Collaborative Brokerage, Generative Creativity, and Creative Success

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Analyzing data on utility patents from 1975 to 2002 in the careers of 35,400 collaborative inventors, this study examines the influence of brokered versus cohesive collaborative social structures on an individual's creativity. We test the hypothesis that brokerage—direct ties to collaborators who themselves do not have direct ties to each other—leads to greater collaborative creativity. We then test interaction hypotheses on the marginal benefits of cohesion, when collaborators have independent ties between themselves that do not include the individual. We identify the moderators of brokerage and argue for contingent benefits, based on the interaction of structure with the attributes, career experiences, and extended networks of individuals and their collaborators. Using a social definition of creative success, we also trace the development of creative ideas from their generation through future use by others. We test the hypothesis that brokered ideas are less likely to be used in future creative efforts. The results illustrate how collaborative brokerage can aid in the generation of an idea but then hamper its diffusion and use by others.●

Although social interaction is generally thought to enhance creativity (Sutton and Hargadon, 1996; Leonard and Swap, 1999; Paulus and Nijstad, 2003; McFadyen and Cannella, 2004), there is still controversy over the optimal structure of that social interaction and, in particular, over the relative creative benefits of brokerage between otherwise disconnected people and a cohesive social structure in which most people have direct ties to each of the others in the network (Brass, 1995; Hargadon and Sutton, 1997; Burt, 2004; Obstfeld, 2005; McEvily and Reagans, 2005; Uzzi and Spiro, 2005). A broker occupies the sole intermediate position between others, such that others can interact only through the broker. Proponents of brokerage argue for the benefits of information control and first access to knowledge and opportunities to recombine ideas (Burt, 2004). Proponents of cohesion argue for the benefits of trust, redundant information paths, shared risk taking, and easier mobilization (Uzzi and Spiro, 2005; Obstfeld, 2005). A variety of results have been found supporting both arguments, and the controversy remains theoretically and empirically open. One reason for the failure to resolve the controversy may be that most previous studies have typically focused on the structure in which social interaction takes place, with little attention to the personal attributes of the collaborators. A second reason may be the focus on only one stage of creativity and, in particular, a failure to differentiate between the initial creative insight and the ultimate social acceptance and success of that insight.

Developing a social definition of creative success and tracing the development of creative ideas from their generation through future use by others should make it possible to reconcile previous divergent findings. The effects of brokerage on generating the initial insight are likely to depend on the interaction of structure with the personal attributes, career experiences, and extended networks of individuals and their collaborators. The effects of brokerage will also extend beyond the initial insight and influence whether the insight gains acceptance beyond the social structure in which it was

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generated. While much research has studied the diffusion of ideas (Rogers, 1995; Hansen, 1999; Singh, 2005) and some research has studied their generation (Campbell, 1960; Burt, 2004), none has considered these phenomena jointly and explained how the structure inherent at conception will influence the future diffusion and use of an idea. We used patent data from 1975 to 2002 to examine the career histories of 35,400 collaborative inventors to determine how brokerage and cohesion affected the generation of novel subclass combinations and future use of those novel combinations.

THE EFFECTS OF BROKERAGE AND COHESION ON COLLABORATIVE CREATIVITY

Although research on creativity has traditionally been the province of psychologists (Ford, 1996), sociologists have recently joined the discussion. Sociologists agree on the importance of social structure for creativity but disagree on the relative creative benefits of opposite types of collaborative social structures: collaboration in a cohesive network, in which most individuals have direct ties to each other, or brokered collaboration, in which one person links two or more others who have no direct ties to each other. Proponents of cohesion usually build on Coleman's (1988) conception of social capital, that closed social structures engender greater trust among individuals (Uzzi, 1997; Reagans and McEvily, 2003; Uzzi and Spiro, 2005). Cohesion occurs when individuals have dense and overlapping ties with each other. For example, if actor A has ties with actors B and C, the lack of a tie between B and C would constitute an open network; a tie between B and C would make it a closed network. Cohesion enables individuals to act collectively (B and C in this example), making it easier to detect and punish undesirable behavior, which in turn makes it easier for group members to develop group norms and to trust each other.

Coleman's (1988) arguments imply a variety of benefits for creative collaborators. If closed networks are trusting networks, and if people are more likely to share information and knowledge with those whom they trust, then closed networks will promote better information flow than open networks will. Because creative efforts generally benefit from new information, better information flow should enhance creativity (Milliken, Bartel, and Kurtzberg, 2003). Closed ties also facilitate the exchange of fine-grained information, which tends to be tacit, complex, or proprietary (Uzzi, 1997; Hansen, 1999; Reagans and McEvily, 2003). Non-information resources also flow more easily between people who, because they trust each other, have less fear of theft or damage and a greater expectation of repayment or reciprocity. Finally, trust facilitates positive affect, learning, and risk taking, all considered to be crucial components of creativity (Milliken, Bartel, and Kurtzberg, 2003; Amabile et al., 2005). For example, a person who proposes a truly creative idea runs a significant risk of ridicule; most people will take such a risk only within a supportive social context (Edmondson, 1999).

While proponents of cohesion often base their arguments on Coleman's model of social capital, proponents of brokerage often build on Granovetter's (1973) concept of the strength of weak ties. The ties within closed networks tend to be strong, in the sense that a person invests a disproportionate share of his or her finite social resources in relationships with a few other people. Thus strong and cohesive networks make connections to dissimilar social circles less likely. In open networks, however, ties tend to be weaker and more likely to connect people with different interests and diverse perspectives. If creativity requires fresh information and new perspectives, then people within open networks will be more creative, assuming that information is freely shared. Brokers occupy the most advantageous position at the nexus of diverse information. In this position, they have the best opportunity to generate new combinations (Brass, 1995; Hargadon and Sutton, 1997; Burt, 2004). And because they occupy a position between two disconnected parties, they can exploit and manipulate the information flow for their own benefit (Burt, 1992; Padgett and Ansell, 1993).

Proponents in both camps have provided substantial supporting evidence. From the cohesive camp, Uzzi (1997), Hansen (1999), and Reagans and McEvily (2003) demonstrated that social cohesion eases information and knowledge transfer for individuals. Obstfeld (2005) found that individuals with cohesive social networks were more likely to report being involved with innovation. At the network level of analysis, Uzzi and Spiro (2005) found that the average cohesion within a network of New York musical collaborations correlates with gate proceeds and critical acclaim for all productions in a given year. From the brokerage camp, much research has found that brokers are the most creative individuals in technical organizations (Allen, 1977; Tushman, 1977; Nerkar and Paruchuri, 2005). Burt (2004) and Rodan and Galunic (2004) also demonstrated that managers who occupy brokerage positions are more often the source of good ideas. At an organizational level of analysis, Hargadon and Sutton (1997) described the advantages of industrial brokering within a design firm that operated between different industries. The widely acclaimed firm routinely took technologies and ideas from one industry and applied them, usually with modification, to another. Given the depth of contradictory results, both camps may be correct, and there is no reason to believe that further studies in the current traditions will yield greater clarity on the issue. Instead, the contradiction may arise from (1) seeking purely structural explanations from the collaborative relationship and (2) treating creativity and its ultimate success as a single outcome rather than an ultimately social process.

Most research on the influence of brokerage has focused on purely structural explanations. For example, previous research that investigated moderators of brokerage has considered the interaction of brokerage with another structural variable, centrality (Nerkar and Paruchuri, 2005). Little research in the controversy has started from the premise that individuals have biographies and experiences and attributes that they bring to their brokered or cohesive collaborations. This unnecessarily narrow structural focus would benefit from a more social-psychological approach that considers the interaction of person and social context. Rather than minimizing or ignoring individual or contextual influences on the phenomenon and seeking all explanation in the structure of collaboration, it would be more productive to embrace such differences and consider how they interact with collaborative structure (in the social-psychological tradition of Woodman, Sawyer, and Griffin, 1993, and Perry-Smith, 2006).

In examining the outcome of creativity, most previous research has focused on a particular stage or treated creative success as the dependent variable. This work includes patent counts or citations (Nerkar and Paruchuri, 2005), involvement in a creative project (Obstfeld, 2005), or managers' evaluations of submitted ideas (Burt, 2004). Some research has developed multiple measures of creativity, such as critical acclaim and financial success (Uzzi and Spiro, 2005), but has observed the measures simultaneously and did not differentiate between them theoretically. Other research has focused less on the creation of knowledge and more on its nature and transfer. This work demonstrates that cohesive networks hamper the search for knowledge but aid in its transfer, particularly if the knowledge is complex and tacit (Hansen, 1999; Reagans and McEvily, 2003). No research, however, has traced the same idea from inception through its ultimate success (or failure to take hold) and identified how the collaborative structure that generated the original idea could have a lasting influence on the idea's ultimate reception. Broadening our conceptions of network structures and creativity by recognizing the role of attributes in social interactions and by treating creativity and its ultimate success as a social process enables us to articulate why one might expect that both cohesion and brokerage can contribute to creativity.

Expanding Structural Explanations of Collaborative Creativity

Creativity defies easy definition (Amabile, 1996). One common theme, however, is the importance of novel combinations or rearrangements of ideas, technologies, processes, military strategies, musical genres, artistic media, and so on. Scientific theorizing, for example, proceeds through combinatorial thought trials (Simonton, 1999), and new technologies can almost always be traced to combinations of prior technologies (Gilfillan, 1970; Nelson and Winter, 1982; Basalla, 1988). Rock-and-roll music is widely thought to have resulted from a fusion of rhythm and blues, folk, country, and gospel music. Languages evolve by concatenating their existing words as well as by borrowing from other languages. Creative individuals have described this combinatorial search process vividly. For example, the mathematician Poincaré (1921: 387) offered this account: "Ideas rose in crowds; I felt them collide until pairs interlocked, so to speak, making a stable combination." Einstein also wrote that "combinatory play seems to be the essential feature in productive thought" (quoted in Simonton, 1999: 29).

If we restrict our consideration of creativity to an initial insight and define this as the assemblage of new combinations, then what we might call generative creativity should be increased by exposure to a wide variety of ideas and components that have not already been combined. This argument is old. Burt (2004: 351) listed previous proponents, including Smith (1982), Mill (1987), Simmel (1955), and Merton (1968). Although exposure to new ideas and components can be increased in a variety of ways, including through reading and education, much, and possibly most exposure occurs through social interactions with other creative people (Katz and Lazarsfeld, 1955; Allen, 1977).

If generative creativity is the assemblage of new combinations, then brokers maintain an advantage because they are ideally positioned to receive new and previously uncombined ideas (Brass, 1995; Hargadon and Sutton, 1997; Burt, 2004). In contrast, collaboration with colleagues who in turn collaborate with one another tends to recycle ideas. Cohesive social structures also increase the possibility of groupthink, so that people will generate fewer new ideas (Hunt, Ogden, and Neale, 2003). If brokerage correlates with weaker ties, and if weaker ties provide non-redundant information that enhances generative creativity, then people who broker relations between their collaborators should generate more new combinations.

Hypothesis 1 (H1): A person is more likely to create new combinations if he or she brokers relations between otherwise disconnected collaborators.

In contrast, cohesion may lead to fewer new combinations than brokerage does, but it may foster creativity in other ways. First, cohesion should correlate with greater trust, if closed networks make it easier to sanction undesirable behavior (Coleman, 1988). In turn, this trust encourages the sharing of information and resources. Second, cohesion leads to better information flow because of the lateral, redundant, and often strong ties within closed networks (Hansen, 1999; Reagans and McEvily, 2003). In turn, this better information flow accelerates the sharing of ideas and feedback, which enhances creativity (Milliken, Bartel, and Kurtzberg, 2003). A variety of research sites, data, and types of evidence support these arguments. Using ethnographic methods, Uzzi (1997) documented how cohesive networks supported richer information flows among New York garment designers and manufacturers. Hansen (1999) and Reagans and McEvily (2003) surveyed research and development engineers and demonstrated that strong ties ease information and knowledge transfer, particularly for tacit and complex knowledge that is difficult to transmit. Though this evidence seems to be contrary to the brokerage arguments of hypothesis 1, the apparent discrepancy can be reconciled by considering the marginal benefits of cohesion in situations of decreased trust and less redundant information.

Even for a particular individual, the benefits of a particular structural position can change over time. As people progress in their careers, some will gather a more diverse array of experiences, ideas, media, technologies, and processes and will bring that knowledge to future collaborations. Describing the creative process at IDEO, a design consulting firm, Hargadon and Sutton (1997: 731) noted that "each engineer has a distinct body of technological knowledge from working with IDEO clients, from past technical training and work experience, and from his or her personal interests and backgrounds. The role this diverse knowledge plays in creating new products is evident." The breadth of people's personal information and experience can counteract the staleness of cohesive networks, which tend to recycle information. In fact, the freer and wider flow of communication in cohesive networks becomes an advantage to the focal individual who brings wide experience because it enables quicker distribution and exploration of opportunities to recombine information. These opportunities arise from the diffusion of ideas in both directions, from the focal individual to his or her collaborators and back again. This breadth of diversity in personal experience should decrease the marginal value of brokerage because the focal actor brings fresh information to the collaborative structure.

Hypothesis 2a (H2a): A person is more likely to create new combinations within a cohesive collaborative structure if he or she brings broad experience to the collaboration.

Just as the focal actor can bring the benefits of non-redundant information to his or her collaborators, so can they bring the benefits of non-redundant information to him or her. Collaborators with greater breadth of experience will confer a marginal benefit to the focal actor because they bring non-redundant information and broader backgrounds to the collective effort and because cohesive groups will diffuse this information more easily. As argued above, this diffusion occurs because (1) collaborators in cohesive networks should develop greater trust, which will facilitate sharing, and (2) the lateral and redundant ties in cohesive networks will transfer information more easily.

Hypothesis 2b (H2b): A person is more likely to create new combinations within a cohesive collaborative structure if his or her collaborators bring broader experience to the collaboration.

The diversity of one's organizational experience and past employers should also increase the marginal benefits of a position in a cohesive collaborative structure. Individuals who have worked in a variety of organizations will bring a greater diversity of ideas, perspectives, assumptions, creative techniques, and other relationships to the collaboration than those who have worked in few (McEvily and Zaheer, 1999); this diversity will counteract the insulating tendencies of cohesion. Such individuals will also benefit from a locally cohesive structure if they are not trusted by their immediate collaborators, for example, if a person has recently changed jobs and is collaborating with people he or she has only recently met. An employee with a reputation for frequent job changes may have an especially hard time gaining colleagues' trust. Professional and temporary contractors, in particular, face problems in being accepted by their coworkers (Barley and Kunda, 2004). The non-redundant information such mobile employees would naturally bring to the collaboration will be of less value unless their social isolation is ameliorated by collaboration within a locally cohesive structure. Such cohesion will facilitate trust and information flow and make it comparatively easy to share information widely.

Hypothesis 2c (H2c): A person is more likely to create new combinations within a cohesive collaborative structure if he or she has recently worked for multiple organizations.

A focal person also benefits from his or her collaborators' external collaborations, mostly because they provide social access to recent, salient, and non-redundant information. Such relationships provide a weak-tie informational benefit that can counteract the insularity problems of cohesion (Granovetter, 1973). At the same time, cohesion facilitates the interpretation of external information and keeps the group focused in the face of external relationships and distractions. When external ties take social resources away from immediate collaborators, a cohesive structure will soothe the difficulties caused by such divided loyalties. This combination of cohesive internal ties and external bridging ties generates the advantage of a "small world" network (Uzzi and Spiro, 2005; Schilling and Phelps, 2007). The argument is not new, but it has been previously framed from the perspective of gatekeepers and teams (Allen, 1977; Tushman, 1978; Reagans and Zuckerman, 2001; Barley and Kunda, 2004; Perry-Smith, 2006) or macro networks (Uzzi and Spiro, 2005; Schilling and Phelps, 2007), rather than from the perspective of an individual who collaborates with others who in turn have external ties. A person whose collaborators have external ties will benefit more if his or her internal network ties are cohesive.

Hypothesis 2d (H2d): A person is more likely to create new combinations within a cohesive collaborative structure if his or her collaborators work with external colleagues.

How the Collaborative Structure That Generates an Idea Influences Its Diffusion and Future Use

Proponents of cohesion raise another argument against the benefits of brokerage for creativity, objecting that brokered structures hamper the development of a creative idea. They argue that it is easier to mobilize people and resources in a cohesive network (Gould, 1991), in which there is greater trust, easier information transfer, and already functioning norms and processes of collaboration. Lacking these advantages for its development, creativity within brokered networks is less likely to succeed. Supporting the arguments that cohesion leads to success, Obstfeld (2005) demonstrated a positive correlation between cohesive network positions and involvement with successful product development, using both ethnographic and survey methods. Uzzi and Spiro (2005) also demonstrated a correlation between cohesive networks and successful musical productions in those networks.

Evidence of a correlation between cohesive networks and creative success can be reconciled with the brokerage arguments of hypothesis 1 if we consider that different creative ideas may have different requirements for implementation. Following the arguments advanced above, if development challenges require more implementation and less creativity, they may benefit from placement in a more cohesive network, even if challenges requiring continued creative insights might benefit from maintaining a more open network. The evidence for the benefits of cohesion, however, may reflect reverse causality and survivor bias—development efforts may themselves lead to the construction of cohesive networks around an idea. As a result, it remains unclear whether the positive relationship between cohesion and success results from development or from the cohesive structure in the original collaboration. The implication is that cohesion in development may actually have little influence on success; instead, the collaborative structure at conception may exert the strongest influence on ultimate success or failure.

Developing this argument on the benefits of brokerage or cohesion requires elaborating the definitions of creativity and creative success. We begin with an early and still widely used definition of creativity: "novel work that is accepted as tenable or useful or satisfying by a group at some point in time" (Stein, 1963: 218; see also Amabile, 1996: 35). We agree with this definition and, as proposed above, also believe that novelty is best identified as a new combination. Following early arguments (Osborn, 1957), however, we separate novelty and usefulness, both theoretically and empirically. A clear separation of novelty and usefulness motivates distinct theories for both and avoids the ex ante selection bias of identifying and studying only successful ideas. It also enables us to formulate a more social and ultimately more accurate conception of usefulness. Because usefulness is a subjective evaluation rather than an invariant property of creative work, creative success is best measured by its reception (Gardner, 1993; Kasof, 1995). Creative individuals can incorporate their own prior work, but their influence will be limited unless others also pick up and build on their ideas. Much social-psychological and even psychological research argues for a social definition of creative success. Csikszentmihalyi (1999: 14), for example, stated that creativity "is not the product of single individuals, but of social systems making judgments about individuals' products." Simonton (1999: 5) proposed that success is best identified by incorporation of the creative product in the wider culture, and an artist, inventor, or scientist will rarely be thought creative until society as a whole and other creative people in particular recognize and use his or her work; for Simonton, "unrecognized genius becomes an oxymoron" (see also Basalla, 1988). Based on these definitions, we propose that generative creativity arising from a brokerage position will be put to use less often than creativity arising from a cohesive position, for reasons of less distributed understanding, less mutual ownership, and slower diffusion.

Given the emergence of a new idea from a collaborative effort, a cohesive collaboration should have created a more distributed understanding of it than a brokered collaboration. Because information flows more freely and redundantly in a cohesive structure, more collaborators in such a social structure will acquire more complete information about the creative work. Creative processes themselves will be more distributed because collaborators will engage one another without the focal broker. In a brokered collaboration, the broker is the only person to recombine the disparate pieces of knowledge together with the opportunity to do so, but in a cohesive collaboration, more individuals are privy to the components, opportunities, and insightful combinations. As a result, each collaborator will probably have contributed a greater portion of the creativity than would have been the case in a brokered collaboration.

Not only do cohesive collaborations create more widely dispersed knowledge, but the collaborators themselves perceive greater mutual ownership of the seminal combination (Burt, 2004) and worry less about "stealing" another's idea. A sense of group ownership makes it more likely that collaborators will adopt the idea and use it in the future. In contrast, brokered collaborators are much more reluctant to build on an idea when it is clearly identified with the broker. This argument should hold for colleagues who collaborated directly on the new combination and for those who were concurrently collaborating on other projects as well. For example, if a person was simultaneously pursuing two separate collaborations and the first of them created a new combination, both groups would be more likely to use that combination in the future, to the extent that the first group worked in a cohesive collaboration.

Finally, new combinations arising from cohesive structures are more likely to be used again because they will diffuse more easily and widely (Hansen, 1999; Reagans and McEvily, 2003). Just as brokerage confines and restricts the inward flow of new information through a single node, it will also confine and restrict the outward flow of recombinant results. The broker will be the only source of complete knowledge and understanding of the new combination, in contrast to the multiple sources found in a distributed and cohesive effort. People who collaborate with a central broker are more likely to differ in their domain and experience backgrounds; they will therefore have a harder time appreciating and understanding at least one component of the new combination (Cohen and Levinthal, 1990; Obstfeld, 2005). As a result, and even though a broker may be better placed to distribute new ideas to a greater number of domains, the difficulty of moving ideas across domain boundaries will hamper the distributional advantages of brokering (Sorenson and Fleming, 2004). Diffusion will also be impeded by uncertainty about the broker's reputation. As Coleman (1988) argued, reputation can't arise within an open structure. Cohesion among collaborators will facilitate the development and diffusion of an individual's reputation, but a broker's reputation, whether positive or negative, will remain less certain. Increased uncertainty will increase the risk others perceive in adopting ideas that come through a broker and thus will slow the diffusion of those ideas. For these three reasons—more distributed understanding, more distributed ownership, and easier diffusion—new combinations that arise from cohesive collaborations will be used more in the future.

Hypothesis 3 (H3): A person's new combinations are more likely to be used again if they arise from a cohesive collaborative structure.

METHODS

Data

Most previous empirical research on brokerage and creativity has used field methods and surveys (Hargadon and Sutton, 1997; Burt, 2004; Obstfeld, 2005; McEvily and Reagans, 2005; Perry-Smith, 2006). Testing our theory, however, requires us to observe the first time a new combination occurs, followed by all subsequent uses. This would be extremely difficult with field methods because of the time required to observe use and the possibility that participants might change their behavior because they were aware that prior generative creativity was being tracked. These issues would be compounded by the need for a large enough number of observations to generate enough statistical power needed to test hypotheses. To accommodate these empirical demands, we tested our hypotheses with patent data, which allowed us to observe both the social collaborative structure that gave rise to a new combination and the subsequent use of that combination. Archival data such as patents have their drawbacks (discussed below), but they enable us to model thousands of collaborations, new combinations, and the use of those combinations.

The raw data for the analyses come from all U.S. utility patents granted from 1975 to July 2002, inclusive (Hall, Jaffe, and Trajtenberg, 2001), listed in the 2002 United States Patent and Trademark Office bibliography. A utility patent is a patent that protects a new and useful process, machine, manufactured item, or combination of materials. Almost all U.S. patents are utility patents, while a small number are design patents, which protect a new, original and ornamental design for a manufactured item, or plant patents, which protect a distinct and new variety of plant. Most social science research that uses patents only uses utility patents. Each patent record contains the patent number, the date of application and grant, all inventors' last names (with varying information on first and middle names or initials) and home towns, detailed information about the patent's technology in class and subclass references (there are over 100,000 subclasses), and the owner or assignee of the patent, generally a firm, and less often a university or government, if not owned by the inventor. Because inventors are not uniquely identified (patents by the same person often appear under different combinations of initials and names, and there can be multiple inventors with the same name), we developed and applied an inventor-matching algorithm to determine each inventor's patents and other inventors with whom the focal inventor had coauthored, as detailed in Appendix A.

We split the data into three-year periods for each inventor's career. Adopting a career unit of analysis enabled us to take better account of all collaborative and contextual influences on creativity during each period. Similar archival approaches have used five-year windows (McFadyen and Cannella, 2004), but we found no substantive differences for window size and chose the smaller size to maximize observations. The models analyzed nine non-overlapping windows: 1975–1977, 1978–1980, 1981–1983, 1984–1986, 1987–1989, 1990–1992, 1993–1995, and 1996–1998. We did not use patents applied for after 1998 because the grant date can lag the application date by many years and result in missed observations. In addition, the newly generated combinations need time to be observed. Permutations of those windows, for example, considering the set of windows that begins with 1976–1978 rather than 1975–1977, did not change the results. All variables were calculated by patent application date because the time lag between patent application and grant dates are variable; calculating by the application date offers the most accurate measure of the inventive context. The data base includes 2,058,823 inventor career-period observations and 2,862,967 patents. Approximately half the inventors resided outside the U.S. and were not considered because foreign names and inconsistent address data made it difficult to identify them uniquely. Approximately half the inventors also did not work with two or more collaborators and thus did not have an opportunity to broker collaborations.

We took a random sample of inventors' careers, sampling entire careers rather than three-year windows or individual patents, to avoid network autocorrelation. Network autocorrelation is a problem because many variables are the same for a set of collaborating inventors, for example, the number of their patents and collaborators, the nature of their organization (firm or university), or the age of their technology. Hence, observations of collaborators will be dependent. Because this violates the most basic assumption of independent observations in statistical estimations, we sampled 10 percent of our population, which resulted in 53,570 observations of 35,400 inventors. Sampling makes it much less likely that connected and statistically dependent inventors will be included together in the estimation. As a result, it avoids overestimating the degrees of freedom and thus producing spuriously high *p* values, rendering our estimates more accurate and conservative.

Dependent Variables

New combinations. The U.S. Patent Office organizes all technology into approximately 100,000 categories and periodically updates and reorganizes the subclasses for all patents back to the system's founding in 1790. We used the 2004 concordance. The models use the number of new subclass pairs within each of a focal inventor's patents as a measure of generative creativity. To calculate the measure, we stepped through the assignments and identified the first appearance of a previously uncombined pair of subclasses. We then summed this indicator measure for all patents during each three-year window of the focal inventor's career.

Uses of the combination. The second dependent variable counts how many times other inventors used the focal inventor's new combinations. When a new combination is used twice within a single three-year window, only the first use is counted as a new combination; the second adds to the uses variable. Appendix B describes subclass combinations and the dependent measures in greater detail.

Explanatory Variables

Cohesion. We measured the cohesion of the focal inventor's network by calculating a density measure of the ties between each of the others in the focal inventor's network (Podolny and Baron, 1997; Obstfeld, 2005). We calculated density as the unique number of pairwise collaborations between a focal inventor's collaborators that did not include the focal inventor, divided by the total possible pairwise collaborations. For bibliographic data such as patents, this includes all of the unique pairwise relationships from collaborators' patents that did not include the focal inventor in the three-year time period. The unit of analysis is not individual patents, and the design does not model the cohesion of inventors who coauthor a single patent. As with any bipartite grouping, coauthors of a single patent have a cohesive relationship by definition (see Uzzi and Spiro, 2005). The data show that most individuals broker their collaborative relationships: 67 percent of the observations indicate no relationships between the other collaborators, and 63 percent of the individuals never patent in cohesive collaborations. Because of the preponderance of values at zero, for brokerage, we did not center the variable for interpretation of interactions, though the substantive results are unchanged if we do.

Focal inventor's experience. We calculated the ln of the number of unique subclasses in which the focal inventor had worked prior to the current time period, which controls for the breadth of experience that the inventor brings to the creative effort.[1] We predicted in H2a that the interaction of cohesion and the focal inventor's experience would be positive. To measure *collaborators' experience,* we calculated the ln of the number of unique subclasses in which the focal inventor's collaborators had worked prior to the current time period. We predicted in H2b that the interaction of cohesion and collaborators' experience would be positive.

Assignees. The models include the ln of the number of assignees that appear in the inventor's patents over the three-year time period. This indicates whether or not the inventor has worked in multiple firms over the time period. Hypothesis 2c would predict a positive interaction of multiple assignees and cohesion.

External ties. The models include the ln of the number of external ties to a focal inventor's collaborators. External ties are ties to the focal inventor's collaborators who do not have a direct tie to the focal inventor. We predicted in H2d that the interaction between cohesion and external ties would be positive. As illustrated below, we found a strong and increasingly non-monotonic relationship for the external ties variable by itself and hence included a second-order term.

Control Variables

The models include the ln of the number of patents by the inventor during the three-year window, because prolific inventors should create more new combinations and their work should be used more often in the future. To control for the size of the inventor's larger extended network, the models also include the ln of the number of inventors in the inventor's direct and indirect collaborative network *(ln of component network size).* Larger networks should increase the probability of use, due to easier diffusion along social paths (Singh, 2005). We also controlled for the ln of the number of new subclasses in the inventor's patents *(ln of new subclasses).* The number of new combinations variable only counts new combinations; that is, a new subclass by itself does not

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All count variables were logged because the models enter the variable as an exponent to avoid predicting negative counts (logging undoes this exponentiation); 0.01 was added before the transformation to avoid taking the log normal of a zero value (other offset values demonstrated similar results).

constitute a new combination (the results are insensitive to the inclusion of the control variable). Yet the appearance of a new subclass obviously increases the opportunities for new subclass pairs.

The generative models include the ln of the number of new subclass pairs *(ln of potentially new subclass pairs)* that an inventor might create, given the set of subclass pairs that he or she works with in a given time period. We calculated this variable as the total possible number of subclass pairs, minus the number of those subclass pairs that have been combined previously by any inventor in the history of U.S. patents. The variable essentially controls for the combinatorial space and potential creativity of the inventor's component set. If an inventor only works in one subclass (1.8 percent of the data), this control takes on a zero value. This control is most important for inventors who work at the boundaries of technological communities. Such inventors probably invent more new combinations, simply because they are working in a much more fertile space with components that have never been previously combined. Including this control enables us to identify a separate effect for social brokerage (the experience and experience overlap controls further sharpen this identification).

Prior art age. The models include the average of the patent numbers that the inventor cites as patent prior art. Because patents are numbered sequentially, this measure correlates very strongly with age—smaller values of this number indicate that the inventor is citing and working with older technologies, on average. Older technologies are probably more well known and less fertile. Inventors who lacked any prior art cites were given an average value of the variable, zero, or were dropped; no modeling assumption changed the substantive results. We divided the number by one million to avoid excessively small coefficients. Patent citation data enter the regressions only as part of the calculation of the technology age control; the models never enter citation counts or use the number of citations as a measure for use or creativity.

Non-patent references. The models include the ln of the number of non-patent references made by the inventor's patents. Most of these references are to peer-reviewed science and can be interpreted as an awareness of the scientific literature. The scientific literature makes the search process less random (particularly with interdependent components), identifies new components (Fleming and Sorenson, 2004), and enables faster diffusion of technical knowledge across organizational, technological, and geographic boundaries (Sorenson and Fleming, 2004). This variable should also control for the tacitness and codification of knowledge within the collaboration (Hansen, 1999). We also controlled for the ln of the number of the inventor's patents assigned to a university *(ln of university patents)* because the collaborative structure in university labs likely differs from that in private firms. For example, a professor might work individually with a variety of students, a position similar to brokering. To control for any greater or lesser creativity as a result of collaborating with inventors from similar or dissimilar backgrounds, the models include the ln of the number of subclasses in common between the focal inventor's breadth of experience variable and the collaborators' breadth of experience variable *(ln of similar prior subclasses).*

Because personnel turnover in groups has both positive and negative effects on creativity (Argote and Kane, 2003; Levine, Choi, and Moreland, 2003), the models include the number of current collaborators with whom the focal inventor has worked previously, divided by the total number of collaborators *(repeated collaboration ratio).* The models include the ln of the number of unique inventors with whom the focal inventor collaborates over the time period. The variable has a minimum of two collaborators, given that brokerage requires at least two other collaborators *(degree of collaboration).* The models include a count of repeated collaborative ties, divided by the number of unique ties *(strength of direct ties).* With archival publication data such as patents and papers, multiple collaborations are not unusual, and a measure of the tie strength can be calculated. This measure is one if a focal inventor does not collaborate more than once with any individual in the three-year time period; it increases as the ratio of repeated collaborations to unique collaborations increases. The models include a count of repeated indirect ties by collaborators divided by the number of unique indirect ties, analogous to the strength of direct ties measure *(strength of indirect ties).*

All models also include indicator variables for time period and career period of the inventor. Time period indicators control for differences in patenting processes and in the time that combinations are at risk of use in further applications. Career period indicators control for differences in productivity and creativity over a career.

Selection hazard controls. By definition, brokerage cannot occur unless an individual works with more than one collaborator. The many inventors who work alone or with one other inventor will have no effect on the estimations. To control for the possibility of selection bias, we estimated a first-stage selection model (Heckman, 1976) for all inventors and entered the inverse Mills ratio in the collaborative models. The ratio essentially controls for the probability that the inventor will collaborate with more than one other inventor. The first stage used variables that would correlate with an inventor's number of collaborators, including number of patents and time and career period indicators. To identify the procedure, the final models included the cumulative number of patents and citations in the inventor's career up to that point and the number of patents without assignees or prior art citations. The usage models also impose a severe selection bias, in that an inventor must first create a new combination in order for it to be used in future search. To calculate the usage model selection hazards, the first stage estimated invention of at least one new combination as a function of all variables in the second stage. To identify the procedure, the second stage included the ln of the number of new combinations (an important control) and did not include the control for the size of the combinatorial space. Both generative and use results were robust to the inclusion of the selection hazards. Tables 1 and 2 provide descriptive and correlation statistics.

Table 1

Descriptive Statistics (N = 53,570 observations, 35,400 inventors)

Variable	Mean	S.D.	Min.	Max.
New combinations	1.41	49.78	.00	4436.00
Future usage	32.55	279.66	.00	26659.00
Cohesion	.12	.26	.00	1.00
Ln number of patents	.55	.69	.01	5.33
Ln component network size	4.51	4.28	1.10	11.90
Ln new subclasses	–4.58	.32	–4.61	1.39
Ln potential combinations	3.52	3.52	–4.61	13.77
Age of prior art	3.74	1.48	.00	6.60
Ln non-patent refs.	–2.11	3.13	–4.61	8.09
Ln university patents	–4.35	1.09	–4.61	3.43
Ratio repeat collaborations	.16	.32	.00	1.00
Strength of direct ties	1.32	.74	1.00	35.09
Strength of indirect ties	1.35	1.42	1.00	75.00
Ln degree	1.26	.57	.70	4.41
Ln number of assignees	–.10	.94	–4.61	2.20
Ln focal experience	–1.40	3.52	–4.61	6.24
Ln collaborators' experience	1.48	3.36	–4.61	7.51
Ln similar experience	–2.54	3.07	–4.61	5.86
Ln external ties	1.52	1.43	–4.61	6.10

Table 2

Correlation Statistics (N = 53,570 observations, 35,400 inventors)

Variable	1	2	3	4	5	6	7	8	9
1. New combinations									
2. Future use	.48								
3. Cohesion	.00	.00							
4. Ln number of patents	.24	.13	–.03						
5. Ln component network size	.07	.01	.17	.27					
6. Ln new subclasses	.03	.08	–.01	.03	–.02				
7. Ln potential combinations	.20	.11	.22	.49	.54	.02			
8. Age of prior art	.01	.01	.01	.02	–.02	.01	.03		
9. Ln non-patent refs.	.13	.11	.00	.33	.13	.04	.20	.21	
10. Ln university patents	.01	.02	–.03	.02	–.01	.01	–.02	.02	.21
11. Ratio repeat collaborations	.07	.04	–.01	.26	.10	–.01	.15	.02	.14
12. Strength direct ties	.20	.12	.05	.63	.13	.01	.26	.01	.22
13. Strength indirect ties	.05	.03	.29	.15	.22	–.01	.26	–.02	.06
14. Ln degree	.15	.07	–.03	.50	.44	.01	.46	.00	.23
15. Ln focal experience	.11	.04	–.04	.37	.16	.00	.23	.04	.15
16. Ln collaborators' experience	.10	.04	.15	.30	.42	–.02	.50	.02	.14
17. Ln similar experience	.12	.05	–.01	.38	.21	–.01	.27	.03	.18
18. Ln number of assignees	.04	.03	.03	.21	.13	.01	.18	.02	.11
19. Ln external ties	.09	.04	.20	.25	.66	.00	.58	.00	.16

Variable	10	11	12	13	14	15	16	17	18
11. Ratio repeat collaborations	.05								
12. Strength direct ties	.02	.19							
13. Strength indirect ties	–.01	.05	.16						
14. Ln degree	.01	.19	.21	.16					
15. Ln focal experience	.00	.53	.16	.05	.21				
16. Ln collaborators' experience	–.02	.31	.17	.18	.39	.33			
17. Ln similar experience	.02	.76	.21	.08	.29	.77	.44		
18. Ln number of assignees	.07	.06	.09	.04	.16	.12	.17	.11	
19. Ln external ties	–.01	.12	.16	.25	.65	.12	.48	.22	.14

RESULTS

Both dependent variables demonstrate skewed count distributions. Use of linear regression on such distributions can result in inconsistent, biased, and inefficient estimations (Stock and Watson, 2003). Count models provide more accurate results, and given that the variance was greater than the mean in both distributions, negative binomial models provide more accurate error estimations. Given that our theory argues for variation across inventors and that our data provide repeated observations of individuals over their inventive careers, we estimated random-effects conditional logit models (Hausman, Hall, and Griliches, 1984) in STATA Version 8. We found similar results with fixed-effects and non-conditional models, as described below. Table 3a includes all control variables with cohesion alone, followed by each interaction entered separately, for the generative models. Table 3b includes full models and robustness checks, again for the generative models.

Though some of the effects are small, the results are consistent across the models and support the predictions. We use model 7 to interpret the size of the generative effects. Cohesion demonstrates a strong and consistently negative influence on the generation of new combinations. A one-standard-deviation increase in cohesion correlates with 14.8 percent fewer new combinations. From model 7, the effect size can be calculated as the exponent of a standard deviation change in the explanatory variable multiplied by the coefficient, or $e^{(-0.6160 \times 0.26)} = 0.852$. $1 - 0.852 = .148 = 14.8$ percent. The interaction of cohesion with the focal inventor's experience correlates with a 1.3 percent increase; the interaction of the collaborators' experience correlates with a 3.0 percent increase; the interaction of multiple assignees with cohesion correlates with a 3.6 percent increase in new combinations; and the interaction of external ties correlates with a 2.7 percent increase. The positive interaction of cohesion with external ties provides evidence at the inventor level that the small-world interaction improves creativity (Uzzi and Spiro, 2005; Schilling and Phelps, 2007). Yet the models also indicate very strong and negative first-order effects of external ties. We were unable to find a non-monotonic relationship between small-world measures and creativity (Uzzi and Spiro, 2005). From these data, it appears that external ties and the first-order effect of brokerage swamp the positive small world interaction, at least with regard to the generation of new combinations.

We tested the robustness of the results in three additional ways. In model 8, we modeled the proportion of patents that contained a new combination instead of the count of new combinations. Model 8 illustrates the result from an arc sine transformation to take account of the distribution of values in a proportion between 0 and 1, and the results were robust to this transformation. Although count models naturally account for extremely skewed dependent variables, the consistency of results with the proportion models increases our confidence that the results are not idiosyncratic outcomes of the choice of model. Results also remained robust to the exclusion of outliers in both the count and proportion models.

Table 3a

Conditional Logit Negative Binomial Models of Number of New Subclass Combinations, U.S. Inventors, 1975–1998 (N = 53,570 observations, 35,400 inventors)*

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Ln number of patents	.2657•••	.2673•••	.2666•••	.2652•••	.2661•••
	(.0111)	(.0111)	(.0111)	(.0111)	(.0111)
Ln component network size	–.0246•••	–.0245•••	–.0246•••	–.0247•••	–.0247•••
	(.0018)	(.0018)	(.0018)	(.0018)	(.0018)
Ln new subclasses	.1422•••	.1418•••	.1427•••	.1428•••	.1424•••
	(.0104)	(.0104)	(.0104)	(.0104)	(.0104)
Ln potential combinations	.3927•••	.3929•••	.3932•••	.3934•••	.3932•••
	(.0035)	(.0035)	(.0035)	(.0035)	(.0035)
Age of prior art	.0150•••	.0148•••	.0149•••	.0150•••	.0150•••
	(.0043)	(.0043)	(.0043)	(.0043)	(.0043)
Ln non-patent refs.	.0098•••	.0098•••	.0098•••	.0098•••	.0098•••
	(.0018)	(.0018)	(.0018)	(.0018)	(.0018)
Ln university patents	.0015	.0018	.0013	.0018	.0017
	(.0047)	(.0047)	(.0047)	(.0047)	(.0047)
Ratio repeat collaborations	–.0595•	–.0596•	–.0605•	–.0596•	–.0603•
	(.0245)	(.0245)	(.0245)	(.0245)	(.0245)
Strength of direct ties	.0842•••	.0834•••	.0835•••	.0838•••	.0835•••
	(.0057)	(.0057)	(.0057)	(.0057)	(.0057)
Strength of indirect ties	–.0241•••	–.0244•••	–.0270•••	–.0243•••	–.0275•••
	(.0039)	(.0040)	(.0040)	(.0039)	(.0040)
Ln degree	.4822•••	.4832•••	.4863•••	.4844•••	.4899•••
	(.0147)	(.0147)	(.0147)	(.0147)	(.0148)
Ln number of assignees	–.0408•••	–.0405•••	–.0398•••	–.0520•••	–.0410•••
	(.0059)	(.0059)	(.0059)	(.0061)	(.0059)
Ln focal experience	–.0053	–.0073	–.0055	–.0050	–.0053
	(.0046)	(.0046)	(.0045)	(.0046)	(.0046)
Ln collaborators' experience	–.0437•••	–.0434•••	–.0475•••	–.0434•••	–.0436•••
	(.0019)	(.0019)	(.0020)	(.0019)	(.0019)
Ln similar experience	.0083•••	.0078•	.0087••	.0082•	.0086•
	(.0033)	(.0033)	(.0033)	(.0033)	(.0033)
Ln external ties	–.3291•••	–.3300•••	–.3295•••	–.3304•••	–.3357•••
	(.0061)	(.0061)	(.0061)	(.0061)	(.0062)
Ln external ties^2	–.0697•••	–.0699•••	–.0703•••	–.0701•••	–.0717•••
	(.0014)	(.0014)	(.0014)	(.0014)	(.0015)
Cohesion	–.4660•••	–.4276•••	–.5623•••	–.4534•••	–.6514•••
	(.0230)	(.0251)	(.0283)	(.0231)	(.0450)
Cohesion × Focal experience		.0213•••			
		(.0059)			
Cohesion × Collab. experience			.0469•••		
			(.0073)		
Cohesion × Assignees				.1730•••	
				(.0320)	
Cohesion × External ties					.1083•••
					(.0221)
Constant	–.9100•••	–.9098•••	–.8987•••	–.9063•••	–.8927•••
	(.1035)	(.1035)	(.1035)	(.1035)	(.1037)
Ln likelihood	–137923.53	–137917.17	–137902.02	–137905.63	–137911.38

• $p < .05$; •• $p < .01$; ••• $p < .001$.
* Standard errors are in parentheses. All models are random effects with year and career period effects.

Because our data only record collaborations after the fact, we cannot determine if they were formed to exploit an opportunity that had already been identified or whether the brokerage role caused an increase in creativity, as hypothesized. Ideally, we would include a control measure for intent to build and exploit a collaborative network in order to create new subclass pairs. Because it would be difficult to obtain such a control—even survey research is not likely to provide this accurately, given problems with informants' accuracy (Wasserman and Faust, 1994: 57)—we instrumented cohesion to remove endogeneity and omitted variable bias (see

Table 3b

Conditional Logit Negative Binomial Models of Number of New Subclass Combinations, U.S. Inventors, 1975–1998 (N = 53,570 observations, 35,400 inventors)*

Variable	Model 6	Model 7	Model 8
Ln number of patents	.2669•••	.5117•••	
	(.0111)	(.0205)	
Ln component network size	–.0247•••	–.0248•••	–.0112•••
	(.0018)	(.0018)	(.0009)
Ln new subclasses	.1428•••	.1457•••	.0760•••
	(.0104)	(.0104)	(.0080)
Ln potential combinations	.3941•••	.3963•••	.1379•••
	(.0035)	(.0035)	(.0011)
Age of prior art	.0149•••	.0164•••	.0070•••
	(.0043)	(.0043)	(.0020)
Ln non-patent refs.	.0098•••	.0099•••	.0018
	(.0018)	(.0018)	(.0009)
Ln university patents	.0018	–.0016	–.0064•
	(.0047)	(.0047)	(.0025)
Ratio repeat collaborations	–.0607•	–.0666••	–.0409••
	(.0245)	(.0246)	(.0137)
Strength of direct ties	.0826•••	.0689•••	.0195•••
	(.0057)	(.0057)	(.0044)
Strength of indirect ties	–.0282•••	–.0306•••	–.0099•••
	(.0041)	(.0041)	(.0020)
Ln degree	.4917•••	.4778•••	.1896•••
	(.0148)	(.0149)	(.0076)
Ln number of assignees	–.0502•••	.1122•••	.2237•••
	(.0061)	(.0131)	(.0051)
Ln focal experience	–.0061	–.0085	–.0102•••
	(.0046)	(.0046)	(.0026)
Ln collaborators' experience	–.0462•••	–.0444•••	–.0174•••
	(.0021)	(.0021)	(.0010)
Ln similar experience	.0083•	.0074•	.0014
	(.0033)	(.0034)	(.0018)
Ln external ties	–.3342•••	–.3393•••	–.1416•••
	(.0062)	(.0063)	(.0034)
Ln external ties^2	–.0715•••	–.0726•••	–.0328•••
	(.0015)	(.0015)	(.0008)
Cohesion	–.5976•••	–.6160•••	–.2831•••
	(.0471)	(.0471)	(.0217)
Cohesion × Focal experience	.0106	.0122•	.0060•
	(.0062)	(.0062)	(.0030)
Cohesion × Collab. Experience	.0355•••	.0342•••	.0144•••
	(.0081)	(.0081)	(.0037)
Cohesion × Assignees	.1590•••	.1458•••	.0447•••
	(.032)	(.0302)	(.0125)
Cohesion × Non-external ties	.0524•	.0715••	.0627•••
	(.0238)	(.0238)	(.0111)
Selection hazard		.8386•••	1.2364•••
		(.0599)	(.0194)
Constant	–.8906•••	–1.6077•••	.0297
	(.1037)	(.116)	(.0806)
Ln likelihood/pseudo R^2	–137881.73	–137787.22	.26

• $p < .05$; •• $p < .01$; ••• $p < .001$.

*Standard errors are in parentheses. All models are random effects with period and career effects. Model 8 regresses the instrumented cohesion variable on the proportion of patents with new combinations.

Stock and Watson, 2003, for an explanation of instrumental variables; for applications in network research, see Ingram and Roberts, 2000; Reagans, Zuckerman, and McEvily, 2005). An effective instrumental variable needs to correlate with cohesion but not with the ultimate outcome of new combinations. Such an instrument enables the outcome measure to be cleansed of any portion that is correlated with an omitted variable, such as agency or purposeful network construction.

The number of unique patent lawyers for each inventor's three-year window provides an instrument for removing endogeneity between collaborative structure and the invention of new combinations, because brokers' inventions are likely to have different patents written by different patent lawyers, while inventors working in a cohesive collaborative structure are likely to have their patents written by the same set of lawyers each time. This argument is strongest in a corporate setting, where lawyers are often assigned without the inventor's knowledge or preference; because 95.7 percent of the observations indicate one or more assignees, this argument pertains to the majority of cases. This application also assumes that the number of unique patent lawyers has no influence on the number of new combinations that the inventors create. In support of this assertion, a regression of combinations on the number of lawyers for the non-collaborative inventors in our sample did not demonstrate a significant correlation. To calculate instrumented versions of our explanatory variables, we applied STATA's xtivreg routine, which adjusts standard errors between stages, and included the ln of unique lawyers and an indicator for no lawyers. Both instrumental variables demonstrated significance in the expected negative direction in the full model (z values of 2.17 and 2.06, respectively) and passed the Stock-Wright-Yogo test for explanatory power, providing an expected decrease in bias over ordinary least squares of at least 90 percent (see Stock, Wright, and Yogo, 2002). With all second-stage predictors plus the instruments, the first stage R^2 reached 81.3 percent, of which the instruments provided an additional 0.1 percent of explanatory power. Because inventors sometimes choose their lawyers, and brokers may choose differently than members of cohesive networks, we hesitate to claim more than an incremental robustness check for our reduced form models.

Table 4 reports use models and the frequency of use by different categories of potential adopters. Model 9 estimates the influence of brokerage on use by all inventors. Models 10 and 11 split model 9's outcomes between the focal inventor and all others. Models 12–14 split model 11's outcomes into use by co-inventors of the original combination, collaborators during the three-year period who did not co-invent the original combination, and all other inventors who were not directly tied to the focal inventor during the three-year period, whom we label external. Model 9 supports hypothesis 3, which proposed that generative creativity arising from a cohesive collaborative structure is more likely to be used. The additional models enable us to explore the individual arguments behind the prediction in hypothesis 3. Given the severe selection involved (an inventor's new combinations cannot be used in the future unless they exist), we included the selection hazard in all models (reduced form models returned similar results). The frequency of use by category is also listed at the bottom of the table; 85.1 percent of the uses are by inventors with no direct link to the focal inventor, while 9.5 percent, 3.7 percent, and 1.7 percent are by co-inventors, the focal inventor him- or herself, and collaborators during the time period who did not invent the original new combination.

Table 4

Conditional Logit Negative Binomial Models of Future Use of New Subclass Combinations, U.S. Inventors, 1975–1998 (N = 35,247 observations, 24,659 inventors)*

Variable	Model 10 Total	Model 11 Focal	Model 12 Non-focal	Model 13 Co-inventors	Model 14 Collaborators	Model 15 Non-local
Ln new combinations	.6186•••	.5038•••	.6182•••	.4585•••	.4698•••	.6175•••
	(.0059)	(.0121)	(.0059)	(.0113)	(.0194)	(.0061)
Ln number of patents	.1836•••	.8744•••	.1561•••	.3080•••	1.0767•••	.1517•••
	(.0146)	(.0300)	(.0146)	(.0281)	(.0484)	(.0154)
Ln component network size	.0127•••	–.0159•••	.0133•••	–.0089•	.0031	.0158•••
	(.0021)	(.0046)	(.0021)	(.0044)	(.0079)	(.0022)
Ln new subclasses	.1333•••	.1163•••	.1326•••	.0969•••	.0735•	.1328•••
	(.0106)	(.0231)	(.0106)	(.0220)	(.0357)	(.0109)
Age of prior art	.0976•••	.0190	.0989•••	.0234	.0797••	.1095•••
	(.0066)	(.0142)	(.0067)	(.0129)	(.0277)	(.0070)
Ln non-patent refs.	.0493•••	.0366•••	.0494•••	.0334•••	.0062	.0503•••
	(.0022)	(.0047)	(.0022)	(.0045)	(.0079)	(.0023)
Ln university patents	.0124•	.0235•	.0127•	.0368•••	.0028	.0094
	(.0054)	(.0108)	(.0054)	(.0102)	(.0189)	(.0056)
Ratio repeat collaborations	–.0288	–.0933	–.0284	–.1786••	–.1240	.0054
	(.0299)	(.0640)	(.0299)	(.0619)	(.0989)	(.0309)
Strength of direct ties	.0469•••	.0742•••	.0490•••	.1617•••	–.0606•••	.0037
	(.0063)	(.0108)	(.0063)	(.0112)	(.0176)	(.0077)
Strength of indirect ties	–.0002	–.0181•	.0002	–.0025	.0129	.0022
	(.0038)	(.0087)	(.0038)	(.0071)	(.0107)	(.0039)
Ln degree	.0828•••	–.1602•••	.0986•••	.1615•••	.3925•••	.0667•••
	(.0155)	(.0330)	(.0155)	(.0320)	(.0554)	(.0161)
Ln number of assignees	.0178•	–.0076	.0178•	.0234	.0086	.0182•
	(.0075)	(.0188)	(.0075)	(.0182)	(.0371)	(.0077)
Ln focal experience	–.0091	–.0293•	–.0094	–.0223	–.0683••	–.0078
	(.0053)	(.0124)	(.0053)	(.0119)	(.0208)	(.0054)
Ln collaborators' experience	–.0078••	.0080	–.0077••	.0235•••	.0168	–.0110•••
	(.0024)	(.0058)	(.0024)	(.0056)	(.0112)	(.0025)
Ln similar experience	–.0103•	–.0278••	–.0089•	.0050	–.0278	–.0049
	(.0040)	(.0090)	(.0041)	(.0088)	(.0146)	(.0042)
Ln external ties	.0148•	.0065	.0157•	.0780•••	.0362	.0186••
	(.0066)	(.0138)	(.0067)	(.0159)	(.0259)	(.0069)
Cohesion	.1158•••	.0245	.1202•••	.5096•••	.4320•••	.0915•••
	(.0264)	(.0629)	(.0265)	(.0526)	(.1145)	(.0274)
Selection hazard	.1207••	.4372•••	.1049••	.1203	–.3493	.0986•
	(.0397)	(.0941)	(.0398)	(.0850)	(.1914)	(.0411)
Constant	–3.1571•••	–4.1220•••	–3.1854•••	–4.4774•••	–6.7311•••	–3.4738•••
	(.1361)	(.2459)	(.1369)	(.2404)	(.3424)	–.15
Ln likelihood	–121258.67	–28075.46	–120167.33	–37024.59	–12108.40	–114873.55
Number of uses	1743470	63472	1679998	166390	29808	1483530
Proportion of total occurrences	100%	3.70%	96.30%	9.50%	1.70%	85.10%

• $p < .05$; •• $p < .01$; ••• $p < .001$.

* Standard errors are in parentheses. All models are random effects with period and career effects.

Model 10 considers uses by the focal inventor only and shows that cohesion has no correlation with use. Model 11 looks at the complement of model 10's dependent variable, all other uses besides those of the focal inventor. The effect of cohesion is positive and indicates a 3.0 percent increase in use by other inventors for combinations that originate within a cohesive structure (one standard deviation for the cohesion variable, conditional on having created a new combination, is 0.248). Model 12, use by co-inventors of the new combination, drives much of the positive influence observed in model 11, as indicated by a 13.5 percent increase in the positive effect of cohesion. This result provides evidence that brokerage inhibits mutual ownership and understanding of the new combination. Model 13 indicates an 11.3 percent positive influence of cohesion on use by collaborators who are not coauthors of the new combination. This result provides strong evidence that knowledge and understanding flow more freely within cohesive social contexts; although these inventors were not part of the original project, they are still much more likely to use the new combination if both they and the people who came up with it are part of the same cohesive network. Finally, model 14 indicates a 2.3 percent increase in all other use for combinations invented in a cohesive context. This positive, though comparatively smaller magnitude result provides evidence that creativity arising from cohesive structures diffuses more readily.

We performed additional robustness analyses on the usage models. Conditional likelihood models (Hausman, Hall, and Griliches, 1984) allot the number of events—in this case, the number of new combinations or times an inventor's new combinations are used again—to outcome possibilities, in this case, the various three-year windows of a creative career. It is possible that cohesion has a positive effect on some categories of outcomes but a negative effect overall. We explored this possibility by estimating basic negative binomial count models (with robust standard errors to account for repeated observations of the same inventor) and panel logit models of any use of a new combination. As in model 8, we also estimated instrumental variable regressions of the proportion of new combinations that were used again. All robustness checks were consistent with the original estimations.

Given that the interaction effects together are two-thirds of the negative influence of cohesion on generative creativity (a total of 10.6 percent for all the interactions vs. 14.8 percent for brokerage by itself), it is not surprising that qualitative researchers have argued for both positive and negative influences on creativity (Hargadon and Sutton, 1997; Uzzi, 1997; Obstfeld, 2005). The marginal interactions are very common in creative contexts and would make it difficult to disentangle the unmoderated effects without a quantitative and completely specified model. Furthermore, the use results (and success of any particular combination) depend subtly on the category of user and would be extremely difficult for qualitative researchers to determine for a representative and statistically significant sample.

DISCUSSION AND CONCLUSION

This study offered a reconciliation of the controversy over the benefits of brokerage and cohesion for creativity by expanding a heretofore structural focus and elaborating a social definition of creative success. Although sociological research on creativity has recently flourished, little of it has considered how individuals interact with the structure around them and with the personal characteristics of the other people around them. By expanding the structural discussion, we demonstrated that cohesion offers marginal benefits for generative creativity (1) when a focal inventor or his or her collaborators have broader experience, (2) when focal inventors have worked in multiple organizations, and (3) when the focal inventor's collaborators also work with external collaborators.

In these cases, the marginal benefits of cohesion are two-thirds as much as the negative first-order effect of cohesion. By expanding the definition and differentiating between the initial insight and ultimate success of an idea, we demonstrated that ideas that arise from a brokered collaboration are less likely to be used in the future. Our contribution was to trace the full history of new combinations and demonstrate that brokered collaborations increase generative creativity; conditional on generating a new idea, however, brokered collaborations decrease the use of that creativity by other inventors. Furthermore, while the diffusion of knowledge is relatively well understood and research has begun to address the structural influences on generative creativity, less work has jointly considered the generation and ultimate success of creativity. These arguments and evidence provide an explanation for how previous research, both qualitative and quantitative, could arrive at contradictory conclusions about the effect of brokerage on collaborative creativity.

Methodological Issues with Archival Data

Although archival approaches have been used for over 30 years to study productivity in scientific networks (Gordon, 1980; McFadyen and Cannella, 2004), using them to study collaborative structure and creativity is relatively novel and warrants a closer examination. Archival approaches have a variety of problems and advantages (Katz and Martin, 1997). As an example, authors of scientific papers can claim and publish collaborative work as their own, although field work found this to be the case in only 12 out of 195 randomly sampled papers (Melin, 2000). Patents, however, can be invalidated if a contributor is excluded, so even this low rate can be considered an upper bound on the problem. Selection bias in getting published can also be a problem because unpublished creativity remains unobserved. With patent data, for example, one only observes successful patent applications. To explore this possible bias, Fleming, Juda, and King (2007) sampled 18 inventors and provided them with illustrations of the collaborative networks in their careers. None could recall a failed invention that relied on a different inventor network, but one did indicate that his patent network failed to reflect his scientific collaboration network. These interview results are obviously vulnerable to various biases but remind us that patent coauthorship networks represent only one type of tie and obviously miss a wide variety of other ties that influence creativity. Use of the dependent variable of new combinations ameliorates some of the selection bias because it models wide variation in creativity, conditional on at least two successful patent applications in each three-year period.

It is important to realize that archival data cannot provide direct evidence of the underlying processes that we hypothesized. Our predictions for the contingent relationship between cohesion and creativity rely on the popular argument that cohesive networks engender trust, but our data could not be used to measure directly the social-psychological state of trust (for evidence of a correlation between trust and cohesive structures, see Tsai and Ghoshal, 1998; Glaeser et al., 2000; Levine and Cross, 2004). Similarly, we could not measure attitudes about mutual ownership, understanding, and in-group preferences. This limitation is not atypical of empirical work on social networks, given that few studies have attempted to measure both the structure and the underlying mechanisms posited by social network theory. Similarly, the diffusion arguments of hypothesis 3 need elaboration. Although our data indicated that 85 percent of the future uses were by inventors who did not have a single indirect tie to the original inventor, there were surely uses by inventors with multiple indirect ties and other social network ties as well, for example, membership in the same organization. Though both issues can and should be addressed in future studies, examining the correspondence between structure and underlying mechanisms strikes us as a particularly important next step for the field of social network research.

Despite their drawbacks, archival publication data can make a unique contribution to our understanding of creativity. Because they do not rely on interviews, publication data avoid response bias and the risk of influencing the creative process as it occurs. Publication data can also capture a complete network of coauthorship relationships, whereas surveys must bound their sampling. Highlighting the importance of this advantage, our regressions demonstrated strong effects for collaborators' external networks and even for the size of the extended indirect network beyond. Observing the broader network is particularly important when studying the emergence and diffusion of an idea. For example, if inventors work in a small and isolated cluster, their ideas are less likely to be incorporated by external inventors, as demonstrated by the positive effect of the component network size variable. This effect would be extremely difficult to identify with survey methods. Archival data, in addition to being able to capture an entire network, can trace an individual's creativity as he or she moves across organizations or creative realms. This makes the results more general, for example, across firms and technologies. An archival data set is especially appropriate for the current research problem, which has already been well described qualitatively (Uzzi, 1997; Hargadon and Sutton, 1997; Obstfeld, 2005); by identifying the conception and future use of a new combination, we could reconcile the contradictory results by tracing the generation and use of the same idea over time and social space.

The archival data also provide repeated and longitudinal observations spanning an individual's career. This enables exploration of the variance within, as opposed to between, individuals. While our theory focused on differences between people, and hence was appropriately tested with a random effects model, it could easily be extended to consider within-person variation as well. To explore this opportunity, we estimated conditional logit fixed-effects models.[2] They indicated similarly significant though attenuated results. The positive first-order effect of brokerage in the fixed-effects generative models was 60 percent of the size of the effect in the random-effects models. This indicates both a within-person and an across-person advantage to brokering. The implication is that everybody can benefit from brokering, but some people are better at benefiting from it than others. In the use mod-

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Recent research has demonstrated that Hausman, Hall, and Griliches's (1984) conditional logit model does not estimate a true fixed-effects model (Allison and Waterman, 2002). Our data sample remained too large, however, for software specifically developed to implement the true fixed effects on large data sets (as explained via e-mail by William Greene, an author of LIMDEP, the only package that implements true fixed effects for a large negative binomial panel). True fixed-effects analyses on randomly selected subsets of our data indicated similar but less consistent results, which reflects a known problem with true fixed-effects count models (Allison and Waterman, 2002).

els, the fixed-effects coefficients ranged between 75 percent and 88 percent of the random-effects coefficients. Taken together, these results imply that an individual, collaborating as a broker, is more likely to create a new but ultimately less successful idea. That very same person, collaborating within a cohesive structure, would be less likely to create a new idea, but having done so, would be more likely to have it used in the future. The lack of substantive differences between fixed- and random-effects models provides additional evidence that the results are not driven by individual differences such as intelligence or collaborative strategy.

Organizational Creativity Research

Our elaboration and social definition of creativity and creative success combines four ideas from classic research on the topic: creativity is novel and useful (Stein, 1963; Amabile, 1996); novelty is a new combination (Simonton, 1999); the definition and measurement of useful remains necessarily social (Gardner, 1993; Csikszentmihalyi, 1999; Simonton, 1999); and the generation of novelty should be separated from an evaluation of its usefulness (Osborn, 1957). Though elements of these definitions are very common, these four ideas have not been combined in this particular way. This may result from the difficulty of measuring new combinations and usefulness separately with the non-archival methods that are most popular in creativity research. Important questions might be addressed, however, with this novel definition. For example, Kasof (1995: 312) lamented that "not much is known or even hypothesized about the situational factors that influence the reception of creative products." As an example of the theoretical potential of combining these ideas, we provided an explanation for how one situational factor, namely, the collaborative structure that gave rise to an idea, can influence the reception of that idea.

The analyses of inventors in different situations over the courses of their careers also address calls from the organizational creativity literature to explain how creative behavior varies across individuals, situations, and time (Kasof, 1995). The career focus spotlights the individual, while at the same time, the network focus inherently avoids the fundamental attribution error (see Ross, 1977). The fundamental attribution error overestimates the influence of personal attributes on behavior and underestimates the influence of situation and context. In creativity research, it leads to an overly narrow focus on the characteristics of very creative people (Brass, 1995; Ford, 1996; Paulus and Nijstad, 2003: 3). The fundamental attribution error has been called "the bias that perhaps most blinds us to achieving a comprehensive view of the influences on creativity" (Ford, 1996: 20). At the other extreme, and in direct contrast to the fundamental attribution error, sociological reductionism ignores personal attributes (Kroeber, 1944; Mayhew, 1980); for example, with a purely structural focus, all causation is sought in relationships. Reality, as social-psychological researchers have long recognized, lies between the two extremes. Instead of adopting an extreme sociological perspective (creativity results from collaborative structure) or an extreme psychological perspective (creativity results from individual genius), the current work adopts an interactionist view that some people are more creative than others and that personal characteristics interact with situations (Brass and Burkhardt, 1993; Marsden and Friedkin, 1994; Amabile et al., 1996; Ford, 1996; Woodman, Sawyer, and Griffin, 1993; Oldham and Cummings, 1996; Amabile et al., 2005; Perry-Smith, 2006). Building on this line of research, we demonstrated an approach that inherently avoids both fundamental and structural attribution errors.

Because our research design disentangles the person from the situation, it also implies stronger managerial prescriptions. This follows because fixed-effects models, which control for time-invariant characteristics of an individual such as innate intelligence, provide the weak equivalent to a repeated experiment on the same person in different situations. They essentially wash out the differences between persons and enable cleaner estimation of the situational influence. The models can also identify the influence of time-varying personal characteristics and demonstrate how the interaction of structure and personal characteristics can vary over time. For example, the positive interaction between cohesion and breadth of experience indicates that everyone might benefit from brokering relations between their collaborators earlier in his or her career.

Social Network Research

This work makes a number of theoretical and empirical contributions to research on social networks and creativity. The theoretical contributions stem from the ability to differentiate between original and secondary sources of new ideas. By identifying the first and the subsequent uses of a new combination, our work differentiated between whether a new idea was truly original or was only original in a particular context. We might call the latter "creative arbitrage," by analogy to financial arbitrage, which involves buying in one market and selling in another. Generative creativity, as we proposed, occurs when someone contrives a new idea. In contrast, creative arbitrage occurs when someone exports an idea from a context in which the idea is already known to a context in which it is not (Hargadon and Sutton, 1997). Much of the network and creativity literature has failed to distinguish between these two phenomena. Burt (2004) provided an exception and defined three levels of arbitrage and one of synthesis or generation. The preponderance of arbitrage in Burt's typology suggests that it is much more frequent and valuable than generation. Although our work does not address the relative frequency or importance of the two mechanisms, it does demonstrate a purely generative benefit to brokerage. This is important to the wider innovation literature as well, because that literature tends to focus on idea transfer and ignore idea generation (Damanpour, 1991; Rogers, 1995). Yet new ideas keep appearing—and they must come from somebody.

This differentiation between generative and creative arbitrage also raises new questions about the classic image of the influential opinion leader who straddles boundaries (Katz and Lazarsfeld, 1955; Coleman, Katz, and Menzel, 1957). Though such boundary-spanning leaders (Allen, 1977; Tushman,

1978) are often seen as the sources of new opinions and ideas, the mechanisms that underlie their creativity remain undertheorized. Do such boundary spanners (1) generate more original ideas than others do, (2) transfer their original ideas more effectively, (3) transfer unoriginal ideas more effectively, or (4) some combination of these? We can identify at least three mechanisms that could make a boundary spanner appear more creative: social brokerage, social cohesion, and domain straddling, for example, an electrical engineer working with biologists. Although some of these roles can correlate, they remain conceptually and empirically distinct.

There are several ways in which the three proposed mechanisms—social brokerage, social cohesion, and domain straddling—could make a boundary spanner more creative. If boundary spanners collaborated as brokers, then by our generative results they would invent more new ideas. They would probably also be in a better position to identify opportunities for creative arbitrage. On the downside, given our usage results, they would be less effective at diffusing ideas. But if this diffusion handicap were counterbalanced by sheer quantity of either original or arbitraged ideas, these boundary spanners might still be perceived as a more prolific source of successful creativity. Alternately, if boundary spanners collaborate within cohesive networks (see Fleming and Waguespack, 2007, for an illustration of cohesive collaboration networks across boundaries), they should generate or broker fewer ideas but diffuse them more effectively. Again, the benefits of the position for diffusion would need to be weighed empirically against the handicap of decreased generation or arbitrage. Finally, social brokerage or cohesion should be differentiated from positions that straddle domains. For example, though weak ties and non-redundant information surely correlate, there is nothing to prevent an individual from brokering collaborators with redundant information from similar domains (Rodan and Galunic, 2004). Likewise, an individual might span a boundary between two organizations with similar domain content. Social brokerage, social cohesion, and domain straddling thus each provide different opportunities and mechanisms for boundary-spanning opinion leaders to generate original ideas, broker others' ideas, and disseminate ideas from both sources. The questions of exactly how those mechanisms work and which ones dominate remain undertheorized and empirically open.

Using the focal inventor's career as a unit of analysis also enables innovations that can address unreconciled methodological problems in network analysis. For example, network autocorrelation, or the lack of independence between proximal nodes in a network, can result in smaller standard errors and spurious correlation. Large archival data sets make it possible to avoid this problem simply by randomly sampling subsets of the larger data set. Endogeneity can bias the estimations as well, when individuals purposefully create and exploit network positions, obscuring the causal advantages (Ingram and Roberts, 2000; Reagans, Zuckerman, and McEvily, 2005). For example, it has yet to be established whether brokerage leads to improved performance or a certain level of performance leads to brokerage (Ryall and Sorenson, 2007). It is quite possible that creative individuals are assigned to brokerage roles or intentionally seek them out. Though we suspect that both processes occur, the instrumented variable models establish the direction from brokerage to creativity. More generally, very little network research controls for agency or ability; career-focused data sets with effective instruments can provide a solution to this difficulty. Aggregating observations also complicates the levels-of-analysis issues (for example, averaging a measure of individual cohesion across a network); ecological analyses that make inferences for individuals from average effects across a network may be unpredictably biased (Robinson, 1950; Woodman, Sawyer, and Griffin, 1993; Ibarra, 1993). Career-focused research completely avoids such aggregation bias. Finally, the patent-subclass-pair variables enable crudely consistent measures of creativity across content domains, and the panel data set enables the individual and the environment to be disentangled. Burt identified both as difficult problems (Burt, 2004: 355 and 387, respectively).

Implications for Organizational Design

The managerial implications of our research are reasonably clear for creative professionals who wish to generate more new ideas and to see those ideas used in the future. Brokerage provides clear benefits for generative creativity. The fixed-effects models indicated that, while some people take better advantage of brokerage than others, all can benefit. Less-experienced individuals may benefit more from brokerage, given that they bring less depth of background and fresh information to the collaboration. Creative brokers who wish to see their creativity used, however, should pay attention to the diffusion and adoption of their ideas. They will need to explain their new ideas well, enhance perceptions of group ownership, and see that diffusion paths remain open and functional.

Managers have an important role to play as well. When a good idea emerges from a collaborative effort, a manager should determine the structure that gave rise to the seminal combination. Based on our results, brokered conceptions are fundamentally more likely to fail; managers need to ensure that the expertise behind the creativity is widely distributed, encourage perceptions of group ownership, and see that the idea gets effectively transferred for development. Managers should also proactively design their organizations from an interactionist perspective (Reagans, Zuckerman, and McEvily, 2004). Neither structure nor individual genius and background alone will suffice to generate creative and successful ideas. Managers with diverse and experienced employees should encourage cohesive collaborations; this combination should generate almost as many ideas as brokered networks, and at the same time, these ideas should be easier to develop and transfer. Managers with inexperienced and less diverse employees should encourage brokering but devote additional resources to transferring and publicizing the creative output.

Our results have particular managerial implications for the care and feeding of boundary spanners, also known as gatekeepers (see Allen, 1977; Tushman, 1977). These individuals play an important role in most creative organizations, and research continues to elaborate the importance, for both groups and firms, of managing external relationships (Reagans, Zuckerman, and McEvily, 2005). Our results on the interaction of cohesion and multiple organization memberships identify a previously overlooked correlate of boundary spanners' creativity. If we interpret our control variable of the number of assignees as a measure of boundary spanning, it appears that the interaction of boundary spanning with cohesive collaboration can increase the value of the boundary spanning position by 32 percent.[3] Hence, while boundary spanners have often been assumed to be social brokers, their creativity is actually increased substantially by cohesive collaboration within an organization. While we hesitate to claim causality for the multiple organizational affiliations, because more creative inventors appear to change employers more often (see Marx, Strumsky, and Fleming, 2006), our work suggests two reasons why a manager should embed new hires from other firms in a cohesive structure, especially if the inventor brings a breadth of previous experience to the new firm. First, a cohesive structure will enable the new firm to assuage any concerns about trust, and second, it will enable the new firm to learn more effectively from its new hire.

Finally, our theory contributes to three classic discussions on the evolution of science and technology. First, why can some organizations invent but not commercialize breakthroughs? For example, Xerox PARC invented a plethora of incredible breakthroughs—including the graphic interface, the mouse, and networking technology—yet failed to transfer most of its technology to a commercial division, let alone to a market. Based on our results, we might speculate that the internal structure of the organization was highly brokered, such that many creative breakthroughs could occur. The same structure that facilitated breakthroughs, however, may have made it more difficult to develop and transfer the technology. Our results cannot address the many challenges of product development, marketing, and manufacturing, but these issues become moot if the technology cannot be diffused beyond its original inventors. Our perspective also suggests a reinterpretation of the not-invented-here syndrome (Allen, 1977; Katz and Allen, 1982). Anecdotal reports, perceptions, and recollection of the not-invented-here syndrome would be more likely the more creative the invention that failed in its transfer. If creative inventions were more likely to have been invented by a broker, they would also have been inherently more difficult to transfer. While the not-invented-here problem has typically been cast as a problem on the receiving end, our study shifts the focus back to the original creator and organization and provides a more fundamental explanation for the difficulty. It also calls for a reexamination of the benefits of cross-functional ties in product development; extensive ties between functions are probably cohesive ties, in which case a firm would generate fewer new ideas but get more of them into production, consistent with the research of Wheelwright and Clark (1992). Finally, the arguments imply an opportunity to reexamine "doubles" or simultaneous dis-

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From model 7, the benefit of a one-standard-deviation increase in the number of assignees is 11 percent and the benefit of the interaction with closure is 3.6 percent, hence 3.6/11 = 32 percent.

coveries in science and why one researcher gets more credit or fame than another for the same discovery (Simonton, 1999). Based on the arguments, one would expect the inventor or scientist with a more cohesive network to be accorded greater fame and credit. Underlying all these insights is the irony that the collaborative structure that enhances generative creativity inherently diminishes the likelihood of that creativity ever being used again.

REFERENCES

Allen, T. J.
1977 Managing the Flow of Technology. Cambridge, MA: MIT Press.

Allison, P. D., and R. P. Waterman
2002 "Fixed-effects negative binomial regression models." Sociological Methodology, 32: 247–265.

Amabile, T. M.
1996 Creativity in Context. Boulder, CO: Westview Press.

Amabile, T. M., S. G. Barsade, J. S. Mueller, and B. M. Staw
2005 "Affect and creativity at work." Administrative Science Quarterly, 50: 367–403.

Amabile, T. M., R. Conti, H. Coon, J. Lazenby, and M. Herron
1996 "Assessing the work environment for creativity." Academy of Management Journal, 39: 1154–1184.

Argote, L., and A. Kane
2003 "Learning from direct and indirect experience in organizations: The effects of experience content, timing, and distribution." In P. Paulus and B. Nijstad (eds.), Group Creativity: Innovation through Collaboration: 277–303. New York: Oxford University Press.

Barley, S. R., and G. Kunda
2004 Gurus, Hired Guns, and Warm Bodies: Itinerant Experts in a Knowledge Economy. Princeton, NJ: Princeton University Press.

Basalla, G.
1988 The Evolution of Technology. Cambridge: Cambridge University Press.

Brass, D. J.
1995 "Creativity: It's all in your social network." In C. M. Ford and D. A. Gioia (eds.), Creative Action in Organizations: 94–99. Thousand Oaks, CA: Sage.

Brass, D. J., and M. E. Burkhardt
1993 "Potential power and power use: An investigation of structure and behavior." Academy of Management Journal, 36: 441–470.

Burt, R. S.
1992 Structural Holes: The Social Structure of Competition. Cambridge, MA: Harvard University Press.
2004 "Structural holes and good ideas." American Journal of Sociology, 110: 349–399.

Campbell, D.
1960 "Blind variation and selective retention in creative thought as in other knowledge processes." Psychological Review, 67: 380–400.

Cohen, W. M., and D. Levinthal
1990 "Absorptive capacity: A new perspective on learning and innovation." Administrative Science Quarterly, 35: 128–152.

Coleman, J., E. Katz, and H. Menzel
1957 "The diffusion of an innovation among physicians." Sociometry, 20 (4): 253–270.

Coleman, J. S.
1988 "Social capital in the creation of human capital." American Journal of Sociology, 94: S95–S120.

Csikszentmihalyi, M.
1999 Creativity. New York: Harper Collins.

Damanpour, F.
1991 "Organizational innovation: A meta-analysis of effects of determinants and moderators." Academy of Management Journal, 34: 555–590.

Edmondson, A.
1999 "Psychological safety and learning behavior in work teams." Administrative Science Quarterly, 44: 350–383.

Fleming, L., A. Juda, and C. King, III
2007 "Small worlds and regional innovative advantage." Organization Science, vol. 18 (in press).

Fleming, L., and O. Sorenson
2004 "Science as a map in technological search." Strategic Management Journal, 25: 909–928.

Fleming, L., and D. Waguespack
2007 "Boundary spanning, brokerage, and the emergence of leadership in open innovation communities." Organization Science, 18: 165–180.

Ford, C. M.
1996 "A theory of individual creative action in multiple social domains." Academy of Management Review, 39: 1112–1142.

Gardner, H.
1993 "Seven creators of the modern era." In J. Brockman (ed.), Creativity: 28–47. New York: Simon and Schuster.

Gilfillan, S.
1970 The Sociology of Invention, reprint ed. (Originally published in 1935.) Cambridge, MA: MIT Press.

Glaeser, E., D. Laibson, J. Scheinkman, and C. Soutter
2000 "Measuring trust." Quarterly Journal of Economics, 115: 811–846.

Gordon, M.
1980 "A critical reassessment of inferred relations between multiple authorship, scientific collaboration, the production of papers and their acceptance for publication." Scientometrics, 2 (3): 193–201.

Gould, R.
1991 "Multiple networks and mobilization in the Paris Commune, 1871." American Sociological Review, 56: 716–729.

Granovetter, M.
1973 "The strength of weak ties." American Journal of Sociology, 78: 1360–1379.

Hall, B., A. Jaffe, and M. Trajtenberg
2001 "The NBER patent citations data file: Lessons, insights and methodological tools." National Bureau of Economic Research Working Paper No. 8498.

Hansen, M. T.
1999 "The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits." Administrative Science Quarterly, 44: 82–111.

Hargadon, A., and R. I. Sutton
1997 "Technology brokering in a product development firm." Administrative Science Quarterly, 42: 716–749.

Hausman, J., B. Hall, and Z. Griliches
1984 "Econometric models for count data with an application to the patents R&D relationship." Econometrica, 52: 909–938.

Heckman, J. J.
1976 "Sample selection bias as a specification error." Econometrica, 47: 153–161.

Hunt, M., T. Ogden, and M. Neale
2003 "Who's really sharing? Effects of social and expert status on knowledge exchange within groups." Management Science, 49: 464–477.

Ibarra, H.
1993 "Network centrality, power, and innovation involvement: Determinants of technical and administrative roles." Academy of Management Journal, 36: 471–501.

Ingram, P., and P. Roberts
2000 "Friendships among competitors in the Sydney hotel industry." American Journal of Sociology, 106: 387–423.

Kasof, J.
1995 "Explaining creativity: The attributional perspective." Creativity Research Journal, 8: 311–366.

Katz, E., and P. F. Lazarsfeld
1955 Personal Influence. New York: Free Press.

Katz, J., and B. Martin
1997 "What is research collaboration?" Research Policy, 26: 1–18.

Katz, R., and T. Allen
1982 "Investigating the Not Invented Here (NIH) syndrome: A look at the performance, tenure, and communication patterns of 50 R&D project groups." R&D Management, 12: 7–19.

Kroeber, A.
1944 Configurations of Culture Growth. Berkeley: University of California Press.

Leonard, D., and W. Swap
1999 When Sparks Fly: Igniting Creativity in Groups. Boston: Harvard Business School Press.

Levine, J., H. Choi, and R. Moreland
2003 "Newcomer innovation in work teams." In P. Paulus and B. Nijstad (eds.), Group Creativity: Innovation through Collaboration: 202–224. New York: Oxford University Press.

Levine, D. Z., and R. Cross
2004 "The strength of weak ties you can trust: The mediating role of trust in effective knowledge transfer." Management Science, 50: 1477–1490.

Marsden, P. V., and N. E. Friedkin
1994 "Network studies of social influence." In S. Waserman and J. Galaskiewicz (eds.), Advances in Social Network Analysis: 3–25. Thousand Oaks, CA: Sage.

Marx, M., D. Strumsky, and L. Fleming
2006 "Inventor mobility and non-competes: The Michigan experiment." Working paper, Harvard Business School.

Mayhew, B. H.
1980 "Structuralism versus individualism: Part 1, Shadowboxing in the dark." Social Forces, 59: 335–375.

McEvily, B., and R. Reagans
2005 "Networks and knowledge transfer: The search-transfer problem reconsidered." Working paper, Carnegie Mellon University.

McEvily, B., and A. Zaheer
1999 "Bridging ties: A source of firm heterogeneity in competitive capabilities." Strategic Management Journal, 20: 1133–1156.

McFadyen, M., and A. Cannella
2004 "Social capital and knowledge creation: Diminishing returns of the number and strength of exchange relationships." Academy of Management Journal, 47: 735–746.

Melin, G.
2000 "Pragmatism and self-organization: Research collaboration on the individual level." Research Policy, 29: 31–40.

Merton, R. K.
1968 "The bearing of empirical research on sociological theory." In R. K. Merton, Social Theory and Social Structure: 156–171. (First published in 1948.) New York: Free Press.

Mill, J. S.
1987 Principles of Political Economy. (First published in 1948.) Fairchild, NJ: Augustus M. Kelley.

Milliken, F., C. Bartel, and T. Kurtzberg
2003 "Diversity and creativity in work groups: A dynamic perspective on the affective and cognitive processes that link diversity and performance." In P. Paulus and B. Nijstad (eds.), Group Creativity: Innovation through Collaboration: 32–62. New York: Oxford University Press.

Nelson, R. R., and S. G. Winter
1982 An Evolutionary Theory of Economic Change. Cambridge, MA: Belknap Press.

Nerkar, A., and S. Paruchuri
2005 "Evolution of R&D capabilities: The role of knowledge networks within a firm." Management Science, 51: 771–786.

Obstfeld, D.
2005 "Social networks, the *tertius iungens* orientation, and involvement in innovation." Administrative Science Quarterly, 50: 100–130.

Oldham, G. R., and A. Cummings
1996 "Employee creativity: Personal and contextual factors at work." Academy of Management Journal, 39: 607–634.

Osborn, A.
1957 Applied Imagination. New York: Scribner.

Padgett, J. F., and C. K. Ansell
1993 "Robust action and the rise of the Medici, 1400–1434." American Journal of Sociology, 98: 1259–1319.

Paulus, P., and B. Nijstad
2003 "Group creativity: An introduction." In P. Paulus and B. Nijstad (eds.), Group Creativity: Innovation Through Collaboration: 3–14. New York: Oxford University Press.

Perry-Smith, J. E.
2006 "Social yet creative: The role of social relationships in facilitating individual creativity." Academy of Management Journal, 49: 85–101.

Podolny, J. M., and J. N. Baron
1997 "Resources and relationships: Social networks and mobility in the workplace." American Sociological Review, 62: 673–693.

Poincaré, H.
1921 The Foundations of Science: Science and Hypothesis, the Value of Science, Science and Method. G.B. Halstead, trans. New York: Science Press.

Reagans, R., and B. McEvily
2003 "Network structure and knowledge transfer: The effects of closure and range." Administrative Science Quarterly, 48: 240–267.

Reagans, R., and E. Zuckerman
2001 "Networks, diversity, and performance: The social capital of R&D units." Organization Science, 12: 502–517.

Reagans, R., E. Zuckerman, and B. McEvily
2004 "How to make the team: Social networks vs. demography as criteria for designing effective teams." Administrative Science Quarterly, 49: 101–133.

Reagans, R., E. W. Zuckerman, and B. McEvily
2005 "On firmer ground: A 'hedonic approach' to verifying structural exogeneity in collaborative teams." Working paper, Tepper School of Business, Carnegie Mellon University.

Robinson, W.
1950 "Ecological correlations and the behavior of individuals." American Sociological Review, 15: 351–357.

Rodan, S., and C. Galunic
2004 "More than network structure: How knowledge heterogeneity influences managerial performance and innovativeness." Strategic Management Journal, 25: 541–562.

Rogers, E.
1995 The Diffusion of Innovations, 4th ed. New York: Free Press.

Ross, L.
1977 "The intuitive psychologist and his shortcomings: Distortions in the attribution process." In L. Berkowitz (ed.), Advances in Experimental Social Psychology, 10: 173–220. New York: Academic Press.

Ryall, M., and O. Sorenson
2007 "Brokers and competitive advantage." Management Science, 53: 566–583.

Schilling, M. A., and C. C. Phelps
2007 "Interfirm collaboration networks: The impact of large-scale network structure on firm innovation." Management Science, 53: 1113–1126.

Simmel, G.
1955 Conflict and the Web of Group Affiliations. (First published in 1922.) New York: Free Press.

Simonton, D. K.
1999 Origins of Genius: Darwinian Perspectives on Creativity. New York: Oxford University Press.

Singh, J.
2005 "Collaborative networks as determinants of knowledge diffusion patterns." Management Science, 51: 756–770.

Smith, A.
1982 Lectures on Jurisprudence. (First published in 1766.) Indianapolis, IN: Liberty Fund.

Sorenson, O., and L. Fleming
2004 "Science and the diffusion of knowledge." Research Policy, 33: 1615–1634.

Stein, M.
1963 "A transactional approach to creativity." In C. W. Taylor and F. Barron (eds.), Scientific Creativity: Its Recognition and Development: 217–227. New York: Wiley.

Stock, J., and M. Watson
2003 Introduction to Econometrics. Boston: Addison Wesley.

Stock, J., J. Wright, and M. Yogo
2002 "A survey of weak instruments and weak identification in generalized method of moments." Journal of Business and Economic Statistics, 20 (4): 518–529.

Sutton, R., and A. Hargadon
1996 "Brainstorming groups in context: Effectiveness in a product design firm." Administrative Science Quarterly, 41: 685–718.

Trajtenberg, M.
2005 "The mobility of inventors and the productivity of research." Working paper, Tel Aviv University; NBER and CEPR, NBER SI.

Tsai, W., and S. Ghoshal
1998 "Social capital and value creation: The role of intrafirm networks." Academy of Management Journal, 41: 464–476.

Tushman, M. L.
1977 "Special boundary roles in the innovation process." Administrative Science Quarterly, 22: 587–605.
1978 "Technical communication in R&D laboratories: The impact of project work characteristics." Academy of Management Journal, 21: 624–636.

Uzzi, B.
1997 "Social structure and competition in interfirm networks: The paradox of embeddedness." Administrative Science Quarterly, 42: 35–67.

Uzzi, B., and J. Spiro
2005 "Collaboration and creativity: The small world problem." American Journal of Sociology, 111: 447–504.

Wasserman, S., and K. Faust
1994 Social Network Analysis: Methods and Applications. Cambridge: Cambridge University Press.

Wheelwright, S., and K. Clark
1992 Revolutionizing Product Development. Boston: Harvard Business School Publishing.

Woodman, R. W., J. E. Sawyer, and R. W. Griffin
1993 "Toward a theory of organizational creativity." Academy of Management Review, 18: 293–321.

APPENDIX A: Inventor-Matching Algorithm

We refined the name-matching algorithm from the procedure developed by Trajtenberg (2005). Trajtenberg's algorithm includes matching criteria based on an inventor's city, assignee, patent technology classes, shared co-inventors, citations, and the SOUNDEX coding method applied to inventors' names (to correct for phonetic misspellings). We included additional criteria for scoring based on the population in which the inventor resided. Accordingly, a relatively common name in a zip code with a very small population received a higher score than the same name in a zip code with a larger population. Also, we used a combination of the U.S. Census Bureau's Frequently Occurring First Names and Surnames list (http://www.census.gov/genealogy/www/freqnames.html) and the occurrence of an inventor's name in the patent data base to create a ratio for scoring a possible name match. A name that occurred with relative frequency in the population, but only once or twice in the patent data base, received a higher score than a name that was more common in both the data base and the U.S. Census name list. For 30 randomly selected inventors, the algorithm correctly assigned 215 of their 226 patents (as determined by resume searches and personal contact). The 11 incorrectly determined patents were assigned to four isolated individual nodes.

APPENDIX B: Subclass Description and Variable Example

The U.S. Patent Office organizes all technology into approximately 400 classes and over 100,000 subclasses. Each patent is assigned to one and often more classes and subclasses. The office periodically updates the organization within selected classes and backdates that organization to 1790, such that all U.S. patents are consistently organized. We used the 2004 concordance in our analyses. Because the hierarchy and numbering in the class and subclass organization is inconsistent across classes, we did not rely on hierarchical class assignments. Instead, we took the finest unit of technology, the subclass, and considered the first pairwise combinations and future use of any particular subclass combination.

To provide an example of how subclass combinations measure generative creativity and use, we consider the first author's two patents during the period 1990–1992 (patents 5,029,133 and 5,136,185). Consistent with the modal outcome for each inventor period (35,247 of 53,570 observations), the patents had at least one new subclass combination. Also consistent with the modal outcome for use (23,983 of 35,247 observations), at least one of the combinations appeared again. We explain what the most popular new subclass combination represents, describe its invention, and trace its use in future inventions.

Three of the five new subclass combinations appeared again; two were used just once and one has been used 10 times. Subclasses 326/31 (signal level or switching threshold stabilization) and 326/82 (current driving fan in/out or off chip driving) first appeared together in patent 5,136,185, which was applied for in 1991, assigned to Hewlett Packard Company, and was granted to two inventors living in Silicon Valley. Subclasses 326/16 (test facilitate feature) and 326/56 (tristate feature) were also combined in that invention. Subclass 326/31 comprises electronic circuits that must switch and stabilize a single valid voltage level (high or low) in the presence of other driving circuits. Subclass 326/82 comprises circuits that drive or are driven by a large number of other circuits. These last two subclasses were combined to solve the problem of generating automatic test patterns that did not cause bus contention (buses are multiple sets of signals, usually connected to 16-bit or 32-bit registers; bus contention occurs when two circuits drive opposite voltages on a bus). Engineers design computer chips to avoid bus contention in normal operation, but automatically generated tests can manipulate the chip in abnormal ways, such that two circuits can fight for control. In the worst cases, this damages the chip by connecting a direct path between power and ground. Even in the absence of damage, contention makes the test invalid.

The inventor in this case was a broker between two other inventors, but it was five years before another inventor used this same combination. After that time, the combination appeared increasingly frequently, with a total of 10 appearances by the end of data collection in 2002. The second and subsequent appearances all came from outside Hewlett Packard, and no geographically local, Silicon Valley uses occurred until the sixth and eighth appearances. Hence, there were no additional uses in the inventor's immediate network, and diffusion beyond the immediate network was extremely slow, consistent with Singh (2005). All future uses were for a similar application, that is, methods of designing hardware that would support automatic test pattern generation and application.