Interregional Inventor Collaboration and the Commercial Value of Patented Inventions: Evidence from the U.S. Biotechnology Industry

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Abstract

This paper analyzes the relative importance of the spatiality of inventor collaboration links for the quality of invention. It uses patent citation and renewal data to estimate (expected) economic values for a sample of U.S. biotechnology patents, controlling for a set of inventor and owner characteristics. The investigation extends the research by differentiating the quality of knowledge flows while at the same time refining patents as a source of innovation information. The results of the clustered logistic regression and continuation ratio models provide some support for the hypothesis that interregional (non-local) collaboration results in commercially more valuable inventions relative to patents that are product of intraregional (local) collaboration. The same empirical results also indicate that (1) inter-industry (related) knowledge flows contribute to the patent value more than inter-industry (unrelated) or intra-industry knowledge flows; and (2) general purpose technologies/products as measured by citations of patented inventions received from diverse sets of industries are indicative not only of technological/scientific quality but also of the economic value of patented inventions. These results are robust in different citation-window designations, exclusion of self-citations, different regional definitions, and different patent classifications.

Keywords: Patent citations; biotechnology industry; inventor collaborations; interregional; technological value; commercial value.

1. Introduction

The importance of knowledge sharing for firms' viability in high-tech sectors can hardly be overemphasized (Antonelli 2000; Becker and Dietz 2004; Boschma and Ter Wal 2007; Al-Laham et al. 2011). As innovation is an outcome of a complex process, the locus of innovation is not usually the individual inventor or the firm, but is often the integration of internal capabilities with the network in which the individual or the firm is embedded (Tödtling et al. 2009). Particularly in knowledge-intensive industries, firms increasingly view collaborations strategically as an important way for improving their competencies and gaining new capabilities in order to be innovative (Doloreux et al. 2015).

In parallel to this renewed understanding, there has been a shift in the research agenda of regional scientists. Highlighting the role of geography in collective knowledge production, sharing and innovation, over the years the economic geography literature has broadened its emphasis in cluster research from an analysis of forces of agglomeration to forms and contents of organizational learning and knowledge exchange. Specifically, the original scholarly interest in industrial clusters as mere geographic concentrations of sectors and firms has been converted to a search for institutions for knowledge management and organizational learning (Steiner and Ploder 2008). Within this stream of research, the spatial dimension of knowledge-based relationships has been at the heart of theoretical debates on innovation and central to geographical analyses of inventive activity for almost a decade now (Autant-Bernard et al. 2014).

The purpose of this study is to contribute to this stream of research by ascertaining the relative importance of local and non-local linkages in the innovation process using the United States biotechnology industry as a case study. We are specifically testing to see if inventor collaborations built at different geographical scales result in qualitatively different inventions. The analytical approach taken in this study differs from that of previous studies. While previous research almost exclusively focused on firms or regions as the main unit of analysis, the present study focuses on inventions (approximated by patents) as the main unit of analysis. Although for policy purposes adopting an explicit spatial perspective and focusing on regional scale is understandable, we argue that this restricts analysis to aggregate statistics which may result in concealing important details in observations (i.e. technological and commercial value of inventions). In most empirical models developed for the regional scale, innovative performance is operationalized through the number of patents produced by firms located in the region. Such an approach requires a rather strong assumption that patents developed in different places (states or provinces) are equally commercially exploitable. As noted by Balland and Rigby, "Although earlier research has explored the geography of patenting, this work largely treats individual patents as homogeneous, assuming that each patent adds only as much technological potential to a region's economy as the next. However, not all patents hold the same value" (2017: 18). To our knowledge, outside the management literature, very little research on innovative performance takes both the spatiality of collaborative research relationships and the quality of the output of these relationships into account. Some notable exceptions include the following. Singh (2008), who examines the role of cross-regional knowledge integration on innovation; Ejermo (2009), who distinguishes innovations from patent grants and shows that the former is more geographically concentrated than the latter; Briggs and Wade (2014), who investigate the relationship between joint patent ownership and the quality of an innovation; and Balland and Rigby (2017), who explore the linkage between the quality of patents and the geographical patterns of their production.

The rest of the paper is organized as follows. The next section briefly reviews the theoretical literature on knowledge sharing and collaboration in the innovation process and presents competing propositions as to the importance of local versus inter-regional collaborations for innovation. Section 3 discusses empirical findings from recent studies. Section 4 reviews conceptual and analytical issues surrounding the use of patent renewal data as a measure of innovation value. Section 5 explains the reasons for focusing on the biotechnology industry as a case study and discusses sample construction using patent data. Section 6 presents hypotheses and results. The final section concludes with the study's contribution, its limitations, and suggestions for future research.

2. Theoretical Background

2.1. The Case for Knowledge Sharing and Collaborations

There are both theoretical and empirical reasons why any single firm can no longer keep pace with the development of all related technologies and why firms must have access to external knowledge sources to remain viable in today's economy (Pyka 1997; Nagaoka et al. 2010). The literature focuses on two factors that explain the near necessity of knowledge sharing activity for businesses: uncertainty and the changing nature of competition based on innovation. Incomplete information means a lack of certainty in the decision making process, and as a result, the current actions of entrepreneurs or business decisions are considerably determined by already existing knowledge. This entrepreneurial behavior constraining reality in the business world explains the path dependent nature of innovation. Continuity, sequentiality and cumulativity of technical, organizational and managerial knowledge collectively mean the dependency of innovative activities on past, and within and across present organizational knowledge flows (Capello 1999; Foray 2004).

Related to uncertainty is the cost associated with conducting research and development. Although the number of distinct fields within which a firm might have competencies is theoretically limitless, the costs of developing and maintaining a broad array of different competencies often outweigh the benefits (Pavitt 1999; Bathelt et al. 2004). Lacking the necessary financial and technical resources, many firms are not capable of conducting large scale research and development projects on their own (Fornahl et al. 2011). Accordingly, firms broaden and deepen their collaboration with other firms through research and development.

These external partnerships shift the basis of competition to a new level: from firm versus firm to rival interregional or even transnational groupings of collaborators (Becker and Dietz 2004; Ceccagnoli et al. 2010). Similarly, increased specialization in technological development and innovation and the spread of these activities across the globe mean that all components of knowledge for a certain technology and production process are unlikely to be found in the same organization or place (Simmie 2003; van Geenhuizen 2005). For instance, Ceccagnoli and his colleagues' (2010) survey of major pharmaceutical firms find that new drug approvals rely extensively on external know-how. They report that for the majority of firms with more than 10 new drug approvals between 1989 and 2004, more than 50 percent of patents attached to the new drug were not held by the commercializing firm. For nearly two-thirds of the companies, more than half of their new drugs relied heavily on externally accessed technology.

2.2. Local versus Inter-regional Collaboration

Although there is an agreement in the literature that the access to external knowledge sources is important for firms, there is an ongoing debate as to whether and how the geography of this knowledge source matters in terms of its contribution to the innovative performance of firms. For years, our view about knowledge generation and innovation production processes in industrial clusters was in large part based on the application of the notion of embeddedness to knowledge diffusion in such places. According to this view, owing to trustful interpersonal relations and territorially confined shared institutions, knowledge circulates more easily within certain places than across their boundaries. In addition, since the transmission of partly tacit and non-codifiable nature of knowledge also requires physical proximity, this view suggests the diffusion of knowledge is limited to particular physical geographic borders (van Geenhuizen 2007). In fact, there is ample evidence indicating a strong local dimension of knowledge flows (Jaffe et al. 1993; Breschi and Lissoni 2009; Singh and Marx 2013). This perspective therefore views collective learning and localized knowledge spillovers for local firms as a major benefit of industrial agglomerations. According to this view, benefits of non-local linkages are non-existent or trivial.

However, the re-interpretation of the notion of embeddedness and its application within the economic geography literature has recently been seriously questioned because the concept of embeddedness was originally developed without a connection to any specific geographic scale (Hess 2004; Moodysson 2008). It is argued that the reinterpretation of this concept and understanding of different dimensions of embeddedness is crucial for examining the spatial manifestations of inventor interactions and firm relations. In the seminal article, Boschma (2005) argued that geographical proximity is neither necessary nor sufficient for knowledge transmission and its relevance is limited to the extent to which it enables other forms of proximity – social, institutional, organizational. Similarly, emphasizing that social proximities may be developed in the absence of spatial proximity, Breschi and Lissoni (2001: 268) note: "social bonds are often the outcome, and not the premise, of the economic or professional partnerships." Recent theorizing on knowledge dynamics and cluster competitiveness points to benefits of access to both local *and* global sources of knowledge. These suggestions require a comparative study of the role of organizational and technological relations in connecting emergent processes of knowledge creation across a range of geographical scales (MacKinnon et al. 2002; Bathelt et al. 2004).

In order to sustain a regional competitive advantage, local interactions and outside linkages must be balanced so as to generate synergies and to introduce new knowledge at the same time. As noted by Rosenkopf and Almeida (2003: 764) "every firm is embedded in a context that has limits in terms of the breadth of knowledge possessed". Extra-local linkages enable firms to overcome the limitations of local context by giving them access to non-redundant knowledge. For the cluster, such outside linkages bring new knowledge into the cluster and prevent lock-ins. Extra-regional linkages ensure the local cluster has access to the most recent and/or complementary knowledge in the industry in order to maintain its competitiveness (Bathelt et al. 2004; Bell and Zaheer 2007; Liu 2014).

In sum, local collaborations may be associated with high innovative performance because geographical proximity provides an advantage to individuals and firms by facilitating face-to-face contact. Frequent encounters can make interactive learning easier for participants and the performance of innovation processes may be increased (Cassi and Plunket 2014; Capaldo and Petruzzelli 2014). Alternatively, interregional collaborations may be associated with high innovative performance because of inventors' and organizations' access to complementary and different knowledge components created by interacting non-local actors. Interregional collaborations serve as bridges to distant knowledge contexts that offer collaborating firms access to unique knowledge. Therefore, non-local linkages could be important triggers of innovations for firms (Rosenkopf and Almeida 2003; Bathelt 2005; Moodysson 2008; Liu 2014; Bolivar-Ramos 2017).

2.3. Technological Proximity and Re-Combinative Innovation

Novel combinations along with the cumulativeness of knowledge are generally recognized as the important determinants of much of the scientific progress in society (Rosenberg 1994; Arthur 2007; Jaffe and de Rassenfosse 2017). Studies of innovation note that there are two types of technological and product development: (1) Incremental and (2) Radical. While both types of innovation require the combining of existing and new knowledge, radical innovations also necessitate the synthesis of knowledge from different technological domains. As such, incremental inventions tend to be more extensively rooted in the same industry, whereas more complex, path-breaking inventions are likely to have a long list of antecedents from different sectors. A successful combination of knowledge from multiple technological domains requires a certain level of absorptive capacity that firms may not have or the assimilation of external knowledge may take extra investment and considerable time to develop (Cuijpers et al. 2011). Thus, if firms lack complementary assets such as human and financial capital, the benefits of the resulting inventions are likely to be difficult to sufficiently appropriate (Nemet and Johnson 2012).

That new product introductions in an industry are influenced by the design of existing products is an example of incremental innovation. Various factors reinforce the incremental invention process, the most important of which is technological proximity. Technological proximity can be defined as the extent of overlap between two knowledge bases (Guan and Yan 2016).[1] The successful exchange of knowledge between two collaborating organizations is usually proportional to the degree to which their technical expertise overlaps. That explains why knowledge sharing is more pervasive among firms classified in the same or similar industries than among firms classified in different industries (Cecere and Ozman 2014; Jaffe and de Rassenfosse 2017). The tendency toward within industry search by innovators when they encounter an innovation challenge reinforces this pattern further. The literature on knowledge management notes that although it is generally more efficient for firms to process knowledge drawn from technologically similar domains, long-term competitiveness requires them to move beyond the technologically proximate search in their innovation efforts (Rosenkopf and Almeida 2003; Kesidou and Snijders 2012; McNamee and Ledley 2012).

3. Empirical Literature

Studies that directly focus on the importance of local and non-local linkages for the organizational and regional level innovativeness in the biopharmaceutical industry have produced mixed evidence.[2] Rees (2005) focuses on the medical biotechnology industry in Vancouver. Based on interviews conducted with research, development and production managers, he reports that non-local linkages are enhancing local innovative capacity by complementing local innovation capabilities. His findings show not only that the majority of collaboration links are non-local in orientation but also that local firms view collaborations with institutions located in the United States and other countries to be more important. Similarly, in studying Canada, Gertler and Levitte (2005) find that knowledge networks of innovative biotech firms are largely global, rather than local. Yamin and Otto (2004) report that external (non-local) knowledge flows have a positive influence on the multinational enterprise (MNE)'s innovative performance. They examine the relationship between knowledge flows and innovative performance, and show that subsidiary embeddedness in external (non-local) knowledge centers stimulates innovation in MNEs. In a more recent study, using the U.S. pharmaceutical industry as a case, Liu (2014) examines the relationship between the spatial dispersion of inventors on the inventor team and the economic value of patents. The researcher reports that having inventors from multiple locations significantly increases the chances of producing commercially valuable innovations (approximated by the patent renewal incidence).

On the other hand, there are studies that show contrasting evidence. For example, Gallie (2009) shows that inventors' local collaborations have a greater impact than non-local collaborations on the number of patents produced at the provincial level in France. Using three different patent databases that record French inventors' patent applications in biotechnology, this researcher developed and tested a model of knowledge diffusion in which, in addition to spillovers related to the R&D level and their spatial dimension, the spatial

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[1] Knowledge base is usually operationalized at the firm level or at the sectoral level in the economic geography literature, but it is also possible to examine the knowledge base of products/inventions.

[2] As noted in the introduction, empirical research examining the impacts of the spatiality of collaborative relationships on inventive activity to date has been limited to quantifying impacts on the organizational and regional level of innovativeness. Such studies were selected for review to give a current state of empirical findings and provide a basis for comparison with our results.

dimension of cooperation is explicitly considered. Gallie offers several explanations for the relative importance of geographical proximity. Very long distance might prevent the frequent meetings necessary to the majority of cooperative projects and, consequently, spillovers. She also notes that cultural, institutional, and linguistic differences observed outside of the European Union (EU) might be also the reason behind these results.

Using the patent applications of German biotechnology firms at the European Parent Office (EPO) and the World Intellectual Property Organizations (WIPO), Fornahl et al. (2011) report that while co-located biotech firms in German biotechnology clusters benefit from local knowledge spillovers they do not benefit from inter-regional knowledge network ties. Broekel et al. (2015) report similar results for the German biotechnology industry. Utilizing data on the co-application of patents for 270 German labor market regions, the researchers note a positive relationship between the intraregional (local) cooperation intensity and regional innovation efficiency. In a more recent study, de Noni et al (2017) examine the impact of interregional collaborations on regional knowledge productivity, measured as the number of patents produced. They found that interregional collaborations have a negative effect on the knowledge productivity of regions, but this effect becomes positive in regions where the local knowledge base is sufficiently diverse to absorb knowledge from non-local sources.

In short, empirical evidence still varies on the relative importance of intraregional versus interregional linkages for innovation in the biotechnology industry. As noted by Gertler and Vinodrai (2009: 238), "the relative importance of local and non-local flows of knowledge remains somewhat indeterminate and a point of contention within the literature on clusters, innovation and learning." The primary purpose of this study is to contribute to this growing body of empirical evidence by ascertaining the relative importance of local and non-local linkages in the innovation process.

4. Analytical Considerations Regarding the Use of Patent Data as a Measure of Innovation

Before discussing the sample data and case, a brief review of analytical issues surrounding the use of patent-related statistics as a proxy measure of innovation seems warranted. Related to that, a distinction is made between the private and the public value of patents.

4.3. The Relevance of Renewal Fees as Proxy for Patent Value

Patent renewals are a well-established indicator of the private value of a patent in the innovation studies. The inference of commercial value for patents from patent renewal fee payments is based on the following reasoning. Because patent holders derive rents from their patents only so long as those patents remain in force, the owners' decision of renewal (or expiration) should indicate the economic value they expect from their patents. If the anticipated level of rent is not larger than the fees required to keep the patent in effect, patent owners will let the patent expire (Bessen 2008; Liu 2014). In other words, the longer fees are paid, the higher a patent's implied value is (Harhoff et al. 1999). Such relationship was validated by numerous empirical studies (Bessen 2008; Liu et al. 2008; Baron and Delcamp 2012; Liu 2014).[3]

The use of renewal fees as a proxy for patent value is not without limitations. First, for those patents renewed three times (the maximum number of renewals for legal protection), the renewal fees provide a lower rather

[3] Beyond being indicators of patent value, Lee (2009: 627) notes that "patent renewals are informative about various features of the process of innovation, including the nature of the process by which the market for an innovation opens up and the extent to which the returns from an innovation become obsolete over time."

than an upper bound for patent value. The implication of this limitation for empirical analysis is that all patents renewed to full statutory term are assumed to represent same value to the owner. This also suggests that categorical renewals do not account for the discontinuity in the patent value over its life. Second, renewal fees might provide partial information as to what extent owners derive profits from the underlying invention given that the renewal decision is based on patent premium – "the extra value that the invention generates to the assignee when it is patented" (Petruzzelli et al. 2015: 209).

We acknowledge that renewals are an indirect measure of patent value and certain assumptions are made when using maintenance fees as an indicator of patent values. An alternative indicator of patent value used in the literature is forward citations (see for example, Trajtenberg 1990; Hall et al. 2005; Petruzzelli et al. 2015). As discussed in detail below, however, forward citations are often determinants rather than indicators of private patent value. As such, we argue that forward citations are a suitable measure of the public or technological value of patents, but not necessarily economic value. Also, some of the shortcomings discussed above for renewals are applicable to forward citations as well. For example, citations are an incomplete measure of private patent value because owners derive economic value from the exploitation of the knowledge that underlies the patented invention which is not made public in published patent documents. Thus, the use of forward citations as an indicator of patent value presumes that citing patents attest to the economic success of the cited patent only in expected value terms. Unlike forward citations, the patent renewal decision is beyond the sole influence of technological determinants such as the degree to which patented invention stimulated new patenting activity in other firms. The decision to renew or let a patent expire is a strategic choice made by assignee firms based on insights provided by innovation managers and patent attorneys. Therefore, "the strategic nature of patent renewal provides the analyst with an opportunity to observe how a firm differentiates patents of sufficient private value from other patents of lesser value" (Liu 2014: 619).

4.4. Public vs. Private Value of Patents

While the private value of patents designates the economic value of the underlying invention for its owner, the public or social value of patents represents how the public views the technological importance of patents (Baron and Delcamp 2012; Liu 2014).[4] The private value allows the owner to collect returns on her or his earlier investment by excluding rival firms from appropriation of, or by selling them the right to use, patented product or technology. Reflecting one of the primary functions of patent institution, the public value of patents is related to the extent to which scientific and technological knowledge revealed in patent documents contributes to social welfare by refining current commercial applications and aiding future inventions. Following these lines of reasoning, private (economic) value is considered to be a subset of (public) technological value of patents. The technological value of a patent tends to exceed its economic value because economic value is derived from the underlying technology of the patent (Bessen 2008; Lee 2009; Liu 2014). The technological value of patents is commonly measured by the number of forward citations they receive. It has been shown that patents of higher technological significance are cited more frequently by subsequent inventions (Trajtenberg 1990; Liu 2004; Nemet and Johnson 2012; Petruzzelli et al. 2015). Recognizing this distinction between technological and economic value of patents, the present study focuses on the economic value of patents as a subset of technological value.

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[4] Some authors refer to public and private value of patents respectively as technological and economic values (e.g., Bessen 2008; Lee 2009).

5. Case, Patent Data, and Sample Construction

There are strong analytical and practical reasons for focusing on the biotechnology industry. First, it is one of the most research and knowledge intensive sectors, measured in both industrial R&D spending and its reliance on academic scientific advancement for growth (Dimasi and Grabowski 2007; Cooke 2007). The successful maintenance of intellectual assets is a key distinguishing feature of this industry. Given the importance of knowledge for their success, firms in this industry make strategic choices as to which knowledge they need to maintain monopoly over and for how long (Liu 2014). Second, the selection of this industry was driven by a crucial analytical necessity: the validity of empirical findings. Being a highly regulated industry, biomedical organizations largely rely on patenting activity for the protection of intellectual property.[5] Therefore, patent statistics should reflect the invention activities in this industry fairly well (Fornahl et al. 2011). This data is available to researchers as a nearly complete historical record. The relatively large extent of the traceability of knowledge production and inventive activities in this industry enhances the internal validity of research findings and the applicability of the conclusions to the issues observed in the industry in general.

The initial sample included all patent applications at USPTO from 1976 to 2010 that were granted in one of eight 4-digit IPC (International Patent Classification) biotechnology classes.[6] From this sample, patents that report at least one U.S. inventor and were assigned to a US-based firm were selected. Such a sampling generated 34,269 (granted) patent applications. Harvard University's Patent Network Dataverse and Kauffman Foundation's COMETS (Connecting Outcome Measures in Entrepreneurship Technology and Science) were utilized to identify inventors' and assignee organizations' locations. As a final step in the dataset construction, maintenance fee payment status were recorded by using the U.S. Patent Grant Maintenance Fee Events File. This file contains recorded maintenance fee events for patents granted from September 1, 1981, to the present, and includes data on patentees' decisions to pay renewal fees to keep their patents in force for additional time periods. Patents applied for on or after 11 December 1980 accrue fees after 3.5, 7.5 and 11.5 years in order to remain in force beyond 4, 8 and 12 years, respectively. The fee schedules vary over time and depend on whether the assignee has small entity status (Bessen 2008). The data are cumulative and are updated and available weekly. It was possible to obtain all first, second, and third term renewal information for nearly all the patents in the sample (33,458 out of 34,269). The models presented below have 25,715 observations because patents granted after 2005 had to be dropped to compute consistent forward citation variables for all observations in the dataset. In the final sample, 3,257 patents were not renewed at all (13%), 4,805 were renewed only once (19%), 5,308 were renewed only twice (21%), and 12,345 were renewed three times (48%).

6. Analysis and Results

The goal of the analysis is to examine factors that determine an invention's economic value. The role of backward / forward citations and interregional collaboration of inventors in influencing the value of patented inventions in the biopharmaceutical industry is tested while controlling for relevant organization and inventor level characteristics. The following three hypotheses were tested in two different regression frameworks (binary logistic and sequential logit).

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[5] Nagaoka et al. (2010) argue that because there is no way to invent around new chemical entities in drugs (as protected by a compound patent), patents are a relatively effective mechanism for appropriating rents from innovation in the biopharmaceutical industry.

[6] The World Intellectual Property Organization -WIPO- considers biotechnology sectors comprised of the following classes: C07G, C07K, C12M, C12N, C12P, C12Q, C12R, C12S (Schmoch 2008). These classes roughly correspond to those US Patent Classes that are used to identify innovations in the biotechnology industry (see Boschma et al. 2015).

Hypothesis 1: *Inventions that are the product of interregional collaboration have higher (expected) economic value.*

Hypothesis 2a: *Inventions resulting from inter-industry knowledge flows are economically more valuable than those resulting from intra-industry knowledge flows.*

Hypothesis 2b: *Inventions resulting from related-industry knowledge flows are economically more valuable than those resulting from unrelated-industry knowledge flows.*

Hypothesis 3: *The more the patent is subsequently cited by same-technology inventions, the lower the invention's (expected) economic value is.*

In Hypothesis 1, the positive relationship between the commercial value of a patent and interregional collaboration is based on implications from the social networks literature that non-local relations are relatively costlier and difficult to maintain. There are both organizational and cognitive reasons for this. First, the ability of a firm to gain access to sources of knowledge (from non-local actors) and make successful use of such knowledge depends not only on its absorptive capacity but also the extent to which it is connected to other firms. Second, different types of languages are used in inter-regional and regional networks. While formal and technical languages are dominant in the former, more practical and contextualized languages are common in the latter (Dornbusch et al. 2013). In addition, recent studies that examined knowledge-based linkages of firms in clusters suggest that non-local linkages are important triggers of innovations for firms (Moodysson 2008; Liu 2014; Noni et al. 2017). Through non-local (inter-regional) connections, inventors and firms access to new and complementary knowledge sources, which provides such actors comparative advantage over their regional counterparts. Based on these insights, it is reasonable to expect that patents developed by inventors located in different regions should be, on average, technologically and economically more valuable than patents that are not the product of interregional collaboration.

Hypothesis 2a is based on the observation that major scientific and technological breakthroughs are result of the transfer of knowledge from different sectors. In the case of biotechnology, insights gained from seemingly different technology fields (such as macromolecular chemistry or pharmaceuticals) might offer solutions to long-held problems in the industry or help firms develop novel products. However, it might be costly and risky for firms to process knowledge gained from outside their standard domains with which they are closely familiar.

Hypothesis 2b is based on the theoretical insight that inventors and organizations tend to process more efficiently the knowledge gained from related technological areas (in contrast to knowledge from unrelated or very different fields). Relative familiarity with the related knowledge domains is often associated with a level of absorptive capacity that is sufficient in enabling the firm to incorporate external knowledge into the invention process successfully. In light of these insights and recent empirical findings on technological proximity and innovation performance, we expect that biotechnology patents that are built on related inventions (as measured by patent citations) are more likely to be renewed (Broekel and Boschma 2012; Fornahl et al. 2011).

Hypothesis 3 is based on the reasoning that if a patented invention is seen as an important precursor for subsequent inventions and receives multiple citations, this cited patent would have a high technological value and probably a correspondingly high economic value. Here citation is considered a realization of this judgment on the part of citing inventors. Patents renewed more frequently (2 or 3 times) are significantly more highly cited than patents allowed to expire before their full term (Harhoff et al. 1999; Bessen 2008; Liu 2014; Jaffe and de Rassenfosse 2017). The relation between forward citations, which is approximated by the number of times a patent is cited subsequently, and the technological value is validated by numerous studies (Trajtenberg et al. 2002; Harhoff et al. 2003; Wartburg et al. 2005; Gambardella et al. 2008; Nagaoka et al. 2010; Abrams et al. 2013). Studies generally recognize, however, that the relationship between citations and patent value is "noisy" and only a limited number of those studies quantify the actual increase in value associated with an incremental citation received (Sampat and Ziodenis 2004; Bessen 2008; Liu 2014).

Because citations come from different technology classes as well as the same technology class of the cited patent, the differential impact of those citations must be taken into account in modeling. If the patents that cite the subject (originating) patent come from a large number of technology classes, then generality will be high for the cited patent. Correspondingly, if the patents that cite the subject patent come from mostly the same technology class, then generality will be low for the cited patent. High generality suggests that the cited invention is a general-purpose technology/product with many applications while low generality suggests that cited invention's applications is limited to certain fields (Helpman 1998; Maurseth 2005; Lipsey et al. 2005; Bessen 2008; Petruzzelli et al. 2015). In terms of economic value, it is expected that patents with high generality scores will have high economic value because of the wider applicability of more general patents. Alternatively, rent potential from wider applications might be balanced by comparatively more exploitable rents from few specific sources in patents with low generality score.[7]

6.3. Variables and Model Construction

The dependent variable (*Y*) is the number of times a patent is renewed (nominal). Predictor variables are interregional collaboration, organizational collaboration, technological breadth, generality, organization size, inventor team size, organization patent stock, inventor patent stock, and claims. The first four variables are the variables of interest, and the other variables serve as controls in the models.

Independent variables

Interreg_Collab1: Interregional collaboration variable captures the degree of complementarity in knowledge creation based on the geographical dispersion of the inventor team (Mariani 2004; Liu 2014). Patents whose inventors reported residential addresses in different regions are coded to be based on interregional collaboration. It is important to note that interregional collaboration was operationalized at the inventor level instead of organizational level due to the fact that organizational co-ownership data does not reveal research collaborations among organizations completely. Because co-possessing a patent is legally complex for companies, firms rarely apply jointly for a patent. Due to this behavior, quite a substantial portion of inter-organizational cooperation remains invisible when just taking co-patenting as a proxy for joint research projects. This shortcoming is considerably compensated for by taking multi-applicant inventorship as a mean of retracing [inter-organizational] knowledge-based relationships (Hagedoorn et al. 2003, in Ter-Wal and Boschma 2009).

Interreg_Collab2: This variable is measured as the number of unique regions inventors are located in, and can be considered as a continuous version of *Interreg_Collab1* variable. While *Interreg_Collab1* examines the role of interregional collaboration of any kind in explaining patent value, *Interreg_Collab2* captures the impact

[7] Maurseth (2005) characterizes within-technology class citations as a "*creative destruction* effect in research rivalry." That is, citations from same-technology fields to a patent are indicative of this patent being obsolete. This characterization is consistent with the Hypothesis 3 and to the extent this is the case in the U.S. biotechnology industry, patents with low generality scores are less likely to be renewed.

of each additional external collaborator in predicting patent value. We expect the direction of relationship between this variable and patent value to be positive.

The selection of appropriate geographic scale for regional collaboration should be based on theoretical insights and empirical findings as to how inventors gain access to new knowledge external to the region in which they are located. There are multiple factors that make BEA economic areas an appropriate geographic level for this analysis. First, consisting of one or more inter-related economic nodes (surrounding metropolitan or micropolitan statistical areas that serve as regional centers of economic activity), these areas represent the relevant regional markets for labor, products, and most importantly for information. And because they are mainly determined by labor commuting patterns that delineate local labor markets, it is reasonable to assume that knowledge and information circulates relatively easily within these areas (mainly through labor mobility and other means of interactions and communications). Second, previous studies that examine the geographic extent of knowledge flows show that such flows are more intense at the MSA (Metropolitan Statistical Area) or CMSA (Consolidated Metropolitan Statistical Area) levels (Sonn and Storper 2008; Breschi and Lissoni 2009) - geographic units similar to BEA's economic areas in size. These empirical findings indicate that a large portion of knowledge circulating at these levels are internal to most inventors and cannot be considered as external to the region. Considering these findings and given their economic homogeneity and status as a single market for information BEA economic areas constitute an acceptable geographic level.

Nevertheless, we experimented with alternative measures of inter-regional collaborations based on different regional delineations to ensure that the results are not driven by the way regions are defined. Specifically, we considered those inventor collaborations as inter-regional if at least one of the inventors on the invention team is located a certain distance away from the rest of the team. Choosing 15 miles, 30 miles, and 60 miles as thresholds for external linkages, we constructed three alternative measures of inter-regional collaboration.[8] First, using latitude and longitude information for inventor locations in the sample, for each pair of inventors we calculated the linear distance between them. Second, we found the number of pairs an each invention team that is located away from each other more than the selected thresholds (i.e., external collaborators). Because the inter-regional collaboration variable is designed to capture the extent to which the patent incorporates external knowledge with locally existing knowledge, we counted only unique external collaborators. For instance, consider a patent with three inventors: if inventors A and B are located within 15 miles of each other, but they live 100 miles away from inventor C, the number of external collaborators for this patent was coded as 1.

Org_Collab: Organizational collaboration variable accounts for co-patenting among different companies to the extent that this activity is captured via joint patent applications. The inclusion of this variable with the *Interreg_Collab* variable in an interaction variable enables us to distinguish between the effects of within-organization and inter-organization interregional collaborations.

Tech_Breadth: Technological breadth variable measures the breadth of the technological base upon which a given patent is built. It was computed based on a Herfindahl index that reflects the dispersion of backward citations across patent classes (Thursby et al. 2009; Sterzi 2013; Petruzelli et al. 2015). The equation is:

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[8] 15 miles was selected as the lowest threshold point because it is the average commuting distance in the U.S. (U.S. Depart of Transportation 2003). Although somewhat arbitrary, other thresholds are multipliers of 15 and serve as comparison points. Variables that were constructed using these thresholds are named *Interreg_Collab3, Interreg_Collab4, and Interreg_Collab5,* respectively.

$$Tech\_Breadth = 1 - \sum_{j}^{N_j} s_{ij}^2$$

where s_{ij}^2 refers to the fraction of patents cited by patent *i* that belong to technological class *j* out of *N* technological classes assigned to the patents by the USPTO. A score of 0 indicates that all citations to prior art are in a single patent class and scores close to one indicate citations to many classes. A patent is considered to have a broad technological base if it cites prior art from many rather than few technology classes.

Relatedness: We used a method developed by Breschi et al. (2003) to construct knowledge relatedness measure (see Broekel and Boschma 2012, and Fornahl et al. 2011 for more recent applications). The procedure consists of four steps. First, utilizing technology classification codes (both primary and secondary) assigned to patents by patent examiners at USPTO, we constructed a symmetrical *matrix of co-occurrences* (***C***) whose generic cell *Cij* reports the number of patent documents classified in both technological fields *i* and *j*. As a next step, this matrix of co-occurrences was used to derive a measure of relatedness between technological fields. Specifically, following Breschi et al. (2003), we used the Cosine index to record the frequency of co-occurrences of technological fields *i* and *j* in relation to all other technological fields.

$$S_{ij} = \frac{\sum_{k=1}^{335} C_{ik} C_{jk}}{\sqrt{\sum_{k=1}^{335} C_{ik}^2 \sqrt{\sum_{k=1}^{335} C_{jk}^2}}}$$

The values of S_{ij} vary between 0 and 1, and the interpretation of the index is similar to that of the correlation coefficient. Greater values of S_{ij} indicates two fields *i* and *j* co-occur more frequently with the same technological fields and vice versa. Applying the cosine index calculation to a 335 × 335 matrix of the joint occurrences, we constructed a second matrix called the *knowledge-relatedness matrix* whose elements are *Sij* (*i* = 1, . . . , 335; *j* = 1, . . . , 335). (Breschi et al. 2003). As a final step, using S_{ij} index values we calculated an average knowledge relatedness score for each patent based on the overlap between its technological classes and the technological classes of those patents that it cited (i.e., backward citations).

Generality: This variable captures the degree to which citations to the given patent are concentrated in one technology class or coming from diverse technology classes. The generality score was computed the same way as the technological breadth score above (Henderson et al. 1998; Sterzi 2013).

$$Generality = 1 - \sum_{j}^{N_j} s_{ij}^2$$

where s_{ij}^2 refers to the percentage of citations to patent *i* that belong to technological class *j* out of *N* technological classes. A score of 0 indicates that all forward citations fall into one technological class, while scores close to one indicate citations come from many different classes. As noted by Sterzi (2013: 569) "this measure also reflects the patent quality to the extent that the more citations a patent gets, the greater the probability that the citations spread across a larger number of technological fields."

The three forward citation variables discussed below serve as a substitute for the generality score.

Frwd_Cit_Internal: Forward citations (internal) variable equals the number of citations a given patent receives from patents classified in the same 4-digit IPC technology class. It captures the extent to which the patent is specific and thus its technological influence is limited to subsequent *same-technology* patents.

Frwd_Cit_Near: Forward citations (near) variable equals the number of citations a given patent receives from patents classified in one of the eight 4-digit IPC biotechnology classes. It captures the extent to which the given patent has technological influence on subsequent *same-industry* patents.

Frwd_Cit_External: Forward citations (external) variable equals the number of citations a given patent receives from patents classified in any of the 4-digit IPC technology classes other than biotechnology. It captures the extent to which a given patent has broad application, and thus influenced subsequent inventions across *a range of industries*.[9]

In modeling the value of patents as a function of forward citations, there is no clear time frame within which a patent is expected to receive a citation. The probability of receiving a citation depends on the subsequent speed of patenting in the industry, the technology class of the invention, etc. In addition, it is not unusual that some patents start receiving citations after many years (rediscovery of old inventions as novel insights into current discoveries) or very old patents keep receiving citations years after their publication. Finally, as noted earlier, the outcome of the dependent variable is time-variant. Because we do not observe all citations made, but only those made by patents granted by the end of 2010, we have to assume that citation-receiving patents are both sufficiently technologically and conceptually similar to subsequent patents that the designation of a specific time period within which they are expected to receive a citation would not be influenced by their content. To the extent that this assumption is violated, the positive outcome for dependent variable Y would be underestimated. However, as long as the error in measuring Y is uncorrelated both with the regression errors and the independent variables, we do not expect that it would bias the coefficient estimates. Nevertheless, such an error inhibits the model's ability to estimate the relationship very precisely, as the estimated variances will be larger.

With these analytical implications in mind, following one of the common practices in the literature, we considered only those citing patents filed within a 5-year time window after a given patent's grant year to account for the fact that older patents have a higher likelihood of being cited by subsequent patents. However, to check the sensitivity of the results to this time period, we also computed all three forward citation variables by using a longer 10-year citation window.[10] The longer citation window "accounts for the possibility that novel combinations take longer to be used in subsequent inventions" (Nemet and Johnson 2012: 192). Finally, forward citation variables (both for 5-year and 10-year citation windows) are computed with and without self-citations at the assignee level.[11]

Control variables

Org_Size: Organization size variable measures whether the assignee is a small or a large firm. USPTO classifies firms whose number of employees, including affiliates, does not exceed 500 persons as small entity.

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[9] In order to check the robustness of the results to inconsistencies in patent examiners' classification decisions, we computed all three forward citation variables using 3-digit U.S. patent technical classes. Results are available upon request.

[10] The analysis of patent citations in our dataset showed that during a 15 year time window, more than 50% of the citations were made within five years following the publication of the patent and more than 90% of the citations were made within the first ten years. Therefore, a 10-year citation window captures nearly all possible citations made.

[11] It is noted in the literature that self-citations are usually added for strategic reasons by the applicants and therefore cannot be considered to signal technological impact or value (Mariani 2004; Hall 2005; Nemet and Johnson 2012). We ran all regression models by excluding self-citations and obtained very similar results. These results are available upon request.

This criterion is adopted for the definition of small in this study. Big firms with greater financial resources are more likely to renew their patents.

Team_Size: Team size variable equals the number of inventors involved in a patent. It accounts for the fact that collaboration pools complementary knowledge and ensures superior ideas advance while inferior ideas are screened out early (Singh and Fleming 2010; Liu 2014).

Org_Patent_Stock: Organization patent stock equals the number of patents assigned to the organization in the five years prior to the application year of the current patent. This variable captures the inventive capacity of the organizations.

Inv_Patent_Stock: Inventor patent stock equals the number of patents filed by inventors in the five years prior to the application year of the current patent. This variable captures the inventive capacity of the inventors.

Claims: The number of claims each patent makes. Patent claims establish the boundaries or scope of an invention. As such, a larger number of claims the swath of intellectual property occupied by the given patent (Nemet and Johnson 2012). The expectation is that patents with more claims are more likely to be renewed.

Table 1 reports descriptive statistics and correlation between the variables. With two exceptions, all bivariate correlations are below the recommended 0.7 threshold. We also computed variance inflation factors (VIFs) to check if multicollinearity is an issue among the model predictors. The maximum VIF value was 1.74, which is well below the common cut-off threshold of 10 (Studenmund 2010; Liu et al. 2014).

[Table 1]

We first estimated a binary logistic model to predict the probability of renewal. Correlated data are fairly common in organizational research. If such correlations are not taken into account, the data will be incorrectly analyzed and more specifically the standard error of the estimates will be incorrect (usually underestimated), rendering significance tests too optimistic. In this case, some of the organizations in the sample own multiple patents. In order to ensure that the observational independence assumption is unlikely to be violated, all logistic models were calculated with the assignee firms designated as the clustering variable.

The model results are provided in the table below. The OR column presents the odds ratios for the predictors. They are the exponentiation of the co-efficients (e^{β}). A β value greater than 1 increases the odds of occurrence and a β less than 1 decreases the odds of occurrence. The greater the distance from zero in either direction, the greater the impact of the predictor variable. A β value around zero means an odds ratio around 1, which means the variable has a negligible impact on the outcome. Model 1 is a baseline model comprising control variables only. The effects from the three hypotheses were added sequentially to Model 2 through Model 5. Model 5 is the complete model with all variables. The results from likelihood ratio tests indicate that each subsequent model represents a substantial improvement over the respective baseline models ($p < 0.01$ or lower). In Model 1, all control variables are significant and most of them have the expected sign. Patents assigned to large firms and those prepared by a higher number of inventors are more likely to be renewed. Impacts of inventor patent stock, organizational patent stock, and claims appear to be negligible.

Hypothesis 1, which states that inventions that are the product of interregional collaboration have higher (expected) economic value, is tested in Model 2 and 3. Although interregional and organizational collaboration variables have the expected positive sign, their effects are not significant - organizational collaboration reaches significance only at the 0.1 level. The lack of significance is also reflected in the marginal improvement in the likelihood ratio test result. This result remains mostly unchanged in Model 8 which includes all effects. To check the sensitivity of these findings to the way the interregional variable is constructed, in Table 3 in the Appendix we present results based on alternative regional variables (*Interreg_Collab3, Interreg_Collab4, and Interreg_Collab5).* [12] Although similar effects are observed for the interregional collaboration variables, organization collaboration has a large positive effect.

Hypothesis 2a, which suggests that inter-industry knowledge flows contribute to the patent value more than intra-industry knowledge flows, finds support in Model 4. Technology breadth has a strong, positive relationship with the probability of renewal. For a one unit increase in *Tech_Breadth*, the odds of being renewed (versus not being renewed) increase by a factor of 1.39. However, this effect decreases substantially in the full model and becomes insignificant.

Hypothesis 2b, which states that biotechnology patents that are built on related inventions are more likely to be renewed, finds considerable support in Model 5. Knowledge relatedness has a strong, positive relationship with the probability of renewal. For a one unit increase in *Relatedness*, the odds of being renewed (versus not being renewed) increase by a factor of 3.5. In the full model, this effect decreases slightly, but it is still substantial and highly significant.

Hypothesis 3 suggests that patents that receive citations from a wide range of technology fields are more likely to be renewed. According to Model 6 results, a one unit increase in the generality score increases the likelihood of patent renewal by more than 100 percent. This positive relationship remains unchanged in the full model, though its magnitude declines. In order to check the sensitivity of the results to the way the generality score is constructed, we reran the complete logit model using the generality score and forward citation variables constructed based on a 10-year citation window (see Table 1 in the Appendix). Model 1 in Table 1 (in the Appendix) is the first alternative model with a generality score calculated based on a 10-year citation window. The coefficient for this variable is still positive and larger than provided below. Model 2 in Table 1 (in the Appendix) is the second alternative model in which the generality score is replaced with three forward citation variables. [13] Although citations received from the same technology class of the focal patent have no effect on the probability of renewal, citations from near and external technology classes increase the likelihood of renewal. These results show that the impact of generality on the probability of renewal is robust in different citation-windows (5 years versus 10 years) and different ways of measuring the invention generality (generality score versus three mutually exclusive forward citation variables).

Finally, in order to ensure that the results are not driven by spatial dependencies, the final models (Model 8 below as well as those presented in the Appendix) were tested whether or not inventive activity in neighboring regions play a role in the results. We used both the number of inventors and number of patents to construct the spatial dependency variable (two variables as a proxy for potential source of knowledge

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[12] The interpretation of findings in first columns of Table 3 (i.e, Renewal 0 vs. Renewal 1,2,3) are the same of that of binary logistic regression.

[13] These three variables together serve as a substitute for the generality score.

spillovers). One way of constructing spatial dependency variable is aggregating patents or R&D efforts of all neighboring regions (Bode 2004; Castaldi et al. 2015). We took a slightly different approach from this convention in the literature. Instead of aggregating inventive activity in all regions, we multiplied the total for neighboring regions with that of the home region. This product approach is based on the notion that having a lot of inventive activity in a neighboring location will only spill over to raise activity in the home location if the home location has the capacity to absorb or make use of that spillover – i.e., someone to act upon the knowledge gleaned (Boschma 2005; Kemeny 2007; De Noni et al. 2017). So multiplying the sum of neighboring regions by the home region means that the measure of potential spillover is large if both neighboring regions and home region are large, and small otherwise. The stability of coefficients in the model with the *Neigh_Inv* variable indicates that spatial dependence does not have effects on the results.[14] [15]

[Table 2]

The logistic regression results above show that organizational collaboration and interregional inventor collaboration does not have impact on the probability of patent renewal. However, this model does not say anything about how such collaborations might affect the probability of second or third renewal after the patent's first renewal. In order to examine the impacts of the predictors on different stages of patent renewal, we estimate a continuation ratio model. This modeling approach is a subset of generalized linear models that estimate cumulative and conditional probabilities for categorical outcomes with more than two levels. The renewal categories, which are ordered, constitute the outcome variable in our case. Thus, ordinal logistic regression is an appropriate choice for modeling this type of outcome variable. However, besides ordinality, the fact that renewals occur in a sequence of stages (i.e., a patent has to be renewed once in order for it to be renewed twice and so on) needs to be taken into account in the modeling process. The probability of interest is thus the conditional probability (i.e., probability of being in a category given that the patent has progressed to that stage). This conditional probability is estimated with the continuation ratio regression equation where $\pi(Y > j \mid x_1,\ x_2, \dots x_p)$ is the conditional probability of being beyond a category j, conditional on being in that category, given a set of factors. j equals to the number of categories and j-1 and α_j are the cut points. $\beta_1,\ \beta_2, \dots \beta_p$ are logit coefficients (Fullerton 2009, Liu et al. 2011). Our outcome variable has four categories (no renewal, renewal 1, renewal 2, and renewal 3) and has three stages (0 vs. 1-3, 1 vs. 2-3, and 2 vs. 3). Similar to ordinal logistic regression, a continuation ratio approach needs to satisfy the proportional odds assumption (i.e., equal coefficients across stages) to be valid. Our graphical inspection at the individual predictor level showed that this assumption is violated for most of the independent variables in the model (see Figure 1 in the Appendix).[16] In addition, the likelihood ratio test comparing the constrained model to a model in which the coefficients for the model covariates are allowed to vary freely was significant ($p<0.001$), suggesting that the assumption of proportional odds does not hold at the model level (Hosmer et al. 2013).

[14] Note that we experimented with the sum approach and still got the same results. Similarly, no difference is observed in the model results when the spatial dependence variable (*Neighbor_Inv*) is replaced with the alternative variable which was constructed using patents (*Neighbor_Pat*).

[15] We checked the regression residuals for potentially remaining spatial dependencies using Moran's I. The results indicate that the spatial distribution of residuals is likely random (Index: 0.0043, z-score: 0.2022, p-value: 0.8397). Similarly, this statistic is not significant for any of the models presented in the following pages. We thank anonymous reviewers for recommending this robustness check.

[16] The assumption appears to hold for three variables only: *Inv_Patent_Stock, Frwd_Cit_Internal, Frwd_Cit_Near.* That means we will observe constant differences in log odds (logits) across outcome levels for these variables.

Based on these results, we decided to run the unconstrained version of the continuation ratio model (i.e., sequential logit) in which the proportional odds assumption is relaxed completely (Fullerton 2009).

The results are presented in Table 3 below.[17] In the baseline model, nearly all control variables are statistically significant, but with the exception of the organization size variable, none of them has any impact on the outcome of patent renewal stages (odds ratio is close or equals to 1). The effect of organization size declines as the renewal stages progress. Similar to a logistic regression model, the impacts of inventor patent stock, organizational patent stock, and claims appear to be negligible and nearly identical across stages.

According to the full model results, the first set of variables of interest (*Interreg_Collab1* and *Org_Collab*) has significant effects at second and third renewal stages.[18] The odds ratio of 1.19 and 1.13 for *Interreg_Collab1* indicates that patents that are prepared by inventors from the same organization who live in different regions are more likely to be renewed (compared to those that are prepared by inventors from different organizations who live in different regions). The effect of *Org_Collab* is even larger. The odds ratio of 4.77 indicates that if a patent is prepared by inventors from different organizations who live in the same region, it is more than 4 times more likely to be renewed second time (conditional on the patent being renewed once). Similarly, once the patent passes the stage 2 it is 3 times more likely to be renewed third time. As a robustness check, we reran the full model with alternative interregional collaboration variables (*Interreg_Collab3, Interreg_Collab4, and Interreg_Collab5)* (Table 3 in the Appendix). While both variables have positive effects, interregional collaboration is significant only at the second renewal stage (relatively small coefficient and odds ratios for this variable is not surprising because these models examine the impact of each additional external collaborator on the likelihood of patent renewal).

The significant and negative effect of the interaction variable confirms the main effects. Multiple locations among the collaborating inventors from different organizations reduces the positive impact associated with the organizational collaboration. Taken together, these results suggest that interregional inventor collaboration leads to more valuable patents only if inventors belong to the same organization, and that organizational collaboration on average results in more valuable inventions when collaborating inventors reside in the same region. These results have implications for the way in which technologically and commercially valuable knowledge flows among inventors located in different regions and belonging to different companies. These findings partially support Hypothesis 1.

One directly comparable study for these findings is Liu's (2014) study of patent renewals in the U.S. pharmaceutical industry. This researcher reports that having authors from multiple locations on the inventor team considerably increases the likelihood of both 4- and 8-year patent renewals. Our findings are partially consistent with those results. Similarly, we find a significant relationship between interregional collaboration and the probability of 8-year patent renewal, but the relationship between interregional collaboration and the probability of 4-year patent renewal is not significant in our study. The difference is likely due to the way the "multiple location" dimension is defined in the two studies. Liu considers the inventor team to be multilocational when inventors are located in different U.S. states or different countries, whereas we define the inventor team being interregional when inventors are located in different BEA-designated (the U.S.

[17] We present results for only the baseline and full models.

[18] Note that the results in the first column (Model 2 in Table 3) are the same as the logistic regression results (Model 8 in Table 2, as the sequential logit regression equation suggests).

Bureau of Economic Analysis) functional economic areas. Another potential explanation is the choice of industry. The present study's focus is biotechnology patents while Liu examines patents filed by U.S. pharmaceutical firms. Although a large number of biotechnology patents are filed and owned by U.S. pharmaceutical firms (e.g., Merck, Pfizer, Abbott Labs), there are many biotechnology patents owned by relatively small, non-pharmaceutical firms.

Tech_Breadth and *Relatedness* are the second set of variables of interest in Model 2 (Table 3). Although the former has a positive relationship with the probability of renewals across all stages, its impact significant (marginally) only at the second renewal stage. In stage two (Renewal 1 vs. Renewal 2-3), a one unit increase in the *Tech_Breadth* score increases the likelihood of patent renewal by 12 percent. *Relatedness*, on the other hand, has a large and statistically significant effects. In stage two (Renewal 1 vs. Renewal 2-3), the odds ratio of 5.22 indicates that each knowledge relatedness point increases the likelihood of patent renewal by a factor of 5. Relatively small, but substantial effect is observed for stage 3 (Renewal 2 vs. Renewal 3) for this variable. Based on these findings, we conclude that Hypothesis 2a is not supported, but Hypothesis 2b finds significant support.

To the best of our knowledge, the relationship between the technological breath and patent renewals has not been examined before. Studies that analyzed the impact of this variable on patent quality (approximated by the number of forward citations) provide an indirect comparison for our results. Similar to the findings reported above, Sterzi (2013) reports a positive relationship between technological breadth (called "invention originality") and patent quality. This researcher's study is based on patents prepared by academics in the U.K. between 1990 and 2001. On the other hand, Petruzzelli et al. (2015) find no significant relationship between the technological breadth of a patent and the influence it exerts on subsequent technological developments. Similar to the current study, the latter study analyzed a sample of 5,671 patents granted to 293 US biotechnology firms from 1976 to 2003. Knowledge relatedness received relatively more attention in the empirical literature. Our findings confirm previous studies that report positive relationship between technological relatedness and the value of innovations or the innovative performance of regions (Petruzzelli 2011; Castaldi et al 2015).

The final variable of interest is Generality. This variable has a positive relationship with all renewal categories although the size of its effects increases as renewal stages progress. Once a patent is renewed once, a one unit increase in the Generality score increases the likelihood of patent renewal by 54 percent at stage two and by more than 70 percent at stage three. In order to check the sensitivity of the results to the way the generality score was constructed, we reran the same sequential logit model using the generality score and forward citation variables constructed based on a 10-year citation window (see Table 2 in the Appendix). The results are consistent with the findings provided below. Although citations received from the same focal patent technology class have no effect on the probability of renewal across stages, citations from near and external technology classes increase the likelihood of renewal across all stages. The relatively small effects associated with forward citation variables (compared to Generality variable) is explained by the spread of the distribution (see descriptive statistics in Section 6.1). These findings support Hypothesis 3.

The positive relationship associated with patent generality is consistent with findings reported by some previous studies while inconsistent with some others. Using a sample of patents prepared by U.K. university faculty members between 1990 and 2001, Sterzi (2013) reports a positive relationship between generality score and patent quality (approximated by the number of forward citations). On the other hand, Lee (2009) reports that there is no relationship between the degree of dependence on other technology domains and patent technological value (approximated by the number of forward citations), direct economic value (measured as revenue from patent licensing) or indirect economic value (measured as patent life). In a more recent study, Nemet and Johnson (2012) find that citations to external industry patents is a less important predictor of technologically important inventions (approximated by forward citation frequency) than citations to within industry patents. The difference between previous findings and the findings of the present study could be due to the types of patents studied. While Lee's analysis is limited to Korean-invented US patents from public research institutes, Nemet and Johnson analyze all U.S. patents granted from 1976 to 2006. This suggests that an industry-focused approach could produce more precise and nuanced understanding of interindustry knowledge flows in terms of influencing patent economic value. It is also important to note that the dependent variable in those studies are "patent quality" or "technological value," which is close to, but not exactly same as, the dependent variable in the present study.[19]

[Table 3]

7. Conclusion

Highlighting the role of geography in collective knowledge production and innovation, Feldman and Kogler (2010) note that firms are not alone in organizing modern economic activities, though they are the dominant venue. Resources required to generate innovations are increasingly not confined to a single firm and in such cases geography functions as an additional venue to organize the factors of production by making multifaceted relationships among firms possible. Differentiating the spatiality of one of those relationships precisely and examining its relative importance in determining inventive quality, the present study contributes to the understanding of the role geography plays in the process of innovation.

The results show that the importance of inventor collaboration for the quality of invention varies depending on the spatiality (intra-regional versus interregional) and organizational nature (intrafirm versus interfirm) of such collaborations. In addition, examining citation counts' relationship with the economic value estimate of patents contributes to higher level methodological debates about the usefulness of patent citations as a valid measure of analysis in science and technology studies. The approximate quantification of knowledge flows is methodologically and theoretically desirable in the geography of innovation studies because when knowledge flows are examined, usually their contribution to innovation is assumed rather than empirically shown.

The findings related to backward citations (captured by the variable *Tech_Breadth* and the complementary variable *Reladtedness*) indicate that inventions resulting from inter-industry knowledge flows *that are technologically similar* are on average more valuable than those that are based on inter-industry knowledge flows *that are technologically dissimilar*. The findings related to forward citations (captured by the variable *Generality*) highlight that that citations received from diverse sets of industries are indicative not only of technological/scientific quality but also of the economic value of patented inventions.

The industrial cluster literature's overemphasis on local knowledge-based interactions as a dominant factor determining local firms' innovativeness and by extension the trajectory of local economic development was the main motivation behind this study. The regression models provide mixed results as to the importance of local and non-local knowledge-based interactions. The results in Table 3 indicate that interregional inventor collaboration leads to more valuable patents when collaborating inventors belong to the same organization. However, they also suggest that organizational collaboration on average results in more valuable inventions when collaborating inventors reside in the same region. Although mixed, these findings illustrate the partial

[19] As noted above, we recognize that those studies provide an indirect comparison for our findings.

importance of the extra-local and extra-firm knowledge linkages for firms' innovativeness as measured by the economic value of patented inventions.

This study is not without limitations. First, the positive relationship we report between interregional collaboration and patent renewal (in second and third stages) could be challenged on the grounds that the impact results from other factors not accounted for in the regression models. As noted by Liu (2014), firms might have allocated more resources to invention projects with multiple inventors or inventors from multiple locations to ensure the success of such projects. The number of inventors cannot be used as an alternative explanation because it is controlled by the variable *Team_Size*. However, the latter could be an explanation for the observed impact. The necessity of interregional collaboration for such patents' preparation reflects the spatial spread of expertise in their content. Such patents may be selective since inventions anticipated to be more economically valuable require more collaboration, perhaps because (1) the invention is more radical and thus needs more diverse attention, or because (2) the greater economic return makes collaboration over long distances among participants less unattractive, as long distance collaboration is almost always relatively costly and risky.

A second limitation relates to the research setting. Our study focuses on the U.S. biotechnology industry; therefore the interpretations of our findings may be limited by the characteristics of this particular industry. However, taking an industry-based approach is in line with recent contributions (Massard and Autant-Bernard 2015) that note the variation in the spatial dimensions of knowledge flows across industries, and the need to produce industry-specific empirical evidence to better inform science and technology policy making.

Third, we chose to restrict our observations to patents granted to firms and focused only on collaborations between inventors who signed patents for business entities. We did not include patents owned by non-business entities (i.e. universities, hospitals, and federal government agencies) because our analysis showed that there are substantial differences between business and non-business patents in terms of the number of years they require to be granted and the frequency with which they receive citations. Future research efforts may be directed at finding ways to include patents owned by non-business entities.

There are several lines of investigation for future research that could refine and improve the findings reported in this study. Researchers can investigate to what extent the observed relationships between the patent value, citations, and the spatiality of inventor collaborations vary across different time periods. It has already been noted that while overall inventor collaborations are becoming less geographically localized, there is paradoxically an increase in the extent of the localization of knowledge flows over time (Sonn and Storper 2008; Cappelli and Montobbio 2016; Sonmez 2017). This suggests that either interregional collaborations are becoming increasingly less selective in terms of contributing to new knowledge production or geographical distance still continues to inhibit the diffusion of knowledge. Understanding the implications of such trends for the importance over time of interregional collaboration in the innovation process would be a valuable contribution to the literature. One implication could be that increased interregional collaborations result in relatively few successful inventions (worthy of renewal) while failures (not worthy of renewal) are becoming more prevalent over time.

Another potential area for future research is the influence that the specific geographical location of collaborating inventors or organizations may exert on patents. Given that the U.S. biotechnology industry is highly clustered (Powell and Sandholtz 2012), there might be variation in the economic value of patents depending on whether the inventors or firms are located in a large or emerging small cluster. Future research efforts could be directed to systematically incorporating region-specific factors that are theoretically shown to influence the quality and productivity of inventor collaborations. For instance, to the extent that different clusters are specialized in different subfields, the results reported in this study may vary based on the subfields of the biotechnology industry in which inventors perform research and development activity. Note that this implies an informed research effort that goes beyond accounting for technology or regional specific effects simply including patent class or regional dummies in the model. Some of the key regional factors/dimensions that are associated with a vibrant biotechnology cluster may include (1) complementary technological competencies – i.e. patenting activity in a combination of several related technology classes; (2) the presence of various anchor institutions such as multinational biopharma firms, universities, hospitals; (3) the availability of venture capital.

In terms of policy implications, the findings of this study provide useful insights for both regions dedicated to promoting innovation in the biotechnology industry and firms exploring new innovation solutions by collaborating with other firms. Joint patent projects are likely to succeed (i.e., resulting in commercial applications or generating other economic benefits to their owners) when (a) inventors from the same organization collaborate interregionally or (b) collaborating firms are located in the same region. Our findings indicate that multiple geographic locations among the collaborating inventors from different organizations reduces the positive impact associated with the organizational collaboration variable. That could be due to geographic distance inhibiting the development of long-term and lasting relationships between partners that facilitate knowledge sharing and creation. This factor should be considered in partner selection process by firms. Regarding the effective exploitation of existing knowledge bases, our results suggest that inventions that are built upon related technological knowledge tend to be more valuable, suggesting that it might be relatively easy for firms to process knowledge gained from domains with which they are closely familiar. As for regional-level policies, our findings suggest that organizational collaboration (intraregional) should be encouraged. Specifically, the positive relationship between knowledge relatedness and patent value implies that policy makers should design R&D funding programs and incentives in ways that lead to partnerships among firms that share similar knowledge bases. Considering potential policy implications of better understanding the link between specific inventor, organizational, regional factors and the successful innovation in biotechnology, our study makes only a modest contribution to an area of research that deserves more attention in the coming years.

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Appendix

[Table 1]

[Figure 1]

[Table 2]

[Table 3]

Table 1: Descriptive statistics and correlation matrix (N= 25,715)

Variables		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	*Renewal*	1.00														
2	*Interreg_Collab1*	0.03***	1.00													
3	*Interreg_Collab2*	0.02***	1.00***	0.10***												
4	*Org_Collab*	0.03***	0.07***		1.00											
5	*Tech_Breadth*	0.27***	0.31***	0.06***	0.24	1.00										
6	*Generality*	0.14	0.16**	0.02**	0.09	0.16***	1.00									
7	*Relatedness*	0.83***	0.85***	0.04***	0.87***	0.39***	0.06***	1.00								
8	*Frwd_Cit_Internal*	0.08***	0.05*	0.02***	0.03	0.06***	0.32**	0.07***	1.00							
9	*Frwd_Cit_Near*	0.09***	0.06	0.01*	0.03	0.07***	0.40***	0.06***	0.82***	1.00						
10	*Frwd_Cit_External*	0.10***	0.06***	0.03***	0.10***	0.14***	0.49***	0.06***	0.26***	0.31	1.00					
11	*Org_Size*	0.14***	0.02**	0.02***	0.04	0.31***	0.15	-0.02***	0.04	0.06*	0.05*	1.00				
12	*Team_Size*	0.06***	0.40***	0.42***	0.38***	0.06***	0.04***	0.01	0.02***	0.02*	0.03***	0.12***	1.00			
13	*Org_Patent_Stock*	0.34***	0.25***	0.02***	0.68***	-0.01	-0.04***	-0.01	-0.03***	-0.04***	-0.04***	0.45***	0.04***	1.00		
14	*Inv_Patent_Stock*	0.13***	0.19***	0.06***	0.37***	0.00	-0.05***	-0.00	-0.03***	-0.03***	-0.02	0.11	0.22***	0.02***	1.00	
15	*Claims*	0.11***	0.11	0.05***	0.13***	0.13***	0.11***	0.11***	0.09***	0.08***	0.10***	0.10***	0.08***	-0.08***	0.02***	1.00
	Mean	*0.87*	*0.24*	*1.29*	*0.01*	*0.35*	*0.17*	*0.22*	*0.77*	*0.33*	*1.57*	*0.80*	*2.80*	*221.90*	*7.61*	*17.90*
	Std. Deviation	*1.08*	*0.43*	*0.58*	*0.10*	*0.32*	*0.26*	*0.13*	*2.19*	*3.45*	*3.61*	*0.40*	*1.97*	*22.67*	*22.67*	*18.39*
	Minimum	*0*	*0*	*1.00*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*1*	*0*	*0*	*0*
	Maximum	*1*	*1*	*9.00*	*1*	*0.96*	*0.91*	*0.60*	*66*	*99*	*151*	*1*	*40.00*	*11,950*	*1,006*	*683*

Notes: *p < 0.05, **p < 0.01, ***p < 0.001 (two-tailed). The association between the numeric variables are measured with Pearson's correlation while the relationship between categorical variables and categorical and numeric variables are measured with Cramer's V. Mean value for the nominal variables represents the portion of observations coded as 1 (or greater).

Table 2: Logistic Regression Results

Variables	Model 1 β	Model 1 OR	Model 2 β	Model 2 OR	Model 3 β	Model 3 OR	Model 4 β	Model 4 OR	Model 5 β	Model 5 OR	Model 6 β	Model 6 OR	Model 7 β	Model 7 OR	Model 8 β	Model 8 OR
Interreg_Collab1			0.041	1.00									-0.0094	0.99	-0.0098	0.99
			(0.0566)										(0.0571)		(0.0574)	
Interreg_Collab2					0.0290	1.03										
					(0.0399)											
Org_Collab			0.4050	1.50	0.9636	2.62†							0.3561	1.43	0.3552	1.43
			(0.3328)		(0.5788)								(0.3310)		(0.3303)	
Interreg_Collab1x Org_Collab			0.4997	1.65	-0.1826	0.83							0.5575	1.75	0.5579	1.75
			(0.4811)		(0.2796)								(0.4837)		(0.4832)	
Tech_Breadth							0.3297	1.39***					0.0936	1.10	0.0934	1.10
							(0.0741)						(0.0778)		(0.0778)	
Relatedness									1.2751	3.58***			1.1324	3.10***	1.1310	3.10***
									(0.1699)				(0.1768)		(0.1762)	
Generality											0.7230	2.06***	0.6954	2.00***	0.6956	2.00***
											(0.0960)		(0.0961)		(0.0961)	
Org_Size	0.6354	1.89***	0.6335	1.88***	0.6333	1.88***	0.6526	1.92***	0.6504	1.92***	0.6417	1.90***	0.6580	1.93***	0.6504	1.92***
	(0.0517)		(0.0520)		(0.0520)		(0.0520)		(0.0516)		(0.0519)		(0.0525)		(0.0516)	
Team_Size	-0.0046	1.00	-0.0114	0.99	-0.0121	0.99	-0.0066	0.99	-0.0045	1.00	-0.0103	0.99	-0.0166	0.98	-0.0045	1.00
	(0.0110)		(0.0120)		(0.0121)		(0.0109)		(0.0110)		(0.0111)		(0.0121)		(0.0111)	
Org_Patent_Stock	-0.0002	1.00***	-0.0002	1.00***	-0.0002	1.00***	-0.0002	1.00***	-0.0002	1.00***	-0.0002	1.00***	-0.0002	1.00***	-0.0002	1.00***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Inv_Patent_Stock	-0.0080	0.99***	-0.0080	0.99***	-0.0080	0.99***	-0.0078	0.99***	-0.0077	0.99***	-0.0077	0.99***	-0.0075	0.99***	-0.0077	0.99***
	(0.0011)		(0.0011)		(0.0011)		(0.0011)		(0.0011)		(0.0011)		(0.0011)		(0.0011)	
Claims	0.0152	1.02***	0.0151	1.02***	0.0151	1.02***	0.0143	1.01***	0.0139	1.01***	0.0136	1.01***	0.0122	1.01***	0.0140	1.01***
	(0.0019)		(0.0019)		(0.0019)		(0.0019)		(0.0019)		(0.0018)		(0.0018)		(0.0019)	
Neighbor_Inv															0.0000	1.00
															(0.0000)	
Tech_Class_Dummies		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes
Year_Dummies		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes
α	*0.6944*	*2.00†*	*0.7098*	*2.03†*	*0.6732*	*1.96†*	*0.5623*	*1.75*	*0.4125*	*1.51*	*0.6989*		*0.4257*		*0.4269*	
	(0.3727)		*(0.3739)*		*(0.3794)*		*(0.3736)*		*(0.3698)*		*(0.3788)*	*2.01†*	*(0.3768)*	*1.53*	*(0.3770)*	*1.53*
N		25,715		25,715		25,715		25,715		25,715		25,715		25,715		25,715
X^2		3650.1***		3658.4***		3658.3***		3672.2***		3707.7***		3714.9***		3778.1***		3778.2***
ΔX^2				8.3*		8.2*		22.1***		57.6***		64.8***		128.0***		128.1***

Notes: Values in parentheses are cluster-robust standard errors; †p<0.1, *p < 0.05, **p < 0.01, ***p < 0.001 (two-tailed). β: log odds. OR: Odds Ratio (exp(β))

Table 3: Continuation Ratio (Sequential) Logit Regression Results

	Model 1						Model 2					
	Renewal 0 vs. Renewal 1,2,3		Renewal 1 vs. Renewal 2,3		Renewal 2 vs. Renewal 3		Renewal 0 vs. Renewal 1,2,3		Renewal 1 vs. Renewal 2,3		Renewal 2 vs. Renewal 3	
Variables	**β**	**OR**	**β**	**OR**	**β**	**OR**	**β**	**OR**	**β**	**OR**	**β**	**OR**
Interreg_Collab1							-0.0098	0.99	0.1715	1.19***	0.1197	1.13**
							(0.0530)		(0.0422)		(0.0441)	
Org_Collab							0.3552	1.43	1.5620	4.77***	1.0950	2.99***
							(0.3359)		(0.3752)		(0.3001)	
Interreg_Collab x Org_Collab							0.5579	1.75	-1.0480	0.35*	-0.7393	0.48*
							(0.5167)		(0.4382)		(0.3764)	
Tech_Breadth							0.0934	1.10	0.1109	1.12†	0.0510	1.05
							(0.0772)		(0.0601)		(0.0625)	
Relatedness							1.1310	3.10***	1.6520	5.22***	0.9293	2.53***
							(0.1813)		(0.1431)		(0.1539)	
Generality							0.6956	2.00***	0.4296	1.54***	0.5439	1.72***
							(0.0932)		(0.0692)		(0.0711)	
Org_Size	0.6361	1.89***	0.3295	1.39***	0.3767	1.46***	0.6504	1.92***	0.3581	1.43***	0.3866	1.47***
	(0.0505)		(0.0424)		(0.0458)		(0.0508)		(0.0428)		(0.0461)	
Team_Size	-0.0045	1.00	-0.0308	0.97***	-0.0210	0.98*	-0.0045	1.00	-0.0539	0.95***	-0.0403	0.96***
	(0.0110)		(0.0084)		(0.0094)		(0.0120)		(0.0092)		(0.0104)	
Org_Patent_Stock	-0.0002	1.00***	-0.0001	1.00*	-0.0001	1.00***	-0.0002	1.00***	-0.0001	1.00*	-0.0001	1.00***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Inv_Patent_Stock	-0.0080	0.99***	-0.0025	1.00**	0.0004	1.00	-0.0077	0.99***	-0.0031	1.00**	-0.0007	1.00
	(0.0009)		(0.0010)		(0.0012)		(0.0009)		(0.0010)		(0.0013)	
Claims	0.0152	1.02***	0.0102	1.01***	0.0048	1.00***	0.01140	1.01***	0.0077	1.01***	0.0032	1.00**
	(0.0017)		(0.0011)		(0.0010)		(0.0016)		(0.0011)		(0.0010)	
Neighbor_Inv	0.0000	1.00	0.0000	1.00***	0.0000	1.00***	0.0000	1.00	0.0000	1.00***	0.0000	1.00***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Tech_Class_Dummies		Yes		Yes		Yes		Yes		Yes		Yes
Year_Dummies		Yes		Yes		Yes		Yes		Yes		Yes
α	0.9000	2.46*	0.4104	1.51	-0.2281	0.80	0.4269	1.84	0.0497	1.05	-0.4443	0.64
	(0.3976)		(0.3991)		(0.4269)		(0.3994)		(0.4045)		(0.4287)	
N						25,715						25,715
X^2						6290.4***						6838.1***
ΔX^2												547.7***
AIC						58415						57904
BIC						59467						59102

Notes: Values in parentheses are standard errors; †p<0.1, *p < 0.05, **p < 0.01, ***p < 0.001 (two-tailed). β: log odds. OR: Odds Ratio (exp(β)).

Appendix

Table 1: Logistic Regression Results (10-year citation window)

	Model 1		Model 2	
Variables	**β**	**OR**	**β**	**OR**
Interreg_Collab1	-0.1025	0.90	-0.0924	0.91
	(0.0834)		(0.0830)	
Org_Collab	-1.0354	0.36*	-0.9940	0.37*
	(0.4438)		(0.4485)	
Interreg_Collab x Org_Collab	2.5324	12.58	2.4886	12.04*
	(1.1526)		(1.1465)	
Tech_Breadth	-0.1877	0.83†	-0.1629	0.85
	(0.1057)		(0.1051)	
Relatedness	0.7391	2.09**	0.6765	1.97**
	(0.2384)		(0.2389)	
Generality	0.8695	2.39***		
	(0.1048)			
Frwd_Cit_Internal			-0.0307	0.97
			(0.0240)	
Frwd_Cit_Near			0.0820	1.09***
			(0.0165)	
Frwd_Cit_External			0.0243	1.02**
			(0.0090)	
Org_Size	0.7623	2.14***	0.7371	2.09***
	(0.0697)		(0.0692)	
Team_Size	0.0063	1.01	0.0016	1.00
	(0.0189)		(0.0189)	
Org_Patent_Stock	-0.0003	1.00***	-0.0002	1.00***
	(0.0000)		(0.000)	
Inv_Patent_Stock	-0.0100	0.99**	-0.0094	0.99**
	(0.0033)		(0.0033)	
Claims	0.0117	1.01***	0.0100	1.01***
	(0.0029)		(0.0029)	
Neighbor_Inv	0.0000	1.00	0.0000	1.00
	(0.0000)		(0.0000)	
Tech_Class_Dummies		Yes		Yes
Year_Dummies		Yes		Yes
α	0.8506	2.34*	0.9747	2.65*
	(0.4009)		(0.3889)	
N		16,207		16,207
X^2		3519.2***		3586.9***
ΔX^2		102.8***		170.5***

Notes: Values in parentheses are cluster-robust standard errors; †p<0.1, *p < 0.05, **p < 0.01, ***p < 0.001 (two-tailed).

Appendix

Table 2: Continuation Ratio (Sequential) Logit Regression Results (10-year citation window)

	Model 1a						Model 2a					
	Renewal 0 vs. Renewal 1,2,3		Renewal 1 vs. Renewal 2,3		Renewal 2 vs. Renewal 3		Renewal 0 vs. Renewal 1,2,3		Renewal 1 vs. Renewal 2,3		Renewal 2 vs. Renewal 3	
Variables	**β**	**OR**	**β**	**OR**	**β**	**OR**	**β**	**OR**	**β**	**OR**	**β**	**OR**
Interreg_Collab1	0.1025	0.90	0.2682	1.31***	0.0919	1.10	-0.0924	0.91	0.2632	1.30***	0.0882	1.09
	(0.0708)		(0.0578)		(0.0572)		(0.0710)		(0.0578)		(0.0574)	
Org_Collab	-1.0354	0.36*	0.1308	1.14	0.2448	1.28	-0.9940	0.37*	0.1331	1.14	0.2220	1.25
	(0.4341)		(0.4680)		(0.5083)							
Interreg_Collab x	2.5324	12.58	0.2288	1.26	0.0216	1.02	2.4886	12.04*	0.2470	1.28	0.0854	1.09
Org_Collab	(1.1030)		(0.6241)		(0.6352)		(1.1040)		(0.6247)		(0.6362)	
Tech_Breadth	-0.1877	0.83†	0.0064	1.01	0.0978	1.10	-0.1629	0.85	0.0096	1.01	0.0771	1.08
	(0.1013)		(0.0798)		(0.0802)		(0.1007)		(0.0795)		(0.0801)	
Generality	0.8695	2.39***	0.6715	1.96***	0.5600	1.75***						
	(0.0957)		(0.0744)		(0.0770)							
Relatedness	0.7391	2.09**	1.3840	3.99***	0.5522	1.74**	0.6765	1.97**	1.3250	3.76***	0.5218	1.69**
	(0.2336)		(0.1809)		(0.1874)		(0.2339)		(0.1813)		(0.1882)	
Frwd_Cit_Internal							-0.0307	0.97	0.0004	1.00	-0.0107	0.99
							(0.0219)		(0.0133)		(0.0111)	
Frwd_Cit_Near							0.0820	1.09***	0.0406	1.04***	0.0328	1.03***
							(0.0155)		(0.0090)		(0.0076)	
Frwd_Cit_External							0.0243	1.02***	0.0210	1.02***	0.0224	1.02***
							(0.0055)		(0.0039)		(0.0036)	
Org_Size	0.7623	2.14***	0.4548	1.58***	0.4933	1.64***	0.7371	2.09***	0.4293	1.54***	0.4742	1.61***
	(0.0672)		(0.0569)		(0.0592)		(0.0673)		(0.0570)		(0.0594)	
Team_Size	0.0063	1.01	-0.0664	0.94***	-0.0377	0.96*	-0.0016	1.00	-0.0399	0.96***	-0.0002	1.00**
	(0.0205)		(0.0145)		(0.0151)		(0.0206)		(0.0146)		(0.0151)	
Org_Patent_Stock	-0.0003	1.00***	-0.0001	1.00***	-0.0001	1.00**	-0.0002	1.00***	-0.0001	1.00**	-0.0001	1.00*
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Inv_Patent_Stock	-0.0100	0.99***	-0.0052	1.00*	0.0005	1.00	-0.0094	0.99**	-0.0048	1.00†	-0.0009	1.00
	(0.0030)		(0.0026)		(0.0029)		(0.0030)		(0.0026)		(0.0029)	
Claims	0.0117	1.01***	0.0017	1.01***	0.0013	1.00	0.0100	1.01***	0.0085	1.01***	0.0001	1.00
	(0.0024)		(0.0017)		(0.0013)		(0.0024)		(0.0017)		(0.0013)	
Neighbor_Inv	0.0000	1.00	0.0000	1.00***	0.0000	1.00***	0.0000	1.00	0.0000	1.00***	0.0000	1.00***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Tech_Class_Dummies		Yes		Yes		Yes		Yes		Yes		Yes
Year_Dummies		Yes		Yes		Yes		Yes		Yes		Yes
α	0.8506	2.34	-0.2730	0.76	-0.7007	0.50	0.6171	1.85	-0.0976	0.91	-0.5387	0.58
	(0.4114)		(0.4128)		(0.4476)		(0.4109)		(0.4112)		(0.4478)	
N						16,207						16,207
X^2						4494.7***						4756.1***
ΔX^2						371.1***						632.4***
AIC						35132						34883
BIC						36148						35945

Notes: Values in parentheses are standard errors; †p<0.1, *p < 0.05, **p < 0.01, ***p < 0.001 (two-tailed). β: log odds. OR: Odds Ratio (exp(β)).

Table 3: Continuation Ratio (Sequential) Logit Regression Results (5-year citation window with alternative regional delineations)

	Model 1					
	Renewal 0 vs. Renewal 1,2,3		Renewal 1 vs. Renewal 2,3		Renewal 2 vs. Renewal 3	
Variables	**β**	**OR**	**β**	**OR**	**β**	**OR**
Interreg_Collab3	0.0000	1.00	0.0174	1.02***	0.0014	1.00
	(0.0022)		(0.0031)		(0.0023)	
Org_Collab	0.7386	2.09**	1.4670	4.34***	0.6412	1.90**
	(0.2839)		(0.2444)		(0.2139)	
Interreg_Collab3 x Org_Collab	-0.0094	0.99	0.0268	0.97**	0.0043	1.00
	(0.0070)		(0.0085)		(0.0130)	
Tech_Breadth	0.0936	1.10	0.1190	1.13*	0.0502	1.05
	(0.0772)		(0.0601)		(0.0625)	
Relatedness	1.1280	3.09***	1.6560	5.24***	0.9427	2.57***
	(0.1813)		(0.1432)		(0.1538)	
Generality	0.6936	2.00***	0.4295	1.54***	0.5449	1.72***
	(0.0932)		(0.0692)		(0.0711)	
Org_Size	0.6562	1.93***	0.3590	1.43***	0.3844	1.47***
	(0.0509)		(0.0429)		(0.0461)	
Team_Size	-0.0122	0.99	0.1098	0.90***	-0.0398	0.96**
	(0.0163)		(0.0148)		(0.0144)	
Org_Patent_Stock	-0.0002	1.00***	-0.0001	1.00*	-0.0001	1.00***
	(0.0000)		(0.0000)		(0.0000)	
Inv_Patent_Stock	-0.0076	0.99***	-0.0032	1.00**	0.0005	1.00
	(0.0009)		(0.0010)		(0.0013)	
Claims	0.0122	1.01***	0.0079	1.01***	0.0032	1.00**
	(0.0016)		(0.0011)		(0.0010)	
Neighbor_Inv	0.0000	1.00	0.0000	1.00***	0.0000	1.00***
	(0.0000)		(0.0000)		(0.0000)	
Tech_Class_Dummies		Yes		Yes		Yes
Year_Dummies		Yes		Yes		Yes
α	0.6017	1.83	0.1530	1.17	0.4324	0.65
	(0.3998)		(0.4044)		(0.4288)	
N						25,715
X^2						6856.8***
ΔX^2						566***
AIC						57885
BIC						59084

Notes: Values in parentheses are standard errors; †p<0.1, *p < 0.05, **p < 0.01, ***p < 0.001 (two-tailed). β: log odds. OR: Odds Ratio (exp(β)).

Table 3: (Continued)

	Model 2					
	Renewal 0 vs. Renewal 1,2,3		Renewal 1 vs. Renewal 2,3		Renewal 2 vs. Renewal 3	
Variables	**β**	**OR**	**β**	**OR**	**β**	**OR**
Interreg_Collab4	0.0006	1.00	0.0216	1.02***	0.0042	1.00
	(0.0031)		(0.0041)		(0.0031)	
Org_Collab	0.7432	2.10**	1.3600	3.90***	0.6521	1.92**
	(0.2820)		(0.2421)		(0.2150)	
Interreg_Collab4 x Org_Collab	-0.0121	0.99	0.0430	0.96	0.0033	1.00
	(0.0087)		(0.0117)		(0.0169)	
Tech_Breadth	0.0929	1.10	0.1120	1.12†	0.0502	1.05
	(0.0772)		(0.0601)		(0.0625)	
Generality	0.6936	2.00***	0.04268	1.53***	0.5440	1.72***
	(0.0932)		(0.0692)		(0.0711)	
Relatedness	1.1290	3.09***	1.6660	5.29***	0.9418	2.56***
	(0.1812)		(0.1432)		(0.1538)	
Org_Size	0.6557	1.93***	0.3605	1.43***	0.3855	1.47***
	(0.0509)		(0.0429)		(0.0461)	
Team_Size	-0.0104	0.99	-0.0770	0.93***	-0.0422	0.96***
	(0.0138)		(0.0112)		(0.0121)	
Org_Patent_Stock	-0.0002	1.00***	-0.0001	1.00*	-0.0001	1.00***
	(0.0000)		(0.0000)		(0.0000)	
Inv_Patent_Stock	-0.0076	0.99***	-0.0032	1.00**	0.0005	1.00
	(0.0009)		(0.0010)		(0.0013)	
Claims	0.0122	1.01***	0.0077	1.01***	0.0033	1.00**
	(0.0016)		(0.0011)		(0.0010)	
Neighbor_Inv	0.0000	1.00	0.0000	1.00***	0.0000	1.00***
	(0.0000)		(0.0000)		(0.0000)	
Tech_Class_Dummies		Yes		Yes		Yes
Year_Dummies		Yes		Yes		Yes
α	0.5988	1.82	0.1021	1.11	0.4290	0.65
	(0.3995)		(0.4043)		(0.4286)	
N						25,715
X^2						6851***
ΔX^2						560.5***
AIC						57891
BIC						59090

Notes: Values in parentheses are standard errors; †p<0.1, *p < 0.05, **p < 0.01, ***p < 0.001 (two-tailed). β: log odds. OR: Odds Ratio (exp(β)).

Table 3: (Continued)

	Model 3					
	Renewal 0 vs. Renewal 1,2,3		Renewal 1 vs. Renewal 2,3		Renewal 2 vs. Renewal 3	
Variables	**β**	**OR**	**β**	**OR**	**β**	**OR**
Interreg_Collab5	0.0017	1.00	0.0319	1.03***	0.0060	1.01†
	(0.0038)		(0.0047)		(0.0034)	
Org_Collab	0.7569	2.13**	1.3420	3.83***	0.6894	1.99***
	(0.2799)		(0.2358)		(0.2089	
Interreg_Collab5 x Org_Collab	-0.0149	0.99	-0.0545	0.95***	-0.0029	1.00
	(0.0092)		(0.0124)		(0.0169)	
Tech_Breadth	0.0934	1.10	0.1076	1.11†	0.0495	1.05
	(0.0771)		(0.0602)		(0.0625)	
Relatedness	1.1270	3.09***	1.6610	5.26***	0.9422	2.57***
	(0.1813)		(0.1433)		(0.1538)	
Generality	0.6930	2.00***	0.4263	1.53***	0.5432	1.72***
	(0.0932)		(0.0692)		(0.0711)	
Org_Size	0.6567	1.93***	0.3643	1.44***	0.3861	1.47***
	(0.0509)		(0.0429)		(0.0461)	
Team_Size	-0.0144	0.99	-0.0756	0.93***	-0.0422	0.96***
	(0.0132)		(0.0103)		(0.0115)	
Org_Patent_Stock	-0.0002	1.00***	-0.0001	1.00*	-0.0001	1.00***
	(0.0000)		(0.0000)		(0.0000)	
Inv_Patent_Stock	-0.0076	0.99***	-0.0034	1.00***	0.0006	1.00
	(0.0009)		(0.0010)		(0.0013)	
Claims	0.0122	1.01***	0.0077	1.01***	0.0033	1.00**
	(0.0016)		(0.0011)		(0.0010)	
Neighbor_Inv	0.0000	1.00	0.0000	1.00***	0.0000	1.00***
	(0.0000)		(0.0000)		(0.0000)	
Tech_Class_Dummies		Yes		Yes		Yes
Year_Dummies		Yes		Yes		Yes
α	0.6053	1.83	0.0987	1.10	-0.4292	0.65
	(0.3995)		(0.4043)		(0.4285)	
N						25,715
X^2						6875.8***
ΔX^2						585.3***
AIC						57866
BIC						59065

Notes: Values in parentheses are standard errors; †p<0.1, *p < 0.05, **p < 0.01, ***p < 0.001 (two-tailed). β: log odds. OR: Odds Ratio (exp(β)).

Appendix

Figure 1: Assessing the Ordinality of Y (renewal categories) for each X (predictors)

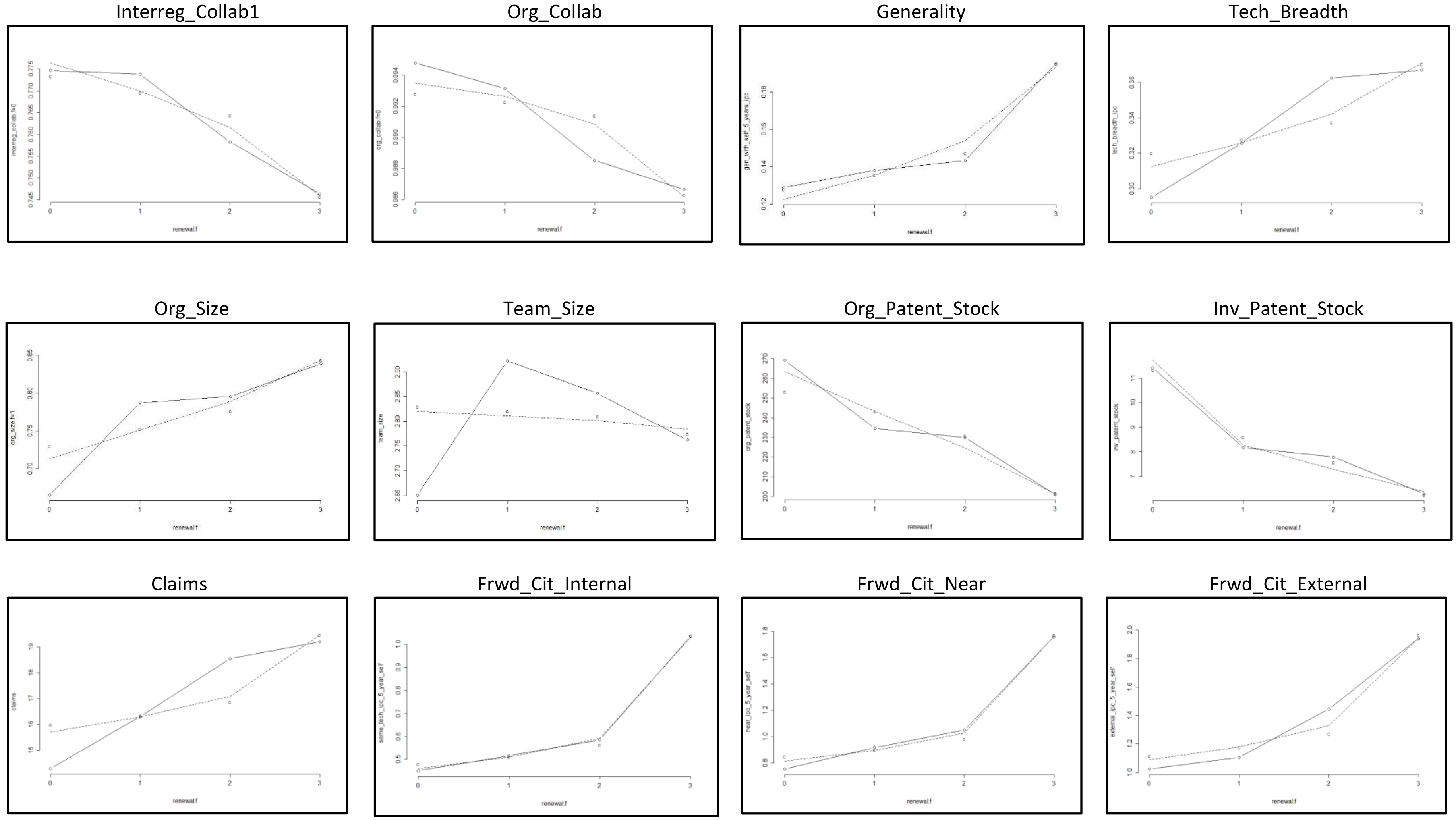
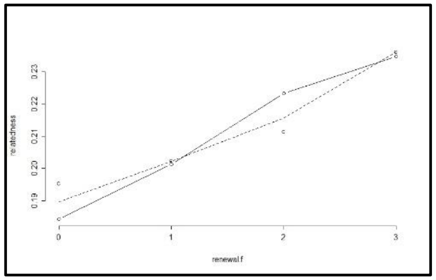
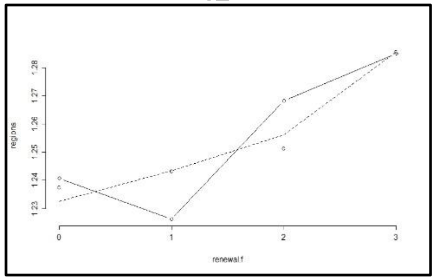


Figure 1 (Continued)

Relatedness



Interreg_Collab2



The plots show the mean of *X* versus levels of *Y*. The dotted line represents the proportional odds assumption, the expected value of the predictor for each *Y* value (Harrel, 2015).