DEGREE ASSORTATIVITY IN INTRAORGANIZATIONAL NETWORKS: IMPLICATIONS FOR INVENTION PERFORMANCE

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Degree Assortativity in Collaboration Networks and Invention Performance

Abstract: We investigate the implications of the degree assortativity of intra-firm networks for firms' innovation performance. We argue that prevalent patterns of collaborative relationships between organizational members can lead to variations in the levels of degree assortativity in intra-firm networks, ranging from disassortative structures (highly central members connect with peripheral members) to assortative ones (highly central members connect with other highly central members and vice versa). These patterns influence knowledge access and resource mobilization pathways and are thus associated with various firm-level invention outcomes. Using coarsened exact matching methodology and controlling for other characteristics of the intra-firm network structures, we find that assortative structures in the pharmaceutical industry are associated with larger invention output, but inventions originating from assortative structures have lower average novelty and impact.

Managerial Summary: A central challenge in knowledge-based industries is the design of collaborative teams to increase innovative output. In this paper, we show that firms in the pharmaceutical industry vary in the extent to which central inventors within a firm collaborate with peripheral inventors. Further, the ideal composition varies based on the desired innovative output: Firms with frequent collaborations between central inventors have higher inventive productivity, while firms with higher mixing between central and peripheral inventors generate inventions that are on average more novel and have higher impact. Results have implications for organizational design toward desired innovative outcomes, as well as management of strategic human capital.

keywords: Local search; distant search; assortativity; innovation; invention; intra-firm network; pharmaceutical industry

INTRODUCTION

Researchers have long been interested in understanding the social structure of organizational innovation (Allen & Cohen, 1969; Tichy, Tushman, & Fombrun, 1979; Tushman, 1977). Based on the important role that collaboration networks play in the transmission of knowledge (Hansen, 2002; Phelps, Heidl, & Wadhwa, 2012), a recent body of literature reveals how the overall patterns of collaboration within a firm are associated with innovation (e.g., Fang, Lee & Schilling, 2010; Guler & Nerkar; 2012; Lazer & Friedman, 2007; Mason & Watts, 2012). Given variations in firm-level returns to innovation efforts (e.g., Knott, 2008), these studies help uncover the sources of heterogeneous innovation capabilities (Helfat, 2000).

While this literature has made important strides in explaining the relationship between intra-firm collaboration networks and innovation, it also has some limitations. For instance, studies have mainly focused on various structural characteristics of intra-firm networks such as centralization or connectedness but largely ignored the tie formation mechanisms prevalent in those networks, or the question of who collaborates with whom. At the same time, the literature on collaborative teams suggests that tie formation mechanisms matter for innovation outcomes. For instance, collaborations between individuals possessing similar types of knowledge or resources may generate different outcomes than those with access to diverse knowledge or resources (e.g., Reagans & Zuckerman, 2001; Taylor & Greve, 2006; Hsu *et al.*, 2021). As a result, firms that look similar in terms of the typical structural characteristics may not achieve the same innovation outcomes because the prevalent tie formation mechanisms may affect the paths of knowledge recombination and resource mobilization within the firm.

This study aims to address this issue by highlighting the assortativity of intra-firm networks as an important but often overlooked correlate of firm innovation (Ahuja, Soda, & Zaheer, 2012). The assortativity of an intra-firm network captures the level of homophily prevalent in that network. Homophily is the individual preference to connect with similar others and is widely accepted as a general law of tie formation (Lazarsfeld & Merton, 1954; McPherson, Smith-Lovin, & Cook, 2001). Its implications for knowledge access and job performance are well studied in the literature on individuals and dyads (e.g., Ertug *et al.*, 2018; Hegde & Tumlinson, 2014; Ibarra, 1992; Hansen, 1999). What is novel in this study is the notion that intra-firm networks may vary in the extent to which they are composed of collaborations among similar individuals and that these variations may be correlated with persistent firm-level differences in innovation performance.

More specifically, the research question in this study is on how degree assortativity in intra-firm network structures influences innovation outcomes. In networks with high degree assortativity, inventors at similar degree (centrality) ranks are more likely to connect with one another than with those at different ranks (Ahuja *et al.*, 2012; Newman, 2002). Our thesis is that this is a correlate of innovation performance at the firm level because it captures systematic differences in how knowledge is combined and resources are mobilized for recombinant innovation. Our focus on degree assortativity breaks from prior work focusing solely on intra-firm knowledge flows (e.g., Aggarwal, Hsu & Wu, 2020; Fang *et al.*, 2010; Phelps *et al.*, 2012; Hansen, 2002) in that it simultaneously captures issues pertaining to knowledge access as well as mobilization of organizational resources to generate and develop ideas. In this sense, degree assortativity highlights the role of collaborative ties as both pipes that transfer knowledge as well as prisms that reflect the social standing of inventors in resource mobilization and idea selection (Podolny, 2001). Degree assortativity thus potentially influences both the search and selection processes in inventive activity (Nelson & Winter, 1982; Zollo & Winter, 2002; Simon, 1955; Knudsen & Levinthal, 2007). Indeed, our empirical examination of collaboration structures in the pharmaceutical industry suggests meaningful correlations between degree assortativity and invention performance after controlling for other structural characteristics of internal networks as well as the overall distribution of knowledge within a firm.

A second limitation of the current work on intra-firm networks and innovation is that there exists a wide variation in the conceptualization and measurement of innovative outcomes. Some of these studies focus on collaborative learning and problem-solving (e.g., Lazer & Friedman, 2007; Mason & Watts, 2012), others highlight search scope (e.g., Paruchuri & Awate, 2017) or recombinant innovation (Carnabuci & Operti, 2013). Yet others examine the commercial viability of inventions as an outcome (Guler & Nerkar, 2012). While these studies broadly point to similar mechanisms, the subtle differences in their emphases might obscure an understanding of the pathways between collaboration structures and innovation performance.

In this study, we attempt to disentangle the relationship between degree assortativity and various dimensions of invention outcomes. We argue that degree assortativity will be positively correlated with the quantity of inventions generated by a firm's inventors, but negatively correlated with the novelty and impact of the resultant inventions. This is because assortative networks enjoy efficiencies in knowledge sharing within same-rank collaborations but miss out on complementarities that mixed-rank collaborations possess in knowledge access as well as resource mobilization. Given the uncertainty and complexity inherent in the process of invention, our focus on multiple inventive outcomes helps uncover the heterogeneous impact of intra-firm networks on various inventive outcomes and the tradeoffs involved. By doing so, this study contributes to a recent stream of research that has called for more clarity in the definitions of inventive outcomes as well as their relationships (Kaplan & Vakili, 2015) and joins recent work that acknowledges the importance of studying multiple outcomes in the context of inventive activity (e.g., Lazzarini *et al*., 2020).

INTRA-FIRM COLLABORATION AND INNOVATION

In discussing innovation, we keep with prior literature and distinguish between invention, which is the development of a new idea, and innovation, which refers to the commercialization of an invention (Ahuja & Lampert, 2001; Schumpeter, 1934). While not all inventions may result in commercial success, invention is an essential step for successful innovation. We build on the recombinant perspective, which represents invention as a process of combining new or existing knowledge components to generate a solution to a problem (Hargadon, 2003; Schumpeter, 1939). Given the limits to the cognitive capacity and knowledge of any individual inventor, collaboration is critical for inventors searching for useful combinations (Fleming, 2001; Sorenson, Rivkin, & Fleming, 2006).

Researchers have often highlighted invention quantity, impact, and novelty as desirable outcomes of the invention process (e.g., Ahuja & Lampert, 2001; Kaplan & Vakili, 2015; Trajtenberg, 1990). Invention quantity refers to the number of inventions produced, and impact refers to the influence of those inventions on future work. We define novelty as the extent to which inventions include knowledge components that are unfamiliar to the inventors in a firm, regardless of whether they have been in existence elsewhere (Ahuja & Lampert, 2001). While all these objectives are important, they are often at odds with one another. Exploratory search that leads to novel inventions is risky and often leads to failure, potentially decreasing invention quantity in the short run. Exploitation, on the other hand, leads to higher quantity but often incremental outcomes (March, 1991; Levinthal & March, 1993). In building our theory about degree assortativity and firm innovation, we consider these classic tradeoffs.

Collaborative Network Structure and Invention Outcomes

There are two key mechanisms through which intra-firm networks of collaborations between inventors may influence invention outcomes: knowledge access and resource mobilization. Scientific invention requires knowledge exchange among inventors within the firm, as well as mobilization of organizational resources such as funding, support, and legitimacy (Perry-Smith & Mannucci, 2017). During search and idea generation, access to diverse sources of knowledge is critical, and patterns of collaboration influence which knowledge components get shared and recombined (Allen & Cohen, 1969; Perry-Smith & Mannucci, 2017). The second key mechanism, resource mobilization, is necessary in the selection process, in which some ideas are developed into concrete inventions while others are abandoned (Nelson & Winter, 1982; Simon, 1955; Knudsen & Levinthal, 2007). While organizational resources are essential during implementation of innovations (Perry-Smith & Mannucci, 2017), they are also important in the early phases of knowledge production, where uncertainty is high, resources are limited, and ideas are under selection pressure (e.g., Girotra, Terwiesch, & Ulrich, 2007; Simonton, 1999). Networks play an important role in gathering organizational resources such as funding, inventor team and gatekeeper support, and are especially important for novel, untraditional ideas that may not otherwise survive the typical processes of selection (e.g., Ibarra, 1993; Kanter, 1983).

Prior work at the whole-network level examines the relationship between firm-level structures emanating from collaborations and collective innovation, mainly with a focus on knowledge access. In a recent review, Ahuja *et al.* (2012) catalog whole-network structure dimensions as degree distribution (centralization), connectivity, clustering, density, and degree assortativity. Past studies of intra-firm networks and innovation have often focused on the first four. This literature suggests a positive link between connectivity and effective integration of internal and external knowledge for innovation (e.g., Carnabuci & Operti, 2013; Grigoriou & Rothaermel, 2017; Moreira, Markus, & Laursen, 2018). At the same time, extreme connectivity may hamper exploration by inhibiting 'slow learning' and leading to premature convergence to an inferior solution (Fang *et al.*, 2010; Lazer & Friedman, 2007; March, 1991) as well as impose costs of coordination between research initiatives (Guler & Nerkar 2012). Similarly, centralization of the intra-firm knowledge network may have contrasting effects on knowledge sharing and innovation. Centralized information exchange may facilitate a coordinated response to external change by ensuring that members of an organization have access to similar knowledge (Argote, Aven, & Kush*,* 2018; Shore, Bernstein, & Jang, 2020), but the resultant knowledge uniformity also inhibits the generation of diverse ideas (Schilling & Fang, 2014).

Examining degree assortativity allows us to look beyond these previously examined dimensions by incorporating tie formation patterns in intra-firm networks. Interestingly, this aspect of intra-firm networks has received relatively less attention than other structural characteristics (Ahuja *et al.*, 2012). In addition, while separate streams of work have pointed out the importance of network ties for innovation development and implementation (e.g., Perry-Smith & Mannucci, 2017; Nerkar & Paruchuri, 2005), the intra-firm network literature has put larger emphasis on the role of collaboration structures in knowledge recombination but less on resource mobilization. Below, we describe degree assortativity, discuss its relationship with other network characteristics, and explain its association with various invention outcomes.

Degree Assortativity in Intra-firm Networks

Degree assortativity refers to the tendency of nodes to attach to those with similar degree centrality ranks in a network (Ahuja *et al.,* 2012; Newman, 2003). In an intra-firm network with high degree assortativity, central (peripheral) actors are more likely to establish collaborations with other central (peripheral) actors.[1] At the whole-network level, degree assortativity implies tie formation based on similar centrality ranks, but it is distinct from the centrality of individual members or the centralization of an intra-firm network. While centralization refers to degree distribution, or the extent to which some members of a network occupy more central positions than others, degree assortativity refers to degree association, or the extent to which members in central positions are likely to connect with one another (as opposed to those in lower ranks). Two networks with the same level of centralization or density may have different levels of degree assortativity depending on the tie formation mechanism adopted by the members. Figures 1a and 1b illustrate this point by exhibiting two stylized networks which are similar along typical network dimensions but differ considerably in their assortative mixing. The difference in the assortativity of otherwise similar networks are important for inventions because a tie between two central members is likely to comprise different levels of knowledge and resource exchange from one between a central and peripheral member.

--------------------------------- Insert Figures 1a and 1b here --------------------------------

How do intra-firm networks come to be more or less assortative? On the one hand, network structures may emerge from the choices of individual actors to form, maintain, or sever collaborative ties (Ahuja *et al.,* 2012; Baum, Shipilov, & Rowley, 2003; Coleman, 1988). The tie formation mechanism adopted by most of the inventors in the intra-firm network influences the level of degree assortativity. The tie formation mechanism underlying assortative structures is degree homophily, whereas the dominant tie formation logic in disassortative networks is complementarity (heterophily) (Ahuja *et al.,* 2012). On the other hand, homophily may be induced by the structure of opportunities for interaction (McPherson *et al.,* 2001). Individuals

[1] In the rest of the paper, when we use the terms "assortative" or "assortativity", we only refer to degree assortativity.

who are part of the same organizational unit, geography, or activities tend to have more homophilous ties than others (Kleinbaum, Stuart, & Tushman, 2013; McPherson & Smith-Lovin, 1987). This suggests that managers may have some control over the level of assortativity through organization design. It is plausible that both processes coevolve (Baum *et al.*, 2003). For instance, initial dyadic preferences and organization design elements that favor homophily may become entrenched through inertia in subsequent collaboration choices and get coded into the norms and values of a firm (Li & Rowley, 2002), influencing the formation of subsequent ties through a self-reinforcing dynamic.

Reconciling Degree Assortativity, Individual Centrality, and Dyadic Homophily

The relationship between degree assortativity and invention performance may reflect the mechanisms of knowledge access and resource mobilization at the nodal, dyadic, and organizational levels (Table 1). At the nodal level, assortativity reflects variations in the knowledge and resources available to individual inventors at various degrees of centrality. Central network positions provide inventors with greater access to the knowledge in the intra-firm network (Hansen, 2002; Nerkar & Paruchuri, 2005). As a result, central inventors and units tend to be more innovative (e.g., Tsai, 2001; Maoret, Tortoriello, & Iubatti, 2020). Moreover, central inventors often enjoy high status (Nerkar & Paruchuri, 2005; Paruchuri, 2010) and higher access to organizational resources necessary for development of ideas (Ibarra, 1993; Merton, 1968; Perry-Smith & Mannucci, 2017; Podolny, 1993). On the flipside, the knowledge possessed by central inventors may heavily reflect the prevailing norms and assumptions of the firm (e.g., Arts & Fleming, 2018; Dahlander & Frederiksen, 2012; Jeppesen & Lakhani, 2010). Central inventors may therefore miss or undervalue the diverse and unique pockets of knowledge that exist at the fringes of a network (Cummings & Cross, 2003; Everett & Borgatti, 1999; McEvily, Soda, & Tortoriello, 2014). In sum, one may expect central inventors to be highly productive but mainly engaged in path-dependent, local search (Maoret, *et al.* 2020). Conversely, peripheral inventors may possess knowledge and perspectives that are new to the firm but experience lower productivity, especially due to disadvantages in resource mobilization (Cattani & Ferriani, 2008).

At the dyadic level, an assortative network reflects structural and status-based homophily in dyads and teams (Ahuja *et al.,* 2012; McPherson *et al.,* 2001). Similarity among collaborators leads to higher trust between collaborators, a common cognitive frame, and motivation to share knowledge (Aggarwal *et al.*, 2020; Phelps *et al.,* 2012; Reagans, Zuckerman & McEvily, 2004; Thomas-Hunt, Ogden, & Neale, 2003). The downside of such connections is that they limit access to complementary knowledge and resources that dissimilar others might have. In all, structural homophily may increase the productivity of inventor teams but decrease their ability to explore diverse sources of knowledge in inventions. In addition, a distinct impact of structural or status-based homophily is to shape the patterns of interaction. For instance, status asymmetry between collaborators may influence the extent to which they are willing and able to share knowledge (Bunderson & Reagans, 2011; Tzabbar & Vestal, 2015).

At the organizational level, assortative mixing often leads to core-periphery structures with a core of densely connected central inventors and a periphery consisting of inventors with low centrality (Ahuja *et al.,* 2012; Borgatti & Everett, 2000). Highly assortative networks are fragmented and feature few connections between the core and the periphery, leading to distinct clusters. The fragmentation in assortative structures suggests rich information and resource flows within each cluster of inventors but limited flows between them (Fang *et al*., 2010). In the next section, we explore the implications of these observations for invention performance.

Degree Assortativity and Quantity of Inventions Produced

The extent of degree assortativity may influence the ease with which inventors share knowledge and mobilize resources through the composition of inventor teams. The similarity of inventors in teams and dyads in an assortative network facilitates communication and resource sharing, increasing efficiency and productivity in the invention process. In contrast, mixed-rank collaborations often found in networks with lower assortativity may experience lower output due to challenges in establishing trust, creating a common cognitive frame and sharing knowledge (Aggarwal *et al.* 2020; Reagans, *et al.*, 2004; Shipilov, Li, & Greve, 2011).

Inventor team member similarity is not the only reason to expect differences in the quantity of inventions in collaboration networks with varying levels of degree assortativity. The nodal ranks of the inventors in each team also matter. To simplify, consider a stylized network of dyadic ties only. A highly assortative network has more collaborations between central inventors (C-C) and between peripheral inventors (P-P) while less assortative networks have more mixed-rank (C-P) collaborations. Among these three collaboration types, C-C are likely to be especially prolific. Prior work repeatedly shows that central inventors and teams are more productive, and that a large proportion of inventive output is due to a few 'star' inventors with high social capital (e.g. Maoret *et al.*, 2020; Tzabbar & Kehoe, 2014; Zucker, Darby & Armstrong, 2002). The disproportionate impact of C-C teams on invention output likely compensates for the low productivity of P-P collaborations. This suggests a positive aggregate relationship between degree assortativity and invention quantity.

In sum, due to the efficiency of similar-rank collaborations in sharing knowledge and resources, and the disproportionate ability of C-C collaborations to produce patentable inventions, we expect:

Hypothesis 1 (H1): An increase in the degree assortativity of a firm's intra-firm network is associated with an increase in the quantity of its inventive output.

Degree Assortativity and Novelty of Inventions

At the same time, we expect degree assortativity to be negatively correlated with the novelty of the inventions produced. Novel inventions often require distant search among diverse knowledge components frequently found in other fields or the fringes (e.g., Cattani & Ferriani, 2008; Fleming, 2001; Hargadon, 2003; Uzzi *et al.,* 2013). Distant search is often conducted through collaborations with inventors who possess nonredundant knowledge (Kogut & Zander, 1992; Singh & Fleming, 2010). Assortative structures, while increasing the efficiency with which knowledge is shared and inventions are produced, may limit the ability of inventors to perform distant search and make original discoveries. The knowledge required for combining distant components may reside in different parts of the firm (Ethiraj & Levinthal, 2004; Hargadon & Sutton, 1997). The fragmentation typical of assortative structures may limit the knowledge flow required for such combinations. Highly assortative structures in which collaborations are characterized by degree similarity may not be conducive to distant search.

In our stylized depiction of highly assortative structures, C-C collaborations may especially be inclined toward local search. While central inventors have more collaborative relationships and wider access to knowledge sources in the firm, they are less likely to have access to fresh and localized knowledge components often found in the periphery (Cummings & Cross, 2003; Everett & Borgatti, 1999; McEvily, Soda, & Tortoriello, 2014). Search in these collaborations is more likely to get trapped in familiar technological areas and neighborhood of known solutions, relying heavily on what has worked before (Ahuja & Lampert, 2001; Hargadon & Sutton, 1997). They are less likely to lead to surprising and creative insights that can only be achieved through unusual combinations of knowledge (Cattani & Ferriani, 2008). P-P collaborations, on the other hand, may have lower knowledge overlap and more divergent perspectives, to the extent they come from different knowledge spheres. While they may have a higher potential to generate unusual combinations of distant knowledge, they are unlikely to bring highly novel work to fruition, given their challenges in securing organizational resources (Gulati, Nohria, & Zaheer, 2000; Nerkar & Paruchuri, 2005).

In contrast, in firms with low assortativity, inventors may be able to overcome these shortcomings by leveraging complementarities (Ahuja *et al.,* 2012). Mixed-rank collaborations may lead to novel inventions by combining the expertise and resources of central inventors with new knowledge and fresh ideas from peripheral inventors. These collaborations may experiment more with new knowledge, generating and supporting more diverse sets of insights (Ahuja & Lampert, 2001; Amabile, 1988; Hargadon & Sutton, 1997). This is consistent with the findings that balanced teams comprised of core and periphery members generate more creative outcomes (Cattani & Ferriani, 2008; Guimera *et al.,* 2005), and integrated network structures exhibit more effective knowledge combination and reuse (Carnabuci & Operti, 2013).

Assortativity of intra-firm networks may generate organizational externalities beyond the nodal and dyadic characteristics of each collaboration. Mixed-rank collaborations in highly assortative networks are not only smaller in number but may also be less effective in generating novelty due to the overall climate of collaboration. Norms of collaboration in highly assortative networks may hamper the success of the few mixed-rank collaborations that are in existence (Bunderson & Reagans, 2011; Perry-Smith & Mannucci, 2017). If similar-rank collaborations are more typical in a firm, mixed-rank collaborations may be beset by the unwillingness of peripheral members to share ideas or voice their opinions, and of the central members to listen to them (Bunderson & Reagans, 2011; Tzabbar & Vestal, 2015). In other words, a mixed-rank collaboration in an assortative network may not lead to knowledge exchange as effectively as a similar collaboration in a disassortative network. Therefore, we expect a higher rate of novel inventions in less assortative structures due to the prevalence and overall effectiveness of mixed-rank collaborations in leveraging complementarities.

Hypothesis 2 (H2): An increase in the degree assortativity of a firm's intra-firm network is associated with a decrease in the average novelty of inventive output.

Degree Assortativity and Invention Impact

Inventions generated in less assortative networks are not only more likely to be novel, but they may also be more impactful, since novelty and scientific impact often go hand in hand [2]. Technological inventions that combine diverse sources of knowledge that have rarely been combined in earlier work are more likely to have higher impact on subsequent research (*e.g.,* Ahuja & Lampert, 2001; Amabile, 1988; Kneeland, Schilling, & Aharonson, 2020; Rosenkopf & Nerkar, 2001). While not all novel inventions are highly impactful (Amabile, 1983), novelty increases the likelihood that an invention will have higher impact on later work (Ahuja & Lampert, 2001). The early uses and recombinations of a knowledge component challenge inventors and their ways of thinking, resulting in fresh perspectives that others gradually build on (Ahuja & Lampert, 2001; Fleming, 2001). Over time, repeated use of the same knowledge components depletes the technological usefulness of the knowledge, a phenomenon known as technological exhaustion (Fleming, 2001). Recent research suggests that ideas with the highest impact are those that combine extremely new knowledge elements with conventional ones (Uzzi

[2] While the link between invention novelty and impact has been extensively studied, other characteristics of inventions, such as originality or generality, may also be correlated with their impact on subsequent research. We explore these alternative pathways in supplementary analyses.

et al., 2013). Conventionality reflects the deep foundational knowledge required to comprehend and meaningfully contribute to problems in an established research domain, while fresh knowledge components are instrumental in finding superior solutions to those problems (Kaplan & Vakili, 2015). Collaborations that allow inventors to generate such combinations are, therefore, more likely to lead to scientific impact.

Since the mixed-rank collaborations found in less assortative structures can combine novel insights from the periphery with the deep expertise of the core, such structures may be more conducive to impactful inventions. As detailed in prior sections, mixed-rank collaborations not only are likely to generate ideas that incorporate more novel knowledge elements, but they are also more likely to be able to bring these ideas to fruition by mobilizing organizational resources. Less assortative structures will facilitate the permeation of new ideas and knowledge into firms' existing repertoires of knowledge, and firms are more likely to discover impactful solutions to problems. The heterogeneity in the ways in which inventor teams can solve problems will enable them to identify superior solutions that may otherwise go unobserved, increasing overall impact. In contrast, inventive output in assortative structures may drift toward conventionality and result in incremental improvements with lower average impact. Therefore,

Hypothesis 3 (H3): An increase in the degree assortativity of a firm's intra-firm network is associated with a decrease in the average impact of inventive output.

DATA AND METHODS

We test our hypotheses in the context of collaboration networks in the pharmaceutical industry. Innovation and technological development are critical to the success of pharmaceutical firms (Jaffe, 1986; Cockburn & Griliches, 1988). Patented inventions represent 80% of the innovations in the industry as compared to an average of 35% in other industries (Arundel & Kabla, 1998).

Collaboration networks in drug discovery provide an appealing proxy for knowledge transfer within firms, as each invention effort is long-term and requires intense knowledge exchange and joint problem solving (Argyres & Silverman, 2004; Hansen, 1999; Paruchuri, 2010). Patent records also provide a rare opportunity to empirically examine the collaboration networks of firms within the same industry over time and the associated inventions.

We obtained patent data from The United States Patent and Trademark Office (USPTO) to construct collaboration networks. We identified all patents in the pharmaceutical industry through USPTO classes 514 and 424 (Khanna, Guler, & Nerkar, 2018). Since we examine informal structure through a firm's patents, we excluded firms that did not patent consecutively for ten years. After accounting for missing values, the final sample contains 95 firms between 1985 and 1999, leading to a panel of 1,425 firm-year observations. We restricted the sample period to 1999 to allow patents enough time to accumulate forward citations, reducing the concern for right censoring. In addition, the time period is especially suited to capturing inventive activity through USPTO patenting records. Carley, Hegde & Marco (2015) report that USPTO approval rates of patent applications were around 80% before 2000 and have steadily declined since. This suggests that potential concern about unobserved inventive activity due to patent rejections is minimal in our dataset.

Dependent variables

The first dependent variable is the quantity of inventive output, measured as the total number of patents a firm produced in a year (e.g., Ahuja, 2000; Rothaermel & Thursby, 2007). The second dependent variable is the novelty of the inventive output, measured using the USPTO-assigned subclasses that the patent combines. Technological subclasses represent *"very fine divisions of technology"* (Fleming, 2001: 122) and reliably represent the knowledge components underlying a patented invention. Consider as an example patent 6,166,092, which contains knowledge on the derivation of perfluorocarbon from common organic compounds (subclass 772, ‘compositions containing nonbioactive organic compound’) by replacing carbon-bound hydrogen atoms with fluorine atoms (subclass 653, ‘hydroxy attached to the acyclic carbon or chain by acyclic nonionic bonding’). The resulting composition is in emulsion form (subclass 937, ‘composition in the form of a dispersion or emulsion’) and used to deliver drugs to the lungs of patients. As illustrated in this example, the subclasses assigned to patents by the USPTO represent basic building blocks that constitute inventions and meaningfully differ from each other in terms of their scientific functions.

The approach to measure the novelty of inventive output has multiple stages. First, we estimated the familiarity of a subclass using the approach described in Fleming (2001). The measure of familiarity aims to capture 1) the extent to which the subclass was combined with other subclasses in prior patents and 2) the recency of these patents. The idea is that if the focal subclass is combined with several other subclasses in recent patents, inventors are more familiar with the focal subclass. Formally, familiarity of patent a’s subclass i is:

$$F_{ai} = \sum_{\substack{all\ patents\ b\ granted \\ before\ patent\ a}} 1\,\{patent\ b\ uses\ subclass\ i\} \times e^{-\left(\frac{application\ date\ of\ patent\ a - application\ date\ of\ patent\ b}{time\ constant\ of\ knowledge\ base}\right)} \quad (1)$$

Following Fleming (2001), we used the time constant of a knowledge base as five years to reflect 18% knowledge decay per year. We subtracted the measure of familiarity of each subclass from one to measure novelty. We calculated N_{ai}, the novelty of patent a’s subclass i, as follows:

$$N_{ai} = 1 - F_{ai} \quad (2)$$

The novelty of a patent increases with the novelty of the subclasses on the patent. The novelty of patent a, N_a, was measured as:

$$N_a = \frac{\sum_{all\ subclasses\ i\ of\ patent\ a} N_{ai}}{\sum_{all\ subclasses\ i\ of\ patent\ a} 1} \quad (3)$$

Finally, we took the average of the novelty values of all patents granted to a firm in the focal year to compute our dependent variable, *novelty of inventive output*, at the firm level.

The final dependent variable is the *impact of inventive output,* measured as the average number of forward citations to a firm's patents (e.g., Pavitt, 1988; Trajtenberg, 1990). At the firm-year level, we calculated the number of forward citations received by a firm's patents granted in a given year, normalized using the total number of patents granted in that year.

Independent variable

The independent variable is the degree assortativity of an intra-firm network. In constructing intra-firm networks, we only considered patent co-authorship ties between inventors employed in each firm and excluded the collaborations that occurred outside the firm boundaries (Fleming, King, & Juda, 2007; Nerkar & Paruchuri, 2005). To compute degree assortativity, we measured the extent to which similar nodes are connected with each other (Newman, 2003). Formally, let us consider two nodes of types x and y. In a perfectly assortative network, the probability e_{xy} that an edge joins nodes of types x and y would be 0, *i.e.,*

$$e_{xy} = probability\ that\ an\ edge\ links\ node\ of\ type\ x\ with\ a\ node\ of\ type\ y = 0 \quad (4)$$

On the other extreme, in a perfectly disassortative structure, e_{xy} would be equal to 1 as no two nodes that are connected in the network are of the same type. In an undirected network, e_{xy} is symmetric and satisfies the sum rule:

$$e_{xy} = e_{yx}; \qquad \sum_y e_{xy} = a_x; \qquad \sum_x e_{xy} = b_y \quad (5)$$

For the values in between, degree assortativity of a network, r, is estimated using the Pearson correlation coefficient:

$$r = \frac{\sum_x e_{xx} - \sum_x a_x b_x}{1 - \sum_x a_x b_x} \tag{6}$$

where e is the matrix with elements containing all possible values of e_{xy}, Tr (e) is the trace of matrix e, *i.e.*, the sum of elements in the diagonal, and $\|e^2\|$ is the sum of all elements in the matrix e^2. In equation (6), the value of r is 0 when mixing is random, as in this case $e_{xy} = a_x b_y$. In case of perfect assortativity, $r = 1$ and $e_{xy} = 1$. When the network is perfectly disassortative, $r = -1$ and $e_{xx} = 0$ because no two connected nodes have the same degree centrality. Thus, the value of r ranges between -1 and 1 with negative values representing disassortative structures and positive values indicating assortative structures.

At this point, it may be helpful to demonstrate the concept of degree assortativity with two intra-firm networks in our sample. Figures 2a and 2b represent the topology and degree distribution of intra-firm networks of Roche and Eli Lilly respectively in 1985, and Figures 3a and 3b show their respective degree correlations. As shown in Figure 2a, the degree distribution of Roche indicates a negative slope between the degree centrality of nodes and the frequency of nodes with identical degree ranks, which is characteristic of most social networks as there are fewer nodes with high degrees (lower rank) and more nodes with low degrees (higher rank). The topology of the network indicates a low level of degree assortativity, as peripheral nodes connect with central nodes in Figure 2a. To further assess the level of assortativity in this network, we plotted the degree correlation of nodes in the Roche network (Figure 3a). Degree correlation plots show the relationship between the degree centrality of a focal node and the average degree centrality of nodes that are connected to that node. Figure 3a indicates that the degree correlation is positive, suggesting assortativity in the Roche intra-firm network, but the shallow slope supports our earlier observation that assortativity is low. Based on the methodology described above (Newman, 2003), the assortativity of the Roche intra-firm network is 0.11.

We observe in Figure 2b that Eli Lilly's degree distribution also has a negative slope, and the topology of Eli Lilly's intra-firm network also suggests a tendency of nodes with similar degree centralities to connect with each other. We plot the degree correlation for Eli Lilly's intra-firm network in Figure 3b. The slope for the relationship between the degree centrality of a node and average degree centrality of its neighbors is positive and steeper than the slope for Roche, which suggests that the intra-firm network of Eli Lilly is more assortative than that of Roche. The degree assortativity of Eli Lilly's intra-firm network is 0.56. This suggests that inventors of similar degree centralities tend to collaborate more with each other in Eli Lilly than in Roche, whereas collaborative ties between peripheral and central inventors are more prevalent in Roche than in Eli Lilly.

------------------------ Insert Figures 2a, 2b, 3a, and 3b here ------------------------

Control variables

We controlled for several potential confounders in our empirical model. First, we controlled for the alliances of each firm since external sources of knowledge can influence a firm's invention performance (Ahuja, 2000; Ahuja & Katila, 2001). Next, we controlled for geographical diversity, which may affect innovation by increasing the availability of resources and capabilities for innovation (Kobrin, 1991). Thus, we included the number of countries in which a firm patents in a given year. A firm's experience with failures in R&D can also influence its subsequent invention performance (Khanna, Guler, & Nerkar, 2016). We therefore controlled for the number of failed attempts at innovations using voluntary discontinuations of patents each year. We also controlled for the number of lawsuits against each firm based on the Lexis-Nexis Legal Research database, since this may be correlated with firms' patenting strategies and outcomes. Next, we controlled for the number of claims normalized by the number of patents assigned to each firm, as these indicate the scope of the contributions and the future value of a firm's patents (Lanjouw & Schankeman, 2004). The commercial success of a firm in a technological area may influence collaborations as well as subsequent technological trajectory. Thus, we controlled for the number of patent-protected drugs that each firm has on the market in a given year. We also controlled for the number of new inventors joining a firm (based on patenting activity) each year, because it can disrupt collaboration between inventors as well as influence innovation outcomes (Carnabuci & Operti, 2013).

In addition, we controlled for several whole-network properties that may be correlated with assortativity and firms' invention outcomes (Ahuja *et al.*, 2012). First, we controlled for network density (Reagans & McEvily, 2003), calculated as the ratio of the actual number of ties to the total number of potential ties in a firm's intra-firm network. Another property of whole networks that can impact creativity and invention is connectivity (Schilling, 2005; Schilling & Phelps, 2007), an indication of how quickly knowledge can spread between any two nodes. We calculated this as the average of path lengths between all pairs of inventors within a network. Next, we controlled for the clustering coefficient of intra-firm networks (Newman, 2001), or the average of densities of ego networks of all inventors in the firm, which reflects benefits such as trust and shared beliefs that facilitate a smooth transfer of knowledge among inventors (e.g., Fleming *et al.,* 2007). We controlled for centralization, calculated as the ratio of the sum of the differences in the centralities of nodes in a network to the maximum sum of differences in centralities and varies between zero and one (Freeman, 1978). We also controlled for the average centrality of inventors in the intra-firm network to consider the benefits of inventor positions for firms' invention performance (Paruchuri, 2010). We measured average centrality in the (1) collaboration network of inventors, (2) citation networks within the firm. Since inventors' external (industry-wide) collaborations may also impact the firm's invention outcomes, we controlled for the average centrality of inventors in the external (industry-wide) collaboration and citation networks. To generate the citation networks, we considered two inventors to have a tie if one inventor cites a patent of the other in a given year. All control variables were measured using three-year moving averages to smooth out sharp changes and control for lasting effects.

Estimation procedure

It is possible that firms with a high level of degree assortativity differ systematically from firms with low degree assortativity. This could lead to biased estimates of regression coefficients and render them causally uninterpretable. While it is not possible to completely rule out this issue, one way to partially address it is to match firms with high assortativity (treated) and those with low assortativity (control) on observable characteristics. The procedure results in a more balanced sample and makes a comparison between the two groups more meaningful.

We used Coarsened Exact Matching (CEM) procedure to obtain covariate balance between the treatment and control sets (Iacus, King, & Porro, 2011). CEM is superior to other matching methods as it uses the information in the data more efficiently and reduces model dependence (Iacus *et al.,* 2011). Since the matching procedure requires the treated variable to be binary, we created a variable that takes the value of 1 for firms with high assortativity (> 0.5)[3] and 0 for firms with low assortativity (< 0.5). The basic idea behind the matching procedure is to compare the outcomes of the treated group with the outcomes of a control group of similar observations that could have been treated but were not (Abadie & Imbens, 2002, 2011). For this purpose, we constructed the control set by choosing covariates on which the treatment is likely to be conditional (Abadie *et al*., 2004). relied on prior theory to choose four variables that proxy for

[3] We chose 0.5 as the cut-off since almost half of the firms in the sample had assortativity above 0.5 and half above 0.5. We tried different cut-offs (0.45 and 0.55) for sensitivity and results were largely unchanged.

the formal structure and individual collaboration choices. The first two matching criteria are the size and age of the firm, which may influence the formalization of the structure and, in turn, the patterns of collaboration (Burns & Stalker, 1961; Stinchcombe, 1965). We measured firm size as the number of inventors within a firm and firm age as the number of years since the firm's first patent. The third matching criterion is the knowledge diversity within each firm, which may influence collaboration patterns through the ease of knowledge exchange among inventors (Hansen, 1999; Rodan & Galunic, 2004). We measured knowledge diversity using the Herfindahl Index of technological subclasses that have appeared in a firm's patents each year (e.g., Gambardella & Torrisi, 1998). Last, we used the number of mergers and acquisitions (M&As) that a firm has carried out in the past 10 years, as M&As may change the network structure and influence the degree of collaborative integration between inventors within firms (Hernandez & Shaver, 2019; Kapoor & Lim, 2007). We repeated the matching process in each year to account for changes in matching criteria over time.[4] As CEM prunes the unmatched observations (almost half in our sample), the final sample includes a firm-year panel of 788 observations.[5] Table A1 in Online Appendix 1 reports the descriptive statistics and tests for differences in means for the matching variables in the treatment and control sets before and after CEM. The table shows that the procedure meaningfully increases the balance between the sets. We ran all models on the balanced dataset by incorporating weights obtained from CEM. In addition, our models include robust standard errors clustered at the firm level, a full set of firm fixed effects to account for the time-invariant and firm-specific sources of heterogeneity not captured by the control variables, and year fixed effects.

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[4] We obtained characteristically similar results when we performed the matching once, at the beginning of the study period (1985) (available upon request).
[5] Analyses with the larger pre-CEM sample yield similar results, available on request.

The first dependent variable is the quantity of inventions, or the number of patents granted to firms each year. Because of the count nature of this variable, we used a fixed-effects Poisson estimator (Hausman, Hall, & Griliches,1984). The quasi-maximum likelihood (QML) estimator is consistent and has several desirable robustness properties. The second dependent variable, novelty of firms' inventive output, takes values between 0 and 1, and we modeled it using the fractional logit method (Papke & Wooldridge, 2008) using generalized linear models (*glm*) command in Stata with a Bernoulli variance and a logit link function (McDowell & Cox, 2004). The third dependent variable, the number of forward citations at the firm-year level, is a continuous variable, and thus we employed an OLS model.

RESULTS

Table 2 presents the descriptive statistics and correlation matrix for the variables used in the analysis. The correlations between independent variables are 0.53 or below, and the average variation inflation factor (VIF) statistic of 3.5 is also below the accepted cutoff of 10, reducing concerns for multicollinearity. Degree assortativity is correlated with the other dimensions of intra-firm network structure at 0.3 or below, supporting our expectation that it is a distinct dimension of structure not captured by those dimensions.

------------- Insert Tables 2 and 3 here ---------------

Table 3 reports the results for H1-H3 with models incorporating weights obtained from CEM as well as firm and year fixed effects. Model 1 in Table 3 tests the relationship between assortativity and the quantity of inventive output (H1). The coefficient of assortativity is 0.360 at a *p-value* of 0.000. To examine effect sizes, we compare firms with high assortativity (at one standard deviation above the mean) with those at mean levels of assortativity. Firms with high assortativity generate 4.8% $\left(= exp^{(0.360*0.13)} - 1\right)$ higher quantity of inventive output than those with average assortativity, consistent with H1. Model 2 in Table 3 tests H2 that degree assortativity is negatively associated with the novelty of inventive output. The coefficient of assortativity is -0.558 at a *p-value* of 0.000. Since we used the logit link with the binomial family in the GLM specification, the coefficients can be interpreted as in a count model. Firms with high assortativity are 7% lower in novelty of inventive output than those with average assortativity. The result is consistent with H2. Model 3 reports the result for H3, which predicted a negative association between assortativity and impact of inventive output. The coefficient of assortativity in Model 3 is -3.519 at a *p-value* of 0.000, consistent with H3. The result indicates that the average impact of inventive output in firms with high assortativity is 0.46-units lower than that in firms with average degree assortativity. The mean impact of inventive output for firms in our sample is 5.32, and this corresponds to an 8.6% lower impact.

SUPPLEMENTARY ANALYSES

We conducted several supplementary analyses to further investigate the relationships proposed in the study. These analyses are explained in detail in Online Appendix 2, and a summary is available in Table 4. Some of the main findings from the supplementary analyses are as follows: (1) We were able to validate our assumptions about peripheral inventors' access to new knowledge and central members' relative productivity by comparing the mean novelty and quantity values for C-C, C-P and P-P collaborations. Mean novelty of inventive output from C-P collaborations is higher (0.48) than that from C-C (0.38) and P-P (0.37) collaborations. C-C collaborations produce more patents on average (5.9) than C-P (4.3) and P-P (3.7) collaborations. (2) We also tested whether C-P collaborations resulted in higher novelty when they reside in a firm with low assortativity than in a firm with high assortativity, as argued, and found this to be the case. The t-value for the difference in mean novelty between low and high assortativity (bottom and top 25%) firms is 7.77 with a p-value of 0.000. (3) Since our theory suggested that the relationship between assortativity and invention quantity was mainly due to search activity, we tested whether novelty of inventions mediated the relationship between assortativity and quantity of inventions. Similarly, since we theorized that the relationship between assortativity and invention impact was primarily due to the novelty, we also tested whether invention novelty mediated the relationship between assortativity and average impact. We did indeed find that novelty partially mediated both relationships. Casual mediation analyses (Elmsley & Liu, 2013) suggested that novelty of inventive output mediated 23.9% of the relationship between assortativity and quantity of inventive output, and that novelty mediated 29.6% of the relationship between assortativity and impact. (4) We used alternative measures of novelty (based on past knowledge use) as well as alternative measures of impact (based on the number of breakthrough inventions and dispersion of the number of citations). The results were similar when we used alternative measures of novelty based on past knowledge use rather than technological subclasses, consistent with the idea that assortativity is related to search. In addition, we found that firms with low assortativity had more breakthrough patents and higher dispersion in terms of invention impact. (5) We examined the relationship between assortativity and patent originality and generality (Hall, Jaffe, & Trajtenberg, 2001). Assortativity was associated with low originality but high generality. While the results are exploratory, it is interesting that assortativity may be associated with more general technologies. (6) We tested the possibility that the results were fully explained by the distribution of knowledge among a firm's inventors, which might make assortativity redundant as an explanator of invention outcomes. Both the inclusion of knowledge diversity as a matching criterion in the CEM analysis and the addition of an alternative knowledge distribution measure over inventors (Teachman, 1980;

Carnabuci & Operti, 2013) suggested that the results are not fully explained by knowledge distribution. (7) We found robust results using an alternative matching estimator (nearest-neighbor matching) and additional matching criteria.

---------------------------- Insert Table 4 here ----------------------------

DISCUSSION AND CONCLUSION

The study generated several insights. Controlling for other attributes of intra-firm networks and a wide variety of firm characteristics, we found that degree assortativity of intra-firm networks was associated with higher inventive output but with lower average novelty and impact. Supplementary analyses suggested that the impact of degree assortativity on both outcomes is partially mediated by the novelty of the inventive output, consistent with the expectation that collaborations in assortative structures are more efficient but produce less novel outcomes. Moreover, they provided further evidence that disassortative structures were associated with more distant search and a higher likelihood of breakthrough inventions.

The findings from the paper underscore the critical role of the structure of intra-firm networks on a firm's invention performance (e.g., Carnabuci & Operti 2013; Guler & Nerkar, 2012; Moreira *et al.,* 2018). We add to that literature by demonstrating that degree assortativity, an often-overlooked property of firms' intra-firm networks, influences overall invention performance in nuanced ways. While assortative matching has often been accepted as a general principle of tie formation, our study is the first to document variation in the levels of degree assortativity in different firms, as well as meaningful associations between levels of degree assortativity and firm-level inventive outcomes. In addition, in contrast with prior work that has focused on knowledge transfer as the main mechanism linking intra-firm network structures and inventive outcomes (Davis & Aggarwal, 2020), our findings highlight that knowledge transfer only partially explains the assortativity-invention link. We conclude that differences in assortativity also capture variations in resource mobilization around ideas. As such, degree assortativity has implications not only for the search for new ideas through knowledge recombination but also for the selection of ideas through access to organizational resources.

Broadly, our study joins a recent conversation linking intra-firm interactions of individuals to firm-level knowledge outcomes (e.g., Davis & Aggarwal, 2020). Starting with the premise that knowledge creation is subject to individual, team and organizational-level factors, this body of work develops an emerging understanding of microfoundations based on articulating how patterns of interactions between individuals yield macro-level outcomes (Aggarwal, Posen & Workiewicz, 2020; Bhaskarabhatla *et al.*, 2021). By simultaneously considering the consequences of individual inventor characteristics and their collaboration patterns in recombinant innovation, assortativity promises to extend our understanding of how individual inventors come to influence innovation outcomes within firms.

The insights in the paper are useful in considering how organizational design through team composition may help firms achieve invention outcomes. A firm focusing on invention productivity may promote more assortativity in its intra-firm network, whereas another aiming at novel solutions may prefer lower assortativity. This application, however, raises a key question: To what extent can managers alter the level of degree assortativity in their firms to influence invention outcomes? On the one hand, intra-firm networks of collaboration are emergent and evolve over time (McEvily *et al.*, 2014). Inventors' decisions to work with each other is voluntary and depends on their research interests (e.g., Fleming *et al.,* 2007; Liebeskind *et al.,* 1996). At the same time, recent work suggests that firms may be able to influence informal structures by providing the environment and incentives for certain types of connections (e.g., Kleinbaum, Stuart, & Tushman, 2013; Puranam, 2018). The issue of how managers can nudge intra-firm networks toward preferred patterns is one that requires more research.

The paper raises interesting questions for strategic human capital (Agarwal, Ganco, & Ziedonis, 2009; Ganco, 2013; Khanna, 2021a). Scholars have examined the consequences of star mobility for firms and individuals (Azoulay *et al.*, 2019; Groysberg & Lee, 2009; Khanna, 2021b; Oldroyd & Morris, 2012). An implication of this study is that the impact of the departure of a star inventor on inventive outcomes may vary with the level of assortativity in a firm's collaboration network. Furthermore, assortativity may have implications for the arrival, integration and productivity of new star inventors. We invite future work on these relationships.

This study focuses on a specific type of assortativity based on centrality in the organizational network (Newman, 2002, 2003; Newman & Park, 2003). Assortative mixing can be based on other characteristics, such as technological expertise, educational background, gender or other demographic traits (e.g., Becker, 1973; Bhaskarabhatla *et al.*, 2021). We argued that the process of tie formation based on the logic of degree assortativity could result in non-trivial structural changes in collaboration networks and explain heterogeneity in the performance of firms within an industry. Other dimensions of assortativity may be equally important in explaining collaboration and innovation patterns; furthermore, they may vary in the extent to which they present accurate performance cues, influence collaboration dynamics and shape resource allocation. The paper invites further work examining various types of assortativity.

The findings of the study likely apply to a broad range of contexts where innovations are generated through collaborative and iterative processes of recombinant search and selection. However, in contexts where innovation is generated through other processes such as improvisation, knowledge access and resource mobilization may not be as critical to output.

Moreover, the implications of assortativity for other aspects of innovation performance is an open question. Even though we can reasonably assume that novel and impactful inventions are more likely to be commercialized, we do not know the extent to which they actually are. There could be further associations between assortativity and invention development and commercialization, as resource mobilization mechanisms gain more importance in those phases. Future work that considers measures of innovation of commercialization performance can further establish the role of the informal structure in firms' innovation performance.

It is important to underscore that the results of the study are correlational and provide suggestive evidence for a relationship between assortativity of collaboration networks and invention outcomes. The earlier discussion highlights that assortativity is not exogenously determined nor randomly distributed but likely influenced by other individual and organizational factors. Even so, the evidence of a correlational relationship between assortativity and innovation contributes towards a better understanding of the process by which structures of collaboration shape invention outcomes within firms and become a potential source of competitive advantage.

Overall, research in strategic management has long focused on the heterogeneity in performance across firms (Helfat, 2000). One of the ways firms can gain a competitive advantage, especially in high-technology industries, is through innovation (Helfat & Peteraf, 2003; Rosenkopf & Nerkar, 2001). Recent work has made headways into understanding the sources of heterogeneous innovation performance at multiple levels of analysis (Davis and Aggarwal, 2020; Aggarwal, Posen & Workiewicz, 2020). By providing evidence on the relationship between informal structure and invention performance, the current study contributes to our understanding of the factors underlying firm-level heterogeneity in innovation capabilities.

REFERENCES

Abadie A, Drukker D, Herr JL, Imbens GW. 2004. Implementing matching estimators for average treatment effects in Stata. *The Stata Journal* **4**(3): 290-311.
Abadie A, Imbens GW. 2002. Simple and bias-corrected matching estimators for average treatment effects, National Bureau of Economic Research Technical Working Paper Series, http://www.nber.org/papers/t0283 .
Abadie A, Imbens GW. 2011. Bias-corrected matching estimators for average treatment effects. *Journal of Business & Economic Statistics* **29**(1): 1-11.
Agarwal R, Ganco M, Ziedonis RH. 2009. Reputations for toughness in patent enforcement: Implications for knowledge spillovers via inventor MOBILITY. *Strategic Management Journal* **30**(13): 1349-1374.
Aggarwal VA, Posen HE, Workiewicz M. 2017. Adaptive capacity to technological change: A microfoundational approach. *Strategic Management Journal* **38**(6): 1212-1231.
Aggarwal VA, Hsu DH, Wu A. 2020. Organizing knowledge production teams within firms for innovation. *Strategy Science* **5**(1): 1-6.
Ahuja G. 2000. Collaboration networks, structural holes, and innovation: A longitudinal study. *Administrative Science Quarterly* **45**(3): 425-455.
Ahuja G, Katila R. 2001. Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal* **22**(3): 197-220.
Ahuja G, Lampert CM. 2001. Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strategic Management Journal* **22**(6-7): 521-543.
Ahuja G, Polidoro JF, Mitchell W. 2009. Structural homophily or social asymmetry? The formation of alliances by poorly embedded firms. *Strategic Management Journal* **30**(9): 941-958.
Ahuja G, Soda G, Zaheer A. 2012. Introduction to the Special Issue: The Genesis and Dynamics of Organizational Networks. *Organization Science* **23**(2): 434-448.
Allen TJ, Cohen SI. 1969. Information flow in research and development laboratories. *Administrative Science Quarterly* 14(1): 12-19.
Amabile TM. 1983. The social psychology of creativity: A componential conceptualization. *Journal of Personality and Social Psychology* **45**(2): 357.
Amabile TM. 1988. A model of creativity and innovation in organizations. *Research in Organizational Behavior* **10**(1): 123-167.
Argote L, Aven BL, Kush J. 2018. The effects of communication networks and turnover on transactive memory and group performance. *Organization Science* **29**(2): 191-206.
Argyres NS, Silverman BS. 2004. R&D, organization structure, and the development of corporate technological knowledge. *Strategic Management Journal* **25**(8-9): 929-958.
Arts S, Fleming L. 2018. Paradise of novelty—or loss of human capital? Exploring new fields and inventive output. *Organization Science* **29**(6): 1074-1092.
Arundel A, Kabla I. 1998. What percentage of innovations are patented? Empirical estimates for European firms. *Research Policy* **27**(2): 127-141.
Azoulay P, Fons-Rosen C, Zivin JSG. 2019. Does Science Advance One Funeral at a Time? *American Economic Review* **109**(8): 2889-2920.
Baum JA, Shipilov AV, Rowley TJ. 2003. Where do small worlds come from? *Industrial and Corporate Change* **12**(4): 697-725.
Becker, G.S., 1973. A theory of marriage: Part I. *Journal of Political economy* **81**(4): 813-846.
Bhaskarabhatla A, Cabral L, Hegde D, Peeters T. 2021. Are Inventors or Firms the Engines of Innovation? *Management Science* **67**(6), 3899-3920.
Borgatti SP, Everett MG. 2000. Models of core/periphery structures. *Social Networks* **21**(4): 375-395.
Bunderson JS, Reagans RE. 2011. Power, status, and learning in organizations. *Organization Science* **22**(5): 1182-1194.
Burns T, GM Stalker (1961). *The management of innovation*. London: Tavistock.

Carley M, Hegde D, Marco, A. 2015. What is the Probability of Receiving a US Patent. *Yale Journal of Law and Technology* **17**.
Carnabuci G, Operti E. 2013. Where do firms' recombinant capabilities come from? intraorganizational networks, knowledge, and firms' ability to innovate through technological recombination. *Strategic Management Journal* **34**(13): 1591-1613.
Cattani G, Ferriani S. 2008. A Core/Periphery Perspective on Individual Creative Performance: Social Networks and Cinematic Achievements in the Hollywood Film Industry. *Organization Science* **19**(6): 824-844.
Cockburn I, Griliches Z. 1988. The estimation and measurement of spillover effects of R&D investment-industry effects and appropriability measures in the stock market's valuation of R&D and patents. *The American Economic Review* **78**(2): 419-423.
Coleman JS. 1988. Social capital in the creation of human-capital. *American Journal of Sociology* **94**: S95-S120.
Cummings JN, Cross R. 2003. Structural properties of work groups and their consequences for performance. *Social Networks* **25**(3): 197-210.
Dahlander L, Frederiksen L. 2012. The Core and Cosmopolitans: A Relational View of Innovation in User Communities. *Organization Science* **23**(4): 988-1007.
Davis, J.P. and Aggarwal, V.A., 2020. Knowledge mobilization in the face of imitation: Microfoundations of knowledge aggregation and firm-level innovation. *Strategic Management Journal* **41**(11): 1983-2014.
Emsley, R. and Liu, H., 2013. *PARAMED*: Stata module to perform causal mediation analysis using parametric regression models, https://EconPapers.repec.org/RePEc:boc:bocode:s457581.
Ertug G, Gargiulo M, Galunic C, Zou T. 2018. Homophily and Individual Performance. *Organization Science* **29**(5): 912-930.
Ethiraj SK, Levinthal D. 2004. Modularity and innovation in complex systems. *Management Science* **50**(2): 159-173.
Everett MG, Borgatti SP. 1999. The centrality of groups and classes. *The Journal of Mathematical Sociology* **23**(3): 181-201.
Fang C, Lee J, Schilling MA. 2010. Balancing Exploration and Exploitation Through Structural Design: The Isolation of Subgroups and Organizational Learning. *Organization Science* **21**(3): 625-642.
Fleming L. 2001. Recombinant uncertainty in technological search. *Management Science* **47**(1): 117-132.
Fleming L, King C, Juda A. 2007. Small worlds and regional innovation. *Organization Science* **18**(6): 938-954.
Freeman LC. 1978. Centrality in social networks conceptual clarification. *Social Networks* **1**(3): 215-239.
Gambardella A, Torrisi S. 1998. Does technological convergence imply convergence in markets? Evidence from the electronics industry. *Research policy* **27**(5): 445-463.
Ganco M. 2013. Cutting the Gordian knot: The effect of knowledge complexity on employee mobility and entrepreneurship. *Strategic Management Journal* **34**(6): 666-686.
Girotra K, Terwiesch C, Ulrich KT. 2007. Valuing R&D projects in a portfolio: Evidence from the pharmaceutical industry. *Management Science* **53**(9): 1452-1466.
Grigoriou K, Rothaermel FT. 2017. Organizing for knowledge generation: internal knowledge networks and the contingent effect of external knowledge sourcing. *Strategic Management Journal* **38**(2): 395-414.
Groysberg B, Lee LE. 2009. Hiring Stars and Their Colleagues: Exploration and Exploitation in Professional Service Firms. *Organization Science* **20**(4): 740-758.
Guimera R, Uzzi B, Spiro J, Amaral LAN. 2005. Team assembly mechanisms determine collaboration network structure and team performance. *Science* **308**(5722): 697-702.
Gulati R, Nohria N, Zaheer A. 2000. Guest editors' introduction to the special issue: Strategic networks. *Strategic Management Journal* **21**(3): 199-201.
Guler I, Nerkar A. 2012. The impact of global and local cohesion on innovation in the pharmaceutical industry. *Strategic Management Journal* **33**(5): 535-549.

Hall BH, Jaffe AB, Trajtenberg M. 2001. The NBER patent citation data file: Lessons, insights and methodological tools, National Bureau of Economic Research Working Paper Series: 8498.
Hansen MT. 1999. The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. *Administrative Science Quarterly* **44**(1): 82-111.
Hansen MT. 2002. Knowledge networks: Explaining effective knowledge sharing in multiunit companies. *Organization Science* **13**(3): 232-248.
Hargadon A, Sutton RI. 1997. Technology brokering and innovation in a product development firm. *Administrative Science Quarterly* **42**(4): 716-749.
Hargadon AB. 2003. Organizations in action: Social science bases of administrative theory. *Administrative Science Quarterly* **48**(3): 498-501.
Hausman JA, Hall BH, Griliches Z. 1984. Econometric models for count data with an application to the patents-R&D relationship, National Bureau of Economic Research Technical Working Paper Series 17, www.nber.org/papers/tt0017.
Hegde D, Tumlinson J. 2014. Does social proximity enhance business partnerships? Theory and evidence from ethnicity's role in US venture capital. *Management Science* **60**(9): 2355-2380.
Helfat CE. 2000. Guest editor's introduction to the special issue: The evolution of firm capabilities. *Strategic Management Journal* **21**(10-11): 955-959.
Helfat CE, Peteraf MA. 2003. The dynamic resource-based view: Capability lifecycles. *Strategic Management Journal* **24**(10): 997-1010.
Hernandez E, Shaver JM. 2019. Network synergy. *Administrative Science Quarterly* **64**(1): 171-202.
Hsu DH, Hsu PH, Zhou T, Ziedonis AA. 2021. Benchmarking U.S. university patent value and commercialization efforts: A new approach. Reseach Policy **50**(1): 104076
Iacus SM, King G, Porro G. 2011. Multivariate matching methods that are monotonic imbalance bounding. *Journal of the American Statistical Association* **106**(493): 345-361.
Ibarra H. 1992. Homophily and differential returns - sex-differences in network structure and access in an advertising firm. *Administrative Science Quarterly* **37**(3): 422-447.
Jaffe AB. 1986. Technological opportunity and spillovers of R&D: evidence from firms' patents, profits and market value, *American Economic Review* **76**(5): 984-999.
Jeppesen LB, Lakhani KR. 2010. Marginality and Problem-Solving Effectiveness in Broadcast Search. *Organization Science* **21**(5): 1016-1033.
Kanter RM. 1983. *The change masters: Innovation for productivity in the American corporation*. New York: Simon and Shuster.
Kaplan S, Vakili K. 2015. The double-edged sword of recombination in breakthrough innovation. *Strategic Management Journal* **36**(10): 1435-1457.
Kapoor R, Lim K. 2007. The impact of acquisitions on the productivity of inventors at semiconductor firms: A synthesis of knowledge-based and incentive-based perspectives. *Academy of Management Journal* **50**(5): 1133-1155.
Khanna R. 2021a. Peeking Inside the Black Box: Inventor Turnover and Patent Termination. *Journal of Management* 0149206321997910.
Khanna R. 2021b. Aftermath of a tragedy: A star's death and coauthors' subsequent productivity. *Research Policy* **50**(2): 104159.
Khanna R, Guler I, Nerkar A. 2016. Fail often, fail big, and fail fast? Learning from small failures and R&D performance in the pharmaceutical industry. *Academy of Management Journal* **59**(2): 436-459.
Khanna R, Guler I, Nerkar A. 2018. Entangled decisions: Knowledge interdependencies and terminations of patented inventions in the pharmaceutical industry. *Strategic Management Journal* **39**(9): 2439-2465.
Kleinbaum AM, Stuart TE, Tushman ML. 2013. Discretion Within Constraint: Homophily and Structure in a Formal Organization. *Organization Science* **24**(5): 1316-1336.
Kneeland MK, Schilling MA, Aharonson BS. 2020. Exploring uncharted territory: Knowledge search processes in the origination of outlier innovation. *Organization Science* **31**(3): 535-557.
Knott AM. 2008. R&D/returns causality: Absorptive capacity or organizational IQ. *Management Science* **54**(12): 2054-2067.

Knudsen T, Levinthal DA. 2007. Two faces of search: Alternative generation and alternative evaluation. *Organization Science* **18**(1): 39-54.
Kobrin SJ. 1991. An empirical-analysis of the determinants of global integration. *Strategic Management Journal* **12**: 17-31.
Kogut B, Zander U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science* **3**(3): 383-397.
Lanjouw JO, Schankeman M. 2004. Patent quality and research productivity: Measuring innovation with multiple indicators. *Economic Journal* **114**(495): 441-465.
Lazarsfeld PF, Merton RK. 1954. Friendship as a social process: A substantive and methodological analysis. *Freedom and control in modern society* **18**(1): 18-66.
Lazer D, Friedman A. 2007. The network structure of exploration and exploitation. *Administrative Science Quarterly* **52**(4): 667-694.
Lazzarini SG, Mesquita LF, Monteiro F, Musacchio A. 2020. Leviathan as an inventor: An extended agency model of state-owned versus private firm invention in emerging and developed economies. *Journal of International Business Studies* **26**: 1-35.
Maoret M, Tortoriello M, Iubatti D. 2020. Big Fish, Big Pond? The Joint Effect of Formal and Informal Core/Periphery Positions on the Generation of Incremental Innovations. *Organization Science* **31**(6): 1538-59.
Levinthal DA, March JG. 1993. The myopia of learning. *Strategic Management Journal* **14**: 95-112.
Li SX, Rowley TJ. 2002. Inertia and evaluation mechanisms in interorganizational partner selection: Syndicate formation among US investment banks. *Academy of Management Journal* **45**(6): 1104-1119.
Liebeskind JP, Oliver AL, Zucker L, Brewer M. 1996. Social networks, learning, and flexibility: Sourcing scientific knowledge in new biotechnology firms. *Organization Science* **7**(4): 428-443.
March JG. 1991. Exploration and exploitation in organizational learning. *Organization Science* **2**(1): 71-87.
Mason W, Watts DJ. 2012. Collaborative learning in networks. *Proceedings of the National Academy of Sciences* **109**(3): 764-769.
McDowell A, Cox NJ. 2004. How do you fit a model when the dependent variable is a proportion. *STATA FAQ http://www. stata. com/support/faqs/stat/logit. html.*
McEvily B, Soda G, Tortoriello M. 2014. More formally: Rediscovering the missing link between formal organization and informal social structure. *Academy of Management Annals* **8**(1): 299-345.
McPherson JM, Smith-Lovin L. 1987. Homophily in voluntary organizations: Status distance and the composition of face-to-face groups. *American sociological review*: 370-379.
McPherson M, Smith-Lovin L, Cook JM. 2001. Birds of a feather: Homophily in social networks. *Annual review of sociology* **27**(1): 415-444.
Merton RK. 1968. The Matthew effect in science: The reward and communication systems of science are considered. *Science* **159**(3810): 56-63.
Moreira S, Markus A, Laursen K. 2018. Knowledge diversity and coordination: The effect of intrafirm inventor task networks on absorption speed. *Strategic Management Journal* **39**(9): 2517-2546.
Nelson RR, Winter SG. 1982. *An Evolutionary Theory of Economic Change,* Cambridge: Harvard University Press.
Nerkar A, Paruchuri S. 2005. Evolution of R&D capabilities: The role of knowledge networks within a firm. *Management Science* **51**(5): 771-785.
Newman MEJ. 2002. Assortative mixing in networks. *Physical Review Letters* **89**(20).
Newman MEJ. 2003. Mixing patterns in networks. *Physical Review E* **67**(2).
Newman MEJ, Park J. 2003. Why social networks are different from other types of networks. *Physical Review E* **68**(3).
Oldroyd JB, Morris SS. 2012. Catching falling stars: A human resource response to social capital's detrimental effect of information overload on star employees. *Academy of Management Review* **37**(3): 396-418.

Papke LE, Wooldridge JM. 2008. Panel data methods for fractional response variables with an application to test pass rates. *Journal of Econometrics* **145**(1-2): 121-133.
Paruchuri S. 2010. Intraorganizational Networks, Interorganizational Networks, and the Impact of Central Inventors: A Longitudinal Study of Pharmaceutical Firms. *Organization Science* **21**(1): 63-80.
Paruchuri S, Awate S. 2017. Organizational knowledge networks and local search: the role of intra-organizational inventor networks. *Strategic Management Journal* **38**(3): 657-675.
Perry-Smith JE, Mannucci PV. 2017. From creativity to innovation: The social network drivers of the four phases of the idea journey. *Academy of Management Review* **42**(1): 53-79.
Phelps C, Heidl R, Wadhwa A. 2012. Knowledge, networks, and knowledge networks: A review and research agenda. *Journal of Management* **38**(4): 1115-1166.
Podolny JM. 1993. A status-based model of market competition. *American Journal of Sociology* **98**(4): 829-872.
Podolny JM. 2001. Networks as the pipes and prisms of the market. *American Journal of Sociology* **107**(1): 33-60.
Puranam P. 2018. *The microstructure of organizations*. Oxford University Press.
Reagans R, McEvily B. 2003. Network structure and knowledge transfer: The effects of cohesion and range. *Administrative Science Quarterly* **48**(2): 240-267.
Reagans R, Zuckerman E, McEvily B. 2004. How to make the team: Social networks vs. demography as criteria for designing effective teams. *Administrative Science Quarterly* **49**(1): 101-133.
Reagans R, Zuckerman EW. 2001. Networks, diversity, and productivity: The social capital of corporate R&D teams. *Organization Science* **12**(4): 502-517.
Rodan S, Galunic C. 2004. More than network structure: How knowledge heterogeneity influences managerial performance and innovativeness. *Strategic Management Journal* **25**(6): 541-562.
Rosenkopf L, Nerkar A. 2001. Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal* **22**(4): 287-306.
Rothaermel FT, Thursby M. 2007. The nanotech versus the biotech revolution: Sources of productivity in incumbent firm research. *Research Policy* **36**(6): 832-849.
Schilling MA. 2005. A" small-world" network model of cognitive insight. *Creativity Research Journal* **17**(2-3): 131-154.
Schilling MA, Fang C. 2014. When hubs forget, lie, and play favorites: Interpersonal network structure, information distortion, and organizational learning. *Strategic Management Journal* **35**(7): 974-994.
Schilling MA, Phelps CC. 2007. Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Management Science* **53**(7): 1113-1126.
Schumpeter, J. A. 1934. *The Theory of Economic Development*. Harvard University Press, Cambridge, MA.
Schumpeter JA. 1939. *Business cycles*. McGraw-Hill New York.
Shipilov AV, Li SX, Greve HR. 2011. The Prince and the Pauper: Search and Brokerage in the Initiation of Status-Heterophilous Ties. *Organization Science* **22**(6): 1418-1434.
Shore J, Bernstein E, Jang AJ. 2020. Network Centralization and Collective Adaptability to a Shifting Environment. *Available at SSRN 3664022*.
Simon HA. 1955. A behavioral model of rational choice. *The Quarterly Journal of Economics* **69**(1): 99-118.
Simonton DK. 1999. Creativity as blind variation and selective retention: Is the creative process Darwinian?. *Psychological Inquiry* **1**: 309-28.
Singh J, Fleming L. 2010. Lone Inventors as Sources of Breakthroughs: Myth or Reality? *Management Science* **56**(1): 41-56.
Sorenson O, Rivkin JW, Fleming L. 2006. Complexity, networks and knowledge flow. *Research Policy* **35**(7): 994-1017.
Stinchcombe AL. 1965. Organizations and social structure. *Handbook of organizations* **44**(2): 142-193.
Taylor A, Greve HR. 2006. Superman or the fantastic four? Knowledge combination and experience in innovative teams. *Academy of Management Journal* **49**(4): 723-740.

Teachman JD. 1980. Analysis of population diversity: Measures of qualitative variation. *Sociological Methods & Research* **8**(3): 341-62.
Thomas-Hunt MC, Ogden TY, Neale MA. 2003. Who's really sharing? Effects of social and expert status on knowledge exchange within groups. *Management science* **49**(4): 464-477.
Tichy NM, Tushman ML, Fombrun C. 1979. Social network analysis for organizations. *Academy of Management Review* **4**(4): 507-519.
Trajtenberg M. 1990. A penny for your quotes - patent citations and the value of innovations. *RAND Journal of Economics* **21**(1): 172-187.
Tsai WP. 2001. Knowledge transfer in intraorganizational networks: Effects of network position and absorptive capacity on business unit innovation and performance. *Academy of Management Journal* **44**(5): 996-1004.
Tushman ML. 1977. Special boundary roles in innovation process. *Administrative Science Quarterly* **22**(4): 587-605.
Tzabbar D, Kehoe RR. 2014. Can Opportunity Emerge From Disarray? An Examination of Exploration and Exploitation Following Star Scientist Turnover. *Journal of Management* **40**(2): 449-482.
Tzabbar D, Vestal A. 2015. Bridging the Social Chasm in Geographically Distributed R&D Teams: The Moderating Effects of Relational Strength and Status Asymmetry on the Novelty of Team Innovation. *Organization Science* **26**(3): 811-829.
Uzzi B, Mukherjee S, Stringer M, Jones B. 2013. Atypical combinations and scientific impact. *Science* **342**(6157): 468-472.
Zollo M, Winter SG. 2002. Deliberate learning and the evolution of dynamic capabilities. *Organization Science* **13**(3): 339-351.
Zucker LG, Darby MR, Armstrong JS. 2002. Commercializing knowledge: University science, knowledge capture, and firm performance in biotechnology. *Management Science* **48**(1): 138-153.

TABLES

Table 1. Degree assortativity and related network concepts at nodal, dyadic and whole network levels

Level of analysis	Network concepts	Examples of relevant work	Impact on knowledge access	Impact on resource mobilization	Implications for invention
Nodal level	Centrality	Everett & Borgatti, 1999; Hansen, 2002; Ibarra, 1993; Nerkar & Paruchuri, 2005; Tzabbar & Kehoe 2014; Tsai, 2001	Central inventors have greater access to knowledge, but their knowledge heavily reflects the prevailing norms and assumptions of the firm. Less central inventors have more limited access, but their knowledge sources may be more varied.	Central inventors can more easily mobilize organizational resources (funding, support) for their ideas. Less central inventors have difficulty in mobilizing organizational resource due to a lack of connections.	Central inventors are disproportionately more productive, but they engage in more local search and their work may have limited novelty. Less central inventors may have novel ideas but lack organizational support to carry them out.
Dyadic level	Structural homophily	Ahuja *et al*. 2009; Ibarra *et al.* 2005; McPherson *et al.* 2001; Shipilov *et al.* 2011	Homophilous collaborations achieve more fluid knowledge transfer due to ease of communication and trust but they have access to lower diversity of knowledge due to overlapping knowledge bases	Heterophilous collaborations may better realize novel inventions compared to homophilous ones if they can complement fresh knowledge with resource mobilization advantages from diverse members.	Structural homophily increases efficiency in collaborations, leading to high invention quantity but limits access to complementary knowledge and resources, lowering novelty and impact.
Whole network level	Degree Assortativity	Ahuja *et al.,* 2012; Borgatti & Everett 2000; Cattani & Ferriani 2012; Fang, Lee & Schilling 2010	Fragmentation suggests rich information and resource flows within clusters of central (or peripheral) actors but limited flows between them. Firm-wide norms of collaboration may influence effectiveness of knowledge sharing.	In assortative structures, organizational resources at the core may not be mobilized to execute the novel ideas in periphery. Disassortative structures more effectively achieve mobilization of organizational resources for novel inventions.	Efficient communication and resource mobilization within core and periphery clusters in assortative networks promote quantity, but lack of knowledge and resource flows across clusters leads to lower novelty and impact.

Table 2: Descriptive Statistics and Partial Correlation Matrix

	Variable	Mean	s. d.	1	2	3	4	5	6	7	8	9	10	11	12	13
1	*Quantity of inventive output*	45	28	1												
2	*Novelty of inventive output*	0.42	0.12	-0.06	1											
3	*Impact of inventive output*	5.32	6.91	-0.02	0.27	1										
4	*Degree assortativity*	0.19	0.13	0.17	-0.21	-0.13	1									
5	*Number of alliances*	2.79	5.09	-0.26	0.36	0.13	-0.22	1								
6	*Geographic diversification*	3.76	0.21	0.31	0.41	0.49	-0.32	-0.37	1							
7	*Number of claims per patent*	13.58	4.29	0.05	0.04	0.02	0.09	0.28	-0.07	1						
8	*Density*	0.05	0.07	-0.05	-0.07	-0.04	-0.21	-0.06	-0.07	-0.17	1					
9	*Connectivity*	5.28	6.37	0.13	-0.32	-0.15	0.07	0.04	-0.18	-0.25	0.34	1				
10	*Clustering*	0.73	0.08	0.41	0.19	0.29	-0.22	-0.19	-0.05	0.07	0.29	0.01	1			
11	*Average centrality (internal collaboration network)*	0.31	0.58	0.04	-0.01	0.04	-0.09	0.40	0.28	-0.08	0.14	0.08	0.01	1		
12	*Average centrality (internal citation network)*	0.15	0.27	-0.11	0.06	-0.05	0.30	0.39	0.29	-0.08	-0.06	-0.08	0.31	0.47	1	
13	*Average centrality (external collaboration network)*	0.06	0.03	0.01	0.11	0.01	0.02	0.08	-0.05	-0.07	0.11	-0.16	0.28	0.18	-0.31	1
14	*Average centrality (external citation network)*	0.13	0.22	0.23	0.16	0.28	0.09	-0.06	-0.31	-0.11	0.25	-0.50	-0.05	0.07	-0.36	0.09
15	*Number of failed attempts*	51	83	0.07	-0.19	0.10	0.12	-0.07	-0.25	0.05	0.17	0.34	0.07	-0.30	-0.38	0.11
16	*Number of lawsuits*	4.58	8.12	0.02	0.03	0.01	0.11	0.17	-0.20	0.26	0.09	-0.03	0.05	0.11	-0.19	0.01
17	*Network centralization*	0.09	0.14	0.32	0.22	0.38	0.12	-0.09	-0.28	-0.11	0.15	-0.49	-0.08	0.08	-0.55	0.09
18	*Number of drugs*	2.4	4.3	0.04	0.32	0.07	-0.03	0.07	0.13	0.22	-0.05	0.17	0.08	-0.14	-0.19	0.22
19	*Number of newcomers*	0.05	0.23	-0.09	0.39	0.11	0.13	0.16	0.10	0.05	-0.03	0.08	0.16	0.11	-0.14	-0.21

	Variable	14	15	16	17	18	19
14	*Average centrality (external citation network)*	1					
15	*Number of failed attempts*	-0.08	1				
16	*Number of lawsuits*	-0.08	0.29	1			
17	*Network centralization*	0.24	0.29	0.17	1		
18	*Number of drugs*	0.18	0.13	-0.09	0.06	1	
19	*Number of newcomers*	0.06	0.39	0.21	-0.07	-0.19	1

Table 3: Fixed-Effects Models for Invention Outcomes

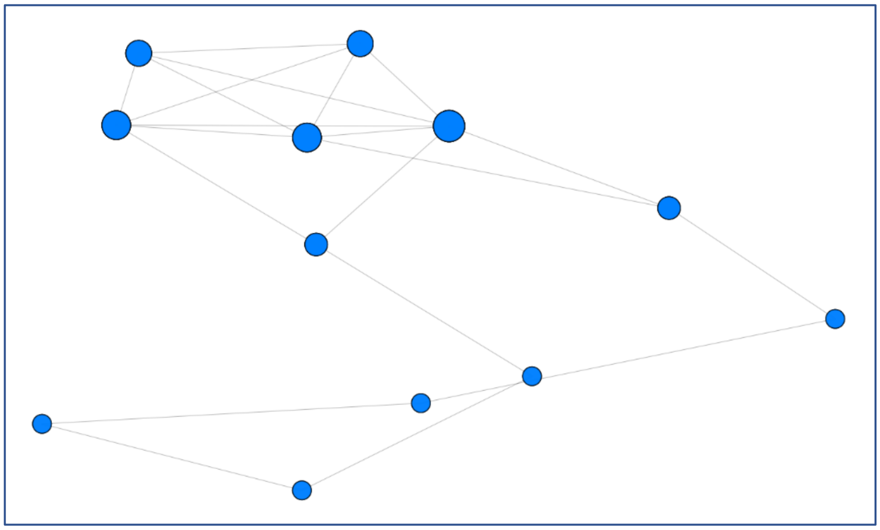
Variable	(1) QML Poisson *(DV: Quantity of inventive output)*		(2) GLM *(DV: Novelty of inventive output)*		(3) OLS *DV: (Impact of inventive output)*	
Degree assortativity $_{i, t-1}$	0.360	***0.000***	-0.558	***0.000***	-3.519	***0.000***
	(0.050)		(0.002)		(0.228)	
Number of alliances $_{i, t-3-t-1}$	-0.011	***0.077***	0.049	***0.000***	0.085	***0.065***
	(0.006)		(0.001)		(0.046)	
Geographic diversification $_{i, t-3-t-1}$	0.015	***0.321***	0.002	***0.030***	0.467	***0.000***
	(0.015)		(0.001)		(0.031)	
Number of claims per patent $_{i, t-3-t-1}$	-0.030	***0.526***	0.121	***0.000***	0.033	***0.000***
	(0.048)		(0.015)		(0.007)	
Density $_{i, t-3-t-1}$	0.024	***0.000***	-0.058	***0.000***	-0.017	***0.000***
	(0.006)		(0.016)		(0.002)	
Connectivity $_{i, t-3-t-1}$	0.018	***0.000***	-0.003	***0.604***	-0.208	***0.507***
	(0.001)		(0.006)		(0.313)	
Clustering $_{i, t-3-t-1}$	0.010	***0.000***	-0.003	***0.112***	0.123	***0.000***
	(0.001)		(0.002)		(0.002)	
Average centrality (internal collaboration network) $_{i, t-3-t-1}$	0.035 (0.024)	***0.146***	-0.003 (0.001)	***0.000***	-0.115 (0.085)	***0.176***
Average centrality (internal citation network) $_{i, t-3-t-1}$	0.002 (0.003)	***0.505***	-0.018 (0.056)	***0.746***	0.011 (0.026)	***0.676***
Average centrality (external collaboration network) $_{i, t-3-t-1}$	-0.015 (0.003)	***0.000***	0.004 (0.002)	***0.056***	0.040 (0.021)	***0.057***
Average centrality (external citation network) $_{i, t-3-t-1}$	-0.003 (0.003)	***0.339***	0.000 (0.000)	***0.412***	-0.018 (0.014)	***0.199***
Number of failed attempts $_{i, t-3-t-1}$	-0.049	***0.000***	0.055	***0.000***	0.044	***0.000***
	(0.014)		(0.015)		(0.011)	
Number of lawsuits $_{i, t-3-t-1}$	-0.011	***0.780***	0.055	***0.037***	0.108	***0.691***
	(0.039)		(0.026)		(0.272)	
Network centralization $_{i, t-3-t-1}$	0.043	***0.160***	-0.036	***0.093***	0.206	***0.114***
	(0.031)		(0.022)		(0.13)	
Number of drugs $_{i, t-3-t-1}$	0.292	***0.000***	0.047	***0.038***	0.260	***0.145***
	(0.032)		(0.023)		(0.179)	
Number of newcomers $_{i, t-3-t-1}$	-0.834	***0.001***	0.128	***0.118***	0.212	***0.032***
	(0.243)		(0.082)		(0.099)	
Constant	-	-	0.898	***0.669***	11.456	***0.007***
	-		(2.100)		(4.219)	
Wald χ^2 (χ_P^2)	2,809 (0.000)		-		-	
F-statistic	-		-		54	
Log pseudolikelihood	-		-344		-	
# Observations	788		788		788	
# Groups	86		86		86	

Standard errors in parentheses and p-values in bold. All models incorporate weights from CEM, and firm and year fixed effects. Controls-only models are presented in online Appendix 1 (Table A2).

Table 4. Summary of supplementary analyses and robustness tests

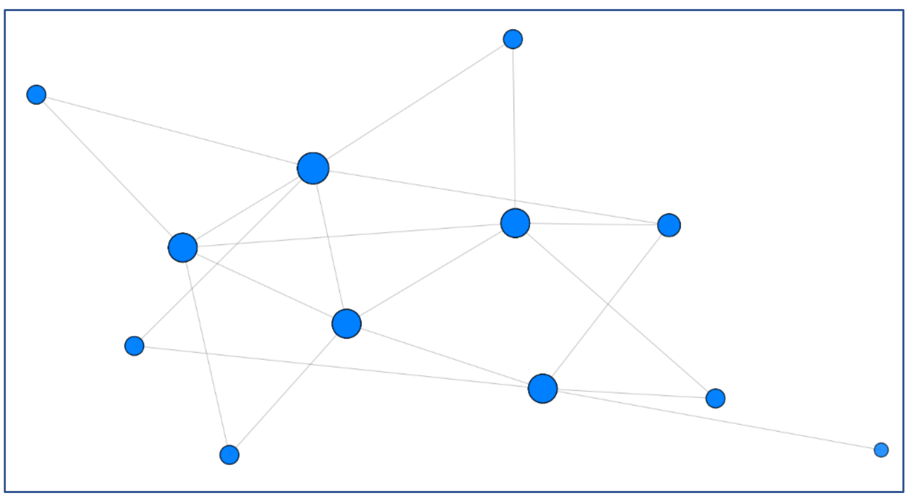
Concern	Testing methodology	Result	Online Appendix 2
Tests of assumptions regarding (1) peripheral members' access to new knowledge, (2) central members' productivity	Comparison of the novelty and quantity of inventions produced by C-C, C-P and P-P teams	Mean novelty of inventive output from C-P collaborations is higher (0.48) than that from C-C (0.38) and P-P (0.37) collaborations. C-C collaborations produce more patents on average (5.9) than C-P (4.3) and P-P (3.7) collaborations.	Tables A3 and A4
Test whether the novelty of output from mixed rank collaborations by firm assortativity.	Comparison of the mean novelty of C-P team inventions in firms with low and high-assortativity	The t-value for the difference in mean novelty between low and high assortativity (bottom and top 25%) firms = 7.77 with a p-value of 0.000	Table A5
Does invention novelty mediate the relationship between assortativity and invention quantity (impact)?	Baron and Kenney (1986) mediation mode, Sobel test (Sobel, 1982), causal mediation analysis (Elmsley & Liu, 2013), test of average causal mediation effect (Hicks & Tingley, 2011).	Novelty of inventive output mediates 23.9% (29.6%) of the relationship between assortativity and quantity of inventive output (impact).	Tables A6 and A7
Robustness to alternative measures of novelty	A-novelty measure based on knowledge use rather than subclasses; pioneering patents with no prior citations.	Results are robust to alternative measures.	Tables A8 and A9
Robustness to alternative measures of impact	Number of breakthrough inventions (top 1% based on forward citations); standard deviation of number of forward citations; alternative impact and influence based on Correidora & Banerjee (2015)	Firms with low degree assortativity have more breakthrough inventions and higher dispersion of citations. Results are robust to the use of alternative impact but weaker with the influence measure	Tables A10, A11, and A12
Alternative measures of inventive output: Patent generality and originality	Repeat models with alternative dependent variable: Average originality and generality (Hall *et al*., 2001)	Negative association between assortativity and originality; positive association between assortativity and generality.	Table A13
Are the results fully explained by knowledge diversity?	1. Include knowledge diversity as matching criterion in CEM; 2. Add alternative knowledge diversity measure (Teachman 1980, Carnabuci & Operti 2013)	Results are robust, suggesting that knowledge diversity only partially explains results	Table A14
Are results robust to the choice of matching estimator?	Employ bias-corrected nearest-neighbor matching (Abadie & Imbens, 2006; 2011)	Results are robust.	Table A15
Are results robust to more stringent matching criteria?	Number of newcomers to firm as matching variable (Carnabuci & Operti 2013)	Results are robust.	Table A16

FIGURES



Number of nodes: 12
Number of edges: 20
Average degree centrality: 3.33
Density: 0.30
Network centralization: 0.29
Assortativity: 0.57

Figure 1a



Number of nodes: 12
Number of edges: 20
Average degree centrality: 3.33
Density: 0.30
Network centralization: 0.29
Assortativity: -0.64

Figure 1b

Figures 1a and 1b depict two stylized networks with high and low assortativity, respectively. For both networks, a node refers to an inventor in a firm, the size of each node represents the degree centrality of the inventor, and edges (ties) represent collaborations between inventors. The two networks are identical along key network characteristics: network size (=12), density (= 0.30), centralization (= 0.29), and average degree centrality (= 3.33). However, degree assortativity varies drastically in the two networks. In Figure 1a, nodes with high degree centrality have more ties to other central nodes than to nodes with lower centrality, leading to high degree assortativity in the network (0.57). In contrast, nodes with high centrality in Figure 1b are relatively more likely to connect to nodes with low degree centrality, leading to low assortativity in the network (-0.64).

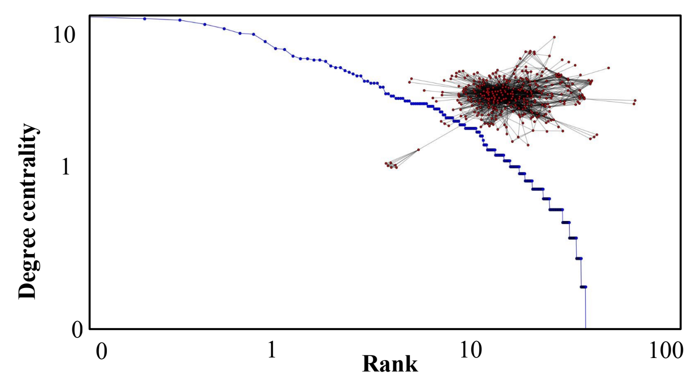


Figure 2a: Degree distribution and topology of the intra-firm network of Roche in 1985

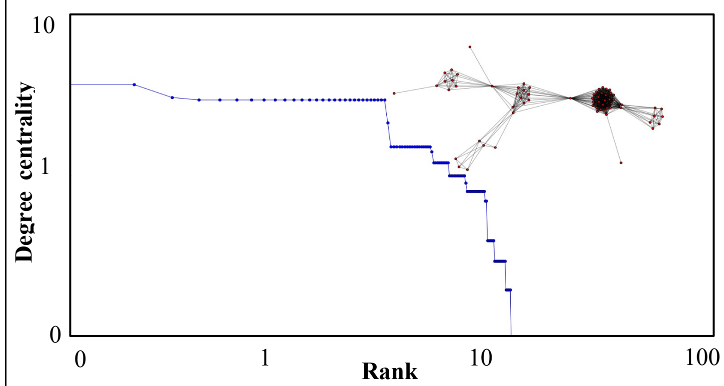


Figure 2b: Degree distribution and topology of the intra-firm network of Eli Lilly in 1985

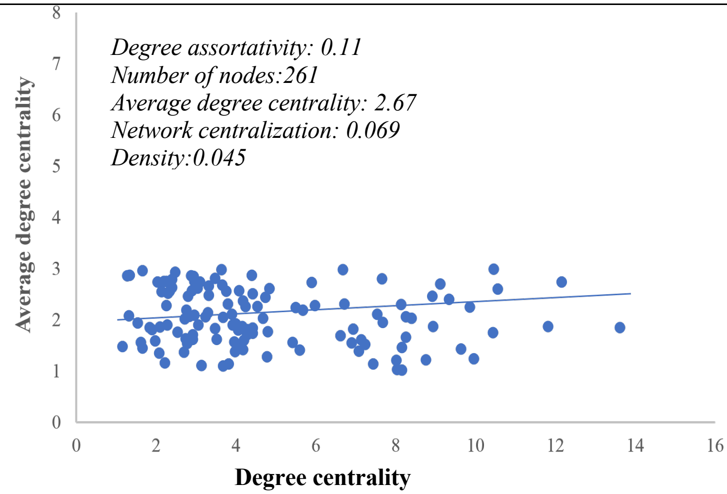


Figure 3a: Degree correlation plot for the intra-firm network of Roche in 1985

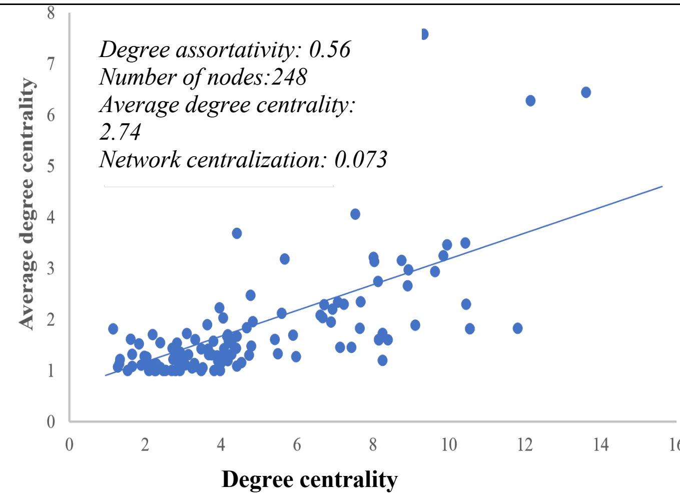


Figure 3b: Degree correlation plot for the intra-firm network of Eli Lilly in 1985