Networks and Innovation: Accounting for Structural and Institutional Sources of Recombination in Brokerage Triads

Sarath Balachandran*
sarathb@wharton.upenn.edu

Exequiel Hernandez*
exequiel@wharton.upenn.edu

The Wharton School
University of Pennsylvania

Version: 25 July 2017

Forthcoming, Organization Science
Comments welcome

Keywords: Innovation, network analysis, institutional theory, strategic alliance networks, international management

Notes and Acknowledgements: **Authors listed alphabetically and contributed equally.* We thank editor-in-chief Gautam Ahuja and the anonymous reviewers at Organization Science, Matthew Bidwell, Adam Cobb, Russell Funk, Mauro Guillen, Witold Henisz, Lori Rosenkopf, Aks Zaheer, and seminar participants at London Business School, SUNY Buffalo, and Tilburg University for helpful comments. We also value the feedback received during the conferences of the Strategic Management Society (2014), the Academy of International Business (2015) and the Academy of Management (2015). Matthew Higgins shared the alliance data used in this study and Russell Funk shared the data on patent radicalness, for which we are deeply thankful. The Mack Institute for Innovation Management provided generous funding. The usual disclaimers apply.

Networks and Innovation: Accounting for Structural and Institutional Sources of Recombination in Brokerage Triads

Abstract: Research linking interorganizational networks to innovation has focused on spanning structural boundaries as a means of knowledge recombination. Increasingly, firms also partner across institutional boundaries (countries, industries, technologies) in their search for new knowledge. When both structural and institutional separation affect knowledge recombination, aggregate characterizations of ego network attributes mask distinct recombination processes that lead to distinct types of innovation outcomes. We address this issue by focusing on triads as the locus of recombination in networks. We partition firms' networks into three configurations of open triads—foreign, domestic, and mixed—based on the distribution of the broker and its partners across or within institutional boundaries. We argue that each configuration embodies distinct recombination processes, with foreign triads offering high access to novel knowledge, domestic triads facilitating relatively efficient knowledge integration, and mixed triads balancing the two. We apply this approach to a global R&D alliance network in the biotechnology industry, using countries as institutional boundaries. The results show that domestic triads affect innovation volume (i.e. the productivity of innovation) more strongly than mixed or foreign triads. In contrast, foreign triads have a greater impact on innovation radicalness (i.e. the path breaking nature of the innovation) than mixed or domestic triads. The findings suggest that different brokerage configurations embody unique recombination processes, leading to distinct innovation outcomes. Our research provides a deeper understanding of how networks and institutions jointly influence distinct aspects of innovation.

Innovation is a process of recombination, whereby firms discover novel bits of knowledge and integrate them in original ways (e.g. Schumpeter 1942, Henderson and Clark 1990, Davis and Eisenhardt 2011). Interorganizational networks play an important role in both aspects of recombination. One the one hand, external ties are sources of diverse, non-redundant knowledge (Burt 1992, Obstfeld 2005). On the other hand, integrating the knowledge flowing through those ties is costly (Ahuja 2000, Aral and Van Alstyne 2011). The net effect of these two forces determines the balance of novelty and integration efficiency embodied in the recombination process, and different types of recombination processes lead to distinct kinds of innovation outcomes (Kaplan and Vakili 2015). Research has focused on structural separation as the main source of novelty access and integration efficiency, in particular by studying the benefits and costs of spanning structural holes (Burt 2004, Ahuja 2000, Tortoriello and Krackhardt 2010). We draw attention to an additional determinant of the recombination process in interorganizational networks: institutional separation. By jointly considering structural and institutional separation, we unmask heterogeneity in recombination processes within a firm's network. This allows us to distinguish between two kinds of innovation outcomes that prior research on networks has largely overlooked (Phelps et al. 2012): volume (the firm's innovation productivity) and radicalness (the path breaking nature of the knowledge produced by the firm).

Firms increasingly partner across institutional boundaries to access novel knowledge. These collaborations include alliances across national borders (Vasudeva et al. 2013), cross-industry R&D partnerships (Davis 2016), or any kind of tie that exposes a focal firm to an environment where institutionalized ideas, practices, and mental models are distinct from those in its own environment (e.g. North 1990, Scott 1995). Like spanning structural holes, crossing institutional boundaries affects the two elements of recombination. Access to novelty is enhanced because the firm is exposed to distinct knowledge (Nelson 1993, Rosenkopf and Almeida 2003) but recombination is costly because transferring knowledge across institutional boundaries is fraught with frictions (Jensen and Szulanski 2004, Davis 2016). When firms participate in these cross-institutional networks with the purpose of innovating, the underlying recombination process is affected by *both* structural and institutional separation. This raises two implications for the relationship between networks and innovation.

The first implication is that the network needs to be partitioned into distinct configurations that jointly account for structural and institutional separation—otherwise the sources of novelty and integration costs driving recombination are conflated. Consider Figure 1, which compares the networks of two firms. Both networks may appear identical at an aggregate (ego) level because each firm spans the same number of structural holes and each has two partners in one institutional boundary and two partners in another institutional boundary. However, the two networks differ in the way structural and institutional separation *combine*. For firm 1, structural and institutional separation coincide, whereas for firm 2 each pair of partners is either structurally or institutionally separated but not both. The knowledge recombination processes in these two scenarios are likely to differ, because distinct mixes of structural and institutional separation could expose the firm to different levels of novelty and integration costs. Characterizing the structural and institutional aspects of these networks separately at the ego level masks this distinction and any resulting variation in innovation outcomes across the two firms.[1] To properly capture the intersection of institutional and structural effects, we build on the insight that the locus of recombination is the open triad: a broker accesses novel ideas and experiences the costs of integrating those ideas across pairs of separated partners (Simmel 1950, Burt 1992, Tortoriello and Krackhardt 2010). Hence, an ego network spanning both structural and institutional boundaries contains distinct types of triads embodying different kinds of recombination processes.

*** FIGURES 1 AND 2 HERE ***

We propose partitioning a firm's network into three configurations of structurally open triads (see Gould and Fernandez 1989): foreign, domestic, and mixed—as illustrated in Figure 2. A foreign configuration consists of a broker whose partners are both embedded in an institutional setting different, or 'foreign', from that of the broker. A domestic configuration is the opposite: a broker whose partners are both from the same, or 'domestic', institutional setting as the broker. A mixed configuration consists of a broker with one partner from a different institutional setting ('foreign') and one from the same as the broker ('domestic'). We argue that foreign triads expose firms to high levels of novelty by facilitating access to diverse sources of institutionalized knowledge, which also creates high costs of knowledge integration. In contrast, domestic triads foster high efficiency in

[1] Note that these considerations apply only when networks are institutionally diverse. Under institutional homogeneity (i.e. all partners are in the same institutional environment), only structural separation drives the recombination process and traditional approaches to characterizing ego networks are applicable.

knowledge integration because of institutional homogeneity, but at the cost of lower levels of novelty exposure. Mixed triads, as their name suggest, expose firms to a balance of the two forces.

This leads to the second implication of jointly considering structural and institutional separation: each network configuration is associated with distinct types of innovation outcomes because each embodies a unique recombination process. The majority of research linking networks to innovation focuses on innovation volume (amount or productivity) as the outcome of interest (Phelps et al. 2012 provide a review). Neglected is the radicalness of the knowledge produced by a firm, or the extent to which it departs from and undermines the status quo—a dimension of innovation distinct from volume (Funk and Owen-Smith 2016, Tushman and Anderson 1986). Research has yet to link different network attributes to these two aspects of innovation. Our classification of triads into distinct configurations provides one useful link. We argue that innovation volume and radicalness are driven by distinct recombination processes, with radicalness relatively more sensitive to the combination of highly original ideas and volume relatively more sensitive to integration efficiency (Chandy and Tellis 1998, Ettlie et al. 1984). We posit that foreign triads in a firm's network will be most strongly associated with innovation radicalness because they expose firms in brokerage positions to high degrees of novelty through ideas from distinct institutional environments. In contrast, we expect domestic triads to be most directly linked to innovation volume because they facilitate knowledge transfer efficiency, and thus productivity, by lowering knowledge exchange frictions stemming from institutional barriers. We expect mixed triads to be more weakly associated to radicalness and volume than foreign and domestic triads, respectively, because they offer moderate access to novelty and knowledge transfer efficiency but do not maximize either one.

To empirically test these ideas, we focus on differences in firm nationality across alliance partners as a manifestation of institutional separation. National boundaries are one significant source of institutional variation that allows firms to access novel ideas (e.g. Andersson et al. 2002, Lavie and Miller 2008, Nelson 1993) and also presents knowledge transfer challenges (e.g. Ghemawat 2001, Gupta and Govindarajan 2000). We use data from a global network of biotechnology R&D alliances during 1985-2005 and a matching methodology to test our hypotheses. We find support for our expectations regarding foreign and domestic configurations: they are most strongly associated with radicalness and volume, respectively. Mixed triads are not associated with either aspect of innovation, contrary to our initial expectations. These effects persist when accounting for various kinds of institutional differences—cultural, administrative, geographic, and economic (Ghemawat 2001).

We make a range of contributions through this study. We add to our understanding of organizational innovation by explaining the network antecedents of two distinct innovation outcomes—volume and radicalness. We emphasize the importance of accounting for structural and institutional separation in interfirm networks to unmask variation in the underlying processes of access to novelty and integration efficiency that drive knowledge recombination. We also introduce a novel typology of brokerage configurations that accounts for institutional boundaries in networks, which can be applied to a wide variety of settings. Our empirical findings speak to research on innovation strategy. Firms seem to benefit from 'extreme' configurations (foreign or domestic) that maximize access to novelty or knowledge transfer efficiency, but each is congruent with distinct aspects of innovation. In contrast, 'moderate' configurations that attempt to balance the two dimensions of recombination do not affect innovation. Broadly, this paper addresses important issues in research on networks, institutions, and innovation.

THEORETICAL BACKGROUND

Innovation as Recombination

Several theories characterize innovation as the outcome of knowledge recombination (e.g. Davis and Eisenhardt 2011, Schumpeter 1942). Ideas, practices, and mental models become entrenched within domains over time, which constrains creativity. Sourcing and combining knowledge from distinct sources helps overcome these constraints and thus facilitates innovation (Ahuja and Morris Lampert 2001, Audia and Goncalo 2007). Any process of recombination includes two basic elements: access to novelty and integration costs. To produce something innovative, a firm must obtain bits of distinct, non-overlapping knowledge—this is the raw material of originality. But those bits of knowledge must be integrated somehow, which is costly because the effort to translate and join disparate ideas is non-trivial (Kogut and Zander 1993, Szulanski 1996). Knowledge recombination processes differ because they exhibit heterogeneity in the balance between novelty and integration costs. Research shows that different recombination processes produce different kinds of innovation outcomes (e.g. Kaplan and Vakili 2015). By different, we do not mean 'more vs. less' or 'better vs. worse' but qualitatively distinct.

Because innovation is a multi-dimensional concept, a firm's innovative output can be characterized in more than one way (Funk 2014, Kaplan and Vakili 2015, Phelps 2010). Prior research examining how interfirm networks affect innovation has largely emphasized the amount or volume of innovation as the outcome of interest (see Phelps 2010 for an important exception). However, whether an innovation enhances or destroys the value of prevailing competencies in an industry has significantly different implications for industry structure and firm outcomes than how efficiently that innovation was produced (e.g. Tushman and Anderson 1986; Chandy and Tellis, 1998). An innovation is competency destroying to the extent that it disrupts the technological trajectory along which knowledge was previously proceeding, and thus degrades the value of prior art in the area. Building on this idea, Funk and Owen-Smith (2016) demonstrate how innovations that are otherwise similar in terms of usage or economic impact can differ significantly in terms of their effect on the prevalent technological trajectory in an area. They emphasize "...the key substantive distinction between new things that are important because they reinforce the status quo and new things that are valuable precisely because they challenge the existing order" (Funk and Owen-Smith 2016:793).

Prior work has demonstrated that firms differ in the types of innovations they produce, but has provided less guidance regarding the network antecedents of distinct dimensions of innovation. Our objective is thus to consider how different recombination processes embodied in a firm's network affect two distinct innovation outcomes: volume (or the firm's innovative productivity) and radicalness (or the extent to which the firm's innovations alter technological domains). We will argue two main points. First, that networks in which partners span both structural and institutional boundaries embody unique recombination processes that may require a fresh approach to how the network is analyzed. These different recombination processes can be captured by partitioning the firm's ego network into distinct types of triadic components. Second, that this approach towards analyzing networks provides a way to explain which portions of a firm's network affect innovation volume and which portions affect innovation radicalness.

Recombination from Structural and Institutional Separation

Many studies have demonstrated the role that interfirm networks can play in driving the process of knowledge recombination (Ahuja 2000, Schilling and Phelps 2007). The need for variety required to access novel knowledge often motivates firms to look beyond their boundaries and establish ties with other firms, such as forming R&D alliances or participating in industry associations. Prior work has demonstrated how having partners that are structurally separated, i.e. not tied to each other, can affect access to distinct knowledge (Burt 1992, 2004). But often, firms partner with others across institutional boundaries as well. This institutional separation is also relevant for the process of recombination, though networks scholars have almost exclusively focused on structural separation when considering innovation, as we discuss next.

Structural Separation. The structure of the ego network affects the two components of recombination. In terms of access to novelty, being connected to structurally separated partners, or spanning structural holes, can be beneficial because it exposes the focal firm to non-redundant sources of knowledge (Kilduff and Brass 2010, Tortoriello and Krackhardt 2010). As Burt (2015:150) explains, "Information becomes homogenous, tacit and therefore sticky within clusters of densely connected [nodes] such that clusters disconnected, buffered from one another by structural holes between them, which gives information breadth, timing and arbitrage advantages to [those] whose networks span structural holes. [Those] who connect across the holes…are more likely to detect productive new combinations of previously segregated information..." But integrating the bits of knowledge gained from structural holes is costly. Transferring knowledge across organizational boundaries is difficult as a baseline because of differences in incentives, culture, and mental models across partners (Gupta and Govindarajan 2000, Inkpen and Tsang 2005, Levin and Cross 2004). Further, research has shown that structural separation constrains knowledge flows because the absence of a cohesive structure means that social mechanisms like trust and shared norms that promote knowledge exchange are less likely to develop (Aral and Van Alstyne 2011, Ahuja 2000, Obstfeld 2005).

Institutional Separation. In the modern economy, knowledge is dispersed across distinct domains: national, industrial, technological, and several others. Each of these domains can be conceptualized as an institutional field with its distinct set of ideas, norms, values, and mental models (e.g. North 1990, Scott 1995). Knowledge within each institutional domain is distinct because organizational practices are imbued with meaning and value beyond their technical utility (Selznick 1957). The institutional environment within which the practices are embedded plays a determining role in the trajectory along which knowledge evolves (Meyer and Rowan 1977). The actors within each institutional field are imprinted by the knowledge and 'ways of knowing' fostered by the rules and norms of their environment (Stinchcombe 1965). Firms across institutional domains develop distinct approaches and routines towards problem solving and innovation (Nelson 1993, Vasudeva et al. 2013). In their quest for innovation, firms increasingly establish ties across institutional boundaries. These links take on many forms, from cross-national R&D alliances to multi-industry associations to collaborations across technological domains. Like partnering across structural boundaries, collaborating across institutional boundaries also influences the two components of the knowledge recombination. Having partners in different domains is an important way to access new and distinct sources of knowledge (Owen-Smith et al. 2002, Rosenkopf and Almeida 2003) for the reasons just mentioned. But the costs of integrating and transferring knowledge across institutional boundaries are also well known (Davis 2016, Vasudeva et al. 2013, Jensen and Szulanski 2004).

This leads to a simple observation: when firms establish networks that span structural and institutional boundaries with the goal of innovating, both kinds of separation shape the resulting knowledge recombination process. This matters because structural and institutional factors *jointly* determine how the network affects a firm's knowledge recombination process—that is, the recombination process may not be adequately understood by considering each factor separately. Pachucki and Breiger (2010:207) emphasize this point: "the notion of bridging in the predominant social network definition may be usefully reconceptualized as having a great deal of cultural contingency". Examining structural and institutional factors separately from each other may thus cause us to miss how they combine to shape the recombination process.

Partitioning the Network into Brokerage Configurations

The value of examining structural and institutional factors in combination may be illustrated by returning to figure 1. If we were to independently characterize structural and institutional attributes of the two focal firm's networks at the ego level, we would conclude that they are identical—each firm spans the same number of structural holes and each has partners with the same institutional characteristics. But the recombination process in a network happens at the locus of each open triad in the network: the focal firm (the broker) gains novel bits of knowledge from its two disconnected partners and then integrates this knowledge at some cost (Burt 1992, 2004). Indeed, it is at the triadic level that the broker executes its boundary-spanning role in the process of innovation (e.g. Rosenkopf and Nerkar 2001, Tushman 1977). The theory of structural holes has its basis in Simmel's (1950) analysis of triads and has been subsequently refined by decompositions of networks into their component triads to enable an understanding of the mechanisms of exchange (Fernandez and Gould 1994, Gould and Fernandez 1989)—though that work focuses on structural separation only. Empirical work typically aggregates every triadic exchange in the firm's ego network into a single measure characterizing the extent to which the firm spans structural holes (e.g. constraint or efficiency) (Burt 1992).

Our contribution is to point out that the aggregation of triadic interactions into a single variable is most appropriate mainly when the recombination process represented by each triad is similar. This is the case when a network is institutionally homogenous: the ties between broker and its partners do not cross boundaries with different levels of access to novelty and integration costs (i.e. only structural separation drives recombination). But aggregating the firm's brokerage opportunities may be inappropriate when the network is institutionally diverse. In that case, as illustrated in Figure 1, the ego network is composed of triads that exhibit variation in the extent to which they expose the focal firm to novel knowledge and in the costs of integrating that knowledge for the broker. In these conditions, it may be necessary to partition the firm's network into groupings of triads that expose the firm to similar knowledge recombination processes.

We thus develop a typology of three brokerage configurations. The notion that a brokerage triad can be partitioned based on the location of network participants in different contexts originated in the pioneering work of Gould and Fernandez (1989). They developed a typology of open triads based on the membership of the broker and its alters in various subgroups and the direction of information flows. We apply a similar idea to interfirm alliance networks spanning institutional boundaries, as depicted in Figure 2.[2]

A triad could be composed of three firms from the same institutional setting, which we label as *domestic*. Or it could be composed of a broker from one institutional setting whose disconnected partners are embedded in institutional settings different from that of the broker, which we label as *foreign*. Alternatively, triads could be composed of a broker with mix of a 'foreign' and a 'domestic' partner, which we label as *mixed*. A few aspects of this typology are noteworthy. It describes individual triads rather than an entire ego network. But a single firm's portfolio of partnerships can (and usually does) contain a mix of the three types, allowing us to partition an ego network into counts of the three configurations. Further, there can be significant variation

[2] We focus on open triads because they are the ones that expose firms to novel knowledge, based on the precedent from the well-established theory of structural holes. We control for closed triads in the empirical analysis, however.

across firms and within firms over time in how their portfolios of triads are distributed across the three categories. We emphasize that, while developing the typology requires thinking of the individual triads that compose the firm's network, the unit of analysis remains at the firm level because ultimately it is the composition of the entire portfolio, and not an individual triad, that affects firm-level innovation.

Effects on Innovation Volume vs. Radicalness

Our objective is to link the different brokerage configurations to distinct innovation outcomes: volume and radicalness. Different dimensions of innovation are probably driven by different kinds of knowledge recombination processes (Kaplan and Vakili 2015). We argue that each of the three triads capture different recombination processes because they embody distinctions in access to novelty and knowledge integration cost. In the domestic triad, knowledge exchange is not impeded by having to cross institutional boundaries, making the knowledge received by the broker easier to recombine. Thus, we expect relatively high knowledge integration efficiency (or low cost) in this configuration. At the same time, knowledge is likely to be more homogenous across partners because of shared context, though novelty still comes from the structural bridging across disconnected actors. The foreign configuration is the mirror image of the domestic: access to novelty is relatively high because the firm can benefit from institutional separation among partners, but this comes at the cost of lower bandwidth in knowledge exchange given the frictions of cross-border integration. Also, the knowledge obtained from different sources is on average less compatible given the institutional disparity of its origins. The mixed configuration represents a 'toned down' amalgam of these forces. The table below Figure 2 provides a schematic representation of the relative expectations regarding novelty and knowledge integration efficiency facilitated by each of the brokerage configurations (using a simple low-medium-high scale).

We expect these distinctions to systematically explain different innovation outcomes at the firm level. Our arguments hinge on the idea that the production functions for innovation volume and radicalness differ. A radical innovation requires putting together a set of ideas that are path breaking, departing from the prior technological trajectory of the industry and making it obsolete. An essential ingredient to a radical innovation is therefore a combination of ideas that is highly unique (Chandy and Tellis 1998, Tushman and Anderson 1986). In contrast, innovation volume is a more a matter of productivity, which can result from sustained incremental improvements and applicability to known uses. The sources of such knowledge may be more 'local' for a firm because they are likely to be part of the daily, ongoing tasks and routines involved in technological invention (Ettlie et al. 1984). This is not to suggest that novelty plays no role in relation to volume or that efficiency is not a consideration in relation to radicalness, only that novelty plays a relatively more prominent role in for radicalness and that volume is relatively more sensitive to integration frictions.

Therefore, we expect that the domestic triads in a firm's ego network should be strongly associated with innovation volume, and relative to the other two kinds of triads be the most strongly related to that outcome. This is because domestic triads provide the greatest efficiency of knowledge integration, followed by mixed and then foreign triads. In contrast, the foreign triads of that firm's network should be strongly associated with radical innovation, and also be the most strongly related to that outcome out of the three types. This is because foreign triads provide the greatest exposure to novelty, followed by mixed and then domestic triads. In summary,

Hypothesis 1: Within a firm's ego network, domestic triads are positively related to innovation volume. Further, domestic triads are the most strongly associated with volume, such that:

Hypothesis 1a: Domestic triads have a stronger positive relationship with innovation volume than mixed triads.

Hypothesis 1b: Domestic triads have a stronger positive relationship with innovation volume than foreign triads.

Hypothesis 2: Within a firm's ego network, foreign triads are positively related to innovation radicalness. Further, foreign triads are the most strongly associated with radicalness, such that:

Hypothesis 2a: Foreign triads have a stronger positive relationship with innovation radicalness than mixed triads.

Hypothesis 2b: Foreign triads have a stronger positive relationship with innovation radicalness than domestic triads.

EMPIRICAL APPLICATION: CROSS-NATIONAL ALLIANCE NETWORKS

The approach to partitioning the network based on institutional separation can be applied to many kinds of institutional boundaries—countries, industries, technological domains, cognitive or mental models, and more. Of course, the boundary has to be relevant to the innovation process and be clearly identifiable. For our empirical application, we examine institutional variation in the form of differences across the nationalities of the firms involved in knowledge alliances. In networks that span national boundaries, the 'distances' between firm's countries often represent the most meaningful and persistent form of institutional difference (Ghemawat 2001).

Furthermore, a substantial body of research has demonstrated the significance of national differences in relation to the knowledge recombination process. Firms from different countries develop distinct knowledge bases—to the point where the innovation system becomes a distinguishing feature of nations and the economic actors within them (Nelson 1993; Vasudeva et al. 2013). And many studies have demonstrated that partnerships that span national boundaries can facilitate access to novel knowledge (Kogut and Zander 1993, Penner-Hahn and Shaver 2005, Zaheer and Hernandez 2011). At the same time, cross-national differences are significant sources of friction in the process of transferring and integrating knowledge (Gulati 1995, Gupta and Govindarajan 2000, Mowery et al. 1996, Simonin 2004).

Data and Variables

Our empirical context is the global biotechnology industry, which is characterized by substantial interfirm activity. Firms rely heavily on resources drawn from external relationships because the complexity of producing a drug requires the capabilities and financial resources of multiple entities. Moreover, innovation directly determines the profitability of firms because the development and commercialization of new molecules make up the majority of the industry's activities. Hence, maintaining a healthy stream of patented innovations is vital to success (Giovannetti and Morrison 2000). Though the industry was originally highly U.S.-centric, it has diffused globally to a substantial degree (primarily in industrialized countries). The 25 biggest biotechnology firms in the world by market capitalization include firms from India, China, and Israel; and five of the ten biggest firms are headquartered outside the U.S. (Genetic Engineering & Biotechnology News 2014).

Our starting point was information on every active alliance between firms in the biotech industry from 1985 to 2005 from the Recombinant Capital (Recap) database, comprising 22,628 unique alliances. Since we are interested in innovation and its attendant knowledge creation processes, we excluded alliances whose purpose was described as 'commercialization', 'licensing', 'marketing', or 'distribution' and started with 11,025 alliances with some form of research and development (R&D) as a stated purpose. In the online appendix, we use non-R&D alliances as the basis for a placebo test to ensure that our results are indeed driven by mechanisms relating to knowledge. We thus began with a list of 4,261 firms engaged in at least one R&D alliance during the time period. We used the announcement year of the alliance as the start date for the tie and followed the convention of a five-year lifespan for the relationship (Gulati 1995, Kogut 1988, Lavie 2007).

Because patenting is a primary driver of innovation in the industry, we retained firms that were granted at least one patent over the study period in any biotechnology class (e.g. Rothaermel and Hess 2007). We obtained patent information from the Harvard IQSS Patent Network Dataverse (Lai et al. 2011). To combine patent and alliance data, we matched the names of firms in the Recap database to the names of patent assignees using a combination of automated and manual techniques. We identified 2,397 firms with at least one patent during 1985-2005 (17,213 firm-years). Because one of our primary dependent variables, innovation radicalness, is not defined for all firm-years (as explained in more detail below) the primary sample contained 1,901 firms, resulting in 11,764 firm-years. We demonstrate the robustness of our findings to the use of the larger sample wherever feasible. The firms come from 37 different countries, mostly from industrialized nations (e.g. U.S., Japan, Western Europe) but there is also meaningful activity from emerging markets (e.g. India, China, Israel).

Dependent Variables. We rely on two distinct patent-based measures to capture innovation volume and radicalness. Though patenting is strictly invention rather than innovation, we use the term innovation to follow the terminology of prior research (e.g. Ahuja, 2000) and based on empirical evidence linking patents to innovation (e.g. Mansfield 1986, Moser 2013). Further, biotechnology exhibits one of the strongest correlations between patenting and commercialization (Giovannetti and Morrison 2000). To capture innovation *volume* we employ patent counts, calculated as $\log(1 + \Sigma_i p_i)$ where p_i is the number of patents granted to firm *i* in during a five-year window.[3] To measure the *radicalness* of the firm's innovations we employ the measure developed by Funk and Owen-Smith (2016), defined as follows for a focal patent at time *t*:

$$R_t = \frac{m_t}{n_t} \Sigma_i \left(-2 f_{it} b_{it} + f_{it}\right)$$

where $i = (i_1, i_2, \ldots, i_{n-1}, i_n)$ is the vector of possible forward citations to the focal patent and/or its prior art at time *t*, m_t = number of citations to the focal patent, n_t = number of citations to the focal patent and all of its prior art, f_{it} = 1 if *i* cites the focal patent and 0 otherwise, b_{it} = 1 if *i* cites any of the focal patent's prior art and 0 otherwise. Hence *radicalness* captures the extent to which patents amplify the use of prior art or diminish it by enhancing use of the focal patent's ideas without reference to prior ideas. Funk and Owen-Smith (2016)

---

[3] The results are very similar if we use citation-weighted patent counts as a proxy for innovation volume, but we believe patent counts better reflect the concept of volume (or productivity). Introducing citations into the measure raises factors, such as impact or economic value, that may be unrelated to theoretical mechanisms we are interested in capturing.

demonstrate that this measure accurately captures the extent to which a patent preserves or disrupts technology streams and that it is distinct from innovation volume. We aggregate this measure at the firm level by taking its average value across all of the firm's patents during a five-year window. The firm's number of patents (i.e. volume) does not influence radicalness, but radicalness cannot be calculated for firms without any patents. This limits the analysis of radicalness to firm-years in which firms successfully apply for at least one patent.

Since the innovation efforts of firms take time to bear fruit, we captured the dependent variables during the 5-year window following the year of observation (i.e. $t+1$ to $t+5$). For example, if the focal year is 2002, we capture innovation volume and radicalness based on the firm's patents during 2003-2007. Jaffe et al. (1993) have shown that most patent applications occur within the five-year window following an investment in R&D (in our case, the alliance activity), which backs this assumption. As is conventional, we use the application date to determine the period of innovation, though we only include patents that were eventually granted.

Brokerage Triad Configurations. For each year, we counted the number of triads of each type (described in Figure 2) within a focal firm's ego network (the focal firm is the broker): *domestic, mixed,* and *foreign*. We generated these counts using NetworkX in Python and verified their accuracy using Ucinet 6 (Borgatti et al. 2002). We used the log(1 + the number of each triad type) as independent variables.

Our main measures of domestic, mixed, and foreign triads consider foreignness in a purely binary fashion (i.e. domestic vs. foreign), based on the well-established idea that national boundaries create distinct institutional domains of knowledge (e.g. Nelson 1993). Of course, there is additional nuance in the degree and dimensionality across which countries differ. For instance, a broker based in the United States with one Canadian and one Chinese partner occupies a foreign triad. But clearly these two partners are not foreign to the same degree. The effects we find may be driven by the similarity of the Canadian partner or the dissimilarity of the Chinese one, but we may mistakenly attribute these effects to 'foreign' ties in general. And countries vary across multiple dimensions (Ghemawat 2001).

We incorporate these considerations into our analyses by clustering countries according to their cultural, administrative, geographic, and economic 'distances' to one another (Ghemawat 2001, Alcacer 2006) and re-calculating the triad counts based on whether firms belong to the same or different clusters (instead of countries). We create four distinct sets of country clusters based on cultural, administrative, geographic, and economic similarity (Ghemawat 2001, Lavie and Miller 2008). For each of these dimensions, we first measure the distance between every pair of countries based on the appropriate scale (described below). Then we use Johnson's (1967) hierarchical clustering algorithm, implemented in Ucinet 6, to group countries into clusters. The algorithm works sequentially: initially every country is in a cluster of its own, in each subsequent step the two clusters that are closest to each other are fused, until every country is in one cluster. The process results in as many sets of clusters as these are countries. We select the set that represents the median step between the two extremes of every country being in a separate cluster and every country being in the same cluster. The clusters are detailed in the online appendix. Our results do not change substantially in magnitude or significance when we deviate from the median cluster in either direction.

With the country clusters in hand, we re-calculated the brokerage configurations treating the cluster rather than the country as the relevant boundary. For example, a foreign triad is now one in which the focal firm and its two partners are each located in different clusters. We obtain three new sets of independent variables for each of the four dimensions of cross-national distance. For cultural distance, we use Kogut and Singh's (1988) composite index of Hofstede's (1980) cultural dimensions. We capture administrative distance based on a factor analysis of the World Bank's six governance indicators (e.g. Lavie and Miller 2008). Geographic distance is the great circle distance between the capitals of the countries to which each firm belongs. Economic distance is the difference in Gross National Income (GNI) per capita between countries (Vasudeva et al. 2013). Geographic and cultural distances are invariant over time. For administrative and economic distance, we create the clusters based on the values at the mid-point of our study period, though we verified the robustness of the results to variations in this choice. In the earlier example of a U.S. firm with one Canadian and one Chinese partner, now the U.S. and Canada will be part of the same country cluster for, say, cultural distance, and hence this triad will be treated as mixed rather than foreign. The results are generally robust if we use other sources of data on cross-national differences, such as that made available by Berry et al. (2010).

Control Variables. We account for variation across firms by including firm fixed effects in our estimation (more on this below). We thus focus on including covariates that could correlate with temporal changes in a firm's brokerage triad counts in ways that affect the firm's innovation outcomes for reasons other than the recombination mechanisms we theorized about.

Some alternative explanations could arise from other structural mechanisms. We include an ego-level measure of brokerage, Burt's (1992) *network efficiency*, because the extent to which the firm spans structural holes at an aggregate level has been shown to influence knowledge recombination, as we discussed earlier.[4] We control for the eigenvector *centrality* of the focal firm (Bonacich 1987), since changes in network status affect the firm's power and influence to orchestrate an ego network with desirable attributes (e.g. Podolny 2001), including the mix of triadic configurations. Though our focus is on open triads, research has suggested that triadic closure may play an important role in recombination by fostering trust and lowering the cost of knowledge integration (Ahuja 2000; Aral and Van Alstyne 2011). Further, the distribution of closed triads in a firm's network may be correlated to that of open triads. We therefore control for the closed triads in the firm's network, classified using the same characterization as we do for our independent variables: *closed domestic*, *closed mixed*, and *closed foreign*.

The composition of a firm's alliance partners could also affect the relationship between the triad configurations and innovation. We include the *percentage of foreign partners* in the firm's portfolio to account for the aggregate compositional effect of crossing national boundaries. In addition, the number of other firms from the same country as the focal firm determines the pool of available domestic partners that a firm could potentially choose from, influencing the types of triadic configurations available. We thus include a count of *same country firms* within the focal firm's national boundaries as a control.

Changes in the technological resources available to the firm (either directly or through its partners) could affect the types of ties the firm establishes as well as the firm's ability to access novel ideas and successfully integrate them. We thus include controls accounting for different sources of technological resources. The focal firm's *technological base*, calculated as the cumulative number of biotechnology patents up to the year in question, controls for the accumulated R&D capability and absorptive capacity of the firm. We also include the *technological base of the firm's partners* by averaging the cumulative patents granted to each of the firm's alliance partners up to the year of observation. This represents the accumulated capabilities the firm can access via its network. Furthermore, having partners with complementary technological capabilities could improve

[4] The results do not change substantially in magnitude or statistical significance if we use Burt's (1992) *constraint* measure.

innovation outcomes by lowering the cost of knowledge integration (Grant and Baden-Fuller 1995). We thus include the average *technological distance* of the focal firm to each of its partners, calculated as the mean (across all partners) of $\Sigma(x_i-y_i)^2$, where x_i-y_i is the difference in the percentage of patents belonging to class *i* between the firm and its partner up to the period in question, for all the biotechnology patent classes.

The different types of triads may be related to brokering between firms with different technological profiles. To account for this, we use the aforementioned measure of technological distance to capture each firm's *within triad technological distance*. This captures the technological distance among the focal firm and its two partners, averaged across all the focal firm's open triads. The experience a firm possesses with respect to a particular partner may ease knowledge transfer frictions due to the development of joint routines of exchange (Dyer and Singh 1998). We thus control for *within triad prior ties* by capturing the average number of prior alliances between the focal firm and the partners within each of the focal firm's triads. While we have argued that mixed triads embody a balance between access to novelty and knowledge exchange frictions, the 'balancing' of different recombination processes happens at the aggregate (ego) level. If this were the case, an even distribution among the three types of triads within their portfolios could help firms achieve better innovation outcomes. Hence we include *triad portfolio balance*, a Herfindahl-based index capturing the extent to which the firm has an even spread of foreign, domestic, and mixed triads.

The strength of the intellectual property (IP) legal regime could affect the firm's propensity to file patents, the ease with which it is able to attract partners, and the scope of knowledge shared with alliance partners—all elements affecting recombination. We thus controlled for the *strength of IP protection in the country of the focal firm* and the average strength of *IP protection in the countries of the partners* to which the firm was tied. We used Park's (2008) national IP protection measure for this purpose.[5] Finally, a firm can only engage in brokerage if it has at least two ties active in a particular year, and some firms do not meet this criterion in every year. To the extent that this is correlated with the triad scores and the firm's ability to be innovative, it is a relevant control. We thus add a dummy variable equal to 1 if the firm has *two or more ties* in that year.

---

[5] Park's (2008) measure is calculated every five years starting in 1980. We use the number from the nearest year for the intervals in between the specific year in which data is provided (e.g. the 1995 value is ascribed to 1996).

Estimation and Matching

Based on the panel structure of the data and the continuous dependent variables, we adopted a linear fixed-effects specification. All our models include *firm fixed effects*, which account for time invariant unobserved heterogeneity. We also include *year fixed effects* to account for macro level fluctuations in innovation outcomes. Yet fixed effects do not account for time variant sources of unobserved heterogeneity. Firms do not randomly participate over time in networks with a certain combination of domestic, foreign, and mixed triads—instead, unobservable capabilities or networking opportunities may influence the set of triad types while also influencing innovation outcomes. While such unobservables are inherently hard to get at, using observable variables may mitigate the concern. If firms that share similar observables also share similar unobservables (e.g. capabilities, networking opportunities), introducing fixed effects that group observably similar firms can reduce heterogeneity along problematic unobserved dimensions (e.g. Altonji et al. 2005).

We attempt to do this by adopting a matching procedure, in which each firm in each year is matched to a group of other firms that are statistically indistinguishable along a vector of observable attributes that proxy for similarities in capabilities and networking opportunities. Matching has two principal virtues. First, it allows us to non-parametrically control for the influence of covariates in the data. Second, unmatched observations are pruned out, making matched subgroups more comparable along observable attributes. We assume that those observations that do not have a reasonable comparison set within the sample are likely to also be distinct in other ways. If the assumption is correct, dropping unmatched observations makes it more likely we are making ‘apples-to-apples’ comparisons on both observables and unobservables with the remaining (not dropped) observations. This approach does not fully solve concerns of endogeneity since observations could be distinct on unobservables despite similarity on observables However, matching can help at least mitigate the problem by reducing the range of unobserved variation.

We employ *coarsened exact matching (CEM)*, which breaks observable covariates into less granular ‘bins’ followed by exact matching of observations within these coarsened ranges of values (Iacus et al. 2011). This approach to matching has become increasingly common in the literature (e.g. Rogan and Sorenson 2014, Vidal and Mitchell 2015). The procedure results in strata (or groups) of matched sets of observations, which we can use to estimate regression coefficients ‘within strata’ (e.g. specifying a fixed effect for each stratum). We matched firms by year along a variety of characteristics relating to firms' network structure (total number of open and closed triads, network efficiency), innovation capabilities (technological base) and network composition (cultural, economic, and geographic distance to partners). These variables likely affect the ability and opportunity to establish triads of various types. The procedure produced roughly 2000 strata (or subgroups of similar observations). We then included strata fixed effects in the linear regression models (i.e. a dummy variable for each of the strata), in addition to the firm and year fixed effects and all the control variables. We report the results based on both the matched and non-matched models.

RESULTS

Table 1 provides the descriptive statistics and correlations. The correlation between our two dependent variables (*volume* and *radicalness*) is about 0.07, suggesting that they are distinct constructs. The counts of the three triad types exhibit relatively high correlations with each other, particularly domestic and mixed. The large sample size mitigates these concerns, and in the robustness section we report on a series of additional analysis to verify the stability of the coefficients across specifications. Note that these correlations summarize associations across firm-years. The addition of firm fixed effects reveals important associations between these variables within firms over time that are not apparent from the pairwise correlations.

Table 2 summarizes the results of our main specifications. Models 1, 2 and 3 use the full sample of data with innovation volume as the dependent variable. Model 1 includes only the controls. Model 2 introduces the independent variables, revealing an improvement in the goodness of fit of the model (per the AIC). Furthermore, a Wald test rejects the null hypothesis that the added variables are jointly unrelated to the dependent variable ($p < 0.001$). The positive and significant coefficient of domestic triads indicates support for H1 ($p < 0.001$). A doubling of the *domestic* variable is associated with a 5% increase in *innovation volume*, holding other variables at their means, and a one standard deviation increase the number of domestic triads for the mean firm in our sample would result in its innovation volume increasing by approximately 4 patents (the average firm produces 27 patents during the 5-year observation window). We observe no significant relationship with innovation volume for either the mixed or foreign triads in this model. A Wald test reveals that domestic triads have a stronger effect on volume than foreign ($p < 0.01$, one-tailed) and mixed ($p < 0.05$, one-tailed) triads, indicating support for Hypotheses 1a and 1b.

TABLES 1 AND 2 AND FIGURE 3 HERE

Model 3 introduces the strata fixed effects derived from the matching procedure. Unmatched observations are dropped, hence the decrease in sample size. The results are largely similar to those in model 2. The positive and significant coefficient of domestic triads supports H1 ($p < 0.001$), and the magnitude is slightly higher than in model 2. This coefficient is also statistically distinguishable from those associated with the *mixed* and *foreign* triad counts ($p < 0.01$, one-tailed, in both cases). Models 4, 5 and 6 replicate models 1, 2 and 3, respectively, for the smaller sample of firms that produce at least one patent within five years after the focal year. The results remain similar in sign and statistical significance, though the coefficient of *domestic* triads becomes smaller in magnitude. In Model 5, a doubling of domestic triads is associated with a 3% increase in innovation volume, holding other variables at their means, and a one standard deviation increase in domestic triads for the mean firm in our sample would result in its innovation volume increasing by approximately 3 patents. We plot the results of this model in figure 3.

Models 7, 8 and 9 use *innovation radicalness* as the dependent variable. Model 7 includes only the controls. Model 8 introduces the independent variables, and the AIC decreases to indicate better fit. A Wald test confirms that the added variables are significantly related to *radicalness* ($p < 0.05$). As anticipated by hypothesis 2, we observe that the coefficient of *foreign* triads is positively related to innovation radicalness ($p < 0.01$). Doubling this variable is associated with a 13% increase in *innovation radicalness*. For the mean firm in our sample, which has roughly 4 foreign triads, the effect of an additional foreign triad would be a 2% increase in the radicalness of its innovation output. The coefficient of *foreign* triads is significantly greater than those of either the *mixed* or *domestic* triads ($p < 0.01$ from one-tailed Wald tests), thus providing support to hypotheses 2a and 2b. These results are plotted in Figure 4. Model 9 examines the relationship between radicalness and the independent variables of interest using the specification with strata fixed effects, and the results are substantially similar to those in non-matching models.

TABLES 3 AND 4 AND FIGURE 4 HERE

We now consider the results using country clusters to build the brokerage triad configurations. Table 3 shows the models using innovation volume as the dependent variable. Models 10a – 13a include the results for fixed effects models using unmatched data and models 10b – 13b include those using the matched sample. The four columns in each case summarize the results based on clustering by cultural, administrative, geographic, and economic distances, respectively. The most prominent and consistent result is that domestic triads are positively related to volume regardless of the type of cross-national distance dimension ($p < 0.05$ or lower). This further supports hypothesis 1. We find no significant relationship between mixed or foreign triads and innovation volume. The difference between *domestic* and *mixed* triads is significant across all models, lending support to H1a. The statistical distinction between *domestic* and *foreign* triads is weaker in the fixed effects models ($p < 0.10$ in two of the four cases), but stronger in the matching models ($p < 0.05$ in three of the four cases), per H1b.

Models 14a-17a (unmatched sample) and 14b-17b (matched data) of table 4 summarize the results for innovation radicalness using country clusters to generate the triad counts. *Foreign* triads are positively and significantly associated with *radicalness* for all four types of cross-national differences ($p < 0.05$ in all cases), offering support to H2. Further, *foreign* triads have a significantly more positive impact on *radicalness* than *mixed* and *domestic* triads ($p < 0.05$ in all but one model and $p < 0.10$ in one case), supporting hypotheses 2a and 2b. Overall, the results based on country clusters are consistent with our main findings.

Robustness Checks

We carried out a number of robustness checks. Prior research using patent counts as the dependent variable (innovation volume) typically uses non-linear estimators (e.g. negative binomial, Poisson). We used a linear estimator instead (after log transforming the counts of patents) because it allows us to more easily incorporate firm fixed effects, it produces unbiased estimates, and it results in easily interpretable marginal effects (Allison and Waterman 2002, Angrist and Pischke 2008). However, the findings for innovation volume are robust if we use negative binomial or Poisson estimators (results available upon request).

We varied the timing over which the dependent variables were measured. In the main models, we capture patent counts and patent radicalness for a 5-year window following the year in which the network is observed. The results are robust to using 3-year and 7-year windows instead.

The biotechnology industry is composed of many small and medium sized companies and a few very large pharmaceutical firms. These large firms may behave differently from the rest and exhibit distinct capabilities and innovation patterns, which could bias the results. We thus re-estimated all models after dropping such firms. While we lacked sales or employment information, we dropped firms in the top 10% in terms of patent counts over the study period—which in this industry is a good proxy for firm size. The results remain as before in magnitude and statistical significance (see the online appendix for detailed results).

The theoretical mechanisms we propose apply to networks composed of knowledge-based alliances—in particular issues of access to novelty and efficiency of knowledge integration. If these knowledge-specific mechanisms were indeed driving the results, we would not expect similar findings if we replicated the analysis using networks composed of ties without knowledge content. We therefore carried out a 'placebo' test by redoing our analysis for the same sample of firms, but using independent and control variables based on non-R&D alliances (e.g. marketing, manufacturing, distribution). We observe no systematic relationship between any of the variables of interest and the two innovation outcomes, which provides some assurance regarding the mechanisms driving our main results (see the online appendix for detailed results)

In foreign triads, both partners are foreign with respect to the broker. However, there are two possibilities—they may both be from the same country or they may be from different countries. We explored whether classifying these two variations as distinct types results in different findings, and found that the results for these two types are statistically indistinguishable from each other.

The results in tables 3 and 4 used the median hierarchical cluster to group countries according to various dimensions of cross-national distance, as previously described. To ensure that the findings are not overly sensitive to the choice of cluster, we carried out the same analysis using a number of country clusters within 20% of the median cluster on either side (larger or smaller), which produce progressively finer or coarser aggregations of countries. The coefficients of our variables of interest are not substantially altered in magnitude or significance as a consequence of these changes.

The *radicalness* variable is substantially skewed with long tails on either side of zero. We cannot employ a log transformation of that variable since it takes negative values. To verify that the skewness of radicalness is not driving our results, we employed an inverse hyperbolic sine transformation (Jones and Pewsey 2009). We found that the skewness of the transformed variable is one-tenth of the untransformed one, but our results were not substantially altered in magnitude or significance. The online appendix reports additional robustness tests to deal with potential multicollinearity and to test the assumption that knowledge differs more across than within countries.

DISCUSSION

The balance between access to novelty and knowledge integration efficiency in networks, which embodies the recombination process affecting innovation, arises from both structural and institutional separation. Firms benefit from accessing novelty by reaching across the two types of boundaries, but also experience a cost to integrate the novel ideas obtained from such boundary spanning activities. Research on networks and innovation—and on structural holes in particular—has not usually accounted for the fact that ties span institutional boundaries, conflating the structural and institutional drivers of innovation (Pachucki and Breiger 2010). We sought to integrate ideas from the literatures on networks and institutions to distinguish between these two effects and introduce a more nuanced approach towards examining innovation. We make the point that the institutional environment not only imposes boundary conditions on the relationship between networks and innovation, but that it may lead the very same structure (brokerage, in our empirical case) to produce different innovation outcomes (volume vs. radicalness). We argue and demonstrate that partitioning firms' ego networks into distinct brokerage configurations is one useful approach to capture the distinct recombination processes behind these distinct innovation outcomes.

We theorized that bridging across firms located in the same institutional boundary (domestic) would most strongly impact the volume of innovation by enhancing knowledge transfer efficiency. We also argued that bridging between firms in different institutional boundaries (relative to the broker) would be most strongly associated with radical innovations as a consequence of the novelty of ideas that this configuration maximizes. The results supported both predictions, even when accounting for various dimensions across which countries differ (e.g. cultural, administrative, economic, geographic). Interestingly, mixing moderate novelty and integration efficiency by having partners from both foreign and domestic markets within the same brokerage triad is suboptimal. We expected that recombination processes that balanced both elements of recombination would have a moderate effect on both kinds of innovations. Instead, it was only the 'extreme' configurations that produced an innovation outcome, albeit a distinctly different outcome in each case. This evokes the notion of strategic tradeoffs, which has received significant attention when it comes to firms' competitive positioning in markets (Porter 1996) but not been applied to the interfirm strategies of organizations. It appears that to produce a certain kind of innovation, the network has to contain a strong dose of the main 'active ingredient' related to that kind of innovation (novelty in the case of radicalness, efficiency in the case of volume). Of course, the tradeoff in this case is not across firms but across different subsections of a firm's ego network. The same firm could produce both a high volume of innovations of high radicalness, but different portions of that firm's network influence each outcome. This insight could be valuable for managers seeking to disentangle the benefits they obtain from their interorganizational knowledge activities.

Because we have not established causal effects, an important issue is whether these findings are driven by treatment or selection processes. Data constraints prevent us from empirically distinguishing the two. But it is useful to consider the implications of each process to better assess the meaning of the results. The underlying distinction in recombination processes (radicalness tilted towards novelty, volume towards integration efficiency) remains whether the results are driven by treatment or selection. The issue is whether some firms systematically prefer or are more suited to managing networks prone to one or the other type of recombination, or whether all firms obtain the same outcomes provided they possess networks that expose them to a certain kind of recombination process.

If the results were driven by treatment, any firm—regardless of its capabilities, history, environment, or intentions—could increase its innovation radicalness by increasing the number of foreign triads in which it brokers or its innovation volume by brokering across more domestic triads. Two kinds of time-varying network formation processes could lead to such treatment effects. One would be epiphenomenal to innovation, in the sense that firms do not wittingly establish cross-institutional ties (leading to foreign triads) or within-institution ties (leading to domestic triads) with a certain kind of innovation outcome in mind. Rather, other processes lead them to end up with more or less of each type of triad. This does not imply that firms are naïve—indeed, tie formation mechanisms such as random attachment (Renyi and Erdos 1959), homophily (McPherson et al. 2001), and bounded rationality (Ahuja et al. 2012) explain why it is hard for firms to anticipate the outcomes of their tie formation behaviors. Another kind of network formation process would be more strategic, in the sense that firms establish cross-institutional ties with the goal of gaining highly novel knowledge and within-institution ties with the goal of increasing the rate of innovative output. This would be consistent with certain studies of alliances and innovation, suggesting that firms strategically reach across boundaries for novelty (Lavie and Rosenkopf 2006, Zaheer and Hernandez 2011). We expect that firms' networks result from a mix of strategic and unintentional tie formation choices, and empirically separating the two is beyond the scope of this study. The treatment effect is hard to empirically capture in our case because we do not have a source of exogenous variation in the different types of triads within firms.

If the results were driven by selection, only certain kinds of firms choose to increase the number of each kind of triad over time in our sample. Many factors may influence this choice, so a selection-based explanation would focus on preconditions that motivate firms to prefer or benefit from a certain kind of recombination process. This could be firm-specific factors such as a capability for integrating diverse knowledge (Vasudeva et al. 2013) or relational considerations like trust, tie strength, or repeated exchange that enhance the efficiency of recombination processes (e.g. Gulati, 1995; Zaheer et al. 1998). This is not to imply that under this scenario the choice of configurations for a firm is unconstrained. Partnerships are the outcome of a two-sided matching process and firms are limited by the willingness of others to partner with them. A selection based mechanism would be operating if firms more likely to capture particular types of recombination benefits also preferentially select into configurations that enable these benefits.

We attempted to empirically assess a capabilities argument by focusing on firms following diversified vs. focused technological strategies. The former would be predisposed to manage high diversity, low efficiency recombination processes (leading to radicalness) while the latter would be inclined to manage low diversity, high efficiency recombination (leading to volume). If this were the case, we should observe that increases in firms' technological diversity over time positively affect the number of foreign triads in their ego networks, while decreases in such diversity positively affect the number of domestic triads. To test this, we used seemingly unrelated estimation to regress the three triad types on two indicators of technological diversity: one based on firms' distribution of patents across biotechnology classes and another on firms' distribution of partnered activities across disease areas (e.g. cancer, diabetes). We found no significant differences between the different triad types in their association with either indicator of technological diversity (results in table A3 of the online appendix). This evidence does not support the expectation that firms self-select into certain types of brokerage configurations based on their technological diversity. But there could be other unobservable drivers of selection that we cannot account for.

These selection vs. treatment considerations are important to think through whether firms choose certain types of network configurations for certain types of outcomes, or obtain those outcomes because processes unrelated to innovation goals put them in certain network positions. Clearly the implications of each are different. While we did not find evidence of selection effects using technological diversity, we do not claim that our findings are due to treatment effects because we lack a source of exogenous variation across different types of network configurations. Thus, we limit ourselves to discussing the implications of each possibility.

Studying radicalness as a dimension of innovation is novel for the networks literature, which has emphasized the volume or amount of innovation using counts of new products or patents (Phelps 2010). The findings suggest that the cross-institutional composition of brokerage triads is a driving factor of whether firms produce scientifically path-breaking knowledge. While some of our results in this regard are evocative of what the literature on local vs. distant search has already suggested (e.g. Rosenkopf and Almeida 2003), our key contribution is to show that existing approaches to studying innovation in the networks literature, which usually interact aggregate measures of composition and structure, may not always be able to distinguish between these two aspects of innovation.

This latter claim has some boundary conditions, because our approach of breaking the network into configurations may not always be necessary—which raises the question of what conditions would make our approach relevant. We expect that there are three such conditions: (1) The network is institutionally diverse (i.e. partners are embedded in different institutional jurisdictions such as countries, industries, technological domains) and firms broker across institutional boundaries. (2) The knowledge relevant to the recombination process in differs meaningfully across institutional boundaries, such that recombination across vs. within boundaries exhibits significant differences in the balance between access to diversity and integration efficiency. (3) The institutional boundary is clearly identifiable and measurable. For instance, one alternative application of this framework may be in the context of innovation in autonomous vehicle technology. This is an area which has seen the active involvement of a range of firms from very different institutional backgrounds in terms of industry: automotive firms (e.g. Volvo, GM, Ford), automotive parts suppliers (e.g. Delphi), established information technology firms (e.g. Apple, Google, Baidu), transportation service providers (e.g. Uber, Lyft), and entirely new enterprises (e.g. nuTonomy). There has also been substantial alliance activity between these firms.

Consequently, these networks embody structural and institutional separation, and it would be interesting to examine how they combine to shape innovation outcomes, the ultimate success of individual firms, and the evolution of the technological domain. An approach similar to the one we have outlined here could be employed to characterize the networks of these firms and perhaps explain some of these outcomes.

A deep understanding of the empirical context is important to determine if decomposing the network as we do in this study is warranted. In some, perhaps many, settings our approach may not apply because clearly distinct ways of doing things have not arisen (e.g. a nascent technological field) or because institutional boundaries are irrelevant to the recombination process. In our context, for example, industry differences are less relevant because biotechnology R&D is done mostly within a well-defined and highly regulated industry. But national boundaries are important because of significantly different educational, scientific, and legal regimes across countries. In contrast, in other settings firms across historically distinct industries (autos, software, electronics), with significantly different institutionalized norms and rules, are simultaneously conducting R&D. Hence there is no substitute for a context-specific understanding of the relevant institutional boundaries.

Our study extends some recent work that examines the influence of national characteristics on inter-firm networks (e.g. Lavie and Miller 2008; Guler and Nerkar 2012). The international business literature has long focused on the benefits and costs of knowledge transfer across subsidiaries of multinational firms in different countries (e.g. Bartlett and Ghoshal 1990, Gupta and Govindarajan 2000). But while multinationality increasingly involves external activities, such as alliances, how networks affect the benefits and costs of seeking for international knowledge has received scant attention (e.g. Zaheer and Hernandez 2011). The findings of this paper help fill this void.

While our focus has been on the external activities of firms in the form of alliance networks, firms may also be able to develop internal capabilities and structures that allow them to balance novelty and integration costs. For instance, having internal knowledge activities spread across countries could help firms develop knowledge transfer routines that would make them less prone to cross-national integration costs. But this could also reduce the level of novelty they are able to access through networking across national boundaries because the firm’s foreign subsidiaries are now locally embedded in the host country institutional environment. We would therefore expect that firms with inventors spread out globally should be able to extract greater innovation volume from their foreign triads (by overcoming knowledge transfer frictions) but at the cost of a weaker relationship between foreign triads and radicalness (due to a decline in the novelty accessed through alliances). To check for these effects, we introduced a new variable into our analysis, *inventor dispersion,* which is a Herfindahl-based measure of the extent to which a firm's inventors are spread out across different countries. We found a positive and significant interaction effect between foreign triads and inventor dispersion on innovation volume, but no significant interaction effects on radicalness (results shown in Table A4 of the online appendix).

These results suggest that internal structure may mitigate the challenges of interorganizational knowledge transfer across institutional boundaries, but that access to novelty through external alliances is not necessarily hurt by internalizing knowledge search activities. However, firms do not randomly choose inventor locations, so this is likely driven by unobserved capabilities and opportunities we are not able to model. Also, this result could be a peculiarity of the cross-national context, because ultimately headquarters is the reference point in determining what is 'new' for the firm. That is, local subsidiaries exist to add to the knowledge stock of the parent firm, and headquarters have an outsized influence over the direction of search for new knowledge (e.g. Zaheer and Hernandez 2011). We offer this additional test as indicative of an interesting direction for future research combining internal and external structure. Whether this contingency between internal and external factors is generalizable should be addressed by additional empirical work.

Conclusion. This study provides a step forward to research on networks, innovation, and institutions. We present a novel typology of cross-institutional brokerage triad configurations that allows researchers to distinguish between structural and institutional (or compositional) effects when studying the relationship between networks and innovation. In doing so, we show that structural and institutional diversity in networks jointly affect two key elements of the recombination process (access to novelty and integration costs) that underlie the process of innovation. Since different types of recombination processes lead to distinct innovation outcomes, the typology of brokerage configurations allows us to explain two distinct aspects of innovation—volume and radicalness—that current research on alliance networks has mostly overlooked.

REFERENCES

Ahuja G (2000) Collaboration Networks, Structural Holes, and Innovation: A Longitudinal Study. *Adm. Sci. Q.* 45(3):425–455.

Ahuja G, Morris Lampert C (2001) Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strateg. Manag. J.* 22(6–7):521–543.

Ahuja G, Soda G, Zaheer A (2012) The genesis and dynamics of organizational networks. *Organ. Sci.* 23(2):434–448.

Alcacer J (2006) Location Choices Across the Value Chain: How Activity and Capability Influence Collocation. *Manag. Sci.* 52(10):1457–1471.

Allison PD, Waterman RP (2002) 7. Fixed-Effects Negative Binomial Regression Models. *Sociol. Methodol.* 32(1):247–265.

Altonji JG, Elder TE, Taber CR (2005) Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools. *J. Polit. Econ.* 113(1):151–184.

Andersson U, Forsgren M, Holm U (2002) The strategic impact of external networks: Subsidiary performance and competence development in the multinational corporation. *Strateg. Manag. J.* 23(11):979–996.

Angrist JD, Pischke JS (2008) *Mostly harmless econometrics: An empiricist's companion* (Princeton University Press).

Aral S, Van Alstyne M (2011) The diversity-bandwidth trade-off1. *Am. J. Sociol.* 117(1):90–171.

Audia PG, Goncalo JA (2007) Past success and creativity over time: A study of inventors in the hard disk drive industry. *Manag. Sci.* 53(1):1–15.

Berry H, Guillén MF, Zhou N (2010) An institutional approach to cross-national distance. *J. Int. Bus. Stud.* 41(9):1460–1480.

Bonacich P (1987) Power and centrality: A family of measures. *Am. J. Sociol.*:1170–1182.

Borgatti SP, Everett MG, Freeman LC (2002) Ucinet 6 for Windows. *Harv. Anal. Technol.*

Burt RS (1992) Structural holes: The social structure of competition. *Camb. Harv.*

Burt RS (2004) Structural Holes and Good Ideas. *Am. J. Sociol.* 110(2):349–399.

Burt RS (2015) Reinforced structural holes. *Soc. Netw.* 43:149–161.

Chandy RK, Tellis GJ (1998) Organizing for radical product innovation: The overlooked role of willingness to cannibalize. *J. Mark. Res.*:474–487.

Davis JP (2016) The Group Dynamics of Interorganizational Relationships Collaborating with Multiple Partners in Innovation Ecosystems. *Adm. Sci. Q.*:1839216649350.

Davis JP, Eisenhardt KM (2011) Rotating leadership and collaborative innovation recombination processes in symbiotic relationships. *Adm. Sci. Q.* 56(2):159–201.

Dyer JH, Singh H (1998) The relational view: cooperative strategy and sources of interorganizational competitive advantage. *Acad. Manage. Rev.* 23(4):660–679.

Ettlie JE, Bridges WP, O'keefe RD (1984) Organization strategy and structural differences for radical versus incremental innovation. *Manag. Sci.* 30(6):682–695.

Fernandez RM, Gould RV (1994) A dilemma of state power: Brokerage and influence in the national health policy domain. *Am. J. Sociol.*:1455–1491.

Funk RJ (2014) Making the Most of Where You Are: Geography, Networks, and Innovation in Organizations. *Acad. Manage. J.* 57(1):193–222.

Funk RJ, Owen-Smith J (2016) A Dynamic Network Measure of Technological Change. *Manag. Sci.*

Ghemawat P (2001) Distance still matters. *Harv. Bus. Rev.* 79(8):137–147.

Giovannetti GT, Morrison SW (2000) Convergence: The biotechnology industry report. *Ernst Young Palo Alto CA*.

Gould RV, Fernandez RM (1989) Structures of mediation: A formal approach to brokerage in transaction networks. *Sociol. Methodol.*:89–126.

Grant RM, Baden-Fuller C (1995) A knowledge-based theory of inter-firm collaboration. (Academy of Management), 17–21.

Gulati R (1995) Social Structure and Alliance Formation Patterns: A Longitudinal Analysis. *Adm. Sci. Q.* 40(4):619–652.

Guler I, Nerkar A (2012) The impact of global and local cohesion on innovation in the pharmaceutical industry. *Strateg. Manag. J.*

Gupta AK, Govindarajan V (2000) Knowledge flows within multinational corporations. *Strateg. Manag. J.* 21(4):473–496.

Henderson RM, Clark KB (1990) Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Adm. Sci. Q.*:9–30.

Hofstede G (1980) Motivation, leadership, and organization: do American theories apply abroad? *Organ. Dyn.* 9(1):42–63.

Iacus SM, King G, Porro G (2011) Causal Inference without Balance Checking: Coarsened Exact Matching. *Polit. Anal.*

Inkpen AC, Tsang EW (2005) Social capital, networks, and knowledge transfer. *Acad. Manage. Rev.* 30(1):146–165.

Jaffe AB, Trajtenberg M, Henderson R (1993) *Geographic localization of knowledge spillovers as evidenced by patent citations* (National Bureau of Economic Research).

Jensen R, Szulanski G (2004) Stickiness and the adaptation of organizational practices in cross-border knowledge transfers. *J. Int. Bus. Stud.* 35(6):508–523.

Johnson SC (1967) Hierarchical clustering schemes. *Psychometrika* 32(3):241–254.

Jones MC, Pewsey A (2009) Sinh-arcsinh distributions. *Biometrika* 96(4):761–780.

Kaplan S, Vakili K (2015) The double-edged sword of recombination in breakthrough innovation. *Strateg. Manag. J.* 36(10):1435–1457.

Kilduff M, Brass DJ (2010) Organizational social network research: Core ideas and key debates. *Acad. Manag. Ann.* 4(1):317–357.

Kogut B (1988) Joint ventures: theoretical and empirical perspectives. *Strateg. Manag. J.* 9(4):319–332.

Kogut B, Singh H (1988) The effect of national culture on the choice of entry mode. *J. Int. Bus. Stud.* 19(3):411–432.

Kogut B, Zander U (1993) Knowledge of the Firm and the Evolutionary Theory of the Multinational Corporation. *J. Int. Bus. Stud.* 24(4):625–645.

Lai R, D'Amour A, Yu A, Sun Y, Torvik V, Fleming L (2011) Disambiguation and co-authorship networks of the US Patent Inventor Database. *Harv. Inst. Quant. Soc. Sci. Camb. MA* 2138.

Lavie D (2007) Alliance portfolios and firm performance: A study of value creation and appropriation in the US software industry. *Strateg. Manag. J.* 28(12):1187–1212.

Lavie D, Miller SR (2008) Alliance Portfolio Internationalization and Firm Performance. *Organ. Sci.* 19(4):623–646.

Lavie D, Rosenkopf L (2006) Balancing exploration and exploitation in alliance formation. *Acad. Manage. J.* 49(4):797.

Levin DZ, Cross R (2004) The strength of weak ties you can trust: The mediating role of trust in effective knowledge transfer. *Manag. Sci.* 50(11):1477–1490.

Mansfield E (1986) Patents and innovation: an empirical study. *Manag. Sci.* 32(2):173–181.

McPherson M, Smith-Lovin L, Cook JM (2001) Birds of a feather: Homophily in social networks. *Annu. Rev. Sociol.*:415–444.

Meyer JW, Rowan B (1977) Institutionalized organizations: Formal structure as myth and ceremony. *Am. J. Sociol.* 83(2):340.

Moser P (2013) Patents and innovation: Evidence from economic history. *J. Econ. Perspect.* 27(1):23–44.

Mowery DC, Oxley JE, Silverman BS (1996) Strategic alliances and interfirm knowledge transfer. *Strateg. Manag. J.* 17(1):77–91.

Nelson RR (1993) *National innovation systems: a comparative analysis* (Oxford university press).

North DC (1990) *Institutions, institutional change and economic performance* (Cambridge university press).

Obstfeld D (2005) Social networks, the tertius iungens orientation, and involvement in innovation. *Adm. Sci. Q.* 50(1):100–130.

Owen-Smith J, Riccaboni M, Pammolli F, Powell WW (2002) A comparison of US and European university-industry relations in the life sciences. *Manag. Sci.* 48(1):24–43.
Pachucki MA, Breiger RL (2010) Cultural holes: Beyond relationality in social networks and culture. *Annu. Rev. Sociol.* 36:205–224.
Park WG (2008) International patent protection: 1960–2005. *Res. Policy* 37(4):761–766.
Penner-Hahn J, Shaver JM (2005) Does International Research and Development Increase Patent Output? an Analysis of Japanese Pharmaceutical Firms. *Strateg. Manag. J.* 26(2):121–140.
Phelps C, Heidl R, Wadhwa A (2012) Knowledge, networks, and knowledge networks a review and research agenda. *J. Manag.* 38(4):1115–1166.
Phelps CC (2010) A longitudinal study of the influence of alliance network structure and composition on firm exploratory innovation. *Acad. Manage. J.* 53(4):890–913.
Podolny JM (2001) Networks as the Pipes and Prisms of the Market. *Am. J. Sociol.* 107(1):33–60.
Porter ME (1996) What is Strategy ? *Harv. Bus. Rev.* 74(6):61–78.
Renyi A, Erdos P (1959) On random graphs. *Publ. Math.* 6(290–297):5.
Rogan M, Sorenson O (2014) Picking a (Poor) Partner A Relational Perspective on Acquisitions. *Adm. Sci. Q.* 59(2):301–329.
Rosenkopf L, Almeida P (2003) Overcoming local search through alliances and mobility. *Manag. Sci.* 49(6):751–766.
Rosenkopf L, Nerkar A (2001) Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. *Strateg. Manag. J.* 22(4):287–306.
Rothaermel FT, Hess AM (2007) Building dynamic capabilities: Innovation driven by individual-, firm-, and network-level effects. *Organ. Sci.* 18(6):898–921.
Schilling MA, Phelps CC (2007) Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Manag. Sci.* 53(7):1113–1126.
Schumpeter J (1942) *Capitalism, Socialism and Democracy* (Perennial, New York).
Scott WR (1995) Institutions and organizations. Foundations for organizational science. *Lond. Sage Publ. Ser.*
Selznick P (1957) Leadership in administration: A sociological interpretation. *Evanst. IL Row Peterson*.
Simmel G (1950) *The sociology of georg simmel* (Simon and Schuster).
Simonin BL (2004) An empirical investigation of the process of knowledge transfer in international strategic alliances. *J. Int. Bus. Stud.* 35(5):407–427.
Stinchcombe AL (1965) Organizations and social structure. *J G March Handb. Organ.* (Rand McNally, Chicago), 142–193.
Szulanski G (1996) Exploring internal stickiness: Impediments to the transfer of best practice within the firm. *Strateg. Manag. J.* 17(S2):27–43.
Tortoriello M, Krackhardt D (2010) Activating cross-boundary knowledge: the role of Simmelian ties in the generation of innovations. *Acad. Manage. J.* 53(1):167–181.
Tushman ML (1977) Special Boundary Roles in the Innovation Process. *Adm. Sci. Q.* 22(4):587–605.
Tushman ML, Anderson P (1986) Technological discontinuities and organizational environments. *Adm. Sci. Q.* 31(3):439–465.
Vasudeva G, Zaheer A, Hernandez E (2013a) The embeddedness of networks: Institutions, structural holes, and innovativeness in the fuel cell industry. *Organ. Sci.* 24(3):645–663.
Vasudeva G, Zaheer A, Hernandez E (2013b) The Embeddedness of Networks: Institutions, Structural Holes, and Innovativeness in the Fuel Cell Industry. *Organ. Sci.* 24(3):645–663.
Vidal E, Mitchell W (2015) Adding by subtracting: the relationship between performance feedback and resource reconfiguration through divestitures. *Organ. Sci.* 26(4):1101–1118.
Zaheer A, Hernandez E (2011a) The Geographic Scope of the MNC and its Alliance Portfolio: Resolving the Paradox of Distance. *Glob. Strategy J.* 1(1):109–126.
Zaheer A, Hernandez E (2011b) The Geographic Scope of the MNC and its Alliance Portfolio: Resolving the Paradox of Distance. *Glob. Strategy J.* 1(1):109–126.
Zaheer S (1995) Overcoming the liability of foreignness. *Acad. Manage. J.* 38(2):341–363.

Figure 1: Stylized global R&D alliance networks for firms 1 and 2

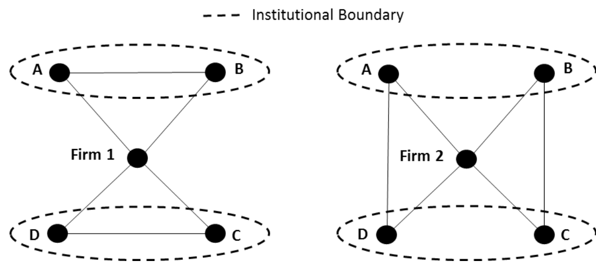

Figure 2: Typology of brokerage configurations

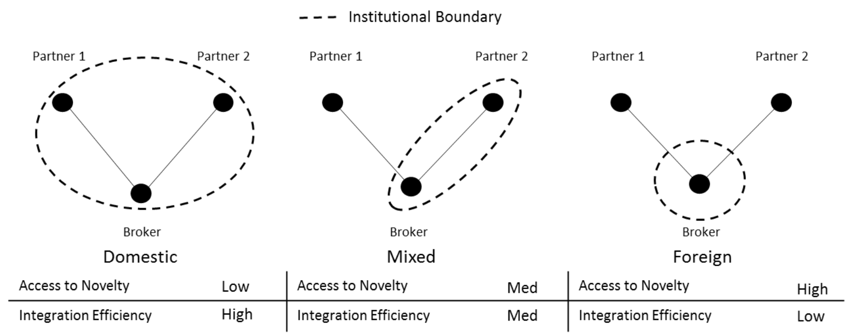

Figure 3: Effect of Triad Configurations on Innovation Volume

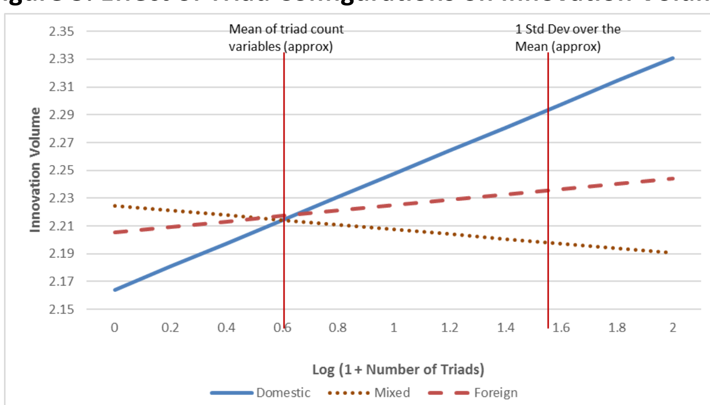

Figure 4: Effect of Triad Configurations on Innovation Radicalness

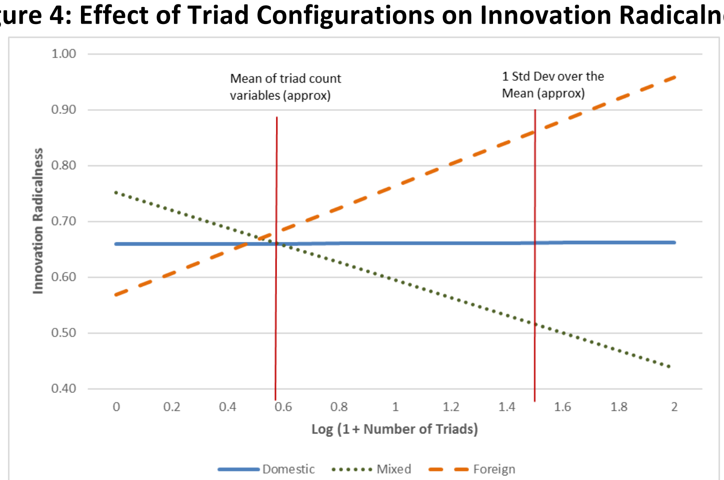

Table 1: Summary statistics and correlations

Sl	Variable	Mean	SD	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	Innovation Volume ^	2.21	1.32	0.69	6.74	1.00																				
2	Innovation Radicalness	0.66	2.72	-34.64	76.15	0.08	1.00																			
3	Domestic ^	0.61	1.11	0	6.66	0.25	0.00	1.00																		
4	Mixed ^	0.58	1.09	0	6.63	0.21	-0.02	0.75	1.00																	
5	Foreign ^	0.47	0.96	0	6.75	0.22	-0.03	0.29	0.58	1.00																
6	Network Efficiency	0.94	0.14	0.13	1	0.00	0.00	0.03	0.03	0.03	1.00															
7	Network Centrality	0.02	0.03	0	0.58	0.23	0.04	0.58	0.57	0.48	-0.15	1.00														
8	Closed Domestic ^	0.15	0.41	0	3.56	0.14	0.00	0.64	0.51	0.21	-0.33	0.58	1.00													
9	Closed Mixed ^	0.11	0.37	0	3.50	0.15	-0.01	0.52	0.60	0.39	-0.26	0.55	0.56	1.00												
10	Closed Foreign ^	0.10	0.35	0	3.69	0.13	-0.01	0.11	0.29	0.59	-0.29	0.42	0.12	0.35	1.00											
11	Within Triad Technological Distance	0.71	0.80	0	5.22	0.13	0.00	0.37	0.39	0.38	0.05	0.27	0.19	0.15	0.15	1.00										
12	Triad Portfolio Balance	0.17	0.30	0	0.78	0.16	-0.01	0.59	0.86	0.42	0.02	0.40	0.33	0.45	0.16	0.42	1.00									
13	Technological Base ^	2.43	1.81	0	8.19	0.64	-0.02	0.23	0.22	0.25	0.03	0.15	0.12	0.14	0.12	0.12	0.16	1.00								
14	Partner Technological Base ^	4.10	2.43	0	9.47	0.10	-0.04	0.48	0.52	0.43	-0.09	0.42	0.31	0.33	0.25	0.41	0.49	0.10	1.00							
15	Avg Technological Distance to Partners	0.36	0.32	0	2	-0.14	0.03	-0.16	-0.14	-0.11	0.04	-0.08	-0.09	-0.11	-0.06	0.06	-0.14	-0.19	-0.17	1.00						
16	No of firms from same country ^	5.41	1.62	0	6.82	-0.03	-0.07	0.33	0.22	-0.18	0.03	0.05	0.21	0.14	-0.20	0.06	0.23	0.00	0.17	-0.06	1.00					
17	Percentage Foreign Partners	0.45	0.43	0	1	0.02	-0.03	-0.30	-0.04	0.31	0.01	-0.04	-0.23	-0.04	0.24	0.03	-0.04	0.08	0.01	0.04	-0.60	1.00				
18	More than two ties	0.60	0.49	0	1	0.19	-0.02	0.44	0.44	0.40	-0.34	0.33	0.29	0.25	0.23	0.72	0.46	0.22	0.56	-0.20	0.10	0.01	1.00			
19	Firm country IP protection	4.67	0.31	1.65	4.88	-0.08	-0.14	0.25	0.19	-0.09	0.04	0.01	0.16	0.12	-0.13	0.07	0.19	0.02	0.20	-0.09	0.79	-0.43	0.11	1.00		
20	Avg Partner country IP protection	4.69	0.24	2.27	4.88	-0.05	-0.17	0.11	0.00	0.00	0.06	-0.03	0.08	0.01	-0.01	0.00	-0.04	0.08	0.10	-0.08	0.22	-0.25	0.01	0.38	1.00	
21	Average Within triad prior ties	0.05	0.18	0.00	6.38	0.10	-0.01	0.30	0.29	0.23	-0.01	0.26	0.27	0.23	0.14	0.22	0.23	0.12	0.22	-0.06	0.07	-0.03	0.23	0.06	0.05	1.00

N = 11,704. ^ Logged Variable

Table 2: Main Results – Fixed Effects and Matching Models. Models 1-3 includes patenting and non-patenting firms, Models 4-9 only includes firms that patent only (radicalness defined only for firms that patent). Heteroscedasticity robust standard errors clustered by firm in parentheses. ^ - Logged Variable. # - p values from one tailed Wald test. + < 0.1, *<0.05, **<0.01, ***<0.001

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9
Dependent Variable	**Volume**	**Volume**	**Volume**	**Volume**	**Volume**	**Volume**	**Radicalness**	**Radicalness**	**Radicalness**
Domestic ^		0.1390***	0.1518***		0.0834**	0.1104**		0.0016	0.0239
		(0.0330)	(0.0397)		(0.0307)	(0.0376)		(0.0687)	(0.0843)
Mixed ^		-0.0686	-0.0769		-0.0171	-0.1108+		-0.1571	-0.2755+
		(0.0454)	(0.0712)		(0.0422)	(0.0652)		(0.1111)	(0.1526)
Foreign ^		0.0650+	0.0075		0.0194	0.0015		0.1953**	0.2973**
		(0.0365)	(0.0474)		(0.0363)	(0.0420)		(0.0624)	(0.0948)
Network Efficiency	0.5257**	0.2451	-5.5561*	0.4909**	0.3275+	-1.8741	0.5867	0.4703	0.7113
	(0.1980)	(0.2036)	(2.2569)	(0.1842)	(0.1933)	(1.7062)	(0.3955)	(0.4381)	(2.6967)
Network Centrality	0.6569	0.1345	-5.1852**	0.6909	0.4122	-2.6291+	-3.0068+	-3.2049*	-6.7959
	(0.7910)	(0.8065)	(1.9752)	(0.7228)	(0.7417)	(1.4777)	(1.6235)	(1.6289)	(4.2231)
Closed Domestic ^	0.0913	-0.0112	0.0534	0.0222	-0.0454	0.1356	-0.0145	0.0362	0.2289
	(0.0596)	(0.0658)	(0.1814)	(0.0605)	(0.0642)	(0.1562)	(0.1904)	(0.1878)	(0.2694)
Closed Mixed ^	0.1014	0.0632	-0.0834	0.1457*	0.1180*	0.2417	0.0833	0.0937	0.0800
	(0.0733)	(0.0732)	(0.1781)	(0.0593)	(0.0598)	(0.1660)	(0.1868)	(0.2026)	(0.2661)
Closed Foreign ^	0.0821	0.0491	0.2053	0.0490	0.0407	0.0425	0.2922**	0.1478	-0.2641
	(0.0899)	(0.0867)	(0.1560)	(0.0793)	(0.0797)	(0.1346)	(0.1059)	(0.1108)	(0.2591)
Within Triad Technological Distance	0.0249	0.0297	-0.0167	0.0096	0.0126	0.0427	0.0747	0.0742	0.0615
	(0.0266)	(0.0261)	(0.0286)	(0.0243)	(0.0238)	(0.0300)	(0.0810)	(0.0802)	(0.0703)
Triad Portfolio Balance	0.0951	0.1400	0.0474	0.0437	0.0301	0.2477*	-0.3667	-0.1136	0.4892+
	(0.0594)	(0.0974)	(0.1061)	(0.0551)	(0.0888)	(0.1105)	(0.2552)	(0.2444)	(0.2521)
Technological Base ^	-0.0534	-0.0622	-0.1037	0.0822*	0.0763+	-0.0279	-0.1313+	-0.1286	0.0985
	(0.0417)	(0.0411)	(0.0782)	(0.0413)	(0.0408)	(0.0469)	(0.0794)	(0.0799)	(0.2364)
Partner Technological Base ^	-0.0058	-0.0136	0.0045	-0.0027	-0.0080	0.0048	0.0196	0.0133	0.0258
	(0.0105)	(0.0106)	(0.0100)	(0.0101)	(0.0102)	(0.0102)	(0.0311)	(0.0309)	(0.0301)
Avg Technological Distance to Partners	0.1430***	0.1445***	-0.0181	0.0669	0.0664	0.0221	0.1446	0.1581	0.2866+
	(0.0420)	(0.0419)	(0.0450)	(0.0461)	(0.0460)	(0.0428)	(0.1527)	(0.1525)	(0.1612)
No of firms from same country ^	-0.0639	-0.0524	-0.1326	-0.1491	-0.1416	-0.2461*	-0.4799*	-0.4691*	-0.2413
	(0.1171)	(0.1160)	(0.1292)	(0.1113)	(0.1112)	(0.1215)	(0.1991)	(0.1946)	(0.4312)
Percentage Foreign Partners	0.0097	0.0509	-0.4577*	0.0455	0.0779	0.1885	0.1162	0.0579	-0.4423
	(0.0674)	(0.0694)	(0.2168)	(0.0633)	(0.0664)	(0.2042)	(0.1787)	(0.1758)	(0.4733)
More than two ties	0.0942+	0.0240	0.0200	0.0542	0.0166	-0.0291	-0.1569	-0.2002	-0.3777*
	(0.0518)	(0.0526)	(0.0590)	(0.0497)	(0.0487)	(0.0518)	(0.1790)	(0.1792)	(0.1809)
Firm country IP protection	0.1145	0.1259	0.1850	0.0602	0.0848	0.2680	1.0286*	0.8938*	0.1257
	(0.1783)	(0.1781)	(0.1742)	(0.1613)	(0.1561)	(0.1990)	(0.4361)	(0.4242)	(0.7833)
Avg Partner country IP Protection	-0.1229	-0.1409	-0.2397*	0.0001	-0.0101	-0.0459	0.0713	0.0684	-0.3917
	(0.1029)	(0.1024)	(0.1122)	(0.0990)	(0.0991)	(0.1158)	(0.3847)	(0.3803)	(0.6154)
Average Within triad prior ties	0.0831	0.0792	0.0305	0.0861	0.0821	-0.0277	0.1668	0.1726	0.2242
	(0.0946)	(0.0940)	(0.0903)	(0.0896)	(0.0892)	(0.0693)	(0.1432)	(0.1431)	(0.1583)
Firm Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Strata Fixed Effects			Y			Y			Y
Num of Obs.	17,213	17,213	11,101	11,764	11,764	7,748	11,764	11,764	7,748
R Squared (Within)	0.2295	0.2345	0.0210	0.2251	0.2279	0.0210	0.1268	0.1282	0.0071
AIC	32,473.0	32,365.7	16172.2	18,184.2	18,148.1	9,517.8	47,741.9	47,729.1	29,320.6
Log-Likelihood	-16,200.5	-16,143.8	-6127.1	-9,056.1	-9,035.0	-3314.9	-23,835.0	-23,825.5	-13,216.3
P (Domestic = Mixed) #		0.000	0.009		0.034	0.007		0.148	0.069
P (Domestic = Foreign) #		0.049	0.002		0.072	0.006		0.010	0.004
P (Mixed = Foreign) #		0.017	0.206		0.280	0.118		0.007	0.004

Table 3: Brokerage configurations based on country clusters (Innovation Volume)

Triad types are determined on the basis of the median hierarchical cluster of countries based on cultural, administrative, geographic or economic distances as indicated. Heteroscedasticity robust standard errors clustered by firm in parentheses. ^ - Logged Variable. # - p values from one tailed Wald test. + < 0.1, *<0.05, **<0.01, ***<0.001.

	Fixed Effects Models				Matched Models			
DV : Innovation Volume	**Model 10a Cultural**	**Model 11a Admin.**	**Model 12a Geographic**	**Model 13a Economic**	**Model 10b Cultural**	**Model 11b Admin.**	**Model 12b Geographic**	**Model 13b Economic**
Domestic ^	0.0653*	0.0934**	0.0836**	0.0765*	0.1041**	0.1128**	0.0954**	0.0847*
	(0.0298)	(0.0297)	(0.0291)	(0.0329)	(0.0339)	(0.0356)	(0.0360)	(0.0331)
Mixed ^	0.0122	-0.0495	-0.0125	-0.0059	-0.1010*	-0.1171+	-0.0795	-0.0860+
	(0.0364)	(0.0354)	(0.0340)	(0.0351)	(0.0444)	(0.0674)	(0.0538)	(0.0456)
Foreign ^	0.0179	0.0331	0.0161	0.0332	0.0221	0.0062	0.0085	0.0494
	(0.0452)	(0.0346)	(0.0374)	(0.0355)	(0.0417)	(0.0412)	(0.0404)	(0.0411)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Strata Fixed Effects					Y	Y	Y	Y
Num of Obs.	11,764	11,764	11,764	11,764	7,748	7,748	7,748	7,748
R Squared (Within)	0.2263	0.2285	0.2281	0.2274	0.0203	0.0213	0.0194	0.0202
AIC	18,171.80	18,137.90	18,144.4	18,155.1	9,357.4	9,351.2	9,366.2	9,160.0
Log-Likelihood	-9,046.9	-9,029.9	-9,033.2	-9038.5	-3,234.7	-3,231.6	-3,239.1	-3136.0
P (Domestic = Mixed) #	0.111	0.001	0.017	0.036	0.000	0.004	0.011	0.003
P (Domestic = Foreign) #	0.182	0.079	0.068	0.170	0.036	0.007	0.023	0.205
P (Mixed=Foreign) #	0.465	0.058	0.297	0.238	0.044	0.099	0.139	0.031

Table 4: Brokerage configurations based on country clusters (Innovation Radicalness)

Triad types are determined on the basis of the median hierarchical cluster of countries based on cultural, administrative, geographic or economic distances as indicated. Heteroscedasticity robust standard errors clustered by firm in parentheses. ^ - Logged Variable. # - p values from one tailed Wald test. + < 0.1, *<0.05, **<0.01, ***<0.001.

	Fixed Effects Models				Matched Models			
DV : Innovation Radicalness	**Model 14a Cultural**	**Model 15a Admin.**	**Model 16a Geographic**	**Model 17a Economic**	**Model 14b Cultural**	**Model 15b Admin.**	**Model 16b Geographic**	**Model 17b Economic**
Domestic ^	0.0519	0.0104	0.0345	0.0254	0.0813	0.0129	0.0135	0.0320
	(0.0774)	(0.0679)	(0.0655)	(0.0644)	(0.0853)	(0.0844)	(0.0815)	(0.0880)
Mixed ^	-0.1412	-0.1702	-0.1616+	-0.0891	-0.1514	-0.1940	-0.0716	-0.1963
	(0.0983)	(0.1068)	(0.0932)	(0.0923)	(0.1062)	(0.1274)	(0.1303)	(0.1241)
Foreign ^	0.2142***	0.2098***	0.2061**	0.1646**	0.2092*	0.2558**	0.2192*	0.2851*
	(0.0637)	(0.0635)	(0.0683)	(0.0620)	(0.0848)	(0.0911)	(0.0856)	(0.1131)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Strata Fixed Effects					Y	Y	Y	Y
Num of Obs.	11,764	11,764	11,764	11,764	7,748	7,748	7,748	7,748
R Squared (Within)	0.1279	0.1284	0.1283	0.1274	0.0065	0.0068	0.0065	0.0071
AIC	47,733.6	47,727.3	47,728.8	47,740.5	29,270.2	29,267.6	29,270.4	29,265.6
Log-Likelihood	-23,827.8	-23,824.6	-23,825.4	-23,831.2	-13,191.1	-13,189.8	-13,191.2	-13,188.8
P (Domestic = Mixed) #	0.099	0.109	0.057	0.188	0.070	0.124	0.316	0.109
P (Domestic = Foreign) #	0.016	0.007	0.027	0.037	0.077	0.007	0.016	0.008
P (Mixed=Foreign) #	0.005	0.004	0.004	0.020	0.015	0.007	0.055	0.011