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Exploring the Locus of Invention: The Dynamics of Network Communities and Firms' Invention Productivity

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Exploring the locus of invention:
The dynamics of network communities and firms' invention productivity

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Abstract

Departing from prior research analyzing the implications of social structure for actors' outcomes by applying either the ego-network or the global-network perspective, this study examines the implications of network communities for the invention productivity of firms. Network communities represent dense and non-overlapping structural groups of actors in the social system. The network-community lens helps identify new ways to study firms' access to diverse knowledge inputs in a dynamic system of interorganizational relationships. Specifically, we examine how the membership dynamics of a network community affect the invention productivity of member firms by either enabling or constraining access to broad, diverse knowledge inputs. Our findings suggest, first, that a firm reaps the greatest invention benefits in a network community with moderate levels of membership turnover. Second, a firm attains the greatest invention productivity when its own rate of movement across different network communities is moderate. Third, we find that community members located in the core of their network community can benefit more from membership dynamics and prior community affiliations than those on its periphery. In empirical analyses, we use the evolving community structure of the network of interorganizational partnerships in the global computer industry over 1981-2001 to predict firms' patenting rates.

INTRODUCTION

In recent years, scholars have made significant advances in understanding how the social structure of markets impacts companies' learning and invention productivity by shaping the flows of resources and information among them (Beckman & Haunschild, 2002; Greve, 2009; Lavie & Drori, 2012). Since the critical knowledge required for developing new inventions is often complex and noncodifiable, interorganizational relationships can be particularly instrumental in facilitating the exchange and transmission of tacit knowledge through joint action, collaborative learning, and direct observation (Mowery, Oxley, & Silverman, 1996). As a result, research suggests that the locus of invention activities is often situated in the networks of interorganizational ties because novel ideas are frequently born at the intersection of knowledge flows among different organizations (Powell, Koput & Smith-Doerr, 1996).

Prior research has generally applied two complementary perspectives to explore the effects of interorganizational networks on firms' invention productivity. The ego-network perspective suggests that a firm's invention outcomes are linked to the magnitude, diversity, and accessibility of knowledge inputs, which are in turn critically shaped by the firm's ties to its partners and the partners' ties among themselves (e.g., Ahuja, 2000; Zaheer & Bell, 2005). In contrast, the global-network perspective has emphasized the benefits of knowledge diffusion through the broader social space, which includes the overall structure of firms and their ties within the industry (e.g., Abrahamson & Rosenkopf, 1997; Schilling & Phelps, 2007; Uzzi & Spiro, 2005). According to this view, a firm's ability to invent is often intricately linked to the extent to which the global network supports or inhibits the flows of knowledge and ideas through the industry. In one application of this approach, Schilling and Phelps (2007) have found that the degree of small-worldness of a global, industry-wide network positively affects the invention rates of firms in that industry.

In this paper, we suggest that both perspectives risk providing an incomplete picture of the relationship between networks and invention because they do not account for the role of network communities in affecting firms' generation of new knowledge. Inventions refer to the "development of a new idea or an act of creation" in the product or service space (Ahuja & Lampert, 2001: 523). As such, inventions are a critical antecedent to innovation, which entails the commercialization of an invention and thus constitutes the cornerstone of firms' entrepreneurial activities (Scherer & Ross, 1990).

Network communities, in turn, represent dense, non-overlapping structural groups within the network, in which actors are connected more to each other than to actors outside the group (see Figure 1) (e.g., Knoke, 2009: 1697). Network communities are prevalent in a range of interorganizational systems (e.g., Baum, Shipilov, & Rowley, 2003; Davis, Yoo, & Baker, 2003; Knoke, 2009). The value of adopting a perspective that focuses on the role of network communities lies in identifying new ways to examine firms' access to diverse knowledge inputs in a dynamic system of interorganizational relationships. This third perspective has thus far escaped the attention of both the ego-network and the global-network perspectives. Specifically, the focus on network communities differs from these perspectives in using the boundaries of network communities, rather than the properties of an ego-network (e.g., Ahuja, 2000) or a global network (e.g., Schilling & Phelps, 2007), to demarcate heterogeneous knowledge inputs in interorganizational systems. Furthermore, examining network communities allows for a unique focus on the dynamics of firms' movement across different communities, which in turn provides new ways to capture how heterogeneous knowledge is redistributed through the interorganizational system over time.

Figure 1 about here

Network communities can impact firms’ invention productivity for two reasons. The first is related to our expectation that information, knowledge, and other critical resources are likely to be more homogeneous *within* rather than *across* network communities. Because the combination of dense connectivity within communities and sparse connectivity across communities can make it easier for firms to exchange knowledge with other members of their own community, such structures can homogenize knowledge within communities, while also engendering some degree of knowledge diversity across communities (Gulati, Sytch, & Tatarynowicz, 2012; Lazer & Friedman, 2007). The second reason is that the short network distances and the reduced transaction costs characterizing dense network structures within communities can make it easier for firms to access and utilize the resources of their own network community, rather than the more distant resources of the broader interorganizational network (Coleman, 1988; Greif, 1989; Gulati, 1995).

Nevertheless, the combination of the relative ease in accessing the knowledge inputs of a firm's own community and the community’s structural isolation from the rest of the network points to a possible tension concerning how network communities can affect firms’ invention output. On the one hand, a network community's cohesion can facilitate the invention productivity of member firms by allowing them to access the local pool of knowledge through either their direct ties or the short, indirect ties to other community members (Ahuja, 2000; Haunschild & Beckman, 1998). Having such a common knowledge platform may also offer the firm a wider and more easily identifiable range of opportunities for recombining the complementary knowledge inputs available in its community. On the other hand, community affiliation can stifle invention productivity because of the structural isolation of network communities from one another and their relative isolation from the broader network. Knowledge, information, and other resources are likely to flow less freely across communities that have sparse connectivity and longer network distances between them. Thus, community members could access only a fragment of the industry's knowledge base, rather than the more heterogeneous knowledge available in the global network (Glasmeier, 1991).

In this paper, we argue that one way to resolve this tension is by focusing on the dynamics of network communities. When analyzed through a dynamic lens, network communities can offer the benefit of easy access to knowledge that is both locally available and diverse. The benefit of diverse knowledge becomes available as firms move across different network communities and thus change the composition of the network communities over time. Firms can benefit from the membership dynamics of network communities either indirectly or directly. The indirect effect results from the turnover of community members, which exposes the incumbents to the new knowledge and resources that are brought in by new community members. The direct effect, in turn, arises when a firm moves across different network communities over time, thus gaining direct exposure to the distinct knowledge bases of those communities. Because both of these effects can shape the diversity of knowledge that is locally available to the firm as a member of a given network community, we expect them both to influence the firm's invention productivity. We further examine how these effects can vary depending on the firm's structural position in its community and the overall diversity of knowledge across the communities.

Exploring the dynamics of network communities can result in significant theoretical implications that extend beyond those offered by the ego-network and global-network perspectives. First, the network-community perspective advances the existing perspectives by capturing the distribution of and access to heterogeneous knowledge and resources in social systems. Most notably, the ego-network perspective links access to diverse knowledge and resources to those ego-network positions that span structural holes between otherwise unconnected actors (Burt, 1992, 2004). We, in turn, extend this reasoning by suggesting that the boundaries of network communities can be used to effectively demarcate the heterogeneity of knowledge inputs. Understanding the structure and dynamics of network communities can thus advance the structural theories of action and outcomes beyond the implications generated by the ego-network perspective.

Second, the dynamics of network communities and their impact on firms' invention productivity are difficult to capture empirically just by analyzing the characteristics of firms' ego networks or the properties of the global network over time. For instance, one can envision a situation where two firms maintain the same structures of ego networks but one could be a member of a highly dynamic network community with a high degree of membership turnover, while the other could be a member of a static community. Similarly, given two firms with the same ego networks, one could move across different network communities frequently, while the other could remain in the same community over time. Furthermore, while the global network can remain stable across a range of structural properties, these stable patterns may conceal the membership dynamics taking place inside network communities. The network-community perspective can thus locate sources of informative variance in these situations that might otherwise be overlooked. Against this backdrop, consider that the existing network models of behaviors and outcomes often leave a lot of unexplained variance. For example, we frequently observe situations in which actors residing in the *same* global network and with the *same* ego-network structure can obtain different outcomes (e.g., Burt, 2012). The present focus on network communities can begin to address this issue, and thus enhance the explanatory power of socio-structural models of action and outcomes.

Taken together, these considerations may lead scholars to incorporate a new stage in the systematic analysis of how network structures affect behaviors and outcomes of individual and corporate actors. This stage would explore how the composition and the dynamics of network communities can affect actor outcomes. The focus on network communities is likely to be equally relevant for scholars examining network change and dynamics (e.g., Powell, White, Koput, & Owen-Smith, 2005; Zaheer & Soda, 2009). Understanding how network communities evolve alongside actors' ego networks and the global network can provide a more comprehensive view of the evolution of social systems.

Our empirical analyses are based on the network of interorganizational partnerships in the global computer industry from 1985 to 2001. This setting is particularly conducive to exploring our research question since firms' invention output in this high-velocity sector not only is essential for competitive success and survival, but also depends critically on firms' ability to access cutting-edge knowledge inputs (Eisenhardt and Tabrizi, 1995; Bourgeois and Eisenhardt, 1988). More importantly, such access has often been linked to interorganizational partnerships that can offer particularly rich and efficient channels for knowledge flows throughout the industry (Hagedoorn, 1993; Lee, 2007; Yang, Lin, & Lin, 2010). Moreover, firms in the computer industry have been observed to agglomerate into distinct network communities (Dedrick & Kraemer, 2005; Rosenkopf & Schilling, 2007). In this context, it is therefore reasonable to expect that firms' invention productivity will be affected by properties of the interorganizational network and, in particular, by network communities within it.

THEORY

Network Communities

Network communities can be found in a wide range of interorganizational settings. For example, many interorganizational networks have been identified as small-world systems featuring multiple dense, non-overlapping groups of firms that are only sparsely interlinked to other groups (e.g., Baum et al., 2003; Davis et al., 2003). Our perspective on network communities derives from structural accounts that define communities as densely connected and cohesive social groups (or clusters) of actors, in which the actors are closer to each other than to other actors in the network. In this tradition, scholars applied sociometric techniques, such as hierarchical clustering, to identify regions of high density in the network structure; they then used these results to evaluate social proximity among corporations, state authorities, or elites (Laumann, Galaskiewicz, & Marsden, 1978; Laumann & Marsden, 1979; Nohria & Garcia-Pont, 1991). Conceptually, this perspective builds on the notion of communities as interactional fields where community boundaries have been shaped predominately by actors' interactions and the resulting social proximity among them (Kasarda & Janowitz, 1974; Kaufman, 1959; Turk, 1970; Upham, Rosenkopf, & Ungar, 2010).

While this research has laid an important foundation for subsequent advances in the study of social systems, it has fallen short of systematically evaluating network communities as robust drivers of action. There are, however, two notable exceptions. One is the recent study by Greve (2009) that empirically documents the fact that firms located in the same network community are more likely to imitate each other than firms from other communities in adopting innovations. The other exception are the two recent studies by Rowley et al. (2004; 2005) that examine how the heterogeneity of firms in a community can affect a firm's decision to leave the community, and show that this heterogeneity can also affect the member firm's market performance. These exceptions notwithstanding, we still lack a systematic inquiry into how firms' affiliations with network communities can shape their invention outcomes.

More broadly, the present focus on network communities has important parallels to the studies of strategic groups and cognitive communities in industrial economics and strategy. Research on strategic groups identifies groups of similar firms along various dimensions of their strategy, such as the extent of their advertising and product branding; whether they operate in regional, national, or multinational markets; and the extent and nature of their diversification into different lines of business (Caves & Porter, 1977: 251). The work on cognitive communities provides an important extension to this perspective by emphasizing that the material aspects of strategy interact in complex ways with the beliefs and perceptions of key organizational decision makers to shape the industry's competitive landscape (Porac, Thomas, & Baden-Fuller, 1989; Porac, Thomas, Wilson, Paton, & Kanfer, 1995). Both of these theoretical lenses thus offer unique but complementary insights into how the groupings of rivals in the same industry can explain firm-level performance, beyond industry-specific or firm-specific factors. As such, these lenses are in alignment with our focus on network communities, in that we also point to an important determinant of organizational outcomes that exists at an intermediate level of analysis, which in our case is located between the structure of a firm's network and the network structure of the industry.

Nonetheless, our focus on network communities as densely connected groups of collaborating firms is distinct from the focus of prior research on groups of rivals. The characteristics typically ascribed to competing firms – similarities in strategic attributes, overlapping claims to the same resource space, and cognitive perceptions of rivalry (Ingram & Yue, 2008; Porac et al., 1995) – are unlikely to have a one-to-one correspondence with patterns of collaboration (see, e.g., Thomas & Pollock, 1999). In fact, since many rivals avoid collaborating with one another, strategic groups are unlikely to be structurally dense (e.g., Madhavan, Koka, & Prescott, 1998: 454-455). Furthermore, research on groups of rivals aims to capture how members of the same group respond in a similar way to market disturbances or have power advantages over other groups in the industry (Caves and Porter, 1977: 252). In contrast, network communities are expected first and foremost to shape the flows of knowledge and its heterogeneity in the broader industry space. As a result of these conceptual differences, studying groups of rivals invites an analytic approach distinct from that needed to study network communities. While network communities are typically identified on the basis of dense patterns of collaborative interactions among firms (Sytch, Tatarynowicz, & Gulati, 2012), groups of rivals are captured through clustering based on similarities in firms' attribute data or through sociometric techniques based on a high density of intragroup rivalry relations (Fiegenbaum & Thomas, 1990; Porac et al., 1995).

Finally, the parallels between our focus on network communities and studies of industrial districts and technological clusters (e.g., Baptista & Swann, 1999; Saxenian, 1994) are worth noting. It is certainly plausible that regional collocation or technological similarity might correlate with pockets of dense organizational interconnectivity, and we account for these possibilities in our empirical strategy. Our focus on network communities is nonetheless distinct and more comprehensive. By examining the exact patterns of how a market's social structure is partitioned into network communities, we are more likely to capture the complex interplay of economic, geographical, technological, and social factors that jointly account for the formation of network communities (e.g., Gomes-Casseres, 1996; Knoke, 2009; Powell & Sandholtz, 2012). More importantly, we can capture the patterns of interorganizational relationships that support the ongoing flows of knowledge, information, and resources that are most likely to affect the member firms' invention outcomes (e.g., Breschi & Malerba, 2005: 13; Cowan, 2005: 31; Whittington, Owen-Smith, & Powell, 2009: 117). These flows and the resultant distribution of knowledge and resources in industry space, which underlie the effect of network communities of firms' invention outcomes, are not related to or conditional on the geographical proximity of firms.

Network Communities and Knowledge Heterogeneity

In comparison to either the ego-network or the global-network perspective, this paper strives to reorient the discussion on the sources of heterogeneity in social systems toward network communities as demarcating the boundaries of heterogeneous knowledge inputs. For ego-network theorists, it is connecting with many alters (Powell et al., 1996; Shan, Walker, & Kogut, 1994), and with those who are not connected to each other (Burt, 1992), that puts the ego at risk of generating new ideas. In other words, knowledge heterogeneity is demarcated by the size of the ego's ego network and the patterns of connectivity among the ego's contacts. Some proponents of this perspective go so far as to suggest that network structures beyond the ego network may be irrelevant for actors' creativity (Burt, 2007). In contrast, for global network theorists, the key sources of heterogeneity lie in the properties of the global network (Abrahamson & Rosenkopf, 1997; Centola & Macy, 2007; Uzzi & Spiro, 2005). For example, some of these scholars have linked the highest levels of creativity to moderate levels of small-worldness in the system, arguing that this structure provides actors with a broad and quick access to knowledge while also preserving its overall diversity (Uzzi & Spiro, 2005). In summary, extant theories suggest that knowledge heterogeneity in social systems – and the concomitant implications for actors' invention output – can be captured by examining the properties of either an ego-network of ties around a single actor, or a global network of all actors and their ties in a given social system.

In contrast to these theories, the community perspective offered here suggests that the boundaries of heterogeneous knowledge inputs in social systems are most precisely demarcated by the boundaries of cohesive network communities among actors. At the heart of this argument is the expectation that increased connectivity among actors within a network community and the resultant information flows between them can homogenize the knowledge stocks and flows inside the community (Gulati et al., 2012; Lazer & Friedman, 2007). As a result, actors may increasingly be tapping into the same or similar technological opportunities within their community and relying on increasingly redundant flows of knowledge and information.

It is worth noting that the homogenization processes within network communities do not necessarily require knowledge and information to flow strictly through interorganizational ties. Relevant technological information could also travel outside of firms' interactions, for example, through publications, trade exhibitions, conferences, or the Internet (Porac et al., 1989; Rosenkopf, Metiu, & George, 2001). Nevertheless, it is reasonable to expect that the presence of a direct tie between two firms can make the diffusion of technological knowledge more likely, particularly in its more tacit and complex forms. The presence of an interorganizational tie allows for direct exposure, observation, demonstration, and experience of new knowledge, which are often essential for effective knowledge transfer between firms (Mowery et al., 1996; Rogers, 2003). Furthermore, interorganizational ties engender both formal governance (Mayer & Argyres, 2004) and informal interactions (McEvily & Marcus, 2005; McEvily, Perrone, & Zaheer, 2003), which jointly enable knowledge and information to travel more effectively across organizational boundaries.

The homogeneity of knowledge within network communities can also be partly related to the patterns of homophilous selection in partnership formation, such that interorganizational ties are more likely to form between two similar firms (Powell et al., 2005). This possibility in turn suggests that members of a given network community could be more similar to each other than to other firms in the network. Many of these similarities, such as having similar organizational cultures or similar experience in interorganizational partnerships, could pull organizations towards each other while also helping them avoid competitive frictions (Lavie, Haunschild, & Khanna, 2012; Wang & Zajac, 2007). These similarities could also make members of the same network community more prone to identifying and focusing on similar technological and market opportunities, and using similar ways to seize these opportunities. In support of this conjecture, there is evidence, for example, that decision makers in similar companies may over time develop similar mental models of their market and competitive environment (Porac et al., 1989; 1995).

While knowledge available inside a given network community is likely to be rather homogeneous due to the higher intensity of knowledge flows and greater similarity among the community members, a substantial degree of knowledge heterogeneity can still be preserved *across* different communities. In contrast to the high density of connections among firms within the same community, the network space between communities is described by rather sparse connectivity, thus lowering the intensity of knowledge transfer, exchange, and absorption across community boundaries. Furthermore, firms that belong to different communities are likely to exhibit lower similarity than those that belong to the same community. Taken together, these features can both preserve and reinforce the heterogeneity of knowledge across different network communities.

Thus, it appears that whether a given network community facilitates or constrains the invention productivity of its members is related in part to the degree to which these firms are exposed to the broader knowledge inputs of the global network. Hence, one way to systematically examine the effects of network communities on firms' invention productivity is to identify which specific features of the community can best enable firms to access diverse knowledge and resources within the global network. In this paper, we explore how the knowledge base of a given network community can get updated through the movement of firms across different communities over time. The indirect effect of such updating for a member firm can be captured when its network community acquires a new member with a different stock of knowledge and expertise, which can potentially enhance the knowledge base available to community members. A direct effect is evident when the firm moves across network communities over time, thus gaining exposure to heterogeneous knowledge and resources.

We further examine to what extent these effects are moderated by the structural position that a firm holds in its network community, and by knowledge diversity across communities, as reflected by the evolving properties of the global network. Taken together, all these effects allow us to establish a more compelling link between the effects of membership dynamics in network communities and the resultant updates to the knowledge base of communities. Our overall argument also identifies some critical interactions between the characteristics of the ego and global networks on the one hand, and the properties of network communities on the other, thus leading to a more encompassing, multilevel analysis of social structures in understanding firms' invention outcomes.

Membership Dynamics in Network Communities

Membership Turnover

Several recent studies have shown that interorganizational systems are characterized by frequent entries and exits of firms, as well as by pronounced changes in the patterns of interorganizational tie formation, all of which can affect the distribution of ties and regions of high density across the global network (e.g., Greve, Baum, Mitsuhashi, & Rowley, 2010; Rosenkopf & Padula, 2008; Rowley et al., 2005). These occurrences are likely to propel changes in the membership composition of network communities over time. Scholars have also noted that compositional variation in social groups can have meaningful implications for the members' invention outcomes and growth, since such diversity stimulates experimentation, flexibility, and the introduction of new ideas (e.g., Florida, 2002; Porter, Whittington, & Powell, 2005; Simmel, 1950). Compositional stability, in contrast, is likely to have the opposite effect.

A network community characterized by some membership turnover may thus be able to avoid the homogenizing tendencies characterizing network communities. Such membership turnover can be realized through vacancy chains, wherein the exits of some companies create a set of community membership opportunities cascading through the network (White, 1970). The departure of old members and the arrival of new ones can reduce conformity pressures and expose community incumbents to outside ideas, diverse resource profiles, novel collaboration routines, and different strategic agendas, all of which can help update the community's knowledge base and enhance the invention activities of the community members.

As the rate of membership turnover increases, however, a community may reach a point of diminishing returns, where the costs of high turnover start to exceed the benefits. High levels of turnover in a community may threaten the stability of its collaborative routines and established knowledge-sharing practices, since trust among corporate actors takes a significant amount of time to develop. In the early stages of a relationship, actors are reluctant to make themselves vulnerable to one another, even though this may be required for a trusting relationship to develop (Blau, 1964). Decreasing levels of trust within a community as a result of too much change may in turn increase the costs of forming and maintaining interorganizational ties, thus curbing firms' access to the knowledge and resource pools located outside of their organizational boundaries and raising the costs and risks of firms' inventions (Zaheer, McEvily, & Perrone, 1998). At least some member firms, however, could benefit from the development of a resource base unique to that community; this could include common training of personnel or the development of a shared technological platform. The development of such a resource base could nonetheless be interrupted or otherwise undermined if excessive membership turnover disrupts the continuity of intracommunity collaboration and its cohesion.

In sum, it is reasonable to expect that a firm will derive the greatest benefits from being in a moderately dynamic network community. Moderate membership turnover reduces lock-in effects by opening up and updating the community's knowledge base, without imposing the costs and risks associated with excessive turnover. Hence, we propose:

Hypothesis 1: *The turnover of community members within a firm's network community has an inverted U-shape effect on the firm's invention productivity, such that the firm will attain the highest invention productivity at a moderate rate of membership turnover.*

A Firm's Movement Across Network Communities

Rather than staying in the same network community over time, a firm can obtain diverse knowledge inputs by moving across different network communities. A firm may move across different communities as a result of the actions of other firms, which may propagate macro-level structural change in the network. In some cases, moving across network communities could be the result of a firm's own pursuit of better resources or opportunities. While research on the implications of firms' movement across network communities has been limited, studies of labor mobility have demonstrated that people who change jobs moderately often acquire the best positions in the labor market: they are more likely to locate job opportunities through short distances in the social network and to offer relevant job information to others. By contrast, staying in the same job for too long limits one's exposure to new opportunities, while excessive job hopping can limit one's ability to capitalize on the information and opportunities offered by each different group of colleagues (e.g., Granovetter, 1974: 85-92).

There are reasons to believe that a similar curvilinear relationship could describe the link between a firm's movement across network communities and its invention outcomes. Moderate mobility across communities could expose the firm to a diverse spectrum of inputs for invention, thereby helping it maintain a robust knowledge base for generating new ideas. In contrast, excessive movement across network communities can become a liability for at least three reasons. First, it can raise the costs of integrating the diverse knowledge stocks while also limiting the amount of organizational resources and attention that the firm can devote to any given recombinant activity (Ocasio, 1997). Second, excessive mobility could also raise the costs of social integration by conferring permanent newcomer status on any firm without a local collaborative history (Gulati, 1995). Such a social position could then raise the transaction costs of accessing the community's knowledge stocks, thus curbing the firm's ability to utilize that knowledge. Finally, in at least some cases, a firm's excessive mobility across network communities could result in a less coherent technological and collaborative profile (Zuckerman et al., 2003), making it harder for community members to discern the value of the knowledge offered by the newcomer. This could result in further hindering the transfer and application of knowledge by creating ambiguity around the new firm and limiting its ability to engage in full-fledged collaborations with community incumbents.

In sum, we expect that moderate levels of mobility across network communities offer the best conditions for a firm to achieve high invention productivity. Such moderate movement can provide the firm with sufficiently diverse knowledge inputs for invention while also enabling it to absorb and utilize the new knowledge more effectively. Hence, we propose:

Hypothesis 2: *A firm's movement across different network communities has an inverted U-shape effect on the firm's invention productivity, such that the firm will attain the highest invention productivity if it moves across network communities at a moderate rate.*

Membership Dynamics and Firms' Position in Network Communities

Our predictions thus far imply that all members of a given network community can benefit equally from the moderate rate of community membership turnover and from the moderate movement across different network communities. However, even in the same network community, some firms may occupy more advantageous structural positions and thus have a more privileged access to the community's knowledge and resources (Dahlander & Frederiksen, 2012). If the benefits of moderate membership turnover and moderate movement across different communities are indeed linked to changes in the community knowledge base, then it is possible that a firm's invention benefits will vary depending on its position in the network community.

One central distinction that can critically shape a firm's access to the knowledge and resources of its network community is the extent to which the firm occupies a core location in its community. This distinction helps understand whether the firm is strongly or weakly embedded in its network community. A core firm is strongly embedded by virtue of holding multiple ties to many firms, both central and less central, in the network community. In contrast, a peripheral firm is weakly embedded because it holds fewer ties to other community members and is significantly less likely to connect to more central community members (Borgatti & Everett, 1999).

These differences in firms' structural positions can be consequential for their ability to capitalize on the knowledge base of the network community. Actors positioned in the core of network structures tend to get superior access to the knowledge and resource base of their social system (Abrahamson & Rosenkopf, 1997; Mintz & Schwartz, 1981). A core firm can exercise a wider reach across its network community, one which includes other core and peripheral members. This, in turn, can provide the firm with a broader and quicker access to the local knowledge base and resources in the network community. By having multiple ties in the network community, core firms can also ensure that they will have redundant channels for accessing the knowledge base of the network community, thus opening wider conduits for knowledge flows and making themselves less vulnerable to the idiosyncrasies of any given partner or interorganizational relationship.

As the knowledge base of the community gets updated through membership turnover, a core firm is likely to reap disproportionate benefits for its inventive activities by virtue of getting a more effective and efficient access to the influx of new knowledge. Similarly, as the firm moves across different network communities, occupying core positions in those communities is likely to provide the firm with a broader access to the diverse knowledge and resources in those communities. It can thus accumulate a better knowledge endowment over time. Thus, holding core positions as a firm moves across network communities is likely to create better opportunities for effectively recombining the knowledge from the firm's prior community affiliations.

In sum, we expect that the extent to which a firm's invention outcomes can benefit from the membership dynamics of its network community and its movement across different network communities depend on the firm’s position in its network community. Specifically, we propose:

Hypothesis 3a: *The inverted curvilinear relationship between community membership turnover and a firm’s invention productivity will be moderated by the firm’s core/periphery location in the community, such that a core firm will benefit more from a moderate rate of membership turnover than a peripheral firm.*

Hypothesis 3b: *The inverted curvilinear relationship between a firm’s movement across network communities and the firm’s invention productivity will be moderated by the firm’s core/periphery location in the communities it encounters, such that a firm occupying core positions will benefit more from a moderate rate of movement than a firm occupying peripheral positions.*

Membership Dynamics and Global Network Reach

Our claim that the benefits of increased knowledge diversity are best conferred by moderate rates of community membership turnover and movement across different communities rests on the assumption that network communities can serve as pockets of diverse and nonredundant knowledge inputs. However, the heterogeneity of knowledge across different network communities depends on whether these communities can remain structurally separated from one another in the global network. Since members of different network communities are either entirely disconnected from one another or are only indirectly connected through long network paths, the flows of knowledge and information are likely to be more intense within, rather than across, network communities. This implies that remaining structurally separated from one another can help communities preserve their relatively diverse knowledge and resource bases (Gulati et al., 2012; Lazer & Friedman, 2007).

The degree of global network reach in the network helps describe the overall separation of actors in the network.[1] Greater global network reach indicates that firms in the network can generally reach one another through shorter network paths. By the logic above, increases in the average global reach of firms in the global network can diminish the relative distinctiveness between the knowledge bases of different network communities. One reason for this is that direct connectivity can catalyze a more robust and continuous exchange of information and resources between firms. In a situation where firms are interconnected by shorter network paths, these paths can also serve as effective conduits for the flows of knowledge across different network communities. This, in turn, can familiarize firms with the resources of different communities and even allow them to internalize some of these resources directly. As a result, the knowledge base of a given network community can become more easily accessible to a wide range of non-member firms. Furthermore, new knowledge produced within a given network community may become more similar to the knowledge produced in other communities as all this knowledge builds on an increasingly homogeneous industry-wide knowledge. This argument draws in part on the recent work which has suggested that the patterns of knowledge flows in a network can shape the available knowledge stocks (Baum, Cowan, & Jonard, 2010; Gulati et al., 2012; Lazer & Friedman, 2007).

In line with this argument, we expect that as firms become more reachable to one another in the global network, network communities may lose their distinct advantage of acting as pockets of

[1] Analytically, global network reach is defined as the average shortest distance (geodesic) between any two actors in the network. To capture the distance between pairs of completely disconnected actors, this measure is based on inverted network distance or *network reach* (Borgatti, 2006), which sets the distance between completely disconnected actors to zero in the limit. Global network reach thus indicates how close (rather than how far) any two actors are to each other (e.g., Schilling & Phelps, 2007).

diverse knowledge in the industry. Thus, even if firms manage to gain exposure beyond their own network community, they are likely to draw on an increasingly redundant pool of knowledge and resources from other communities. As a result, the invention benefits associated with a firm's membership in a moderately dynamic network community, or with moving across different network communities over time at a moderate rate, may decline. Hence, we propose:

Hypothesis 4a: *The inverted curvilinear relationship between community membership turnover and a firm's invention productivity will be moderated by global network reach, such that the positive effect of the moderate rate of membership turnover will be weaker at higher levels of global network reach.*

Hypothesis 4b: *The inverted curvilinear relationship between a firm's movement across network communities and the firm's invention productivity will be moderated by global network reach, such that the positive effect of the moderate rate of movement will be weaker at higher levels of global network reach.*

DATA AND METHODS

In our empirical analyses, we used data on the network of interorganizational partnerships in the global computer industry from 1981 to 2001. To obtain these data, we used the MERIT-CATI database, which provides a comprehensive coverage of partnerships in high-technology sectors and has been extensively used in prior research (e.g., Gomes-Casseres, Hagedoorn, & Jaffe, 2006; Gulati, 1995; Hagedoorn, 1993). These partnerships can take a variety of forms, including joint ventures, contractual collaborative agreements, and licensing deals. Since most of these partnerships entail some form of knowledge flow related to the development of new products or technologies, they are often described as *technology alliances* (Rosenkopf & Schilling, 2007). In these partnerships, the personnel, the goal structures, the incentives, and the formal and informal organizational support mechanisms are geared toward the acquisition and transfer of technological expertise and knowledge. Focusing on the network constituted by these partnerships is therefore particularly useful for examining firms' access to technological knowledge and its effects on firms' invention productivity (e.g., Ahuja, 2000: 435; Rogers, 2003: 319-320; Zaheer & Soda, 2009: 13).

Because computer firms rarely formed partnerships prior to the 1980s (Hagedoorn, Cloodt, & Roijakkers, 2006), we used 1981-2001 as the timeline of the study to capture the evolutionary trajectory of the interorganizational network from its very inception. Given our focus on the computer industry, we considered only those ties in which one or both partners were classified as computer firms. To do so, we tracked the firms' SIC codes and cross-checked them with the descriptive information obtained from business press and company websites. In addition, we used the description of the activities of each partnership to ensure that the database classified the partnership as a technology alliance whose objective was to develop new computer products, services, or technologies. These criteria produced a sample of 410 unique computer firms. About 60 % of these firms were in manufacturing, 30% in services, and 10% in embedded systems (such as firmware or mobile applications). The average number of concurrent partnerships held by a single firm in any given year was 3.6, which includes both horizontal and vertical relationships.[2]

To reconstruct the industry-wide partnership network, we followed the analytic procedures established in prior research. First, any two firms forming a partnership were considered to be connected through a dyadic tie. Thus, if the partnership consisted of more than two firms, we decomposed it into dyads (Stuart, 1998). Second, since alliance terminations were rarely reported and were indicated for only about 10% of the partnerships, we followed prior research and limited the duration of partnerships to five years (e.g., Gulati & Gargiulo, 1999; Kogut, 1988; Lavie & Rosenkopf, 2006; Stuart, 2000). Using 1985 as the first year for which we reconstructed the partnership network, we produced 17 yearly observations of the evolving network until 2001.

[2] Given the broad enumeration of the interorganizational network in this study and the inclusion of both horizontal and vertical ties, it is important to note that the concept of *network community* differs from the concept of *strategic block*. Strategic blocks capture the connectivity among rival firms and have been found to homogenize the industry space in terms of firms' capabilities and performance *across blocks* (Nohria & Garcia-Pont, 1991: 116-117, 122). In contrast, network communities are based on the patterns of collaboration among all companies in the industry, help understand the flows of knowledge in the industry, and associate community boundaries with heterogeneous knowledge endowments. Network communities therefore play an influential role in shaping between-firm differences in invention outcomes.

The global network grew steadily from 27 firms in 1985 to the maximum size of 218 firms in 1996. It subsequently declined to 191 firms in 2001. Consistent with the characteristics of interorganizational networks observed across a range of industries (Rosenkopf & Schilling, 2007), the global network included a number of disconnected components. In our case, we found that the number of these components ranged from 10 in 1985 to 47 in 1996. One of these components was significantly larger than the others, comprising on average 60% of the firms. In contrast, the other components were smaller and mostly comprised just two or three firms. Figure 2 illustrates the global network in 1994.

Figure 2 about here

Dependent Variable

We captured the invention productivity of firms using the counts of their successful patent applications. Patent applications provide an externally validated measure of invention (Griliches, 1990), and are extensively used in the studies of firms' invention productivity in technology-intensive sectors (e.g., Ahuja, 2000; Fleming, King, & Juda, 2007; Gomes-Casseres et al., 2006; Stuart, 2000).[3] We defined the *Number of patents in t+1* as the total number of patents applied for by the focal firm in year *t+1*. We accounted only for the patent applications that were eventually approved. Since patents can have different review lags, we considered the year of application as the point at which the invention was produced, even if the patent was granted at a later time. We extracted the patent data from the NBER database of U.S. patents (Hall, Jaffe, & Trajtenberg, 2001). Even though about one-third of our network consisted of firms from outside the U.S., focusing on U.S. patents was motivated by two factors. First, empirical evidence suggests that many foreign firms apply for U.S. patents simply due to the sheer size of the U.S. market. As a result,

[3] By focusing on a single industry and estimating firm-level fixed effects, we were able to eliminate a significant degree of unobserved heterogeneity related to firms' varying propensiy to patent their inventions (Ahuja, 2000; Schilling & Phelps, 2007).

U.S. patents constitute a major share of all global patents, reflecting the breadth of invention activities of companies across the globe (Griliches, 1990). Second, using the patents from a single country ensures analytic consistency in terms of the legal norms and regulatory regimes (Ahuja, 2000).

Given the timeline of our study and our focus on the computer industry, we extracted patents filed between 1986 and 2002 that were classified under Category No. 2, *Computers & Communications*. This technological category encompasses the following four subcategories: No. 21, *Communications*; No. 22, *Computer Hardware & Software*; No. 23, *Computer Peripherals*; and No. 24, *Information Storage* (Hall et al., 2001: 41). These criteria led us to identify 143,500 patents issued to the 410 firms in the sample, yielding an average of 350 patents per firm. The distribution of patents across firms was skewed, with the top 10% of firms holding over 80% of patents.

Identification of Network Communities

To test our hypotheses, we first analyzed the network in each year for the occurrence of cohesive, non-overlapping communities of firms.[4] Having detected these communities, we then traced their evolution over time. To identify the communities in each year, we followed the approach of Girvan and Newman (2002), which offers one of the most robust methods of community identification (Danon, Diaz-Guilera, Duch, & Arenas, 2005). This approach identifies communities by assessing the difference in the community structure between the actual network and a random network of the same size and degree distribution. To quantify this difference, the method defines *network modularity* as $1/E\sum_{k}(e_{kk}-\{e_{kk}\})$, where E is the total number of ties in the

[4] While in this study we conceptualize network communities as *non-overlapping* groups of firms, some earlier theorists studied overlapping social groups (Blau & Schwartz, 1984; Simmel, 1955). These theorists typically view social structure through the lens of multiple social characteristics of actors that result from occupying different social roles or participating in different social contexts at the same time. For example, actors can simultaneously be colleagues and friends, and thus reside in different, but overlapping, social worlds of work and friendship. In contrast, in our scenario we follow prior research (e.g., Burt, 2005; White, 1961) in isolating the communities of firms, which are formed because of the *realized* interactions among specific sets of corporate actors (McPherson, Smith-Lovin, & Cook, 2001). In many sparsely connected social systems, these communities typically do not overlap (e.g., Girvan & Newman, 2002; Shipilov, Li, & Greve, 2011; Sytch et al., 2012). Note also that such non-overlapping communities need not result in a fragmented social structure since they are often tied together by sparse bridging relationships.

network, e_{kk} is the number of ties in the k-th community, and $\{e_{kk}\}$ is the expected number of such ties in the random network. To ensure robust results, modularity is maximized over all possible community assignments and compared to a large number of random networks in order to assess its statistical significance (Guimerà & Amaral, 2005). Values greater than 0.3 typically indicate a strong degree of community structure that could not be obtained by chance (Newman, 2003).

In addition to offering a statistically validated partitioning of the network, another advantage of this procedure – compared to some alternative methods of community detection (e.g., hierarchical clustering) – is that it does not require any *a priori* assumptions regarding, for instance, the number of communities. Providing such information *ex ante* is difficult in our context, where the network's community structure can be shaped by a range of social, technological, and economic forces. This, in turn, makes it difficult to predict the boundaries of network communities based on some observable attributes of firms, such as their technological or market niche. In addition, specifying communities *ex ante* could bias our subsequent statistical estimation and results.

Our analysis of community structure focused on the global network's main component, which comprised on average 110 firms. By contrast, the remaining components were substantially smaller and comprised on average only 2.2 firms, thus precluding the formal analysis of their community structure. However, we estimated that the average density of ties in the smaller components (defined as the ratio of existing to all possible ties) was 0.86 and the average path length was 1.24. These values mirrored those estimated for the network communities identified in the main component (around 0.81 and 1.28, respectively). We therefore considered the smaller components to be stand-alone communities. Nonetheless, to make sure that this approach did not affect our results, we also controlled for whether a firm was affiliated with the main component in any given year and whether it was in a community that consisted of a single dyadic partnership.

Our analyses revealed the existence of a strong community structure throughout the timeline of the study. The value of modularity varied between 0.36 in 1985 and 0.74 in 1990. The average value was 0.63 across all 17 years, thus substantially exceeding the recommended threshold of 0.3. Furthermore, our tests indicated that the identified community structure was statistically different from random across all years (at $p < 0.001$).[5] The total number of communities in the global network ranged from 11 in 1985 to 55 in 1996. A typical network community consisted of between 3 firms in 1985 and 8 firms in 1992. The mean density of ties within the communities was 0.81, while the mean density of ties in the entire network was less than 0.05. Furthermore, the shortest network distance between any two community members was 1.28 ties, while the shortest distance between any two firms in the main component was 4.14 ties. Overall, these results confirm our expectation that the identified communities reflected pockets of strong relational cohesion among firms. As an example, the structure of network communities in 1996 is shown in Figure 3.

Figure 3 about here

Knowledge Heterogeneity Within and Across Network Communities

In addition to examining the structural characteristics of network communities, we explored whether the identified network communities also represented pockets of homogeneous knowledge within the industry. A thorough test of this argument would entail conducting a detailed analysis of the contents of knowledge stocks and flows among firms. In an interorganizational network of the size analyzed in this study, however, such analysis was impossible. Nevertheless, one useful proxy for testing whether the communities possessed more homogeneous knowledge compared to the rest of the network was to analyze the composition of patent stocks and patterns of patent citations

[5] We compared the value of modularity for the actual network with the mean value estimated for a comparable random network in each year. The values for the random network were estimated over 1,000 randomizations using the size and degree distribution of the actual network. The tests indicated that the identified community structure was statistically different from random at $p < 0.001$.

within and across the identified network communities. To do so, we conducted two sets of analyses. First, we analyzed the patterns of patent citations and the distribution of patents across different technological classes within dyads. This analysis indicated that any two firms from the same network community were on average twice as likely to cite each other's patents as the patents of firms located outside of the community ($p < 0.001$). Furthermore, the patents owned by firms from the same network community were more likely to be distributed across a similar set of three-digit technological classes ($p < 0.001$). Finally, the technological classes of the patents that either cited (i.e., forward citations), or were cited (i.e., backward citations) by, the patents owned by members of the same network community were more similar ($p < 0.001$) compared to the patent citations – whether forward or backward – for any two firms from different network communities. In additional statistically analyses, we have found that these patterns of homogeneity were related to both (i) homogenization of firms' knowledge bases following membership in the same community; and (ii) selection of firms with more similar knowledge bases into the same community.

Second, we used a computer simulation to explore the extent to which not only dyads but also entire network communities represent more homogeneous knowledge stocks. To do so, we randomly redistributed firms across the network communities in each year, while keeping the overall number of communities and the size of each community fixed. We repeated this procedure 1,000 times for each year, and then used the results to compute the baseline similarity of the patent stocks and the forward and backward patent citations of firms within each community (using an inverse of Blau's diversity metric). Subsequently, we compared the real and the baseline similarity scores statistically using a z-score, defined as $(S - \{S\}) / \sigma$, where S is the actual similarity of firms' patents and patent citations with respect to the three-digit technological classes; $\{S\}$ is the baseline similarity estimated over 1,000 randomizations of the network's community structure; and σ is the standard deviation from $\{S\}$. Results indicated that the differences were statistically significant (at $p < 0.001$), thus suggesting that the knowledge stocks of network communities were indeed more homogeneous than one could expect by chance.

Dynamics of Network Communities

To trace the dynamics of the identified network communities over time, we matched them across contiguous years based on the extent to which they consisted of the same firms. Formally, we defined the overlap between two communities as $(C_{i,t} \cap C_{j,t+1}) / (C_{i,t} \cup C_{j,t+1})$, where $C_{i,t} \cap C_{j,t+1}$ was the number of unique community members shared by both communities from year *t* to *t+1*, and $C_{i,t} \cup C_{j,t+1}$ was the number of all community members present in both communities. Zero indicated that the communities did not share any members, while 1 indicated that they shared all members.

Using this rule, we considered $C_{i,t}$ and $C_{j,t+1}$ as a single dynamic community if the overlap between them was at least 30% and no other match provided a greater degree of overlap.[6] Failing to satisfy the 30% requirement meant that the community in year t would be considered as dissolved and the community in t+1 would be considered as new. We identified 126 distinct communities within the 1985 to 2001 timeframe. The lifespan of network communities varied significantly from 1 to 12 years, with the average being about 4 years. Similarly, firms varied significantly in terms of how long they stayed affiliated with a given community, which ranged from 1 to 9 years (2.5 years on average).

Independent Variables

To test the effect of membership turnover in a firm's community on its invention productivity (Hypothesis 1), we defined *Membership turnover* as the extent to which the community comprised distinct firms in year *t* compared with the previous year. We measured this variable as

[6] One possibility is also that an existing network community could break up into two (or more) future communities of roughly equal sizes. This possibility would require us to extend our analysis to more complex evolutionary patterns of communities, including their branching and reunification (see also Vedres & Stark, 2010). Our data did not provide any evidence of such nonlinear chains, most likely because our conceptualization of network communities as non-overlapping social groups does not support such processes.

the inverse of community overlap across both years – formally, $1-(C_{i,t-1} \cap C_{i,t})/(C_{i,t-1} \cup C_{i,t})$. To test the effect of a firm's movement across different network communities (Hypothesis 2), we defined *Prior community affiliations* as the number of distinct communities in which the firm was a member prior to *t*, excluding the current community. This variable was set to zero if the firm had no prior community affiliations (e.g., it just entered the network in year *t*). In line with Hypotheses 1 and 2, we specified linear and squared effects for both of these predictors.

To test the moderating impact of a firm's position in its network community on membership turnover (Hypothesis 3a) and on the firm's movement across different communities (Hypothesis 3b), we interacted the curvilinear effects of *Membership turnover* and *Prior community affiliations* with the firm's *Within-community coreness*. To define the actor-centric measure of coreness, we followed Borgatti & Everett (1999) and used the continuous core/periphery model. This model captures to what extent a firm is positioned closer to the core than the periphery of its network community and is more precise than the discrete model of core/periphery (for a similar approach, see Cattani & Ferriani, 2008). As indicated by Borgatti and Everett (1999: 392), it is reasonable to expect that a core firm will occupy a more central location within its network community. However, a central firm does not necessarily have to be core. In our context, the latter could occur when a peripheral firm connects with numerous other peripheral members of its network community, or with members of other network communities. In such a case, the peripheral firm may obtain a moderate to high level of centrality but still remain outside of the core of its network community. The measure of coreness is thus more likely than alternative measures to capture the benefits that accrue to a firm's central position in its network community.

To test Hypothesis 3a, we captured a firm's coreness in its current network community. To test Hypothesis 3b, by contrast, we captured the *time-varying* average coreness of a firm, measured across all of its prior community affiliations up to the focal year. To obtain this measure, we calculated the firm's within-community coreness in each year and divided the sum by the number of years the firm spent in the network, until *t*. This approach provided an effective way to account for the likely positive moderating effect of a firm’s moving into a more core location versus the likely negative effect of its moving into a more peripheral location (indicated by greater and lower average coreness, respectively). In addition, this approach also provided a more precise way to capture the full moderation effect of coreness with respect to a firm’s all prior community affiliations, rather than just the recent one.

Finally, to test the moderating impact of global network reach on community membership turnover (Hypothesis 4a) and the firm’s movement across different network communities (Hypothesis 4b), we interacted the curvilinear effects of *Membership turnover* and *Prior community affiliations* with *Global network reach*. We specified *Global network reach* as the average network reach between any two firms in the network (Borgatti, 2006) - formally, $1/N_t(N_t-1)\sum_i\sum_{j\neq i}1/d_{ij}$, where N_t was the size of the network in year *t* and d_{ij} was the shortest network distance between two firms *i* and *j*. This measure varied between 0 and 1, with higher values indicating greater global network reach. To test Hypothesis 4b, rather than capturing current *Global network reach* in year *t*, we captured the *time-varying* effect of the firm's *Average global network reach*, which was measured across the firm’s entire history of community affiliations. We calculated global network reach for each year during which the firm was present in the network and then divided the sum by the total number of years the firm spent in the network, until *t*. This approach provided a more precise way to model the moderating effect of the change in global network reach and allowed us to capture moderation across the entire history a firm’s prior community affiliations.

Control Variables

To ensure robust results, we controlled for a range of other possible firm-level and community-level determinants of a firm’s invention productivity. First, using data from Compustat, Worldscope, and Orbis, we controlled for firm size (measured through *Headcount*), financial condition (measured through *Net income* and *Return on Assets*), and investments in R&D (measured through *R&D spending*). These variables were logged to correct for their distributional skewness.

Second, to control for the effect of a firm's ego-network position on its invention productivity, we specified two static measures: (i) logged *Degree centrality* as the total number of ties held by the firm in year t, and (ii) *Ego-network density* as the total number of ties between the firm and its partners and among the partners themselves, divided by the number of all possible ties among these firms. In addition, we also specified two dynamic measures: (i) *Ego-network turnover* as the degree of membership turnover in the firm's ego network (defined as one minus the fraction of the same firms in the ego network from year *t-1* to *t*), and (ii) *Ego-network growth* as the change in the firm's degree centrality from *t-1* to *t*. In line with our non-linear prediction of the effect of community membership turnover, we expected *Ego-network turnover* to have an inverted U-impact on the firm's invention output. The latter variable also helped isolate the effect of ego-network turnover from the mere growth or shrinkage of the ego-network. Finally, we used the binary variable *Main component firm* to control for a firm's position inside the main component.

Third, we accounted for the firm's position in its network community by controlling for the main effect of *Within-community coreness* (as defined above). In addition, we controlled for the firm's position with respect to other network communities by capturing the dispersion of its partners across different communities. To this end, we defined *Cross-community participation* as one minus the diversity of partners' own communities, measured using the Blau index. This control varied between 0 and 1, yielding higher values for those firms whose partners were distributed across a greater number of different network communities.[7] Further, to control for the firm's tenure in its

[7] Our theory and analyses conceptualize and measure network communities as non-overlapping groups of firms. To explore the robustness of this theoretical premise, we conducted exploratory analyses of the data to explore more ambiguous cases, where a given firm could be assigned to more than one community in a given year by virtue of maintaining a large number of ties to communities other than its own. We found that, overall, these cases were extremely rare. First, there were only ten firm-year observations (i.e., just over 1% of the sample), where a firm's total number of ties to other communities exceeded the number of ties to its own community.

current network community, we used the binary variable *Community incumbent*. This control was equal to 1 if the firm was a member of the same community in the previous year and 0 otherwise.

Fourth, we controlled for a range of structural characteristics of the firm's network community. We specified *Community size* as the total number of firms that were members of the firm's network community in year *t*, including the focal firm. *Community centrality*, in turn, reflected the number of other unique communities to which the firm's community was connected in year *t*. We defined *Community constraint* as the extent to which the neighboring communities were also connected among themselves (Burt, 1992). For any community *i*, this index was defined as $\sum_{j \neq i} (\varepsilon_{ij} + \sum_{k \neq i,j} \varepsilon_{ik}\varepsilon_{kj})^2$, where ε_{ij} was the fraction of *i*'s ties with community *j*, ε_{ik} was the fraction of *i*'s ties with community *k*, and ε_{kj} was the fraction of *k*'s ties with *j*. A higher value of this control indicated a more structurally constrained community. We also controlled for *Community age* as the number of years since the firm's community had been formed, until *t*. Finally, to ensure that *Membership turnover* did not reflect a mere change in the size of the firm's community, we controlled for *Community growth* as the absolute change in *Community size* from year *t-1* to *t*.

Fifth, we accounted for the possible common effects of firms' knowledge stocks and geographical locations on their selection into network communities and their invention outcomes. To do so, we specified *Technological diversity* as the extent to which firms' patent stocks in the same network community were distributed across different three-digit classes (using the Blau index). This control yielded higher values for those communities whose patent stocks were more diverse. The alternative measure of technological diversity at the ego-network level correlated with

Second, there was not a single case where a firm's number of ties to a given external community (0.42 on average) exceed the number of ties the firm had within its own community (3.1 on average). These results indicate that if we were to relax the assumption of non-overlapping communities and allow for cross-community overlaps, such sparse external connectivity would put firms into unequivocally peripheral positions in other communities. Therefore, even without modeling community overlaps explicitly, our present analytic approach allows us to account well for firms' positions with respect to multiple communities. We do so by accounting for (a) how firms connect within their focal community using *Within-community coreness*; and how they reach out to other communities in the network using *Cross-community participation,* which accounts for firms' peripheral positions in other network communities.

this measure at over 0.8. In robustness tests, using this alternative control variable produced no changes in the results. Further, we specified *Average geographical distance* as the average spherical distance (expressed in miles) between the corporate headquarters of any two community members.

In addition, we accounted for the dyadic communities in our data using a binary variable called *Single dyadic partnership*, set to 1 if the firm's community consisted of just one dyadic partnership and 0 otherwise. Further, we used the binary variable *Single large partnership*, set to 1 if the firm's community contained only a single partnership consisting of more than two firms, and 0 otherwise (such communities constituted about 5% of our data). We also specified *Global network turnover* as the degree of membership turnover at the level of the entire industry-wide network (defined as one minus the fraction of the same firms in the network from year *t-1* to *t*). In line with our previous arguments, we modeled this control as a curvilinear effect. Coupled with the control for *Ego network turnover*, introducing this effect allowed us to more precisely account for the effect of membership turnover at the level of the firm's network community. To control for the possible exogenous shocks and the changes in network size, we specified the *Number of community and network exits* as the number of firms that left the firm's community in year t, while also leaving the entire network in the same year. After we incorporated all the variables and controls, the effective sample included 918 firm-year observations across 192 unique computer firms.

ANALYSIS AND RESULTS

To test our predictions, we used two complementary statistical approaches. First, to control for unobservable heterogeneity among firms and overdispersion in patent applications, we used negative binomial regression with conditional firm-level fixed effects (Hausman, Hall, & Griliches, 1984). Because our panel was relatively short and contained a large number of firms, estimation with conditional fixed effects is preferred to unconditional estimation. The latter approach could result in inconsistent estimates due to the incidental parameter problem, which arises when relatively few observations are used to estimate a large number of parameters (Cameron & Trivedi, 1998). Since the NB fixed-effects estimator is conditioned on the total sum of patents for each firm, firms that did not apply for a single patent over the entire 17-year period were eliminated from the estimation. This resulted in a truncation of the sample by about 20%, to 720 firm-year observations. Despite this limitation, the fixed-effects estimator should remain unbiased and consistent (Wooldridge, 2002). Nonetheless, we also verified the robustness of our results using alternative models that retained the full sample size (see robustness tests below).

Second, to account for the nested structure of our observations within firms and within network communities, we utilized a three-level Poisson model. The analysis of variance in patent applications revealed that both firm-level groups ($F=18.44, p<0.0001$) and community-level groups ($F=2.89, p< 0.0001$) explained a statistically significant portion of the variance. A multilevel model allowed us to estimate both firm-specific and community-specific intercepts and coefficients as a function of the respective population means plus a random variance component. Doing so helped mitigate the risks of biased parameter estimates and incorrectly estimated standard errors due to the nested data structure (Snijders & Bosker, 1999).

Specifically, we used a three-level Poisson model of firm-year outcomes (Level 1) with random intercepts estimated for firms (Level 2) and their network communities (Level 3). In addition, we also estimated firm-level and community-level random coefficients. The firm-level random coefficients were estimated for the firm's *Prior community affiliations* (H2) and its interactions with *Average within-community coreness* (H3b) and *Average global network reach* (H4b). The community-level random coefficients, in turn, were estimated for the effect of *Membership turnover* in the firm's community (H1) and its interactions with *Within-community coreness* (H3a) and *Global network reach* (H4a). We also estimated random coefficients for community-level controls of *Community size*, *Community age*, *Community constraint*, and the community's *Technological* diversity, because doing so significantly improved model fit ($p<0.001$).

Results

The descriptive statistics and bivariate correlations are reported in Table 1. We verified that multicollinearity did not pose a serious threat in our estimation as the condition indices remained within the recommended range (Belsey, Kuh, & Welsch, 1980). In Tables 2 and 3, we report the results of our negative binomial models with firm-level fixed effects (Table 2, Models 1-7) and the three-level Poisson models with random intercepts and random coefficients (Table 3, Models 8-14). Models 6-7 and 13-14 represent the fully specified regressions containing all predicted effects.

Tables 1, 2, & 3 and Figure 4 about here

In Models 1 and 8, we tested Hypotheses 1 and 2. The results support Hypothesis 1, indicating that membership turnover in a firm's network community affects the firm's invention productivity in an inversely curvilinear manner (see Figure 4a). Lind and Mehlum's (2009) test supported the presence of an inverse u-shaped effect ($t=1.78$, $p=0.038$) with the inflection point at 47% turnover. Over 52% of the observations in our sample fall above this inflection point. A typical member of a moderately dynamic community (i.e., one that retains about 55% of its members from year t-1 to t) tends to file for 19.5% more patents than a member of a static community (i.e., one that retains all of its members), and for 4.2% more patents than a member of a highly dynamic community (i.e., one that retains just 30% of its members). These results are also supported by our fully specified Models 6-7 and 13-14.

Further, the results of Models 1 and 8 also support Hypothesis 2, indicating that the extent to which the firm moves across different network communities affects its invention productivity in an inversely curvilinear manner. The firm thus benefits the most if it moves across different network communities with a moderate frequency (see Figure 4b). Lind and Mehlum's (2009) test supported the presence of an inverse u-shaped effect ($t=2.16$, $p=0.016$), indicating the inflection point at 5 prior community affiliations. Even though this inflection point is well within the data range, only about 2.5% of the observations in our sample fall above this level. Given this small number, in additional analyses we explored whether a logarithmic specification of the firm's prior community affiliations could potentially provide better fit to the data. Comparative analyses of model fit indicated, however, that the quadratic specification (AIC=4040.03) offers better fit than the logarithmic one (AIC=4041.60). A typical firm with a moderate rate of movement across different network communities (i.e., one with about 5 prior community affiliations) thus files for approximately twice as many patents as a firm with no prior community affiliations. It also files for about 50% more patents than a firm with 9 prior community affiliations. The results of our fully specified Models 6-7 and 13-14 support these estimates as well.

In Models 2-3 and 9-10, we tested Hypotheses 3a and 3b. The results consistently support Hypothesis 3a, indicating that the positive effect of the moderate rate of community membership turnover is amplified for those firms that are located in the core of their network community. Specifically, the linear term of *Membership turnover* shows a significant positive interaction with the firm’s *Within-community coreness* (Models 2 and 9). Being located in the core of a moderately dynamic network community thus enables the firm to file for about 5% more patents than being located on the community's periphery (see Figure 4c). The results of our fully specified Models 6 and 13 are consistent. Results, however, provide only partial support for Hypothesis 3b. While the prediction of a positive interaction between the firm's *Prior community affiliations* and its *Average within-community coreness* is not supported by our partial Models 3 and 10, it is supported by our fully specified Models 7 and 14. Based on the estimates of Model 7, Figure 4d demonstrates an interesting nuance to our original prediction: there is a noticeable shift in the inflection point in the effect of *Prior community affiliations* for core firms, from 5 to 3 communities. These results are likely to hint at the significant costs of entering into multiple network communities as a core member, which can exacerbate the cost of integration and create stronger ambiguity around the newcomer's collaborative profile (Zuckerman et al., 2003). These circumstances, in turn, can overwhelm the benefits of accessing new invention inputs for core firms as they move across an increasing number of network communities. Peripheral members, in contrast, seem to be more immune to these risks. While over the range of 0 to 5 prior community affiliations, they register noticeably lower levels of invention productivity relative to core firms, at higher levels of 5 to 9 community affiliations they enjoy superior invention benefits, which are coupled with a higher inflection point.

Finally, our results do not support hypotheses H4a and H4b. These predictions suggested that lower global network reach would help maintain greater knowledge heterogeneity across different network communities, thus creating additional invention benefits to firms with moderate levels of membership turnover and a moderate number of prior community affiliations. In contrast to our expectations, negative binomial models (Models 6 and 7) demonstrate null effects for the respective interactions. The multi-level Poisson models (Models 12 and 13), in turn, provide estimates that are opposite to our expectations (see Figures 4e and 4f). While – given the lack of consistency across these distinct estimation approaches – the results of these models should be interpreted with caution, they could potentially point to a more complex relationship between global network reach, network community dynamics, and firms' invention productivity. Specifically, this relationship could entail not only the heterogeneity of knowledge across communities, but also the degree to which knowledge can be absorbed and integrated by firms as a function of increasing global network reach.

Overall, the results support our theory. We find that a firm's invention productivity benefits the most from moderate community dynamics, which can entail the necessary updates to the knowledge base in the firm's community. This can happen either indirectly, through community membership turnover, or directly through the firm's movement across different network communities. Furthermore, we find that firms located in the core of their network community can most effectively capitalize on the benefits of moderate membership turnover and moderate levels of prior community affiliations.

Robustness Tests

To ensure robust results, we conducted a range of additional tests. First, we explored a key alternative explanation for our findings. It could be that both the community's membership turnover and the firm's movement across different network communities are driven by the firm's new alliance formations (cf. Koka, Madhavan, & Prescott, 2006). Specifically, a greater prior propensity of the firm to form new alliances could boost both the member turnover in the firm's community and the firm's likelihood to move to another community. While, in our main analysis, we controlled for the firm's degree centrality and changes in it, in additional analyses we also modeled the rate of membership turnover in its community from year t to t+1 and its likelihood to move to another community in t+1 as a function of new partnerships formed by the firm in year *t*. Results indicated a weak negative effect of prior ties on the subsequent rate of community membership turnover and no significant effect on the firm's movement across different network communities, thus lending no support to the alternative explanation. From a conceptual standpoint, these results indicate that the observed community dynamics are substantially driven by the behaviors of other firms in the network, rather than the firm's own collaborative pursuits (cf. Ozcan and Eisenhardt, 2009). We also reran all our models while controlling separately for the firm's new partnerships in year *t.*

Second, we explored the sensitivity of our results to alternative ways of constructing the interorganizational network. While in the main analysis we modeled interorganizational ties as lasting for 5 years, in additional analyses we set the duration of ties to 3, 4, 6, and 7 years. In addition, we applied a set of alternative specifications (40%, 50%, and 60%) for the minimum fraction of firms that an evolving network community needs to preserve across two contiguous years. Our results remained substantively unchanged across these tests.

Third, we explored whether the study's observation period from 1981 to 2001 captured the evolution of the interorganizational network in the computer industry from its very inception. To do so, we tracked the MERIT-CATI data all the way back to the 1960s. Our observations indicated that prior to the 1980s, the network was generally very small and sparse, containing only a handful of firms and ties. It was not until 1985 that this network developed a robust main component with some community structure in it. To verify this finding analytically, for all annual networks from the early 1980s and the 1990s we estimated the percolation threshold, or the probability of finding a large main component (Newman & Watts, 1999). We found that the average percolation threshold in 1985-2001 was three times greater than in 1980-1984, and about ten times greater than in 1960-1979. To ensure that these findings were not unique to the MERTI-CATI database, we also verified them using data from the SDC Platinum database and obtained very similar results. Furthermore, to verify the sensitivity of our results to the possibility of missing partnership data, we performed a series of tests by removing up to 50% of the ties in each year at random. Even after such extreme manipulations, we found that the overall structure of network communities remained unchanged.[8]

Fourth, we explored the risk of right-censoring in our patent data. Our data covered all patents filed from 1986 to 2002 and approved by the end of 2006. For the 143,500 patents in our sample, the mean duration of the review process at the USPTO was about 3.17 years. This average duration was consistent across firms, network communities, and the entire 17-year observation period. Given this finding and the four-year lead period with respect to the data used in this study, right-censoring is unlikely to pose a problem. Nevertheless, to verify this conclusion, we extended the lead period to five and six years, respectively, by truncating patent data first in 2001, and then in 2000. We also explored whether accounting for differences in patent quality could affect our estimates. To do so, we weighted each patent by its forward citations. This measure correlated with

[8] This result also echoes some prior findings on the general robustness of social and interorganizational networks to random data omissions (Kossinets, 2006; Schilling, 2009).

firms' raw patent count at 0.9. Finally, rather than capturing the patents filed in year *t+1*, we counted the patents filed within two and three years from *t*, respectively. Our statistical results remained robust to these modifications.

Finally, we verified our statistical results using other estimation techniques. While the negative binomial regression model used in our main analysis can effectively deal with the issue of overdispersion in the dependent variable, it can also lead to biased estimates should the data suffer from autocorrelation or distributional misspecification. We therefore re-estimated our models using the firm-level fixed effects Poisson model (Cameron & Trivedi, 1998). In addition, to ensure that our results were not affected by sample truncation, we also ran a series of OLS models on the logged dependent variable. In contrast to the maximum-likelihood estimator which eliminates all firms with a constant zero outcome, the fixed-effects OLS estimator allows for retaining these firms in the estimation. The results of these additional tests were similar.

DISCUSSION

Departing from prior research that has applied either the ego-network or the global-network perspective to analyze the implications of social structure for the creation of knowledge, this study has examined the implications of network communities for the invention productivity of firms in the computer industry. Our focus on network communities has been motivated by two factors. First, since more heterogeneous inputs are likely to be located across rather than within network communities, the boundaries of network communities and the regions of high network density that they delineate can help evaluate the heterogeneity of critical knowledge inputs for firms’ invention activities. With respect to this argument, the community perspective offers a set of novel and unique theoretical insights that go beyond the findings of prior work that utilized either the ego-network or the global-network perspective. This is because these latter two perspectives draw on different markers in understanding the distribution of knowledge in social systems, and neither of them can adequately account for the structure and dynamics of network communities among firms.

Second, since network communities are characterized by shorter network distances and lower transaction costs of exchange, the locally available inputs are more easily accessible to firms than are inputs located elsewhere in the global network. But the fact that these inputs are locally accessible yet globally isolated, and thus are likely homogeneous, effectively generates a puzzle, in that communities can both enable and constrain firms' invention productivity. This paper has attempted to resolve this puzzle by focusing on how the dynamics of firms' movement across network communities can help update the local knowledge base of a community, thus offering the joint benefits of easy access and diverse local knowledge to its members.

Toward this end, our study produced three key findings. First, we found that the community's membership turnover, defined as changes in its internal composition over time, has an inversely curvilinear effect on the invention productivity of the member firms. Specifically, a moderate rate of membership turnover enhances the member firms' invention outcomes by updating the community's knowledge base, thus conferring an advantage over members of more static communities. Extreme levels of membership turnover, however, constrain the member firms' invention productivity, most likely by increasing the risks and costs of collaboration and thereby eroding the collaborative base of the community. Second, we found that a firm's movement across different communities over time has an inversely curvilinear effect on its invention productivity. Hence, while some mobility can be necessary to ensure exposure to diverse knowledge inputs, excessive movement can increase the costs of integrating these new inputs and adjusting to new environments. Finally, our results indicate that not all members of a given network community benefit equally from the effects of membership turnover. Specifically, our results indicate that the community members who are located in the core of their network community can claim greater benefits from moderate levels membership turnover in their network community than those located on its periphery. This result suggests that core firms may have quicker, broader, and generally more efficient access to the local knowledge base of their network community as it is updated by firms arriving from the outside of their network community. With respect to prior community affiliations, our results indicate that a lower degree of attachment for firms to network communities seems to allow for a greater degree of promiscuity that is effective for enabling their invention productivity. Put differently, our results point to an interesting tension between the costs and benefits of (a) deep integration and search just across a few network communities as a core member and (b) a quick scan and peripheral entry into numerous network communities.

Our research and findings offer several contributions to organization theory. First, by emphasizing the role network communities play in demarcating the boundaries of homogeneous knowledge inputs, the results of this study advance our understanding of the relationship between networks and firms' invention activities beyond the findings of both the ego-network perspective (Ahuja, 2000; Zaheer & Soda, 2009) and the global-network perspective (Schilling & Phelps, 2007; Uzzi & Spiro, 2005). More importantly, we demonstrate that the membership dynamics of network communities, and the knowledge updates they entail, can have fundamental implications for firms' invention outcomes. This finding, therefore, casts doubt on the uniformity of the recent conclusion that only ego-networks matter for actor outcomes (Burt, 2007). It also suggests that future studies applying the ego-network perspective could pay closer attention to whether an ego's alters are located in the same network communities or across different ones, since these structural distinctions critically shape the diversity of the alters' knowledge and information.

Our second contribution lies in explicating how the perspective on network communities helps uncover some novel ways in which global networks can evolve and in which actors' individual network positions can change over time. This, in turn, offers a direct contribution to the studies of network dynamics (Gulati & Gargiulo, 1999; Shipilov & Li, 2012; Zaheer & Soda, 2009). One key aspect of this contribution is related to recognizing membership dynamics in networks as an influential dimension of network change. Our study suggests that the turnover of community members in the firm's network community and the firm's movement across different communities can provide critical access to heterogeneous knowledge and resources. Even more intriguingly, we find that the observed community dynamics are significantly driven by the behaviors of other firms in the network, rather than the firms' own pursuits. This finding, in turn, suggests a more balanced view (cf. Burt, 1992) on the sources of variation in network positions, where individual agency may be significantly constrained. It also points to the importance of considering changes in the broader network structure for understanding the antecedents in individual network positions.

Third, our study shows that the properties of ego networks interact with the key features of network communities to shape actors' behaviors and outcomes. In doing so, our research takes a step toward a more integrative, multi-level approach to the relationship between network structures and actors' behaviors and outcomes (Brass, 2011). In our case, using such an integrative approach not only helps to establish a more comprehensive link between the properties of the global network and firms' invention outcomes, but also provides for a more precise identification of the sources of knowledge heterogeneity in an interorganizational system.

Finally, the perspective on network communities advanced in this study can also contribute to a number of related lines of research. For example, studies of industrial districts and regional economies (Buhr & Owen-Smith, 2011; Lazerson & Lorenzoni, 1999) could benefit from exploring how network communities form and evolve, interlinking firms both within and between districts. Such investigations could shed light on how social structures shape local productivity and invention output by raising or lowering the costs of economic exchange within and across geographical locales, as well as by either enabling or constraining knowledge flows. Similarly, there is promise in examining how an industry structure analysis that simultaneously decomposes the industry into network communities of collaborators and groups of rivals can inform a range of organizational outcomes (Thomas & Pollock, 1999). For example, one can envision various configurations and dynamics in the industry, such that the space between network communities can be populated at a given point in time by various degrees of rivalry relationships. Such multi-dimensional space could allow for a deeper analysis of the flows of knowledge, information, and other resources in the industry. Adding a cognitive lens to the study of this multidimensional space (Porac et al., 1989; Porac et al., 1995) could advance our understanding beyond this study's focus on firms' inventions. To be specific, future research could fruitfully study a wide range of firms' strategic actions and outcomes by examining the perceptions of collaboration and rivalry held by firm executives and by influential third parties (such as financial analysts).

Another promising direction for future work would entail a more systematic analysis of how firm-level attributes interact with the membership dynamics of network communities highlighted in this study (see, e.g., Shipilov, 2006). In our additional analyses, we found that more profitable firms (as indicated by higher ROA) tend to reap the greatest invention benefits from moderate levels of membership dynamics. Other research suggests one possible mechanism underlying this effect: since profitable firms can have a more favorable bargaining position (Lavie, 2007), they may also be able to appropriate greater value from within-community relationships, perhaps at the expense of less successful community members. Taken together with our main findings, these results thus contrast with the findings of some earlier research pertaining to business groups, such as the Japanese *keiretsu.* They suggest that, rather than playing the redistributive role which is common in *keiretsu* (Lincoln, Gerlach, & Ahmadjian, 1996), network communities tend to increase inequality by allowing rich firms and firms in the core of their network community to get even richer. These findings thus indicate some early promise for additional research in this area.

In closing, it is important to note that our theory and results are tailored to the analysis of sparsely connected interorganizational systems, where network communities typically do not overlap with one another. It is in part the lack of overlap and the sparse connectivity among the network communities that sustains the heterogeneity of knowledge and resources among them.

Extending the analysis to systems with overlapping network communities and those where actors could be members in more than one community at a time could generate fruitful novel insights. Furthermore, our theory and results involve an important and rather straightforward boundary condition. The application of the network-community lens to the study of interorganizational systems is contingent on the presence of a robust structure of network communities. While a strong community structure often characterizes a range of interorganizational and interpersonal settings (e.g., Baum, Rowley, & Shipilov, 2004; Davis et al., 2003; Shipilov & Li, 2012; Sytch et al., 2012), this is unlikely to be the case uniformly. To the extent that the global network resembles a random network in its properties, or displays a strong core-periphery structure, the application of the network-community lens would be limited.

Nevertheless, whenever the network-community structure is found to be present, applying the network-community perspective could open up new avenues for analyzing a wider spectrum of different industrial and national contexts. For example, while some economies are organized around business groups, i.e., cohesive agglomerations of firms tied by economic relationships or governance control (see, for example, Carney et al., 2011; Lincoln et al., 1996), not all industrial and national domains feature such groups. Many business groups, such as the Japanese *keiretsu or* the Korean *chaebol*, are also unique in that they incorporate exchange partners and financing entities, have strong institutional support mechanisms, and display remarkable stability in affiliation patterns. Some theorists have thus concluded that these groups have no real counterparts in Western economies (e.g., Lincoln et al., 1996: 71). We believe, therefore, that a focus on network communities would allow for a more inclusive analysis and offer exciting opportunities for future research across a broader range of industrial, national, and institutional systems.

Tables

Table 1. Descriptive statistics and bivariate correlations.

	Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
DV	*Number of patents in t+1*	86.31	197.65																												
1	Headcount (log)	3.24	2.35	-																											
2	Net income (log)	10.07	0.38	0.01	-																										
3	Return on Assets (log)	2.86	0.01	0.14	0.06	-																									
4	R&D spending (log)	5.36	1.92	0.64	0.00	0.19	-																								
5	Degree centrality (log)	1.29	0.64	0.21	0.06	0.10	0.37	-																							
6	Ego-network density (log)	0.78	0.28	-0.25	-0.05	-0.14	-0.49	-0.82	-																						
7	Main component firm	0.73	0.44	0.23	0.00	0.11	0.29	0.28	-0.35	-																					
8	Ego-network turnover	0.22	0.33	0.01	0.02	0.06	0.05	-0.01	-0.01	0.05	-																				
9	Ego-network growth (log)	0.12	0.40	-0.03	0.01	0.05	-0.04	0.06	0.02	0.03	0.63	-																			
10	Within-community coreness	0.36	0.21	-0.10	0.04	0.00	-0.01	0.25	-0.19	-0.60	0.00	0.02	-																		
11	Avg. within-community coreness	0.37	0.19	-0.07	0.05	-0.01	0.02	0.21	-0.18	-0.60	0.01	-0.01	0.84	-																	
12	Cross-community participation	0.14	0.23	0.30	0.05	0.12	0.45	0.71	-0.74	0.38	-0.01	-0.02	0.05	0.04	-																
13	Community incumbent	0.60	0.49	-0.10	-0.03	-0.02	-0.12	0.02	0.07	-0.24	-0.56	-0.31	0.21	0.19	-0.13	-															
14	Community size	10.72	5.64	0.18	0.02	0.07	0.21	0.29	-0.26	0.75	-0.05	-0.02	-0.66	-0.60	0.28	-0.13	-														
15	Community centrality	3.17	2.30	0.19	0.03	0.05	0.18	0.27	-0.24	0.69	-0.01	-0.03	-0.50	-0.47	0.32	-0.17	0.73	-													
16	Community constraint	0.40	0.28	0.18	-0.02	0.11	0.25	0.21	-0.31	0.88	0.08	0.08	-0.48	-0.49	0.30	-0.20	0.52	0.41	-												
17	Community age	3.62	2.51	-0.02	0.01	-0.02	0.06	0.03	-0.08	0.13	-0.17	-0.13	-0.09	-0.02	0.03	0.28	0.20	0.08	0.12	-											
18	Community growth	3.21	5.32	0.11	0.03	0.02	0.12	0.08	-0.12	0.31	0.18	0.15	-0.26	-0.21	0.10	-0.59	0.36	0.30	0.21	-0.39	-										
19	Technological diversity	0.52	0.14	0.26	-0.02	0.04	0.25	0.21	-0.16	0.40	-0.01	0.01	-0.43	-0.41	0.13	-0.10	0.43	0.35	0.33	-0.12	0.24	-									
20	Avg. geographical distance	7.69	0.99	0.18	0.00	0.09	0.22	0.14	-0.17	0.41	0.02	0.01	-0.32	-0.30	0.16	-0.09	0.36	0.33	0.34	0.09	0.12	0.45	-								
21	Single dyadic partnership	0.11	0.32	-0.16	0.00	-0.07	-0.18	-0.33	0.28	-0.58	0.00	-0.07	0.58	0.51	-0.22	0.09	-0.55	-0.45	-0.51	-0.11	-0.18	-0.60	-0.40	-							
22	Single large partnership	0.05	0.22	-0.12	0.00	-0.06	-0.17	0.03	0.19	-0.39	-0.03	0.08	0.16	0.18	-0.15	0.10	-0.28	-0.23	-0.34	-0.06	-0.11	-0.03	-0.14	-0.08	-						
23	Global-network turnover	0.24	0.06	0.02	-0.01	0.07	-0.02	0.06	-0.06	0.02	0.14	0.14	-0.02	0.00	0.05	-0.06	0.00	0.06	-0.02	-0.03	0.02	-0.06	0.03	-0.08	0.03	-					
24	Community and network exits	1.22	3.15	0.03	0.02	0.02	0.11	0.03	-0.02	0.15	-0.11	-0.11	-0.13	-0.12	0.02	0.10	0.22	0.14	0.04	0.22	-0.19	0.10	0.10	-0.10	-0.05	-0.10	-				
25	Global network reach	0.10	0.02	-0.07	-0.06	-0.02	0.05	0.07	-0.13	0.13	0.06	0.08	-0.07	-0.02	0.06	-0.08	0.02	-0.07	0.13	0.00	0.08	0.03	0.06	-0.07	-0.09	0.22	-0.07	-			
26	Avg. global network reach	0.10	0.01	0.03	-0.08	-0.02	0.12	0.24	-0.26	0.18	0.01	-0.08	-0.08	-0.05	0.22	-0.06	0.16	0.15	0.10	0.11	0.04	0.07	0.13	-0.19	-0.12	0.28	-0.10	0.70	-		
27	Membership turnover	0.48	0.35	0.14	0.06	0.08	0.18	0.10	-0.20	0.40	0.42	0.21	-0.20	-0.22	0.21	-0.71	0.24	0.27	0.34	-0.29	0.65	0.13	0.17	-0.19	-0.20	0.12	-0.05	0.14	0.14	-	
28	Prior community affiliations	1.28	1.64	0.28	0.05	0.06	0.37	0.36	-0.42	0.37	-0.06	-0.24	-0.15	-0.20	0.44	-0.28	0.39	0.39	0.22	-0.05	0.26	0.19	0.19	-0.20	-0.18	-0.06	0.17	-0.08	0.25	0.32	-

Table 2. Models 1-7: Negative binomial regression models with firm-level fixed effects.

	1	2	3	4	5	6	7
Constant	3.618	-0.639	4.026	3.399	-0.757	-0.657	0.779
	(10.605)	(10.791)	(10.564)	(10.610)	(10.625)	(10.794)	(10.548)
Headcount (log)	0.097***	0.095***	0.097***	0.096***	0.093***	0.095***	0.094***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Net income (log)	-0.014	-0.006	-0.013	-0.010	-0.010	-0.005	-0.009
	(0.052)	(0.054)	(0.054)	(0.053)	(0.053)	(0.054)	(0.056)
Return on Assets (log)	-0.758	0.801	-0.970	-0.718	0.390	0.787	-0.245
	(3.715)	(3.783)	(3.704)	(3.718)	(3.712)	(3.785)	(3.686)
R&D spending (log)	0.083***	0.078***	0.084***	0.084***	0.090***	0.079***	0.082***
	(0.028)	(0.028)	(0.029)	(0.028)	(0.028)	(0.028)	(0.028)
Degree centrality (log)	0.155	0.076	0.114	0.154	0.071	0.077	0.011
	(0.122)	(0.124)	(0.109)	(0.121)	(0.119)	(0.124)	(0.108)
Ego-network density (log)	0.258	0.131	0.302	0.255	0.025	0.134	0.118
	(0.235)	(0.238)	(0.241)	(0.235)	(0.235)	(0.239)	(0.240)
Main component firm	-0.523**	-0.618***	-0.459**	-0.517**	-0.582***	-0.609***	-0.525**
	(0.216)	(0.218)	(0.218)	(0.215)	(0.210)	(0.218)	(0.211)
Ego-network turnover	0.461***	0.439***	0.461***	0.466***	0.316**	0.443***	0.316**
	(0.160)	(0.160)	(0.159)	(0.160)	(0.157)	(0.160)	(0.157)
Ego-network turnover^2	0.194	0.267	0.199	0.206	0.380	0.268	0.332
	(0.336)	(0.335)	(0.339)	(0.337)	(0.326)	(0.336)	(0.329)
Ego-network growth (log)	-0.184**	-0.179**	-0.210***	-0.191**	-0.208***	-0.182**	-0.211***
	(0.076)	(0.076)	(0.078)	(0.077)	(0.074)	(0.076)	(0.076)
Within-community coreness	-0.223	-0.197		-0.216	-0.206	-0.190	
	(0.269)	(0.266)		(0.268)	(0.263)	(0.266)	
Avg. within-community coreness			0.179				0.533
			(0.421)				(0.416)
Cross-community participation	0.542***	0.626***	0.586***	0.534***	0.510***	0.618***	0.595***
	(0.170)	(0.170)	(0.165)	(0.170)	(0.168)	(0.171)	(0.163)
Community incumbent	0.297***	0.254***	0.288***	0.299***	0.287***	0.256***	0.272***
	(0.078)	(0.078)	(0.076)	(0.078)	(0.076)	(0.078)	(0.075)
Community size	0.006	0.013	0.011	0.004	0.001	0.012	0.007
	(0.010)	(0.011)	(0.009)	(0.011)	(0.010)	(0.011)	(0.009)
Community centrality	0.037**	0.032**	0.035**	0.040**	0.040***	0.034**	0.041***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)	(0.015)
Community constraint	-0.600**	-0.615***	-0.593**	-0.632***	-0.489**	-0.634***	-0.468**
	(0.234)	(0.234)	(0.233)	(0.234)	(0.228)	(0.235)	(0.228)
Community age	0.012	0.013	0.008	0.012	0.021	0.013	0.017
	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)
Community growth	0.008	0.002	0.009	0.009	0.007	0.002	0.007
	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)
Technological diversity	0.393	0.516	0.349	0.377	0.650	0.501	0.555
	(0.410)	(0.408)	(0.410)	(0.412)	(0.409)	(0.409)	(0.408)
Avg. geographical distance	-0.120**	-0.123**	-0.120**	-0.112**	-0.113**	-0.119**	-0.114**
	(0.053)	(0.053)	(0.053)	(0.054)	(0.052)	(0.054)	(0.052)
Single dyadic partnership	-0.321*	-0.231	-0.420***	-0.339**	-0.311*	-0.247	-0.433***
	(0.169)	(0.170)	(0.161)	(0.170)	(0.166)	(0.172)	(0.158)
Single large partnership	0.219	0.290	0.209	0.199	0.246	0.276	0.226
	(0.264)	(0.261)	(0.263)	(0.264)	(0.268)	(0.261)	(0.266)
Global-network turnover	2.472***	2.500***	2.461***	2.464***	2.356***	2.489***	2.327***
	(0.544)	(0.538)	(0.540)	(0.549)	(0.538)	(0.544)	(0.535)
Global-network turnover^2	-28.306***	-27.903***	-27.912***	-28.137***	-23.476***	-27.794***	-22.749***
	(7.176)	(7.103)	(7.108)	(7.266)	(7.003)	(7.183)	(6.947)
Community and network exits	-0.087***	-0.089***	-0.085***	-0.089***	-0.085***	-0.090***	-0.082***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Global network reach	-3.005*	-3.097*	-3.029*	-2.620		-2.870	
	(1.651)	(1.648)	(1.627)	(1.761)		(1.754)	
Avg. global network reach					7.440**		7.572**
					(3.125)		(3.167)
Membership turnover	0.738**	0.659*	0.756**	0.747**	0.768**	0.666*	0.799**
	(0.359)	(0.369)	(0.356)	(0.366)	(0.353)	(0.374)	(0.350)
Membership turnover^2	-0.783**	-0.706**	-0.805**	-0.814**	-0.770**	-0.725**	-0.815**
	(0.350)	(0.349)	(0.348)	(0.354)	(0.344)	(0.354)	(0.343)
Prior community affiliations	0.280***	0.273***	0.302***	0.277***	0.247***	0.272***	0.265***
	(0.053)	(0.053)	(0.055)	(0.053)	(0.052)	(0.053)	(0.053)
Prior community affiliations^2	-0.028***	-0.026***	-0.035***	-0.026***	-0.017**	-0.025***	-0.022**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
Membership turnover x Within-community coreness		3.142**				3.004*	
		(1.568)				(1.585)	
Membership turnover^2 x Within-community coreness		-3.528**				-3.382**	
		(1.365)				(1.382)	
Prior community affiliations x Avg. within-community coreness			0.376				0.611**
			(0.301)				(0.298)
Prior community affiliations^2 x Avg. within-community coreness			-0.116**				-0.126**
			(0.055)				(0.055)
Membership turnover x Global network reach				-15.030		-8.839	
				(16.662)		(16.714)	
Membership turnover^2 x Global network reach				15.175		8.896	
				(13.749)		(13.820)	
Prior community affiliations x Avg. global network reach					-2.650		-2.374
					(4.854)		(4.909)
Prior community affiliations^2 x Avg. global network reach					3.047***		3.090***
					(1.070)		(1.085)
Obs.	720	720	720	720	720	720	720
Log-likelihood	-1989.01	-1983.10	-1986.46	-1988.19	-1977.91	-1982.82	-1975.19
Log-likelihood ratio test relative to controls-only model (χ^2)	32.46***	44.28***	38.59***	34.11***	68.25***	44.84***	73.89***

*Standard errors in parentheses; two-tailed tests: ***p<.01, **p<.05, *p<.10*

Table 3. Models 8-14: Three-level Poisson regression models with random intercepts and random coefficients.

	8	9	10	11	12	13	14
Constant	-17.208**	-18.301**	-15.224*	-18.385**	-12.538	-18.883**	-11.741
	(7.285)	(7.921)	(8.247)	(7.374)	(8.386)	(8.014)	(8.434)
Headcount (log)	0.015	0.020	0.030**	0.013	0.048***	0.017	0.048***
	(0.012)	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)
Net income (log)	-0.034	-0.017	-0.039*	-0.043*	-0.044*	-0.029	-0.044*
	(0.022)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Return on Assets (log)	6.335**	6.620**	5.510*	6.851***	4.193	6.909**	3.930
	(2.550)	(2.753)	(2.873)	(2.580)	(2.926)	(2.776)	(2.941)
R&D spending (log)	0.099***	0.081***	0.137***	0.096***	0.139***	0.079***	0.133***
	(0.016)	(0.017)	(0.019)	(0.018)	(0.020)	(0.018)	(0.020)
Degree centrality (log)	0.545***	0.480***	0.629***	0.539***	0.470***	0.504***	0.377**
	(0.116)	(0.154)	(0.170)	(0.116)	(0.148)	(0.153)	(0.165)
Ego-network density (log)	0.656***	0.637***	0.657***	0.651***	0.564**	0.628***	0.566**
	(0.178)	(0.214)	(0.230)	(0.180)	(0.239)	(0.214)	(0.241)
Main component firm	-0.232	-0.188	-0.402	0.040	-0.422	0.059	-0.487
	(0.300)	(0.323)	(0.352)	(0.303)	(0.318)	(0.322)	(0.333)
Ego-network turnover	-0.003	-0.170**	0.045	-0.034	0.117	-0.172**	0.115
	(0.068)	(0.076)	(0.084)	(0.070)	(0.080)	(0.077)	(0.081)
Ego-network turnover^2	0.715***	0.880***	0.895***	0.731***	0.755***	0.835***	0.699***
	(0.138)	(0.164)	(0.185)	(0.139)	(0.166)	(0.165)	(0.166)
Ego-network growth (log)	-0.280***	-0.167***	-0.292***	-0.266***	-0.326***	-0.145***	-0.274***
	(0.034)	(0.051)	(0.056)	(0.035)	(0.045)	(0.052)	(0.050)
Within-community coreness	0.163	-0.172		0.155	0.289*	-0.225	
	(0.141)	(0.351)		(0.145)	(0.151)	(0.335)	
Avg. within-community coreness			-0.381				0.621
			(0.791)				(0.610)
Cross-community participation	0.235**	0.243**	0.185	0.221**	0.376***	0.201*	0.384***
	(0.103)	(0.118)	(0.125)	(0.106)	(0.113)	(0.117)	(0.117)
Community incumbent	0.055	0.036	0.016	0.044	0.073	0.027	0.064
	(0.037)	(0.039)	(0.043)	(0.038)	(0.045)	(0.039)	(0.046)
Community size	-0.013	0.002	-0.003	-0.025	-0.004	-0.011	-0.002
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.019)
Community centrality	0.003	0.004	0.002	-0.009	0.008	-0.005	0.008
	(0.009)	(0.009)	(0.010)	(0.012)	(0.010)	(0.011)	(0.010)
Community constraint	-0.669***	-0.575**	-0.757***	-0.744***	-0.516*	-0.642***	-0.468*
	(0.233)	(0.258)	(0.280)	(0.190)	(0.274)	(0.235)	(0.274)
Community age	-0.087**	-0.077**	-0.075**	-0.078**	-0.054	-0.073**	-0.052
	(0.034)	(0.033)	(0.037)	(0.033)	(0.038)	(0.034)	(0.038)
Community growth	0.009	0.005	0.003	0.017***	0.005	0.012*	0.003
	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)
Technological diversity	0.275	0.619	0.429	0.011	0.626	0.381	0.493
	(0.446)	(0.474)	(0.494)	(0.584)	(0.502)	(0.518)	(0.508)
Avg. geographical distance	0.069	0.069	0.090*	0.045	0.093*	0.078	0.078
	(0.048)	(0.051)	(0.053)	(0.062)	(0.056)	(0.061)	(0.056)
Single dyadic partnership	-0.507***	-0.361**	-0.500***	-0.514***	-0.701***	-0.276	-0.710***
	(0.144)	(0.155)	(0.171)	(0.163)	(0.155)	(0.170)	(0.160)
Single large partnership	-0.164	-0.146	-0.314	-0.146	-0.262	-0.170	-0.258
	(0.217)	(0.218)	(0.238)	(0.209)	(0.246)	(0.216)	(0.244)
Global-network turnover	1.383***	1.521***	1.473***	1.296**	2.159***	1.509***	2.154***
	(0.388)	(0.405)	(0.409)	(0.526)	(0.441)	(0.466)	(0.445)
Global-network turnover^2	-11.562***	-10.117**	-12.260***	-9.629**	-17.437***	-9.279**	-16.793***
	(3.890)	(4.028)	(4.118)	(4.860)	(4.334)	(4.693)	(4.335)
Community and network exits	-0.061***	-0.066***	-0.064***	-0.060***	-0.072***	-0.064***	-0.073***
	(0.009)	(0.009)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)
Global network reach	-4.845***	-4.601***	-4.883***	-4.776**		-5.848***	
	(1.301)	(1.351)	(1.481)	(2.379)		(2.048)	
Avg. global network reach					4.567		5.572
					(6.819)		(7.051)
Membership turnover	0.983***	-0.081	0.812***	1.185***	0.821***	0.076	0.816***
	(0.216)	(0.445)	(0.238)	(0.253)	(0.239)	(0.471)	(0.240)
Membership turnover^2	-1.355***	-0.300	-1.235***	-1.502***	-1.161***	-0.482	-1.164***
	(0.237)	(0.426)	(0.257)	(0.275)	(0.260)	(0.447)	(0.260)
Prior community affiliations	1.058***	1.026***	1.142***	1.086***	0.793***	1.034***	0.934***
	(0.163)	(0.164)	(0.211)	(0.169)	(0.170)	(0.165)	(0.184)
Prior community affiliations^2	-0.159***	-0.149***	-0.156***	-0.165***	-0.104***	-0.152***	-0.135***
	(0.033)	(0.033)	(0.046)	(0.034)	(0.030)	(0.033)	(0.035)
Membership turnover x Within-community coreness		2.196**				2.128**	
		(0.847)				(0.853)	
Membership turnover^2 x Within-community coreness		-2.214***				-2.065***	
		(0.743)				(0.763)	
Prior community affiliations x Avg. within-community coreness			0.936				1.899**
			(1.070)				(0.850)
Prior community affiliations^2 x Avg. within-community coreness			-0.262				-0.410**
			(0.288)				(0.195)
Membership turnover x Global network reach				13.021		28.143**	
				(16.282)		(14.188)	
Membership turnover^2 x Global network reach				-13.070		-28.086**	
				(15.314)		(14.108)	
Prior community affiliations x Avg. global network reach					18.803**		19.062**
					(9.422)		(9.641)
Prior community affiliations^2 x Avg. global network reach					-2.464		-2.368
					(2.628)		(2.796)
Obs.	720	720	720	720	720	720	720
Log-likelihood	-3106.17	-3084.93	-3045.00	-3098.44	-3021.09	-3079.35	-3019.27
Log-likelihood ratio test relative to controls-only model (χ^2)	335.78***	378.27***	466.08***	351.23***	547.11***	389.41***	559.92***

*Standard errors in parentheses; two-tailed tests: ***p<.01, **p<.05, *p<.10*

Figures

Fig. 1. The perspective on network communities versus the existing ego-network and global-network perspectives.

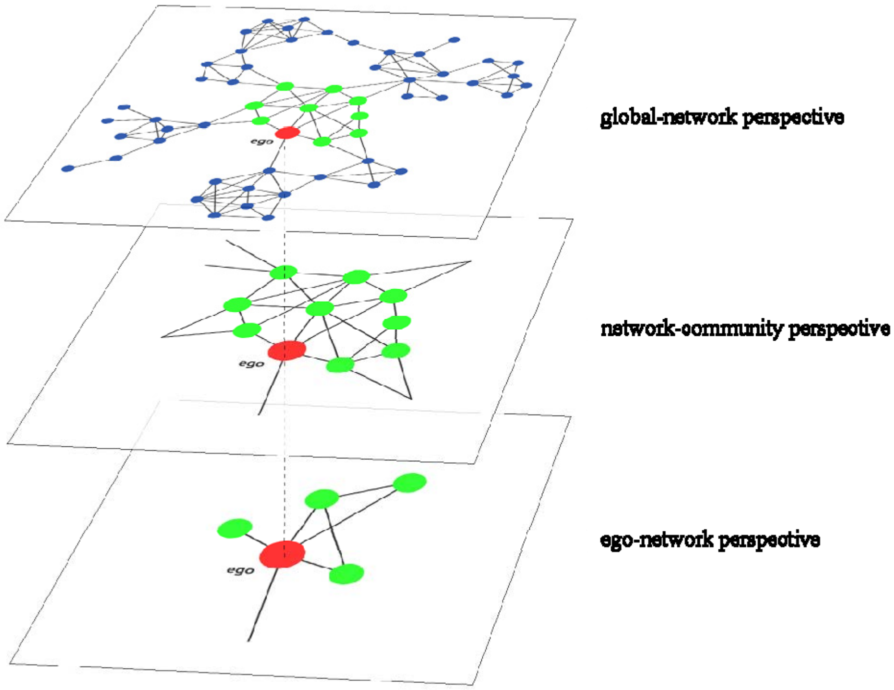


Fig. 2. Structure of the global network in 1994.

Fig. 3. Community structure of the main component in 1994.

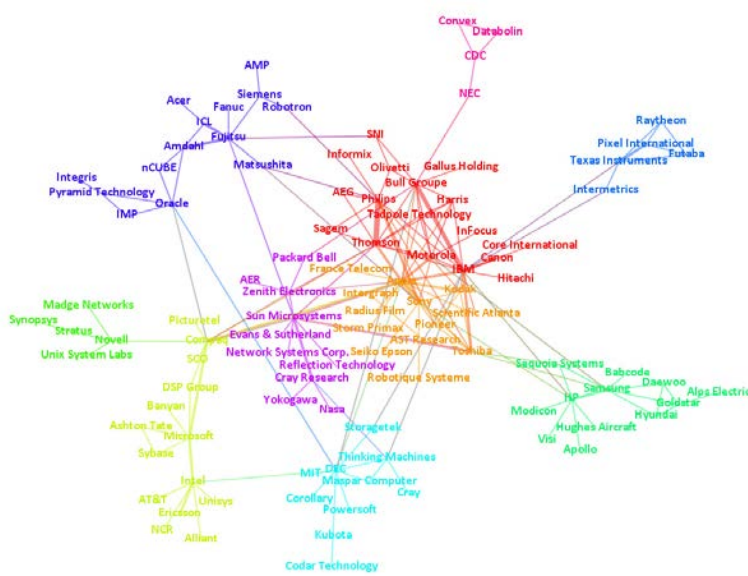
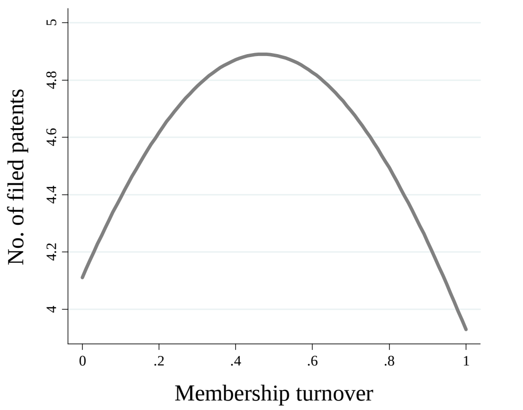
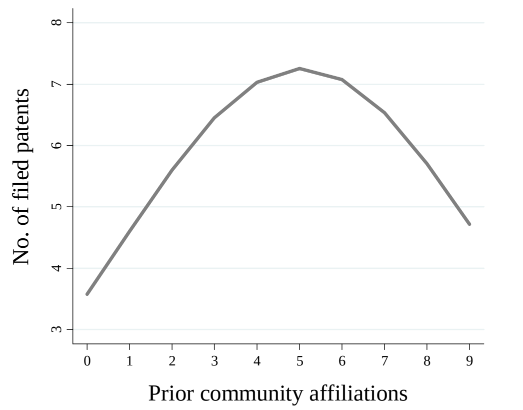


Fig. 4a-4f. Graphical presentation of the main statistical results. Predicted effects are estimated at the means of other covariates.

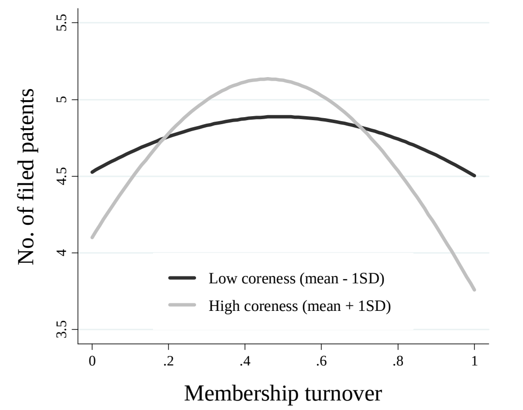
(a) main effect of *Membership turnover* in a firm's network community (Model 1)



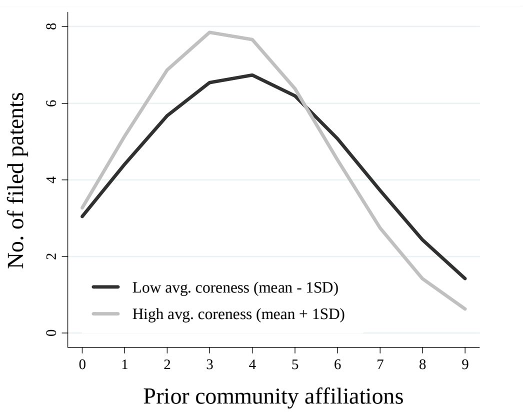
(b) main effect of a firm's *Prior community affiliations* (Model 1)



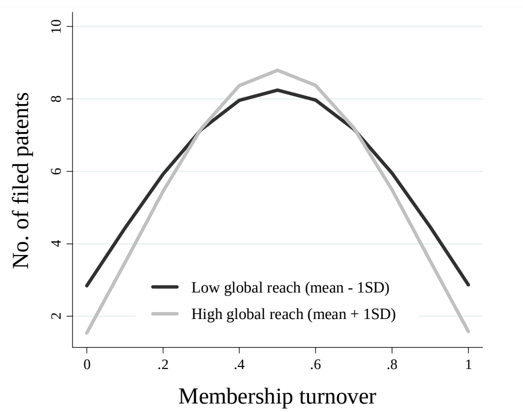
(c) interaction between *Membership turnover* and a firm's *Within-community coreness* (Model 2)



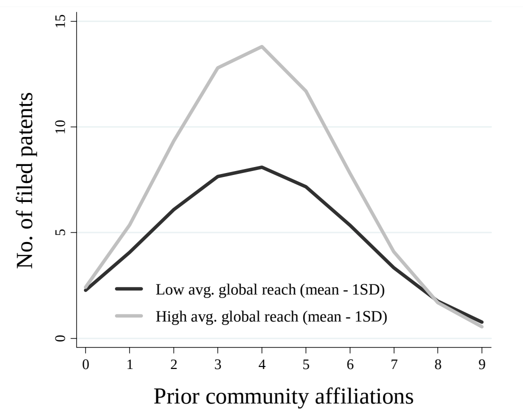
(d) interaction between *Prior community affiliations* and a firm's *Avg. within-community coreness* (Model 7)



(e) interaction between *Membership turnover* and a firm's *Global network reach* (Model 13)



(f) interaction between the linear term of *Prior community affiliations* and a firm's *Avg. global network reach* (Model 12)



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