BEYOND THE HORIZON:

INTRA-FIRM COLLABORATION BETWEEN AND BEYOND CLUSTERS AND THE QUALITY OF FIRM INVENTION

Sohyun Park

park1906@umn.edu

Aks Zaheer

azaheer@umn.edu

Aseem Kaul

akaul@umn.edu

Strategic Management & Entrepreneurship Department

Carlson School of Management, University of Minnesota

Minneapolis, MN, 55455

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ABSTRACT

In this study, we argue that cross-regional collaboration within firms may serve to bridge pockets of knowledge separated by geography, leading to more radical and impactful inventions. Specifically, we contend that cross-regional collaborations may both deepen the firm's knowledge base within its existing technological domain through collaborations between industry clusters, and broaden its knowledge base across new technological domains through collaborations beyond industry clusters, with both relationships being stronger, the more collaborating inventors are able to draw on local knowledge spillovers. Results from a longitudinal study of patenting in the U.S. Medical Device industry over the period 1982-2006 support these predictions.

INTRODUCTION

Internal collaboration as a means of organizational search and innovation has long been a topic of interest to scholars of strategic management (Fleming, Mingo and Chen, 2007; Nerkar and Paruchuri, 2005; Paruchuri, 2010; Reagans and McEvily, 2003; Tortoriello & Krackhardt, 2010; Tortoriello, Reagans, & McEvily, 2012; Toh and Polidoro, 2013; Funk, 2014). Building on insights from the knowledge-based view of the firm (Kogut & Zander, 1992; Grant, 1996a; Liebeskind, 1996), this work highlights the potential for knowledge recombination within organizational boundaries as a means of developing innovative new technologies (Fleming, 2001; Argyres, 1996; Galunic and Rodan, 1998; Carnabuci and Operti, 2013). Early work in this area focused on the role of intra-organizational recombination across technological or knowledge domains (Tushman, 1978; Rosenkopf and Nerkar, 2001; Nerkar, 2003; Ahuja and Lampert, 2001; Katila and Ahuja, 2002; Nahapiet and Ghoshal, 1998), often through ties that spanned intra-organizational units (Hansen, 1999; 2002; Tushman and Katz, 1980; Tortoriello et al., 2012; Tsai, 2001; Nerkar and Paruchuri, 2005; Karim and Kaul, 2015; Grigoriu and Rothaermel, 2017). More recently, a growing body of scholarship has emphasized intra-organizational collaborations across geographies, often in the context of multinational firms, showing that collaborations within such organizations enable them to tap into knowledge sources at a distance, typically abroad (Bell and Zaheer, 2007; Hansen and Løvås, 2004; Paruchuri and Awate, 2017; Frost and Zhou, 2005; Singh, 2005; 2008; Berry, 2014; 2018).

Extant work provides substantial evidence for the role of intra-organizational collaboration as a conduit for cross-geography knowledge flows, but the consequences of such collaborations (and the resulting knowledge flows) for the nature and quality of firm innovation remain unclear. While some prior research suggests that cross-regional collaboration may produce high impact breakthrough inventions (Singh, 2008), others argue that such collaborations mostly protect existing firm knowledge from appropriation (Alcácer and Zhao, 2012). Relatedly, while some studies suggest that cross-regional collaboration may bring together more technologically diverse knowledge (Berry, 2014), thus producing more radical inventions (Berry, 2018), others show that knowledge sharing across regions is only valuable within a knowledge domain (Phene, Fladmoe-Lindquist, and Marsh, 2006) or for relatively imitative innovations (Leiponen and Helfat, 2011).

In this study, we investigate the relationship between cross-regional collaboration and the nature of a firm's inventions. We contend that cross-regional collaborations help inventors search beyond the relatively narrow knowledge base in their immediate geographic vicinity (McEvily and Zaheer, 1999), thus producing more novel and impactful inventions (Ahuja and Lampert, 2001). While the basic idea of reaching out to access novelty is well-grounded in the literature (e.g. Burt, 1992) our contribution goes considerably beyond that to spell out the precise nature of cross-regional invention outcomes in terms of radicalness and impact, as well as their relationship with different types of cross-regional collaboration. Specifically, we not only separate cross-regional collaborations from within-region collaborations, we also distinguish between cross-regional collaborations where inventors are located in different industry clusters (between-cluster collaboration) and those where one or more inventors are outside an industry cluster (beyond-cluster collaboration). Figure 1 maps out these different types of intra-firm collaborations.

Insert Figure 1 about here

We expect cross-regional collaborations to boost the quality of firm invention in two ways. First, we expect them to deepen a firm's knowledge by enabling recombination across geographically separated pockets of knowledge within its existing knowledge domains, thus directly producing more impactful inventions (Ahuja and Katila, 2004; Phene et al., 2006; Singh, 2008). We expect this relationship to be especially strong for collaborations between clusters. Second, we expect cross-regional collaborations to broaden a firm's knowledge by exposing its inventors to a wider range of industries, thus enabling recombination beyond its existing knowledge domains (Rosenkopf and Nerkar, 2001). Such recombination will produce more inventions that are potentially radical—i.e., inventions that bring together previously distant technologies in new to the world combinations (Berry, 2018; Eggers and Kaul, 2018)—which, in turn, are likely to prove more impactful (Ahuja and Lampert, 2001). We expect this indirect relationship to be especially strong for collaborations beyond clusters. We further expect both these relationships to be stronger the more the collaborating inventors are embedded in their local knowledge networks because of the deeper understanding of their local knowledge domain (Frost, 2001; Berry, 2018; Phene and Almeida, 2008) and their resulting ability to draw on local knowledge spillovers (McEvily and Zaheer, 1999; Leiponen and Helfat, 2011; Funk, 2014; Whittington et al., 2009).

We test and find support for these arguments in the context of the U.S. medical device industry from 1982 to 2006. Using data on 26,618 patents by 1,086 firms in the industry, we show that patents that involve collaboration between inventors located in different metropolitan statistical areas (MSAs) within the United States are significantly more likely to make connections between hitherto distant knowledge areas with potentially radical invention outcomes (Berry, 2018; Eggers and Kaul, 2018) as well as significantly more likely to emerge as breakthrough inventions (Ahuja and Lampert, 2001; Phene et al., 2006), with the latter relationship being partially mediated by the former. Consistent with our theory, we also find that these relationships are stronger, the more the patent draws on local knowledge within the collaborators' regions. In particular, we find that local spillovers moderate the positive relationship between collaboration beyond clusters and potentially radical invention, as well as the positive relationship between collaboration between clusters and patent impact. These results strongly support our theoretical predictions. In addition, supplementary analysis at the firm level shows a negative and significant relationship between a firm's tendency to engage in cross-regional collaboration and the number of patents it produces, suggesting that cross-regional collaboration, while beneficial for the quality of firm invention, may hurt invention quantity, possibly due to the challenges of collaborating across geographies.

These findings make several contributions to extant literature. First, we extend research on cross-regional knowledge collaborations within firms, moving beyond the observation that such collaborations are an important conduit of knowledge transfer across geographies (Hansen and Løvås, 2004; Singh, 2005; 2008; Berry, 2014; Paruchuri and Awate, 2017) to systematically investigate the implications of different forms of intra-firm cross-regional collaborations for the quality of firm inventions. We show that such collaborations may boost the quality of firm inventions in two distinct ways—directly, by enabling deeper recombination within existing technology domains to produce higher impact inventions, and indirectly, by enabling broader recombination across technology domains to produce potentially radical inventions—and that these relationships are moderated by the embeddedness of the collaborating inventors in their local knowledge environments, as well as by their location within or outside industry clusters. We thus offer a richer and more nuanced perspective on a phenomenon of growing importance (Singh, 2008; Berry, 2014). In doing so, we also contribute to a more precise understanding of the role of geography in innovation, moving beyond the general benefits from geographically dispersed R&D to elucidate the specific mechanisms through which these benefits arise, and describe the conditions under which such R&D may produce inventions that are radical (Berry 2018) or incremental (Phene et al., 2006; Leiponen and Helfat, 2011) and high or low in their impact (Singh, 2008).

Second, our study contributes to the literature on knowledge agglomeration and industry clusters (Alcácer and Zhao, 2016; Audretsch and Feldman, 1996; Jaffe, Trajtenberg, and Henderson, 1993; Saxenian, 1996; Delgado, Porter, and Stern, 2014) and suggests the conditions under which a firm's presence in these clusters may translate into competitive advantage (Shaver and Flyer, 2000; Tallman, Jenkins, Henry, and Pinch, 2004; Owen-Smith and Powell, 2004; Whittington et al., 2009; Funk, 2014). Our findings indicate that embeddedness in clusters may be especially beneficial for firms that are able to recombine knowledge sourced through local spillovers with more distant knowledge tapped through internal cross-regional collaborations (McEvily and Zaheer, 1999; Bell and Zaheer, 2007); in fact, absent such intra-firm collaborations, the results suggest that reliance on local spillovers may actually be harmful to the quality of firm innovation, being associated with relatively incremental inventions. We also emphasize the benefits of intra-firm ties not only between clusters, but beyond them, showing how an R&D presence outside of an industry cluster may sometimes be beneficial by enabling the firm to broaden its knowledge sources and produce more radical inventions. Our study is also among the first to explore cross-regional intra-firm collaborations between geographies within a single country; most prior work has focused on collaborations across countries (Singh, 2005; 2008; Berry, 2014), despite evidence that knowledge flows between locations within a country may impact innovation differently from such flows across countries (Tallman and Phene, 2007; Leiponen and Helfat, 2011).

Finally, our study contributes to the literature on knowledge recombination within firms (Kogut and Zander, 1992; Ahuja, Lampert, and Tandon, 2008; Galunic and Rodan, 1998). While prior work in this area has frequently looked at knowledge recombination across either technological boundaries (Rosenkopf and Nerkar, 2001; Katila and Ahuja, 2002) or geographic boundaries (Ahuja and Katila, 2004), we bring these two dimensions together, showing that cross-regional collaborations within the firm can not only deepen the firm's knowledge base within existing technological domains (Phene et al., 2006), it can also broaden its base across technological domains. We thus show that intra-firm cross-regional collaborations can be an important source of potentially radical inventions (Dewar and Dutton, 1986; Henderson, 1993; Berry, 2018; Eggers and Kaul, 2018), especially when they involve collaborations beyond industry clusters.

THEORY AND HYPOTHESES

Knowledge recombination and collaboration within firms

The recombination of existing knowledge to create new technologies and products is a fundamental purpose of organizations, and a key source of their competitive advantage (Kogut and Zander, 1992; Grant, 1996a; 1996b; Liebeskind, 1996, Argyres and Zenger, 2012). Building on the view that innovation is fundamentally a recombinant process (Schumpeter, 1934; Nelson and Winter, 1982; Fleming, 2001), a longstanding literature in strategy and management has highlighted the potential for organizations to bring together existing knowledge within their boundaries to create new and valuable innovations (Hargadon and Sutton, 1997; Galunic and Rodan, 1998; Ahuja and Lampert, 2001; Ahuja et al., 2008). In particular, prior scholarship has stressed the ways in which shared incentives and understandings within an organizational boundary (Agryes, 1996; Brown and Duguid, 2001; Tortoriello & Krackhardt, 2010) can allow firms to bring together knowledge across distinct technological domains (Rosenkopf and Nerkar, 2001; Katila and Ahuja, 2002) and organizational units (Tushman, 1977; Tushman and Katz, 1980; Tsai, 2002; Miller, Fern, and Cardinal, 2007; Karim and Kaul, 2015), thus enabling recombination that may not otherwise have been feasible.

Such intra-organizational recombination of knowledge is made possible by the internal networks of ties between organizational actors that allow them to share knowledge with each other (Hansen, 1999; 2002; Tsai, 2001; Reagans and McEvily, 2003; Nerkar and Paruchuri, 2005). Some work in this area focuses on the informal ties of friendship or information sharing between organizational actors (Hansen, 1999; 2002; Hansen and Løvås, 2004; Hansen, Mors and Løvås, 2005; Bell and Zaheer, 2007; Kleinbaum, 2012), though scholars have increasingly come to recognize that such informal ties may prove insufficient for knowledge recombination unless they are strongly embedded in a supportive social structure (Reagans and McEvily, 2003; Tortoriello and Krackhardt, 2010; Tortoriello et al., 2012; Gomez-Solorzano et al., 2019). Consistent with this insight, other research in this area has examined the role of formal ties, especially formal collaborations between inventors, in enabling knowledge recombination within firms (Nerkar and Paruchuri, 2005; Paruchuri, 2010; Carnabuci and Operti, 2013).

One form of intra-organizational collaboration that has received growing attention in recent literature is cross-regional collaboration, i.e., collaboration between inventors in different geographies (Frost and Zhou, 2005; Singh, 2005; 2008; Berry, 2014; Paruchuri and Awate, 2017). Underlying this interest is the recognition that knowledge, being partly tacit (Polanyi, 1966; Nelson and Winter, 1982), is typically sticky and difficult to transfer over long distances (Adams and Jaffe, 1996; Szulanski, 1996; 2002). As a result, technological knowledge tends to cluster by location, with different locations developing deep pools of knowledge and expertise specialized to that location (Jaffe, Trajtenberg, and Henderson, 1993; Audretsch and Feldman, 1996; Furman, Porter, and Stern, 2002; Saxenian, 1996; Almeida and Kogut, 1999; Delgado et al., 2014). This, in turn, means that firms may pursue knowledge-seeking motives when making location choices (Dunning, 1998; Kuemmerle, 1999; Nachum and Zaheer, 2005; Alcácer, 2006; Nachum, Zaheer, and Gross, 2008), establishing R&D operations in knowledge-rich locations so as to benefit from local spillovers (Chung and Alcácer, 2002; Berry, 2006; Alcácer and Chung, 2007; Alcácer and Delgado, 2016). Doing so helps boost the firm's innovativeness, with prior research providing substantial evidence for a positive relationship between a firm's ability to tap into local spillovers and its subsequent patenting (Almeida and Phene, 2004), especially if the firm is strongly embedded (Owen-Smith and Powell, 2004; Whittington et al., 2009) in a location with substantial relevant knowledge (Frost, 2001; Phene and Almeida, 2008) and possesses the relevant internal capabilities (Penner-Hahn and

Shaver, 2005) and structure (Funk, 2014) to absorb spillovers.

While firms with geographically dispersed R&D may thus produce a greater quantity of inventions, the effect of cross-region R&D on the quality of invention remains unclear. Some prior work suggests that spanning multiple locations may boost invention quality (Phene and Almeida, 2008), though the benefits of geographic diversity may diminish beyond a point (Ahuja and Katila, 2004; Lahiri, 2010). Others show that having multiple geographic locations has a negative impact on the quality of a firm's invention (Singh, 2008), perhaps due to the loss of scale and scope economies in R&D (Feinberg and Gupta, 2004; Lahiri, 2010; Leiponen and Helfat, 2011). Evidence is also mixed on the effect of geographic diversity on the nature of firm invention, with some prior studies showing that firms that are able to draw on local knowledge across regions produce more radical inventions (Berry, 2018), while others argue that spanning multiple locations is only valuable for inventions that are imitative (Leiponen and Helfat, 2011) or for recombinations of knowledge within a narrow technological domain (Phene et al., 2006; Chung and Yeaple, 2008).

Cross-regional collaboration and invention quality

In this study, we examine the relationship between cross-regional collaboration within a firm and the quality of its inventions. Cross-regional collaborations between individuals within an organization have been shown to enable knowledge flow across geographies (Ghoshal, Korine, and Szulanski, 1994; Singh, 2005; Frost and Zhou, 2005; Bell and Zaheer, 2007), and thus help to bring together a wider range of knowledge (Berry, 2014; Paruchuri and Awate, 2017). Yet few studies have looked directly at the relationship between such collaboration and the quality of the resulting inventions, except for some evidence that prior ties between inventors may moderate the relationship between geographic dispersion and invention quality (Singh, 2008; Lahiri, 2010). Moreover, as with research on geographic diversity in R&D more generally, prior research has focused on collaboration across countries rather than collaboration across locations within a country (Leiponen and Helfat, 2011), despite evidence that the nature of knowledge flows between countries may differ from those between locations within a country (Tallman and Phene, 2007). Therefore, scholarly understanding on how the latter may impact invention quality is limited. Examining the role of cross-regional collaborations within the firm is thus critical to ascertaining whether, and how, geographic dispersion of R&D activities even within a country may influence invention quality.

Our main contention is that the nature of cross-regional collaborations within organizations provides inventors with access to different kinds of distant and more novel knowledge and thereby allows them to produce more impactful and more radical inventions. In particular, we argue that cross-regional collaboration will allow the firm to recombine distinct bodies of local knowledge that would otherwise remain geographically separated. Figure 2 represents this argument visually.

Insert Figure 2 about here

Consider two inventors, A and B, located in separate regions, as shown in Figure 2. Each inventor benefits from local spillovers, i.e., she has access to diverse sets of knowledge within her region. Her informal ties with other inventors in the region both within and (more importantly) beyond the organization will give her the potential to tap into to a rich store of tacit knowledge that 'sticks' within that region (Saxenian, 1996; Bell and Zaheer, 2007; Whittington et al., 2009), enabling her to develop location-specific technological expertise. Each inventor will then bring this location-specific expertise to the focal cross-regional collaboration, allowing the collaborators to share in each other's unique (though potentially complementary) knowledge. Note that this exchange and recombination of knowledge across locations is made possible by the positions of both inventors within the organizational boundary (Kogut and Zander, 1992; 1993; Carnabuci and Operti, 2013; Paruchuri and Awate, 2017). The fact that both inventors may be joined by their common interest in the firm's success (Argyres, 1996) as well as by a shared community of practice within the organization (Brown and Duguid, 2001), allows them to collaborate and share tacit knowledge in a direct and committed way that ties across organizations, or even informal ties within the same organization, may be unable to achieve (Kogut and Zander, 1993). The strong tie between inventors in different locations within an organization thus gives each access to the other's weak ties with those working in different organizations in the same location. Cross-regional collaboration within an organization thus serves as a bridge between two geographically separated bodies of knowledge (McEvily and Zaheer, 1999), enabling them to be recombined.

What will such recombination mean for the quality of firm invention? To begin with, we expect that knowledge recombinations across regions will result in inventions that are potentially more radical (Berry, 2018; Eggers and Kaul, 2018). Long emphasized in the literature on technology and innovation, radical inventions are those that bring together knowledge from distinct technological domains to create unprecedented or new to the world combinations (Rodan and Galunic, 2004; Nahapiet and Ghoshal, 1998), and in doing so fundamentally shift the prevailing technological trajectory (Dewar and Dutton, 1986; Rosenkopf and Nerkar, 2001; Gatignon, Tushman, Smith, and Anderson, 2002). As prior work has recognized, however, this traditional concept of radical invention is inherently double-barreled, combining the nature of an invention's inputs—whether it brings together knowledge from distant technological domains—with the eventual impact of that invention (Henderson, 1993). To overcome this problem, recent work defines potentially radical[1] inventions as those that make new to the world knowledge recombinations (Dahlin and Behrens, 2005; Berry, 2018; Eggers and Kaul, 2018) but may or may not

[1] Specifically, Eggers and Kaul (2018) use the term potentially radical for patents that make relatively rare citations across citation classes. We use their terminology because, like them, we focus theoretically on the nature of recombination in the invention rather than its success, and because our empirical measures are the same as theirs. Berry (2018) uses a very similar measure, however, and calls it radical invention.

eventually be impactful, so as to avoid sampling on the dependent variable.

The concept of potential radicalness captures recombination across distant knowledge domains rather than distant geographic domains, so recombining knowledge across regions need not necessarily produce potentially radical inventions. Nevertheless, there are at least two reasons why we would expect cross-regional collaborations, which bring together geographically distant knowledge, to be more likely to produce inventions that are also potentially radical. First, different locations will be home to different portfolios of industries (Porter, 1990; Jaffe et al., 1993; Furman et al., 2002). As a result, the technological domains of other inventors in the same location as the collaborating inventors will differ by location. A biotech worker in the Bay Area is likely to be exposed to significant knowledge spillovers from inventors with expertise in computer science and software design, while a biotech worker in Detroit is likely to come into contact with local inventors who specialize in automobile technologies. When an inventor in one location collaborates with an inventor in a different location, she may therefore be exposed to knowledge from domains (industrial or technological) that are different from those available in her local region. Such exposure may spark connections across distant knowledge domains, as the inventors see opportunities to draw on knowledge domains they (and others in their domain) were previously unfamiliar with, potentially producing new-to-the-world recombinations.

Second, even if the mix of industries in the different locations is similar, the specific technological expertise in the two locations may still be different (Audretsch and Feldman, 1996). Firms in the same industry may specialize their R&D activities by location, creating 'centers of excellence' in different regions that focus on different technological domains (Cantwell and Janne, 1999; Frost, Birkinshaw, and Ensign, 2002; Cantwell and Mudambi, 2005). For instance, an automobile engineer in California may specialize in very different technological domains than an automobile engineer in Detroit, so that spillovers in the two locations may belong in different (and potentially distant) technological domains. Thus, other things being equal, we expect that geographically distant knowledge will offer greater potential for new-to-the-world recombinations across distinct technological domains than geographically proximate knowledge (Berry, 2018). We therefore hypothesize:

H1a: Inventions that involve cross-regional collaborations will be more radical than those that do not involve such collaborations.

Not only may cross-regional collaborations produce more potentially radical inventions, they may also lead to inventions that are more technologically impactful. In part, this follows from the more potentially radical nature of inventions involving cross-regional collaboration hypothesized above, since inventions that make new-to-the-world recombinations are also likely to prove more impactful (Henderson, 1993; Eggers and Kaul, 2018). In this way, cross-regional collaborations will have an indirect effect on invention impact, mediated by potential radicalness.

We expect this mediation to be only partial, however, i.e., we expect cross-regional collaboration to also have a direct effect on the impact of a firm's inventions. Specifically, we expect that cross-regional collaboration may also serve to deepen a firm's knowledge within its existing technology domains, thus directly producing more impactful patents. This is because, as already mentioned, knowledge tends to be specialized by location, even within the same industry or technological domain (Cantwell and Janne, 1999; Cantwell and Mudambi, 2005; Berry, 2018). Inventors in one location with expertise in a knowledge domain are likely to possess knowledge that is distinct from, though complementary to, inventors in a different location within the same domain (Chung and Alcácer, 2002; Berry, 2006; Berry and Kaul, 2015). Inventions may be more valuable not only because they draw on a richer set of priors (Ahuja and Lampert, 2001; Katila and Ahuja, 2002;

Ahuja et al., 2008) but because they allow each inventor to combine familiar knowledge from her location with unfamiliar knowledge from her collaborator's location (Nerkar, 2003). Such inventions are also more likely to be seen as novel by others in each location, because they draw on knowledge that is new to other local inventors, and are therefore more likely to be found useful and built on by others, increasing their impact. In contrast, inventions that rely purely on local knowledge[2] will tend to be less impactful because spillovers within a location will tend to make local knowledge partly redundant (Rosenkopf and Almeida, 2003), and the knowledge being recombined will already be familiar to others in the same location so the new invention may have little to set it apart from other inventions in the location (McEvily and Zaheer, 1999). We hypothesize therefore, that:

H1b: Inventions that involve cross-regional collaborations will be more technologically impactful than those that do not involve such collaborations.

The logic for our basic hypotheses regarding invention radicalness from knowledge width and impact from knowledge depth resulting from cross-regional collaboration also implies that these gains are heightened by the embeddedness of the collaborating inventors in their local knowledge environment. If the role of cross-regional collaboration is to serve as a conduit connecting knowledge in two different locations, then the gains from such collaboration will be greater, the more the collaborating inventors are able to draw on local knowledge. Inventors who are well-connected or central in their local environment will have a better access to, and understanding of, local knowledge spillovers (Frost, 2001; Owen-Smith and Powell, 2004; Whittington et al., 2009; Paruchuri and Awate, 2017), and will be able to bring this superior access to the collaborations in

[2] These include both inventions by solo inventors and inventions that involve collaborations between inventors in a single location. We do not distinguish between these two types of inventions in developing our hypotheses, since we expect cross-regional collaborations to outperform both, though we distinguish between them empirically.

which they participate.[3] As a result, collaborations with locally embedded inventors will draw more heavily on knowledge in the inventors' locations (Berry, 2018). This greater use of spillovers will potentially accentuate the already hypothesized benefits of cross-regional collaboration,[4] giving inventors in other locations access to knowledge that is both broader and deeper, and thus enabling recombinations that are both more potentially radical and more technologically impactful. Thus:

H2a: The positive association between cross-regional collaboration and the potential radicalness of an invention will be stronger, the more the invention draws on knowledge spillovers from its inventors' locations.

H2b: The positive association between cross-regional collaboration and the impact of an invention will be stronger, the more the invention draws on knowledge spillovers from its inventors' locations.

Collaboration between and beyond clusters

Thus far, we have spoken of cross-regional collaboration as collaboration between inventors in two different locations, without considering the nature of these locations. The benefits of cross-regional collaboration may depend, however, on the nature of location-specific knowledge it allows the collaborating inventors to access, and therefore on where the collaborating inventors are located. In particular, we distinguish between inventors located in industry clusters, and those located in other locations. Inventors located in industry clusters—i.e., in locations where there is a substantial concentration of firms and individuals operating in the same industry (Marshall, 1920; Alcácer and Chung, 2007; 2014)—will have access to a rich pool of knowledge in their existing (or proximate) technological domains, given that many others in the same location will be working the same fields

[3] In terms of Figure 2, for instance, Inventor B is more embedded in Region 2 than inventor A is in Region 1, and can therefore can help the collaboration draw more strongly on knowledge from Region 2.
[4] Figure 2 also suggests that, absent cross-regional collaborations, greater reliance on local spillovers may lead to comparatively incremental innovations, i.e., the main effect of reliance on local spillovers on both potential radicalness and impact may be negative. In the interests of space, we do not formally hypothesize this relationship, though we test for it in our empirical analyses.

as them. In contrast, investors located outside industry clusters may only have limited access to knowledge in proximate technological domains. This does not mean, however, that they will not have access to local knowledge spillovers. While there may be few inventors working in the same industry in their location, there may be many inventors working in other industries or technological fields;[5] in fact, it is possible that the location may be a cluster for a different industry. If that were the case, such inventors would have access to substantial local knowledge in more distant industrial or technological domains, knowledge that they may bring to bear in their collaborations. Moreover, inventors in non-cluster locations may be more likely to interact with those outside their proximate technological domains given the limited local supply of inventors in their own domains. As a result, we would expect inventors in non-cluster locations to have richer access to spillovers in technologically distant knowledge domains.

These differences have implications for the benefits of cross-regional collaborations. Consider a collaboration between clusters, i.e., a collaboration between two inventors both located in different clusters of the same industry. On one hand, such a collaboration is more likely to deepen each inventor's knowledge base, given the rich supply of technologically proximate knowledge that each inventor will make available to the other. We would thus expect such collaborations to have a stronger direct relationship with invention impact, especially if the collaboration draws heavily on local spillovers. On the other hand, we would not necessarily expect such a collaboration to broaden the inventors' knowledge as much, since both inventors may be relatively focused on spillovers of technologically proximate knowledge. Moreover, even if either or both locations had a substantial concentration of a different industry as well—a location may be a cluster for more than one

[5] Of course, some inventors may live and work in remote and relatively isolated locations where there were few, if any, other inventors in any domain, and therefore little access to knowledge spillovers of any sort. We do not expect this to be the modal case, however, not even for inventors outside industry clusters.

industry—we would expect potential connections between this other industry's technological domains and those of the focal industry to already have been explored, given the strong presence of both industries in the same location. Other things being equal, we would not, therefore expect as strong a relationship between collaboration between clusters and potentially radical inventions.

In contrast, consider collaborations beyond clusters, i.e., collaborations where one or more[6] inventors involved are located outside of an industry cluster. Such collaborations may be especially likely to produce potentially radical inventions, given that they are likely to give the inventors access to a wider range of knowledge outside existing technological or industry domains. This effect may be especially pronounced if beyond-cluster collaborations draw heavily on local knowledge spillovers, since for at least one of the inventors involved this will mean drawing largely on technologically distant knowledge. Conversely, collaborations beyond clusters may play a more limited role in deepening inventors' knowledge within their existing knowledge domains, so the direct effect of such collaborations on invention impact may be relatively muted. In this way, the relationship between beyond cluster collaboration and invention impact may be more indirect, with such collaborations producing more potentially radical patents, some of which may go on to have substantial impact as well. Based on these arguments, we hypothesize:

H3a: Inventions involving cross-regional collaborations beyond clusters are more likely to be potentially radical than inventions involving cross-regional collaborations between clusters.

H3b: Inventions involving cross-regional collaborations between clusters are likely to have greater impact than inventions involving cross-regional collaborations beyond clusters.

H4a: The positive moderating effect of use of local spillovers on the relationship between potential radicalness and cross-

[6] We do not distinguish collaborations where all inventors are outside an industry cluster from those where some of the inventors are outside a cluster because, unsurprisingly, the former are relatively rare in our data.

regional collaboration will be stronger for collaboration beyond clusters.

H4b: The positive moderating effect of use of local spillovers on the relationship between impact and cross-regional collaboration will be stronger for collaboration between clusters.

Figure 3a summarizes our theoretical arguments and Figure 3b summarizes our hypotheses. Cross-regional collaborations may give inventors access to two types of geographically distant knowledge: knowledge that is technologically proximate and knowledge that is technologically distant (Phene et al., 2006). Exposure to knowledge that is technologically proximate but geographically distant, such as might result from collaborations between clusters, will tend to directly increase the impact of a firm's inventions, by allowing inventors to overcome the redundancy of geographically proximate knowledge which may be largely redundant (McEvily and Zaheer, 1999; Phene et al., 2006; Berry and Kaul, 2015). Exposure to knowledge that is both technologically and geographically distant, such as from collaborations beyond clusters, will tend to produce more potentially radical inventions by introducing inventors to knowledge in unfamiliar industry or technological domains, some of which they may find useful for recombination. Such exposure will thus have an indirect positive effect on the impact of a firm's inventions; one that is mediated by their radicalness. These two relationships between cross-regional collaboration and patent impact—direct and indirect—are both likely to be stronger the more an invention draws on local knowledge spillovers in the collaborating inventors' locations.

Insert Figures 3a and 3b about here

DATA AND METHODS

Context, Sample, and Data

We test our theory in the medical device industry. This is an excellent setting for our study because it is a technology-intensive industry where technological innovation is critical to firm success, and patents are extensively used to protect intellectual property, making them a good proxy for firm invention (Theeke, Polidoro, and Fredrickson, 2018; Guistiziero, Kaul, and Wu, 2019). To build our sample, we start with all patents defined as medical device patents by United States Patent and Trademark Office (USPTO)'s Patent Technology Monitoring Team. We match these to the Patent Network Dataverse (Lai, D'Amour, Yu, Sun, Torvik, & Fleming, 2011), which provides disambiguated data on patent inventors, and allows us to identify the location of inventors on each patent. We then match individual patents to firms using data from the NBER Patent Data Project database to identify patent assignees. Firm level financial data is drawn from Compustat and alliance data is drawn from SDC Platinum. After matching across these data sources, our final sample consists of 26, 618 medical device patents applied for by 1,086 publicly listed firms from 1982 to 2006.[7]

Variables

Dependent variables. The dependent variable for Hypotheses 1a, 2a, 3a, and 4a is the potential radicalness of an invention. To measure potential radicalness, we follow recent work and use a measure of the likelihood of each citation of the patent, as the proportion of citations from the citing class that were to the cited class of the focal citation in the previous five years (Eggers and Kaul, 2018).[8] Specifically, the likelihood of a citation from patent class *i* to patent class *j* at time *t* is

$$LINK_{ijt} = \frac{\sum_{t=-5}^{-1} citations_{tij}}{\sum_{t=-5}^{-1} citations_{ti}}$$

[7] Our data ends in 2006 because one of our key data sources, NBER Patent Data Project is available until 2006. We use the data to match patents to patent assignees.

[8] For our study, we use measures made publicly available by Eggers and Kaul at: https://sites.google.com/stern.nyu.edu/jpeggers/data. Please see Eggers and Kaul (2018) for further explanation and justification of this measure and its construction.

The *Radicalness* of a patent is then measured as *1* minus the least likely citation made by that patent. The higher the value of this measure, the less the technological domain the patent draws on has been used by other patents in its class, and therefore the more the patent makes a new to the world recombination. Radicalness scores are standardized by patent class and cohort to account for differences in radicalness by technology and time period.

For Hypotheses 1b, 2b, 3b, and 4b, which focus on the technological impact of an invention, we follow prior literature and use an indicator variable for *Top 5% patent* that equals *1* if the number of citations received by a patent is within the top 5% of all patents from the same class in the same year and *0* otherwise (Phene et al., 2006; Eggers and Kaul, 2018). This measure thus captures whether the patent is a breakthrough invention in its field (Ahuja and Lampert, 2001). In calculating this measure, we exclude self-citations by a firm to its own patents. In robustness checks, we also use *Number of forward citations* as an alternative measure of technological impact, measured as the total number of forward citations received by the patent divided by the average number of citations received by all patents in the same class in the same year (Fleming, 2001; Singh, 2008).

Independent variables. Our main variable of interest is cross-regional collaboration. To measure collaboration across regions at patent level, we identified MSAs of all inventors involved in each patent.[9] *Cross-regional collaboration* is a dummy variable that takes the value of *1* when at least two inventors on the patent are located in different MSAs from each other and *0* otherwise (i.e., when all inventors are located in the same MSA). Where information on inventor locations was missing—generally for foreign inventors—and we were therefore unable to determine whether the patent involved a cross-regional collaboration or not,[10] we excluded these patents from our final sample. To

[9] In our final sample, 3.2% of inventors were in nonmetropolitan areas within the US, and we assigned those inventors to the corresponding states.
[10] Even with missing MSA information, we were able to tell that the patent involved cross-regional collaboration if we had information on at least two inventors who were in different MSAs (in which case it definitely involved cross-region

check whether excluding these samples changes our result, we tried including these cases, with *Cross-regional collaboration* coded as *0*, but with the addition of a dummy variable for cases with missing MSA information. Findings with this alternative approach were consistent with the main results reported below. Note that only 0.1% of patents in our final sample have multiple assignees, so collaborations in our sample overwhelmingly represent collaborations between inventors within the same firm, consistent with our theory.

We further distinguish cross-regional collaboration of patents depending on the regional characteristics of inventors' locations: collaboration among inventors in medical device industry clusters (*Collaboration between clusters*) and collaboration among inventors outside these industry clusters (*Collaboration beyond clusters*) as shown in Figure 1. In identifying industry clusters, economic activity, the geographic unit, and economic concentration need to be considered (Alcácer and Zhao, 2016). In our study, the geographic unit is an MSA and we gauge the level of economic activity of a location by the number of medical device firms in that MSA. We used County Business Pattern (CBP) data from Census, which provides substantial economic data by industry. For economic concentration, we adopt Ellison and Glaeser's (1997) dartboard approach. Ellison and Glaeser (1997) propose that the concentration of activities across regions that would have been determined by random chance — expected level of economic activity based on regional characteristics (e.g., population, surface area, natural advantage) — should be taken into account when determining geographic clusters of industry. Thus, the degree of concentration is the difference between the actual level of activity and this threshold value (i.e., the activity level by random chance). To apply this method, we first calculate total number of medical device firms in each year. Then, we use Monte Carlo simulation to obtain the number of firms expected by random chance (weighted by

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collaboration) or if it had only one inventor (in which case it definitely did not involve cross-region collaboration). Such patents were included in our final sample.

population) in each region-year. Finally, we calculate z-score for each region-year, using the observed (actual) number of firms and mean and standard deviation of data from repeated simulation. For each year, we define 10%[11] of MSAs with the highest z-score as (medical device) industry clusters and the rest as (medical device) industry non-clusters. *Collaboration between clusters* equals *1* for patents that are cross-regionally collaborated (*Cross-regional collaboration=1*) and whose inventors are all located in industry clusters, and *0* otherwise. In a similar vein, *Collaboration beyond clusters* equals 1 for patents that are cross-regionally collaborated (*Cross-regional collaboration=1*) and one or more inventors are in non-clusters.

To study the moderating effect of local spillovers (Hypotheses 2a and 2b, 4a and 4b), we identified MSAs of all patents cited by our focal patents. Citation to a patent is "local" when one or more inventors listed on the cited patent are in the same MSA as at least one of the inventors of the citing patent. For each patent, we defined *Local spillovers* as the number of local citations made divided by the total number of citations. We excluded self-citations from both the numerator and the denominator because our local spillovers measure is intended to capture how much a firm draws on knowledge from other firms within its region. Note that while our sample is limited to medical device patents of publicly listed firms, our spillover measure includes citations to patents in any patent class belonging to any other firm (public or private) with inventors in the same MSA.

Control variables. We include several patent and firm characteristics as controls. First, we include a dummy variable that indicates whether or not a patent involves a collaboration within a region (*Within-region collaboration*). This variable takes the value of *1* when there are two or more inventors located in a single MSA and *0* otherwise (i.e., when there are inventors in two or more MSAs or when there is only one inventor on patent). We include this control variable because our *Cross-*

[11] We also tried coding an MSA as a cluster if its z-score was in the top 25%, and the results were consistent.

regional collaboration measure compares patents that involve a collaboration across regions to those that do not include such a collaboration, but the latter category includes both solo inventor patents and within-region collaborations, as shown in Figure 1. We expect our hypotheses to hold relative to both types of patents, but it is interesting to separate the two comparisons, so we include a control for within-region collaboration and make single inventor patents the omitted category.

Second, we include *Baseline tendency for local spillovers*, which measures the patent's expected or baseline level for local spillovers. We include this variable to account for the fact that given the distribution of prior patents in an MSA a focal patent is likely to cite a certain number of local patents by random chance alone. Moreover, to the extent that knowledge relevant to the focal patent is clustered within its region(s), the expected proportion of local citations due to random chance may be quite high. In studying the effect of local spillovers, we are interested in the use of local knowledge above this baseline rate, so we need to control for it in our analysis. To calculate this variable, we first measure the tendency for local spillovers at (patent) class-year-region level. For each class-year-region, we divide the total number of local citations made by class-year in a region by the total number of citations made by class-year. Self-citations are excluded, as they were in calculating *Local spillovers*. We then aggregate these values across the locations of the inventors. For example, consider a patent in class 128 (Surgery) (patent number: 6619291) that was applied for in 2001 and has inventors located in Palo Alto in California (MSA 41940: San Jose-Sunnyvale-Santa Clara) and Louisville in Kentucky (MSA 31140). Patents in class 128 in 2001 made 5% of their citations in San Jose-Sunnyvale-Santa Clara and 0.1% in Louisville, so the *Baseline tendency for local spillovers* for this patent will be 0.05 + 0.001=0.051.

Third, we included several firm level variables in patent level analysis as controls. To begin with, we controlled for the firm's *Number of patents* to account for its level of patenting activity. Next, we controlled for *Patent class concentration*, calculated as Herfindahl-Hirschman index of patent classes in which a firm patented, because technological diversity of a firm may affect the firm's innovative outcomes (Eggers and Kaul, 2018). In addition, we controlled for several financial metrics of firms. We used (logged) *Total assets* to control for firm size. We also included (logged) *R&D expense*, *Return on assets* (net income divided by total assets), and *Absorbed slack* (selling, general, and administrative expenses divided by sales).

Finally, we controlled for *Alliance network centrality*. Previous studies suggest that centrality in regional and global knowledge network has implications for firm innovation (Bell & Zaheer, 2007; Whittington et al., 2009; Zaheer & George, 2004), and it is important to account for the effect of collaboration across firm boundaries while examining the role of collaboration within them. We construct our alliance network using alliances that involve at least one medical device firm in SDC Platinum Alliance Database. We construct the alliance network at time t based on all alliance relationships formed among firms from *t-5* to *t-1* and measure *Alliance network centrality* as the focal firm's closeness centrality in that network. Since many of the firms in our sample have no alliances, this measure is missing for many of our observations. In such cases, we coded *Alliance network centrality* as *0* and included a dummy variable that equals *1* for these observations and *0* otherwise (*Alliance centrality exists*).

Table 1 provides summary statistics for, and correlations between, our main variables. While we see a few high correlations (mostly between variables that are correlated with firm size) the average VIF is 2.71, with no individual VIF being greater than 8.3 so we do not see multicollinearity as a concern. Note that our *Radicalness* measure has a (slightly) negative mean value (-0.02); this is because the measure is standardized in comparison to all patents in the relevant patent class, not only the patents in our final sample. Given the standard deviation of this measure (0.19), this mean value is not significantly different from *0*, as we would expect for a standardized measure.

Insert Table 1 about here

Empirical Specification

For our *Radicalness* measure, we use linear panel regression model with firm fixed effects to control for time-invariant firm heterogeneity. For our second dependent variable, *Top 5% patent*, which is binary, we use a panel logit model with firm fixed effects.[12] All our models use robust standard errors clustered at the firm level and include year dummies. In patent level regressions, all firm level control variables are lagged one year.[13] All other explanatory variables and dependent variables are measured in the same year.

It is important to note that our regression analyses are intended to measure an association rather than a causal relationship. We do not claim to prove that cross-regional collaboration is driving the potential radicalness or technological impact of patents. It may be, for instance, that inventors seek out collaborators in other regions when they are trying to pursue more radical inventions. Our analysis does not account for the endogeneity of the decision to pursue a cross-regional collaboration, nor for the choice of such collaborations either between or beyond clusters. All we intend to test and show is that cross-regional collaboration is associated with both greater potential radicalness and greater technological impact, and that these relationships are moderated by local spillovers and locations within and outside clusters, as hypothesized.

[12] 4,357 patents of 840 firms are dropped in models using Top 5% patent because those firms did not have Top 5% patent during our study period so that there is no within-firm variation for those firms to estimate.
[13] Total number of patents, patent class concentration, current assets, R&D expense, return on assets, absorbed slack, alliance network centrality, and alliance centrality exists are lagged one year in patent level analysis.

RESULTS

Main findings

Table 2 reports the results of our main regression analyses. Models 1 to 3 show OLS panel fixed effects models with *Radicalness* as the dependent variable, while Models 4 to 9 show fixed-effects logit models with *Top 5% patent* as the dependent variable. Model 1 and Model 4 are baseline models with controls, Model 2 and Model 5 add *Cross-regional Collaboration* as a predictor, and Models 3 and 6 include the interaction between *Cross-regional Collaboration* and *Local spillovers.* Models 7 to 9 are the same as Models 4 to 6, except with the addition of *Radicalness* as an independent variable, to test whether the relationship between cross-regional collaboration and technological impact is mediated by the potential radicalness of the patent.

In Hypothesis 1a we predicted that patents involving cross-regional collaboration would have greater potential radicalness. Model 2 in Table 2 shows support for this prediction, with *Cross-regional Collaboration* taking a positive and significant coefficient. Interestingly, we also see a positive and significant coefficient for *Within-region Collaboration* implying that patents that have more than one inventor tend to be more potentially radical on average. However, the coefficient of *Within-region Collaboration* in Model 2 is much smaller than that for *Cross-regional Collaboration* (the *p*-value of a t-test comparing the two coefficients is 0.062). This means that patents involving cross-regional collaborations are significantly more likely to make new to the world connections than those with either single inventors or multiple inventors within the same region. Hypothesis 1a is thus supported.

Hypothesis 2a predicted that this positive association between cross-regional collaboration and potential radicalness would be stronger, the more the patent draws on local spillovers. Model 3 in Table 2 shows support for this prediction. We see a positive and significant coefficient for the interaction between *Cross-regional collaboration* and *Local spillovers,* consistent with Hypothesis 2a. Note that the main effect of *Local spillovers* across Models 1 to 3 is consistently negative, implying that, other things being equal, patents that rely heavily on local knowledge are more likely to be incremental. The result in Model 3 suggests that cross-regional collaboration helps to overcome the constraints of local knowledge, producing inventions that make use of local knowledge but still manage to make potentially radical connections.

These results are economically significant as well. Holding all other variables at their average level, the result in Model 3 implies that a patent involving a cross-regional collaboration has a 0.1 standard deviation greater radicalness than a patent involving no collaboration, and this difference rises to 0.14 standard deviations for values of local spillover one standard deviation above the mean. Figure 4a plots the comparison between the predicted radicalness of patents with no collaboration and those with cross-regional collaboration for different levels of local spillovers.[14] It clearly shows the gap between the two types of patents in terms of potential radicalness increasing as the extent of local spillovers increases.

Insert Table 2 and Figure 4 about here

Hypothesis 1b predicted that patents involving cross-regional collaboration would have greater technological impact. Consistent with this, Model 5 in Table 2 shows a positive and significant coefficient for *Cross-regional collaboration* when predicting *Top 5% patents.* As with radicalness, we see a positive and significant coefficient for *Within-region collaboration* as well, but again, the two coefficients are significantly different (*p*-value of a t-test comparing them is 0.007). Patents involving cross-regional collaborations are thus more likely to prove breakthrough

[14] As explained earlier, the mean *Radicalness* in our sample is slightly below *0*, which is why the graphs in Figure 4 show negative values.

inventions, compared to both patents with solo inventors and patents with collocated inventors. Hypothesis 1b is thus supported. Importantly, we continue to see a positive and significant coefficient for *Cross-regional collaboration* that is greater than the corresponding coefficient for *Within-region collaboration* (p-value of comparison is 0.012) even after we account for the *Radicalness* of the patent in Model 8, even though *Radicalness* itself is positively and significantly related to patent impact. Thus, the relationship between cross-regional collaboration and technological impact is not fully mediated by the potential radicalness of the invention, consistent with our predictions.

Hypotheses 2b predicted that the positive association between cross-regional collaboration and technological impact would be moderated by the extent to which the invention drew on local knowledge. Models 6 and 9 in Table 2 confirm this prediction, showing a positive and significant coefficient for the interaction between *Cross-regional collaboration* and *Local spillovers.* Note that these models also show a negative and significant main effect of *Local spillovers,* implying that inventions that draw heavily on local knowledge are less likely to be impactful, unless they recombine this knowledge across geographies through cross-regional collaboration.

Again, these results are economically significant. Based on Model 9, and holding all else at their mean values, the predicted probability of a patent involving a cross-regional collaboration proving to be a breakthrough invention is 4.87% compared to a predicted probability of just 3.35% for a patent with a solo inventor: an increase of 45%. For patents with local spillovers one standard deviation above the mean, the corresponding values are 4.84% for a cross-regional collaboration patent vs. just 3.1% for a solo inventor patent, implying a 57% increase. Figure 4b plots the difference in predicted probability of being a *Top 5% Patent* between patents with cross-regional collaboration and those with no collaboration as a function of *Local spillovers.* Given the non-linear nature of our dependent variable, we interpret the interaction using a simulation-based approach

(Zelner, 2010) that plots the point estimate of the difference between predicted probabilities and the confidence interval around it. As Figure 4b clearly shows, the predicted difference between patents with cross-regional collaboration and those with no collaboration is significant across the full range of *Local spillovers* and rises in value as *Local spillovers* rise, further confirming support for Hypotheses 1b and 2b.

Among the control variables in Table 2 we see a positive and significant coefficient for *Alliance Centrality* when predicting technological impact, suggesting that firms that are able to draw on external knowledge through the use of alliances may be more likely to produce breakthrough patents. We also see a negative and significant coefficient for *Patent class concentration* suggesting that firms with greater technological diversity within their boundaries are likely to produce more impactful inventions (Ahuja and Lampert, 2001; Katila and Ahuja, 2002).

Collaboration between and beyond clusters

Table 3 shows the results of our tests for Hypotheses 3 and 4. It follows the same pattern of results as presented in Table 2, only now we split overall *Cross-regional collaboration* into *Collaboration between clusters* and *Collaboration beyond clusters.* Model 2 in Table 3 shows that both types of collaborations have a positive and significant relation with *Radicalness,* with no significant difference between them. Hypothesis 3a is therefore not supported. We do, however, see support for Hypothesis 4a, with the coefficient of the interaction between *Collaboration beyond clusters* and *Local spillovers* being positive and significant. This is in contrast to the coefficient of the corresponding interaction with *Collaboration between clusters*, which shows no evidence of a moderating effect of local spillovers in the case of between cluster collaboration, with the coefficients of the two interaction terms being significantly different from each other (*p*-value of comparison: 0.052). H4a is thus supported. More generally, we see these results as consistent with our argument that the primary way in which cross-regional collaboration boosts the potential radicalness of a firm's inventions is by allowing it to tap into local knowledge outside industry clusters. Figure 5a plots the interaction between *Collaboration beyond clusters* and *Local spillovers*, showing that the gap between the predicted radicalness of solo inventor patents and patents involving collaborations beyond clusters increases with the patent's reliance on local spillovers, in a way very similar to what we saw in Figure 4a for all collaborations.

Insert Table 3 and Figure 5 about here

Models 4 through 9 of Table 3 show the results for breakthrough inventions. They show no support for Hypothesis 3b, with the coefficients of both *Collaboration between clusters* and *Collaboration beyond clusters* being positive and significant in Models 5 and 8. While it is true that the coefficient of *Collaboration between clusters* is greater than that of *Collaboration beyond clusters* in these models as predicted, the difference between them is not significant.

Models 6 and 9 do show support for Hypothesis 4b, however. As predicted, they show a strong and positive coefficient for the interaction between *Collaboration between clusters* and *Local spillovers* that is significantly greater than the (insignificant) coefficient for the corresponding interaction with *Collaboration beyond clusters* (*p*-value of comparison: 0.096 and 0.091 in Model 6 and 9). This is consistent with the idea that the moderating effect of local spillovers on the relationship between cross-regional collaboration and technological impact comes primarily from collaborations between industry clusters. Figure 5b shows this result graphically, plotting the interaction of *Local spillovers* with *Collaboration between clusters* and (separately) with *Collaboration beyond clusters,* in the same way as Figure 4b. As these graphs show, local spillovers have essentially no effect on the difference in technological impact between patents that involve beyond cluster collaboration and those that involve no collaboration, but it substantially increases the gap between patents involving between cluster collaborations and no collaborations.

Robustness and supplementary analyses

We undertake several checks to confirm the robustness of our findings. First, we re-run our analysis of technological impact using the number of forward citations received as an alternative measure of impact (Fleming, 2001; Singh, 2008). As Table 4 shows, our results are robust to the use of this alternative measure. We continue to see a positive and significant relationship between *Cross-regional collaboration* and *Number of citations received,* with this relationship being stronger, the more the patent draws on local spillovers, especially for collaborations between clusters, and all these relationships continue to hold even after we account for the patent's potential radicalness. Hypotheses 1b, 2b, and 4b thus continue to be supported.

Insert Tables 4, 5, and 6 about here

Next, we re-examine our moderating hypotheses using a split sample approach. We do so because recent scholarship has questioned the interpretation of interaction terms in fixed effects models (Shaver, 2019) and because the binary nature of our main collaboration variables makes it easy to look at the effect of local spillovers on potential radicalness and technological impact in different types of patents. Models 1 through 4 in Table 5 show the relationship between *Local spillovers* and *Radicalness* in patents involving no collaboration, any cross-regional collaboration, collaboration between clusters, and collaboration beyond clusters, respectively. We find that reliance on local spillovers have a negative relationship with a patent's potential radicalness for all patents except those involving collaborations beyond clusters, with the coefficient of *Local spillovers* in Model 4 being significantly different from the corresponding coefficient in both Model 1 and Model 3 (p-value of test comparing coefficients is 0.005 and 0.03 respectively). We also find that this coefficient is less negative in Model 2 than in Model 1 (p-value 0.031). These results are consistent with

Hypothesis 2a and Hypothesis 4a.

Similarly, Models 5 through 8 in Table 5 show support for Hypotheses 2b and 4b. As expected, we see no significant relationship between *Local spillovers* and *Top 5% patent* for patents involving either cross-regional collaborations or collaboration between clusters, with the coefficient of *Local spillovers* in both Models 6 and 7 being significantly different from the corresponding (negative and significant coefficient) in Model 5 (*p*-value of comparison is 0.029 and 0.019, respectively). The coefficient for Model 8, which looks at patents with collaborations beyond clusters, is negative but insignificant and lies between that of Model 5 and Model 7, being insignificantly different from either.

Finally, Table 6 shows the results of a supplementary analysis looking at the effect of cross-regional collaboration on the quantity of firm invention. While cross-regional collaboration may be associated with patents that are both more potentially radical and more technologically impactful, as we have shown, it may also require greater effort on the part of the inventors, given the challenges of communicating across regions (Adams and Jaffe, 1996; Szulanski, 1996, 2002). While we did not hypothesize a relationship between cross-regional collaboration and invention quantity, we nevertheless test for this relationship to more fully understand the relationship between cross-regional collaboration and firm invention. To study this relation between cross-regional collaboration and quantity of invention, we have to aggregate our variables up to the firm level (since quantity is not defined at the level of an individual patent). Table 6 shows the results of this analysis, regressing *Number of patents* on average levels of cross-regional collaboration and local spillovers.[15]

Table 6 shows a negative and significant main association between the proportion of a firm's patents that involve cross-region collaborations and *Number of patents*, with no evidence of this relationship being moderated by the average level of local spillovers. We see a similar pattern when we break down the proportion of patents with cross-region collaborations into the proportion with collaborations between clusters and those with collaborations beyond clusters: both proportions have a negative and significant relationship with invention quantity, with no evidence of a statistically significant difference between them. Overall, this supplementary analysis highlights a key trade-off associated with the use of cross-regional collaboration within firms: while such collaboration may boost the quality of a firm's inventions because of the ability to recombine knowledge across geographic domains, the greater effort required to do so may also reduce the quantity of inventions the firm is able to develop.

DISCUSSION

Our study investigates the relationship between cross-regional collaboration within firms and the quality of firm invention. We show that patents that involve cross-regional collaboration are both more potentially radical and more impactful than those that have a single inventor or that involve collaborations within a single region. These two relationships are both independent and additive: not only is cross-regional collaboration directly associated with a greater likelihood of a breakthrough invention, it also indirectly associated with invention impact through its relationship with potential radicalness, since potentially radical patents are in turn associated with greater impact. We further show that this association is stronger when the patent draws heavily on its inventor's

[15] Dependent variable, *Number of patents,* is forwarded one year. In addition to the control variables included in our main analyses, we also control for the total number of inventors and total number of MSAs. We also aggregate patent-level measures to the firm level, including our main variables of interest.

local knowledge. Absent cross-regional collaboration, greater reliance on local knowledge is associated with patents that are more incremental and less impactful; cross-regional collaboration helps to overcome this constraint. These associations are also found to differ based on the location of the collaborating inventors. For radicalness, they are strongest for collaborations beyond industry clusters, with patents being most likely to make new to the world connections when they combine local knowledge of inventors within and outside clusters. For impact, they are strongest for collaborations between clusters, with patents being most likely to prove breakthroughs when they draw on local knowledge of inventors in different clusters. Together, these results provide strong evidence in support of our theory of the nuanced associations of intra-firm collaborations that reach out beyond local geographies: that cross-regional collaborations serve to bridge pools of local expertise, allowing inventors to recombine knowledge from the region in which they are embedded with knowledge from other regions where their collaborators are located, producing inventions that are both more radical and more impactful, and that these effects are enhanced the more inventions are locally embedded.

These findings contribute to the existing literature in several ways. To begin with, they provide fresh insight on the phenomenon of cross-regional collaboration within firms. While such cross-regional ties between inventors have received growing attention in recent years (Berry, 2014; Paruchuri and Awate, 2017), based on the recognition that they serve as a key conduit for knowledge transfer between locations (Gupta and Govindarajan, 2000; Hansen and Løvås, 2005; Singh, 2005; Frost and Zhou, 2005), relatively little is known about the impact of such collaborations on invention quality, beyond some work suggesting that such collaborations may moderate the relation between geographically dispersed R&D and the impact of inventions (Singh, 2008; Lahiri, 2010). We address this gap, not only providing direct evidence for the relationship between cross-regional collaboration and the impact of an invention, but also explicating the mechanisms through which this relationship comes about by showing that it is partly driven by the greater radicalness of cross-regionally collaborating patents (Berry, 2018), and moderated by the patent's reliance on local knowledge and the location of its inventors between and beyond clusters. In this way we offer a deeper and more nuanced understanding of the relationship between cross-regional collaboration and firm invention quality. We do so, moreover, while focusing on collaboration between regions within a country, rather than the cross-country collaborations that have been the focus of prior work. This is important because within-country cross-regional ties have been shown to work differently from cross-country ties (Tallman and Phene, 2007; Leiponen and Helfat, 2011), yet the effect of the former on invention quality remains largely unexplored.

As such, our study also contributes to the literature on industry clusters and knowledge agglomeration (Audretsch and Feldman, 1996; Jaffe et al., 1993; Saxenian, 1996; Chung and Alcácer, 2002; Alcácer and Chung, 2007; Alcácer and Zhao, 2016). In recent years, this literature has increasingly come to focus on the heterogeneity between firms in benefiting from being located in a knowledge cluster, with studies pointing to the role of local embeddedness (Owen-Smith and Powell, 2004), alliance ties (Whittington et al., 2009), internal structure (Funk, 2014), or absorptive capacity (Penner-Hahn and Shaver, 2005) in determining which firms gain the most from knowledge spillovers. Where cross-regional collaborations have been considered in this context, they have often been seen as a way to defend a firm's knowledge by limiting local rival's access to valuable knowledge (Shaver and Flyer, 2000; Zhao, 2006; Alcácer and Zhao, 2012). Our study points to a distinct, though complementary, benefit from internal linkages within a firm beyond cluster boundaries. It suggests such linkages may boost the quality of firm inventions by allowing the firm to recombine the knowledge it gains from local spillovers with knowledge from elsewhere, thus overcoming the constraints of local knowledge (McEvily and Zaheer, 1999; Bell and Zaheer, 2007). Absent such recombination, our study shows, greater reliance on local spillovers results in increasingly incremental inventions, presumably because local knowledge is relatively narrow and potentially redundant. Moreover, we highlight that these collaborations need not be only between clusters; collaborations beyond clusters may also produce valuable recombination by allowing firms to tap into relevant but less explored expertise from other industry or technology domains.

Third, our study contributes to work on intra-firm collaboration and the role of interpersonal networks in bridging pockets of knowledge within the firm (Hansen, 1999; Reagans and McEvily, 2003; Fleming et al., 2007; Tortoriello and Krackhardt, 2010; Tortoriello et al., 2012). Research in this area has examined the role of collaborations between inventors in enabling knowledge recombination within the firm (Carnabuci and Operti, 2013; Nerkar and Paruchuri, 2005; Paruchuri, 2010; Kogut and Zander, 1992; 1993). We build on and extend this literature by showing how intra-firm collaborations between regions may play an important role in bridging pockets of geographically dispersed knowledge (McEvily and Zaheer, 1999), producing inventions that are more radical and more impactful even compared to intra-firm collaborations within a single region. Further, our results suggest that these strong ties between inventors in different regions within a firm may be most effective when they are accompanied by weak ties between inventors in the same region in different firms, as reflected in greater reliance on local knowledge spillovers.

Finally, our study contributes to research on firm recombination and invention (Fleming, 2001; Ahuja and Lampert, 2001; Ahuja et al., 2008). While this work has examined the benefits from recombination across technological domains (Rosenkopf and Nerkar, 2001; Katila and Ahuja, 2002) and geographic regions (Ahuja and Katila, 2004; Lahiri, 2010), the two have often been looked at separately. Moreover, where the two have been examined together, they have often been seen as incompatible, with studies showing that geographic dispersion is most valuable for recombination within existing technological domains (Phene et al., 2006) or for relatively imitative innovation

(Leiponen and Helfat, 2011). We argue and show, however, that cross-regional collaborations within firms may help enable recombination across both geographic and technological boundaries simultaneously, producing patents that are not just more impactful, but also more potentially radical (Berry, 2018). We thus highlight the role of such collaborations—especially collaborations beyond industry clusters--as an important source of potentially radical, new to the world recombination (Eggers and Kaul, 2018).

As with any research, our study has several limitations, which provide opportunities for further research. First, our empirical analysis does not account in any way for the endogeneity of cross-regional collaboration (or the choice of whether to collaborate between or beyond clusters). Our findings are thus best thought of as showing an association between cross-regional collaboration and invention radicalness or impact; we make no claim that this relationship is causal. Future work could look more carefully at the drivers of cross-regional collaboration, and better estimate their effect on invention quality after accounting for these antecedents. Second, our study is limited to a single industry (medical devices) in a single country (the United States). While we see our focus on cross-regional collaborations between regions within a country rather than cross-country ties as a feature of our work, given the relative scarcity of work examining the former compared to the latter, it would certainly be interesting for future work to examine whether the relationships we document hold for cross-country collaborations as well. Future work could also seek to replicate our findings in other industry contexts. Finally, our study relies on patent data to measure firm invention. While patents have been widely used to measure organizational search and innovation, including in the medical device industry (Theeke et al., 2018; Guistiziero et al., 2019), they are not without their limitations. Patent-based measures may capture only some part of a firm's innovation and search efforts; moreover, some patent citations may be added by examiners rather than by the firm itself (Alcácer and Gittleman, 2006). While these concerns make our measures somewhat noisy, we see no reason why they should systematically bias our study in favor of our hypotheses. In addition, while forward citations have frequently been used to measure technological impact (Ahuja and Lampert, 2001; Phene et al., 2006; Eggers and Kaul, 2018), they are only loosely related to commercial value (Harhoff et al., 1999). As such, our results are best thought of as speaking to the technological impact of a firm's inventions, rather than the financial value of its innovations. Future work could look more directly at the relationship between cross-regional collaboration and firm financial performance.

To conclude: we examine the relationship between cross-regional collaboration and invention quality, arguing that cross-regional collaborations within firms help to bridge local pools of knowledge, enabling firms to recombine more diverse knowledge both within and outside their existing technological domains, and thus produce inventions that are both more radical and more impactful. Consistent with this, we show that medical device patents that involve collaborations between inventors located in different MSAs within the United States are more likely to be make new to the world combination and more likely to be breakthrough inventions, especially if they draw on the collaborating inventors' local knowledge. We further find that this relationship is stronger for collaborations beyond clusters in the case of potential radicalness, but for collaborations between clusters in the case of technological impact, furthering supporting our theory. Our study thus offers a more nuanced view of the role of intra-firm cross-regional collaboration in helping firms to overcome the constraints of local search and benefit from their location in regions rich with spillovers, while also contributing to research on intra-firm bridging ties and organizational search and innovation.

REFERENCES

Adams, J. D., & Jaffe, A. B. 1996. Bounding the effects of R&D: An investigation using matched establishment-firm data. ***RAND Journal of Economics,*** 27: 700-721.

Ahuja, G., & Katila, R. 2004. Where do resources come from? The role of idiosyncratic situations. ***Strategic Management Journal,*** 25: 887-907.

Ahuja, G., & Lampert, C. M. 2001. Entrepreneurship in the large corporation: a longitudinal study of how established firms create breakthrough inventions. ***Strategic Management Journal***, 22: 521–543.

Ahuja, G., Lampert, C. M., & Tandon, V. 2008. Moving beyond Schumpeter: Management research on the determinants of technological innovation. ***Academy of Management Annals***, 2: 1–98.

Alcácer, J. 2006. Location choices across the value chain: How activity and capability influence collocation. ***Management Science,*** 52: 1457-1471.

Alcácer, J., & Chung, W. 2007. Location strategies and knowledge spillovers. ***Management Science***, 53: 760–776.

Alcácer, J., & Chung, W. 2014. Location strategies and agglomeration economies. ***Strategic Management Journal,*** 35: 1749-1761.

Alcácer, J., & Delgado, M. 2016. Spatial organization of firms and location choices through the value chain. ***Management Science,*** 62: 3213-3234.

Alcácer, J., & Gittelman, M. 2006. Patent citations as a measure of knowledge flows: The influence of examiner citations. ***The Review of Economics and Statistics,*** 88: 774-779.

Alcácer, J., & Zhao, M. 2012. Local R&D strategies and multilocation firms: The role of internal linkages. ***Management Science***, 58: 734–753.

Alcácer, J., & Zhao, M. 2016. Zooming in: A practical manual for identifying geographic clusters. ***Strategic Management Journal***, 37: 10–21.

Almeida, P., & Kogut, B. 1999. Localization of knowledge and the mobility of engineers in regional networks. ***Management Science,*** 45: 905–917.

Almeida, P., & Phene, A. 2004. Subsidiaries and knowledge creation: the influence of the MNC and host country on innovation. ***Strategic Management Journal,*** 25: 847–864.

Argyres, N. 1996. Capabilities, technological diversification and divisionalization. ***Strategic Management Journal***, 17(5): 395-410.

Argyres, N. S., & Zenger, T. R. 2012. Capabilities, transaction costs, and firm boundaries. ***Organization Science,*** 23: 1643-1657.

Audretsch, D. B., Feldman, M. B. 1996. R&D spillovers and the geography of innovation and production. ***American Economic Review,*** 86: 630-640.

Bell, G. G., & Zaheer, A. 2007. Geography, networks, and knowledge flow. ***Organization Science***, 18: 955–972.

Berry, H. 2006. Leaders, laggards, and the pursuit of foreign knowledge. ***Strategic Management Journal,*** 27: 151-168.

Berry, H. 2014. Global integration and innovation: Multicountry knowledge generation within MNCs. ***Strategic Management Journal,*** 35: 869-890.

Berry, H. 2018. The influence of multiple knowledge networks on innovation in foreign operations. ***Organization Science,*** 29: 855-872.

Berry, H., & Kaul, A. 2015. Global sourcing and foreign knowledge seeking. ***Management Science,*** 61: 1052-1071.

Brown, J. S., & Duguid, P. 2001. Knowledge and organization: A social-practice perspective. ***Organization Science,*** 12: 198-213.

Cantwell, J., & Janne, O. 1999. Technological globalization and innovative centres: The role of corporate technological leadership and locational hierarchy. ***Research Policy,*** 28: 119-144.

Cantwell, J., & Mudambi, R. 2005. MNE competence-creating subsidiary mandates. ***Strategic Management Journal,*** 26: 1109-1128.

Carnabuci, G., & Operti, E. 2013. Where do firms' recombinant capabilities come from? Intraorganizational networks, knowledge, and firms' ability to innovate through technological recombination. ***Strategic Management Journal,*** 34: 1591-1613.
Chung, W., & Alcácer, J. 2002. Knowledge seeking and location choice of foreign direct investment in the United States. ***Management Science,*** 48: 1534-1554.
Chung, W., & Yeaple, S. 2008. Internaitonal knowledge sourcing: Evidence from US firms expanding abroad. ***Strategic Management Journal,*** 29: 1207-1224.
Dahlin, K. B., & Behrens, D. M. 2005. When is an invention really radical?: Defining and measuring technological radicalness. ***Research Policy,*** 34: 717-737.
Delgado, M., Porter, M., & Stern, S. 2014. Clusters, convergence, and economic performance. ***Research policy,*** 43: 1785-1799.
Dewar, R. D., & Dutton, J. E. 1986. The adoption of radical and incremental innovations: An empirical analysis. ***Management Science,*** 32: 1422-1433.
Dunning, J. H. 1998. Location and the multinational enterprise: A neglected factor? ***Journal of International Business Studies,*** 29: 45-66.
Eggers, J. P., & Kaul, A. 2018. Motivation and ability? A behavioral perspective on the pursuit of radical invention in multi-technology incumbents. ***Academy of Management Journal***, 61: 67–93.
Ellison, G., & Glaeser, E. L. 1997. Geographic concentration in U.S. manufacturing industries: A dartboard approach. ***Journal of Political Economy***, 105: 1–39.
Feinberg, S. E., & Gupta, A. K. 2004. Knowledge spillovers and the assignment of R&D responsibilities to foreign subsidiaries: ***Strategic Management Journal,*** 25: 823-845.
Fleming, L. 2001. Recombinant uncertainty in technological search. Management Science, 47: 117-132.
Fleming, L., Mingo, S., & Chen, D. 2007. Collaborative brokerage, generative creativity, and creative success. ***Administrative Science Quarterly,*** 52: 443-475.
Frost, T. S. 2001. The geographical sources of foreign subsidiaries' innovations. ***Strategic Management Journal,*** 22: 101-123.
Frost, T. S., Birkinshaw, J. M., & Ensign, P. C. 2002. Centers of excellence in multinational corporations. ***Strategic Management Journal,*** 23: 997-1018.
Frost, T. S., & Zhou, C. 2005. R&D co-practice and 'reverse' knowledge integration in multinational firms. ***Journal of International Business Studies,*** 36: 676-687.
Funk, R. J. 2014. Making the most of where you are: Geography, networks, and innovation in organizations. ***Academy of Management Journal***, 57: 193–222.
Furman, J. L., Porter, M. E., & Stern, S. 2002. The determinants of national innovative capacity. ***Research Policy,*** 31: 899-933.
Galunic, D. C., & Rodan, S. 1998. Resource recombinations in the firm: Knowledge structures and the potential for Schumpeterian innovation. ***Strategic Management Journal,*** 19: 1193-1201.
Gatignon, H., Tushman, M. L., Smith, W., & Anderson, P. 2002. A structural approach to assessing innovation: Construct development of innovation locus, type, and characteristics. ***Management Science,*** 48: 1103-1122.
Ghoshal, S., Korine, H., & Szulanski, G. 1994. Interunit communication in multinational corporations. ***Management Science,*** 40: 96-110.
Gómez-Solórzano, M., Tortoriello, M., & Soda, G. 2019. Instrumental and affective ties within the laboratory: The impact of informal cliques on innovative productivity. ***Strategic Management Journal,*** 40: 1593-1609.
Guistiziero, G., Kaul, A., & Wu, B. 2019. The dynamics of learning and competition in Schumpeterian environments. ***Organization Science,*** 30: 668-693.
Gupta, A. K., & Govindarajan, V. 2000. Knowledge flows within multinational corporations. ***Strategic Management Journal,*** 21: 473-496.
Grant, R. M. 1996a. Toward a knowledge-based theory of the firm. ***Strategic Management Journal***, 17: 109–122.
Grant, R. M. 1996b. Prospering in dynamically-competitive environments: Organizational capability as knowledge integration. ***Organization Science,*** 7: 375-387.

Grigoriou, K., & Rothaermel, F. 2017. Organizing for knowledge generation: Internal knowledge networks and the contingent effect of external knowledge sourcing. ***Strategic Management Journal,*** 38: 395-414.

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

Hansen, M. T. 2002. Knowledge networks: Explaining effective knowledge sharing in multiunit companies. ***Organization Science***, 13(3): 232–248.

Hansen, M. T., & Løvås, B. 2004. How do multinational companies leverage technological competencies? Moving from single to interdependent explanations. ***Strategic Management Journal,*** 25: 801-822.

Hansen, M. T., Mors, M. L., & Løvås, B. 2005. Knowledge sharing in organizations: Multiple networks, multiple phases. ***Academy of Management Journal,*** 48: 776-793.

Hargadon, A., & Sutton, R. I. 1997. Technology brokering and innovation in a product development firm. ***Administrative Science Quarterly,*** 42: 716-749.

Harhoff, D., Narin, F., Scherer, F. M., & Vopel, K. 1999. Citation frequency and the value of patented inventions. ***Review of Economics and Statistics,*** 81: 511-515.

Henderson, R. 1993. Underinvestment and incompetence as responses to radical innovation: Evidence from the photolithographic alignment equipment industry. ***RAND Journal of Economics,*** 24: 248-270.

Jaffe A., Trajtenberg M., & Henderson, R. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. ***Quarterly Journal of Economics,*** 108: 577-598.

Karim, S., & Kaul, A. 2015. Structural recombination and innovation: Unlocking intraorganizational knowledge synergy through structural change. ***Organization Science,*** 26: 439-455.

Katila, R., & Ahuja, G. 2002. Something old, something new: A longitudinal study of search behavior and new product introduction. ***Academy of Management Journal***, 45: 1183–1194.

Kleinbaum, A. M. 2012. Organizational misfits and the origins of brokerage in intrafirm networks. ***Administrative Science Quarterly,*** 57: 407-452.

Kogut, B., & Zander, U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. ***Organization Science,*** 3: 383-397.

Kogut, B., & Zander, U. 1993. Knowledge of the firm and the evolutionary theory of the multinational corporation. ***Journal of International Business Studies***, 24: 625–645.

Kuemmerle, W. 1999. The drivers of foreign direct investment into research and development: An empirical investigation. ***Journal of International Business Studies,*** 30: 1-24.

Lahiri, N. 2010. Geographic distribution of R&D activity: How does it affect innovation quality? ***Academy of Management Journal,*** 53: 1194-1209.

Lai, R., D'Amour, A., Yu, A., Sun, Y., & Fleming, L. 2011. ***Disambiguation and co-authorship networks of the US patent inventor database (1975-2010).*** Harvard Dataverse. V5. Retrieved from http://hdl.handle.net/1902.1/15705.

Leiponen, A., & Helfat, C. E. 2011. Location, decentralization, and knowledge sources for innovation. ***Organization Science,*** 22: 641-658.

Liebeskind, J. P. 1996. Knowledge, strategy, and the theory of the firm. ***Strategic Management Journal,*** 17: 93-107.

Marshall, A. 1920. **Principles of Economics: An Introductory Volume.** London, UK: MacMillan.

McEvily, B. & Zaheer, A. 1999. Bridging ties: A source of firm heterogeneity in competitive capabilities. ***Strategic management journal,*** 20: 1133-1156.

Miller, D. J., Fern, M. J., & Cardinal, L. B. 2007. The use of knowledge for technological innovation within diversified firms. ***Academy of Management Journal,*** 50: 307-325.

Nachum, L., & Zaheer, S. 2005. The persistence of distance? The impact of technology on MNE motivations for foreign investment. ***Strategic Management Journal,*** 26: 747-767.

Nachum, L., & Zaheer, S., & Gross, S. 2008. Does it matter where countries are? Proximity to knowledge, markets and resources, and MNE location choices. ***Management Science,*** 54: 1252-1265.

Nahapiet, J., & Ghoshal, S. 1998. Social capital, intellectual capital, and the organizational advantage. ***Academy of Management Review***, 23: 242–266.

Nelson, R. & Winter, S. 1982. *An evolutionary theory of economic change.* Cambridge, MA: Harvard University Press.

Nerkar, A. 2003. Old is gold? The value of temporal exploration in the creation of new knowledge. *Management Science,* 49: 211-229.

Nerkar, A., & Paruchuri, S. 2005. Evolution of R&D capabilities: The role of knowledge networks within a firm. *Management Science,* 51: 771-785.

Owen-Smith, J., & Powell, W. W. 2004. Knowledge networks as channels and conduits: The effects of spillovers in the Boston biotechnology community. *Organization Science*, 15: 5–21.

Paruchuri, S. 2010. Intraorganizational networks, interorganizational networks, and the impact of central inventors: A longitudinal study of pharmaceutical firms. *Organization Science,* 21: 63-80.

Paruchuri, S., & Awate, S. 2017. Organizational knowledge networks and local search: The role of intra-organizational inventor networks. *Strategic Management Journal,* 38: 657-675.

Penner-Hahn, J., & Shaver, J. M. 2005. Does international research and development increase patent output? An analysis of Japanese pharmaceutical firms. *Strategic Management Journal,* 26: 121-140.

Phene, A., & Almeida, P. 2008. Innovation in multinational subsidiaries: The role of knowledge assimilation and subsidiary capabilities. *Journal of International Business Studies,* 39: 901-919.

Phene, A., Fladmoe-Lindquist, K., & Marsh, L. 2006. Breakthrough innovations in the US biotechnology industry: The effects of technological space and geographic origin. *Strategic Management Journal,* 27: 369-388.

Polanyi, M. 1966. *The Tacit Dimension.* New York, NY: Doubleday.

Porter, M. 1990. *The competitive advantage of nations.* New York, NY: Free Press.

Reagans, R., & McEvily, B. 2003. Network structure and knowledge transfer: The effects of cohesion and range. *Administrative Science Quarterly*, 48:240-267.

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

Rosenkopf, L., & Almeida, P. 2003. Overcoming local search through alliances and mobility. *Management Science*, 49: 751–766.

Rosenkopf, L., & Nerkar, A. 2001. Beyond local search: Boundaries-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal*, 22: 287–306.

Saxenian, A. 1996. *Regional Advantage.* Cambridge, MA: Harvard University Press.

Schumpeter, J. A. 1934. *The theory of economic development.* Cambridge, MA: Harvard University Press.

Shaver, J. M. 2019. Interpreting interactions in linear fixed-effect regression models: When fixed-effect estimates are no longer within-effects. *Strategy Science,* 4: 25-40.

Shaver, J. M., & Flyer, F. 2000. Agglomeration economies, firm heterogeneity, and foreign direct investment in the United States. *Strategic Management Journal*, 21: 1175–1193.

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

Singh, J. 2008. Distributed R&D, cross-regional knowledge integration and quality of innovative output. *Research Policy,* 37: 77-96.

Szulanski, G. 1996. Exploring internal stickiness: Impediments to the transfer of best practice within the firm. *Strategic Management Journal,* 17: 27-43.

Szulanski, G. 2002. *Sticky knowledge: Barriers to knowing in the firm.* Thousand Oaks, CA: Sage.

Tallman, S., & Phene, A. 2007. Leveraging knowledge across geographic boundaries. *Organization Science,* 18: 252-260.

Tallman, S., Jenkins, M., Henry, N., & Pinch, S. 2004. Knowledge, clusters, and competitive advantage. *Academy of Management Review,* 29: 258-271.

Theeke, M., Polidoro, F., & Fredrickson, J. W. 2018. Path-dependent routines in the evaluation of novelty: The effects of innovators' new knowledge use on brokerage firms' coverage. *Administrative Science Quarterly,* 63: 910-942.

Toh, P. K., & Polidoro, F. 2013. A competition-based explanation of collaborative invention within the firm. *Strategic Management Journal,* 34: 1186-1208.

Tortoriello, M., & Krackhardt, D. 2010. Activating cross-boundaries knowledge: The role of Simmelian ties in the generation of innovations. *Academy of Management Journal*, 53: 167–181.
Tortoriello, M., Reagans, R., & McEvily, B. 2012. Bridging the knowledge gap: The influence of strong ties, network cohesion, and network range on the transfer of knowledge between organizational units. *Organization Science*, 23: 1024–1039.
Tsai, W. 2001. Knowledge transfer in intraorganizational networks: Effects of network position and absorptive capacity on business unit innovation and performance. *Academy of Management Journal*, 44: 996–1004.
Tushman, M. L. 1977. Special boundary roles in the innovation process. *Administrative Science Quarterly,* 587-605.
Tushman, M. L. 1978. Technical communication in R & D laboratories: The impact of project work characteristics. *Academy of Management Journal,* 21: 624-645.
Tushman, M. L., & Katz, R. 1980. External communication and project performance: An investigation into the role of gatekeepers. *Management Science,* 26: 1071-1085.
Whittington, K. B., Owen-Smith, J., & Powell, W. W. 2009. Networks, propinquity, and innovation in knowledge-intensive industries. *Administrative Science Quarterly*, 54: 90–122.
Zaheer, A., & George, V. P. 2004. Reach out or reach within? Performance implications of alliances and location in biotechnology. *Managerial and Decision Economics*, 25: 437–452.
Zhao, M. 2006. Conducting R&D in countries with weak intellectual property rights protection. *Management Science,* 52: 1185–1199.

Figure 1. Types of Intra-firm Collaboration

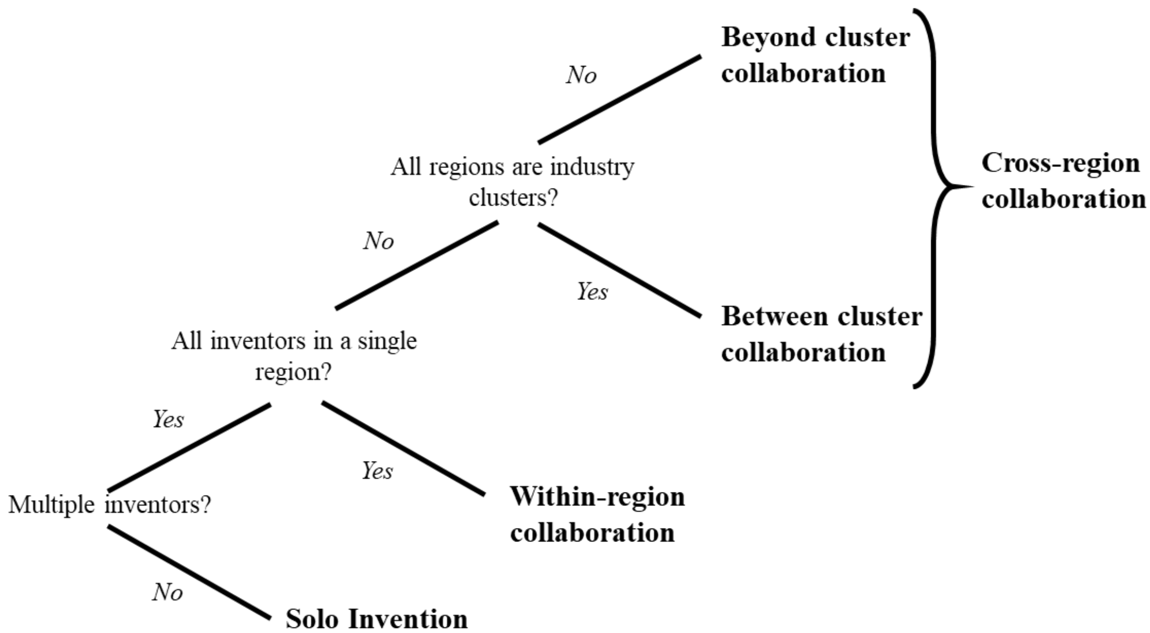

Figure 2. Intra-firm Collaboration & Knowledge Recombination

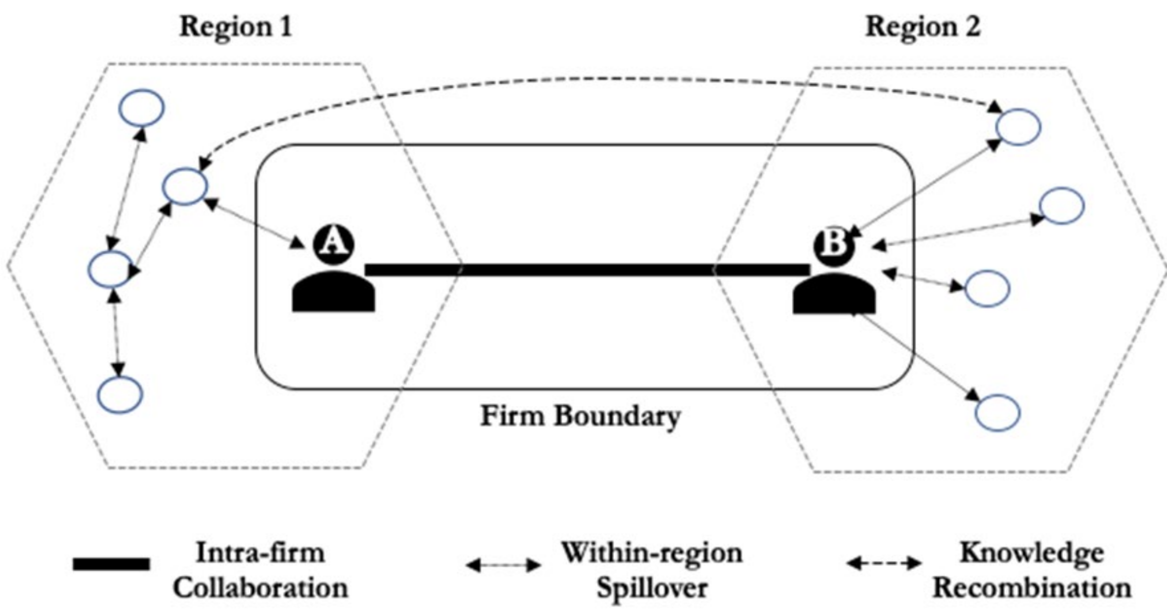

Figure 3a. Recombination across Technology & Geography

	Solo Inventions	Within-region	Between cluster	Beyond cluster
Technological proximity of knowledge	High	High / Low	High	Low
Geographic proximity of knowledge	High	High	Low	Low
Potential radicalness	Low	Moderate	Moderate	High
Invention impact	Low	Moderate	High (direct)	High (indirect; mediated by radicalness)
Invention quantity	High	Moderate	Low	Low

Figure 3b. Hypothesized Relationships

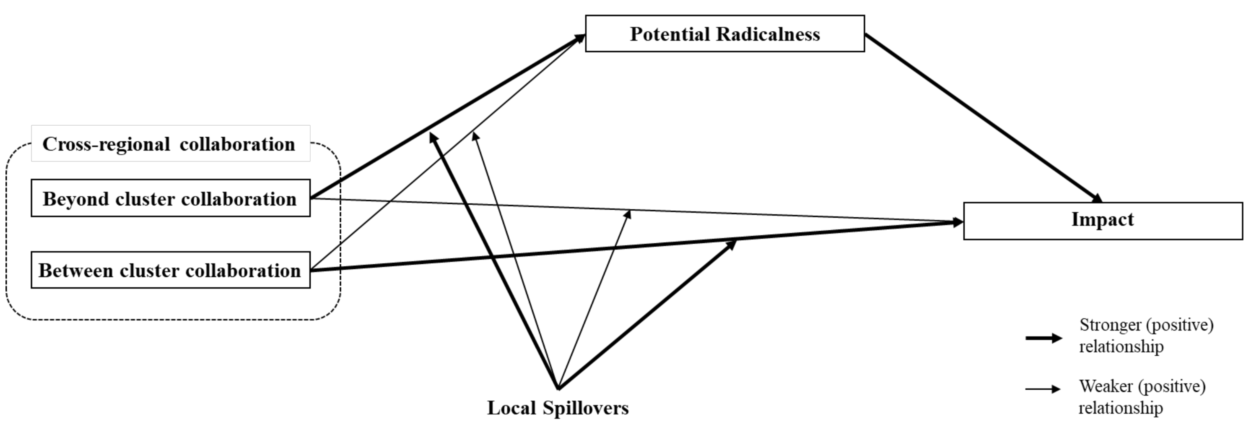

Table 1. Descriptive Statistics and Correlation, Patent Level

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Radicalness	1.00															
2. Top 5%	0.03*	1.00														
3. Cross-regional collaboration	0.03*	0.04*	1.00													
4. Collaboration between clusters	0.02*	0.03*	0.60*	1.00												
5. Collaboration beyond clusters	0.02*	0.02*	0.67*	-0.19*	1.00											
6. Local Spillovers	-0.07*	0.00	0.13*	0.16*	0.01*	1.00										
7. Within-region collaboration	0.00	0.00	-0.54*	-0.32*	-0.36*	-0.04*	1.00									
8. Baseline tendency for local spillovers	-0.01	0.05*	0.26*	0.37*	-0.02*	0.32*	-0.08*	1.00								
9. Number of patents (firm) †	0.00	0.02*	-0.02*	0.03*	-0.05*	0.10*	0.05*	0.25*	1.00							
10. Patent class concentration†	-0.01*	0.02*	0.04*	0.06*	-0.01*	0.03*	-0.01	0.04*	-0.20*	1.00						
11. Total asset†	-0.03*	-0.06*	-0.04*	-0.06*	0.01*	-0.02*	0.04*	0.00	0.41*	-0.49*	1.00					
12. R&D expense†	-0.04*	-0.03*	-0.04*	-0.03*	-0.02*	0.01	0.06*	0.09*	0.49*	-0.48*	0.92*	1.00				
13. Return on assets†	0.01	-0.04*	-0.04*	-0.04*	-0.01*	-0.02*	0.01	0.01	0.21*	-0.32*	0.44*	0.35*	1.00			
14. Absorbed slack†	-0.01	0.03*	0.02*	0.02*	0.01	0.02*	0.00	0.04*	-0.05*	-0.13*	-0.13*	-0.10*	-0.19*	1.00		
15. Alliance centrality†	-0.04*	0.01	-0.03*	0.02*	-0.06*	0.05*	0.05*	0.18*	0.61*	-0.20*	0.41*	0.51*	0.18*	-0.04*		
16. Alliance centrality exists†	-0.03*	0.00	-0.02*	0.06*	-0.07*	0.04*	0.05*	0.15*	0.53*	-0.11*	0.34*	0.41*	0.14*	-0.05*	0.70*	
Mean	-0.02	0.07	0.32	0.14	0.18	0.11	0.38	0.05	61.18	0.24	13271.40	548.01	0.00	0.81	0.00	0.43
S.D.	0.19	0.26	0.47	0.35	0.38	0.16	0.49	0.04	82.57	0.23	46742.81	895.15	0.35	5.51	0.01	0.49
Min	-0.65	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-7.68	0.00	0.00	0.00
Max	0.46	1.00	1.00	1.00	1.00	1.00	1.00	0.33	326.00	1.00	750507	7779	1.31	283.5	0.03	1.00

*$p < 0.05$
†Consistent with regression models, lagged one year.
‡Untransformed values are used for descriptive statistics. Log-transformed values are used for correlations and regressions.

Table 2. Results on Cross-regional Collaboration

Dependent variable	Radicalness			Top 5% patent					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Cross-regional collaboration		0.02**	0.01*		0.40**	0.29**		0.38**	0.28**
		(0.006)	(0.006)		(0.074)	(0.083)		(0.074)	(0.084)
Cross-regional collaboration X Local spillovers			0.06**			0.92**			0.90**
			(0.020)			(0.341)			(0.344)
Radicalness							0.70**	0.67**	0.66**
							(0.156)	(0.157)	(0.157)
Local spillovers	-0.08**	-0.08**	-0.10**	-0.41*	-0.44*	-0.87**	-0.37†	-0.40*	-0.83**
	(0.017)	(0.016)	(0.018)	(0.185)	(0.185)	(0.251)	(0.187)	(0.188)	(0.254)
Within-region collaboration	-0.00	0.01**	0.01*	0.02	0.22**	0.23**	0.02	0.22**	0.23**
	(0.004)	(0.004)	(0.004)	(0.055)	(0.068)	(0.068)	(0.055)	(0.068)	(0.068)
Baseline tendency for local spillovers	-0.00	-0.07	-0.08	2.08**	0.85	0.79	2.18**	0.98	0.92
	(0.127)	(0.134)	(0.133)	(0.796)	(0.827)	(0.826)	(0.797)	(0.829)	(0.829)
Number of patents (firm)	0.00	0.00	0.00	-0.00**	-0.00**	-0.00**	-0.00**	-0.00**	-0.00**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Patent class concentration	-0.00	0.00	0.00	-0.42*	-0.41*	-0.41*	-0.41*	-0.41*	-0.41*
	(0.009)	(0.009)	(0.009)	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)
Total assets	-0.00	-0.00	-0.00	-0.11†	-0.10*	-0.11†	-0.11†	-0.11†	-0.11†
	(0.004)	(0.004)	(0.004)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)
R&D expense	0.00	0.00	0.00	0.06	0.05	0.05	0.06	0.05	0.05
	(0.006)	(0.006)	(0.006)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)
Return on assets	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.006)	(0.006)	(0.006)	(0.103)	(0.103)	(0.103)	(0.103)	(0.103)	(0.103)
Absorbed slack	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.000)	(0.000)	(0.000)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Alliance centrality	-0.32	-0.28	-0.27	39.62**	39.80**	40.09**	39.91**	40.04**	40.30**
	(0.840)	(0.834)	(0.820)	(11.283)	(11.314)	(11.323)	(11.295)	(11.326)	(11.335)
Alliance centrality exists	0.00	0.00	0.00	-0.29**	-0.28*	-0.28*	-0.29**	-0.28*	-0.28*
	(0.008)	(0.008)	(0.008)	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)
Constant	0.01	0.00	0.01						
	(0.022)	(0.022)	(0.022)						
Observations	26,618	26,618	26,618	22,261	22,261	22,261	22,261	22,261	22,261
R-squared	0.007	0.009	0.009						
Number of firms	1,086	1,086	1,086	246	246	246	246	246	246

Notes: Ordinary least squares (OLS) model with firm fixed effects is used in Model 1, 2, and 3. Logit model with firm fixed effects is used from Model 4 to Model 9. Year dummies are included in all models. Robust standard errors clustered at the firm level in parentheses in Model 1, 2, and 3. Standard errors in parentheses from Model 4 to Model 9.
†$p < 0.1$, *$p < 0.05$, **$p < 0.01$

Figure 4a. Marginal Effect of Cross-regional Collaboration on Invention Radicalness

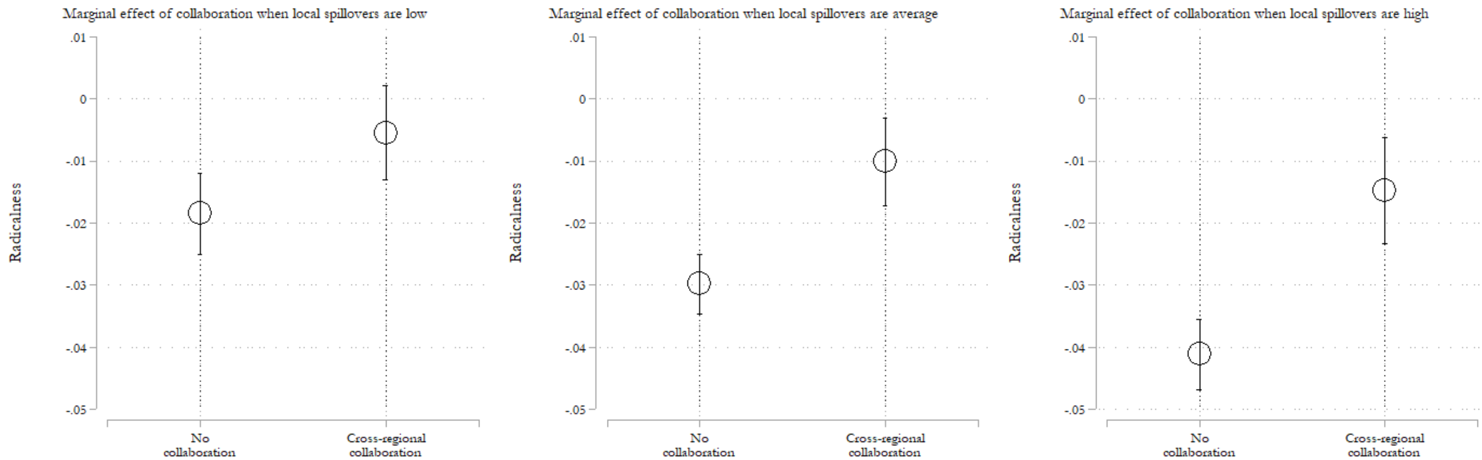

Figure 4b. Difference in Predicted Probabilities: Cross-regional Collaboration and No Collaboration

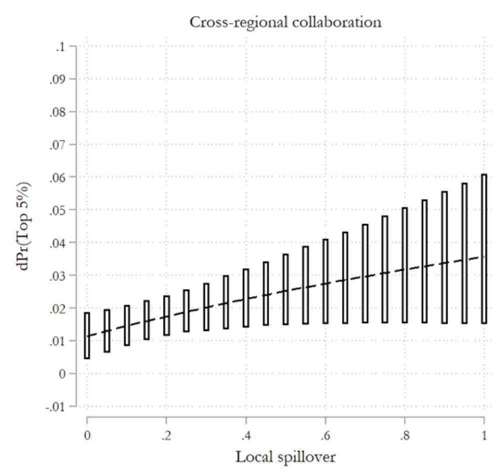

Table 3. Distinguishing Collaboration Between Clusters and Beyond Clusters

Dependent variable		Radicalness				Top 5% patent			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Collaboration between clusters		0.02**	0.02**		0.44**	0.26*		0.42**	0.25*
		(0.007)	(0.007)		(0.090)	(0.108)		(0.090)	(0.109)
Collaboration beyond non-cluster		0.02**	0.01		0.36**	0.33**		0.35**	0.32**
		(0.006)	(0.006)		(0.085)	(0.097)		(0.086)	(0.097)
Collaboration between clusters X Local spillovers			0.03			1.22**			1.21**
			(0.024)			(0.391)			(0.394)
Collaboration beyond clusters X Local spillovers			0.09**			0.39			0.36
			(0.027)			(0.472)			(0.475)
Radicalness							0.70**	0.67**	0.66**
							(0.156)	(0.157)	(0.157)
Local spillovers	-0.08**	-0.08**	-0.10**	-0.41*	-0.45*	-0.87**	-0.37†	-0.41*	-0.83**
	(0.017)	(0.017)	(0.018)	(0.185)	(0.186)	(0.252)	(0.187)	(0.188)	(0.254)
Within-region collaboration	-0.00	0.01*	0.01**	0.02	0.22**	0.23**	0.02	0.22**	0.23**
	(0.004)	(0.004)	(0.004)	(0.055)	(0.068)	(0.068)	(0.055)	(0.068)	(0.068)
Baseline tendency for local spillovers	-0.00	-0.08	-0.09	2.08**	0.71	0.75	2.18**	0.85	0.88
	(0.127)	(0.135)	(0.134)	(0.796)	(0.843)	(0.842)	(0.797)	(0.845)	(0.845)
Number of patents (firm)	0.00	0.00	0.00	-0.00**	-0.00**	-0.00**	-0.00**	-0.00**	-0.00**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Patent class concentration	-0.00	0.00	0.00	-0.42*	-0.42*	-0.41*	-0.41*	-0.41*	-0.41*
	(0.009)	(0.009)	(0.009)	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)
Total assets	-0.00	-0.00	-0.00	-0.11†	-0.10†	-0.11†	-0.11†	-0.11†	-0.11†
	(0.004)	(0.004)	(0.004)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)
R&D expense	0.00	0.00	0.00	0.06	0.05	0.05	0.06	0.05	0.05
	(0.006)	(0.006)	(0.006)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)
Return on assets	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.02	-0.01
	(0.006)	(0.006)	(0.006)	(0.103)	(0.103)	(0.103)	(0.103)	(0.103)	(0.103)
Absorbed slack	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.000)	(0.000)	(0.000)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Alliance centrality	-0.32	-0.28	-0.26	39.62**	39.67**	39.79**	39.91**	39.91**	40.02**
	(0.840)	(0.834)	(0.811)	(11.283)	(11.313)	(11.321)	(11.295)	(11.325)	(11.333)
Alliance centrality exists	0.00	0.00	0.00	-0.29**	-0.28*	-0.28*	-0.29**	-0.28*	-0.28*
	(0.008)	(0.008)	(0.008)	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)
Constant	0.01	0.01	0.01						
	(0.022)	(0.022)	(0.022)						
Observations	26,618	26,618	26,618	22,261	22,261	22,261	22,261	22,261	22,261
R-squared	0.007	0.009	0.010						
Number of firms	1,086	1,086	1,086	246	246	246	246	246	246

Notes: Ordinary least squares (OLS) model with firm fixed effects is used in Model 1, 2, and 3. Logit model with firm fixed effects is used from Model 4 to Model 9. Year dummies are included in all models. Robust standard errors clustered at the firm level in parentheses in Model 1, 2, and 3. Standard errors in parentheses from Model 4 to Model 9.

†$p < 0.1$, *$p < 0.05$, **$p < 0.01$

Figure 5a. Marginal Effect of Cross-regional Collaboration Between and Beyond Clusters on Invention Radicalness

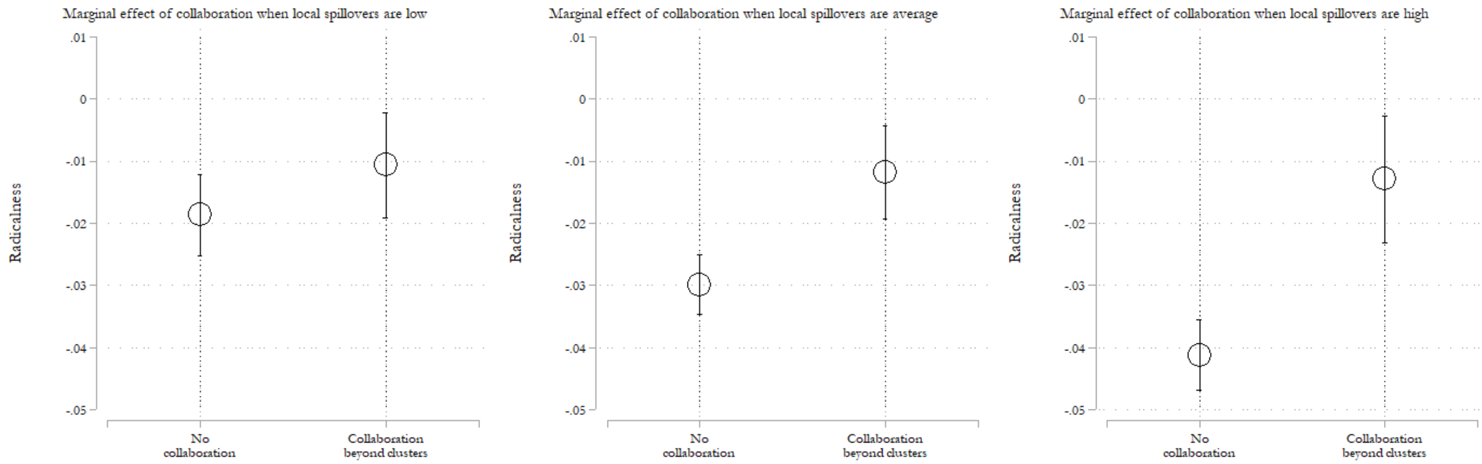

Figure 5b. Difference in Predicted Probabilities Against No Collaboration: Collaboration Between and Beyond Clusters

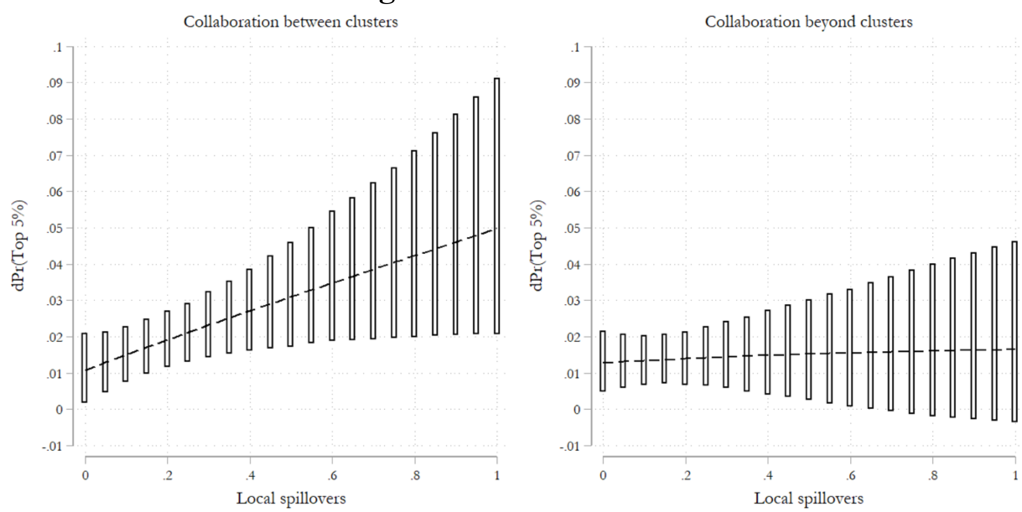

Table 4. Robustness Check: Number of Forward Citations Received

	Model 1	Model 2	Model 3	Model 4
Cross-regional collaboration	0.21**	0.21**		
	(0.042)	(0.042)		
Collaboration between clusters			0.26**	0.21**
			(0.076)	(0.069)
Collaboration beyond clusters			0.19**	0.22***
			(0.047)	(0.055)
Cross-regional collaboration X Local spillovers	0.37†	0.36†	0.34†	
	(0.211)	(0.209)	(0.191)	
Collaboration between clusters X Local spillovers				0.58*
				(0.245)
Collaboration beyond clusters X Local spillovers				0.01
				(0.223)
Radicalness		0.30**		0.31**
		(0.050)		(0.050)
Local spillovers	-0.33**	-0.30*	-0.32**	-0.29*
	(0.127)	(0.126)	(0.121)	(0.120)
Within-region collaboration	0.15**	0.15**	0.15**	0.15**
	(0.043)	(0.043)	(0.043)	(0.043)
Baseline tendency for local spillovers	0.62	0.65	0.50	0.54
	(0.641)	(0.642)	(0.599)	(0.591)
Number of patents (firm)	-0.00	-0.00	-0.00	-0.00
	(0.001)	(0.001)	(0.001)	(0.001)
Patent class concentration	-0.18*	-0.18*	-0.18*	-0.18*
	(0.083)	(0.084)	(0.083)	(0.084)
Total assets	-0.08*	-0.08*	-0.08*	-0.08*
	(0.039)	(0.039)	(0.039)	(0.039)
R&D expense	0.05	0.05	0.05	0.05
	(0.057)	(0.057)	(0.057)	(0.057)
Return on assets	-0.03	-0.03	-0.03	-0.03
	(0.073)	(0.073)	(0.073)	(0.073)
Absorbed slack	0.00	0.00	0.00	0.00
	(0.004)	(0.004)	(0.004)	(0.004)
Alliance centrality	8.57	8.65	8.51	8.42
	(9.526)	(9.473)	(9.562)	(9.522)
Alliance centrality exists	-0.11	-0.11	-0.11	-0.11
	(0.087)	(0.088)	(0.087)	(0.087)
Constant	1.64**	1.64**	1.65**	1.64**
	(0.201)	(0.201)	(0.201)	(0.200)
Observations	26,618	26,618	26,618	26,618
R-squared	0.026	0.027	0.027	0.028
Number of firms	1,086	1,086	1,086	1,086

Notes: Ordinary least squares (OLS) model with firm fixed effects is used. Year dummies are included in all models. Robust standard errors clustered at the firm level in parentheses.
†$p < 0.1$, *$p < 0.05$, **$p < 0.01$

Table 5. Split samples

Dependent variable	Radicalness				Top 5% patent			
Sample	Cross-regional Collaboration = 0	Cross-regional Collaboration = 1	Collaboration between clusters = 1	Collaboration beyond clusters = 1	Cross-regional Collaboration = 0	Cross-regional Collaboration = 1	Collaboration between clusters = 1	Collaboration beyond clusters = 1
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Radicalness					0.52**	0.88**	2.06**	0.46
					(0.183)	(0.326)	(0.608)	(0.414)
Local spillovers	-0.10**	-0.05*	-0.08**	-0.01	-0.80**	-0.06	0.17	-0.37
	(0.018)	(0.020)	(0.022)	(0.030)	(0.267)	(0.283)	(0.381)	(0.489)
Within-region collaboration	0.01**				0.23**			
	(0.003)				(0.069)			
Baseline tendency for local spillovers	-0.21	0.08	0.02	0.08	0.24	2.34†	2.71	1.23
	(0.164)	(0.109)	(0.121)	(0.146)	(1.186)	(1.254)	(1.845)	(1.991)
Number of patents (firm)	0.00	-0.00	-0.00	-0.00	-0.00**	-0.00†	-0.00	-0.01*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)
Patent class concentration	-0.01	0.02	0.05†	0.01	-0.59*	-0.48	0.04	-0.85†
	(0.012)	(0.015)	(0.025)	(0.021)	(0.236)	(0.334)	(0.530)	(0.495)
Total assets	-0.00	-0.00	-0.00	-0.01	-0.03	-0.23*	-0.31†	-0.16
	(0.005)	(0.005)	(0.006)	(0.008)	(0.082)	(0.106)	(0.161)	(0.162)
R&D expense	-0.00	0.01	0.00	0.01	-0.06	0.18	0.29	0.10
	(0.007)	(0.008)	(0.009)	(0.011)	(0.110)	(0.152)	(0.228)	(0.233)
Return on assets	0.00	-0.00	0.02	-0.01	0.10	-0.16	0.61	-1.03*
	(0.007)	(0.010)	(0.014)	(0.009)	(0.124)	(0.222)	(0.374)	(0.455)
Absorbed slack	0.00	-0.00	0.00	-0.00	0.00	0.00	0.01	-0.01
	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.006)	(0.009)	(0.009)
Alliance centrality	-0.45	-0.37	-0.21	-0.50	58.95**	8.94	-34.43	25.55
	(0.839)	(0.975)	(1.145)	(1.373)	(13.803)	(20.896)	(33.659)	(29.391)
Alliance centrality exists	0.00	-0.00	-0.01	0.01	-0.56**	0.24	0.54†	-0.00
	(0.009)	(0.009)	(0.011)	(0.014)	(0.141)	(0.192)	(0.281)	(0.306)
Constant	0.02	0.04	-0.03	0.13*				
	(0.026)	(0.044)	(0.045)	(0.056)				
Observations	18,044	8,574	3,857	4,717	14,668	6,713	2,966	3,471
R-squared	0.011	0.009	0.015	0.013				
Number of firms	953	631	393	474	188	127	71	92

Notes: Ordinary least squares (OLS) model with firm fixed effects is used in Model 1, 2, 3, and 4. Logit model with firm fixed effects is used in Model 5, 6, 7, and 8. Year dummies are included in all models. Robust standard errors clustered at the firm level in parentheses in Model 1, 2, 3, and 4. Standard errors in parentheses in Model 5, 6, 7, and 8.

†$p < 0.1$, *$p < 0.05$, **$p < 0.01$

‡The coefficient on local spillovers is also significantly different between Model 3 and 4 (1.88 (0.030)) at $p<0.05$

Table 6. Estimation of Number of Patents (Firm Level)

	Model 1	Model 2	Model 3	Model 4
Proportion of patents collaborated across regions	-1.18**	-1.23**		
	(0.472)	(0.510)		
Proportion of patents collaborated between clusters			-0.84*	-0.88
			(0.508)	(0.563)
Proportion of patents collaborated beyond clusters			-1.38**	-1.42**
			(0.546)	(0.565)
Proportion of patents collaborated across regions X Local spillovers		0.58		
		(1.281)		
Proportion of patents collaborated between clusters X Local spillovers				0.35
				(1.584)
Proportion of patents collaborated beyond clusters X Local spillovers				0.50
				(1.504)
Local Spillovers	-0.47	-0.68	-0.46	-0.62
	(0.754)	(0.883)	(0.755)	(0.889)
Proportion of patents collaborated within a region	-1.08***	-1.07***	-1.07***	-1.07***
	(0.293)	(0.293)	(0.292)	(0.292)
Baseline tendency for local spillovers	-2.90	-3.03	-4.02	-4.08
	(4.977)	(5.066)	(5.026)	(5.130)
Total number of inventors	0.49***	0.49***	0.49***	0.49***
	(0.020)	(0.020)	(0.020)	(0.020)
Total number of MSA	-0.21	-0.22	-0.21	-0.21
	(0.204)	(0.204)	(0.204)	(0.204)
Patent class concentration	-0.74	-0.75	-0.74	-0.74
	(0.692)	(0.694)	(0.691)	(0.693)
Total assets	-0.18	-0.18	-0.18	-0.18
	(0.541)	(0.543)	(0.541)	(0.543)
R&D expense	0.05	0.05	0.05	0.06
	(0.490)	(0.492)	(0.490)	(0.492)
Return on assets	0.49	0.49	0.50	0.50
	(0.419)	(0.420)	(0.420)	(0.420)
Absorbed slack	0.00	0.00	0.00	0.00
	(0.001)	(0.001)	(0.001)	(0.001)
Alliance centrality	1,452.80**	1,453.27**	1,453.10**	1,453.48**
	(727.812)	(728.188)	(728.106)	(728.528)
(dummy) Alliance centrality	-2.49*	-2.50*	-2.51*	-2.51*
	(1.377)	(1.381)	(1.386)	(1.388)
Constant	2.83	2.86	2.87	2.89
	(1.809)	(1.823)	(1.814)	(1.827)
Observations	4,432	4,432	4,432	4,432
R-squared	0.606	0.606	0.606	0.606
Number of firms	1,086	1,086	1,086	1,086

Notes: Linear panel regression model with firm fixed effects are used and year dummies are included. Robust standard errors clustered at the firm level in parentheses.
†$p < 0.1$, *$p < 0.05$, **$p < 0.01$