Changing Patterns or Patterns of Change: The Effects of a Change in Technology on Social Network Structure and Power

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The effects of a change in technology on organizational structure and power were investigated in a longitudinal study of the introduction and diffusion of a computerized information system. Employees increased their power and network centrality following the change in technology. In particular, early adopters of the new technology increased their power and centrality to a greater degree than later adopters. Results of cross-lagged correlation analyses suggest that centrality precedes power. While the diffusion process occurred via the network structure, it also imposed changes in the structure. Adoption patterns were found to be more closely related to network structure after the change than prior to the change.•

Does technology drive structure? Or does technology adapt to existing structure, reinforcing established, stable patterns? The relationship between technology and structure has been the topic of much writing and research (Woodward, 1965; Perrow, 1967; Thompson, 1967; Hickson, Pugh, and Pheysey, 1969; Mohr, 1971; Hage and Aiken, 1969; Barley, 1986). Although the accumulation of research studies has modified the concept of technological imperative, technology is still considered an important variable in relation to organizational structure (Rousseau, 1979). Yet, after decades of research relating organizational technology to organizational structure, "the evidence for technology's influence on structure, is at best, confusing and contradictory" (Barley, 1986: 78). The same may be said for the multitude of conceptions and methodologies employed in such studies (Rousseau, 1979). While technology may be generally defined as the transformation of organizational inputs into organizational outputs (Perrow, 1967; Rousseau, 1979), numerous definitions and operationalizations at varying levels of analysis and contexts demonstrate the diversity of technology research (Comstock and Scott, 1977; Rousseau, 1979; Fry, 1982).

Despite this diversity, little attention has been paid to the effects of technology over time. Cross-sectional research has typically focused on existing technologies and corresponding formal organizational structures. The majority of these cross-sectional studies treat technology as the independent variable, based on an assumption that organizational technology is inflexible and, correspondingly, that there is a need for structure to adapt to the requirements of technology. These assumptions are questionable. Technology can be a flexible organizational strategy that can be modified by an organization's structure, in particular, the informal structure. Structural arrangements act as the conduits of technological change and, as such, may influence organizational technology as well as be influenced by it. Investigation of the effects of a change in technology may illuminate the process by which structure affects technology, or vice versa.

Few studies relating technology to structure have considered the relationship between organizational structure and power. Structural position is an important source of power in that it provides access to people, information, and other resources. As Pfeffer (1981) noted, power is first and foremost a structural phenomenon. Likewise, power strengthens existing structural configurations. Those in power seek to maintain

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power by reinforcing the existing organizational structure (Pfeffer, 1981). Thus, a change in structure may necessitate a change in the distribution of power, and vice versa.

Although minor, incremental changes in power and structure may occur gradually over long periods of time, the likelihood of a major restructuring may only occur when the organization encounters an "exogenous shock" (Barley, 1986: 80) such as the implementation of a new technology. Such a shock might be conceptualized as a sudden, dramatic increase in uncertainty (Tushman and Anderson, 1986). Attempts to reduce uncertainty may foster changes in interaction patterns, with those able to cope with uncertainty adjusting their social location and increasing their power (Salancik and Pfeffer, 1977; Tushman and Romanelli, 1983). Thus, it is possible that a change in technology may produce changes in structure, power, or both.

However, as Pfeffer (1981) noted, stability, not change, is typical of the distribution of power and influence in most organizations. Those in power seek to perpetuate their power advantage. Such processes as commitment to previous decisions, institutionalization of beliefs and practices, and the ability of those in power to generate additional power contribute to stability (Pfeffer, 1981). Likewise, structural patterns of interaction become institutionalized over time and contribute to organizational stability. Thus, while a technological change may provide the opportunity for a redistribution of power and organizational structure, it does not guarantee it.

The current study is a longitudinal, cross-level investigation of a change in technology within an organization. The change involved the introduction and development of a computer system with distributed processing capabilities available to all employees. We adopted a social network perspective on structure and included power as a key variable. Although the technology change occurs at the organizational level, the effects of this change are evidenced at the individual level. Individuals adopt or reject the new technology and maintain or change their interaction patterns and influence relationships. Interaction and influence are relational; a change by individuals results in a change in the entire system. Social network measures reflect the cross-level nature of this research.

Our study explored possible changes in social network structure and individual influence brought about by the introduction and diffusion of new technology in an organization. The focus was on stability versus change. Does the diffusion of new technology follow established network patterns, with those in power reinforcing their positions? Or does the introduction of uncertainty result in changing patterns of interaction and influence?

To investigate the process of change, we used a contingency model whereby technology provides the occasion for structuring. Whether stability or change occurs is a function of the power and social network position of those who are first to adopt the new technology. When central, powerful employees are early adopters, existing patterns are reinforced and stability is maintained. Conversely, if less powerful, peripheral persons are first to adopt, changes in structure and the distribution of power will result.

TECHNOLOGICAL CHANGE: THE INTRODUCTION OF UNCERTAINTY

A change in an organization's technology entails adjusting the tools, devices, knowledge, or techniques that mediate between inputs and outputs and/or create new products or services (Rosenberg, 1972; Tushman and Anderson, 1986). In their industry-level study, Tushman and Anderson (1986) described technological change as an incremental, cumulative process, punctuated by major discontinuities that represent major breakthroughs in process or product. Technological changes can be classified as competence-enhancing or competence-destroying. Competence-enhancing adjustments, which build on existing know-how within the organization, tend to consolidate industry leadership: "the rich get richer" (Tushman and Anderson, 1986: 460). In contrast, the introduction of fundamentally different technologies or competence-destroying discontinuities is associated with major changes in the distribution of power and control (Chandler, 1977; Barley, 1986; Tushman and Anderson, 1986). Competence-destroying discontinuities disrupt industry structure (Mensch, 1979).

Regardless of the extent to which a technological discontinuity is competence-enhancing or competence-destroying, the change in technology increases uncertainty as attempts are made to master new tools, devices, or techniques (Tushman and Anderson, 1986). Uncertainty can be generally defined as an inability to predict future outcomes. More specifically, uncertainty has been defined as "the difference between the amount of information required to complete a task and the amount of information already possessed" (Galbraith, 1977). Both types of discontinuities create technological uncertainty as individuals struggle to understand new and incompletely specified processes or products. This introduction of uncertainty is the theoretical key to hypothesized change, or stability, in both structure and power.

Effects of Uncertainty on Structure

In their review of the literature, James and Jones (1976: 76) defined structure "as the enduring characteristics of an organization reflected by the distribution of units and positions within an organization and their systematic relationships to each other." In this paper we have adopted a social network perspective on organizational structure consistent with this definition: structure is viewed as patterned, repeated interaction among social actors (Weick, 1969; Mintzberg, 1979). Although this approach differs from the traditional views of structure, social network researchers have provided examples of the successful application of this approach to organizations (Weiss and Jacobson, 1955; Rogers and Rogers, 1976; Tichy and Fombrun, 1979; Tushman, 1979; Roberts and O'Reilly, 1979; Tichy, 1981; Brass, 1981, 1984, 1985; Krackhardt and Porter, 1985, 1986).

As technological uncertainty is introduced, changes in interaction patterns may occur. As Galbraith (1977) proposed and research findings substantiate, increased complexity and uncertainty result in increased communication (Van de Ven, Delbecq, and Koenig, 1976; Katz and Tushman, 1979). Individuals are uncomfortable with uncertainty and will work to structure, organize, and interpret the world they experience (Katz, 1980). This structuring and organizing will take the form of increased communication within the organization to interpret the change in organizational technology and reduce uncertainty. The result may be a change in organizational structure.

Although changes in communication patterns may occur, many of the early sociotechnical studies have pointed to the stability of established social ties (Rice, 1958; Susman, 1976). Taylor and Utterback (1975) found that although intensity of communication increased, communication roles (such as gatekeeper) remained intact despite changes in project assignments and groupings in a research and development laboratory. More recently, Robey (1981) reported on eight organizations that had introduced new technology in the form of computer systems. Using post-hoc interviews and focusing on formal structure, he concluded that existing structure was reinforced by technological change. Other studies focusing on the decision-making structure have reported both centralizing (Whisler, 1970) and decentralizing tendencies (Bruns and Waterhouse, 1975; Blau et al., 1976).

Effects of Uncertainty on Power Distribution

The introduction of technological uncertainty may affect the distribution of power just as it may affect structure. "Those who get the upper hand in the game are those who control most of the crucial uncertainties" (Crozier and Friedberg, 1980: 8). Because a new technology introduces crucial uncertainties, it represents an opportunity for employees to gain influence. Those who are able to reduce uncertainty for themselves and others can increase their power (Hickson et al., 1971; Pfeffer, 1981; Tushman and Romanelli, 1983). The result may be a redistribution of power within the organization.

However, as previously noted, the distribution of power within an organization is relatively stable (Pfeffer, 1981). Those in power are unlikely to relinquish their power. As in the case of competence-enhancing discontinuities, powerful individuals as well as industry-leading organizations may increase their dominance (Tushman and Anderson, 1986). Influential individuals may build on their existing power bases to become more powerful.

Early adopters. In investigating a change in technology, we used a model that differentiates two types of technology adopters, those who are first to adopt the new technology and those who adopt later (Mohr, 1987). Early adopters are those who become early, frequent, and effective users of the new technology. They are the first in the organization to cope with the uncertainty created by the change. They are likely to be identified as experts and be sought out by others within the organization. Thus, early adopters who have the ability to reduce technological uncertainty for others within the organization have what is tantamount to a recipe for increased network centrality and power. As an example, when a new computer system is introduced, technological uncertainty may become high for those individuals within the organization who had previously relied on the manual manipulation of information to meet workflow requirements. These individuals may seek out and come to depend on those capable of reducing this technological uncertainty. The latter may become more central in the network of interactions. Thus, we hypothesize:

Hypothesis 1: Early adopters will increase their network centrality following a change in technology.

Early adopters may also increase their power by being able to reduce technological uncertainty for others. This, however, is contingent on the extent to which there are few other substitutes for their ability to reduce uncertainty (Hickson et al., 1971). As technology is first introduced, their ability to reduce others' uncertainty is expected to be highly nonsubstitutable, since only a few individuals (the early adopters) will be adept at working with the new system. Thus, we hypothesize:

Hypothesis 2: Early adopters will increase their power following a technological change.

While early adoption of a technology provides the opportunity for some individuals to increase their centrality and power, there is also a risk that the new technology will not be successful. Tushman and Anderson (1986) noted several examples at the industry level of innovative technologies that did not become the dominant design in the industry. As they noted, technological discontinuities and dominant designs are only known as such in retrospect, since competence-destroying discontinuities create a period of technological competition until a dominant design emerges. For individuals within an organization, some of the risk and uncertainty of early adoption is absorbed by the organization, because the organization adopts and approves the new technology. When an organization is a late adopter (adopts an already established technology), there is little risk for the individual adopter, although the firm may lose its competitive advantage within the industry if it waits too long to adopt a technology.

Even within early adopting firms the risk of early adoption for individuals may be less than for the organization. At the intraorganizational level of analysis, the dominant technology has been established once the decision to change technologies has been made. There may be a great deal of uncertainty and competition among the decision makers in the organization, but, once the decision is made, the design is established and change is mandated.

Thus, we predict early-adopting individuals will increase their centrality and power within the organization regardless of the success of the technology industrywide. When the organization's decision is correct, in that it adopts the industry's eventual dominant design, individual early adopters will maintain and even strengthen their power and position. When the organization's decision to change technology is wrong (an alternative dominant design emerges in the industry), individual increases in power and centrality may be temporary and last only until the organization makes the decision to abandon and replace the unsuccessful technology (or, in the extreme case, the firm fails). At this point, a new technology will be mandated, and the process of technological change begins again. Uncertainty is again created by the change, and the early adopters of the new technology increase their power and centrality.

Stability versus Change

Just as the previous studies of technology and structure have found mixed effects, we have thus far suggested the possibility of both stability and change in organizational structure and the distribution of power. In Barley's (1986) longitudinal study, he found different effects from the same technology. Similarly, Tushman and Anderson (1986) found different effects in industry stability depending on the type of discontinuity introduced. Likewise, we have adopted the notion that a change in technology provides the occasion for structuring. We predict that stability or change is contingent on the social network position and power of early adopters.

Whether or not changes in structure will occur is contingent on the previous centrality of those who are able to reduce uncertainty for others. If centrality provides access to information allowing for uncertainty reduction, these central people become the early adopters and it is unlikely that a change in structure will occur. This proposition is consistent with Tushman and Anderson's (1986) finding that little change occurred in industry structure when the technological discontinuity was competence-enhancing. Additional support is found in the adoption of innovation literature. When the innovation was normative (consistent with the social system's norms), early adopters were central and well integrated in the system, often referred to as opinion leaders (Rogers, 1971). However, early adoption is not related to centrality when the innovation runs counter to system norms (Rogers, 1971).

If uncertainty is absorbed by individuals who were previously less central, their gain in centrality may adjust the overall structure of the organization. Interaction patterns will change as those who were previously peripheral are sought out by others. Thus, we generate the following contingency hypotheses:

Hypothesis 3a: If early adopters are more central than late adopters prior to a technological change, the existing structure will be reinforced.

Hypothesis 3b: If early adopters are less central than late adopters prior to a technological change, a structural change will occur.

Similarly, those who become early adopters may increase their level of influence relative to late adopters, thereby redistributing power throughout the organization. Or those currently in power may remain in power by adopting early, thus reinforcing the existing power distribution. These two possible scenarios, political stability versus the redistribution of power, are thus contingent on the previous power of early adopters. The following contingency hypotheses are thus generated:

Hypothesis 4a: If early adopters are more powerful than late adopters prior to a technological change, a redistribution of power is unlikely.

Hypothesis 4b: If early adopters are less powerful than late adopters prior to a technological change, a redistribution of power will occur.

A redistribution of power is most likely to occur when the less powerful become the early adopters and the more powerful are late adopters. This is more likely to happen if early adoption is not related to centrality or power. Tushman and Romanelli (1983) found that the greater the task uncertainty, the greater the influence of boundary-spanning individuals relative to those internally central to the organization. At the industry level, Tushman and Anderson (1986) found that industry dominance changed when technological discontinuities were competence-destroying. Within an organization, the most likely scenario would include some early adopters among both those in central, powerful positions and those less central and powerful. Thus, it is likely that a change in technology would not result in a total upheaval but, rather, in a moderate redistribution of power.

A total redistribution of power becomes even less likely when the connection between power and network centrality is considered. As earlier noted, those persons occupying central positions in the organization's network are likely to be perceived as powerful (Tushman and Romanelli, 1983; Brass, 1984). Because this study is longitudinal, we can explore whether power leads to centrality, or vice versa. Are powerful individuals sought out by others, thus increasing their centrality in the network? Or does being in a central position give one access to people and information such that one becomes powerful?

Regardless of whether these central positions are the source of power or the result of power, they will be instrumental in the diffusion of technology. They represent the key nodes through which information flows and is dispersed throughout the organization. Therefore, change becomes particularly difficult when persons in central positions are resistant. Thus, any change in the power distribution may necessitate a corresponding change in the informal structure. Over time, changes in the informal structure may necessitate changes in the formal organizational structure. While these changes are thought of as difficult ones, they are more likely to occur with the introduction of new uncertainties created by technological discontinuity.

Predicting Early Adoption

Identifying the attributes of early adopters of a change process may aid in predicting those who are able to reduce organizational uncertainties and thus in predicting possible changes in power and structure. Adoption of innovation studies have found that attitude and education level are related to early adoption; results concerning age have been mixed (Rogers, 1971). In our study, we predict that individual characteristics will be related to early adoption of the new computer system. In particular, we hypothesize:

Hypothesis 5: The following characteristics will be related to early adoption: (1) age, (2) education level, (3) previous computer training, (4) attitudes toward computers, and (5) feelings of efficacy regarding computer use.

Individual characteristics hypothesized to be related to early adoption may also be related to power and centrality. Roberts and O'Reilly (1979) found that individual characteristics were related to various roles in communication networks. This possibility suggests stability. Only if individual characteristics are related to early adoption and not positively related to power and centrality would we expect changes in power and structure.

Rogers (1971) noted that when organizational change is first introduced, the relevance of individual characteristics is heightened. As the diffusion process continues, individual attributes are overshadowed by structural characteristics. The spread of ideas and practices becomes contingent on the way in which social structure brings people together (Burt, 1987a).

The Diffusion Process

Researchers in sociology and related disciplines have made extensive use of network analysis in investigating the diffusion of innovations (see Rogers, 1962, 1971; Burt, 1982). These studies trace the communication of new ideas and adoption of innovations over time through channels of communication in a social system. Although the types of innovations and the social systems studied have varied tremendously, some consistent results concerning communication channels have been found. Awareness of innovations is often accomplished via mass media input from outside the social system; the evaluation and decision to adopt an innovation is primarily the result of interpersonal communication within the system (Rogers, 1971). Although initial adopters tend to be more cosmopolitan, the diffusion of innovations to later adopters tends to follow social network patterns of interaction (Rogers, 1971).

Late adopters are expected to adopt as a result of a socialization process referred to as contagion. In particular, an individual is likely to adopt an innovation based on contact, communication, or competition with an individual who has already adopted (Rogers, 1971; Burt, 1987a). This likelihood is based on an analysis of the social structural circumstances of the individual who has not yet adopted. The contagion model focuses on the spread of innovation attributable to communication between the individual who has not adopted, or ego, with an individual who has already adopted, the alter. The model also accounts for the adoption of innovation to the extent that ego and alter are in a similar position in the social structure, i.e., the extent to which they occupy the same roles and talk to the same other people within a social unit. Thus, it is hypothesized:

Hypothesis 6: The diffusion of a technological change will occur through structural patterns of interaction.

Thus, whether or not people adopt a new innovation is a function of the social context in which they act and speak (Burt, 1987a). It is also likely, however, that the social context may be changed by the introduction of the innovation itself. Diffusion may occur through existing structural patterns, or changes in these patterns may occur as a result of a technological change. As suggested previously, individuals may adjust whom they communicate with in order to reduce technological uncertainty. Thus,

Hypothesis 7: If existing patterns change, adoption of a new technology via contagion will be more closely related to network structure after the change than prior to the change.

The Change

Our study involved a four-part longitudinal analysis tracking the introduction and diffusion of a computer system in a federal agency responsible for the analysis and dissemination of a national data base of nutrient data. The computer system offered distributed processing capabilities, including file editing, data-base management, statistical analysis, spreadsheet analysis, and word processing to all employees. Prior to the introduction of distributive processing capabilities, an external computing facility was accessed for computer analysis of research data for all employees. The prohibitive cost of this service was the primary motivator for the purchase of the computer system. The head of the agency's survey statistics branch proposed the implementation of the computer system to the agency's director as a feasible undertaking that would provide substantial cost savings to the agency.

While the system was still in the planning stages, employees were queried as to their computer needs. However, lack of computer experience left the majority of employees uncertain as to what their needs were. Although training was originally scheduled to occur shortly after system implementation, problems with scheduling and the decision to use trainers from outside the agency delayed it considerably. Employee interviews conducted throughout the study suggested that the delayed training increased the employees' uncertainty and aggravation.

Most employees had not had direct work experience with computer applications prior to the introduction of this system. The computer functions substantially changed their method of analyzing nutrition data and preparing documents for publication. For example, rather than submitting a request for data analysis, nutrition analysts began to program and run their own statistical analyses. Thus, by almost any of the varied definitions of technology, the introduction of computer capabilities can be regarded as a major change in the organization's technology.

METHOD

Data Collection

All questionnaire data were collected on site at four points in time. The first questionnaire administration (T1) was approximately three months prior to the introduction of the computer system; the second (T2) occurred three months after the system configuration was in place and approximately six months following T1. The third questionnaire administration (T3) was three months following the second and immediately preceding a formal three-day training period. The last data collection (T4) was three months after training, approximately one year after system implementation and 15 months following T1. Interviews with various informants were conducted by the researchers before, during, and following the questionnaire administrations. Participation was voluntary and respondents were assured that their individual responses were confidential and would be used for research purposes only.

Ninety-four full-time employees were employed by the agency at T1. Of these, thirteen left the agency during the time of the study, resulting in a sample size of 81 over the four time periods for measures of power and centrality. Because centrality and power scores were obtained from sources independent of the focal person, it was possible to receive 81 scores for these variables at all four questionnaire administrations. Thus, for analyses of changes in power and centrality over time, our sample was 81. Forty-nine of these 81 employees completed questionnaires at all four times.

The total number of persons completing questionnaires at each of the four time periods was 75, 84, 74, and 66, respectively. Thus, for analysis of correlates of early adoption, involving only T1 data, the sample included the 75 employees who completed questionnaires at T1.

Measures

Network analysis. Respondents were provided with a list of all agency employees and were asked to circle the names of people with whom they communicated as part of their job during a typical week. Prior to each questionnaire administration the roster of names was updated. Names of employees who quit were dropped and names of new employees were added. This data was entered as a binary matrix and analyzed to determine the following network measures. Two operationalizations of network centrality were calculated, closeness and in-degree.

Closeness. The closeness measure of centrality accounts for both direct and indirect links and conceptually represents ease of access to others. For example, in addition to employees who are directly connected to the focal person, there are typically many other employees who are indirectly connected to him or her. These others are indirectly connected to the focal person by being directly connected to a person with whom the focal person is directly connected. For example, focal person A talks with B, B talks with C, but A does not talk with C. A has a one-link, direct connection to B and a two-link, indirect connection to C. For this closeness measure of centrality, we ignored the direction of the links and treated them all as reciprocated (Knoke and Burt, 1983).

The closeness measure of centrality was calculated for each of the 81 individuals in the sample by adding the minimum number of links between the focal individual and all others within the organization (Freeman, 1979; Knoke and Burt, 1983). This sum was then divided by $n - 1$, where n equals the number of persons in the organization. The closeness centrality means were transformed by the formula $1 - [(d - 1)/d\text{max}]$ (Lincoln and Miller, 1979; Brass, 1984), where d equals the path distance and $d$max equals the largest observed value of d. This transformation normalizes closeness scores to a range of zero to one and results in higher scores, reflecting higher closeness centrality. This transformation does not change the magnitude of the relationships of other variables with closeness, but it reverses the sign of the relationships.

In-degree. A second measure of centrality focuses simply on the number of employees with whom an individual is directly connected, referred to as degree (Freeman, 1979). Degree centrality typically includes direct connections in which the focal person is either the source or object of the connection. In-degree takes into account the direction of the link, including only those links in which the focal person is the object of the connection. In-degree centrality was operationalized as the number of times an individual was chosen by coworkers on the communication roster, divided by the number of persons completing a particular questionnaire.

An example will illustrate the practical difference between the two centrality measures. A focal employee can increase his or her closeness centrality by seeking out a highly central other. The other's direct links become the focal person's indirect links, thereby substantially increasing the focal person's closeness centrality. If we ignore the direction of the link, the other's closeness centrality is also increased. However, by considering the direction of the link, only the other's in-degree centrality is increased—the other is chosen by the focal person.

If diffusion follows established communication patterns, neither closeness nor in-degree centrality measures should change. If communication patterns change, both early and late adopters may increase their closeness centrality, but only early adopters are expected to increase their in-degree centrality.

Power. Individual power was assessed by asking each respondent in contact with the focal individual to rate that individual on a 5-point Likert-type scale (1 = very little influence, 5 = very much influence). The individual ratings obtained for each focal person were averaged to obtain an overall power score for that person. Thus, all 81 persons in the sample received power scores for all four time periods. The average number of ratings per focal person was 18.19.

Individual characteristics. Five individual characteristics were measured on the questionnaire. Respondents were asked to indicate their age in years, their education level (1 = high school, 2 = some college, 3 = bachelor's degree, 4 = master's degree, 5 = Ph.D.), and hours of previous computer training. To measure computer attitude, respondents were asked to consider eight pairs of adjectives, each pair anchoring the ends of a 7-point Likert-type scale (Shaft, 1986). For example, polar adjectives such as helpful/harmful; easy to use/difficult to use; threatening/nonthreatening; boring/intriguing; and enjoyable to use/frustrating to use were included. The average score on the eight items was used as a measure of computer attitude (alpha = .84).

The final individual attribute measured on the questionnaire was computer efficacy. Respondents were asked the extent to which they agreed or disagreed on a 7-point Likert-type scale (1 = disagree strongly, 7 = agree strongly) with three statements about their feeling of efficacy regarding computers. One example was "I have the capability to effectively use computers in my job." Scores on the three items were averaged to form an index of computer efficacy (alpha = .92).

These five individual characteristics (age, education level, computer training, computer attitude, and computer efficacy) were chosen because of their hypothesized relationship to adopting the new technology. With the exception of age, we hypothesized that all would be positively related to computer adoption.

Early adoption. Early adopters were identified through analysis of data collected after system implementation (T2 questionnaire administration) but prior to the formal training provided by the agency. It was during this time that early adopters were expected to be highly differentiated from coworkers. Individuals were categorized as early or late adopters depending on their response to three different questionnaire items at T2. We asked respondents to indicate the date on which they started using the new computer system. Date was coded in terms of months following T1 ($\bar{X}$ = 10.5, S.D. = 8.2). We asked them to indicate how many hours per week they were currently using the new computer system (T2 $\bar{X}$ = 8.0, S.D. = 9.7), and we asked them to respond to the following item: "I am effectively using the new computer system" (1 = strongly disagree, 7 = strongly agree; T2 $\bar{X}$ = 3.58, S.D. = 1.89).

To be categorized as an early adopter, an employee must have been using the computer at least 10 hours per week at the T2 survey distribution, list his or her date of adoption as prior to T2, and agree that his or her computer use was effective by indicating a 5, 6, or 7 on the computer effectiveness item. Interviews conducted by the researchers following the T2 administration were used to confirm many of the early adopters. Others were checked against the agency's roster of assigned computer IDs for confirmation. Seventeen employees who met all the above criteria were identified as early adopters. All other employees were considered late adopters.

RESULTS

Correlates of Early Adoption

To test hypotheses regarding characteristics related to early adoption and as our first test of the stability versus change hypotheses, we correlated individual attributes and centrality and power prior to the change (T1) with early adoption. To the extent that power and centrality are predictive of early adoption, patterns of organizational structure and power are expected to remain the same. If individual attitudes are predictive of early adoption and not positively related to power and centrality, changes in organizational patterns are expected. Table 1 presents the intercorrelations of power, centrality, individual characteristics, and early adoption. Because hours of training was highly skewed, correlations were calculated with the logarithm of the values. With the exception of age and education, the individual attributes were positively and significantly related to early adoption, consistent with hypothesis 5.

As expected, power and centrality were highly correlated at T1; however, neither was positively related to early adoption. In fact, both measures of centrality at T1 were negatively associated with early adoption. Results of hierarchical regression analyses were consistent with the zero-order correlations. Individual attributes, when entered following centrality and power, added significantly to the variance explained in early adoption. When individual attributes were en-

Table 1

Correlates of Early Adoption (*N* = 75)

Variable	Mean	S.D.	1	2	3	4	5	6	7	8
1. T1 Power	2.67	.67								
T1 Centrality										
2. Closeness	.71	.08	.62••							
3. In-degree	.27	.11	.55••	.72••						
Individual characteristics										
4. Age	41.80	11.07	.24•	.21•	.17					
5. Education	3.38	1.16	.43••	.10	.19	.08				
6. Hours of training*	34.58	54.05	−.17	−.01	−.02	−.17	.11			
7. Computer efficacy	5.21	1.54	−.13	.08	−.02	−.23•	.11	.24•		
8. Computer attitude	5.32	.85	.07	.23•	.05	−.13	.13	.23•	.53••	
Early adoption			−.01	−.13	−.11	−.13	.19	.21•	.27••	.26••

• $p < .05$; •• $p < .01$.
* Logarithm of hours of training used to calculate correlations.

tered first, centrality and power did not add significantly to the regression equation.

Table 2 presents the results of multivariate analysis of variance assessing changes in power over time for early versus late adopters. The results show a significant interaction effect between early adoption and time. The means across time indicate that early adopters gained more in power over time than late adopters, lending support for hypotheses 2 and 4b. Furthermore, there was a significant main effect for time. In general, power increased following the technological change.

Table 2

MANOVA: Results for Power over Time of Early vs. Late Adopters

Effect	d.f.	*F*	*p*<
Early vs. late	1, 79	1.33	.252
Time	3, 77	18.33	.000
Early vs. late × time	3, 77	4.14	.009

	Means			
	T1	T2	T3	T4
Entire sample	2.63	2.79	2.81	2.90
Early adopters	2.65	3.05	2.96	3.13
Late adopters	2.62	2.74	2.77	2.85

MANOVA analysis of both operationalizations of centrality, closeness and in-degree (Table 3), showed similar results. An interaction effect was significant at the .05 level for the in-degree measure of centrality but not for the closeness measure. A main effect for time was evidenced for both closeness and in-degree. These results indicate that communication patterns changed, with all employees increasing their closeness centrality. Employees increased their interaction with early adopters more than with late adopters, as indicated by the significant interaction effect of early adop-

Table 3

MANOVA: Results for Network Centrality over Time of Early vs. Late Adopters

		Closeness		
Effect		**d.f.**	***F***	***p*<**
Early vs. late		1, 79	.03	.855
Time		3, 77	9.22	.000
Early vs. late × time		3, 77	1.71	.172
			Means	
	T1	**T2**	**T3**	**T4**
Entire sample	.692	.721	.715	.702
Early adopters	.671	.721	.712	.715
Late adopters	.696	.721	.715	.700
		In-degree		
Effect		**d.f.**	***F***	***p*≤**
Early vs. late		1, 79	.01	.911
Time		3, 77	3.90	.012
Early vs. late × time		3, 77	2.79	.046
			Means	
	T1	**T2**	**T3**	**T4**
Entire sample	.263	.239	.246	.256
Early adopters	.239	.236	.266	.274
Late adopters	.268	.240	.242	.253

tion by time for the dependent variable in-degree. This finding lends support for hypotheses 1 and 3b.

An overall measure of network density (MacEvoy and Freeman, 1986) was used to assess the degree to which all actors were interconnected. Density measures the extent to which actors in a system are connected, on average, to one another (Burt, 1982). The network densities for each time period were as follows: T1 = .262; T2 = .116; T3 = .286; and T4 = .287. These findings lend additional support to predictions of structural change.

Network Structure and Power

As expected, centrality was significantly related to power at all four time periods (closeness: T1, $r = .62$; T2, $r = .43$; T3, $r = .32$; and T4, $r = .33$; in-degree: T1, $r = .55$; T2, $r = .51$; T3, $r = .39$; T4, $r = .41$). In order to investigate a temporal ordering of increases in centrality and power, cross-lagged correlation analysis (Campbell and Stanley, 1963) was performed. If power precedes centrality, the correlation between T1 power and T2 centrality should be greater than the correlation between T1 centrality and T2 power. If centrality leads to power, the reverse should be true, i.e., T1 centrality with T2 power greater than T1 power with T2 centrality.

Table 4 presents the results of this analysis for both measures of centrality, closeness and in-degree, for all four time periods. To test for statistically significant differences between the cross-lagged correlations, we used a test that allows the correlations to be correlated (Kenny, 1979).[1] Although few of the differences are significant, the overall

1

$$1k = (r_{12} - r_{24}r_{14})(r_{34} - r_{24}r_{23}) + (r_{13} - r_{12}r_{23})(r_{24} - r_{12}r_{14}) + (r_{12} - r_{13}r_{23})(r_{34} - r_{13}r_{14}) + (r_{13} - r_{14}r_{34})(r_{24} - r_{34}r_{23}),$$

where 1, 2, 3, and 4 are variables and N is sample size. The following then has an approximately standard normal distribution:

$$Z = \frac{(N)^{1/2}(r_{14} - r_{23})}{[(1 - r^2_{14})^2 + (1 - r^2_{23})^2 - k]^{1/2}}$$

Table 4

Cross-lagged Correlation Analyses of Power and Network Centrality Measures

	Power and Closeness		
	P1C2 P2C1	P1C3 P3C1	P1C4 P4C1
Early	.42 > .30	.19 < .20	.19 < .40
Late	.57 > .50	.41 < .51	.37 < .47
Entire sample	.55 > .44	.39 < .44	.35 < .43
	P2C3 P3C2	P2C4 P4C2	
Early	.26 < .54	.08 < .53	
Late	.30 < .50•	.25 < .43	
Entire sample	.29 < .49••	.24 < .43•	
	P3C4 P4C3		
Early	.01 < .41		
Late	.34 > .30		
Entire sample	.31 > .30		
	Power and In-degree		
	P1N2 P2N1	P1N3 P3N1	P1N4 P4N1
Early	.42 < .59	.38 < .61	.23 < .69
Late	.61 > .44•	.41 < .45	.46 > .45
Entire sample	.58 > .43•	.41 < .45	.43 < .45
	P2N3 P3N2	P2N4 P4N2	
Early	.57 < .65	.47 < .57	
Late	.32 < .54••	.37 < .50	
Entire sample	.36 < .55••	.39 < .50	
	P3N4 P4N3		
Early	.49 < .66		
Late	.43 > .31		
Entire sample	.44 > .36		

•$p < .05$; ••$p < .01$.

trends are clear. Correlations with closeness preceding power were stronger than correlations with power preceding closeness. There are, however, two anomalies to this trend, P1C2 versus P2C1 and P3C4 versus P4C3. The same trends exist when using in-degree measures of centrality. However, subgroup analysis of early adopters shows no anomalies for in-degree and power cross-correlations and only one anomaly for cross-lagged analysis with closeness scores. That is, for early adoption, centrality precedes power in almost all comparisons.

Diffusion Processes

For analysis of the diffusion process (hypothesis 6), we adopted a structural equivalence model (Burt, 1982). Diffusion by structural equivalence reflects the extent to which individuals adopt a technology based on the adoption of those with whom they have similar patterns of interaction. This model does not require that two individuals communicate with each other directly, only that they have similar positions in the social structure. Similar or structurally equivalent positions are defined by the extent to which individuals talk to the same other individuals in the social system. A special form of structural equivalence in which individuals directly interact with each other is referred to as cohesion (Burt, 1982).

Although the structural equivalence model of contagion includes the possibility of direct interaction, theoretical and methodological differences exist between this model and one based solely on cohesion. Burt (1982) provided a detailed review of the differences between the positional (structural equivalence) and relational (cohesion) approaches. Although there is some debate about the merits of the two approaches, the structural equivalence model includes a broader range of possible types of interaction and has been shown to be a useful method for analyzing contagion (Burt, 1987a).

Measures of structural equivalence were used to weight the date of adoption of individuals within the network to determine contagion effects through these social processes. The normative or predicted responses were correlated with the observed or actual dates of adoption to determine the extent to which adoption timing is a function of structural equivalence. A high correlation indicates that the diffusion of the innovation follows the interaction patterns as depicted by structural equivalence. The observed dates of adoption are the same for T1 and T4 analyses. Patterns of interaction, however, may be different. A different correlation between observed and normative responses for T1 and T4 would indicate that patterns of interaction changed. Whether the T1 or T4 autocorrelation is higher reflects the extent to which the diffusion process more closely followed pre-existing (if the T1 autocorrelation is higher) or new (if the T4 autocorrelation is higher) interaction patterns. A detailed discussion of the analyses is contained in the Appendix.

Jackknife estimates of Fisher *Z*-transformed correlations were obtained to determine the contagion effect's significance (see Appendix). The jackknife estimate of the Fisher *Z*-transformed correlation for T1 was .278 with a standard deviation of .206. A *t*-test on the jackknife analysis was 1.352 (n.s.) for a correlation of .271. The jackknife estimate of the Fisher *Z*-transformed correlation for T4 was .524 with a standard deviation of .150, yielding a *t*-test of 3.491 ($p < .001$). These results support hypothesis 6: diffusion occurred through structural patterns of interaction. Furthermore, they indicate that contagion more closely followed the T4 interaction patterns than the T1 interaction patterns. This finding lends support to hypothesis 7: patterns of communication changed to enable the diffusion process to occur.

DISCUSSION AND CONCLUSIONS

Despite the forces supporting stability, considerable change in both structure and power occurred following a technological change within an organization. Being central and powerful prior to the introduction of a new technology was not related to early adoption. Rather, early adoption was a function of individual characteristics relevant to the change process. Thus, in accordance with theoretical predictions, the ingredients for structural change were in place.

Early adopters were able to reduce uncertainty for others, and this uncertainty reduction ability enabled them to gain power and centrality. Because they were not central, powerful players prior to the technological change, the possibility for structural and power redistribution on the organizational level was likely. Early adopters gained more in-degree centrality and power than later adopters. At T2, late adopters actually decreased their in-degree centrality to a great extent. This drop is reflected in an overall decrease in network density at T2. Thus, while structure is difficult to change, a technological change provided opportunity for restructuring and consequent changes in the organization's power configuration.

Results also lend support to the view that diffusion itself occurred as a result of the restructuring process. Individuals adjusted their patterns of interaction in order to learn from those who were already adept at using the new technology. Hence, contagion is a process that occurred not as a result of prior structural configurations but, rather, structural configurations changed to enact contagion.

Prior influence. Although results indicated changes in network centrality and power those employees who were powerful, central figures in the organization prior to the change (T1) were not totally displaced by early adopters. Although early adopters gained substantially more influence, those with prior power maintained much of their power. The zero-order correlation between T1 power and T4 power was .84. One possible explanation is that those in power at T1 derived their influence from sources that were not affected by the change. They may also have taken advantage of their organization centrality to be the first of the later adopters to contact and learn from the early adopters. That is, persons in central positions may have a better understanding of the network (Krackhardt, 1989) and be able to use it to their advantage to adapt to a change. Our interviews at T2 provided some evidence of the latter. As one early adopter said, "All of a sudden, the bigwigs are coming to me, asking my advice."

The further possibility exists that those in power prior to the change were responsible for making the decision to change the technology. These individuals may not have been the first to adopt but may have maintained their power by being responsible for and receiving credit for the decision. The decision to implement the computer system would not necessarily require the specific expertise needed to operate the system.

Greater total influence. Overall, the total amount of individual influence in the organization increased as individual centrality increased and the network became more interconnected. One possible explanation is that employees felt less dependent on external sources of data processing. The new computer system gave them more control over their work outcomes. This possibility was indicated during our interviews and might have been more evident had we obtained self-ratings of power. Another explanation for the increased influence was also suggested in interviews and is consistent with our use of external sources for rating individual influence. In establishing new communication links with early adopters, late adopters became aware of the expertise of the early adopters and rated the latter higher on influence. This explanation of contact preceding awareness of influence is consistent with the results of our cross-lagged correlation analysis suggesting that centrality preceded power.

Training. A formal training program conducted by representatives of the manufacturer of the new system was available to all employees directly following the T3 questionnaire administration. Although originally scheduled to occur sooner, the training was delayed, and in interviews prior to T3, employees indicated that the lack of training was their major complaint. We felt that this delay might have emphasized the nonsubstitutability of the early adopters. Although closeness centrality and power means showed little change between T2 and T3, in-degree centrality increased significantly for early adopters. Interviews indicated that some of the later adopters were simply waiting for training before attempting to learn the system.

Although we had expected that training might decrease the nonsubstitutability of the early adopters, it appears that training had the opposite effect. Mean changes between T3 and T4 suggest that early adopters again increased closeness centrality and power as they had between T1 and T2. Those who had been waiting for training were attempting to learn the system following T3. Interviews following training indicated that later adopters were seeking out early adopters for their expert help on the new system.

Limitations. One limitation of the current study involves the lack of an appropriate control group. Unfortunately, all the employees in the agency were subject to the change in technology. Thus, we could not identify and study a group of employees who did not experience the change.

We were also limited by the lack of additional, nonreputational measures of power. Although the study was based on perceptions of influence, we feel that the multiple-rater methodology provides credible reliability and validity. Power is a social phenomenon, dependent on the attributions of others. If behavior is consistent with attributions, then those perceived as powerful are powerful.

Generalization of findings. The particular type of technological change may limit the generalizability of these results to other changes in technology or to organizational change in general. For example, there is a long history of the effects of automation on the routinization of work and loss of control by employees (cf. Kipnis, 1984). While our results suggest that computer systems do not decrease employee influence, other types of technological innovations may produce different results. Taken in combination with previous studies, our results indicate the importance of accounting for the type of technology introduced.

It is also important to consider individual characteristics in relation to power and centrality. In the event that central organizational members possess characteristics associated with early adoption, a redistribution of power and centrality is unlikely to take place. In our study, only age and education level were significantly related to T1 power, and neither was significantly related to early adoption. However, it is not unreasonable to imagine a situation in which individual characteristics such as internal locus of control (Rotter, 1966) or general self-efficacy (Bandura, 1986) are related to power, centrality, and early adoption, with all contributing to stability in power and communication patterns.

This study also differs from many previous adoption-of-innovation studies (Rogers, 1971; Burt, 1987a; Fennell and Warnecke, 1988) in that adoption was not voluntary but mandatory. Although employees could choose not to use the system and continue relying on previous work methods, there were clear expectations that the new system be used. This may explain why we found very little evidence of organized resistance to the change. Our T2 interviews suggested the possibility that one department might resist. However, T3 and T4 data indicated its late but eventual adoption.

When adoption is voluntary rather than mandatory, it is likely that complete diffusion will not occur, as socialization is never completely successful (Berger and Luckmann, 1967). Resisters may try to influence coworkers against using the new technology, sharing their resistance with other workers in the network. If resistance is particularly strong, these "late" adopters may never adopt the change.

Implications for Theory and Research

One might be tempted to include the results of this study with those of previous studies that support technology's influence on structure. However, the importance of this research is not whether it adds, one way or the other, to the debate concerning the existence of a technological imperative. One more set of results will not conclusively decide the argument either way. Rather, its significance lies in the attempt to understand the process by which technology may affect structure, or vice versa. As a longitudinal study, it is best considered in relation to Barley's (1986) study. Although it employs considerably different theories and methodologies, the results are not inconsistent. Changes in technology provide the occasion for structuring.

The results of this study are also consistent with those found by Tushman and Anderson (1986) in their industry-level study of technological change. In retrospect, the installation of the computer system can best be classified as a competence-destroying process discontinuity. While the service remained essentially unchanged, the process by which it was rendered was fundamentally changed. The skills and knowledge base required to transform the inputs into outputs shifted dramatically. When combined with Tushman and Anderson's findings, our results suggest a multilevel perspective on technological change. Individuals who are the first to recognize and exploit technological opportunities (early adopters) increase their power and centrality within the organization, just as innovative organizations increase their competitive advantage within an industry.

Other similarities across levels and studies can be noted. For example, the process of change appears to be the same. Technological change produces uncertainty. Just as individuals attempt to cope with uncertainty, so do organizations. Although the present study did not measure uncertainty, our interviews with employees, coupled with Tushman and Anderson's (1986) measures of uncertainty, provide support for this underlying assumption. However, the types of uncertainty may not be the same across levels. At the interorganizational level of analysis, environmental uncertainty occurs as organizations and technologies compete for the dominant industry design. At the intraorganizational level, the design is mandated; the uncertainty for individuals involves learning the new technology.

Further research is needed to extrapolate the industry-level findings to the intraorganizational level, and vice versa. We attempted to predict early adopters at the individual level based on individual characteristics. Similarly, we might speculate that particular organizational characteristics such as age, culture, or strategy might predict early adopters within industries. For example, new organizations with "prospector" strategies and innovative cultures are likely to be the first to take advantage of competence-destroying discontinuities (Miles and Snow, 1986; Tushman and Anderson, 1986).

Network analysis can also be applied at the organizational level of analysis in order to study the structure of an industry. For example, Boje and Whetten (1981) found that centrality within a network of manpower agencies was associated with influence. Miles and Snow (1986) have suggested the concept of dynamic networks within industries. Within industries, certain organizations may take the early-adopter role. Miles and Snow suggest that "prospectors" may possess the distinctive research and development competence to generate technological innovations that push the industry forward. The study of an industry network may also provide information on the diffusion of innovation among organizations. The structural equivalence model of contagion is particularly suited for analysis of competing organizations (Burt, 1982), which need not be directly linked in order to be considered equivalent.

Following Tushman and Anderson's suggestions, future research might combine intra- and interorganizational levels of analysis. For example, do adoption and diffusion patterns among individuals in early-adoption organizations differ from those in later-adoption firms? In our study, the federal agency's adoption of the computer system could only be classified as a late adoption within the industry.

Late adoption by an organization may indicate that the technological change runs counter to prevailing organizational norms. Although we did not measure the agency's norms, we found that individual attitudes toward computer technology were positively associated with early adoption and were not related to T1 power. Our results were consistent with the extensive diffusion-of-innovation literature. When innovation was counter to system norms, persons not well integrated into the system tended to be early adopters (Rogers, 1971).

Although it would seem likely that industry-level competence-destroying technological discontinuities would violate intraorganizational norms, it is possible that organizational norms differentiate early- and late-adopting organizations. Tushman and Anderson (1986) suggested that if competences will be destroyed, an organization is unlikely to be an early adopter. Mitchell's (1989) findings indicate that the greater the competitive threat, the less likely an industry incumbent is to enter a new technical subfield but the earlier it will do so if it does plan to enter. However, a competence-destroying change may not be inconsistent with the organizational norms of an early-adopting organization. For example, Mitchell suggests that an organization may possess industry-specialized supporting assets. In such a situation, the technological change may result in a major shift in competitive advantage within the industry but no major shift in power and structure within the early-adopting organization. Conversely, a competence-enhancing industry discontinuity may result in major changes in power and structure within a late-adopting organization. In this case, the industry structure would not change, but the organizational structure of the late-adopting organization would change.

Thus, it is possible that organizational norms rather than technological discontinuities may be more predictive of intraorganizational change. Although speculative, we cannot rule out this possibility in that this study involved both a competence-destroying discontinuity and the late adoption by the agency. The possibility is also consistent with Barley's (1986) finding that the same technological change had different effects on different organizations.

We are suggesting that future studies adopt a multilevel strategy. Industry-level competence-enhancing technological discontinuities will be consistent with the norms of a majority of industry-leading organizations. The powerful organizations will be the first to adopt and thereby maintain and increase their industry position. Likewise, the central powerful individuals within these leading organizations will maintain and increase their intraorganizational positions.

The opposite will occur when the industry-level technological discontinuity is competence-destroying. This change will run counter to the norms of industry-leading organizations, resulting in shifts in competitive advantage within the industry and shifts in power and structure within the previously powerful but late-adopting organizations. At the same time, this competence-destroying discontinuity will be consistent with the norms of a small minority of new and/or innovative organizations within the industry. While individual power shifts within these early-adopting organizations will not occur, these organizations will acquire power within the industry.

We have attempted to provide a framework for examining the process of technological change. Although caution should be used in generalizing the specific results, we believe that the proposed change model is applicable to other types of technological change and to organizational change in general. We expect early adopters to increase or reinforce their influence and centrality by virtue of their ability to cope with the uncertainties created by the change. Whether these increases result in major changes in the existing structure and power distribution will depend on the match between early adoption and established power and communication channels.

Overall, this study highlights the importance of investigating an organization over time. The relationship between a technological change and structure and power may have been interpreted quite differently if one had investigated a cross-sectional picture of organizational processes. Instead, this research illuminated how technology is diffused and how this diffusion process affects structure and power. From a longitudinal perspective, two areas remain for further research. First, an investigation of the decision-making process prior to the change is needed. As Tushman and Anderson (1986) suggested, those who control the decision-making process may control their own and their organization's future power. Secondly, further research is needed on the process by which changes in technology, structure, and power become institutionalized. Will the changed distribution of power and structure continue to reinforce itself, or will the former (prior to change) relationships resurface to challenge the newly established patterns? Thus, while evidence of change is apparent, questions on the institutionalization of change are yet to be determined.

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APPENDIX: Contagion Analysis

Normative response data were generated using the following network autocorrelation model (Burt, 1987b):

$$x_j^* = w_{j1}x_1 + w_{j2}x_2 \ldots + w_{jn}x_n,$$

where x_j is the date of adoption for person j, and w_{ji} are network weights reflecting the extent to which some person i is structurally equivalent with j. The normative response is thus a predicted date of adoption based on the date of adoption of other workers whereby those individuals who are more structurally equivalent with the focal individual are assumed to be more influential in terms of adoption timing. Thus, the normative response of j is simply the weighted average of observed responses by people defining the social context of j's responses (Burt, 1987b). The network weight, w_{ji}, equals $(d\max_j, - d_{ij})/[\Sigma_i\,(d\max_j - d_{ij})]$, $i = j$, where d_{ij} is the distance between the pattern of i's relations and the pattern of j's relations and $d\max_j$ is the largest distance between person j and anyone in the system (Burt, 1987b).

For T1, the correlation between observed and normative responses was .126. The correlation between observed and normative responses was .313 for T4. However, these ordinary least squares estimates of contagion effect are not maximum likelihood (Burt, 1987b), thus they cannot be assessed with routine statistical tests (see Burt, 1987b; Dow, Burton, and White, 1982, for further explanation of the statistical problem). Therefore, to determine the contagion effect's significance, jackknife subsampling results were obtained by using Burt's (1987b) jackknife analysis in his network program, STRUCTURE.

Jackknife analysis entailed using the observed data distribution to construct a sampling distribution for the contagion effect in order to draw statistical conclusions about its magnitude (Burt, 1987b). The autocorrelation, r, of observed and normative data was recomputed N times from the data without each actor j. Each generation of the network autocorrelation varies from the overall estimate as a function of individual responses to contagion. The difference between the complete and subsample results is represented by the following difference between the estimates: $r^*_j = Nr - (N - 1)r_j$, which provides an estimate of the contagion effect in the deleted observation (Burt, 1987b). The mean of these values is the jackknife estimate, r^*, of the network autocorrelation model.

A t-test with N-1 degrees of freedom is carried out for the null hypothesis of no contagion effect, whereby $t^* = r^*/s^*$. The Fisher's Z transformation is also calculated, because such a transformation is more nearly normal than the raw correlations (Burt, 1987b).