Network Churn: The Effects of Self-Monitoring Personality on Brokerage Dynamics

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The apparent stability of social network structures may mask considerable change and adjustment in the ties that make up the structures. In this study, we theorize and test—using longitudinal data on friendship relations from a radiology department located in the Netherlands—the idea that the characteristics of this "network churn" and the resultant brokerage dynamics are traceable to individual differences in self-monitoring personality. High self-monitors were more likely than low self-monitors to attract new friends and to occupy new bridging positions over time. In comparison to low self-monitors, the new friends that high self-monitors attracted tended to be relative strangers, in the sense that they were unconnected with previous friends, came from different functions, and more efficiently increased the number of structural holes in the resultant network. Our study suggests that dispositional forces help shape the dynamic structuring of networks: individuals help (re)create the social network structures they inhabit.●

Organizations are, among other things, social arenas in which people form, change, and dissolve relationships with their colleagues. We know that the structure of these relationships considered at a given point in time matters. In particular, there is considerable evidence that individuals who occupy brokerage positions bridging the "structural holes" between disconnected others in the workplace receive higher performance evaluations and faster promotions (e.g., Burt, 1992, 2005, 2010). While it is no doubt useful to know that certain network structures can be advantageous, a theory that accounts for the appearance, transformation, and disappearance of network structures may provide us with a better understanding of the mechanisms responsible for observed network effects (Emirbayer and Goodwin, 1994) and a richer appreciation for how collective action is organized (Salancik, 1995).

Research has tended to treat social networks as relatively static (e.g., Moreno, 1953; cf. Nadel, 1957: 125–152). But there is growing recognition that networks are in fact dynamic systems (e.g., Weesie and Flap, 1990; Barabasi and Albert, 1999; see Doreian et al., 1996; Newman, Barabasi, and Watts, 2006). Certain global characteristics of a network (such as its overall connectivity) can appear to be stable, but this apparent stability may mask ongoing change and adjustment in the ties that constitute the network. A recent reanalysis of a classic study of friendship networks (Newcomb, 1961) found that whereas earlier studies had concluded that the network had quickly stabilized, there was in fact considerable evidence of change at the level of individual ties throughout the observation period (Moody, McFarland, and Bender-deMoll, 2005). The origins of these network dynamics are important to understand because they could help explain how network structures appear to retain their stability even as the ties they are composed of are changing.

Over time, brokers may try to create new bridging relations with new people, keep apart the people they have been bridging, or attempt to bring together the people they previously bridged. Although structural holes theory makes

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inferences about the brokerage dynamics that underlie the performance advantages of brokerage, empirical research on network brokerage has rarely examined the opening or closing of holes (notable exceptions are Burt, 2002; Obstfeld, 2005). Instead, the tendency has been to put aside the question of agency by assuming that self-interested, rational actors are universally motivated to maintain their brokerage positions and create new ones (e.g., Ryall and Sorenson, 2007; Buskens and van de Rijt, 2008; see the discussion in Burt, 2010: 221–227). This assumption has had the merit of simplifying theory and analysis, allowing network researchers to concentrate their attention on the effects of network structure on performance. But it is inconsistent with substantial evidence from psychology indicating that individuals differ markedly in terms of their social motivations and abilities (for a recent review, see John, Robins, and Pervin, 2008).

Network research, at least since the 1970s, has largely eschewed analytical approaches that direct attention to individual differences (e.g., Mayhew, 1984; Wellman and Berkowitz, 1988; Marin and Wellman, 2011; cf. Boissevain, 1974), but it is likely to be precisely such individual differences that influence network dynamics. To the extent that brokerage in workplace social networks creates competitive advantage, there is a strong incentive for becoming a broker. At the same time, bridges are difficult to build, costly to maintain, and vulnerable to decay (Burt, 2002; Kossinets and Watts, 2006; Ryall and Sorenson, 2007). Bridge building may be profitable, but it seems unlikely that everyone has the motivation or ability to build bridges. Moreover, the results of mathematical simulations suggest that if all individuals were equally motivated and skilled at pursuing the performance advantages of brokerage, the result would likely be a competitive battle in which it is unclear how brokerage positions could emerge or persist (Ryall and Sorenson, 2007; Buskens and van de Rijt, 2008). It seems more likely that some actors may be natural brokers while others may lack the motivation to step into brokerage roles, or they may simply fail to detect opportunities for network brokerage in the network around them. The relationship between network brokerage and workplace success may apply across different kinds of people, as prior research has shown. But the possibility that different kinds of people may be more likely to construct different kinds of networks deserves greater attention (cf. Burt, 2005: 47–50; Buskens and van de Rijt, 2008; Kilduff and Krackhardt, 2008: 4).

Previous cross-sectional work has suggested that individual differences in personality are related to the structure of individuals' social networks (e.g., Klein et al., 2004; Oh and Kilduff, 2008). The personality construct of self-monitoring may be particularly relevant because of its theoretical emphasis on how identity and impression management skills influence the structuring of interpersonal relationships (Snyder, 1987: 59–70; Mehra, Kilduff, and Brass, 2001; Flynn et al., 2006). Work organizations are sites of self-presentation activities that are vital to the formation and dissolution of friendships (Snyder and Copeland, 1989; cf. Fine, 1986) and form the backdrop for changes in the volume, composition, and patterns of changes in individuals' personal networks, which we refer to as "network churn," and the resultant brokerage dynamics (the opening and closing of brokerage positions over time).

In this paper, we take actor heterogeneity explicitly into account in the form of differences in self-monitoring and examine whether self-monitoring theory offers insight into network churn and the dynamics that underlie network brokerage. Of the different social network ties in the workplace, the one we focus on here is friendship. Not only do affect-intensive ties such as friendship play a crucial role in workplace success and satisfaction (e.g., Roethlisberger and Dickson, 1939; Fine, 1986; cf. Casciaro and Lobo, 2008), they are relatively discretionary and are therefore most likely to be shaped by personality differences. If the relationship between self-monitoring and network brokerage proves to be stable despite (or due to) network churn, this would support our overarching theoretical contention that dispositional forces help shape the dynamics of social networks in predictable ways.

EFFECTS OF SELF-MONITORING ON NETWORK CHURN

Drawing on the impression management tradition initiated by William James and Erving Goffman, the theory of self-monitoring concerns the "processes by which individuals actively plan, enact, and guide their behavioral choices in social situations" (Snyder and Cantor, 1980: 222; Snyder, 1974). Evidence for the validity of the self-monitoring construct is extensive. Hundreds of studies have tested theoretically based hypotheses about the role of self-monitoring in the behavioral, cognitive, and interpersonal domains (for reviews and meta-analyses, see Snyder, 1987; Gangestad and Snyder, 2000; Day et al., 2002; Day and Schleicher, 2006). Self-monitoring appears to be stable across the lifespan (e.g., Gangestad and Snyder, 1985).

At the heart of self-monitoring theory is the idea that individuals differ markedly in the extent to which they are able and motivated to engage in the expressive control required to create appropriate self-presentations. Like good actors, high self-monitors carefully control their expressive behaviors (for evidence that professional stage actors tend to be high self-monitors, see Snyder, 1974). A number of studies have found that high self-monitors are able to accurately convey a variety of intended emotions through both vocal and facial channels of expression (Snyder, 1974; Snyder and Monson, 1975; Riggio and Friedman, 1986; for a review, see Gangestad and Snyder, 2000).

Not only do high self-monitors carefully control their expressive behaviors, they are highly attuned to cues of situational appropriateness (e.g., Harris, 1989). Studies have shown that high self-monitors closely monitor the thoughts, actions, and feelings of those around them (e.g., Funder and Harris, 1986; Ickes et al., 1990; Toegel, Anand, and Kilduff, 2007). When offered the opportunity to do so, high self-monitors consult information about their peers more often and longer than do their low self-monitoring counterparts (Rhodewalt and Comer, 1981), a tendency that has been documented—using a children's version of the self-monitoring scale—in children as young as seven years old (Leone et al., 1984). Experimental evidence suggests that the attention high self-monitors pay to others is such that they are willing to "buy," at some cost to themselves, information that may help them create appropriate self-presentations (Elliott, 1979). The close attention they pay to others, moreover, is not restricted to their verbal expressions but extends to their non-verbal expressive behaviors (e.g., Brandt, Miller, and Hocking, 1980) and even to the structure of others' social networks (Flynn et al., 2006).

Theory and evidence suggest that high self-monitors are motivated to use the rich information they collect about others tactically to create value by creating favorable images of themselves in the eyes of their interaction partners. For example, high self-monitors use their (relatively accurate) knowledge of exchange relations among organizational members to gain high-status reputations among colleagues (Flynn et al., 2006) and supervisors (Mehra, Kilduff, and Brass, 2001). High self-monitors have been described as "consummate social pragmatists," able and motivated to project images designed to evoke positive affect and conferrals of status in their relations with others (Gangestad and Snyder, 2000: 531; DeBono, 1987).

Low self-monitors, by contrast, are less attuned to social expectations than to their own beliefs and values. Whereas the prototypic high self-monitor is motivated to produce situationally appropriate emotions and behaviors designed to win status conferrals, the prototypic low self-monitor strives to produce emotions and behaviors that are consistent with internal beliefs and values, even when these beliefs and values are situationally inappropriate. Low self-monitors seem "not only unwilling but also unable to carry off appearances"; they live as if "put-on images are falsehoods, as if only those public displays true to their privately experienced self are principled" (Gangestad and Snyder, 2000: 531). Although it has the benefits of providing self-validation, the principled approach to self-presentation characteristic of low self-monitors runs the risk of narrowing the set of conditions under which they will be seen as likable (Day and Schleicher, 2006), which may be reflected in differences between low and high self-monitors in network churn—the volume, composition, and patterns of changes in their networks over time.

Network Churn

Volume. One way to conceptualize network churn is in terms of the volume or number of ties added over time. A popular network account of tie emergence relies on a preferential-attachment logic whereby those with many ties tend to accumulate even more ties over time (e.g., Price, 1965; Barabasi and Albert, 1999; Gulati and Gargiulo, 1999; Zaheer and Soda, 2009; for a detailed discussion, see Newman, 2010). Going beyond this structural logic, individual differences in self-monitoring personality may offer insight into why some people gain more friendship ties over time.

We know that high self-monitors tend to be adaptable and flexible in their self-presentations. But fine-grained analyses of expressive self-presentation (Lippa, 1976a, 1976b) have shown that the shifting behavior of high self-monitors takes place against a consistent background of expressive behavior that projects the general appearance of a friendly and outgoing person (see Snyder, 1987: 37). Most social contexts, and perhaps especially the workplace (see Argyle, 1992: 78–86), require people to project just such an image. The expectation that high self-monitors will be more capable of gaining the friendship of others is consistent with previous work suggesting that they expend considerable effort in providing emotional help (e.g., Toegel, Anand, and Kilduff, 2007) and advice (Flynn et al., 2006) to their colleagues. High self-monitors put considerable effort into using a wide repertoire of social skills to make their interpersonal interactions go smoothly (Ickes et al., 2006). In conversation, they are more likely to use the first-person plural pronouns (e.g., we, us, our) over the first-person singular (e.g., I, me, mine) (Ickes, Reidhead, and Patterson, 1985), convey an immediate sense of intimacy (Riggio, Friedman, and DiMatteo, 1981), and employ effective conversational pacing (Dabbs et al., 1980) and humor (Turner, 1980). The friendly and helpful image that high self-monitors project, coupled with their considerable social skills, makes it more likely that, relative to their low self-monitoring counterparts, high self-monitors will attract more new friends over time.

Hypothesis 1: The higher the self-monitoring score, the larger the number of new friends an individual will attract over time.

Composition. High self-monitors may gain more friends over time, and self-monitoring theory can offer insight into the kinds of friends they might attract. Prior work has found that demographically different people who are high self-monitors appear to be more capable than low self-monitors of disconfirming stereotyped images others may have of them (Flynn, Chatman, and Spataro, 2001). By effectively presenting an image that disconfirms negative stereotypes of out-group members, high self-monitoring individuals may be more effective than their low self-monitoring counterparts at gaining diverse friends over time. In work organizations, formal boundaries can lead members from one function to view those belonging to other functions as out-group members. Given that behaviors, opinions, and skills tend to vary across functional groups (Hambrick and Mason, 1984), it is unsurprising that most friendships tend to occur among members who belong to the same functional groups (e.g., Lincoln and Miller, 1979). The same impression-management skills and focus on others that facilitate high self-monitors' ability to disconfirm negative stereotypes, however, should lead to their attracting new friends from different functional groups over time.

It is also possible that high self-monitors are more motivated than low self-monitors to actively seek out friends from outside their functional groups. Cross-functional coordination is both challenging and prized in work organizations (Katz and Kahn, 1966). Individuals who are positioned to enhance cross-functional coordination stand to gain influence and status in the organization (Shaw, 1964; Pfeffer, 2010), and self-monitoring theory suggests that high self-monitors are especially motivated to elicit status conferrals in their social relations (Gangestad and Snyder, 2000; Flynn et al., 2006).

Hypothesis 2: The higher the self-monitoring score, the larger the number of new friends an individual will attract from functional groups other than his or her own functional group.

Pattern. One can conceptualize network churn not only in terms of volume and composition but also in terms of the pattern of connections between new ties and previous ones. A theory that is often used to explain patterns of network change focuses on "structural balance" (Cartwright and Harary, 1956; Davis, 1963; Davis and Leinhardt, 1972). Expressed in colloquial terms, the gist of this theory is that friends of friends tend to become friends. From the perspective of balance theory, relations tend to be "transitive" because people are assumed to have an affective and cognitive preference for transitive structures. Intransitive structures, in which friends of friends are not friends, are believed to produce anxiety and cognitive strain in people (cf. Heider, 1958) and are therefore less preferred than balanced structures (Jordan, 1953). Investigations have found that the evolution of friendship networks appears to follow a pattern of increasing transitivity over time (e.g., Newcomb, 1961; van de Bunt, 1999; cf. Carley and Krackhardt, 1996; Krackhardt and Kilduff, 1999). Given that studies also suggest that transitivity can be elusive and unstable in human groups (e.g., Doreian et al., 1996), however, it could be that transitivity over time is characteristic of the networks of some people and not others.

Drawing on self-monitoring theory, the traditional logic of network growth through transitivity should apply, but only to low self-monitors. For high self-monitors, by contrast, network growth is more likely to follow a pattern in which new friends are relative strangers, in the sense of being unconnected to previous friends. The rationale for this prediction is grounded in self-monitoring theory and evidence, which suggest that high self-monitors tend to be less affectively invested in their friendships than low self-monitors and are less likely to suffer from cognitive strain when their friends are not friends with each other (Snyder and Smith, 1986; cf. Caldwell and O'Reilly, 1982). Moreover, the superior social skills of high self-monitors may make it easier for them to overcome the discomfort that people typically feel in interacting with relative strangers. For example, in one laboratory study of spontaneous encounters, researchers arranged for pairs of strangers to spend time together in a waiting room (Ickes and Barnes, 1977). While the participants ostensibly waited for the experiment to begin, researchers surreptitiously recorded the behavior of the participants. Results showed that high self-monitors took a more active posture in the conversations, talking first and initiating subsequent conversation. High self-monitors also talked more about the other person than about themselves. By taking this active role, high self-monitors were able to enhance their ability to influence the course of the conversation and to promote desired images. These social skills, combined with the relative lack of cognitive strain they seem to experience when their friends are not connected, suggest that the new friends high self-monitors attract are likely to be relative strangers.

Hypothesis 3: The higher the self-monitoring score, the less likely that an individual's new friends will have been friends of his or her previous friends.

A different aspect of network churn involves the dissolution of ties. Given high self-monitors' attentiveness to rules of social conduct (cf. Argyle and Henderson, 1984) and the effort they put into helping (Flynn et al., 2006) and emotionally supporting (Toegel, Anand, and Kilduff, 2007) others, one might expect self-monitoring to be negatively related to the dissolution of friendship relations. Yet studies also suggest that high self-monitors tend to adopt a noncommittal stance to their friendship relations (Snyder, Gangestad, and Simpson, 1983; Gaines et al., 2000), which would lead one to expect self-monitoring to be positively related to tie dissolution. Given these potentially opposing forces, we did not expect to find a straightforward relationship between self-monitoring and the dissolution of friendship ties. Nonetheless, in the spirit of theory building, we report below the results of relevant analyses concerning tie dissolution, although our main focus is on brokerage dynamics.

Brokerage Dynamics

New structural holes. Organizations are often competitive arenas in which information does not spread evenly across players. Individuals whose networks are optimized to bridge structural holes between people are positioned to reap information, control, and vision benefits that allow them to outperform and outcompete those whose networks contain few structural holes (for a summary of evidence, see Burt, 2010). The performance and career benefits of brokerage may be an incentive for bridge building, but not everyone has what it takes to build bridges (Burt, Jannotta, and Mahoney, 1998). There are challenges. For one thing, brokerage opportunities are hard to spot: they represent holes in social structure, and most people have a tendency to see ties where holes exist (Janicik, 1998). For another, it is easier to gain the trust of someone who is a friend of a friend than to gain the trust of someone whose friends are not one's friends. But brokers have to get people who may not especially like one another to like and trust *them*. Accomplishing this requires brokers to have flexible identities (Padgett and Ansell, 1993; Reagans and Zuckerman, 2008). Thus, although brokerage may be profitable, not everyone may be motivated or sufficiently skilled to overcome the interpersonal hurdles to bridge building.

Prior research has shown that high self-monitors tend to be brokers in friendship networks (Mehra, Kilduff, and Brass, 2001). As in most previous studies, the cross-sectional nature of that work precluded investigating the emergence of new structural holes and their disappearance over time. An exception is Burt's (2002) work on bridge decay. Using four years of data on the social networks of bankers, his study showed that bridge relations decay quickly: nine in ten bridges in one year were gone the next. The rate of decay was slower in the networks of bankers who had experience with bridges, a pattern that is consistent with experimental work (Janicik and Larrick, 2005) showing that individuals whose networks contain bridge relations are able to recognize and capitalize on new bridging opportunities more quickly. Social capital, in the form of bridging relations, accrues to those who already have it (Burt, 2002; for similar results at the level of teams, see Zaheer and Soda, 2009). Going beyond, and controlling for, this rich-get-richer dynamic, we hypothesize that self-monitoring will be positively related to the emergence of new holes over time.

Hypothesis 4: The higher a broker's self-monitoring score, the larger the number of new structural holes in his or her network over time.

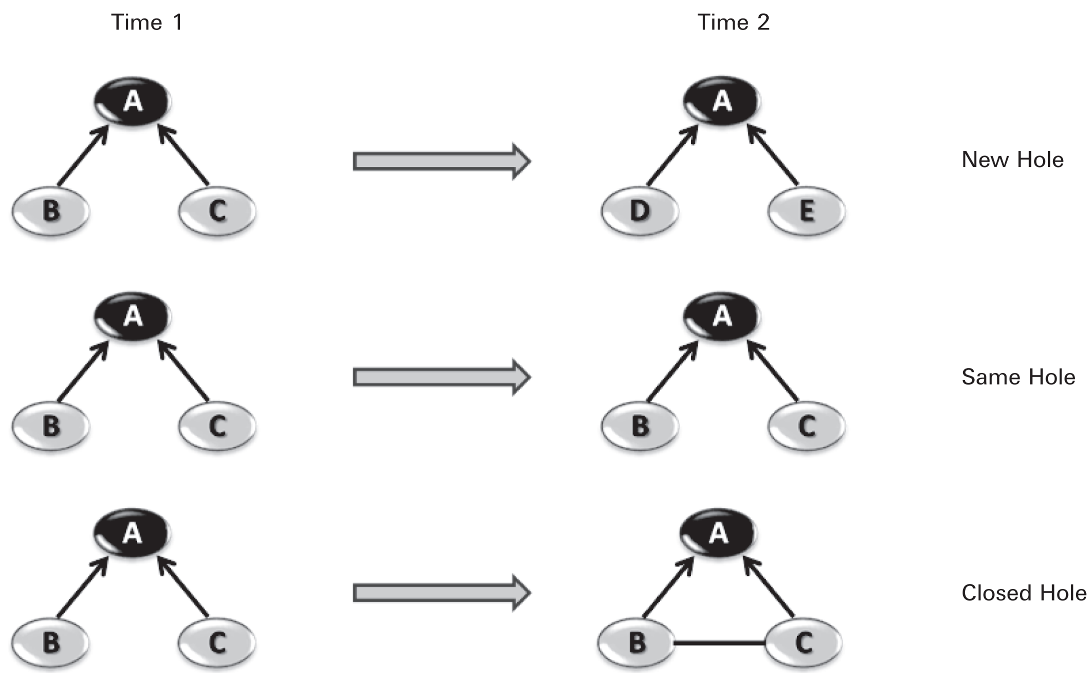
A related implication of these differences in self-monitoring has to do with the rate at which new friendship partners add to the number of structural holes in an individual's resultant network. The addition of certain people to a friendship network adds more to the number of structural holes in the resultant network than the addition of other people to the network. The extent to which a new friend adds to the number of holes in the resultant network is greater if the person added is (a) unconnected to others who are added and (b) is relatively unconnected to others in the resultant network. We have explained above the reasons that high self-monitors may be more motivated and skilled at acquiring new structural holes than low self-monitors. If the new friends high self-monitors attract remain unconnected to their other friends, they will allow for more efficient expansion of the possibilities for network brokerage (see Burt, 1992: 20–21). The number of structural holes that are added to a network as a result of the addition of each new friend should be greater for high self-monitors than for low self-monitors.

Hypothesis 5: The higher a broker's self-monitoring score, the higher the rate at which the addition of new friends adds to the number of structural holes in the resultant network.

Dynamics of existing holes. Self-monitoring may be related not only to the emergence of new holes over time but also to brokerage dynamics with respect to existing holes, as shown in figure 1. Imagine that at time 1 person A is a broker in the sense that A is considered a friend by B and C, who are not themselves friends. In addition to the possibility of developing new holes at time 2, this existing hole could remain unchanged at time 2 (same hole), or the hole could close at time 2 because of the emergence of a direct relationship between B and C.

The first two brokerage dynamics—the formation of new brokerage positions and the retention of existing ones—are consistent with the *tertius gaudens* ("the third who enjoys") strategy at the heart of structural hole theory (Burt, 1992, 2005). This theory suggests that brokers benefit by retaining or obtaining positions in which they connect otherwise unconnected others, as such positions offer the potential for superior access to information and greater opportunities for control. The last brokerage dynamic, the closing of structural holes, is more consistent with the contrasting *tertius iungens* ("the third who connects") strategy (Obstfeld, 2005). In this

Figure 1. Three types of brokerage dynamics.



Note: Each node represents a person. A directed line from B to A represents a friendship tie from B to A. Non-directed ties between B and C imply that there is a friendship tie from C to B, a friendship tie from B to C, or both.

scenario, the broker benefits by closing the gap between previously disconnected others by bringing them into direct contact.

Brokerage dynamics should follow the *tertius gaudens* pattern or the contrasting *tertius iungens* pattern depending on the self-monitoring orientation of the broker. People are attracted to network structures that are congruent with their dispositions (Snyder and Gangestad, 1982). Dispositionally congruent network structures are more likely to provide opportunities for the manifestation and reinforcement of dispositional preferences. Brokerage positions in friendship networks require incumbents to flexibly adapt to the expectations of people who are not themselves friends, and self-monitoring theory and evidence suggest that high self-monitors are more skilled at managing diverse role expectations than low self-monitors (e.g., Caldwell and O'Reilly, 1982; cf. Flynn, Chatman, and Spataro, 2001).

In addition, brokerage positions may be ideally suited to the preference of high self-monitors for "audience segregation" (Goffman, 1959), which refers to efforts to insure that those individuals to whom high self-monitors have presented one image do not get to see them presenting a potentially incongruent image to others. The segmentation of friendship relations that is characteristic of brokerage facilitates the high self-monitors' interpersonal tendency to assume different identities with different people. Brokerage positions therefore may help preserve the credibility of high self-monitors' social performances (cf. Snyder, 1987: 64). To the extent that high self-monitors prefer to have different friends for different occasions (Snyder, Gangestad, and Simpson, 1983), they may also be unmotivated to bring their friends together.

The implications of these skill-based and motivational differences in self-monitoring for brokerage dynamics seem clear. We expect that high self-monitors will be more likely than low self-monitors to maintain the brokerage positions they occupy and less likely to close structural holes over time.

Hypothesis 6a: The higher a broker's self-monitoring score, the more likely that structural holes are maintained over time.

Hypothesis 6b: The higher a broker's self-monitoring score, the less likely that structural holes are closed over time.

METHODS

Research Setting

Data for our study were collected at the radiology department of a hospital located in the south of the Netherlands. The study included all 170 employees of the radiology department. The occupational structure and roles of members of a radiology department have been detailed in previous research (e.g., Barley, 1986; Black, Carlile, and Repenning, 2004). Administrative personnel were responsible for making appointments with patients, managing an archive of patient records, and typing diagnostic findings. Technologists executed examinations, such as taking an X-ray. Radiologists interpreted results of examinations, determined a diagnosis, and, in close cooperation with technologists, executed several types of advanced examination, such as angiography or magnetic resonance imaging.

Given our interest in the dynamics of friendship networks, we collected data during a period when the organization was undergoing change, specifically, adoption of a new information processing system. Prior work has shown that such changes provide a window of opportunity for observing the restructuring of social network ties (e.g., Barley, 1986; Burkhardt and Brass, 1990; cf. Tyre and Orlikowski, 1994). Studying friendship dynamics in the absence of such change would probably have required us to study network change over a longer time scale than the nine months over which we examined network dynamics. Our research design therefore took advantage of a technologically induced "jolt" to study how personality shapes the dynamics of social networks (cf. Meyer, 1982).

The organization we studied was in the process of implementing new information technology, consisting of a picture archiving and communication system (PACS) and a radiology information system (RIS). The RIS is used to schedule appointments and record a patient's information as a patient moves through the primary work process of the department. RIS also includes a speech recognition system that forms the basis for a digital recording of the findings of an examination in a final report. The PACS allows for digital recording, editing, archiving, and access to images. Analyses (available from the authors) indicated that network churn was broadly spread across different functions as opposed to being concentrated in any one function.

Sample

We conducted a paper-and-pencil sociometric survey at the radiology department at two different times. The first survey took place approximately three months before the implementation of the new information system (T1). It was administered to all 163 employees (48 men and 115 women). The second questionnaire was administered nine months later (T2) to all 162 employees (47 men and 115 women) of the department, including the full range of functions. At T1, there were 12 radiologists, 7 radiology assistants, 84 technologists, 22 technology assistants, and 38 members of the administrative staff. At T2, the functional composition of the respondents was similar, with 12 radiologists, 8 radiology assistants, 89 technologists, 19 technology assistants, and 34 members of the administrative staff. Over the period of nine months between T1 and T2, eight respondents left and seven respondents joined the department; these respondents were removed from the longitudinal analyses.

Data on gender, function, and tenure came from departmental records. We gathered data on self-monitoring as part of the first survey for each participant. We received 163 responses to the self-monitoring measure (96 percent). In total, 142 individuals responded to the sociometric question at T1 (response rate: 87.7 percent) and 139 at T2 (response rate: 85.8 percent). The effective size of the final dataset varied between 123 and 155, depending on the type of analysis. Non-respondents did not significantly differ from respondents with respect to age, gender, function, rank, tenure, or performance.

Measures

Self-monitoring. Self-monitoring was measured at T1 using a Dutch language version of the 18-item revised Self-Monitoring Scale (Gangestad and Snyder, 1985; Snyder and Gangestad, 1986; translation validated by Vinkenburg, 1997). Items include "I would probably make a good actor," and "I have trouble changing my behavior to suit different people and different situations" (reverse coded). Snyder and Gangestad (1986) argued that the revised scale was more reliable and factorially pure than the original 25-item scale, described in Snyder (1974). We used a response format based on a 5-point Likert scale because a meta-analysis of self-monitoring at work (Day et al., 2002) showed that this scale format was more reliable than the original true-false scoring format. We followed the standard practice in using the average score on the scale to code self-monitoring. Cronbach's alpha for the scale in our study was .77.

Friendship network. We asked each respondent to look down an alphabetical list of fellow employees and check the names of the people whom he or she considered "a personal friend, e.g., a person you like to spend breaks with, or with whom you like to take part in different social activities." A validation study conducted at a dialysis and nursing department of a Dutch hospital showed that this question reliably distinguishes a “friendly relationship” from a “friend” (van de Bunt, 1999: 97). Friendship, in comparison to friendly relationships, includes ties that are more intimate, voluntary, and unique (van de Bunt, van Duijn, and Snijders, 1999). The question was translated (and back-translated) from English to Dutch by three independent translators and pre-tested for face validity and acceptability at a different radiology department.

The data on friendship relations were arranged in a 142 x 142 binary adjacency matrix at T1 and 139 x 139 binary adjacency matrix at T2. In each matrix, a value of 1 in the cell x_{ij} corresponded to i nominating j as a friend. A value of 0 indicated no relation from i to j. The first matrix contained 20,022 observations on all possible pairs of people at T1, and the second matrix contained 19,182 observations on all possible pairs of people at T2. To calculate the network indexes and brokerage measures, we used the network software program UCINET VI, version 6.289 (Borgatti, Everett, and Freeman, 2002). The density of the friendship network at both points in time was .12.

Volume of network churn. We assessed the volume of network churn by counting, for each person in our sample, (1) the number of new ties that emerged between T1 and T2 (i.e., ties that existed at T2 but not at T1) and (2) the number of ties that dissolved between T1 and T2 (i.e., ties that existed at T1 but not at T2). Self-monitoring is primarily a theory of the impressions individuals create in the eyes of others, so we focused on incoming friendship ties. Because self-monitoring was self-reported, reliance on out-going friendship ties would also have inflated the likelihood of spurious results.

Composition of network churn. We examined the composition of network churn by counting the number of new friends who came from a different functional group within the department than the focal respondent.

Pattern of network churn. To assess the pattern of network churn, we used the “egonet change” routine available in the social network software package UCINET VI (version 6.289). This routine assesses the degree of connectedness between an individual’s new friends and the individual’s previous friends. We used the routine to calculate, for each individual in our sample, the proportion of ego’s new friends who were friends with ego’s friends at T1. We then divided this number by the maximum number of such ties that was possible, given the number of friends ego possessed at T1 and the number of friends added at T2. The resulting measure can vary between zero and one.

Network brokerage. To assess brokerage in the friendship network, we used the “honest broker index” in UCINET VI (version 6.289). This index reflects the frequency with which a node directly connects pairs of nodes that are not themselves directly connected. We focused on brokerage at the local, triadic level rather than using more global measures of brokerage, such as betweenness centrality that take long chains of indirect relations into account (see Freeman, 1979), because the effects of personality on network change are most likely to be concentrated in the network immediately surrounding the focal individual. Individuals are more likely to be able to influence their proximal ties rather than their distant ones, which may also be one reason that the performance benefits of network brokerage appear to be concentrated in the immediate network surrounding the individual (see Burt, 2010).

To compute the extent to which person A is a broker, the measure counts the number of times A is part of a triad such that (1) B reports a friendship tie to A, (2) C reports a friendship tie to A, and (3) neither B nor C report a friendship tie to each other. The three conditions above were minimum criteria that had to be satisfied for A to be considered as a broker. Our measure permitted triads in which these minimum conditions were met but in which A also had a tie to B and/or C. Thus, consistent with our approach to measuring network churn, our measure of network brokerage focused on incoming friendship ties as a necessary condition for the establishment of brokerage relationships. As a test of robustness, we also computed an alternative measure of brokerage, "ego betweenness," which was computed as the sum of the proportion of times ego lies on the shortest path between each pair of alters (Everett and Borgatti, 2005). The pattern of results was unchanged.

Brokerage dynamics. To assess brokerage dynamics, we first calculated the number of brokerage positions that remained unchanged between T1 and T2 (*same holes*). That is, we calculated the number of times A occupied a brokerage position between the same pair (B and C) at both T1 and T2. Second, we counted the number of brokerage positions that were *closed holes* between T1 and T2. We considered a brokerage position to have been closed over time if A occupied a brokerage position between B and C at T1, but at T2 there was either a friendship tie from B to C or a friendship tie from C to B or both. Third, we calculated the number of new brokerage positions (*new holes*) that were formed at T2. These are structural holes in which at T2 a person A brokers between a different pair of alters than at T1. We computed this measure by subtracting the number of same holes between T1 and T2 from the number of structural holes counted at T2. The Appendix provides more details on the matrix algebra behind how these measures of brokerage dynamics were calculated.[1]

New holes per new friend. To examine the rate at which new friends increase the number of holes in the resultant network, we constructed an additional measure related to brokerage dynamics: *new holes per new friend*. This measure reflects the average number of structural holes that a person added to his or her network for each new friend he or she gained between T1 and T2.

Control Variables

Gender. We controlled for gender because prior research has shown that it influences the structure of social networks in work organizations (e.g., Brass, 1985; Ibarra, 1992). The variable gender was coded as 0 for males and as 1 for females.

1
We considered and ruled out the possible effects of "opened holes" on our results. Imagine that at T1, A was considered a friend by both B and C and that there was a friendship relation between B and C. This closed hole would become an open hole if the friendship relation between B and C were to disappear at T2. This dynamic is the temporal opposite of that described as "closed holes." We conducted a sensitivity analysis in which we counted the number of *opened holes* and subtracted this number from our current measure of new holes. Analyses using this "purified" measure of new holes yielded results that were consistent with those reported in table 6, below.

Function. We controlled for job function because of its likely influence on friendship relations. Functional affiliation can be seen as a proxy for workflow in the radiology department. We coded function as 1 = radiologist, 2 = radiology assistant, 3 = technologist, 4 = technology assistant, and 5 = administrative staff. We treated function as a categorical variable in the regression analyses and created four dummy variables to differentiate between functional groups. This allowed us to account for the possible effects of function-specific characteristics, such as group size.

Tenure. The longer a person's tenure, the more opportunities he or she has had for interaction with other colleagues and developing relationships (e.g., van de Bunt, 1999). It is also possible that individuals with longer tenure may be less likely to have structural holes in their networks than individuals with shorter tenures. We coded tenure as the length of time, in years, that a respondent had been an employee of the radiology department.

Performance. Prior individual work performance may be related to the amount of network churn and brokerage dynamics. For instance, Burt (2002) has shown that high-performance bankers experienced less decay in their bridge and non-bridge relations (fewer lost ties), and they were more likely to acquire new bridge relations. We assessed job performance using supervisory ratings based on a 4-item scale. Three of the scale items were adapted from Tsui et al. (1997), and the fourth was adapted from Mehra, Kilduff, and Brass (2001). The reliability of the scale was .93 (scale items are available upon request).

Analyses

For analyses with interval-scaled dependent variables (e.g., average number of new structural holes per new friend), we used ordinary least squares (OLS) regression. In most of our analyses, the dependent variables are count variables (e.g., the number of new friends, the number of times a person occupies a brokerage position). Because OLS is inappropriate in these cases, we used the negative binomial model, which is designed specifically for the analysis of count variables (Greene, 1997). The negative binomial model is a generalization of a Poisson model that accounts for the overdispersion (variance exceeding the mean) present in our data (cf. Barron, 1992; Hausman, Hall, and Griliches, 1984). The dependent variable in our analysis predicting the pattern of network churn is expressed as a proportion so that its values vary between zero and one. For analysis involving this dependent variable, we used the fractional logit regression model proposed by Papke and Wooldridge (1996).

RESULTS

Descriptive Statistics

Table 1 presents means, standard deviations, and zero-order correlations. Men made up 28 percent of the sample at both time periods. The composition of the sample by function changed only slightly between T1 and T2: at T1, there were 12 radiologists (7.4 percent), 7 radiology assistants (4.3 percent), 84 technologists (51.5 percent), 22 technology

Table 1

Means, Standard Deviations, and Correlations

Variable	Mean	S.D.	1	2	3	4	5	6	7	8
1. Gender (0 = male)	–	–								
2. Function	–	–	.24••							
3. Tenure	12.29	9.20	.08	–.14						
4. Performance T1	3.53	0.80	.15	.30••	–.02					
5. Self-monitoring	2.32	0.49	–.38••	–.14	–.26••	–.07				
6. Brokerage T1	61.53	57.77	.04	.07	.00	.19•	.23••			
7. Network size T1	16.94	7.36	.06	.11	.09	.26••	.16•	.85••		
8. Brokerage T2	60.76	58.03	.02	.08	–.03	.24••	.21••	.67••	.76••	
9. New friends	6.09	3.94	.09	.03	–.22••	.17••	.22••	.45••	.47••	.74••
10. Lost friends	7.15	3.83	–.08	.01	.04	.11	.18•	.71••	.80••	.51••
11. New friends from different functions	3.15	2.73	.01	.11	–.32••	.11	.26••	.34••	.33••	.59••
12. Pattern of churn	0.33	0.15	.15	.07	–.14	–.05	–.23••	–.28••	–.27••	–.17
13. Same holes	10.95	12.53	–.03	.06	–.02	.21•	.20•	.66••	.75••	.77••
14. Closed holes	5.32	6.36	–.10	.00	–.10	.10	.19•	.65••	.75••	.68••
15. New holes	46.06	43.30	.07	.12	–.12	.25••	.22•	.63••	.69••	.91••
16. New holes per new friend	4.96	2.92	.10	.13	.06	.28••	.20•	.68••	.77••	.87••

Variable	9	10	11	12	13	14	15
10. Lost friends	.42••						
11. New friends from different functions	.82••	.31••					
12. Pattern of churn	–.01	–.32••	–.17				
13. Same holes	.31••	.40••	.18•	–.16			
14. Closed holes	.35••	.48••	.26••	–.15	.78••		
15. New holes	.83••	.48••	.67••	–.17	.67••	.66••	
16. New holes per new friend	.62••	.48••	.45••	–.32••	.75••	.66••	.89••

• $p < .05$; •• $p < .01$; two-tailed tests.

assistants (13.5 percent), and 38 members of the administrative staff (23.3 percent). At T2, there were 12 radiologists (7.4 percent), 8 radiology assistants (4.9 percent), 89 technologists (54.9 percent), 19 technology assistants (11.7 percent), and 34 members of the administrative staff (21 percent).

We used ANOVA to analyze the relation between self-monitoring and function. None of the multiple comparisons in the post-hoc analyses showed a statistically significant difference in self-monitoring score between functions. On average, respondents had been with the department for just over twelve years.

Over the nine-month period spanned by our study, there was clear evidence of both considerable network stability at the level of the overall network structures and considerable churn at the level of individual ties. The results of correlation analyses in UCINET VI—which correct for autocorrelation present in network data by assessing significance using the Quadratic Assignment Procedure (QAP)—showed that there was a reasonable degree of stability at the overall network level between T1 and T2: a non-parametric measure of association (Goodman-Kruskal Gamma) between the friendship adjacency matrix at T1 and the friendship adjacency matrix at T2 was .91 ($p < .001$). The Pearson correlation coefficient also suggested moderate to high levels of association between T1 and T2 (r = .52; $p < .001$). Yet beneath this apparent stability there was evidence of network churn. Of a total of 2,690 ties at T1, 1,459 were "stable," in the sense that they existed at T1 and still existed at T2; 1,160 new ties were "created" by T2 that did not exist at T1; and 1,231 ties that existed at T1 were "lost" by T2. This rate of churn in friendship ties is comparable to that reported by van de Bunt (1999: 127) in his study of network changes in a dialysis department over a period of approximately one year.

Network Churn

Volume. Hypothesis 1 predicted a greater volume of network churn in the social networks of high self-monitors than in the social networks of low self-monitors. The results of the negative binomial regressions presented in table 2 show support for this hypothesis. Controlling for gender, function, tenure, and performance, the results indicate that the friendship networks of high self-monitors (relative to those of low self-monitors) exhibited a greater volume of network churn. As shown in models 1 and 3 of table 2, self-monitoring was positively related to both the formation of new friendship ties ($p < .01$) and their loss ($p < .05$). In both cases, adding

Table 2

Results of Negative Binomial Regression Predicting Self-Monitoring Differences in the Volume of Network Churn (N = 147)*

	New Friends		Lost Friends	
Variable	Model 1	Model 2	Model 3	Model 4
Gender	.08	.13	–.19	–.00
	(.10)	(.10)	(.11)	(.07)
Function = 1	–.25	–.11	–.44	.06
	(.26)	(.26)	(.23)	(.17)
Function = 2	.30	.41	–.34	.06
	(.23)	(.23)	(.24)	(.18)
Function = 3	.64•••	.55•••	.26•	–.04
	(.11)	(.12)	(.11)	(.08)
Function = 4	1.14•••	1.05•••	.21	–.12
	(.14)	(.14)	(.15)	(.11)
Tenure	–.00	-.00	.01	.00
	(.01)	(.01)	(.01)	(.00)
Performance T1	.12•	.07	.05	–.06
	(.06)	(.06)	(.06)	(.04)
Self-monitoring	.27••	.22•	.21•	.01
	(.09)	(.09)	(.09)	(.06)
Network size T1		.02••		.06•••
		(.01)		(.00)
Pearson χ^2	152.77	146.99	143.62	141.27
Log likelihood	860.63	865.37	1079.13	1139.06
Likelihood ratio test†	4.67••	4.75••	2.47•	59.93•••

• $p < .05$; •• $p < .01$; ••• $p < .001$.
* Entries represent parameter estimates; standard errors are in parentheses. The intercept and dispersion parameters were included in the negative binomial regression models but are not reported here.
† A likelihood ratio test compares the goodness of fit of a model with the previous nested model. Models 1 and 3 reported here are compared with the models with control variables (gender, function, tenure, and performance).

self-monitoring to the regression significantly improved overall model fit, as indicated by the results of the likelihood ratio (LR) test.[2]

We also checked to see if the relationship between self-monitoring and the volume of network churn would be significant after controlling for the initial size of each person's friendship network. We included network size as a control variable because the size of an individual's network at T1 should be positively related to both the number of new friends an individual gains over time (the familiar "rich-get-richer" dynamic underlying preferential attachment models—e.g., Merton, 1968) and the number of friends an individual loses over time (the larger the network, the greater the likelihood of tie loss through random attrition). The results presented in model 2 of table 2 show that the relation between self-monitoring and the appearance of new friendship ties remained significant even after controlling for network size at T1 ($p < .05$). By contrast, the relation between self-monitoring and the number of lost ties was not statistically significant after including network size at T1 in model 4. This pattern of results suggests that high self-monitors were forming more new friendship ties over time than low self-monitors, and this was not just because high self-monitors initially had more friends.[3] The greater number of friendships "lost" by high self-monitors was because they initially had larger friendship networks.[4]

Composition. Our second hypothesis predicted that self-monitoring is positively related to the tendency to attract friends from different functions over time. As the results of negative binomial regressions presented in table 3 show, self-monitoring was positively related to the number of new friends who came from functions other than that of the focal individual ($p < .01$ in model 1). Not surprisingly, the size of an individual's network at T1 was a significant predictor of the number of new friends from different functions an individual gained by T2 ($p < .001$ in model 2). But controlling for the effects of network size, self-monitoring remained positively related to the tendency of new friends to come from functions different from that of the focal individual ($p < .05$ in model 2). These results support hypothesis 2.

Pattern. Hypothesis 3 predicted that self-monitoring would be negatively related to the tendency of new friends to be connected to ego's previous friends. The results of the fractional logit regression analysis presented in table 4 support this hypothesis. Controlling for gender, function, tenure, and performance, the results indicate that self-monitoring was negatively related to the tendency of ego's new friends to have been connected with ego's previous friends ($p < .001$). Whereas the new friends that low self-monitors attracted tended to be friends of their previous friends (the familiar dynamic of network evolution through transitivity), the new friends that high self-monitors attracted tended to be relative strangers in the sense that they tended to be unconnected with their previous friends. Note that the dependent variable in this analysis is conditioned by network size at T1 because it is expressed as a density.

2
We used the likelihood ratio (LR) tests to statistically assess an improvement of the goodness of fit of our hierarchically nested models. Adding additional parameters to a baseline model that includes only control variables (gender, function, tenure, and performance) always results in a higher likelihood score. The LR test allows us to test whether adding an additional parameter (e.g., self-monitoring score) is justified in terms of a significant improvement in model fit (cf. Huelsenbeck and Rannala, 1997).

3
The size of the reported coefficients in negative binomial regressions can be interpreted as the effect of the variable on the logarithm of the dependent (count) variable. Thus controlling for gender, function, tenure, performance at T1, and network size at T1 in model 2 of table 2, a one-unit increase in self-monitoring score is related to a higher number of new friends by approximately 25 percent [exp (.22)]. In this sample, self-monitoring has a mean of 2.32 and a standard deviation of .49 (see table 1). A person with an average self-monitoring score of 2.8 is expected to have approximately 12.5 percent more new friends than a person with a self-monitoring score of 2.3.

4
In a supplementary analysis, we computed a composite measure that captured "network expansion" (new friends – lost friends) relative to "overall churn" (new friends + lost friends). Controlling for gender, function, tenure, performance, and network size at T1, self-monitoring was positively related to this composite measure of network churn ($p < .01$).

Table 3

Results of Negative Binomial Regression Predicting Compositional Effects in Network Churn (N = 155)*

	New Friends from Different Functions	
Variable	Model 1	Model 2
Gender	.24 (.15)	.30• (.14)
Function = 1	.04 (.31)	.30 (.31)
Function = 2	.21 (.28)	.44 (.27)
Function = 3	–.04 (.15)	–.21 (.15)
Function = 4	.77••• (.18)	.60••• (.18)
Tenure	–.01 (.01)	–.02• (.01)
Performance T1	.07 (.08)	–.01 (.08)
Self-monitoring	.36•• (.13)	.25• (.12)
Network size T1		.04••• (.01)
Pearson χ^2	140.75	137.20
Log likelihood	162.60	170.90
Likelihood ratio test†	3.94••	8.31•••

• $p < .05$; •• $p < .01$; ••• $p < .001$.
* Entries represent parameter estimates; standard errors are in parentheses. The intercept and dispersion parameters were included in the negative binomial regression models but are not reported here.
† A likelihood ratio test compares the goodness of fit of a model with the previous nested model. Model 1 is compared with the model with control variables (gender, function, tenure, and performance).

Table 4

Results of Fractional Logit Regression Predicting Self-Monitoring Differences in the Pattern of Network Churn (N = 124)*

Variable	Pattern of network churn
Gender	–.02 (.16)
Function = 1	–.52 (.35)
Function = 2	–.18 (.39)
Function = 3	.11 (.21)
Function = 4	–.05 (.23)
Tenure	–.02•• (.01)
Performance T1	–.14 (.09)
Self-monitoring	–.41••• (.11)
Pearson χ^2	10.03
Log pseudolikelihood	53.85

• $p < .05$; •• $p < .01$; ••• $p < .001$.
* Entries represent parameter estimates; standard errors are in parentheses. The intercept was included in the fractional regression model but is not reported here.

Brokerage Dynamics

Previous cross-sectional work has shown that high self-monitors tend to be brokers in friendship networks (Mehra, Kilduff, and Brass, 2001). The results presented in table 5 show that this was also true for our sample. The addition of self-monitoring significantly improved overall model fit (compared with the model including only the control variables) at both T1 and T2, as indicated by the results of the LR test ($p < .001$ for T1 and $p < .01$ for T2). Controlling for gender, function, tenure, and performance, self-monitoring was positively related to occupying brokerage positions in the friendship network at both T1 ($p < .001$) and T2 ($p < .01$).[5]

New holes. High self-monitors may have been more likely to occupy brokerage positions in the friendship network at both time periods (i.e., both before and after the implementation of the new information system), but we wanted to determine if they occupied new brokerage positions over time. The results of the negative binomial regressions presented in table 6 show that, controlling for gender, function, tenure, and performance, high self-monitors were more likely than low self-monitors to occupy new holes ($p < .001$ in model 1). Adding self-monitoring to this regression model improved overall model fit, as indicated by the significance of the LR test.

The number of structural holes occupied by an individual at T2 should be positively related to the number of structural holes the individual occupied at T1, because experience with managing brokerage is likely to influence the extent to which individuals are subsequently able to observe, maintain, and fill

5
The coefficients for self-monitoring in models 1 and 2 of table 5 indicate that, controlling for gender, function, tenure, and performance at T1, an increase of one standard deviation in the self-monitoring score is related to an increase in the number of brokerage positions of approximately 40 percent [exp (.59) = 1.8] at T1 and a 34 percent [exp (.52) = 1.68] increase in the number of brokerage positions at T2.

Table 5

Results of Negative Binomial Regression Predicting Brokerage in the Friendship Network at T1 and T2*

Variable	Brokerage at T1 (N = 154)	Brokerage at T2 (N = 149)
Gender	.02	–.04
	(.19)	(.19)
Function = 1	–.65	–.64
	(.37)	(.38)
Function = 2	–.41	–.61
	(.39)	(.36)
Function = 3	.46•	.64•••
	(.18)	(.18)
Function = 4	.86•••	1.17•••
	(.25)	(.26)
Tenure	.01	.01
	(.01)	(.01)
Performance T1	.16	.29••
	(.10)	(.10)
Self-monitoring	.59•••	.52••
	(.17)	(.16)
Pearson χ^2	136.51	177.12
Log likelihood	34620.01	33687.16
Likelihood ratio test†	6.05•••	5.11••

• $p < .05$; •• $p < .01$; ••• $p < .001$.
* Entries represent parameter estimates; standard errors are in parentheses. The intercept and dispersion parameters were included in the negative binomial regression models but are not reported here.
† The likelihood ratio test compares the goodness of fit of the two reported models with respective models with control variables (gender, function, tenure, and performance).

Table 6

Results of Negative Binomial Regression Predicting Brokerage Dynamics in the Friendship Network (N = 124)*

	New Holes		Same Holes		Closed Holes	
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gender	.03	–.01	–.38	–.45	–.46	–.57••
	(.19)	(.16)	(.29)	(.24)	(.26)	(.22)
Function = 1	–.78	–.63	–.53	.07	–.62	–.17
	(.42)	(.37)	(.63)	(.54)	(.62)	(.55)
Function = 2	–.47	–.25	–1.06	–.62	–.21	.24
	(.38)	(.33)	(.60)	(.51)	(.54)	(.47)
Function = 3	.74•••	.73•••	.63•	.82••	1.13•••	1.10•••
	(.20)	(.17)	(.30)	(.26)	(.29)	(.26)
Function = 4	1.41•••	1.20•••	.98•	.33	1.61•••	1.14•••
	(.26)	(.23)	(.41)	(.35)	(.37)	(.32)
Tenure	.01	.00	.01	–.00	.00	–.00
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Performance T1	.27•	.21•	.34•	.36•	.13	.11
	(.11)	(.10)	(.17)	(.15)	(.14)	(.13)
Self-monitoring	.55•••	.35•	.51•	.07	.47	.13
	(.16)	(.14)	(.25)	(.21)	(.24)	(.20)
Brokerage T1		.01•••		.01•••		.01•••
		(.00)		(.00)		(.00)
Pearson χ^2	155.38	154.46	105.95	132.36	130.15	129.09
Log likelihood	18365.34	18384.64	2530.78	2552.35	711.94	734.28
Likelihood ratio test†	5.52•••	19.30•••	2.08•	21.57•••	1.90	22.35•••

• $p < .05$; •• $p < .01$; ••• $p < .001$.
* Entries represent parameter estimates; standard errors are in parentheses. The intercept and dispersion parameters were included in the negative binomial regression models but are not reported here.
† A likelihood ratio test compares the goodness of fit of a model with the previous nested model. Models 1, 3, and 5 are compared with the models with control variables (gender, function, tenure, and performance).

new brokerage opportunities (Burt, 2002; Janicik and Larrick, 2005). To control for these structural effects, we included the number of structural holes occupied by a person at T1 as an additional control in table 6, model 2. The results show that the number of structural holes a person occupied at T1 was a significant predictor of new holes at T2 ($p < .001$). But even after controlling for these significant structural effects, self-monitoring was a significant predictor of the number of new brokerage positions that emerged in an individual's network over time ($p < .05$ in model 2). Thus even controlling for the effects of structural opportunity and possible learning benefits that may arise from occupying bridging positions, high self-monitors were more likely than low self-monitors to occupy new structural holes over time.[6] These results provide strong support for hypothesis 4.

Hypothesis 5 predicted that self-monitoring would be positively related to the rate of formation of new structural holes through gaining new friends. The results of OLS regressions presented in table 7, model 1 show that controlling for gender, function, tenure, and performance, self-monitoring is significantly and positively related to our measure of new holes per new friend ($p < .001$). Self-monitoring in model 1 explains an additional 7 percent of the variance in the number of new holes per new friend in comparison to the model

6
Controlling for gender, function, tenure, performance at T1, and brokerage at T1 in model 2 of table 6, a one-standard-deviation increase in self-monitoring score is related to approximately a 21 percent higher number of new structural holes [exp (.35) = 1.42].

containing only control variables. The results in model 2 of table 7 show that the relationship between self-monitoring and the rate at which new holes were formed remained significant ($p < .01$) even after we controlled for the positive effects of network size on our dependent variable.[7] These results support hypothesis 5.

Dynamics of existing holes. Hypotheses 6a and 6b predicted the effects of self-monitoring on brokerage dynamics for existing holes. We theorized that high self-monitors will tend to occupy the same brokerage positions over time and their structural holes are less likely to close. In total we identified 10,275 structural holes at T1 and 9,904 structural holes at T2. The average person occupied 62 such holes in the friendship network at T1 and almost 61 at T2. Despite the relatively high correlation between our measures of brokerage at T1 and at T2 ($r = .67$; $p < .01$), only 1,369 structural holes were stable. This survival rate of 13.3 percent is comparable to the 10 percent survival rate reported in Burt (2002). Over the nine-month course of the study, 767 of the structural holes at T1 were closed by T2, and 8,535 holes that did not exist at T1 appeared at T2. Although the number of structural holes in the network was about the same over the nine months spanned by our study, these numbers clearly

7
The coefficient of self-monitoring in model 2 of table 7 is equal to 1; hence a one-unit increase in a respondent's score on the self-monitoring scale was expected to lead to one additional structural hole formed per each new friend, a substantial increase compared with the average number of new holes per new friend of 4.96 (see table 1).

Table 7

Results of OLS Regression Predicting Self-Monitoring Differences in the Rate of Structural Hole Formation (N = 123)*

	New Holes per New Friend	
Variable	Model 1	Model 2
Gender	–.16	.60
	(.60)	(.44)
Function = 1	–1.46	.58
	(1.29)	(.96)
Function = 2	–1.46	.06
	(1.14)	(.84)
Function = 3	1.41•	.18
	(.61)	(.46)
Function = 4	3.17•••	1.66••
	(.83)	(.62)
Tenure	.06•	.04
	(.03)	(.02)
Performance T1	.91••	.43
	(.33)	(.24)
Self-monitoring	1.79•••	1.00••
	(.51)	(.38)
Network size T1		.27•••
		(.03)
Model F	6.88•••	23.10•••
F change†	12.42•••	103.37•••
R^2	.33	.65
R^2 change†	.07	.32
Adjusted R^2	.28	.62

• $p < .05$; •• $p < .01$; ••• $p < .001$.
* Entries represent parameter estimates; standard errors are in parentheses. The intercept was included in the OLS regression models but is not reported here.
† F change and R^2 change statistics compare the goodness of fit a model with the previous nested model. Model 1 is compared with the model with control variables (gender, function, tenure, and performance).

indicate that there was also substantial churn in brokerage positions during that period.

Results reported in table 6, model 3 show that self-monitoring was positively associated with occupying the same holes ($p < .05$), though individuals who initially have more structural holes in their networks may be more likely, through chance alone, to retain and close holes over time. Results reported in model 4 show that the effect of self-monitoring on same holes was fully mediated by the number of brokerage positions individuals occupied at T1. Finally, the results reported in model 6 in table 6 show that, controlling for the significant effects of the number of prior structural holes in an individual's network, the individual's self-monitoring personality was not significantly related to hole closure. Overall, these results show weak support for hypothesis 6a and no support for hypothesis 6b.

DISCUSSION

Our study of friendship relations in a radiology department produced evidence of considerable network churn, and we were able to trace the volume, composition, and pattern of this churn to individual differences in self-monitoring personality. High self-monitors were more likely than low self-monitors to attract new friends over time; and whereas the new friends that low self-monitors attracted tended to be friends of their previous friends, the new friends that high self-monitors attracted tended to be relative strangers, unconnected to their previous friends. The influence of self-monitoring personality appeared to extend even to the changing composition of individuals' friendship networks with regard to functional area. Furthermore, not only were high self-monitors more likely to occupy brokerage positions bridging disconnected others in the friendship networks at a given point in time, they were more likely to occupy new brokerage positions over time, a relationship that was significant even after we controlled for the effects of prior job performance and prior occupancy of brokerage positions. The overall picture painted by these results is one of personality shaping the dynamics of individuals' social networks.

Implications for Theory and Research

We found that the relationship between self-monitoring and network brokerage was stable over a period of nine months, but the stability of this relationship did not imply stability in network ties. Although the number of structural holes in the overall friendship network was about the same, some of the structural holes at T1 had been closed by T2 (7.5 percent), some remained open (13 percent), and a number of new structural holes came into existence (86 percent). These results depart from the conventional expectation that workplace friendships will be stable and add to the scant evidence (e.g., Burt, 2002) on the appearance and disappearance of structural holes over time. We found that individual differences in self-monitoring personality were related to the addition of new holes in one's friendship network. The relationship between network brokerage and workplace success may apply across different kinds of people, as prior research has shown (Burt, 2005). But the possibility that different kinds of people may be more likely to gravitate toward different kinds of network structures nonetheless deserves attention if we are to gain a better understanding of how the network structures we inhabit appear to retain their stability even as the ties underlying these structures change over time (cf. Moody, 2002).

Our study shows that apparently stable network forms such as structural holes can emerge through a set of fluid changes in the ties that make up the structures. To capture more fully the fluidity of network relations, we urge researchers to consider additional dimensions of network churn, such as its acceleration and the temporal ordering or sequence of tie changes (Moody, McFarland, and Bender-deMoll, 2005). We examined changes from one network state to another. A more fine-grained understanding of the sequence of interactions that generated this change will require research designs that capture network changes in a more continuous fashion than was possible through the two discrete snapshots of network structure in our study (for a discussion of possible options, see Doreian and Stokman, 2003; Dorogovtsev and Mendes, 2003).

One of the persistent criticisms of social network research has focused on its neglect of human agency (see Kilduff and Brass, 2010). Under the historical influence of structural sociology, organizational network research has largely bypassed the role of individuals in creating the very social networks that constrain their attitudes and behaviors. When network theories have acknowledged the psychology of individuals at all, the tendency has been to assume a generalized individual, best resembling the homo-economicus of neo-classical economics (Burt, 1992). Some have argued that richer psychological theories may be necessary to correct for the overreliance on rational choice models of individual action in social networks (e.g., Kilduff and Krackhardt, 2008; Burt, 2010). We have tried to inject greater agency into network theorizing by explicitly accounting for actors' heterogeneity in terms of individual differences in self-monitoring personality. Future work could build individual differences in self-monitoring into templates for agent-based models (and network theorizing more generally) to provide richer, more realistic explanations of how and why network structures emerge and change over time (cf. Buskens and van de Rijt, 2008; Reagans and Zuckerman, 2008).

The results of our study are consistent with previous cross-sectional work that has shown a link between self-monitoring and the occupancy of brokerage positions in workplace friendship networks (Mehra, Kilduff, and Brass, 2001). Our study shows how self-monitoring influences not just the structure of social networks at a given point in time but also the dynamics that help (re)produce networks over time. Relative to their low self-monitoring counterparts, high self-monitors were more likely to attract new friends who were unconnected with their previous friends and who helped them more efficiently increase the number of brokerage opportunities present in their networks over time. Our research extends previous theorizing by identifying some of the mechanisms that help produce the previously reported correspondence between individuals' self-monitoring orientations and the structure of their social networks.

Our study has emphasized the seemingly natural tendency for people to gravitate toward network structures that fit their personality. Understanding the extent to which such agency is deliberative and goal-oriented rather than routine and habitual will require further study (on the different components of human agency, see Emirbayer and Mische, 1998). What is clear is that theoretical accounts of how social networks influence individual attitudes and behaviors should take more seriously the agentic processes that help shape social networks over time. People may have no control over the situations they are assigned in experimental studies, but they have considerably more latitude in choosing and shaping their social situations in the "real" world. Although the degree of control people exercise over their social networks may be larger than traditionally assumed in network research, we are not suggesting that it is unbounded. Our results show that whereas self-monitoring was positively related to the addition of new structural holes, contrary to expectations, self-monitoring was not related to their maintenance after controlling for the number of structural holes each individual occupied at T1. A broker may wish to maintain a bridge, but the parties being bridged may prefer to close the hole by forging a direct connection with each other. Future work should attempt to model how the potentially competing structural preferences of interacting individuals shape the patterning of social networks over time.

We have emphasized the effects of personality on network dynamics, but we are not suggesting that personality is destiny. One of the practical implications of our study is that it may be worthwhile for organizations to invest in programs to help people better understand and potentially modify their preferred approach to managing social relations. Similarly, to the extent that high self-monitors appear to be natural brokers, it may be useful to train managers to identify individuals in terms of their self-monitoring personality and to use this information in deciding who might be best suited to the task of building desired bridges to help improve the coordination of work (cf. Salancik, 1995).

Whereas the effects of structural holes on performance have been the topic of numerous investigations, the effects of performance on structural holes are rarely studied. Although not the focus of our investigation, we found that workplace performance predicted the occupancy of new brokerage positions nine months later. The direction of causality here seems to run in the opposite direction to that posited in structural holes theory. Rather than superior performance being the result of the information and control advantages of spanning structural holes, it may be that those who exhibit superior performance are better able to leverage their reputational resources to create advantageous social networks. Our results suggest that it is important to understand the mechanisms that generate the distribution of network structures if one is to determine whether performance advantages arise from occupancy of network structures (cf. Lee, 2010).

We analyzed the effects of self-monitoring personality on friendship relations. Unlike workflow or advice relations, friendship in the workplace is relatively discretionary and is therefore likely to reflect the effects of individual personality. There is evidence that high self-monitors are more likely to be sought out for advice (Flynn et al., 2006). But the relationship between self-monitoring and brokerage dynamics in such instrumental relations is unclear. Individuals may think more strategically about their advice relations than they do about their friendship relations at work. Low self-monitors may be more willing to forge and dissolve their advice relations (as compared with their friendship relations) to achieve instrumental goals, even if this requires them to act in ways that are incongruent with their natural dispositions. Future work should examine the effects of self-monitoring on brokerage across a broader set of workplace relations.

We have examined the effects of personality differences on the structure and dynamics of brokerage in friendship networks within a work organization. Future work, drawing inspiration and ideas from the strategic choice (Child, 1972) and upper echelons (Hambrick and Mason, 1984; see Hambrick, 2005, for a review) perspectives, could examine how the self-monitoring personalities of powerful corporate officers influence the structure and dynamics of their firms' networks. Given the evidence for a chief executive officer's (CEO's) personality shaping firm-level strategic action (e.g., Chatterjee and Hambrick, 2007; Nadkarni and Herrmann, 2010), the self-monitoring personality of CEOs may be especially relevant for understanding the volume, composition, and patterning of alliances that a firm enters and disbands over time. Previous work at the organizational level of analysis has emphasized how the existing network of a firm's collaborative ties influences the subsequent ties the firm forms (e.g., Gulati and Gargiulo, 1999; Zaheer and Soda, 2009). We encourage researchers studying interfirm networks to supplement this structural logic by considering the possible effects of psychological differences in CEO personality on the dynamics of interorganizational networks.

Our study has deliberately given more attention to tie generation than to tie dissolution because self-monitoring theory offers a clearer rationale for the former than the latter. Network churn, however, involves not just the generation of new ties but also their dissolution over time. Although published data on tie dissolution in organizations are rare, a study of employees in the investment banking division of a large financial organization (Burt, 2000) found that the pattern of decay in social network ties was similar to that predicted by the "liability of newness" mechanism posited by the theory of population ecology (Stinchcombe, 1965; Hannan and Freeman, 1989). Decay was a power function of time in which the probability of decay decreased with the years that a relationship had existed. It could be that this structural tendency is moderated by self-monitoring personality, a possibility we could not test in this study because we lacked data on the length of time that a relationship had been in existence. A fuller appreciation of how self-monitoring is related to network churn will require richer temporal data on relationships.

A potential limitation of our study was our exclusive focus on the self-monitoring theory of personality. We focused on self-monitoring because it is a theory of expressive control and impression management—skills that are important for brokerage in social networks. It may be that other measures of personality are useful for predicting other aspects of network structure (e.g., Klein et al., 2004) and dynamics. For example, measures of "entrepreneurial personality" (Burt, Jannotta, and Mahoney, 1998) could be relevant for predicting the strategic dissolution of ties because, unlike high self-monitors, such individuals are less concerned with preserving a friendly image than with strategically maximizing the possibilities for control available through brokerage, even if this means dissolving ties. There are concerns that the number of measures of personality one must consider is large (e.g., Burt, 2010: 224), but the number of measures of network structure that are available for use is also large (and expanding). We believe that clear theory is necessary to guide decisions about which variables—whether these are personality variables or network variables—are likely to be relevant in the pursuit of specific research questions (cf. Kilduff and Brass, 2010).

The organization we examined in this study was located in the Netherlands. The fact that our longitudinal results were consistent with previous results from a North American sample enhances confidence in our results. Yet it is possible that had we selected for study an organization located in a country with vastly different views about the relative desirability of brokerage in friendship networks—or had we selected an organization with a vastly different normative culture, irrespective of the country in which it was located—our results may have been different (cf. Emirbayer and Goodwin, 1994; Pachucki and Breiger, 2010). In contexts that emphasize the desirability of network closure, high self-monitors, given their greater sensitivity to normative expectations, may prefer closed networks (cf. Xiao and Tsui, 2007). High self-monitors may also prefer closed networks in contexts in which value and influence are generated through the closing of holes (e.g., Simmel, 1950: 145–162; Coleman, 1990: 175–196; Brass, 2009). Future work using diverse organizational samples is needed to better understand the boundary conditions of the relationship between self-monitoring personality and brokerage dynamics.

Social network research has been preoccupied with demonstrating that the structure of social networks powerfully influences important outcomes, such as workplace performance and career success (Borgatti et al., 2009). This almost exclusive focus on outcomes has meant that the origins and dynamics of social networks have received comparatively little attention. In this study, we have not focused on the effects of network structure on individuals but on the effects of individuals on network structure. Building on the idea that individuals inhabit social structures that reflect their conceptions of self, our study has suggested that the etiology and dynamics of churn in workplace friendship networks are rooted in individual differences in self-monitoring personality. By helping shape the characteristics of their social networks over time, individuals help determine which structures have an opportunity to influence their behaviors. To understand a person's behaviors and attitudes as a function of their social networks is to provide but a partial and potentially misleading picture because social networks are themselves shaped and sustained through individual action. The more we are able to move away from static conceptions of networks and toward an appreciation of the rule-governed pattern of changes in networks over time, the closer we will be to understanding the processes responsible for the effects of social networks in organizations.

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APPENDIX

We used the following procedures to compute the measures for same holes, closed holes, and new holes:

1. *Same holes* denote the number of brokerage positions that remained the same at T1 and at T2. We calculated the number of times A occupied a brokerage position between B and C at both T1 and T2, using the following formula:

$$Y_1 = \left((X_1.X_2)^T \, x \left(\bar{X}_1^{S\max}.\bar{X}_2^{S\max}\right)\right).(X_1.X_2)^T$$

Where

X_1 and X_2 denote the adjacency matrices for the friendship network at T1 and T2;
"." denotes an elementwise multiplication;
"x" denotes a product of matrices;
"^{T}" denotes a transpose of a matrix;
"^{Smax}" symmetrization using the maximum rule;
and "$^{-}$" matrix manipulation where no ties are coded as 1 and reported ties as 0.

Elementwise multiplication of the adjacency matrices and transposing the resulting matrix ensured that ego had the same pair of incoming friendship ties at T1 and T2. Symmetrization using the rule that there is a tie between two alters if either of them reported it, recoding no ties as 1 at both T1 and T2, and then computing the product of resulting matrices, which was on a final step multiplied cell by cell by the transposed matrix ensured that there were no ties between ego's pair of alters. The number of *same holes* was then calculated as a row sum of matrix Y_1 divided by two, because the procedure counted no tie from B to C and no tie from C to B as two occurrences of a structural hole.

2. *Closed holes* are brokerage positions that have been closed over time: A brokered between B and C at T1, but at T2 there was either a friendship tie from B to C or a friendship tie from C to B or both. We first counted a raw number of such occurrences. More specifically, we calculated the number of ties between alters at T2 for which there were structural holes at T1 as a row sum of matrix Y_2 using the following formula:

$$Y_2 = \left((X_1.X_2)^T \, x \left(\bar{X}_1^{S\max}.X_2\right)\right).(X_1.X_2)^T$$

Where

X_1 and X_2 denote the adjacency matrices for the friendship network at T1 and T2;
"." denotes an elementwise multiplication;
"x" denotes a product of matrices;
"^{T}" denotes a transpose of a matrix;
"^{Smax}" symmetrization using the maximum rule;
and "$^{-}$" matrix manipulation where no ties are coded as 1 and reported ties as 0.

As in the measure of same holes, elementwise multiplication of the adjacency matrices and transposing the resulting matrix ensured that ego had the same pair of incoming friendship ties at T1 and at T2. Symmetrization and recoding of no ties as 1 in the adjacency matrix at T1, then multiplying cell by cell with the adjacency matrix at T2 (resulting matrix contains new ties), and subsequently computing the product of the resulting matrices ensured that there was no tie between ego's pair of alters at T1, and a tie appeared (in either direction) between the same pair of alters at T2. Because this procedure counts each tie between a pair of alters separately, if there are ties in both directions (from B to C and from C to B), they would be counted as two separate occurrences of *closed holes*. To correct for this, we computed the number of times a hole was closed with a bidirectional tie between B and C, using the following formula, which is similar to the formula described above, with the exception that the adjacency matrix at T2 is first symmetrized using the minimum rule to count only ties between alters that were in both directions at T2 and that did not exist at T1:

$$Y_3 = \left((X_1.X_2)^T \, x \left(\bar{X}_1^{S\max}.X_2^{S\min}\right)\right).(X_1.X_2)^T$$

Where

X_1 and X_2 denote the adjacency matrices for the friendship network at T1 and T2;
"." denotes an elementwise multiplication;
"x" denotes a product of matrices;
"^{T}" denotes a transpose of a matrix;
"^{Smax}" symmetrization using the maximum rule;
"^{Smin}" symmetrization using the minimum rule;
and "$^{-}$" matrix manipulation where no ties are coded as 1 and reported ties as 0.

Finally the number of *closed holes* was computed by subtracting the row sum of Y_3 divided by two (because a tie from B to C and a tie from C to B at T2 were counted separately) from the row sum of Y_2.

3. *New holes* are structural holes, defined in the same way as above (a friendship tie from B to A and from C to A, and no friendship tie between B and C), but in which at T2 a person A brokers between a different pair of alters than at T1. This measure was computed by subtracting the number of same holes between T1 and T2 from the number of structural holes counted at T2.

4. *Opened holes* are a subset of new holes that developed in a specific way: at T1 there was a closed triad (a friendship tie from B to A and from C to A, and a friendship tie between B and C). At T2 there was no friendship tie between B and C, while the ties from B to A and C to A remained unchanged, leaving an open structural hole. We calculated the number of structural holes that developed in this way as a row sum of matrix Y_4 using the following formula:

$$Y_4 = \left(\left(X_1 . X_2 \right)^T x \left(X_1 . \bar{X}_2^{\,S\max} \right) \right) . \left(X_1 . X_2 \right)^T$$

Where

X_1 and X_2 denote the adjacency matrices for the friendship network at T1 and T2;
"." denotes an elementwise multiplication;
"x" denotes a product of matrices;
"^{T}" denotes a transpose of a matrix;
"^{Smax}" symmetrization using the maximum rule;
and "$^{-}$" matrix manipulation where no ties are coded as 1 and reported ties as 0.

As in the measures of same and closed holes above, elementwise multiplication of the adjacency matrices and transposing the resulting matrix ensured that ego had the same pair of incoming friendship ties at T1 and at T2. Symmetrization and recoding of no ties as 1 in the adjacency matrix at T2, then multiplying cell by cell with the adjacency matrix at T1 (resulting matrix contains lost ties), and subsequently computing the product of the resulting matrices ensured that there was a tie between ego's pair of alters at T1 and that tie disappeared between the same pair of alters at T2.

The number of *opened holes* needs to be subtracted from the number of *new holes* when we want to investigate the net effects on the number of ego's structural holes of adding a new alter.