evolution of shared perceptions. If two people belong to the same neighborhood, they receive social information from groups of similar people and it seems likely this facilitates shared perceptions—even if the two are themselves dissimilar. Thus, this intermediate social structure may help explain how subcultures emerge and evolve in large organizational settings, connecting individuals to the organizations in which they work.

Figure 1 About Here

THEORY

Organizational Reference Groups

Within or across organizations, an individual's distinctive array of information sources represents his or her organizational reference group, "the set of people an individual perceives as belonging to his or her work environment that defines the social world of work in which he or she engages, including people with whom the individual does and does not communicate and those with whom awareness is the only connection" (Lawrence, 2006, p. 80). Although an individual's organizational reference group includes instrumental and expressive relationships (Ibarra, 1993), it also includes distant associations of whom the individual is aware, but with whom he or she has never spoken. This distinguishes organizational reference groups from weak ties (Granovetter, 1973, 1983), which typically depend on actual communication or salient

relationships. An organizational reference group also differs from a psychological group (Turner, 1985) because it does not have to be and probably isn't recognized by others. It is an individual-level phenomenon that denotes the individual's social context as he or she perceives it: potentially shared with but potentially independent from that perceived by others.

It seems likely that the demographic composition of individuals' organizational reference groups is non-random. Consistent with research on homophily, the tendency of an individual to associate with similar others (Lazarsfeld & Merton, 1954), individuals are more likely to include t others who hold similar rather than different attributes (McPherson, Smith-Lovin, & Cook, 2001). Women are more likely to include women than men and younger individuals are more likely to include younger individuals than older ones. However, the strength of these patterns increases with changes in other attributes as well. For instance, Lawrence (2006) found that the probability of including women increases if the subject is a woman, but it also increased with the subject's increasing age, decreasing organizational tenure and higher education. Her results also showed significant multi-attribute associations for each of eight compositional outcomes: proportion women, proportion Black, proportion Hispanic, proportion Asian, average age, average organizational tenure, average education and average career level. The strong associations, with 40% average explained variation across the eight outcomes, suggest that organizational reference groups themselves bear compositional similarities. It seems possible these similarities index a more macro social structure.

Tacit Neighborhoods

We propose that this structure involves neighborhoods, where each neighborhood is a group of organizational reference groups distinguished by their similar demographic composition. Neighborhoods represent an intermediate form of social structure, falling between

small work groups and larger social systems such as functional areas, regional offices or organizations. Neighborhood boundaries are induced and largely tacit. Each neighborhood represents a distinct social arena defined by its "most-typical" organizational reference group; consequently representing a demographic configuration likely to draw individuals' attention and acquire meaning. The set of these groups then is the organization's neighborhood structure: a differentiated social territory whose neighborhoods define the arena within which individuals are most likely to negotiate symbolic and social boundaries (cf. Lamont & Molnar, 2002).

Two streams of research support this argument. The first emphasizes individuals' oft-noted tendency to interact with demographically-similar others {McPherson, 2001 #84}. The literatures on social identity and self-categorization[3] suggest that demographic attributes often acquire salience for individuals because they are chronically accessible (Fiske & Taylor, 1991) and related to status differences (Ridgeway, 1991). As a result, individuals attach meaning to demographic attributes as explanations for "How I am similar to and different from you" (Brewer, 1991) and then identify with demographically-similar others as a means of uncertainty reduction (Hogg & Terry, 2000).

The result is that individuals tend to cluster with others who share similar demographic attributes creating in-groups and out-groups (Tajfel, 1974; Turner, 1985) that influence the distribution of social information. When individuals share more than one attribute and when no one attribute is dominant, crossed-attribute categories emerge (Ashforth & Johnson, 2001; Vescio, Hewstone, Crisp, & Rubin, 1999). In laboratory studies, such crossed-attribute categories come to acquire their own meaning independent of the meaning of each separate

[3] See Hogg and Abrams Hogg, M. A. & Abrams, D. 1999. Social identity and social cognition: Historical background and current trends. In D. Abrams & M. A. Hogg (Eds.), Social Identity and Social Cognition, Vol. Blackwell: 1-25. Oxford, UK. for a social psychological perspective on this literature and Hogg and Terry Hogg, M. A. & Terry, D. J. 2001. Social Identity Processes in Organizational Contexts. Philadelphia: Psychology Press. for an organizational one.

category (Vescio et al., 1999). However, much of this multiple-attribute work focuses on situations with only two salient attributes. For instance, distinctiveness theory (McGuire, McGuire, Child, & Fujioka, 1978; Mehra, Kilduff, & Brass, 1998) suggests that when an individual belongs to two minority groups, he or she is likely to identify with the smaller of the two groups. Consequently, while suggestive, this work provides little information on what happens in an organizational context where there are more than two ways in which individuals categorize themselves and others.

The second stream of research focuses on more macro-level social systems. The literatures on homophily (McPherson et al., 2001) and consolidation (Blau, 1977b) both suggest that the distribution of attributes in a population constrains and facilitates individuals' opportunities to become aware of and develop relationships with one another. Independent of any psychological bases for relationships, homophily research suggests that for any two individuals there is a baseline probability that they will interact within a given population. For instance, the probability that two Brazilians sitting next to one another on the London Underground will discuss the weather increases with the number of Brazilians visiting London. Inbreeding homophily represents the difference between the observed probability of a relationship and its baseline (McPherson et al., 2001).[4] If both Brazilians take the Underground and are students at the same university, this increases the probability they will meet over the baseline probability. Basic structural sources of homophily include geography, family, organizational foci and roles.

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[4] In an earlier review, McPherson and Smith-Lovin McPherson, J. M. & Smith-Lovin, L. 1987. Homophily in voluntary organizations: Status distance and the composition of face-to-face groups. American Sociological Review, 52(3): 370-379. called these choice and induced homophily rather than baseline and inbreeding. Ibarra Ibarra, H. 1993. Personal networks of women and minorities in management: A conceptual framework. Academy of Management Review, 18: 56-87. introduced the original terms to the organizational literature.

Blau (1977b) suggests that a social system's heterogeneity and inequality are defined by the distribution of individuals' multiple attributes. Consolidation is the extent to which these attributes are positively correlated. As consolidation increases, the number of groups comprising the social structure decreases, and this decreases intergroup social interactions.[5] Consolidated nominal attributes, such as gender or ethnicity, produce lower heterogeneity; consolidated graduated attributes, such as age and gender, produce higher status differences. This highly abbreviated version of Blau's (1977a) theory of social structure suggests that population distributions shape actual group boundaries and status differences; thus, it seems likely that they also influence individuals' perceptions.

Independent of whether individuals choose others or organizations constrain choices, all of these mechanisms produce the same result: individuals receive social information from non-random groups of others that evolve around common demographic attributes. This is reflected in the individual outcomes of many organizational studies. Organizations tend to attract applicants similar to existing employees (Geraci & Tolbert, 2002), managers tend to hire applicants similar to existing employees, and existing employees who do not fit in, tend to leave (Schneider, 1987; Schneider, Goldstein, & Smith, 1995). Individuals use their perceptions of an organization's demography as signals of their own career options (Taylor, Audia, & Gupta, 1996). These consistent results make it probable that neighborhoods represent distinctive work environments that shape individuals' perceptions, experiences and shared understandings through common views of what's-going-on-around-here.

The Emergence of Shared Perceptions and Meaning

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[5] Blau (1977, p. 276) provides the following definition of group: "Groups are broadly defined as all nominal categories of persons who share a social position (social attribute) that influences their role relations. Groups are parts of a society (or other large collectivity). They have boundaries and no rank-order."

Shared perceptions and meaning feature prominently in organizational culture and climate studies (Ashkanasy, Wilderom, & Peterson, 2000). It seems possible that both emerge, in part, because neighborhoods influence the social information that individuals access and thus play a role in shaping their identity (Ibarra, Kilduff, & Tsai, 2005). Recent research in neuroscience suggests that individuals first engage in categorical thinking and then attach experiences, observations and meaning to each category. People use two different parts of the brain when making sense out of social information (Macrae & Bodenhausen, 2000). The neocortical system includes individuals' somewhat fixed mental models, including their personal beliefs and perceptions of norms and expectations. The hippocampal system provides the ability to make quick, temporary assessments of stimuli, which gives individuals the ability to adapt to new situations. When such temporary stimuli are activated on a regular basis, they transfer to the neocortical system. Thus, information automatically gets assessed through the neocortical system unless it doesn't fit with existing mental models. Discrepancies are processed through the hippocampal system and used either to revise or create new scripts and routines.

This processing routine facilitates the development of socially-meaningful categories. We know for instance that social categories such as age and gender (Linton, 1940) become rich repositories for attitudes and beliefs about individuals. These repositories exert considerable influence on perception because the information is encoded in the neocortical system, the part of the brain to which people have immediate access. As a result, awareness of others in these categories is evoked even before individuals go about the work of perceiving them. Stereotyping increases processing efficiency and provides the "ground" against which contradictions can be evaluated. Individuals are particularly likely to use social categories when they lack "the motivation, time, or cognitive capacity to think deeply (and accurately) about others" (Macrae &

Bodenhausen, 2000, p. 105). Thus, individuals are likely to use demographic attributes to process their awareness of others as well as attach meaning to the categories.

The idea that individuals use demographically-similar neighborhoods to facilitate shared meaning is also consistent with both macro and micro explanations for how individuals connect with organizations. Institutional theory, for instance, posits that social structure places cognitive constraints on individual behavior through symbolic and relational systems, routines and artifacts (Scott, 2001, p. 48). These cognitive constraints operate through scripts, the "observable, recurrent activities and patterns of interaction characteristic of a particular setting." (Barley & Tolbert, 1997, p. 98). Individuals observe and encode scripts in everyday life, enact them and then behave, either consciously or unconsciously, in ways that replicate or revise them. Thus, individuals who observe the same neighborhood, are likely to develop common scripts.

On the other end of the continuum, sense-making theory suggests that individuals produce social reality through the perceiving, interpreting and acting they do to reduce uncertainties in everyday life (Weick, 1979). From this perspective, individuals create social structure through their retrospective processing of perceptual cues, which may result either through unconscious, automatic responses or by conscious reasoning (Weber & Glynn, 2006). This processing involves an iterative dynamic between individuals observing their social context, making sense of selected observations, and typifying enacted meanings for future reference (Weick, Sutcliffe, & Obstfeld, 2005). The description of how individuals perform this activity assumes they observe social information, and it seems likely that what they observe makes a difference in the meanings that evolve.

Questions

Our goal in this study, then, was to explore a single, large organization and examine whether neighborhoods make sense as an emic social structure that shapes shared perceptions. Our first question is whether neighborhoods, characterized by demographically-distinct groups of individuals' organizational reference groups, can be identified. The second is whether neighborhoods simply discern individuals with common attributes, or whether they index distinct work environments. The third is whether these work environments appear related to members' perceptions and interactions with others, independent of members' own demographic attributes.

METHOD

The analysis uses secondary data from a utility with 2,685 managers.[7] Management employees were selected for analysis because management careers consist of a hierarchy of positions, known to all employees. The company's description of career levels thus means the same thing to everyone, which facilitates status comparisons. Demographic data on this population were obtained from the firm. A 20% systematic, stratified sample of this population (N=537) was sent a survey requesting perceptions of career opportunity at the firm as well as a list of names of the people they know. Survey results were received from 77% of subjects in the sampling frame (N=411). This study includes only subjects whose organizational reference groups included both close and distant associations, which reduces the sample to 358.[8] We compared this reduced sample to the population and found no significant demographic differences (gender: X^2=0.25, p=0.62; ethnicity: X^2=0.38, p=0.94; age: t=-1.36, p=0.17; organizational tenure: t=0.30, p=0.77; education: t=0.14, p=0.89; career level: t=0.09, p=0.93).

Variables

[7] To the best of our knowledge, this is the only organizational data set with the sample size and detail required for examining these questions. See Lawrence (2006) for additional information on the data and data collection.
[8] Of the 53 subjects dropped, 42 identified no close work associations, 1 identified no distant work associations and 10 identified no close or distant work associations.

Organizational Reference Groups. A subject's organizational reference group was identified using his or her responses to the question "Please copy the names of employees you know." Name generation is a standard technique used to discern social networks in large social systems where interviewing large numbers of individuals is impractical. A complete list of the population of managers was provided for reference and subjects provided an average of 50 names. These lists are right censored because available survey space only accommodated 56 names. Thus, it seems likely that these lists do not include everyone in each subject's organizational reference group. While not ideal, these data hold several attributes that make them appropriate for this exploratory study. First, the survey design resulted in six times as many names as obtained in the average name generator survey (Lawrence, 2006). Standard survey design requires writing in names for each question, and this leads subjects to limit the number of names they provide. Second, the names solicited in this study include subjects' close associations, with whom they work frequently, as well as distant associations, with whom they work seldom or never. Studies in large organizations typically include only close or salient relationships because name generators solicit individuals who play these roles. For instance, Obstfeld (2005) obtained an average of 13.2 names per subject by asking them five questions. These requested names of those "with whom they discussed important matters, with whom they communicated to get work done, who were influential in getting new projects approved, with whom they socialized informally, and to whom they turned for advice" (p. 112). Third, the name generator used in this study requested names prior to asking questions about those listed. As a result, subjects were not primed to provide names because of their perceived relevance to the questions. Finally, all attribute information was obtained from company records, suggesting that subjects were not primed by asking them for the attributes of the people they knew.

Neighborhoods. Neighborhoods are an organizational-reference-group-level variable where each neighborhood is composed of individuals clustered together because their organizational reference groups share similar demographic composition. An individual's neighborhood is independent of his or her own attributes. Classification was accomplished using a latent class cluster analysis (LCCA, Hagennars & McCutcheon, 2002) of the demographic attributes of each individual's organizational reference group. LCCA is an inductive technique that produces independence among observed variables by relating people to classes (for related discussion see Muthen & Muthen, 2000). In contrast to factor analysis, where subjects' attributes have loadings on each of N dimensions, this analysis takes organizational reference groups' attributes and clusters them into N discrete categories. Thus, all organizational reference groups that fall in category N_i are demographically-similar and independent of organizational reference groups in categories N_{i+j}. Although both standard cluster analysis and regular equivalents could be used to classify individuals into discrete categories, neither can be used when the level-of-analysis is the organizational reference group. A multi-core computer was constructed for this computationally-intensive analysis. As LCCA is relatively new to organizational research, Appendix A provides a more detailed description.

Individual Demographic Data. Data on individuals' gender, ethnicity (White, Black, Hispanic and Asian), age, organizational tenure, education and career level were obtained from company records.

Outcome Variables

We selected two career-related perceptions—individuals' career expectations and the level of individuals' career referents, and two social network attributes—individuals' centrality and the number of redundancies in their organizational reference groups, to assess whether

shared perceptions and associations emerge from neighborhood membership. Positive results for these outcomes do not prove the existence of shared meaning. However, they provide some evidence that neighborhoods provide distinctive information about how individuals think about work and interact with others.

Careers pose critical sensemaking opportunities (Arthur, Hall, & Lawrence, 1989). People continuously evaluate their own careers against those of others and ask: How did those people become successful? Why did others fail? How do I fit in this organization? Martin and her colleagues (1983), for instance, suggest that renditions of "can the little person rise to the top?" constitute one of seven common stories told across organizations. Careers are the negotiated outcome over time between individuals' work offered and rewards received and organizations' work received and incentives provided (Arthur & Kram, 1989). As a result, social categories associated with the careers of valued employees are particularly likely to acquire salience for individuals. Making sense of whether one is valued by others plays an important role in feelings of self-worth (Hall & Chandler, 2005), thus if neighborhoods influence sensemaking, it is likely to involve sensemaking about careers and career-related outcomes. Whether a neighborhood influences or simply carries meaning, individuals located in different neighborhoods are likely to have different views about how careers work and what expectations are reasonable.

Social networks play many important roles in individuals' organizational experiences. We selected two individual-level outcomes that address structural approaches to organizational culture (Kilduff & Corley, 2000). One of the most frequently studied is the relationship between an individual's position within a social network and his or her access to information. Individuals who are central in an organization often are or become sources of power and influence

(Burkhardt & Brass, 1990). The more well-known an individual is to others, the more likely he or she is to be a conduit for information. Burt (1992) suggests that individuals' strategic value as brokers who control information increases with decreasing redundancies in their relationships. This strategic value can be used to exploit or mediate differences (Obstfeld, 2005). Because individuals' relationships frequently correspond to their demographic attributes (Ibarra, 1992) and because neighborhoods are defined by an underlying social structure, individuals located within the same neighborhood may develop similar kinds of structural relationships: higher or lower centrality and more or fewer redundant associations within the organization.[9]

Career expectations. Subjects' career expectations were assessed using responses to the question "What salary level do you hope to attain by the time you leave [Company Name]?" Salary level is the term the company uses to define career levels. This makes a single-item variable preferable to a multiple-item variable, as additional questions would necessarily obscure the information requested. There are fifteen salary levels in managers' hierarchical careers.

Level of career referents. Subjects' level of career referents was identified by their responses to three questions about their list of organizational reference group members: 1) How similar are you to each person on the list in terms of the types of jobs you have held during your career, 2) How similar are you to each person on the list in terms of the pace of your advancement during your career, and 3) How similar are you to each person on the list in terms of your future work opportunities at [COMPANY NAME]. These questions reflect previous research suggesting that individuals create subjective definitions of who is ahead of schedule, on schedule and behind schedule and use these definitions to assess their own careers (Ancona,

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[9] The structural similarity proposed here corresponds to but is distinct from structural equivalence, which is used to define organizational fields (Breiger, R. L. & Mohr, J. W. 2004. Institutional logics from the aggregation of organizational networks: Operational procedures for the analysis of counted data. Computation & Mathematical Organization Theory, 10: 17-43.) It is more similar to regular equivalence (de Nooy, W., Mrvar, A., & Batagelj, V. 2995. Exploratory Social Network Analysis with Pajek. New York: Cambridge University Press.

Goodman, Lawrence, & Tushman, 2001; Lawrence, 1984). Subjects provided answers on a five-point scale: 0 = don't know, 1 = very dissimilar; 2 = somewhat dissimilar; 3 = somewhat similar and 4 = very similar. For each question, career levels of those identified as somewhat or very similar were averaged. The three averages were then averaged. Coefficient alpha for the level of career referents variable is 0.96. Career levels were assessed using company records.

Centrality. An individual's centrality was measured by the number of times he or she is listed by other members of the survey sample. This measure, also known as in-degree centrality (Burkhardt & Brass, 1990), is typically used in complete networks where every individual provides responses about every other individual. Generally it is difficult to assess in-degree centrality in ego networks because the number of names generated is so small that few individuals are listed by others. The large lists obtained here facilitate at least an imprecise indication of subjects' in-degree centrality. On average, each subject was mentioned by eight other subjects (s.d.= 4.99).

Redundant Associations. An individual's redundant associations is assessed as the number of people among his or her organizational reference group members who both belong to the sample and mention one another (Borgatti, 1997).

Descriptive Statistics

Table 1 provides descriptive statistics of all the variables, including means, standard deviations and correlations. Because many of these variables are correlated significantly, variance inflation factor values were assessed in all regression analyses. All values fall below the suggested maximum value of ten (Chatterjee & Price, 1991) suggesting that multicollinearity may attenuate estimates, but does not otherwise harm them.

Table 1 About Here

Analysis

We identified neighborhoods using latent class cluster analysis (Mplus version 5.1, see Muthen & Muthen, 1998-2008). Following the neighborhood analysis, we examined the extent to which individuals' own attributes influence the odds of their neighborhood classification using multinomial regression. Finally, we explored the impact of neighborhoods on individual perceptions with four individual-level outcome variables using multiple regression.

Figure 1 About Here

RESULTS

Question 1. Can neighborhoods, characterized by demographically-distinct groups of individuals' organizational reference groups, be identified and if so, what do they look like?

The analysis uncovered five distinct neighborhoods, loosely-labeled Newcomers, Old-Timers, Fast-Trackers, High-Level Managers and Fast-Track Women. To select the correct number of classes, we ran multiple LCCA models, beginning with two classes and ending with ten. For each of these, 10,000 initial models were estimated with randomly-generated starting values for organizational reference group attributes. Models were allowed to complete 500 iterations. The 100 best-fitting models were then iterated until model convergence was reached.

All models were evaluated using BIC and entropy values followed by a sensitivity analysis. BIC values decreased substantially as more classes were added, until a sixth class was added. Although additional classes reduce BIC values further, the reduction nets little significant improvement. Entropy values were relatively high for all models, indicating good classification quality across all solutions. Finally, the number of subjects in each class starts to decrease

rapidly after reaching six classes. Both the 5-class and 6-class solutions provide meaningful results based on the authors' knowledge of the company. However, given the BIC and entropy results as well as parsimony guidelines, we selected the 5-class LCCA model to represent the underlying structure of the data.[10] Table 2 shows means and proportions of the demographic attributes describing each of the five neighborhoods as well as population values for those attributes. Analysis of variance comparing the means across the five neighborhoods shows significant differences on all demographic attributes: gender, ethnicity, age, organizational tenure, education and career level. This provides additional support for classification quality.

Table 2 About Here

The following qualitative descriptions of each neighborhood highlight the neighborhood's attributes relative to those of the population. Neighborhood 1, the Newcomers, includes organizational reference groups characterized by somewhat more women, who are somewhat more likely to be Asian, slightly younger, with slightly lower tenure and higher education than are average in the population. Neighborhood 2, Old-Timers, includes organizational reference groups characterized by older white and Hispanic men who have higher tenure and lower education than are average in the population. This neighborhood has the lowest average career level of any neighborhood. Neighborhood 3, the Fast-Trackers, includes organizational reference groups characterized by younger white and Asian employees with lower tenure and higher education than are average in the population. This neighborhood is the least likely to include Black employees and has the highest average career level and education of any neighborhood. Neighborhood 4, the High-Level Managers, includes organizational reference

[10] Analyses of all study results with the 6-class model show no improved explanation over the 5-class model. These findings also suggest remaining with the 5-class model. Additional analyses are available from the first author.

groups characterized by older white employees, with higher tenure than is average in the population. This neighborhood appears less likely to include Asian employees than expected given their proportion in the population and has the second highest average career level of any neighborhood. Neighborhood 5, Fast-Track Women, includes organizational reference groups characterized by young Asian women, with lower tenure and higher education then are average in the population. This neighborhood is the least likely to include White employees.

Two interesting patterns in neighborhood composition emerged. One is that all five neighborhoods contain organizational reference groups characterized by above-average career levels relative to the population. It appears that, when asked to list the people they know, subjects identify others who on average hold jobs at 1.3 levels higher than their own. A second interesting pattern is that, relative to the population, no neighborhoods include organizational reference groups characterized primarily by Black or Hispanic members. Neighborhoods 1 and 5 are characterized by Asian members, and those in Neighborhoods 3 and 4 by White members. Neighborhood 2 includes organizational reference groups with a slightly higher than average proportion of Hispanic members but it also includes a slightly higher than average proportion of Whites.

Question 2. Do neighborhoods simply discern individuals with common attributes, or do they identify work environments distinct from the individuals whose organizational reference groups fall within them?

Numerous theories suggest that individuals tend to associate with similar others, thus it is possible that the neighborhood structure identified here merely reflects individual differences. While some relationship between an individual's neighborhood and his or her individual attributes is expected, it is unknown to what extent individual attributes predict the odds of

neighborhood membership or which attributes or combination of attributes would be the best predictors. Table 3 shows the results of a multinomial logit analysis with neighborhood as the dependent variable (Long & Freese, 2003). The results show that knowing individuals' demographic attributes significantly increases the odds of predicting neighborhood membership [LR $\chi^2(32)=469.10$, p=0.000)]. Two pseudo R^2 measures show that the model accounts for a moderate percentage of correct classifications. McFadden's adjusted R^2 suggests that the likelihood of the full model is 38% higher than the likelihood of the intercept only model after adjusting for the number of independent variables. The adjusted count R^2 suggests that the model makes 22% more correct classifications than would be predicted by a baseline model. A Wald test examining all possible combinations of the five neighborhood classes rejects the hypothesis that any can be combined without reducing model fit ($p<0.001$). This again supports the selection of the five-class model as a reasonable representation of the data.

Table 3 About Here

An omnibus likelihood ratio test suggests that an individual's gender, Asian ethnicity, age, tenure, education and career level significantly increase the odds of predicting his or her neighborhood membership (all $p<0.001$, except for age, which is $p<0.002$). Black and Hispanic do not make significant contributions (Black, $p=0.18$; Hispanic, $p=0.73$). The individual attribute that exerts the greatest increase in the log odds of subjects' membership in a specific neighborhood is career level, followed by Asian, tenure and gender (Career level, $\chi^2=57.02$; Asian, $\chi^2=46.82$; tenure, $\chi^2=44.82$; gender $\chi^2=38.08$; *df* for all models=4).

These results suggest that, as expected, an individual's attributes play a large role in his or her neighborhood membership. However, there is still unexplained variation, which could

result from random factors, systematic factors, such as occupational segregation, or a latent construct that represents the social meaning attached to multiple attribute categories as suggested by Vescio (1999). If neighborhoods carry social meaning, then neighborhood membership should be related to individual outcomes, independent of the individuals' own demographic attributes. The next question is, given that an individual's attributes are related to the neighborhood in which his or her organizational reference group falls, does neighborhood social structure provide any additional information about the individual's perception of the organization? In other words, if neighborhoods come to have shared meaning to members, then these meanings and their effects should be, to some extent, independent of the individuals' attributes themselves.

Question 3. Does an individual's neighborhood appear related to shared career-related perceptions and common social network attributes independent of individuals' own demographic attributes?

The results in Table 4 show a significant relationship between neighborhoods and individuals' career-related perceptions and social network attributes independent of their own demographic attributes. Knowledge of individuals' neighborhood membership adds 4% ($p<0.001$) to the explained variation in their career expectations and 6% ($p<0.001$) to the level of their career referents. It adds 5% ($p<0.001$) to the explained variation in individuals' centrality and 11% ($p<0.001$) to their number of redundant associations.

Table 4 About Here

DISCUSSION

The goal of this study was to explore the plausibility of neighborhoods: tacit social structures defined by demographic commonalities among the people individuals know. Neighborhoods describe the social arena between individuals and organizations in which individual perceptions become shared and acquire meaning. Diverse theories ranging from institutionalization to sense-making focus on the content of or mechanisms through which individuals' attitudes, beliefs and values acquire shared meaning and influence behavior. In contrast, neighborhoods focus on the people from whom individuals acquire the social information they use to "make sense." In small organizations, these people are evident because everyone is aware of everyone else. In large organizations or work environments dispersed across several organizations, each individual constructs an organizational reference group, an idiosyncratic group of people from whom he or she acquires social information (Lawrence, 2006).

We explored the possibility of neighborhood structure using secondary data from a large organization. The results of a latent class cluster analysis (LCCA) of individuals' organizational reference groups suggest that this organization contains five neighborhoods. Each neighborhood includes individuals whose organizational reference groups share similar attributes. For instance, Neighborhood 2, the Old-Timers, includes individuals who know a large number of older Caucasian and Hispanic men with higher organizational tenure and lower education relative to their numbers in the population. Neighborhoods are defined by multiple attributes, thus the demographic attributes of each neighborhood overlap with those of others. Boundary differences appear clear for some individual attributes and not for others. Thus, although organizational reference groups are placed in discrete classes, the boundaries of multi-attribute

neighborhoods are more ambiguous when examined one attribute at a time. This suggests that neighborhoods identify more than single-attribute homophily.

After identifying this neighborhood social structure, a multinomial logit analysis shows that the five neighborhoods are related to but independent of the demographic attributes of the individuals within them. The pseudo R^2 values, which provide some indication of correct classification, suggest that knowing an individual's attributes increases the odds of correctly classifying him or her between 22% and 45%. Thus, while individuals do tend to fall into neighborhoods whose attributes can be predicted from their own, there is still considerable remaining variation in the odds of being classified in a given neighborhood. This is consistent with the possibility that neighborhoods operate as latent indicators of a work environment defined by multiple attributes (Vescio et al., 1999).

The final question was whether neighborhood social structure appears related to differences in individuals' perceptions and social network position. An analysis of four individual-level outcomes shows that, independent of individuals' own attributes, neighborhood classification contributes between 4% and 11% (all $p < 0.001$) to the explained variation in individuals' career expectations, the level of their career referents, their centrality and the number of their redundant associations. These individual-level outcome results are significant but not large. However, they do suggest that neighborhoods define distinctive work environments that influence the social information individuals acquire in this large organization.

Limitations

This study presents data at three levels-of-analysis: individuals, organizational reference groups and neighborhoods. There are a number of limitations. First, this is a case study. Studying one organization produces the usual generalization difficulties, and these may be

exacerbated because this organization is one in which there is a high probability of observing a neighborhood social structure. It is an old organization in which employees have long tenure and high regional mobility. Despite the organization's size, employees know many others and have had ample time for shared perceptions to develop. As a result, the findings from this study may be an organization-specific phenomenon. Alternately, it is possible that these organizational characteristics are less likely to produce distinct neighborhoods. Employees know many others through their mobility and long tenure and this might tend to decrease differences in organizational reference group composition.

A second limitation is the organizational reference group measure. Although subjects' lists of known others include an unusually large number of names for an ego network study, these lists are unlikely to include everyone subjects' know. This raises questions about the implicit random or nonrandom criteria employees used when retrieving names from memory. Third, we induced neighborhoods from six individual-level demographic attributes, but it is unclear whether these are the most relevant or salient attributes driving social information in this organization. Fourth, although the available statistical data support a five-class structure, selecting the correct number of classes is a judgment call and it's unclear that additional qualitative data, such as interviews, would help resolve this question. In the same way that people are frequently unaware of the taken-for-granted unless presented with a violation (e.g., Garfinkel, 1967), it seems likely that they are also unaware of neighborhoods and this makes it difficult to develop direct measures.

Future Research

In an historical time with increasing mobility, new communication modes, geographic dispersion, contingent work and boundaryless careers, the people who constitute an individual's

work environment represent an important phenomenon. Prior research in many literatures suggests that the people in this environment matter. However, little is known about its underlying structure, perhaps because it has been difficult to theorize and acquire appropriate data for the multiple levels of analysis involved. Moreover, until recently, there was no statistical method available to analyze the data.

A neighborhood social structure suggests a number of issues relevant for understanding how shared perceptions and meaning evolve. One question involves which factors influence the people an individual observes. Most research on social cognition has been conducted in experimental laboratory settings and it seems unlikely that this translates directly to large, geographically-dispersed organizations. For instance, vividness is a criterion that predicts who individuals are likely to observe during the categorization process (Nisbett & Ross, 1980). Yet, it is unclear what makes a person vivid in a large, geographically-dispersed organization. Do emails, telephone calls or video-conferences make someone as vivid as face-to-face meetings? Do emails, IM'ing, bulletin boards and blogs eliminate age- and ethnicity-based categorization because they camouflage this information? Research suggests that geographic-dispersion influences intergroup relations (Polzer, Crisp, Jarvenpaa, & Kim, 2006); thus it would not be surprising if different communication modes were related to differences in the sets of people of whom an individual becomes aware.

A second question concerns the size of the social arena in which individuals construct symbolic and social boundaries (Lamont & Molnar, 2002). These boundaries are critical to shared perceptions and meaning because they provide the information that individuals use to enact their understanding of how-things-work-around-here. Yet, most social network studies in large organizations include small numbers of salient others each individual knows rather than

their broader picture of others. Lawrence (2006) suggests that individuals' distant associations provide important, cognitive boundaries for sense-making—perhaps even more important than their close associations. Moreover, research suggests that individuals can identify several hundred people when asked about the people they know (de Sola Pool & Kochen, 1978; Hill & Dunbar, 2003; McCarty, Killworth, Bernard, Johnsen, & Shelley, 2001). If more distant associations do define important boundaries, then we need to know at what point the number of people involved sufficiently captures the phenomenon.

A related implication is that neighborhoods may help explain how subcultures emerge in large organizations. The hypothesis is that because neighborhoods circumscribe the people from whom individuals acquire social information, they also provide boundaries for subculture development. As Trice and Morand (1991, p. 70) note: "Organizational subcultures may be defined as distinct clusters of understandings, behaviors and cultural forms that identify groups of people in the organization." In the same way that individual actions influence organizations and organizations as influence individual actions, it seems likely that subcultures identify groups of people and that groups of people identify subcultures. Faultline research (Lau & Murnighan, 1998), for example, suggests that high positive correlations among the demographic attributes of a group's members denote likely divisions that influence conflict, performance, coordination and decision quality (Li & Hambrick, 2005; Rico, Molleman, Sanchez-Manzanares, & Van der Vegt, 2007). Thus, neighborhood boundaries, with their multiple attribute correlations, may index individuals' categorizations of the organization in a way that generates subculture.

Conclusion

At the outset, we noted that more inductive approaches are necessary for studying social structures in modern, widely-dispersed work environments. The results suggest that inducing

neighborhoods is one possibility. Neighborhoods represent a plausible phenomenon describing the social arena in which individuals' perceptions become shared and acquire meaning. This approach and others like it may thus be a reasonable first step in exploring work environments where individuals' possible associations are both flexible and emergent. The answer to the question "which native?" is an important empirical concern for organizational research.

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APPENDIX A
Description of Latent Class Cluster Analysis (LCCA)

LCCA employs a maximum-likelihood-based, covariance approach to classification, creating linear independence among observed variables. This differs from traditional cluster-analysis in several ways. First, it facilitates clustering where a group of attributes, rather than an individual, is the level of analysis. Second, it is less sensitive to differences in variance and scale across multiple observed variables. Larger variances often cause an overweighting of variables when determining cluster membership (DiStefano & Kamphaus, 2006). LCCA overcomes this limitation by utilizing the covariance among observed variables, which allows a mixture of underlying distributions among them. Consequently, LCCA provides consistent results regardless of linear transformations performed on observed variables, while cluster analysis does not (Hagennars & McCutcheon, 2002).

Evaluating LCCA results requires attention to both quantitative and qualitative information (Muthen, 2003). Quantitatively, LCCA models are assessed using relative fit and quality of classification indices. LCCA does not lend itself to standardized fit indices because models with different numbers of classes are not nested as traditional structural equation models often are (Nyland, Asparouhov, & Muthen, 2007). Statisticians recommend two quantitative methods of model comparison: the Bayesian information criterion (BIC) and entropy. The BIC, in many cases, outperforms alternative metrics of model fit and methods of model comparison for returning the correct number of latent classes associated with a dataset (for a non-empirical discussion see Magidson & Vermunt, 2004; Nyland et al., 2007). Information criteria like the BIC integrate a model's chi-square value, the number of model parameters, and sample size, such that model fit and model parsimony both contribute to the BIC, and lower values indicate better model fit (for details see Schwartz, 1978).

Entropy is a standardized metric that captures the extent to which individuals who have a high probability of membership in their assigned class to show a low probability in all other classes. This is calculated by examining the aggregate posterior probability of individuals' belonging to all classes in a given model. As noted by Muthen and Muthen (2000, p. 887), "The average posterior probability for each class for individuals whose highest probability is for that class should be considerably higher than the average posterior probabilities for the other classes for those individuals." In brief, if individuals have high posterior probabilities of membership in multiple classes, it is difficult to assume that they truly belong to their assigned class. This, in turn, calls into question not only the latent class model, but also the legitimacy of assigning individuals to the class with which they have the highest probability of membership. Entropy values range from 0.0 to 1.0 and are computed by taking the probability of membership in the class with which an individual has the highest probability of membership, and weighting it as an inverse function of probability of membership in all other classes (Muthen & Muthen, 2000).

After examining BIC and entropy values, the model's adequacy is assessed using a theoretically-grounded understanding of the phenomenon (Muthen, 2003). For example, if a 3-class model produces classes that are very different along all observed variables, but with the same data a 4-class solution produces an additional class that only varies along a single variable in comparison to another of the classes in the 4-class model, then this would suggest that adding a 4th class to the model is not justified. Such qualitative assessments, in conjunction with the quantitative aspects of model evaluation described above, allow researchers to balance the richness of qualitatively evaluating model results, and the precision and relative certitude associated with quantitative model outcomes.

FIGURE 1
The Emergence of Neighborhood Social Structure: Three Levels of Analysis

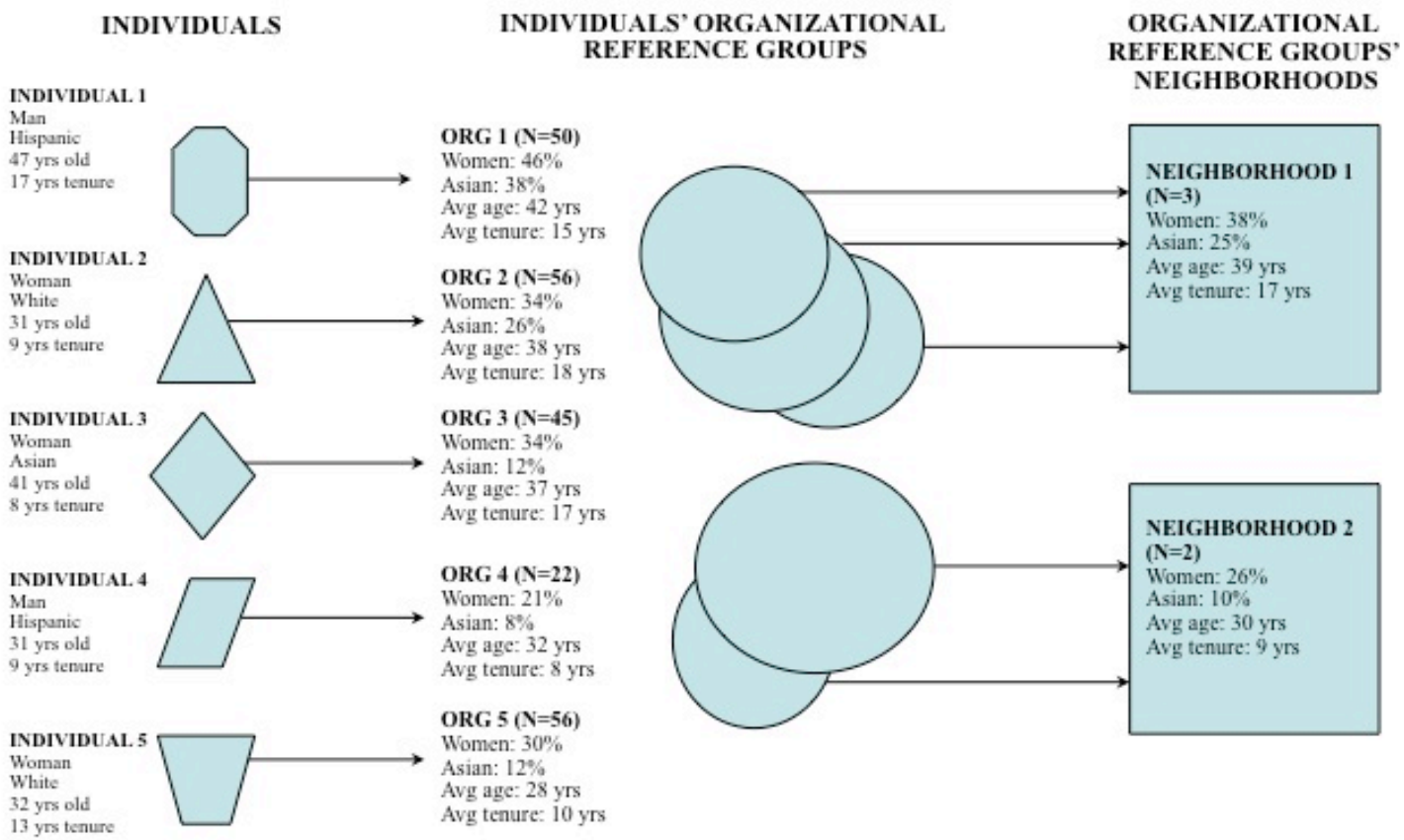

TABLE 1
Means, Standard Deviations and Correlation Matrix (N=358)

				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Individual Attributes		X	SD																	
1.	Gender	0.30	0.46																	
2.	White	0.62	0.49	-0.16																
3.	Black	0.09	0.29	0.05	-0.40															
4.	Hispanic	0.16	0.37	0.01	-0.56	-0.14														
5.	Asian	0.13	0.33	0.19	-0.49	-0.12	-0.17													
6.	Age	42.99	8.32	-0.12	0.16	0.07	-0.11	-0.18												
7.	Organizational Tenure	17.20	9.72	-0.19	0.19	0.06	-0.03	-0.30	0.81											
8.	Education	5.75	1.07	0.03	-0.07	-0.06	-0.11	0.28	-0.27	-0.42										
9.	Career Level	7.55	2.90	-0.21	0.13	0.00	-0.15	-0.04	0.15	0.09	0.34									
Neighborhoods																				
10.	(1) Newcomers	0.20	0.40	0.16	-0.15	0.08	0.01	0.00	-0.26	-0.27	0.10	0.02								
11.	(2) Old-Timers	0.38	0.49	-0.24	0.11	0.04	0.07	-0.26	0.21	0.35	-0.47	-0.33	-0.40							
12.	(3) Fast-Trackers	0.09	0.29	-0.11	0.02	-0.07	-0.04	0.08	-0.31	-0.37	0.40	0.22	-0.16	-0.25						
13.	(4) High-Level Managers	0.23	0.42	-0.09	0.10	-0.03	-0.04	-0.13	0.41	0.37	-0.01	0.27	-0.28	-0.43	-0.18					
14.	(5) Fast-Track Women	0.09	0.28	0.16	-0.29	-0.06	-0.08	0.57	-0.28	-0.38	0.25	-0.10	-0.16	-0.24	-0.10	-0.17				
Individual-Level Outcomes																				
15.	Career Expectations	12.95	2.52	-0.14	0.01	-0.04	-0.03	0.06	-0.20	-0.29	0.43	0.55	0.02	-0.41	0.34	0.17	0.04			
16.	Level of Career Referents	11.46	1.53	-0.23	0.19	-0.10	-0.15	-0.03	0.14	0.04	0.36	0.77	-0.03	-0.39	0.30	0.38	-0.16	0.67		
17.	Centrality	8.00	4.99	-0.11	0.07	0.12	-0.05	-0.14	0.18	0.25	0.04	0.39	-0.04	-0.11	-0.13	0.31	-0.09	0.21	0.31	
18.	Redundant Associations	21.35	4.83	0.06	-0.02	0.16	-0.04	-0.07	0.25	0.22	0.05	0.36	-0.07	-0.27	-0.09	0.47	-0.05	0.22	0.42	0.43

All values greater than 0.104 are significant at $p < 0.05$

TABLE 2
Description of Neighborhoods Based on Organizational Reference Group Attributes (N=358)

	Individual Attribute Means & Proportions in the Population	Neighborhood Means & Proportions (N=358)					Differences Across Neighborhoods	
		(1) Newcomers	(2) Old-Timers	(3) Fast-Trackers	(4) High-Level Managers	(5) Fast-Track Women	*F*	*p*
Gender	0.316	0.386	0.207	0.281	0.353	0.477	31.20	***
Ethnicity:								
White	0.617	0.588	0.689	0.693	0.666	0.351	46.39	***
Black	0.098	0.105	0.107	0.052	0.098	0.083	3.51	**
Hispanic	0.159	0.140	0.172	0.079	0.152	0.120	13.03	***
Asian	0.121	0.162	0.030	0.173	0.080	0.437	284.22	***
Age	43.59	42.29	46.20	38.97	46.53	38.33	337.82	***
Org Tenure	17.05	15.61	22.16	11.40	21.54	10.44	530.76	***
Education	2.71	2.95	2.21	3.27	2.83	3.11	321.18	***
Career Level	7.55	8.83	8.06	9.94	9.56	8.11	73.71	***
N	2685	73	136	34	84	31		

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

TABLE 3
Multinomial Logit of Neighborhoods on Individual Attributes (N=358)

Individual Attributes:	LR Test	Neighborhood											
		(1) Newcomers			(3) Fast-Trackers			(4) High-Level Managers			(5) Fast-Track Women		
Gender	***	1.50	***	b.c	0.06	ns	a, d	2.28	***	b, c	1.06	ns	
Black	ns	0.80	ns	d	0.27	ns		-0.78	ns	d	1.23	ns	
Hispanic	ns	-0.06	ns		1.05	ns		0.27	ns		0.22	ns	
Asian	***	2.77	**	b,c,d,e	4.60	***	a,b,d,e	1.06	ns	a,c,e	6.28	***	a,b,c,d
Age	***	-0.02	ns	c,d	-0.12	†	a,d	0.10	**	a,b,c,d	-0.03	ns	d
Org Tenure	***	-0.16	***	b,c,d,e	-0.32	***	a,b,d	-0.02	ns	a,c,e	-0.38	***	a,b,d
Education	***	0.67	***	b,c	1.53	***	a,b,d	0.64	**	b,c	1.04	**	b
Career Level	***	0.29	***	b,c	0.71	**	a,b,e	0.44	***	b,e	0.09	ns	c,d

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

LR $\chi^2(32) = 469.10$, =0.000, Pseudo R^2=0.45, McFadden's Adjusted R^2=0.38, Adjusted Count R^2=0.22.
Reference group for neighborhood class is (2) Old-Timers.

[a] = significant difference with Newcomers ($p< 0.05$)
[b] = significant difference with Old-Timers ($p< 0.05$)
[c] = significant difference with Fast-Trackers ($p< 0.05$)
[d] = significant difference with High-Level Managers ($p< 0.05$)
[e] = significant difference with Fast-Track Women ($p< 0.05$)

TABLE 4
Regression of Individuals' Career-Related Perceptions and Social Network Attributes on Neighborhoods

	Career-Related Perceptions				Social Network Attributes			
Step 1: Individual Attributes	Career Expectations		Level of Career Referents		Centrality		Redundancies	
Gender	-0.47		-0.23	*	0.15		-1.71	***
Black	0.29	*	-0.44	**	1.31	†	-2.54	***
Hispanic	0.50	†	-0.10		0.40		-1.05	†
Asian	-0.42		-0.11		-0.70		0.20	
Age	-0.02		0.01		-0.11	*	-0.04	
Org Tenure	-0.07	***	-0.00		0.20	***	-0.12	**
Education	0.35	**	0.25	***	0.23		-0.12	
Career Level	0.45	***	0.39	***	0.69	***	-0.59	***
F	36.14	***	71.14	***	14.39	***	13.44	***
R^2	.45		0.63		0.23		0.22	
Step 2: Neighborhood								
(1) Newcomers	-0.11		0.58	*	-1.11		1.39	
(2) Old-Timers	-0.21		0.18		-1.20		2.16	†
(3) Fast-Trackers	0.68		1.01	***	-3.80	**	1.86	†
(4) High-Level Managers	1.13	*	1.22	***	0.85		-2.27	†
F	25.69	***	55.69	***	9.16	***	13.85	***
R^2	.49		0.69		0.28		0.33	
ΔR^2	0.04	***	0.06	***	0.05	***	0.11	***

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

Unstandardized estimates, dummy variable for minority categories = 1, reference group for ethnicity = White, reference group for neighborhood class is (5) Fast-Track Women.