Brokerage vs. Cohesion and Collaborative Creativity: An Evolutionary Resolution

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Abstract: How do collaborative networks influence an individual's creativity? Some have argued that structural brokerage – having direct ties to collaborators who do not have direct ties with one another - leads to greater creativity. Others have argued for the benefits of cohesive and redundant ties between an individual's collaborators. To resolve the controversy, we argue that brokerage confers contingent benefits, based on the degree of trust and non-redundant information between collaborators, the professional experiences of the individual, and whether the outcome is initial creativity or its eventual impact upon future creative search. We demonstrate that the very same social structure that enables generative creativity also inhibits its diffusion and subsequent impact. Evidence from the structural career histories of over 50,000 collaborative inventors supports the arguments.

Introduction

What is the relationship between networks and knowledge? The question has attracted a huge amount of attention recently. While even casual observation reveals correlation between networks, knowledge flow, and creativity, the causal relationships remain in dispute. Though scholars understand the diffusion of knowledge relatively well (Rogers 1995), less work considers its creation, and little considers creation and diffusion jointly. Recent work has focused on how brokerage, as opposed to cohesion, influences creativity (Hargadon and Sutton 1997; Burt 2004; Obstfeld 2005; Uzzi and Spiro 2005; McEvily and Reagans 2005). Brokerage occurs when one individual provides the sole tie between creative collaborators; in this situation, collaborators do not work with one another in the absence of the focal broker. In contrast, collaborators within cohesive networks interact widely without depending upon the focal actor as the sole or "hub" connection. Proponents of brokerage argue for the benefits of information control and first access to knowledge and recombinant opportunity. Proponents of cohesion argue for the benefits of trust, redundant information paths, commitment, and shared risk taking. Unfortunately, a variety of results can be cited for both arguments, and the controversy remains theoretically and empirically unresolved.

We offer a resolution to this controversy by demonstrating contingent benefits for both positions. After first reviewing the conflicting arguments and results, we detail possible causes of such conflicts. Theoretical causes of the controversy include multiple levels of analysis, failure to recognize individual differences and contextual influences, and different concepts of creativity. Additional empirical causes include aggregation bias and network endogeneity and autocorrelation. Restricting our analysis to individuals, we argue and demonstrate that brokerage enhances seminal creativity but decreases the impact of that same creativity in future search. Cohesion demonstrates marginal benefit in contexts with non-redundant information and lacking in trust, and for individuals with professionally varied and richer creative backgrounds. A ten percent sample of all the career histories of inventors of U.S. patents from 1975 through 1999 provide empirical support for our arguments.

Brokerage vs. Cohesion and Creativity

How does collaborative structure influence an individual's creativity? Will an individual be more creative if her collaborators work only with her, or if they work with one another as well, in her absence? Although social interaction is generally thought to enhance creativity (Sutton and Hargadon 1996; Leonard and Swap 1999), the optimal social structure of that interaction remains controversial, and in particular, whether brokerage or cohesion confers creative benefits. Brokerage occurs when an individual bridges otherwise unconnected individuals (Burt 1992). A broker occupies the sole intermediate position between alters, such that alters can interact only through the broker. For example, a scientist who worked individually with her graduate students, but did not allow her students to communicate directly or collaborate without her, would occupy a brokerage position in her collaboration network. All the laboratory's results, ideas, and new knowledge would flow through her, such that she alone would direct its diffusion across students and projects. Cohesion constitutes the opposite of brokerage and occurs when alters interact directly with the focal actor and one another, independent of the focal individual (Coleman 1988). Flipping the example cited above, a scientist who encouraged communication and collaboration among her students without her participation would occupy a cohesive position in her collaboration network. The laboratory's results, ideas, and new knowledge would diffuse directly between the members of this cohesive group.

Proponents of cohesion usually build upon Coleman's (1988) conception of social capital. Coleman proposed that closed social structure engenders greater trust amongst individuals. Closure occurs when individuals have dense and overlapping ties between one another. 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 and a tie between B and C would constitute a closed network. Closure enables individuals to act collectively (B and C in this example) and punish undesirable behavior. It enables and facilitates the development of group norms and trust between individuals:

> "Closure of the social structure is important not only for the existence of effective norms but also for another form of social capital: the trustworthiness of social structures that allows the proliferation of

> obligations and expectations. Defection from an obligation is a form of imposing a negative externality or another. Yet, in a structure without closure, it can be effectively sanctioned, if at all, only by the person to whom the obligation is owed. Reputation cannot arise in an open structure, and collective sanctions that would ensure trustworthiness cannot be applied. Thus, we may say that closure creates trustworthiness in a social structure." (Coleman 1988: S107-108)

Coleman's conception of social capital implies a variety of benefits for creative collaborators. If closed networks are trusting networks, and individuals are more likely to share information and knowledge with someone they trust, then closed networks will experience improved information flow. Since creative efforts generally benefit from new information, this should enhance the effort. Redundant and cohesive ties also facilitate the exchange of fine-grained information that is tacit and more proprietary (Hansen 1999; Uzzi 1997; Reagans and McEvily 2003). Strong ties and dense social networks allow sharing not only generative knowledge, but also "knowledge about the social and political context in which innovations are conceived and pursued over time" (Obstfeld 2005: 106). Non-information resources also flow more easily within trusting networks, as individuals can share with less fear of theft or damage and a greater expectation of repayment or reciprocity. As the creative challenge becomes more interdependent, it requires closer coordination, reciprocity, and mutual understanding. Such norms will be easier to develop within social structures that encourage "…the proliferation of obligations and expectations." (Coleman 1988: S107-108) Interdependence is a common challenge in technological contexts, which also require the mobilization of diverse and complex physical resources (Ahuja 2000; Obstfeld 2005). Finally, trust facilitates risk taking (Amabile 1996; Edmondson 1999), a crucial component of social creativity. Proposing truly creative ideas exposes an individual to social failure and ridicule; most individuals will only take such public risks within a supportive social context.

In contrast to arguments based on Coleman's model of cohesion's benefits, proponents of brokerage often build upon Granovetter's (1973) concept of the strength of weak ties. The ties within closed networks tend to be strong, in the sense that they take a disproportionate share of an individual's resources for social interactions. Strong and

closed networks make connections to dissimilar social circles less likely. Weaker ties, in contrast, tend to occur in open networks and often connect people with different interests and diverse perspectives. If creativity requires fresh information and new perspectives, and closed networks lead to insularity and the recycling of redundant information, then individuals within open networks will be more creative. Exposure to different kinds of ideas and diverse information flows afford greater creative opportunities and more possibilities of creating new innovations (Hargadon and Sutton 1997; Perry-Smith and Shalley 2003; Burt 2004). The individual in a brokerage position can also control information in the network more effectively. An actor positioned between two disconnected parties can exploit and manipulate the information flow for her own benefit (Burt 1992; Padgett and Ansel 1993; Cross and Cummings 2004; Rodan and Galunic 2004; Obstfeld 2005). In a creative context, she can extract the best ideas from her disconnected alters. For all these reasons, it is expected that brokers will generate more creative output.

Research has recently begun to integrate these opposed perspectives (Obstfeld 2005). Reagans, Zuckerman and McEvily (2004) propose a trade-off between the generation of ties that expand access to information and those that increase control over the terms of exchange. They differentiate between structurally equivalent and nonequivalent alters. The absence of relations between structurally equivalent alters remains essential for the broker's control advantage but does not necessarily broaden access to non-redundant information. In order to widen the access to information, a structural hole composed of nonequivalent alters is needed. Time also has contingent effects. In their study of the Italian TV production industry, Soda, Usai and Zaheer (2004: 893) find that "current structural holes rather than past ones, but past closure rather than current closure, help current network performance." Earlier research, though it did not address the controversy between cohesion and brokerage, found that weak ties help a project team search for useful knowledge in other subunits but impede the transfer of complex knowledge Hansen (1999). Still, the controversy remains unresolved; as described by Obstfeld (2005), "…the fundamental social mechanics of innovative combination remain underspecified."

Proponents of both camps have adduced evidence in their favor. From ethnographic research amongst New York garment entrepreneurs, Uzzi (1997) found that the information exchanged in embedded ties was more tacit, proprietary and holistic in nature than in the case of arm's-length ties. Ahuja (2000) found that brokerage in strategic alliance relationships correlated with a decreased rate of patenting for firms in the chemical industry. Reagans and McEvily's (2003) data from a contract R&D firm demonstrated that social cohesion eases information and knowledge transfer. Uzzi and Spiro find a correlation between the average cohesion across a small world network and gate proceeds and critical acclaim for New York musicals in a given year. Obstfeld (2005) found that dense social networks and a *tertius iungens* orientation correlated with ex-ante and managerially identified innovations. A *tertius iungens* orientation is a behavioral orientation that emphasizes creating or facilitating ties among people in one's social network, actively introducing dissimilar others (Obstfeld 2005).

Other research has demonstrated the creative and innovative benefits of brokerage. Technological gatekeepers and boundary spanning individuals[1] were found to be creative and high technical performers (Allen 1977; Tushman 1977; Tushman and Scanlan 1981a, 1981b). 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. Burt (2004) analyzed the networks around managers in a large American electronics company using archival and survey data and showed that compensation, positive performance evaluations, promotions, and good ideas are more frequent in the individuals spanning structural holes, i.e., individuals in brokering positions. Cross and Cummings (2004) demonstrated a positive correlation between performance and betweeness amongst engineers. Rodan and Galunic's (2004) surveyed 106 middle managers in a European company to demonstrate that a manager's innovation

[1] Allen (1977) uses the concept of *technological gatekeeper* to refer to a person who keeps her organizational colleagues in touch with current developments by means of her informal connections with the outside. Tushman (1977) also identifies the key role played by *boundary spanning individuals* in the innovation process. Boundary spanning individuals are internal communication stars with significant connections with the outside. Though boundary spanning and brokerage correlate significantly, the effect is not strong (Fleming and Waguespack 2005).

performance correlates with the sparseness of her network. Nerkar and Paruchuri (2005) found a weak relationship between brokerage and future patent citations amongst Dupont inventors.

The conflicting arguments and evidence for cohesion vs. brokerage arise from a host of theoretical and empirical causes. Part of the theoretical disagreement arises from different levels of analysis. A structural position that benefits an individual may not benefit her local work group or her larger organization or creative community. Likewise, a structural position that benefits a firm may be different from one that benefits an individual. Local context can also influence the marginal benefit of brokerage or cohesion, for example, cohesion may help individuals within well connected small worlds (Schilling and Phelps 2004; Uzzi and Spiro 2005). Scholars have also generally ignored (for exceptions, see Burt 2004) differential personal abilities. Some individuals create most productively by sharing their ideas and learning widely; others find it most productive to be the sole integrator and nexus of information flows. Furthermore, these productivity differentials may change over an individual's career. Basic differences also exist in the definition of creativity, for example, between invention vs. innovation (Schumpeter 1934), creation vs. impact (Simonton 1999), and both direct and indirect involvement (Obstfeld 2005).

Empirical challenges further complicate the theoretical problems. Autocorrelation, or the lack of independence between proximal nodes in a network, can result in spurious correlation. Endogeneity can potentially bias the estimations as well, when individuals purposefully create and exploit network positions, and thus obscure the causal advantages. Little empirical network research controls for individual agency or abilities, mainly because of the data collection challenges of longitudinal observations and effective instruments. Aggregation of observations complicates the levels of analysis issues (for example, averaging a measure of individual cohesion across a network); ecological analyses that infer individual level properties from average effects across a network of individuals may be unpredictably biased (Robinson 1950).

We address these issues with a variety of arguments, perspectives and definitions, more comprehensive data, and methodological rigor. We adopt an evolutionary perspective and define creativity as the assemblage of new combinations and its impact as the usage of those new combinations in future creative search. We restrict our theorizing and claims to the individual level of analysis and take that individual's local creative context into account. The hypotheses also explore how an individual's career experiences will influence their return to brokerage. We demonstrate that brokerage will enhance an individual's creation of new combinations and simultaneously hamper the usage of those new combinations in future creative search, by the broker, her creative collaborators, and all others as well. We overcome empirical problems with a large and random sample of longitudinal career data and an instrument for network endogeneity.

Theory

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, or artistic media. 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 1935; Basalla 1988). Rock and roll music is also widely thought to have resulted from a fusion of rhythm and blues and folk music, country, and gospel. Creative individuals describe this combinatorial search process vividly, for example, the mathematician Poincare (1913: 387) described the process: "Ideas rose in crowds; I felt them collide until pairs interlocked, so to speak, making a stable combination." Einstein also wrote that (in Simonton 1999: 29): "…combinatory play seems to be the essential feature in productive thought."

If we restrict our consideration to the initial insight and define *generative* creativity as the assemblage or rearrangement of new combinations, then creativity should be increased by exposure to a wide variety of ideas and components that have not been previously recombined. Burt (2004) notes that, "Novelty is not a feature of this hypothesis," and lists previous proponents, including Smith (1766), Mill (1848), Simmel (1922), and

Merton (1948). Exposure can be increased in a variety of non-social ways, through changes in domain-focus to literature and new education. Much and possibly the majority of exposure, however, occurs through social interactions with other creative individuals (Katz and Lazarsfeld 1955; Allen 1977).

If generative creativity requires the creation of new combinations, then brokers maintain an advantage because they are in a preferred position to receive new and previously uncombined ideas (Hargadon and Sutton 1997; Burt 2004). Individuals who collaborate with colleagues who in turn collaborate with one another are exposed to recycled ideas. In technology, inventors in cohesive communities are more likely to work with previously used components and to refine previously invented combinations. Open social structure also remains less vulnerable to pressures for conformity and group-think (Hunt et al. 2003). Inventors that broker their colleagues, however, are more likely to use new components and generate new combinations of components.

H1: An individual is less likely to create new combinations within a cohesive collaborative structure.

As detailed above, counter arguments to this hypothesis stress how cohesion increases trust, information flow and resource sharing, and collective risk taking. We agree with these classic arguments but believe that their main influence is on the margin. Brokerage leads to greater generative creativity as a first order effect, but cohesion confers marginal benefits when trust is lacking or the collective effort has access to fresh sources of information. In order to test this argument, we consider the marginal effects of cohesion in different psychological and social contexts.

Despite the recent surge of work on brokerage and creativity, little work has considered how the interaction of personal characteristics and collaborative structure influence creativity.[2] People differ greatly, however, in their preferences for roles, strategic

[2] Obstfeld (2005) did not test an interaction but found significant individual correlations between a propensity to join others (a "tertius iungens" orientation), technical knowledge, network density, and the maximum of self-reported innovation involvement across a variety of an organization's managerially identified innovations. The result is difficult to interpret with our theoretical differentiation between

behavior, and abilities to profit from brokerage. More intelligent individuals, for example, can simultaneously consider more divergent views and thoughts (Simonton 1999). This implies that more intelligent people can exploit greater exposure to recombinant potential before suffering cognitive overload. Such individuals might seek and create brokerage opportunities. Even within individuals, the benefits of a structural position will change over time. As individuals progress in their careers, some will gather a more diverse palette of experience and ideas. They will have worked with a wider variety of ideas, media, technologies, and processes and bring knowledge of that diversity to the collaborative relationships. As Hargadon and Sutton (1997) describe, "…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." This diversity in personal experience will decrease the marginal value of brokerage because the focal actor herself will bring fresh information to the collaborative structure (Obstfeld 2005). In contrast, an individual with little previous experience will be forced to rely upon others for recombinant diversity, and benefit more from a brokerage position.

H2a: An individual is more likely to create new combinations within a cohesive collaborative structure if she brings richer creative experience to the collaboration.

Diversity in organizational experience and employers should also increase the marginal benefits of a cohesive position, for two reasons. Consistent with the arguments above, individuals who work across a variety of organizations will bring a greater diversity of ideas to the collaboration, as well as different perspectives, assumptions, and creative techniques (McEvily and Zaheer 1999). This background will bring non-redundant information to the collaboration and decrease the insularity problems of cohesion. Such individuals will also benefit from a cohesive structure if they suffer from a lack of trust by their collaborators. Individuals who have recently changed jobs, for example, will be collaborating with individuals they have only recently met. They will lack the history of

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generative creativity and its impact, since the innovation involvement measure spans a variety of creative work (Ibarra 1989).

repeated interactions which builds trust. Professional and temporary contractors in particular will face problems in being accepted by their fellow employees (Barley 2004). As a result, the non-redundant information they bring to the collaboration will be of less use, unless it can be widely shared and diffused. Such problems will be ameliorated by collaboration within a cohesive structure.

H2b: An individual is more likely to create new combinations within a cohesive collaborative structure if she works across multiple organizations.

In addition to a lack of research on how collaborative structure interacts with personal characteristics, little work has considered how the collaborators' characteristics might influence the efficacy of the focal actor's brokerage. Similar to the benefits of non-redundant information that the focal actor can bring to her collaborators, she will also benefit from greater non-redundant information amongst her colleagues. Because they bring non-redundant and deeper backgrounds to the collective effort, and because cohesive groups will share this information more easily, collaborators with richer creative experiences will confer a marginal benefit to the focal actor in cohesive collaborations.

H3a: An individual is more likely to create new combinations within a cohesive collaborative structure if her collaborators bring richer creative experience to the collaboration.

Outside collaborative ties will also increase the non-redundant and fresh information within the collaboration. Non-local collaborative ties bring important benefits to a local collaboration, because they provide access to recent, salient, and newly generated information. Such ties provide a "weak tie" informational benefit that can counteract the insularity problems of cohesion (Granovetter 1973). Local cohesion also facilitates interpretation of external information and keeps the group focused in the face of external relationships and distractions. The combination of non-local ties and occasional bridging ties generates the local advantage that results in a "small world" network (Uzzi and Spiro 2004; Schilling and Phelps 2004).

H3b: An individual is more likely to create new combinations within a cohesive collaborative structure if her collaborators work with non-local colleagues.

If brokerage increases creativity, how useful is that creativity? Will it have greater or lesser influence upon future creative search? Combinatorial search and insight are only the first stage of creative work. Amabile proposes that creativity needs to be both, "…a novel *and* appropriate, useful, correct or valuable response to the task at hand" (1996: 35, italics added). This definition raises the obvious question of determining whether a new combination is appropriate, useful, correct, or valuable. Perhaps the most classic answer to this question adopts an evolutionary analogy; like influential genes that become widespread, creative products are those that influence future recombinant search.

Though Schumpeter (1934) and Gilfillan (1935) made evolutionary analogies to explain technological change, Campbell developed the first evolutionary analogy to explain creativity (1960). He proposed a (mostly blind) search process of combining ideas, followed by a selection stage of thought trials and the occasional retention of an idea that withstood deeper reflection. Simonton (1999) elaborated the idea and proposed that creativity is best measured by its impact upon wider culture and further search; an artist, inventor, or scientist will rarely be thought creative until society and other creative individuals recognize and use her work. By Simonton's definition, "Unrecognized genius becomes an oxymoron" (1999: 5). Basalla (1988) argues that the ultimate value of a technology can only be judged by its popularity as the basis for future recombinant search. "Only a few variants have the potential to start a new branching series that will greatly enrich the stream of made things, have an impact on human life, and become known as 'great inventions' or 'turning points' in the history of technology" (Basalla 1988: 34). Creative individuals often incorporate their own prior work, but their influence will be limited unless others pick up and build upon their ideas. As Simonton (1999: 7) argues, "Homage is paid when the discoveries and inventions of the past are used to construct the miracles of today, whether they be drugs, telephones, computers, automobiles, bridges, jet airliners, or rockets."

This focus on retention is perhaps the most useful contribution of an evolutionary perspective, because it separates creativity from ultimate success. An inventor can be very creative and develop radically new combinations of components and technologies,

and yet fail to influence future inventions because her work provides no generative basis for future work. Such a perspective avoids the normative bias that creativity and innovation are desirable by definition, or the selection bias of identification of only successful innovations after they have occurred. Avoiding these biases enables a more detailed study of the processes and outcomes of creativity. Consistent with Simonton's (1999) definition of impact, we define an individual's influence on future creative search by the future usages of a new combination. We propose that generative creativity that arises from a brokerage position will have less impact on future creative search, for reasons of refinement, distributed understanding, mutual ownership, and diffusion.

Brokerage positions expose inventors to recombinant opportunity, but such positions provide no guarantee that the resultant combinations are any good. A broker may generate more ideas, but the quality of those ideas may be less, for two reasons. First, a broker may put together higher variance or less workable combinations, because she lacks adequate expertise in the different areas she is integrating. Second, cohesive creativity structure will subject potential ideas to more rigorous scrutiny. Cohesive collaborations will witness wider discussions, more rigorous debate, and more difficult thought experiments, because such experiments will be posed by a wider and greater number of collaborators and tangentially involved colleagues. The increased trust of a cohesive environment will also enhance debate, as collaborators will feel greater psychological safety when questioning the focal inventor's work (Edmondson 1999).

In addition to improved refinement processes, cohesive collaborations will also give rise to a more distributed understanding of any creativity that occurs. Because information flows more freely and redundantly in a cohesive structure, more collaborators will have complete information about the work. Creative processes themselves will be more iterative and distributed, with the result that each collaborator will probably have contributed more to the creativity than in a brokered collaboration. More individuals will have had access to all the components of creativity in a cohesive collaboration. Unlike the broker who was the only person to put together disparate pieces of knowledge and

recombinant opportunity, more individuals will have been privy to the components and opportunity and insightful breakthroughs.

In addition to increased functional knowledge, cohesive creativity will also give rise to a greater sense of mutual ownership (Burt 2005). Collaborators will perceive greater ownership of the creativity and worry less about "stealing" another's idea. In contrast, brokered collaborators will be much more reluctant to build upon an idea that is clearly identified with a particular individual. Such perceptions of group ownership will also ease the challenge of motivating newcomers to develop the idea (Obstfeld 2005). Few ideas spring forth without need of elaboration, testing, and refinement, and often these phases of creativity require different skills, expertise, and background. Cohesive structures will facilitate broader mobilization and collective action.

New combinations arising from cohesive structures are also more likely to be used in future creative search because they will diffuse more widely and easily. Just as brokerage confines and restricts the flow of information through a single node as it arrives, 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 of a distributed and cohesive effort. People around structural holes also have unique backgrounds and by definition, will lack appreciation or understanding of some component of the new combination (Obstfeld 2005). Diffusion will also be impeded by uncertainty about the broker's reputation. As Coleman (1988) argued, reputation can't arise within open structure. Cohesion amongst collaborators will facilitate the development and diffusion of an individual's reputation. Regardless of whether it is positive or negative, brokers' reputations will be less certain. Increased uncertainty will increase the risk of adoption of the ideas and slow their diffusion. Due to these four reasons – improved refinement processes, more distributed understanding, more distributed ownership and easier mobilization, and easier diffusion – new combinations that arise from brokers will have less impact on future creative search.

H4: An individual's new combinations are more likely to be used again if they arise from a cohesive collaborative structure.

Data and Methods

The raw data for the analyses come from all U.S. utility patents granted from 1975 through July of 2002, inclusive (USPTO. 2002). Each patent record contains the patent number, the date of application and grant, all inventors' last names (with varying degrees of first and middle names or initials), inventors' home towns, detailed information about the patent's technology in class and subclass references (over 100,000 subclasses exist), 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, we applied an inventor-matching algorithm to determine each inventor's patents and other inventors with whom the focal inventor had co-authored (for details, *see* Fleming *et al.* 2005). 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 nodes.

We split the data into three year time periods for each inventor's career. Similar archival approaches have used five year windows (McFadyen and Cannella 2004); we found no substantive differences for window size and chose the smaller size to maximize observations. The models analyzed non-overlapping windows, starting with 1975-1977 (this resulted in the following nine windows: 75-77, 78-80, 81-83, 84-86, 87-89, 90-92, 93-95, 96-98). 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. Permutations of those windows (for example, considering the set of windows that starts from 1976-1978, as opposed to 1975-1977) did not change the results. All variables were calculated by application date, that is, the inventor applied for the patent during the three year time period. The database includes 2,058,823 inventors and 2,862,967 patents. Given that network autocorrelation makes proximal observations dependent and thus violates the assumption of independent observations in statistical estimations, we sampled 10% of the U.S. inventors for our analyses.

Dependent Variables

New combinations: The models use the number of new subclass pairs in an inventor's patents as a measure of creative *variation*. The subclasses come from the U.S. Patent Office's organization of all technology into approximately 100,000 categories (Carr 1994). The patent office also periodically updates its classification system and subclass assignments for all patents back to the system's founding in 1790 (we used the 2004 concordance). 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 the focal inventor's three year window. An alternate measure and model of the proportion of patents with new combinations in the three year window returned very similar results to the count variable and model.

Future usages of the combination: The second dependent variable counts the inventor's *impact* as number of times that future inventors use the focal inventors' new combinations. The variable therefore measures the influence of the inventor's work upon future inventive search. More influential inventors will have more of their new combinations used in future search. When a new combination is used twice within a single three year window, only the first usage is counted as a new combination; the second adds to the future uses variable. Given recent concerns about prior art citations as a measure of inventive success or diffusion (Alcacer and Gittleman 2005), future usage remains a cleaner and more easily interpreted variable. Following Nerkar and Paruchuri (2005), we also found that brokerage had a weak positive effect on future prior art citations. The measure remains difficult to interpret for our theory, however, because it conflates generative variation and future impact.

Explanatory Variables

Cohesion: We measured the opposite of brokerage by calculating a density measure of the ties between each focal actor's alters (Podonly and Baron 1997). This measure therefore calculates the cohesion, or opposite of brokerage, of the focal inventor's network. We calculated density as the unique number of pair wise collaborations

between a focal actor's collaborators that did not include the focal inventor, divided by the number of potential collaborations (the number of unique alters choose 2). For bibliographic data such as patents, this means all the pair wise relationships on patents that did not include the focal inventor. It is interesting to note that most individuals fully broker their collaborative relationships – 67% of the observations indicate no relationships between alters and 63% of the individuals never patent within cohesive collaborations. As a robustness check and to account for repeated collaborations between individuals, we also developed a measure that counted the non-unique number of patent collaborations between an inventor's alters that did not include the focal inventor. Results improved with this pseudo-density measure.

Explanatory variables that interact with cohesion:

Ln of assignees: The models include the ln of the number of assignees that appear in the inventor's patents (all count variables were logged to account for their exponentiated entry into the count models). We predict a positive interaction of multiple assignees and cohesion, due to the mobile inventor's difficulty of gaining trust as she works in multiple organizations.

Ln of focal inventor's experience: We calculated the cumulative total of unique subclasses that the focal inventor has worked in, divided by the cumulative number of the inventor's patents, prior to the current time period. The models include the ln of the variable due to its extreme skew. We predict that the interaction of cohesion and focal inventors' experience will be positive, due to the non-redundant information she brings to the creative effort.

Ln of collaborators' experience: We calculated the cumulative total of unique subclasses that the focal inventor's collaborators had worked in prior to the current time period, divided by the total number of the collaborators. The models include the ln of the variable due to its extreme skew. The variable controls for the diversity of experience that the inventor's collaborators bring to the creative effort. We predict that the interaction of

cohesion and collaborators' experience will be positive, due to the non-redundant information they bring to the creative effort.

Ln of non-local ties: The models include the ln of the number of non-local ties to a focal inventor's collaborators. Non-local ties are all ties to the inventor's collaborators that do not have a tie to the focal inventor. Non-local ties might improve a focal inventor's creativity by bringing her fresh information, but they also might have the opposite effect if they distracted collaborators from the focal inventor's creative efforts. We predict, consistent with the small worlds hypothesis, that the interaction between cohesion and non-local ties will be positive. This occurs due to the non-local ties bringing non-redundant information to an insular and cohesive group, combined with the effect that cohesion enables the local group to buffer non-local distraction better. As illustrated below, we found a non-monotonic relationship between the variable and creative variation and hence include a second order term.

Control Variables

Ln of number of patents: The models include the ln of the number of patents by the inventor during the three year window. Prolific inventors should create more new combinations and have a greater impact upon future technological evolution. This variable controls for patenting strategies, for example, if an individual chose to include all her creativity or claims in one patent, or split them across multiple patents.

Ln of indirect network size: The models include the ln of the size of the inventor's indirect collaborative network. The measure calculates the number of inventors with direct or indirect ties to the focal inventor's collaborators' collaborators, minus the focal inventor. Singh (2004) demonstrates that collaborative ties aid in the diffusion of knowledge, as measured by future prior art citations.

Ln of new subclasses: The variation models include the number of new subclasses in the inventor's patents. The number of new combinations variable only counts new

combinations, that is, a new subclass by itself does not constitute a new combination (the results are insensitive to the assumption). Yet, appearance of a new subclass obviously increases the opportunities for new subclass pairs.

Ln of potentially new subclass pairs: The variation models include the ln of the number of new subclass pairs that an inventor might create, given the set of subclass pairs that she works with in a given time period. We calculated this variable as the total possible subclass pairs (which is the number of subclasses that the inventor works with in the three year window, choose 2), minus the number of subclass pairs which have been combined previously (by any inventor in the history of U.S. patents). The variable essentially controls for the recombinant potential and combinatorial space of the inventor's component set. For example, if an inventor was working with a small set that inventors had previously worked with, she would be much less likely to create a new subclass pair.

Prior art age: The models include the average of the patent numbers that the inventor cites as prior art. Because patents are numbered sequentially, this measure correlates very strongly with age – smaller values of this number indicate that the inventor is working with older technologies, on average. Newer technologies probably provide more fertile opportunities for inventors and have been repeatedly shown to correlate with impact, as measured by future prior art citations (the effect appears to be robust to whether the inventor or examiner added citations, *see* Alcacer and Gittleman 2005). Inventors that lacked any prior art cites were given an average value of the variable, zero, and were dropped; no assumption changed the substantive results. We divided the number by one million to avoid excessively small coefficients.

Ln of 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. Awareness of the scientific literature makes the search process less random, particularly with interdependent components, identifies new components of recombination (Fleming and

Sorenson 2004), and enables faster diffusion of technical knowledge across organizational, technological, and geographic boundaries (Sorenson and Fleming 2004). We expect non-patent references to demonstrate a positive correlation with generative creativity.

Ln of university patents: The models include the ln of the number of the inventor's patents assigned to a university. Collaborative structure in university labs probably differs from that in private firms. For example, a professor might work individually with a variety of students, similar to a brokering position.

Indicator of similar prior subclasses: The models include an indicator for overlap in sub-class experience between the focal inventor and her collaborators. We included the indicator because a count of overlap variable demonstrated a severely bimodal distribution; either none or all of the previous subclasses overlapped. We expect more similar backgrounds to result in fewer new combinations.

Repeated collaboration ratio: The models include the ratio of current collaborators with whom the focal inventor has worked with previously. We can think of different arguments for the effect of this variable (McFadden and Cannella 2004). Working with prior collaborators could decrease the possibility of creativity, because such colleagues would have already gained most of the potential learning from the prior collaboration. On the other hand, repeat collaborators would know each other's work styles, strengths and weaknesses, experiences, and be able to avoid repeating unsuccessful collaborations.

Degree of collaborators: The models include the ln of the number of unique inventors that the focal inventor collaborates with over the time period. The variable has a minimum of two collaborators, since brokerage requires at least two alters. McFadyen and Cannella (2004) demonstrated that working with a greater number of collaborators increased scientists' impact, although the effect was non-monotonic.

Time and career period indicators: All models include indicator variables for time period and career period of the inventor. Time period indicators control for differences in the time that combinations are at risk of usage in further application and career period indicators control for differences in productivity and creativity over a career.

Selection hazards: By definition, brokerage cannot occur unless an individual works with more than one collaborator. Many inventors work alone or with one other inventor, however, and thus will have no effect on the estimations. To control for the possibility of selection bias, we estimated a first stage selection model (Heckman 1976) and included the inverse mills ratio in the variation models. The first stage used variables that would correlate with an inventor's number of collaborators, including time and career period indicators, number of patents. Variables for identification that were not included in the final models included the cumulative number of patents and citations in the inventor's career and indicator variables for patents without assignees or prior art citations. The impact 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. In this case, the first stage estimated invention of at least one new combination, as a function of all variables in model 7. Both variation and impact results were robust to the inclusion of the selection hazards. Tables 1 and 2 provide descriptive and correlation statistics. Results remained robust to outlier exclusion.

Models and Results

Both dependent variables demonstrate skewed count distributions. Use of linear regression on such distributions can result in inconsistent, biased, and inefficient estimations. 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 argued for variation across inventors, and our data provide repeated observations of individuals over their inventive career, we estimated random effects conditional logit models (Hausman *et al*. 1984) in STATA Version 8.

Table 3a includes all control variables and then cohesion alone, followed by each interaction. First considering the control variables, more prolific inventors invent more new combinations, particularly when they work in new and science based technologies and with more collaborators. The size of creative opportunity of combinatorial space demonstrates an extremely strong positive influence upon generative creativity, as does the number of new subclasses. The number of university patents, the similarity of backgrounds between the focal inventor and collaborators, and ratio of repeated collaborators do not demonstrate significant effects. Considering the first order effects of the predicted interaction variables, inventors' prior diversity of creative experience correlates positively with variation. The number of assignees and non-local ties correlated negatively with variation. The inclusion of a second order non-local ties term greatly increased the ln likelihood of all models, indicating that an inventor whose collaborators are tied to many others is much less creative. Cohesion consistently correlates with decreased creativity and all interactions correlate positively and significantly when included individually.

Table 3b includes full models and robustness checks. Model 6 includes all predicted interactions together. The assignee and collaborative experience interactions remain significant and as predicted, the non-local ties interaction remains marginally significant, and the focal inventor's experience interaction drops below conventional significance thresholds. Model 7, which includes the hazard selection term for collaborating with more than one co-author, demonstrates similar results, with the exception that the non-local tie interaction regains significance at the 5% level. Model 9 uses the alternate formulation of cohesion which includes all collaborations and not just unique ties. It returns similar results, except that the focal inventor experience interaction regains significance at the 5% level. Altogether, there is strong evidence to support the first four of the predictions and weak evidence for the fifth. Brokerage appears to increase generative creativity, but cohesion helps on the margins when collaborations have non-redundant information or suffer from a lack of trust.

We use model 7 to interpret the size of the effects. Cohesion demonstrates a strong and consistent negative influence upon variation. A one standard deviation increase in cohesion correlates with 14.3% fewer new combinations.[3] The interaction of multiple assignees with cohesion correlates with a 3.8% increase in new combinations, the interaction of the focal inventor's experience with a 0.9% (but insignificant) increase, the interaction of the collaborator's experience with a 3.1% increase, and the interaction of non-local ties with a 2.1% increase. Given that the interaction effects together almost offset the negative influence of cohesion, it is not surprising that qualitative researchers have noted both positive and negative influences on generative variation (Uzzi 1997; Hargadon and Sutton 1997). The interactions are very common in creative contexts and would make it difficult to disentangle the separate effects without a quantitative and correctly specified model. The positive interaction with non-local ties provides strong evidence at the inventor level that the small world interaction improves creativity (Uzzi and Spiro 2005; Schilling and Phelps 2004). The models also indicate very strong negative effects of non-local ties, however; combined with the negative first order effect of cohesion, the positive small world interaction is swamped. Overall, it does not appear that small world networks help the focal inventor.

We tested the robustness of these results in three additional ways. First, instead of the count of new combinations we modeled the proportion of patents that contained a new combination in model 8. While count models naturally deal with extremely skewed dependent variables, the consistency increases our confidence that the results are not driven by outliers. Second, we measured density with all repeated ties, not just unique ties, in model 9. While the measure does not technically qualify as a density, it takes tie strength into account, and is arguably a better measure. Results improved as all predicted effects demonstrated significance. Model 9 indicates that resolution of the cohesion vs. brokerage controversy may not depend upon tie strength (Obstfeld 2005).

[3] 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 $e^{(-0.5901*0.26)} = 0.857$. $1 - 0.857 = .143 = 14.3\%$.

We also instrumented cohesion in order to remove endogeneity and omitted variable bias. Because the data only record collaborations after the fact, we cannot determine if they were formed in order to exploit an opportunity that already existed or whether the brokerage role caused an increase in creativity as hypothesized. An effective instrumental variable needs to correlate with cohesion but not the ultimate outcome of new combinations. We argue that the number of unique patent lawyers for each inventor's three year window provides such an instrument. This usage assumes that brokers are more likely to use a greater number of patent lawyers, because they will be working with a greater variety of inventors. In contrast, if inventors worked within a very cohesive collaborative structure, they would be more likely to all use the same set of patent lawyers. This usage 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 upon lawyers for the non-collaborative inventors in our sample did not demonstrate a 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 direction in the full model and passed the Stock test for explanatory power (providing an expected decrease in bias of at least 90%, see Stock *et al.* 2002). The instrument remains weak, however; with all second stage predictors plus the instruments, the first stage R^2 reached 81.3%, of which the instruments provided only an additional 0.1% of explanatory power. As a result, while we have partially addressed the endogeneity problems, we hesitate to claim more than an incremental robustness check for our reduced form models. The issue of network agency and its empirical endogeneity complications strikes us as important and neglected, however, and worthy of future research.

Table 4 illustrates the impact or future usage model results. Model 10 estimates the influence of brokerage upon future usage by all inventors, models 11 and 12 split this usage between focal inventor and all others, and models 13-15 split model 12 into usage by co-inventors of the original combination, collaborators (but not inventors) of the

original combination, and all other inventors who were not directly tied to the focal inventor during the three year time period. Model 10 supports hypothesis 4, that creative variation that arises from a cohesive collaborative structure is more likely to be used in the future. The additional models enable us to test the individual arguments behind the prediction. Given the severe selection involved (an inventor's new combinations cannot be used in future creative search unless they exist), we included the selection hazard in all models (reduced form models returned similar substantive results).

Model 11 considers future uses by the focal inventor only. Cohesion has no correlation with future usage. The size of the component and number of collaborators demonstrate a negative influence upon the focal inventor's future usage. This is understandable, if large components and more collaborators expose the inventor to other possibilities for future work. Model 12 looks at the complement of model 11's dependent variable, or all other usages besides those of the focal inventor. The effect of cohesion is positive and indicates a 3.2% increase in future usage by other inventors for combinations that originate within a cohesive position.[4] Model 13, usage by co-inventors of the new combination, drives much of this positive influence, as indicated by a 15.4% increase in the positive effect of cohesion. As might be expected, degree also has a positive influence on this outcome, though the size of the component remains negative, consistent with a competing opportunities argument. Model 14 indicates a 11.0% positive influence of cohesion upon future usage by collaborators who are not co-authors of the new combination. This result provides strong evidence that knowledge and understanding flow more freely within cohesive social contexts; while these inventors were not part of the original project, they are still much more likely to use the new combination if cohesively embedded. Finally, model 15 indicates a 2.4% increase in all other usage for combinations invented in a cohesive context. This positive – though comparatively smaller – result indicates strong evidence that creativity that arises from cohesive structure diffuses more readily.

[4] One standard deviation for the cohesion variable, conditional on having created a new combination, is 0.248.

Discussion

The results, though supportive of the theory, should be interpreted with caution for a variety of reasons. Archival approaches such as publications or patents have a variety of problems and advantages (McFadyen and Cannella 2004). Problems include selection bias – unsuccessful attempts at creative work remain unobserved. As with all patent data, we only observe successful patent applications. To explore this selection bias, Fleming et. al. (2005) sampled inventors and provided them with illustrations of their historical networks. None could recall failed inventions that relied on a different inventor network, but one indicated that the patent network failed to reflect his scientific collaboration network. Patent co-authorship networks represent only one type of tie and obviously miss a wide variety of other ties that could influence creativity. One advantage, however, of the dependent variable of new combinations, is that it measures the variance in impact across successful patenting outcomes. Another concern is that, despite our liberal and explicit use of an evolutionary framework, we did not theorize or model the selection and retention stages separately. This partly reflects a breakdown of the evolutionary analogy – while recombinations of genetic and creative material can both be observed (or at least proxied), it remains difficult to separately specify selection and retention steps in creative evolution (Simonton 1999; Vincenti 1990). The data probably remain incapable of modeling the steps as well, though the future usage of a new combination arguably proxies the ultimate outcome well.

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. Fixed effects models returned similar results, though both the focal inventor experience and non-local ties interactions lost significance in the generative variation models.[5] All significant results in the impact models stayed significant. More interestingly, the positive first order effect of brokerage in the fixed effects generative

[5] Recent research has demonstrated that the Hausman et al. (1984) specification is not a true fixed effects model (Allison and Waterman 2002). Our data sample was too large, however, for software specifically developed to implement the true fixed effects on large datasets (as explained by William Greene, an author of LIMDEP, the only package that implements true fixed effects for a negative binomial panel). Analyses on subsets of our data indicated similar but inconsistent results, which reflect a known problem with "true" fixed effects models.

models was 60% of the effect in the random effects models. This indicates both within *and* across person advantage to brokering. Some people are better generative brokers than others, but everybody can benefit from a brokerage position. In the impact models, the fixed effects coefficients ranged between 75 to 88% of the random effects coefficients. This lack of difference implies that individuals have relatively little influence upon the impact of their work, once it is created. The lack of qualitative differences between fixed and random effects models provides evidence that the results are not driven by individual differences such as intelligence or collaborative strategy.

The difference in fixed and random effects models should motivate deeper analysis of careers and brokerage techniques. If it is possible to learn more effective brokerage techniques, then creative professionals might all improve their generative creativity. It would also be interesting to investigate if individuals become more or less effective brokers as they gain career experience. Brokers may also gain advantage from introducing others across their structural hole (DiMaggio 1992; Obstfeld 2005), especially as they gain creative experience and lack the time to pursue the creative opportunity themselves. The impact stage could also benefit from increased scrutiny. For example, the large but insignificant effect in model 11 might result from poorer quality, as argued, or it might result from a personal inclination towards variation, at the expense of future usage and refinement, on the part of individuals naturally inclined towards generating variation. Also motivating further research on careers is the fact that most collaborative inventors broker; in our sample, 67% of the observations had a density measure of zero, and 63% of inventors always brokered.

The managerial implications of the research are reasonably clear for creative professionals who chose to collaborate. Brokerage provides clear benefits for generative creativity. Some individuals take better advantage of brokerage, but all individuals benefit. Those benefits are tempered on the margins in situations of fresh information or lack of trust, but not enough to overcome the first order benefit. Less experienced individuals may benefit more from brokerage, since they bring less depth of background and fresh information to the collaboration. Creative brokers that wish to have an impact,

however, must pay attention to the diffusion of their ideas. They will need to explain their creativity well, enhance perceptions of group ownership, and see that diffusion paths are open and functional.

The results also imply managerial opportunity to control the degree of a firm's exploration vs. exploitation (March 1991; O'Reilly and Tushman 2004). Brokered networks are explorative networks; they create new variants, unusual combinations, and future opportunity. Cohesive networks are exploitation networks; they develop ideas, refine new approaches, and mobilize the diverse resources needed to bring a creative opportunity to fruition. Like explorative breakthroughs, brokered networks are more fragile and risky; like exploitive incrementalism, cohesive networks are more robust and assured.A manager should maintain an awareness of her organization's networks and encourage brokerage or cohesion, depending on the firm's immediate and future strategic needs the stages of product development. Network design can thus provide a control to engender the desired creativity from an organization.

Finally, the results imply a reinterpretation of two classic problems in technology management. First, why can some organizations invent but not commercialize breakthroughs? For example, Xerox PARC invented a plethora of incredible breakthroughs, from the graphic interface, mouse, and networking technology, yet failed to effectively transfer the technology to a commercial division (let alone a market). Based on these 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, made it more difficult to transfer the technology. We realize that our results cannot speak to the many challenges of product development, marketing, and manufacturing, but these issues become moot if the technology cannot be diffused beyond its original inventor. Related to this problem of breakthrough invention and commercialization is the observation of Not Invented Here (NIH) syndrome (Allen 1977; Katz and Allen 1982). Anecdotal reports of NIH would be more likely, the bigger the invention that was not successfully transferred. If such inventions were more likely to have been invented by a broker, they would have been

more difficult to transfer. While the NIH problem as classically been cast as a problem on the receiving end, this work shifts the focus back to the originating person and organization, and provides a fundamental explanation for the difficulty. Revisiting these classic problems, given these results, might prove profitable.

Conclusion

This work offered an evolutionary resolution for whether collaborative brokerage hurts or helps creative efforts. Using the career histories of a 10% sample of all U.S. inventors from 1975-1999, we demonstrated that brokerage positions increase generative creativity but decrease the usage of that creativity by other inventors in the future. Based on the classical arguments that cohesive structure creates trust but leads to the recycling of redundant information, we demonstrated marginal benefit for cohesion when focal inventors work across multiple organizations, when collaborators possess richer creative backgrounds, and when collaborators also work with non-local collaborators. The interaction effects, while mostly significant, do not – even when totaled together – come close to the strong first order and negative effect of cohesion. It appears that brokerage provides the most effective position for creating new combinations. Cohesion can improve generative creativity on the margins, when trust is an issue or non-redundant information is available, but the first order is strongly negative. In contrast to the positive effects on generative creativity, the influence of brokerage on the ultimate impact of the creativity is negative. Cohesion has the strongest positive impact on future use for co-inventors and collaborators who were not part of the original creation. It also has a smaller though still significant impact on future use by inventors who have no direct relationship with the focal inventor.

The research makes a number of theoretical and empirical contributions. Sociological research on creativity has become much more common place recently, but little work on creativity has yet investigated how career experiences and personal characteristics can interact with social structure. By using an evolutionary perspective, this research confirmed many of the conflicting arguments in the discussion of brokering vs. cohesion and described the contingencies under which both could be correct. It explained a variety

of mechanisms for the negative influence of brokerage upon impact, including less thorough refinement, less distributed understanding, less mutual ownership, and more onerous paths for diffusion. The individual level of analysis avoided aggregation bias, a common problem for archival organizational level research on creativity. The models remain robust to an instrument for network endogeneity and provide an initial example of how empirical network modeling might account for agency and strategic action. Perhaps most importantly, the research illustrates the irony that the very collaborative structure that enhances generative creativity also diminishes the possibility of its having widespread impact.

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Table 1: Descriptive statistics, n=53,570 observations, 35,400 inventors.

Variable	mean	sd	min	max
new combinations	10.41	49.78	0.00	4436.00
future usage	32.55	279.66	0.00	26659.00
cohesion	0.12	0.26	0.00	1.00
ln number of pats	0.55	0.69	0.01	5.33
ln component size	4.51	4.28	1.10	11.90
ln new subclasses	-4.58	0.32	-4.61	1.39
ln potential combinations	3.52	3.52	-4.61	13.77
age of prioart	3.74	1.48	0.00	6.60
ln non-patent refs	-2.11	3.13	-4.61	8.09
ln univ patents	-4.35	1.09	-4.61	3.43
1{similar experience}	0.32	0.47	0.00	1.00
ratio repeat collaborations	0.16	0.32	0.00	1.00
ln degree	1.26	0.57	0.70	4.41
ln number of assignees	-0.10	0.94	-4.61	2.20
ln focal experience	-1.90	2.93	-4.61	3.58
ln collaborators experience	0.43	2.81	-4.61	6.82
ln non-local ties	1.52	1.43	-4.61	6.10

Table 2: Correlation statistics, n=53,570 observations, 35,400 inventors.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1) new combinations																
2) future usage	0.48															
3) cohesion	0.00	0.00														
4) ln number of pats	0.24	0.13	-0.03													
5) ln component size	0.07	0.01	0.17	0.27												
6) ln new subclasses	0.03	0.08	-0.01	0.03	-0.02											
7) ln potential combinations	0.20	0.11	0.22	0.49	0.54	0.02										
8) age of prioart	0.01	0.01	0.01	0.02	-0.02	0.01	0.03									
9) ln non-patent refs	0.13	0.11	0.00	0.33	0.13	0.04	0.20	0.21								
10) ln univ patents	0.01	0.02	-0.03	0.02	-0.01	0.01	-0.02	0.02	0.21							
11) 1{similar experience}	0.09	0.04	-0.01	0.35	0.19	-0.01	0.24	0.03	0.16	0.02						
12) ratio repeat collaborations	0.07	0.04	-0.01	0.26	0.10	-0.01	0.15	0.02	0.14	0.05	0.75					
13) ln degree	0.15	0.07	-0.03	0.50	0.44	0.01	0.46	0.00	0.23	0.01	0.26	0.19				
14) ln number of assignees	0.04	0.03	0.03	0.21	0.13	0.01	0.18	0.02	0.11	0.07	0.11	0.06	0.16			
15) ln focal experience	0.09	0.03	-0.04	0.32	0.13	0.00	0.20	0.04	0.13	0.00	0.73	0.55	0.18	0.11		
16) ln collaborators experience	0.08	0.03	0.17	0.24	0.37	-0.02	0.45	0.02	0.11	-0.02	0.41	0.30	0.24	0.15	0.30	
17) ln non-local ties	0.09	0.04	0.20	0.25	0.66	0.00	0.58	0.00	0.16	-0.01	0.20	0.12	0.65	0.14	0.10	0.41

Table 3a: Conditional logit negative binomial models of number of new subclass combinations, U.S. inventors 1975-1999. n=53,570 observations, 35,400 inventors. All models random effects with year and career period effects.

	Model 1	Model 2	Model 3	Model 4	Model 5
ln number of pats	0.3430***	0.3421***	0.3436***	0.3427***	0.3425***
	(0.0094)	(0.0094)	(0.0094)	(0.0094)	(0.0094)
ln component size	-0.0249***	-0.0250***	-0.0249***	-0.0248***	-0.0250***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
ln new subclasses	0.1431***	0.1437***	0.1428***	0.1437***	0.1433***
	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)
ln potential combinations	0.3865***	0.3873***	0.3868***	0.3869***	0.3868***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0035)
age of prioart	0.0151***	0.0152***	0.0150***	0.0151***	0.0152***
	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)
ln non-patent refs	0.0104***	0.0103***	0.0104***	0.0104***	0.0103***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
ln univ patents	0.0036	0.0039	0.0038	0.0033	0.0037
	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0048)
1{similar experience}	0.0195	0.0190	0.0175	0.0229	0.0210
	(0.0202)	(0.0202)	(0.0202)	(0.0202)	(0.0202)
ratio repeat collaborations	-0.0242	-0.0248	-0.0251	-0.0256	-0.0250
	(0.0230)	(0.0230)	(0.0230)	(0.0230)	(0.0230)
ln degree	0.4026***	0.4054***	0.4039***	0.4078***	0.4101***
	(0.0145)	(0.0145)	(0.0145)	(0.0145)	(0.0146)
ln number of assignees	-0.0445***	-0.0560***	-0.0442***	-0.0435***	-0.0447***
	(0.0058)	(0.0060)	(0.0058)	(0.0058)	(0.0058)
ln focal experience	0.0114*	0.0118*	0.0092+	0.0112*	0.0115*
	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)
ln collaborators experience	-0.0503***	-0.0500***	-0.0500***	-0.0548***	-0.0502***
	(0.0022)	(0.0022)	(0.0022)	(0.0023)	(0.0022)
ln non-local ties	-0.3174***	-0.3188***	-0.3183***	-0.3181***	-0.3234***
	(0.0060)	(0.0060)	(0.0060)	(0.0060)	(0.0062)
ln non-local ties^2	-0.0702***	-0.0706***	-0.0704***	-0.0708***	-0.0721***
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0015)
cohesion	-0.4798***	-0.4669***	-0.4294***	-0.5466***	-0.6420***
	(0.0223)	(0.0223)	(0.0270)	(0.0252)	(0.0450)
cohesionXassignees		0.1766***			
		(0.0319)			
cohesionXfocal experience			0.0228**		
			(0.0071)		
cohesionXcoll experience				0.0531***	
				(0.0083)	
cohesionXnon-local ties					0.0919***
					(0.0218)
constant	-0.7599***	-0.7569***	-0.7635***	-0.7597***	-0.7480***
	(0.1021)	(0.1021)	(0.1021)	(0.1021)	(0.1022)
ln likelihood	-138020.84	-138001.97	-138015.74	-137999.10	-138011.85

Table 3b: Conditional logit negative binomial models of number of new subclass combinations, U.S. inventors 1975-1999. n=53,570 observations, 35,400 inventors. All models random effects with year and career period effects. Model 8 estimates instrumented variable on proportion of patents with new combinations; model 9 measures cohesive density with repeated ties.

	Model 6	Model 7	Model 8	Model 9
ln number of pats	0.3419***	0.5925***		0.5947***
	(0.0094)	(0.0186)		(0.0186)
ln component size	-0.0249***	-0.0249***	-0.0072***	-0.0248***
	(0.0018)	(0.0018)	(0.0006)	(0.0018)
ln new subclasses	0.1439***	0.1469***	0.0453***	0.1452***
	(0.0104)	(0.0104)	(0.0050)	(0.0103)
ln potential combinations	0.3878***	0.3907***	0.0902***	0.3930***
	(0.0035)	(0.0035)	(0.0007)	(0.0035)
age of prioart	0.0152***	0.0169***	0.0044***	0.0160***
	(0.0043)	(0.0043)	(0.0012)	(0.0043)
ln non-patent refs	0.0103***	0.0103***	0.0014*	0.0105***
	(0.0018)	(0.0018)	(0.0006)	(0.0018)
ln univ patents	0.0038	0.0001	-0.0039*	0.0004
	(0.0048)	(0.0047)	(0.0016)	(0.0047)
1{similar experience}	0.0211	0.0231	-0.0077	0.0251
	(0.0202)	(0.0202)	(0.0070)	(0.0202)
ratio repeat collaborations	-0.0267	-0.0435+	-0.0161+	-0.0454*
	(0.0230)	(0.0231)	(0.0082)	(0.0231)
ln degree	0.4135***	0.4070***	0.1189***	0.4137***
	(0.0146)	(0.0147)	(0.0048)	(0.0145)
ln number of assignees	-0.0544***	0.1221***	0.0935***	0.1277***
	(0.0061)	(0.0130)	(0.0029)	(0.0130)
ln focal experience	0.0106*	0.0101*	-0.0007	0.0106*
	(0.0049)	(0.0049)	(0.0018)	(0.0049)
ln collaborators experience	-0.0536***	-0.0516***	-0.0129***	-0.0524***
	(0.0024)	(0.0024)	(0.0008)	(0.0023)
ln non-local ties	-0.3221***	-0.3296***	-0.0942***	-0.3365***
	(0.0062)	(0.0062)	(0.0022)	(0.0060)
ln non-local ties^2	-0.0718***	-0.0731***	-0.0216***	-0.0748***
	(0.0015)	(0.0015)	(0.0005)	(0.0014)
cohesion	-0.5674***	-0.5901***	-0.1786***	-0.3586***
	(0.0484)	(0.0483)	(0.0141)	(0.0191)
cohesionXassignees	0.1665***	0.1519***	0.0333***	0.0260*
	(0.0319)	(0.0299)	(0.0079)	(0.0115)
cohesionXfocal experience	0.0103	0.0114	0.0030	0.0033+
	(0.0074)	(0.0073)	(0.0022)	(0.0017)
cohesionXcoll experience	0.0446***	0.0421***	0.0123***	0.0278***
	(0.0090)	(0.0090)	(0.0026)	(0.0037)
cohesionXnon-local ties	0.0377+	0.0554*	0.0360***	0.0683***
	(0.0230)	(0.0230)	(0.0068)	(0.0064)
selection hazard		0.9071***	0.5427***	0.9107***
		(0.0595)	(0.0104)	(0.0593)
constant	-0.7544***	-1.5516***	0.2046***	-1.5660***
	(0.1022)	(0.1148)	(0.0500)	(0.1147)
ln likelihood/R^2	-137978.84	-137867.51	0.26	-137839.29

Table 4: Conditional logit negative binomial models of future use of new subclass combinations, U.S. inventors 1975-1999. n=35,247 observations, 24,659 inventors. All models random effects with year and career period effects.

	Model 10 total	Model 11 focal	Model 12 non-focal	Model 13 co-inventors	Model 14 collaborators	Model 15 non-local
ln new combinations	0.6211***	0.5071***	0.6210***	0.4691***	0.4499***	0.6172***
	(0.0059)	(0.0119)	(0.0059)	(0.0111)	(0.0191)	(0.0061)
ln number of pats	0.2358***	0.9793***	0.2106***	0.5349***	0.9653***	0.1545***
	(0.0127)	(0.0258)	(0.0127)	(0.0247)	(0.0409)	(0.0132)
ln component size	0.0115***	-0.0198***	0.0121***	-0.0136**	0.0065	0.0157***
	(0.0021)	(0.0046)	(0.0021)	(0.0043)	(0.0079)	(0.0022)
ln new subclasses	0.1324***	0.1194***	0.1316***	0.0967***	0.0747*	0.1324***
	(0.0106)	(0.0230)	(0.0106)	(0.0219)	(0.0356)	(0.0109)
age of prioart	0.0965***	0.0171	0.0979***	0.0171	0.0839**	0.1091***
	(0.0066)	(0.0141)	(0.0066)	(0.0128)	(0.0276)	(0.0070)
ln non-patent refs	0.0496***	0.0371***	0.0497***	0.0354***	0.0042	0.0503***
	(0.0022)	(0.0047)	(0.0022)	(0.0045)	(0.0079)	(0.0022)
ln univ patents	0.0133*	0.0254*	0.0137*	0.0354***	0.0037	0.0096+
	(0.0054)	(0.0108)	(0.0054)	(0.0102)	(0.0189)	(0.0056)
1{similar experience}	-0.0070	-0.1048+	0.0008	0.0164	-0.1141	0.0177
	(0.0247)	(0.0545)	(0.0248)	(0.0534)	(0.0883)	(0.0257)
ratio repeat collaborations	-0.0727**	-0.1591**	-0.0701*	-0.0879	-0.2897**	-0.0386
	(0.0277)	(0.0589)	(0.0278)	(0.0565)	(0.0907)	(0.0288)
ln degree	0.0504***	-0.2091***	0.0655***	0.0852**	0.4544***	0.0535***
	(0.0152)	(0.0321)	(0.0152)	(0.0314)	(0.0543)	(0.0157)
ln number of assignees	0.0146*	-0.0132	0.0144+	0.0034	0.0163	0.0181*
	(0.0074)	(0.0187)	(0.0074)	(0.0177)	(0.0370)	(0.0077)
ln focal experience	0.0006	0.0134	0.0002	0.0095	0.0027	-0.0008
	(0.0056)	(0.0134)	(0.0056)	(0.0128)	(0.0226)	(0.0058)
ln collaborators experience	-0.0113***	0.0029	-0.0112***	0.0212***	0.0172	-0.0138***
	(0.0027)	(0.0066)	(0.0028)	(0.0063)	(0.0127)	(0.0028)
ln non-local ties	0.0183**	0.0137	0.0193**	0.0912***	0.0288	0.0189**
	(0.0066)	(0.0135)	(0.0066)	(0.0154)	(0.0260)	(0.0069)
cohesion	0.1286***	0.0308	0.1341***	0.5765***	0.4218***	0.0972***
	(0.0258)	(0.0606)	(0.0258)	(0.0508)	(0.1115)	(0.0267)
selection hazard	0.1696***	0.6080***	0.1555***	0.3501***	-0.4850*	0.1058**
	(0.0392)	(0.0916)	(0.0393)	(0.0827)	(0.1905)	(0.0406)
constant	-3.1394***	-4.1064***	-3.1683***	-4.5268***	-6.9054***	-3.5092***
	(0.1351)	(0.2432)	(0.1359)	(0.2402)	(0.3386)	-0.15
ln likelihood	-121288.64	-28102.00	-120198.38	-37168.71	-12125.37	-114876.23