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Abstract

In this paper, we quantitatively characterize the mechanism of collaborative knowledge creation at the individual researcher level à la Berliant and Fujita (2008) by using Japanese patent data. The key driver for developing new ideas is found to be the exchange of differentiated knowledge among collaborators. To stay creative, inventors seek opportunities to shift their technological expertise to unexplored niches by utilizing the differentiated knowledge of new collaborators in addition to their own stock of knowledge. In particular, while collaborators' differentiated knowledge raises all the average cited count, average (technological) novelty and the quantity of patents for which an inventor contributes to the development, it has the largest impact on the average novelty among the three.

Keywords: Knowledge creation, Collaboration, Differentiated knowledge, Technological novelty, Technological shift, Recombination, Patents, Network, Strategic interactions

JEL Classification: D83, D85, O31, R11, C33, C36

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1 Introduction

Knowledge creation has been a key factor in various aspects of economic modeling. Some of the new ideas result in innovations, which in turn fuel economic growth.[1] The structure of market and competition may be subject to the extent of the diffusion and imitations of invented technologies.[2] Furthermore, the concentration of research and development (R&D) activities is the defining feature of the largest cities.[3] Nevertheless, the mechanism of knowledge creation – at the ultimate micro level of individual inventors – has not been explicitly specified in these strands of the literature. Empirical studies are necessarily scarce.[4]

In this study, we investigate data on Japanese patents applied between 1995 and 2009. Given that about 90% of these patents were developed in collaborations, we focus on the causal relationship in collaborative knowledge creation based primarily on the microeconomic model proposed by Berliant and Fujita (2008).[5]

We consider two complementary measures of output from a given patent project: one reflecting *quality* based on forward citation counts and the other reflecting (*technological*) *novelty* based on the timing of each patent application in the relevant technological category. The productivity of a given inventor is then defined by the quality/novelty-adjusted count of patents in which this inventor participated, where each patent count is also discounted by the number of inventors involved in the patent.

Under either measure, our data indicate the presence of substantial downward pressure on inventor productivity: fewer than half of inventors with above-median productivity in a five-year span, 1995–1999 (2000–2004), maintain at least the same relative productivity in the next five-year span, 2000–2004 (2005–2009).[6] At the same time, it is also true that some top inventors stay highly productive, while some inferior inventors overthrow superior ones and climb the productivity ladder. Overall, the substantial churning of the relative productivities of inventors is observed over time.

The extant literature provides plausible explanations for the declining trend of inventor productivity. On the one hand, inventors have an incentive to stick to established technologies since they have accumulated expertise on them through learning-by-doing (Horii, 2012). On the other hand, once made public, technologies face incessant innova-

[1]For example, Romer (1990); Grossman and Helpman (1991a); Aghion and Howitt (1992); Kortum (1997); Klette and Kortum (2004); Acemoglu et al. (2017); Akcigit and Kerr (2018).

[2]For example, Grossman and Shapiro (1978); Chang (1995); Matutes et al. (1996); Schotchmer (1996); König et al. (2014); Panebianco et al. (2016).

[3]For example, Duranton and Puga (2001); Bettencourt et al. (2007); Davis and Dingel (2018).

[4]Somewhat informal studies can be found in, for example, Breschi et al. (2003); Garcia-Vega (2006); Østergaard et al. (2011); Huo and Motohashi (2015); Inoue et al. (2015); Akcigit et al. (2018).

[5]Since an applied patent does not necessarily result in an innovation, our analyses are essentially about knowledge creation rather than innovation, although we use these two terms interchangeably when appropriate.

[6]To compare the productivity of a given inventor at different time points, it is convenient to aggregate multiple years since the output of an inventor is typically intermittent. The basic results remain essentially the same under different timespans.

tions by which new technologies replace old ones (e.g Grossman and Helpman, 1991b; Klette and Kortum, 2004). Publicized technologies also attract imitations that deprive the opportunity to profit by refining them (e.g., Chu, 2009; Cozzi and Galli, 2014; Jell et al., 2017). The latter negative effects eventually dominate the former positive ones since learning-by-doing is subject to decreasing returns (Horii, 2012).

How do successful inventors stay productive in these circumstances? Horii (2012) proposed a theoretical model of innovation associated with technological shifts. In his model, consumers wish to satisfy an indefinite range of wants, which induces an inventor to seek an unexplored technological niche in which he or she can create demand for new products associated with the new technology. While Horii's model lacks a micro mechanism underlying the technological shifts, it is complemented by Berliant and Fujita (2008).[7]

In the Berliant-Fujita model, agents communicate via common knowledge and invent in pairs by utilizing their mutual differentiated knowledge, where an appropriate balance between common and differentiated knowledge facilitates collaborative innovation. A longer duration of collaboration by the same pair increases their common knowledge while decreasing their mutual differentiated knowledge, which at the same time accumulates differentiated knowledge between them and the remaining agents. To maintain the best knowledge composition, agents optimally choose the set of their collaborators and the allocation of time for each collaboration.

Given these facts and the theoretical background, we develop three separate regression models, each of which focuses on one key causality in knowledge creation.

The first model is a reduced form of the pairwise "knowledge creation function" presented by Berliant and Fujita (2008). In this model, we focus on the differentiated knowledge of collaborators, as this is an obvious source of new ideas that would take an inventor to an unexplored technological niche. It is quantified in terms of the novelty/quality-adjusted output of the collaborator *excluding* the patents developed jointly with the inventor. We find that a 10% increases in collaborators' differentiated knowledge for an inventor raises his or her quality- and novelty-adjusted research output by around 2.8% and 3.5%, respectively, which thus implies positive but decreasing returns of this knowledge. The decreasing returns are considered to result from the fact that the collaborators' differentiated knowledge eventually overwhelms the common knowledge with collaborators as well as the differentiated knowledge of the inventor him- or herself. Hence, the key mechanism of knowledge creation by Berliant and Fujita (2008) is shown to be empirically supported.

In the second model, we decompose the contribution by collaborators' differentiated knowledge to the research output of an inventor (computed from the regression of the first model) into the fraction accruing to the quality/novelty and that to the quantity of his or

[7]The Berliant-Fujita model is to our knowledge the only explicit formalization of collaborative innovation at the individual inventor level. Weitzman (1998) and Olsson (2000, 2005) proposed formulations in which new ideas are generated by the recombinations of extant ideas. However, in their models, the process through which such recombinations take place were passive.

her research output. Whereas we find that the contribution is mostly dedicated to increasing the quantity, rather than the quality, of research output under the quality-adjusted productivity measure, as large as around 65% of the contribution accounts for increasing the novelty, rather than the quantity, of research output under the novelty-adjusted productivity measure. This result indicates that a major role of collaboration is to induce the technological shift of an inventor to a new niche, consistent with Berliant and Fujita (2008) as well as Horii (2012).

In the third model, we probe into the factors determining the amount of differentiated knowledge that each inventor obtains from his or her collaborators. In this regression, we focus on the role of the collaborator recombination and find that a more active recombination has a selection effect in collaborations, as it results in the set of new collaborators with a larger average quality/novelty-adjusted differentiated knowledge. We find that a 10% increase in the new collaborators of an inventor raises the average quality- and novelty-adjusted differentiated knowledge of collaborators by around 14% and 18%, respectively.

While we also find that more able collaborators (i.e., those with a larger amount of differentiated knowledge) tend to be attracted to the top inventors with a particularly large stock of knowledge, inventors with a smaller stock of knowledge may still be able to compensate for their shortage of knowledge by conducting more active recombinations of collaborators.

These findings explain the observed upgrading of inferior inventors as well as the persistent productivity of top inventors.

In these regressions, we control for individual fixed effects, period fixed effects, and local factors by using a variety of establishment/firm-level micro geographic data on employment, production output, R&D expenditure, and residential population. Yet, we face identification problems due to network endogeneity, since the differentiated knowledge and recombination of collaborators are derived from endogenous collaborations among inventors, that is, the strategic collaborations among inventors to maximize their productivities.

The identification and estimation of models with endogenous networks are substantial challenges in the econometric literature (e.g., Jackson et al., 2017). We argue, however, that each endogenous variable for an inventor in our models can be reasonably instrumented by the average value of the same variable for his or her indirect collaborators. The relevance of the instrument comes from the assortative matching by productivity among firms and workers, which also involves inventors (e.g., Mori and Turrini, 2005; Behrens et al., 2014; Eeckhout and Kircher, 2018; Gaubert, 2018). The matching is essentially exogenous to individual inventors given that it takes place more broadly than the interactions of R&D activities. Our identification strategy is a methodological contribution which may also be applied in other related problems of strategic interactions in which appropriate instruments for endogenous regressors have been hard to find (e.g., Jackson et al., 2017, §8).

The rest of the paper is organized as follows. We start by making key observations about the dynamics of knowledge creation and inventor productivities in Section 2. The related literature is reviewed in Section 3. The Berliant-Fujita model is described in Section 4 and the corresponding regression models are presented in Section 5. The data are detailed in Section 6, the identification strategy is discussed in Section 7, and the regression results are presented in Section 8. Section 9 concludes and discusses future research directions.

2 Facts

To guide our analyses to follow, we make three observations on patent development in Japan, while postponing the description of the data to Section 6.

2.1 Productivity of an inventor

Our panel data consist of three periods, each of which aggregates five consecutive years: period 0 includes the years from 1995 to 1999, period 1 from 2000 to 2004, and period 2 from 2005 to 2009. We focus on the balanced set I of 107,724 inventors, each of whom participated in at least one patent in each period.

An inventor is typically involved in multiple patents in a given period. Let $\mathcal{G}_{it}$ be the set of patents in which inventor i participates in period t, and G_j for $j \in \mathcal{G}_{it}$ be the set of inventors who participate in patent j. If the output of patent project j is expressed by a scalar $g_j > 0$, then *the productivity of an inventor i* can be defined in terms of the total output of patents in which he or she participated in period t, with the output of each patent being discounted by the number of inventors involved in the patent:

$$\bar{y}_{it} = \sum_{j \in \mathcal{G}_{it}} \frac{g_j}{|G_j|} \tag{2.1}$$

where $|G_j|$ means the cardinality of set G_j. (Hereafter, the expression $|X|$ for any set X means the cardinality of X.)

We consider two aspects of inventor productivity. One is the *quality* based on the cited count. In this case, g_j represents the count of citations that patent j received within three years of publication.[8] The other aspect we consider is *novelty*. In this case, g_j represents the *degree of the* (*technological*) *novelty* of patent j defined by the reciprocal, $1/r_j$, of the order, $r_j = 1,2,\ldots$, of this patent in terms of its application date among all the patents

[8]It is assumed that there is at least one (self-)citation, namely $g_j \geq 1$, under the quality-adjusted measure. That is, the cited count for each patent is inflated by 1 if there is no self-citation to avoid dropping patents without citations. Some authors (e.g., Inoue et al., 2015) argue that the citation-adjusted output of a patent project should exclude self-citations by inventors in the project. Our analyses, however, include them since there is no clear incentive to inflate the cited counts for patents (unlike the case of academic papers); hence, the self-citations tend to reflect genuine technological dependence. We also consider the productivity of an inventor simply based on counts of patents in which he or she participated, that is without citation weights (see Section 6.1.3). We find no qualitative difference between the results with and without citation weights.

classified in the same technological category as j.[9] Thus, our novelty measure reflects the *nicheness* of the technological invention publicized by the patent. It can also be interpreted as an inverse measure of the *crowdedness* of the market for the corresponding technological category.

The technological category of a patent is identified by the "subgroup" of the International Patent Classification (IPC) (see Section 6.1.2). About 40,000 IPC subgroups are active in each period, and a single primary IPC subgroup is assigned to each patent.

2.2 Dynamics of the relative productivities of inventors

By using the productivity measures introduced above, this section discusses the dynamics of the relative productivities of inventors. Let $I_t^{\mathrm{TOP}}(x)$ represent the set of inventors in the top x% in I in terms of their productivity in each period $t = 0, 1$, and 2. The set of inventors in each 5% interval of the productivity percentiles from 0% to 100% can then be expressed by $\Gamma_t(x) \equiv I_t^{\mathrm{TOP}}(x) \backslash I_t^{\mathrm{TOP}}(x-5)$ for $x = 5, 10, \ldots, 100$, where "\" is a set difference operator. Call $\Gamma_t(x)$ the (*productivity*) *class* x of inventors in period t.

For classes, $x = 5, 10, \ldots, 100$, under quality- and novelty-adjusted productivities, the height of each blue bar in Panels (a) and (b) in Figure 1, respectively indicates the share of the inventors of class x in period 0 who stay at least in the same class x' ($\leq x$) in period 1. As essentially the same result is obtained for the transition from periods 1 to 2, we can make the following observation:

Observation 1 (Churning of relative productivities) *Under either measure of productivity, fewer than half of inventors above the median productivity* $x < 50$ *in period* $t-1$ *remain at least as productive in period* $t \in \{1, 2\}$, *indicating a strong pressure to prevent inventors from maintaining their relative productivity. In other words, a sizable proportion of inferior inventors replace superior ones in their productivity ranking in each period.*

As discussed in the Introduction, a major reason for this downward pressure may be the obsolescence and imitations of technologies as well as decreasing returns in learning-by-doing from the extant technologies. Yet, we find that some top inventors stay highly productive, while some inferior ones surpass superior inventors. Each red bar in Figure 1, for example, indicates the share of inventors in the corresponding class in period 0 who transitioned to the top 5% class in period 1. Although upgrading to the top 5% is less likely for inventors in a lower class, the transitions are observed from a wide range of lower classes.[10]

[9] Our data include all the patents applied in 1993 and thereafter as well as some older applications published in 1993 or later. Thus, by construction, our measure of novelty tends to overstate the novelty in technological categories defined before 1993. However, since our regression analyses use novelty data from 2000 and later (i.e., periods 1 and 2), the effect of truncation should not be too problematic as we have a seven-year lead time before 2000. A part of the remaining overstatement is also controlled for by the period fixed effect.

[10] A similar observation was made for US data between 1880 and 1940 by Akcigit et al. (2017), who found evidence that new inventors receive more patent citations than incumbent inventors.

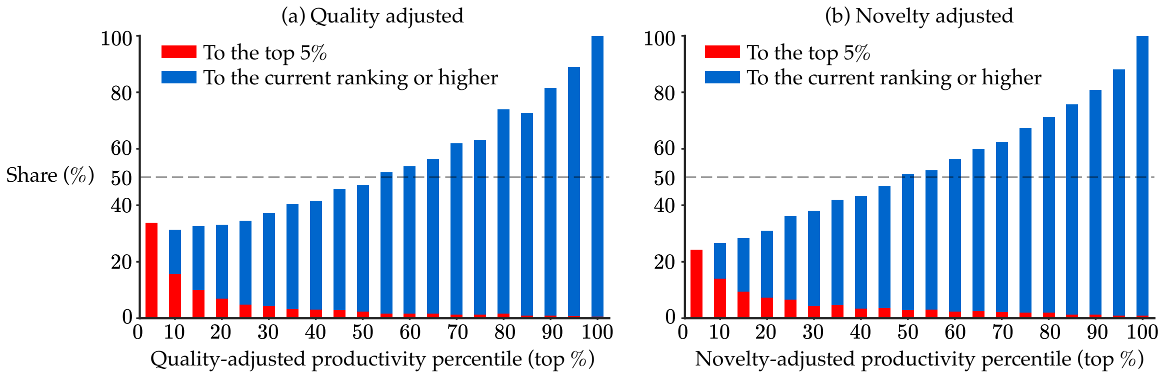


Figure 1: Change in the productivity class of inventors from period 0 to period 1

Taken together, there is thus a substantial churning of the relative productivities of inventors under both productivity measures. From the regression analyses in Section 8.1, we will find that the downward pressure on the productivity of an inventor is represented by the negative net effect of his or her knowledge stock. Our primary objective is to identify the factors that differentiate upgrading inventors from downgrading ones behind the churning of relative productivities among inventors.

2.3 Collaborator recombinations and technological shifts

We next present the key relationship among the productivity, collaboration structure, and technological specialization of inventors that suggests the mechanism behind the creation of knowledge associated higher quality and novelty.

To this end, denote by

$$N_{it} \equiv \cup_{j \in \mathcal{G}_{it}} G_j \backslash \{i\} \tag{2.2}$$

the set of collaborators of inventor $i \in I$ in period t such that each inventor in N_{it} participates in the development of at least one common patent with i in period t. The *collaborator recombination* of inventor $i \in I$ in period t is then defined by

$$\Delta n_{it} \equiv |N_{it} \backslash N_{i,t-1}| \tag{2.3}$$

i.e., the number of new collaborators in period t.[11] The average values of Δn_{it} for inventors in I are 9.84 and 6.37 in periods 1 and 2, respectively. Provided that the number of collaborators is the same across periods, these values coincide with the average numbers of collaborators that were replaced.

Next, define the *technological specialization* of inventor i in period t by set S_{it} of the IPC subgroups associated with the patents in which inventor i is involved in period t. Accordingly, the *technological shift* of inventor i is defined, similarly to the collaborator recombination in (2.3), by the number of IPC subgroups in which i is newly specialized in

[11] Alternatively, it may be defined by the sum of the number of new collaborations and that of separations from the collaborations in the previous period, i.e., $\Delta n_{it} = |N_{it} \backslash N_{i,t-1}| + |N_{i,t-1} \backslash N_{it}|$. The qualitative result remains the same under both definitions.

period t:

$$\Delta s_{it} \equiv |S_{it} \backslash S_{i,t-1}|. \tag{2.4}$$

The average values of Δs_{it} are 4.41 and 2.66 in periods 1 and 2, respectively. The high correlations between $\ln \Delta n_{it}$ and $\ln \Delta s_{it}$, namely 0.55 and 0.54 in periods 1 and 2, respectively, suggest that new collaborations of an inventor are associated with a shift in his or her technological expertise.

For what purpose, then, do inventors shift their technological specialization? As discussed in the Introduction, Horii (2012) considered an economy in which demand for new technologies always exists, meaning that inventors have incentives to shift their technological expertise to unexplored niches and develop novel technologies.

While Horii (2012) did not explicitly specify a micro mechanism underlying the technological shifts, if the collaborator recombination is an effective means for this purpose as modeled by Berliant and Fujita (2008), other things being equal, he or she is more likely to achieve a technological niche (i.e., a larger novelty-adjusted $\bar{y}_{it}$) in the current period through the technological shift, Δs_{it}, realized by a larger collaborator recombination, Δn_{it}, from the previous period.

In the Berliant-Fujita model, the technological shift is realized by utilizing the differentiated knowledge of new collaborators. Our data are highly suggestive of this causality, as the correlations between the novelty-adjusted $\ln \bar{y}_{it}$ and $\ln \Delta s_{it}$ are 0.30 and 0.29 in addition to the high correlation between $\ln \Delta s_{it}$ and $\ln \Delta n_{it}$ mentioned above.

Not surprisingly, these high correlations extend to include the quality-adjusted productivity measure. To see this, consider the sets of inventors who stay in a given quality-adjusted productivity class $x = 5, 10, \ldots, 100$ persistently in both periods 1 and 2, i.e., $\Gamma(x) \equiv \cap_{t=1,2} \Gamma_t(x)$. Denote *the average collaborator recombination* by an inventor in class x in period t by

$$\Delta n_t(x) \equiv \frac{1}{|\Gamma(x)|} \sum_{i \in \Gamma(x)} \Delta n_{it} \tag{2.5}$$

the *average technological shift* by an inventor in class x in period t by

$$\Delta s_t(x) \equiv \frac{1}{|\Gamma(x)|} \sum_{i \in \Gamma(x)} \Delta s_{it} \tag{2.6}$$

and the *average productivity* of an inventor in class x in period t by

$$\bar{y}_t \equiv \frac{1}{|\Gamma(x)|} \sum_{i \in \Gamma(x)} \bar{y}_{it}. \tag{2.7}$$

Figure 2 plots $\Delta n_t(x)$, $\Delta s_t(x)$, and novelty-adjusted $\bar{y}_t$ for $t = 1, 2$ for each quality-adjusted productivity class $x = 5, 10, \ldots, 100$. There is a clear increasing tendency of all three measures for more quality-wise productive inventors (i.e., for a smaller x). Specifically, Δn_t, Δs_t, and the novelty-adjusted $\bar{y}_t$ are 15.3, 13.0, and 0.22 (12.0, 8.60, and 0.14) in period 1 (period 2), respectively for the top 5% inventors quality-wise, while they are only 3.11, 0.75, and 0.003 (3.09, 0.73, and 0.002), respectively for the bottom 5% inventors quality-wise (i.e., $x = 100$). In particular, the novelty of technologies developed by the top 5% inventors quality-wise is more than 60 times higher than that of the bottom 5% inventors quality-wise in both periods.[12]

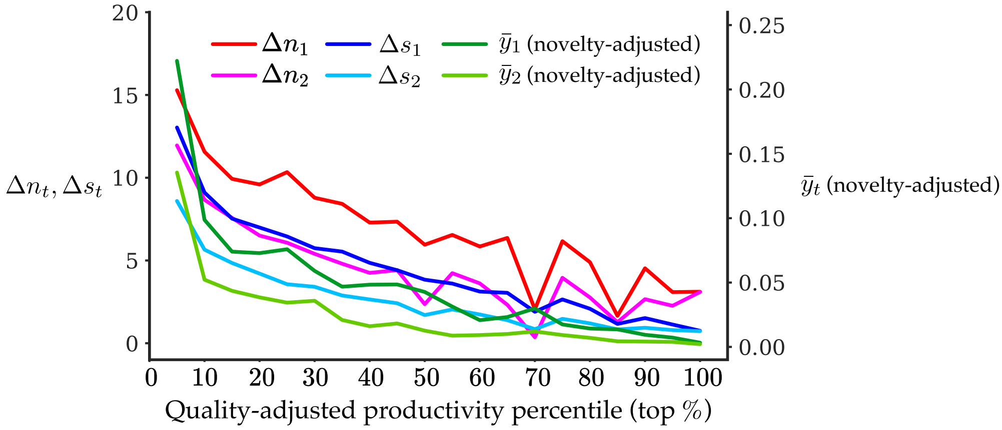


Figure 2: Relationship among collaborator recombinations, technological shifts, and the productivities of inventors

Taken together, our observation can be summarized as follows.

Observation 2 (Recombinations, technological shifts, and inventor productivities) *A more quality-wise productive inventor practices a more active recombination of collaborators and is associated with a larger technological shift as well as higher novelty in the created knowledge on average.*

A causal relationship behind this observation will be identified in Section 8. Specifically, a larger effort for collaborator recombination by an inventor (i.e., a larger Δn_{it}) raises his or her productivity (i.e., a larger $\Delta \bar{y}_{it}$) by selective collaboration, that is by finding new collaborators who have more relevant differentiated knowledge to shift his or her technological expertise to a new niche (i.e., a larger Δs_{it} associated with higher novelty), or to enhance the quality of his or her specialized technological skill.

2.4 Invention strategies by productivity level

Our final observation is on the difference in the actions taken by inventors with different productivity levels. Panels (a) and (b) in Figure 3 show the distributions of collaborator recombinations and the novelty-adjusted productivity of inventors in period 1 for the top 10% and bottom 10% inventors under quality-adjusted productivity, namely $\Gamma(5) \cup \Gamma(10)$ and $\Gamma(95) \cup \Gamma(100)$, respectively.[13] Both distributions are substantially right skewed for the

[12] In fact, the technological novelty of the top 5% inventors is disproportionate. Even compared with the top 10% inventors, the degree of their technological novelty is more than twice as large.

[13] Similar distributions are obtained for period 2.

top 10% inventors. That is, although both Δn_{it} and the novelty-adjusted $\bar{y}_{it}$ are larger on average for the top 10% than the bottom 10% inventors, a substantial population of the top 10% still do not seek new collaborations or novelty in developed technologies.

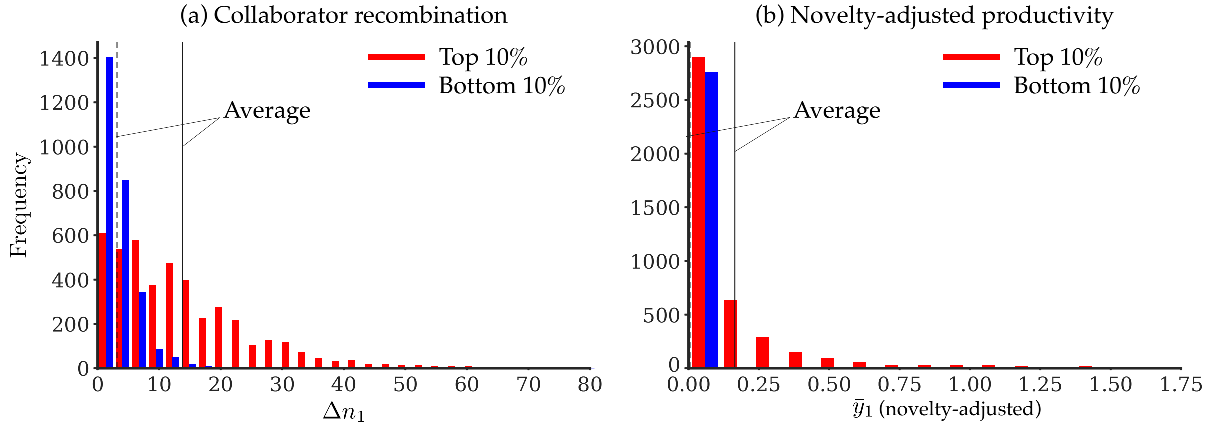


Figure 3: Collaborator recombinations and novelty-adjusted productivity of the top 10% and bottom 10% inventors quality-wise in period 1

On the one hand, the top 10% inventors appear to rely on their high innate ability and/or a large stock of knowledge to maintain their high quality-adjusted productivity without seeking novel technologies. On the other hand, in the context of the Berliant-Fujita model, the right skewness of the red plots in Figure 3 implies that an inventor without high innate ability or a large stock of knowledge may still be able to raise his or her productivity by selective collaboration, that is by finding new collaborators who have more relevant differentiated knowledge to enhance his or her technological expertise.

To see if this conjecture on the difference in invention strategy between more and less established inventors can be verified in the data, let us compare the size of the collaborator recombination and that of the knowledge stock between upgrading and downgrading inventors for each productivity class of inventors.

If the size of the knowledge stock of inventor i in period t is given by $k_{it} = \left|\bigcup_{t'<t} S_{it'}\right|$, then the top 5% inventors quality-wise have on average 3.3 and 2.3 times more stock of knowledge than the bottom 5% quality-wise in periods 1 and 2, respectively. This fact means that established inventors can rely more on their stock of knowledge to create new knowledge than less established ones. However, Berliant and Fujita (2008) suggested that less established inventors can compensate for their lack of knowledge by utilizing the knowledge of their collaborators.

For a given productivity measure, let $\Delta n_t^{\text{Top 5\%}}(x)$ represent the average size of collaborator recombinations by inventors who upgraded their productivity class from x in period $t-1$ to the top 5% in period t. Similarly, let $\Delta n_t^{\text{Down}}(x)$ be the average size of the collaborator recombinations of inventors who downgraded their productivity class from x in period $t-1$ to $x' > x$ in period t for $x = 5, 10, \ldots, 95$.[14] In the same manner, we can construct $k_t^{\text{Top 5\%}}(x)$ and $k_t^{\text{Down}}(x)$ of the knowledge stock for each class $x = 5, 10, \ldots, 95$ in period $t-1$.

[14]The lowest class $x = 100$ is omitted since there is no further downgrade from there.

Panels (a) and (b) in Figure 4 plot the ratio of the relative size of the collaborator recombination, $\Delta n_t^{\text{Top 5\%}}(x)/k_t^{\text{Top 5\%}}(x)$, of upgrading inventors and that, $\Delta n_t^{\text{Down}}(x)/k_t^{\text{Down}}(x)$, of downgrading ones for each productivity class $x = 5, 10, \ldots, 95$ under the quality- and novelty-adjusted measures of productivity, respectively.

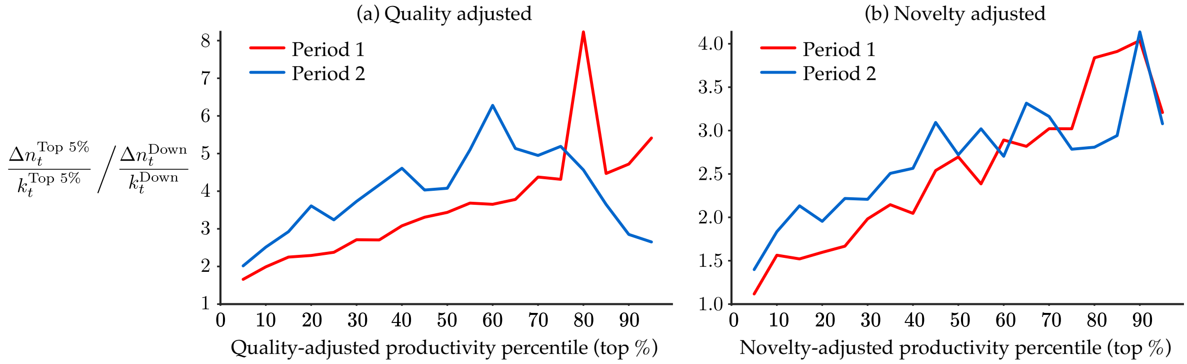


Figure 4: The relative size of the collaborator recombination for upgrading and downgrading inventors in period 1

Although there is an exception at the low end of the quality-adjusted productivity class in period 2 (see Figure 4(a)), one can find a general tendency summarized as follows.

Observation 3 (Collaborator recombination versus stock of knowledge) *Inventors with higher productivity rely relatively more on their own knowledge stock than knowledge from new collaborators, while the opposite is true for inventors with lower productivity.*

In Section 8.3, we will find that the observed difference among inventors in their reliance on their own stock of knowledge and the collaborator recombinations appears in their strategy for realizing higher average quality/novelty of differentiated knowledge of collaborators which in turn raises their research productivity.

3 Literature

The literature related to knowledge creation is diverse, including economic growth, industrial organization, and regional economics. We provide a brief overview of them here as the background of our study.

3.1 Theories

Innovation, a consequence of knowledge creation, is at the heart of economic growth theory. The first appearance of knowledge in this literature was in the form of *learning-by-doing*, which describes the situation in which labor productivity increases with capital accumulation (e.g. Arrow, 1962; Romer, 1986). Later, human capital was distinguished from physical capital (e.g., Lucas, 1988; Caballe and Santos, 1993). The explicit mechanisms behind knowledge accumulation, however, were left unspecified in these models.

The first formalization of intentional innovation was in the public research sector by Shell (1966, 1967). A large variety of market-driven innovations by the private sector were proposed in the 1990s and thereafter (e.g., Romer, 1990; Grossman and Helpman, 1991b,a; Aghion and Howitt, 1992; Kortum, 1997), where investment decisions on R&D were explicitly modeled. The positive externalities from the accumulated human capital improved productivity in knowledge creation and drove economic growth in these models.

There has been a recent surge in the literature initiated by Klette and Kortum (2004), who linked innovation technologies at the firm level to firm dynamics and then to growth at the economy level. They formalized quality ladder-type innovation at the firm level as an outcome of research building on the firm's present product lines. In their model, the product scope of a firm is interpreted as the stock of knowledge, which agrees with the argument by Weitzman (1998) that a new idea can generate a larger number of other new ideas if recombined with a larger number of existing ideas. Among a number of extensions, Akcigit and Kerr (2018), for example, distinguished innovations between new product creation and production process improvement at the firm level, where the former draws more from the prevailing product quality in the economy, while the latter depends more on the present quality of the firm's products. Akcigit et al. (2016) distinguished basic and applied research, which differ in their extent of positive spillovers. Lentz and Mortensen (2008) and Acemoglu et al. (2017) introduced vertical heterogeneity among firms in innovation capacity.

These models of firm-level innovation, however, still abstract from the mechanism through which the stock of knowledge is utilized by inventors in a firm to make innovations happen. As an exception, the recent contribution by Akcigit et al. (2018) extended these quality ladder models of growth by introducing the endogenous formation of a research team in which each ex ante homogeneous individual inventor faces an endogenous choice to become a team leader or a team member.

The strategic aspects of innovation by individual firms have been explored by utilizing the techniques of industrial organization and network science. For example, König et al. (2014) formulated a trade-off between R&D collaborations and product market competition among firms when investment in R&D by a firm reduces not only the production cost of this firm, but also those of collaborating competitors. Panebianco et al. (2016) formalized the mechanism of technology diffusion among firms by explicitly modeling the market for the innovation and the timing of the diffusion in a given network of firms. However, they still abstracted from the mechanism of knowledge creation as well as from the endogeneity of the network of firms within which R&D collaborations or innovation diffusion can take place.[15] This topic has often been studied in conjunction with the cost and benefit of the properties of a given patent system (e.g., Grossman and Shapiro, 1978; Chang, 1995; Matutes et al., 1996; Schotchmer, 1996).

The literature on knowledge creation at the inventor level is more scarce than that at the firm level. To our knowledge, the study by Olsson (2000, 2005) was the first successful

[15] See also Yang and Maskus (2001); Glass and Saggi (2002); Tanaka (2006); Tanaka et al. (2007) for related analyses in the context of economic growth.

attempt to formalize the notion of cogitation by an individual inventor in developing new ideas. Ghiglino and Tabasso (2015) proposed a microeconomic model of the innovation diffusion process that depends on the applicability of knowledge. Knowledge creation in these models, however, is treated as passive, and follows some stochastic process.

The work by Berliant and Fujita (2008) was, to our knowledge, the first to formalize active knowledge creation by individual inventors, with a strong focus on collaborative knowledge creation.[16] In their model, the steady-state size of the collaborating set of agents depends on the relative importance of common versus differentiated knowledge, where a larger size will result if differentiated knowledge is more appreciated.[17]

The typical steady state of the Berliant-Fujita model, however, does not replicate the observed churning of relative productivity among inventors discussed in Section 2. Horii (2012) complemented the Berliant-Fujita model in this aspect. In his model, consumers have an indefinite range of wants and thus demand for new technologies always exists. On the production side, learning-by-doing and local spillovers from the technological vicinity induce innovations to take place at discrete locations in the technological space. As the productivity improvement from learning-by-doing is subject to decreasing returns, there is an incentive to deviate from the extant technology and innovate in a distant unexplored niche in which a firm can rouse demand for the new technology and make a profit.

The cost of the technological shift in this deviation is implicit, and it depends on the distance from the extant technologies that determines the levels of competition and spillovers from these technologies. The collaborative knowledge creation in the Berliant-Fujita model complements this aspect in return by providing a possible micro mechanism for achieving the shift.

3.2 Empirics

A sizable literature on the effects of R&D investment on innovation, firm productivity, and economic growth in a country started in the 1960s (e.g., Griliches, 1964, 1979; Scherer, 1982; Coe and Helpman, 1995). In particular, after Kortum (1997) and Klette and Kortum (2004), studies began to structurally estimate the variations and extensions of their models by using firm-level micro data (e.g., Lentz and Mortensen, 2008; Akcigit et al., 2016; Acemoglu et al., 2017; Akcigit and Kerr, 2018). While these studies relate the innovation behavior, size, and growth of firms to aggregate economic growth, as discussed in the previous section, their models are not designed to disclose the innovation mechanism at the inventor level within a firm, which is the focus of our study. Moreover, in these structural model-adjusted approaches, the innovation technologies are not typically estimated

[16] Jovanovic and Rob (1989) proposed a related search model in which collaborations with more able partners are more likely to result in the development of better knowledge.

[17] A variety of extensions of Berliant and Fujita (2008) have been proposed. Berliant and Fujita (2011) augmented their model with foresights and the possibility of learning from public knowledge; Berliant and Fujita (2012) introduced the variation in distance among agents; and Berliant and Mori (2017) allowed for heterogeneity in the innovation technology among inventors.

directly.

One exception is the work by Akcigit et al. (2018), who estimated a reduced-form model of team-level innovation similar to the knowledge creation function of the Berliant-Fujita model. Their key variable is the quantity and quality of the interactions within a team, which is a sort of composite of the differentiated and common knowledge among collaborators in the Berliant-Fujita model. The crucial difference from our approach is that their research team formation is considered to be exogenous, while the endogeneity of the network is the key factor in the Berliant-Fujita model.

Another large strand of the literature is on knowledge spillover and diffusion (e.g., Jaffe et al., 1993; Thompson and Fox-Kean, 2005; Murata et al., 2014; Kerr and Kominers, 2015). Its concern is on the distance and routes on which innovated technology and knowledge spread, not on how the knowledge is created. However, we still incorporate the results of such studies and show that the creativity of an individual inventor is positively influenced by the spillovers from other inventors in his or her geographic vicinity.

Breschi et al. (2003); Garcia-Vega (2006); Østergaard et al. (2011) developed measures of common and differentiated technological knowledge relevant for innovation, showing that diversified knowledge as well as the mutual relatedness of knowledge within a firm and the innovation productivity of the firm are positively correlated. By using Japanese patent data similar to ours, Huo and Motohashi (2015) found a positive correlation between differentiated (as well as common) knowledge among inventors within a firm and their innovation productivities, whereas Inoue et al. (2015) focused on innovations by firm pairs, thereby avoiding the reflection problem typical in a network environment, and argued that there is a decreasing return to common knowledge between collaborators. However, all these studies ignore the endogeneity of collaborations, and thus the underlying causality is not clear.

Finally, this paper is also related to econometric identification and estimation in the context of a linear model in which some regressors are derived from endogenous network formation. The network endogeneity that arises in this study comes from inventors' strategic interactions to maximize their productivity by collaborations. Most common way to deal with network endogeneity is to consider network formation model to identify and estimate the parameters of interest (e.g., Goldsmith-Pinkham and Imbens, 2013; Hsieh and Lee, 2016; Comola and Prina, 2014; Li and Zhao, 2016; Patacchini et al., 2017).[18] However, this approach imposes parametric restrictions on the network formation model, and the estimation is biased when the model is misspecified. Since the model by Berliant and Fujita (2008) provides no simple econometric model of network formation as will be clear in Section 4, this traditional approach fails in our case. Thus, in contrast, in this paper we do not suppose any parametric model of network formation; instead,

[18] Another typical approach assumes exogeneity of network structure (e.g., Bramoullé and Treich, 2009; Bramoullé and Fortin, 2010). A closely related work by Akcigit et al. (2018) on knowledge creation adopts this approach.

we propose an alternative approach to deal with endogenous regressors for an inventor by instrumental variables that are constructed from the information of his or her indirect collaborators. We argue in Section 7 that this type of instrumental variables work if only the information from sufficiently far indirect collaborators is used and the relevance of the instruments comes from the variation exogenous to the network in question.

4 The Berliant-Fujita model

This section provides a brief overview of the theoretical model of knowledge creation proposed by Berliant and Fujita (2008).

In a given period of time, each agent develops new knowledge either in isolation or by collaborating in pairs, building on the stock of knowledge accumulated in the past. Let I be the set of all the agents who engage in knowledge creation, where all agents are assumed to be symmetric. Let $\delta_{ij} \in [0,1]$ be the proportion of time that agent $i \in I$ allocates for the collaboration with $j \in I$. If a given agent i works in isolation (i.e., collaborates with him- or herself), his or her knowledge creation is subject to constant returns technology, given by

$$y_{ii} = \begin{cases} ak_{ii}, & \delta_{ii} \in [0,1] \\ 0, & \text{otherwise} \end{cases} \tag{4.1}$$

where $a > 0$, k_{ii} is the knowledge stock of agent i, and y_{ii} is the output. If he or she instead collaborates with agent $j (\neq i)$, the joint output, y_{ij}, of this collaboration is given by

$$y_{ij} = \begin{cases} b\left(k_{ij}^C\right)^{\theta}\left(k_{ij}^D\right)^{\frac{1-\theta}{2}}\left(k_{ji}^D\right)^{\frac{1-\theta}{2}}, & \delta_{ij} \in [0,1] \\ 0, & \text{otherwise} \end{cases} \tag{4.2}$$

where $b > 0$, k_{ij}^C is the common knowledge between i and j, k_{ij}^D is the knowledge of agent i differentiated from that of j, and $\theta \in (0,1)$ is the relative importance of common knowledge.

All knowledge is symmetric, and the output from the collaboration of agents i and j becomes their common knowledge. Thus, the common knowledge between i and j increases relative to their differentiated knowledge as their collaboration lasts longer, while the differentiated knowledge between i (as well as j) with other agents increases relative to their common knowledge. To achieve the best combination of common and differentiated knowledge with collaborators, agents collectively decide the group of collaborators, where each agent i optimally chooses δ_{ij} for each $j \in I$ of his or her collaborators.[19]

In this context, the group size that maximizes growth in the knowledge stock is given by $1 + 1/\theta$. Indeed, this is a typical steady-state equilibrium when agents initially have sufficient common knowledge, which is a natural situation for collaborations to start (Berliant and Fujita, 2008, Proposition 1). In a symmetric steady-state equilibrium where all agents follow the same collaboration pattern, the equilibrium time allocation for col-

[19]Myopic core is adopted as the equilibrium concept.

laborations is given by $\delta_{ij} \equiv \delta = 1/(1+1/\theta)$ for all $i, j \in I$.

5 Regression model

In this section, we introduce three reduced-form regression models to identify the causal relationship among the quality/novelty of inventions, collaborators' differentiated knowledge, and magnitude of the collaborator recombination at the inventor level based on the Berliant-Fujita model. In the regressions, we focus on collaborative inventions, and do not address the choice between working in collaboration and working in isolation. In other words, our formulation assumes a positive number of collaborators for each inventor in each period.

Let $t = 0, 1, \ldots, T$ be the consecutive periods in which data are available and let I_t be the set of all inventors who participated in the development of at least one patent in period t. The subset of inventors, each of whom is involved in the development of at least one patent in every period (introduced in Section 2.1), is denoted by $I\,(\subset I_t)$.

Let $\mathcal{G}_t$ represent the set of all patents applied in period t. We call the development of each patent $j \in \mathcal{G}_t$ a *project* j. Then, G_j introduced in Section 2.1 represents the set of inventors who participated in project j, and the set of projects in which inventor $i \in I_t$ participated (also introduced in Section 2.1) can be rewritten as $\mathcal{G}_{it} \equiv \{j \in \mathcal{G}_t \,:\, i \in G_j\}$. Accordingly, the set N_{it} of the collaborators of inventor i in period t is given by (2.2) in Section 2.3, and the output, $\bar{y}_{it}$, of inventor i is given by (2.1) in Section 2.1.

5.1 A reduced-form Berliant-Fujita knowledge creation function

To bring the knowledge creation function (4.2) to the data, we modify the original specification. First, while this is defined for each of the multiple pairwise collaborations,[20] we formulate a reduced-form regression model for a single *average pairwise knowledge creation function*:

$$\ln y_{it} = \alpha + \beta \ln k_{it}^{D} + \gamma_1 \ln k_{it} + \gamma_2 (\ln k_{it})^2 + \ln A_{it} + \lambda_i + \tau_t + \varepsilon_{it} \tag{5.1}$$

in which y_{it} represents the *average pairwise output* by inventor i:

$$y_{it} = \bar{y}_{it} / n_{it} \tag{5.2}$$

[20]Since the average number of inventors per patent in our data is about two (see row 7 in Table 1 as well as Section 6), the assumption of multiple pairwise collaborations is reasonable.

where $n_{it} \equiv |N_{it}|$.[21] It is implicit that the variation in pairwise productivities for a given inventor is random and is captured by the inventor- and period-specific error term, ε_{it}.

Second, in (5.1), we focus on the differentiated knowledge, k_{ji}^D, of collaborators in (4.2), since this is a source of new ideas as discussed in Section 2, while abstracting from the role of the common knowledge, k_{ij}^C, and that of the differentiated knowledge, k_{ij}^D, of inventor i him- or herself in (4.2). This key variable appears as k_{it}^D in the second term on the right-hand side (RHS) of (5.1) in the form of *the average (pairwise) differentiated knowledge of the collaborators of* i, and is defined by the average output that the collaborators of i produced outside the joint projects with i:[22]

$$k_{it}^D = \frac{1}{n_{it}} \sum_{j \in N_{it}} \sum_{k \in \mathcal{G}_{jt} \setminus \mathcal{G}_{it}} \frac{g_k}{|G_k|}. \tag{5.3}$$

Here, k_{it}^D includes only the *fresh* differentiated knowledge of collaborators that they create with inventors other than i in the current period and not their knowledge stock from the past. This definition reflects Observation 1 in Section 2.2 that past knowledge (which is essentially past productivity in our case) is strongly associated with negative effects, possibly from imitation and obsolescence despite the positive effects of learning-by-doing.

The value of k_{it}^D may also be interpreted as the average productivity of i's collaborators outside joint projects with i. This feature is important when we construct an instrument for this variable in Section 7.

Third, as for the common knowledge k_{ij}^C and differentiated knowledge k_{ij}^D of each inventor i in (4.2), their effects are controlled for by the stock of knowledge of each inventor:

$$k_{it} = \Big| \bigcup_{t' < t} S_{it'} \Big|. \tag{5.4}$$

While this approach does not capture the roles of the common knowledge between i and

[21]To understand pairwise productivity à la Berliant and Fujita (2008), consider two groups of inventors. In group A, two inventors together produce two patents, while in group B, three inventors together produce three patents. For simplicity, let $g_j = 1$ for all patents j. It follows that the proportion of output in each project accruing to one inventor is one-half in group A and one-third in group B. The total output of inventor i is then $\bar{y}_i = 1/2 \times 2 = 1$ in group A and $\bar{y}_i = 1/3 \times 3 = 1$ in group B. However, we assume that knowledge is always created in pairs as in the Berliant-Fujita model. For an inventor in group A, his or her share (one-half) of a given patent is an outcome of the pairwise collaborations with his or her only collaborator; in other words, the proportion of the output of a pairwise collaboration in a given project accruing to him or her is one-half $(= 1/2 \div 1)$. Since group A produces two patents, the total pairwise output is given by $y_i = 1/2 \times 2 = 1$ for each inventor i. Since an inventor in group B has two collaborators, the proportion of the output of the pairwise collaboration accruing to an inventor for each patent is one-sixth $(= 1/3 \div 2)$, and the total pairwise output for each inventor i is $1/6 \times 3 = 1/2$. Thus, inventors in group A are more productive in pairwise collaborations than those in group B.

[22]In principle, it is possible to formulate the knowledge creation function in terms of the total output $\bar{y}_{it}$ of inventor i. In that case, k_{it}^D is replaced by $n_{it} k_{it}^D$. However, since we abstract from the common knowledge between inventor i and his or her collaborators and the differentiated knowledge of i by adding $\ln k_{it}$ and $(\ln k_{it})^2$, the effects of n_{it} on these variables are not obvious. Thus, we prefer to follow closely the pairwise knowledge creation function proposed by the Berliant-Fujita model as in (5.1).

his or her collaborators and of the differentiated knowledge of i precisely,[23] they are by definition expected to be positively correlated with the knowledge stock of i.[24]

Moreover, the size of the knowledge stock is expected to control for a variety of other effects, including the learning-by-doing effect as well as imitations and obsolescence effects on the extant technologies discussed in Section 2.2. We include the squared term, the fourth term on the RHS of (5.1), to capture their overall effects up to the second order.

Finally, in the fifth term, A_{it} bundles the inventor- and time-specific productivity shifters for inventor i:

$$A_{it} \equiv e^{\boldsymbol{X}_{it}'\boldsymbol{\eta}}, \tag{5.5}$$

where $\boldsymbol{X}_{it}$ represents a vector including the inventor-specific and time-varying controls such as spillover effects from other inventors in the geographical neighborhood, proximity to R&D expenditure, manufacturing employment/production, and residential population.

In the last three terms on the RHS of (5.1), λ_i, τ_t, and ε_{it} represent the time-invariant inventor fixed effect, period fixed effect, and inventor- and period-specific error, respectively. The values of the parameters $\alpha, \beta, \gamma_1, \gamma_2, \boldsymbol{\eta}$, and τ_t are estimated by the regressions.

5.2 Quality/novelty and quantity decomposition

The definition of quality and novelty of output by an inventor given by (2.1) implies the log-linear relationship between the quality and the quality/novelty of his or her output:

$$\ln y_{it} = \ln y_{it}^{p} + \ln y_{it}^{q}. \tag{5.6}$$

In the first term on the RHS of (5.6), y_{it}^{p} denotes the quantity, i.e., the average count of patents, of inventor i's pairwise output given by

$$y_{it}^{p} \equiv \bar{y}_{it}^{p}/n_{it} \tag{5.7}$$

where $\bar{y}_{it}^{p} \equiv \sum_{j\in\mathcal{G}_{it}} 1/|G_j|$ which is the case of $g_j = 1$ in (2.1) ; whereas in the second term, y_{it}^{q} represents the average quality/novelty of i's pairwise output given by

$$y_{it}^{q} \equiv y_{it}/y_{it}^{p} \left(= \bar{y}_{it}/\bar{y}_{it}^{p} \right). \tag{5.8}$$

We can thus decompose the effect of each explanatory variable in (5.1) into the quantity

[23]Ideally, the knowledge stock may be defined in terms of productivities as in the case of k_{it}^{D} in (5.3). However, this leads to an identification problem because of the endogeneity induced by including the lagged outcomes. Moreover, as shown in Section 2.2, publicized technologies are quickly imitated and thus become obsolete. Hence, the output measures may be unsuitable for defining the knowledge stock.

[24]In principle, it is possible to define average pairwise common knowledge of inventor i, for example, by $k_{it}^{C} = \frac{1}{n_{it}} \sum_{j\in N_{it}} |\bar{S}_{it} \cap \bar{S}_{jt}|$, and average pairwise differentiated knowledge of i by $k_{it}^{D*} = \frac{1}{n_{it}} \sum_{j\in N_{it}} |\bar{S}_{it} \backslash \bar{S}_{jt}|$, where $\bar{S}_i \equiv \cup_{t'<t} S_{it'}$. (Refer to footnote 23 for a reason that we should avoid defining k_{it}^{C} and k_{it}^{D*} in terms of productivities as in k_{it}^{D}.) Since these should strongly correlate with k_{it} by construction, and hence can be controlled for by k_{it} to a large extent, however, we focus on the identification of the most interested causal relationship between k_{it}^{D} and y_{it}, rather than allowing for multiple endogenous variables.

and the quality/novelty of inventors' pairwise output, y_{it}, by estimating the model given by

$$\ln y_{it}^m = \alpha^m + \beta^m \ln k_{it}^D + \gamma_1^m \ln k_{it} + \gamma_2^m (\ln k_{it})^2 + \ln A_{it}^m + \lambda_i^m + \tau_t^m + \varepsilon_{it}^m \tag{5.9}$$

for $m = p$ and q, where the coefficients of each explanatory variable for $m = p$ and q add up to that of the corresponding variable in (5.1). In particular, we have

$$\beta = \beta^p + \beta^q \tag{5.10}$$

for the effect of collaborators' differentiated knowledge.

5.3 Recombinations and the differentiated knowledge of collaborators

Finally, we introduce our third regression model (5.11) to identify the factors determining the value of k_{it}^D in (5.1):

$$\ln k_{it}^D = \tilde{\alpha} + \tilde{\beta} \ln \Delta n_{it} + \tilde{\gamma}_1 \ln k_{it} + \tilde{\gamma}_2 (\ln k_{it})^2 + \ln \tilde{A}_{it} + \tilde{\lambda}_i + \tilde{\tau}_t + \epsilon_{it} \tag{5.11}$$

where Δn_{it} given by (2.3) is considered to be endogenous as it is a result of inventors' endogenous collaboration.

The aim of this regression is twofold. One is to see if the more active recombination of collaborators results in acquiring knowledge associated with higher quality/novelty from collaborators, as we interpreted Observation 2 in the context of the Berliant-Fujita model, while the other is to see if the substitutability between the stock of knowledge and collaborator recombinations suggested by Observation 3 is relevant in raising the quality/novelty of collaborators' differentiated knowledge.

It is to be noted that we present the results of the two separate estimations for (5.1) and (5.11), rather than incorporating the collaborator recombination explicitly in the knowledge creation function given by (5.1), since only the former has a specific microeconomic foundation according to Berliant and Fujita (2008). More specifically, in the Berliant-Fujita model, each inventor optimally chooses the size of the collaborator recombination to balance the common and differentiated knowledge between him or her and his or her collaborators, not just to maximize the value of the differentiated knowledge of collaborators. Thus, (5.11) captures only a part of the entire causality behind the determination of k_{it}^D.

6 Data

In this section, we describe our dataset, focusing primarily on patent data.

6.1 Patent data

The original patent data were taken from the *published unexamined patent applications* of Japan. In particular, we focus on the published patent applications to be examined for approval rather than approved patents. The advantage of using unexamined applications is that the flow of unexamined applications at a given point in time reflects the amount of research activities going on at that point more precisely than the flow based on approved patents. Indeed, it is possible to objectively evaluate the quality of each unexamined patent in terms of cited counts as well as the novelty of the technology proposed by the patent.

The unique feature of our dataset developed by Artificial Life Laboratory (2018) is that each inventor is uniquely identified as long as his or her name and affiliation have not changed.[25] For such individual inventors, we can identify the set of all patents in which each inventor was involved in the development as well as the set of inventors with whom he or she has collaborated at different time points. This feature of our dataset enables us to construct panel data that show the relationship between the productivity and collaboration patterns of individual inventors.

6.1.1 Patent projects

Our analysis targets inventors who helped develop the patents applied between 1995 and 2009 in Japan, while we use information on all the patents applied between 1993 and 2016 to construct the relevant variables. To take into account the fact that patent development is a time-consuming project whose underlying research could take several years, the productivity of an inventor is evaluated in terms of his or her output over five years. The choice of a five-year window for each period also reflects the availability of other relevant data such as population, employment, production, and investment data from the census.

We construct a three-period panel by aggregating five consecutive years in each period: period 0 consists of the years from 1995 to 1999, period 1 from 2000 to 2004, and period 2 from 2005 to 2009. Since k_{it} and Δn_{it} require information on the previous period, period 0 is not included in the regressions.

In addition, we cannot include the years of 2010–2016 in the regression since we need information up to seven years from the application date of each patent to account for the time lag between the date of application and that of publication as well as to allow for three/five years from the publication date to count the forward citations for each patent (see Section 6.1.3). Consequently, our panel for the regressions consists of two periods, 1 and 2.

Table 1 summarizes the basic data. There are 1,758,780 and 1,546,596 patents applied in periods 1 and 2, the development of which $|I_1| = 1,208,197$ and $|I_2| = 1,094,789$ individual inventors were involved, respectively (see rows 1 and 4).[26] Among them, we focus on

[25]The name and address matching in Japanese is highly involved because of the wide variation in expressions meaning the same address, firm name, and so on. This database provides the results from highly reliable matching exercises.

[26]The fact that the number of patents per inventor is declining over time may reflect the influence of the tendencies of block patents (e.g., Chu, 2009; Cozzi and Galli, 2014; Nicholas, 2014; Jell et al., 2017). In particular, after the applied unexamined patents were made public in digitized form in 1993, firms have

the productivities of inventors who have been active throughout all three periods and are located in a part of the country contiguous to the four major islands, the main island (Honshu), Hokkaido, Kyushu, and Shikoku. There are $|I| = 107,724$ such inventors.

While our panel is constructed for these 107,724 inventors present throughout the study period, the information on the other inventors is still used as long as they collaborated with these selected inventors.

Row 7 of Table 1 shows that the average number of inventors in a project throughout the study period is about two. In other words, the assumption of pairwise collaboration in the Berliant-Fujita model is indeed not far from reality, which in turn justifies using our regression model for the pairwise knowledge creation function in (5.1).

Table 1: Descriptive statistics of the basic variables

		Period	
		(1)	(2)
Variable		1	2
(2) Number of IPC classes		120	122
(3) Number of IPC subclasses		608	615
(4) Number of IPC subgroups	$\left\lvert \bigcup_{i\in I} S_{it} \right\rvert$	40,691	38,339
(5) Number of inventors in period t	$\lvert I_t \rvert$	1,208,197	1,094,789
(6) Number of inventors active in all periods	$\lvert I \rvert$	107,724	107,724
(7) Number of inventors per patent	$\lvert G_{jt} \rvert$	2.193 (1.538)	2.244 (1.609)
(8) Share of collaborating inventors	$\left\lvert \{i \in I_t : \lvert N_{it}\rvert > 0\} \right\rvert / \lvert I_t \rvert$	0.896	0.868
(9) Number of collaborators per inventor	$\lvert N_{it} \rvert$	8.518 (9.321)	6.323 (7.579)
(10) Number of new collaborators per inventor	Δn_{it}	6.893 (7.907)	4.354 (5.848)
(11) Number of patents per inventor	$\lvert \mathcal{G}_{it} \rvert$	10.66 (16.21)	6.858 (11.95)
(12) Number of IPC subgroups per inventor	$\lvert S_{it} \rvert$	5.471 (5.223)	3.713 (4.026)
(13) Size of cumulative IPC subgroups per inventor	$\lvert \cup_{t'<t} S_{it'} \rvert$	4.550 (4.659)	8.958 (7.582)

Numbers in parentheses are standard deviations.

Moreover, as row 8 indicates, about 90% of inventors have at least one collaborator, which also justifies our focus on collaborative knowledge creation. A shown in row 9, an inventor is working with six to nine collaborators on average (i.e., collaborations are typically polyadic), which also agrees with the implication from the Berliant-Fujita model.

Each inventor is involved in the development of six to 10 patents in each period (row 11), which are associated with three to five IPC subgroups (see Section 6.1.2) (row 12).[27]

6.1.2 IPC

The technological classification of patents provides useful information for quantifying the knowledge of inventors as well as controlling for the possible incompatibility in the

stronger incentives to block potential competitors from innovating in their common technologies.

[27]We adopt IPC subgroups to describe the technological knowledge associated with patents.

productivity comparison of patents across different technological categories.

Each published patent application is associated with at least one technological classification based on the IPC, which is maintained by the World Intellectual Property Organization. The IPC classifies technologies into eight sections: A (human necessities), B (performing operations; transporting),..., H (electricity). These sections are divided into classes such as A01 (agriculture; forestry; animal husbandry; hunting; trapping; fishing) and B02 (crushing, pulverizing, or disintegrating; preparatory treatment of grain for milling) and then into subclasses such as A01C (planting; sowing; fertilizing) and B02B (preparing grain for milling; refining granular fruit to commercial products by working the surface). Each subclass is subdivided into groups (e.g., A01C1 is "apparatus, or methods of use thereof, for testing or treating seed, roots, or the like, prior to sowing or planting") and then into subgroups (e.g., A01C 1/06 (coating or dressing seed) and A01C 1/08 (immunizing seed)).

Unlike the Standard Industrial Classification (SIC), the IPC's labeling scheme for technology classification is consistent over time (i.e., there is no arbitrary relabeling of the same technology classes). Thus, if a new category is introduced at a given point in time, then it means that the technologies associated with this category have been newly developed.

For example, the classes B81 (microtechnology) and B82 (nanotechnology) introduced in 2000 in section B (performing operations; transporting) refer to the newly emerged technologies for manipulating materials and structures at micro- and nano-scales, respectively around that time. As another example, the shale revolution in the late 2000s in the United States was made possible by some key innovations in excavation technology that mainly belong to a new subclass C09K (compositions for drilling of boreholes or wells; compositions for treating boreholes or wells) that was split from E21B (earth or rock drilling; obtaining oil, gas, water, soluble or meltable materials or a slurry of minerals from wells) in 2006. If there are no fundamental changes in technology in a given category, the classification remains the same. Such a case is found, for example, in A47C (furniture; domestic articles or appliances; coffee mills; spice mills; suction cleaners in general).

Taken together, the set of technological categories specified in the IPC at a given point in time roughly represents the set of the state-of-the-art technologies at that time, and hence makes an appropriate proxy for the set of technological knowledge.

While at least one IPC subgroup (hence, one group, one subclass, one class, and one section) is attached to each published patent application, the applicant can claim more than one IPC subgroup for his or her patent. Thus, the IPC subgroups beyond the primary one associated with a given patent reflect certain subjective standards for the identification of the technology, which may vary across applicants.

For this reason, we only take into account the primary IPC subgroup of each patent to represent its technology. In this regard, we have 121, 609, and 40,691 (123, 616, and 38,339) relevant IPC classes, subclasses, and subgroups, respectively for period 1 (period 2), which are claimed as the primary technological classifications of the applied patents in our data (rows 2–4 in Table 1).

Let S denote the set of all the technological categories (in terms of either one of IPC class, subclasstz, or subgroup) and the technological category assigned to patent j be $\mathsf{s}_j \in S$. The technological specialization of inventor i is then defined by

$$S_{it} = \cup_{j \in \mathcal{G}_{it}} \{\mathsf{s}_j\}. \tag{6.1}$$

For the regressions, we adopt IPC subgroups to construct S_{it} and quantify the cumulative stock of knowledge, k_{it}, defined in (5.4).

Similarly, to quantify the technological novelty defined in Section 2.1, we adopt IPC subgroups as they exhibit the largest variation among inventors. We also control for the IPC class fixed effect to account for the possible incompatibility of the quality/novelty adjustment of patents across different technology categories.

6.1.3 Productivity and differentiated knowledge

Table 2 lists the descriptive statistics for the productivity variables. In addition to the quality- and novelty-adjusted productivities introduced in Section 2.1, we consider two more measures based on claim counts and patent counts for our robustness check (detailed below). The table has two columns for each measure to list the values in periods 1 and 2.

Row 1 shows the adjusted output of a patent project. Our preferred measure of the quality of a given patent is based on the count of forward citations following Trajitenberg (2002); Akcigit et al. (2018).[28] In our baseline analysis, we count the forward citations of each patent within three years of the publication date following Akcigit et al. (2018), while we also conduct the same analysis under the count of forward citations within five years of publication to check the robustness (see Appendix C).

For the applied patents published between 1995 and 2006, Figure 5 shows the frequency distribution of the cited timing in terms of days from publication in the first 10 years after publication. The peak is at around two years. Indeed, the cited counts in the first three years account for more than 75% of the total cited count in the first 10 years for all samples. Thus, using the cut-off of three years from publication to evaluate the quality of the applied patent appears to be reasonable.

Columns 1 and 2 list the numbers for this measure of patent quality for periods 1 and 2, respectively.

Alternatively, we use technological novelty based on the IPC subgroups introduced in Section 2. Since cultivating a novel technology requires knowledge, there may be a more direct relationship between knowledge input and technological novelty. To check the robustness, we also present the second-stage results for novelty-adjusted productivity using the IPC subclasses instead of subgroups in Appendix C.

[28] Cited counts may not be an optimal measure of patent quality when there is an incentive to block follow-up patents as discussed by Abrams et al. (2013).

For robustness, we additionally adopt patent claims as an alternative measure for the technological novelty of a patent. Each claim indicates an aspect of the patent to be protected. Thus, its count can be considered to reflect the technological novelty *within a patent*. While the claims are made by applicants, this is not a fully subjective measure of quality since each claim incurs monetary costs. Columns 3 and 4 list the numbers for this quality measure for periods 1 and 2, respectively.

The last measure to be considered is to count the patents applied as they are (i.e., the output value, g_j, for each patent j is one). Columns 5 and 6 list the numbers for this measure of patents for periods 1 and 2, respectively.

Table 2: Descriptive statistics of the productivity variables

Productivity measure		**Cited counts**		**Novelty**		**Claim counts**		**Patent counts**	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Period		1	2	1	2	1	2	1	2
(1) Output of a patent	g_{jt}	1.535	1.423	0.013	0.009	7.231	8.906	1.000	1.000
		(2.527)	(3.850)	(0.056)	(0.049)	(9.555)	(81.53)	(0.000)	(0.000)
(2) Productivity of an inventor	$\bar{y}_{it}$	7.906	5.048	0.047	0.024	36.67	40.89	4.824	3.099
		(16.83)	(163.31)	(0.134)	(0.084)	(109.14)	(4173.48)	(7.749)	(5.936)
(3) Pairwise productivity of an inventor	y_{it}	1.389	1.728	0.009	0.006	6.682	25.48	0.894	0.677
		(3.160)	(175.04)	(0.049)	(0.032)	(88.27)	(4478.60)	(1.911)	(1.739)
(4) Avg. diff. knowledge of collaborators	k_{it}^D	1.411	1.053	0.008	0.005	6.578	5.646	0.874	0.747
		(7.520)	(4.539)	(0.043)	(0.034)	(49.51)	(25.86)	(4.699)	(3.057)

Numbers in parentheses are stand1ard deviations.

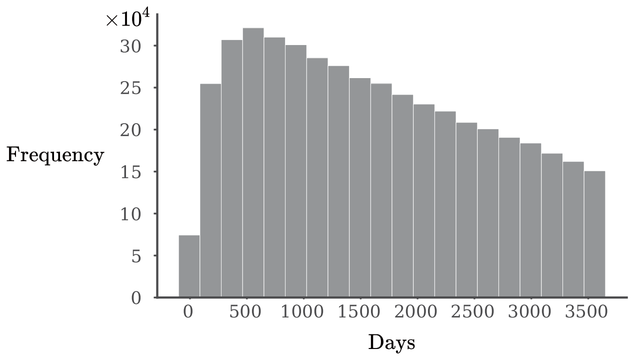


Figure 5: Cited timing in the 10 years after publication

As defined in (2.1), when the output of a project is attributed to each inventor, it is discounted by the total number of inventors involved in the project. Row 2 of Table 2 lists the output, $\bar{y}_{it}$, attributed to inventor i under each alternative productivity measure.

Row 3 of Table 2 lists the average pairwise productivity, y_{it}, of each inventor defined by (5.2), which corresponds to the output of the knowledge creation function (4.2) proposed by Berliant and Fujita (2008) under these alternative productivity measures.

Finally, row 4 of Table 2 lists the average differentiated knowledge of collaborators defined by (5.3) for each productivity measure. These numbers are not surprisingly comparable to the values of the pairwise productivity of an inventor in row 3.

6.2 Locational factors

The possible influence of various exogenous locational factors on productivity in knowledge creation has been suggested by existing studies. Below, we briefly describe each factor included in the regression, with the precise definitions relegated to Appendix A. For factors 2–5 below, the size of the concentration in a circle of a given radius around each inventor $i \in I$ is computed.

Urban agglomerations (UAs): R&D activities are disproportionately concentrated in large cities (see, e.g., Helsley and Strange, 2004; Davis and Dingel, 2018; see also Figure 7(b) in Appendix D). Hence, to correctly account for the heterogeneity in productivity across cities, individual inventors are associated with UAs. Specifically, we define a UA to be a contiguous area of population density at least 1000 per 1km^2 with the total population at least 10,000.[29]

For inventors located within a 10 km buffer of each of the 453 UAs, the closest UA is assigned, while for those located outside the 10 km buffer of any of these UAs, their locations are considered to be rural. In the regression analyses below, the standard errors are clustered by UA. In the regression analyses, the standard errors are clustered by UAs.[30]

Inventor population a_{it}^{INV}: The effects of spillovers and competition from the local population of inventors have been recognized in the literature (e.g., Jaffe et al., 1993; Thompson and Fox-Kean, 2005; Murata et al., 2014; Kerr and Kominers, 2015). To account for these effects of the local inventor population for each inventor i, we exclude his or her collaborators, N_{it}.

R&D expenditure $a_{it}^{\mathrm{R\&D}}$: R&D expenditure naturally influences patent development.[31]

Manufacturing employment and output $a_{it}^{\mathrm{MNF}_e}$ **and** $a_{it}^{\mathrm{MNF}_o}$: R&D may be subject to spillovers from manufacturing concentration (e.g., Griliches, 1979; Coe and Helpman, 1995; Ulku, 2007). Moreover, developed patents may be the most intensively utilized in manufacturing industries; hence, the proximity to them may matter for research productivity.[32]

Residential population a_{it}^{POP}: Residential population in the neighborhood reflects the level of urban infrastructure that might affect the behavior of inventors.[33]

[29] The population data are obtained from the Population Census (2010a) of Japan.

[30] As UAs on average expand spatially over time, we used the boundaries of UAs in 2010, each of which provides on average the largest spatial extent during the study period of 1995–2009. However, the choice of the particular time point should not affect the basic results since most inventors are concentrated in relatively large UAs whose spatial coverage is relatively stable over the study period.

[31] The R&D expenditure values are obtained from the micro data of the Survey of Research and Development (1997-2010b) and from the Corporate Activities Basic Survey (1995-2010).

[32] The manufacturing employment values are obtained from the micro data of the Establishment and Enterprise Census for (1996, 2001, 2006) and Economic Census for Business Frame (2009) of Japan; the manufacturing output values are obtained from the micro data of the Census of Manufacturers (1995, 2000, 2005) and Economic Census for Business Frame (2009) of Japan.

[33] The data are obtained from the Population Census (1995, 2000, 2005) of Japan.

7 Identification by instrumental variables

This section presents our strategy for identifying the causalities behind knowledge creation by dealing with the endogeneity of the differentiated knowledge and recombinations of collaborators for individual inventors. There are two sources of endogeneity. One comes from inventors' endogenous collaboration (i.e., network endogeneity). The other comes from the mutual dependence of the productivities between an inventor and his or her collaborators through k_{it}^{D} in model (5.1) (as well as (5.1)'), which makes the differentiated knowledge, k_{it}^{D}, of collaborators endogenous. This is the so-called reflection problem in the context of econometric network analysis. In our case, however, we argue that the endogenous variables, k_{it}^{D} in model (5.1) and Δn_{it} in model (5.11), for inventor i can be instrumented by the average value of the same variable for the indirect collaborators of i.

Below, we first formally define the instruments for the endogenous variables based on the indirect collaborators of each inventor in Section 7.1, explain their relevance in Section 7.2, and finally the exogeneity of the instruments is established in Section 7.3.

7.1 Instruments

Let $\bar{N}_{it}^{\ell}$ be the set of up to the ℓ-th indirect collaborators of inventor i given by

$$\bar{N}_{it}^{\ell} = \bar{N}_{it}^{\ell-1} \cup \left[\cup_{j \in \bar{N}_{it}^{\ell-1}} N_{jt} \right] \quad \ell = 1, 2, \ldots \tag{7.1}$$

where, for convenience, the set of the "0-th indirect collaborators" is defined by the set of inventors consisting of i and his or her direct collaborators:

$$\bar{N}_{it}^{0} \equiv N_{it} \cup \{i\}. \tag{7.2}$$

Then, to obtain $\bar{N}_{it}^{\ell}$ from $\bar{N}_{it}^{\ell-1}$ for each $\ell = 1, 2, \ldots$, we expand $\bar{N}_{it}^{\ell-1}$ by the union of all the direct collaborators of $j \in \bar{N}_{it}^{\ell-1}$ as in (7.1). The set of the *ℓ-th indirect collaborators* of i can then be obtained as

$$N_{it}^{\ell} = \bar{N}_{it}^{\ell} \backslash \bar{N}_{it}^{\ell-1} \quad l = 1, 2, \ldots \tag{7.3}$$

The instruments, $k_{it}^{\mathrm{IV}_{\ell}}$ for k_{it}^{D} and $\Delta n_{it}^{\mathrm{IV}_{\ell}}$ for Δn_{it}, are constructed as the average value of the differentiated knowledge of collaborators and that of the collaborator recombination, respectively for each ℓ-th indirect collaborator $j \in N_{it}^{\ell}$:

$$k_{it}^{D,\mathrm{IV}_{\ell}} = \frac{1}{n_{it}^{\ell}} \sum_{j \in N_{it}^{\ell}} k_{jt}^{D} \tag{7.4}$$

$$\Delta n_{it}^{\mathrm{IV}_{\ell}} = \frac{1}{n_{it}^{\ell}} \sum_{j \in N_{it}^{\ell}} \Delta n_{jt}. \tag{7.5}$$

Alternatively, indirect collaborators may be weighted by the frequency of their appearance:

$$k_{it}^{D,\mathrm{IV}_\ell} = \frac{1}{\tilde{n}_{it}^{\ell}} \sum_{l \in \bar{N}_{it}^{\ell-1}} \sum_{j \in N_l} k_{jt}^{D} \tag{7.6}$$

$$\Delta n_{it}^{\mathrm{IV}_\ell} = \frac{1}{\tilde{n}_{it}^{\ell}} \sum_{l \in \bar{N}_{it}^{\ell-1}} \sum_{j \in N_l} \Delta n_{jt} \tag{7.7}$$

where $\tilde{n}_{it}^{\ell} \equiv \sum_{j \in \bar{N}_{it}^{\ell-1}} n_j$. Inventor j may appear more than once in the construction of $k_{it}^{D,\mathrm{IV}_\ell}$ in (7.6) and $\Delta n_{it}^{\mathrm{IV}_\ell}$ in (7.7) if $j \in N_l \cap N_{l'}$ for $l, l' \in \bar{N}_{it}^{\ell-1}$ such that $l \neq l'$. As clarified in Section 7.2, weighting by the appearance frequency of indirect collaborators in the linkage tends to strengthen the relevance of the corresponding instruments.

In Table 3, rows 2-6 (8-12) of column 1 show the average numbers as well as the standard deviation in parentheses of the first to fifth indirect collaborators of an inventor in period 1 (period 2). The number of indirect collaborators increases on average dramatically from 79, 344, 1137, 3083, to 7190 (55, 225, 710, 1880, to 4294), respectively in period 1 (period 2).

7.2 Relevance

The correlations between the pairwise productivity, $\ln y_{it}$, of inventor i and those of his or her first and fifth indirect collaborators are on average 0.43 and 0.23 (0.42 and 0.20), respectively for the quality-adjusted (novelty-adjusted) productivity measures. A major reason behind the clustering of similarly productive inventors suggested in the literature is assortative matching among firms and workers (e.g., Mendes et al., 2010; Bartolucci and Devicienti, 2013; Eeckhout and Kircher, 2018). Assortative matching is often considered to induce spatial sorting of firms and workers by productivity (e.g., Mori and Turrini, 2005; Bettencourt et al., 2007; Behrens et al., 2014; Dauth et al., 2016; Gaubert, 2018). Accordingly, inventors are also expected to sort themselves by productivity across both firms and locations.

Since research collaborations tend to take place within a firm, among affiliated firms, as well as among firms with business partnerships, and with more geographical proximity, an inventor tends to face a pool of potential collaborators with relatively similar productivity under assortative matching.

The key feature of our panel data is that both inventors' location and affiliations to establishments as well as firms are exogenous to individual inventors in the observations. Moreover, the externalities underlying the assortative matching among firms and workers discussed in the literature are typically much broader than innovation-specific ones, including production, demand, and labor market externalities. It follows that the similarity in productivity that persists among distant indirect collaborators can be essentially treated as exogenous for collaboration decisions by inventors in our regressions.

Since our measure of collaborators' differentiated knowledge k_{it}^{D} of an inventor given by

(5.3) reflects the quality/novelty of the patents for which these collaborators are involved in the development, it also has an aspect of their productivity. Consequently, collaborators' differentiated knowledge exhibits higher correlations among those inventors located more closely on their research network, which confirms the relevance of the instruments.

As for Δn_{it}, recall Observation 2 in Section 2.3 that inventors with higher productivities conduct more active recombination of collaborators. As a result, the size of the collaborator recombination, Δn_{it}, is expected to be relatively similar among indirect collaborators with similar productivities. Yet, between inventor i and his or her indirect collaborator j, the relevance between Δn_{it} and Δn_{jt} induced by the assortative matching among firms and workers is weaker than that between k_{it}^{D} and k_{jt}^{D}, since the former pair are not related to the productivities of i and j directly unlike the latter pair. Thus, rather than (7.5), we adopt the alternative instrument given by (7.7) for Δn_{it} that puts more weights on the indirect collaborators who are more frequently connected to i.

In Table 3, rows 2-6 (8-12) of columns 2 and 3 list the average correlations between $\ln k_{it}^{D}$ and $\ln k_{it}^{\mathrm{IV}_\ell}$ for $\ell = 1,2,\ldots,5$ for the quality-adjusted (novelty-adjusted) productivity measures. The correlations are as high as 0.37 and 0.29 for the quality- and novelty-adjusted measures, respectively, even for $\ell = 5$ (rows 6 and 12 and columns 2 and 3). The correlations are smaller but still persistent for the collaborator recombinations shown in column 4.[34]

7.3 Exogeneity

Since the network component of an inventor is dense and extensive, as discussed in Section 7.1, relatively distant indirect collaborators (e.g., fifth indirect ones) can be used to construct instruments to reduce the reflection problem. We argue below that the influence of omitted variables that make the inventor's collaboration network endogenous can also be avoided as long as sufficiently distant indirect collaborators are used to construct an instrument.

In our case, the most likely source of unobserved factors that could be shared by inventors may be the technological specialization, S_{it}, of inventor i given by (6.1). Columns 5-8 in Table 3 list the diversity, $|S_{it}|$, of the technological specialization of indirect collaborators by IPC sections, classes, subclasses, and subgroups, respectively. While each inventor shares three to five IPC subgroups with his or her direct collaborators on average (rows 1 and 7 of column 8), the corresponding numbers increase for more distant indirect collaborators; for example, they are as large as 1000-1400 for their fifth indirect collaborators (rows 6 and 12 of column 8). Even for the crudest IPC section, the fifth indirect collaborators cover almost all eight categories on average (rows 6 and 12 of column 5), while each inventor

[34] If (7.5) were used instead of (7.7) to instrument $\ln \Delta n_{it}$, the correlations between $\ln n_{it}$ and $\ln n_{it}^{\mathrm{IV}_\ell}$ for $\ell = 1,2,3,4$ and 5 are 0.377, 0.279, 0.203, 0.145, and 0.114 (0.333, 0.243, 0.183, 0.127, and 0.099), respectively in period 1 (period 2). The qualitative results from the regression of (5.11) to be presented in Section 8.3 do not change under (7.5), although the values of the estimated coefficients are less stable among the alternative sets of indirect collaborators, $\ell = 1,2,\ldots,5$.

and his or her direct collaborator share one or two on average (rows 1 and 7 of column 5). Similar observations can be made for the IPC classes and subclasses listed in columns 6 and 7 of Table 3, respectively.

These more distant indirect collaborators of an inventor are not just more diverse in their technological specialization; each of them also has smaller commonality in technological specialization with the inventor. To see this, column 9 of Table 3 shows the average values of the Jaccar index between the technological specialization S_{it} (in terms of IPC subgroups) of inventor i and those of his or her ℓ-th indirect collaborators $j \in N_{it}^{\ell}$ in period t:

$$\mathrm{j}_{it}^{\ell} = \frac{1}{n_{it}^{\ell}} \sum_{j \in N_{it}^{\ell}} \frac{|S_{it} \cap S_{jt}|}{|S_{it} \cup S_{jt}|} \in [0,1] \tag{7.8}$$

where $n_{it}^{\ell} \equiv |N_{it}^{\ell}|$. A larger value of j_{it}^{ℓ} implies higher average similarity in technological specialization between inventor i and his or her ℓ-th indirect collaborators. In particular, it takes 0 if their technological specializations do not overlap (i.e., $S_{it} \cap S_{jt} = 0$ for all $j \in N_{it}^{\ell}$), while it takes 1 if their technological specializations are the same (i.e., $S_{it} = S_{jt}$ for all $j \in N_{it}^{\ell}$).

Table 3: Relevance and exogeneity of the instruments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Indirect-ness ℓ	Count	Corr. with $\ln k_{it}^{D}$		Corr with $\ln \Delta n_{it}$	Diversity in technological category				j_{it}^{ℓ}
		Citation	Novelty		Section	Class	Subclass	Subgroup	
					Period 1				
(1) 0	1.000	1.000	1.000	1.000	1.812	2.473	2.984	5.404	0.330
					(0.952)	(1.788)	(2.409)	(5.060)	(0.214)
(2) 1	79.17	0.832	0.685	0.407	4.670	17.38	32.49	94.83	0.087
	(117.7)				(2.057)	(14.62)	(32.57)	(102.8)	(0.120)
(3) 2	343.9	0.609	0.500	0.314	5.860	32.48	72.72	242.0	0.045
	(517.9)				(2.074)	(23.65)	(64.70)	(240.9)	(0.083)
(4) 3	1137	0.513	0.416	0.240	6.691	50.07	129.7	492.2	0.025
	(1690)				(1.869)	(30.23)	(97.96)	(433.8)	(0.062)
(5) 4	3083	0.440	0.342	0.185	7.200	67.56	199.2	866.8	0.014
	(4260)				(1.584)	(33.33)	(126.4)	(675.2)	(0.046)
(6) 5	7190	0.363	0.291	0.148	7.501	83.07	275.8	1400	0.009
	(8742)				(1.314)	(33.31)	(146.3)	(969.1)	(0.036)
					Period 2				
(7) 0	1.000	1.000	1.000	1.000	1.533	1.918	2.241	3.683	0.432
					(0.799)	(1.381)	(1.874)	(3.938)	(0.271)
(8) 1	55.09	0.826	0.700	0.360	4.073	12.35	22.07	63.30	0.100
	(88.42)				(2.006)	(10.85)	(23.28)	(74.30)	(0.149)
(9) 2	225.3	0.607	0.506	0.271	5.306	23.84	50.43	164.6	0.054
	(352.4)				(2.147)	(18.70)	(48.17)	(179.4)	(0.106)
(10) 3	709.8	0.504	0.421	0.215	6.256	38.60	93.40	343.9	0.030
	(1111)				(2.022)	(25.89)	(77.71)	(341.1)	(0.077)
(11) 4	1880	0.428	0.353	0.162	6.888	54.59	148.8	617.6	0.018
	(2927)				(1.771)	(30.70)	(106.4)	(548.8)	(0.063)
(12) 5	4294	0.361	0.298	0.126	7.286	70.14	213.3	1007	0.011
	(6107)				(1.506)	(32.81)	(129.8)	(793.7)	(0.049)

Numbers in parentheses are standard deviations.

Between an inventor and his or her direct collaborators, $\mathrm{j}_{it}^{0} = 0.33$ and 0.43 for $t = 1$ and 2, respectively (rows 1 and 7 of column 9). However, the index value steadily decreases for more distant indirect collaborators and reaches $\mathrm{j}_{it}^{5} \approx 0.01$ (rows 6 and 12 of column 9). That is, the technological similarity among distant (say fifth) indirect collaborators is only marginal to the point that the determinants of their collaboration decision are expected to be essentially unrelated. It follows that the endogeneity due to omitted variables is not too much of a concern as long as sufficiently distant indirect collaborators are used to construct the instruments.

Despite the decreasing relevance in technological specialization, recall that the similarity in productivity between an inventor and his or her more distant indirect collaborators remains strong (as shown in Section 7.2). It is thus likely that the similarity in productivity accrues from a source other than the technological linkages between the inventor and his or her indirect collaborators.

In addition, the firm- and location-specific effects underlying the similarity in productivity among indirect collaborators in the outcome of models (5.1) and (5.11) are essentially controlled for by individual fixed effects as well as a variety of local factors. Hence, concern about omitted variable bias behind the productivity similarity among indirect collaborators should be low.

8 Regression results

This section presents our main regression results for models (5.1), (5.9) and (5.11) under the quality- and novelty-adjusted productivity measures. The results under alternative productivity measures are also presented for robustness in Appendix C.[35]

In all the regressions conducted, the fixed effects of inventors, periods, and IPC classes (see Section 6.1.2) are controlled for. The local factors described in Section 6.2 except for residential population are constructed for a circle with a 1 km radius around each inventor to approximate the establishment-specific effects, while it is set to 20 km for residential population to account for the urban environment.[36]

Standard errors in all the regressions are clustered by UAs (refer to Section 6.2),[37] since the productivities of collaborative activities within each UA are expected to be influenced by the stochastic shocks specific to the UA. In this context, since the instruments $\ln k_{it}^{D,\mathrm{IV}_\ell}$ for $\ln k_{it}^{D}$ in (5.1) and (5.9) as well as $\ln \Delta n_{it}^{\mathrm{IV}_\ell}$ for $\ln \Delta n_{it}$ in (5.11) involve inventors located in different UAs, one might suspect that standard cluster-robust standard errors are incorrect because the instruments for any inventor i might be correlated with errors ε_{jt} in (5.1), ε_{jt}^{m} in (5.6) and ϵ_{jt} in (5.11) for any inventor j even if inventors i and j are located different

[35] More specifically, we consider four alternative measures of inventor productivity for models (5.1) and (5.11): (*i*) forward citation counts within five years of publication, (*ii*) technological novelty based on the IPC subclass, (*iii*) patent claim counts, and (*iv*) unweighted counts of patents. For (5.9), we consider (*i*) and (*iii*).

[36] Appendix D presents the results for (5.1) and (5.11) under the alternative radius values for local factors for robustness.

[37] As R&D activities are highly urban and agglomerative, almost all observations in I are found in UAs. In fact, among the 56,464 inventors in I who have at least one fifth-indirect collaborators, and are chosen to be the basic set of observations in all the IV regressions in this section, only four inventors locate outside the UAs.

UAs. However, we consider that the standard cluster-robust standard errors still provide the correct standard errors, since the inventor fixed effects controlled in all the regressions encompass UA specific fixed effects, and that makes the errors free from the correlation with UAs.[38]

8.1 The reduced-form Berliant-Fujita model

Table 4 summarizes the regression results for model (5.1), with columns 1-5 (6-10) presenting the results for quality-adjusted (novelty-adjusted) productivity. Columns 1 and 6 report the results from the ordinary least squares (OLS) regression for quality- and novelty-adjusted productivity, respectively, while the rest report those from the two-stage least squares (2SLS) instrumental variable (IV) regressions. For the IV regressions, we used the third to fifth indirect collaborators to construct the IVs for $\ln k_{it}^{D}$. More specifically, we used all three instruments, $\ln k_{it}^{\mathrm{IV}_\ell}$ for $\ell = 3,4$ and 5, in column 2 (column 7), while we used only one of them, $\ell = 3,4$ and 5, in columns 3, 4, and 5 (8, 9, and 10), respectively for quality-adjusted (novelty-adjusted) productivity.[39] To make the regression results comparable, the observations are restricted to the set of 58,464 inventors (rather than the 107,724 considered in Sections 2 and 6) who have at least one fifth indirect collaborator.[40]

The OLS results for both quality- and novelty-adjusted productivities confirm our earlier finding in Section 2 on the implication from Berliant and Fujita (2008), who predicted a positive effect of collaborators' differentiated knowledge, $\ln k_{it}^{D}$ (row 1, columns 1 and 6).

The estimated positive effect of the knowledge stock, $\ln k_{it}$, of an inventor (row 2, columns 1 and 6) and the negative effect of its squared term, $(\ln k_{it})^2$ (row 3, columns 1 and 6), are consistent with the positive but decreasing returns of learning-by-doing from the extant technologies discussed in Sections 2 and 5.

However, since $\ln k_{it} > 0$ from the definition of $k_{it}\,(\geq 1)$ in our data, the second-order effects appear to dominate the first-order effects; in other words, the net effect of the knowledge stock appears to be mostly negative. The overall negative effects associated with the knowledge stock imply that the positive learning-by-doing effects are dominated by the negative effects from imitations and obsolescence, which accounts for the persistent downward pressure on inventor productivity pointed out in Observation 1 in Section 2.2.

We now turn to the results from the IV regression. For all the choices of IVs, the first-stage F values are large (row 12, columns 2-5 and 7-10), meaning that the relevance of the IVs does not seem to be weak (see Table 8 in Appendix B for the results of the first-stage regressions). To confirm the exogeneity of the IVs, we used $\ln k_{it}^{\mathrm{IV}_\ell}$ for all $\ell = 3,4$ and 5 in columns 2 and 7 for quality- and novelty-adjusted productivities, respectively

[38]Note that standard errors are still allowed to vary across UAs.

[39]Aside from the theoretical gap between (5.1) and (5.11) pointed out in Section 5.3, it in fact looks as if the instrument $\ln \Delta n_{it}^{\mathrm{IV}_\ell}$ for $\ln \Delta n_{it}$ also works as an instrument for $\ln k_{it}^{D}$ in the estimation of (5.1) because $\ln \Delta n_{it}^{\mathrm{IV}_\ell}$ has relevance with $\ln k_{it}^{D}$ via (5.11). However, the relevance turned out to be rather weak between $\Delta n_{it}^{\mathrm{IV}_\ell}$ and k_{it}^{D}, although Δn_{it} has positive significant effect on k_{it}^{D}.

[40]The basic properties of each variable remain the same, as described in Table 1.

and conducted Hansen's (1982) J test for overidentifying restrictions. The p-values of the test are 0.928 and 0.768 for quality- and novelty-adjusted productivities, respectively (row 11, columns 2 and 7), meaning that the exogeneity of the IVs cannot be rejected.[41] Moreover, the estimated coefficients for the alternative choices of the IVs are remarkably similar (compare columns 2-5 with columns 7-10), which is also indicative of these IVs being reasonably exogenous.

The comparison between the OLS and IV results shows that the negative net effect of the knowledge stock persists in the IV result; hence, our explanation above for the OLS regression for Observation 1 continues to be valid.

For the effect of $\ln k_{it}^D$, we found downward bias in the OLS regression (compare columns 1 and 2-5 with columns 6 and 7-10 in row 1).[42] A possible explanation for the bias is that a more productive inventor attracts a larger number of potential collaborators and thus tends to end up with more collaborators (with lower productivity) than he or she actively chose to work with. The removal of this reverse causality left a larger positive selection effect in the estimated coefficient of $\ln k_{it}^D$.

For the OLS regression, this selection effect may be partly picked up by the effect of the local concentration of inventors, $\ln a_{it}^{\mathrm{INV}}$, which has upward bias (compare columns 1 and 2 with columns 6 and 7 in row 4).[43] Larger differentiated knowledge is not necessarily associated with a larger potential inventor population unless inventors actively choose to start new collaborations. However, a larger inventor concentration should naturally induce more fruitful collaborations, resulting in larger differentiated knowledge from collaborators, than a smaller one does. As a consequence, in the IV result, the part of the OLS estimate of the coefficient of $\ln a_{it}^{\mathrm{INV}}$ for which the collaborator recombination is responsible is absorbed into the coefficient of $\ln k_{it}^D$. What is left in the estimated effect of $\ln a_{it}^{\mathrm{INV}}$ may be interpreted as the positive spillover effect from the local inventor concentration.

It is intuitive that the concentration of R&D expenditure has a persistent positive effect for all the specifications (row 5), while the size of manufacturing output has essentially no impact on innovation productivity.

The positive significant effects of local manufacturing employment on quality-adjusted productivity (row 6, columns 1-5) may reflect the fact that innovations are linked to production; and citations are often made by the related production units of nearby firms. On the contrary, the manufacturing employment concentration is insignificant for novelty-adjusted productivity (row 5, columns 6-10), as technological novelty is not necessarily directly related to present production levels.

The local concentrations of residential population do not have a significant influence on inventor productivity as expected.

[41] Of course, this result of Hansen's J test by no means is sufficient to guarantee the exogeneity of the instruments, if all the instruments are subject to the same type and magnitude of bias.

[42] Akcigit et al. (2018) reported a similar downward bias on the effects of interaction levels on innovation productivity within a patent team.

[43] Of course, we cannot single out omitted variable bias, as the bias may be due to the reflection problem.

The estimated coefficient value of $\ln k_{it}^D$ for the IV regression is 0.27-0.29 (0.34-0.38) for quality-adjusted (novelty-adjusted) productivity – still far below 1 (see row 1, columns 2-5 and 8-10) – which is consistent with the Berliant-Fujita model. This finding indicates decreasing returns to the differentiated knowledge of collaborators, as the benefit from collaborators' differentiated knowledge will eventually be dominated by that of common knowledge with collaborators as well as the differentiated knowledge of the inventor him- or herself.[44]

Note that it is not meaningful to make comparison of the magnitudes of the estimated elasticities of y_{it} with respect to k_{it}^D between quality and novelty-adjusted productivities, since we do not know the true value of quality and novelty of a patent.

Table 4: Regression results (Dependent variable: $\ln y_{it}$)

	Citations					Novelty				
Variables	(1) OLS	(2) IV3-5	(3) IV3	(4) IV4	(5) IV5	(6) OLS	(7) IV3-5	(8) IV3	(9) IV4	(10) IV5
(1) $\ln k_{it}^D$	0.163***	0.286***	0.286***	0.287***	0.273***	0.164***	0.344***	0.341***	0.353***	0.377***
	(0.0102)	(0.0254)	(0.0257)	(0.0353)	(0.0399)	(0.00493)	(0.0310)	(0.0335)	(0.0296)	(0.0629)
(2) $\ln k_{it}$	0.110***	0.0931***	0.0931***	0.0929***	0.0949***	0.147***	0.114***	0.115***	0.113***	0.108***
	(0.0153)	(0.0119)	(0.0119)	(0.0143)	(0.0165)	(0.0172)	(0.0228)	(0.0229)	(0.0226)	(0.0248)
(3) $(\ln k_{it})^2$	-0.0890***	-0.0820***	-0.0820***	-0.0820***	-0.0828***	-0.195***	-0.178***	-0.178***	-0.177***	-0.175***
	(0.00967)	(0.00868)	(0.00865)	(0.00954)	(0.00991)	(0.00926)	(0.00594)	(0.00564)	(0.00665)	(0.0108)
(4) $\ln a_{it}^{\mathrm{INV}}$	0.171***	0.117*	0.117*	0.117*	0.123**	0.310***	0.200**	0.202**	0.195**	0.180***
	(0.0579)	(0.0633)	(0.0635)	(0.0597)	(0.0540)	(0.0913)	(0.0939)	(0.0965)	(0.0887)	(0.0672)
(5) $\ln a_{it}^{\mathrm{R\&D}}$	0.0272***	0.0256***	0.0256***	0.0256***	0.0258***	0.0420***	0.0364***	0.0365***	0.0362***	0.0354***
	(0.00786)	(0.00679)	(0.00679)	(0.00664)	(0.00670)	(0.0156)	(0.0127)	(0.0128)	(0.0125)	(0.0120)
(6) $\ln a_{it}^{\mathrm{MNF}_e}$	0.0149***	0.0240***	0.0240***	0.0240***	0.0230***	-0.00859	0.0132	0.0128	0.0143	0.0172
	(0.00566)	(0.00438)	(0.00436)	(0.00533)	(0.00598)	(0.0105)	(0.00989)	(0.00955)	(0.0108)	(0.0158)
(7) $\ln a_{it}^{\mathrm{MNF}_o}$	0.00832	0.00522	0.00522	0.00520	0.00555	-0.00362	-0.00512	-0.00509	-0.00519	-0.00539
	(0.00581)	(0.00804)	(0.00806)	(0.00779)	(0.00732)	(0.00552)	(0.00721)	(0.00717)	(0.00732)	(0.00761)
(8) $\ln a_{it}^{\mathrm{POP}}$	-0.449	-0.660	-0.660	-0.661	-0.637	0.793*	0.0701	0.0837	0.0346	-0.0611
	(0.519)	(0.490)	(0.490)	(0.493)	(0.470)	(0.442)	(0.415)	(0.427)	(0.390)	(0.358)
(9) τ_1	0.227***	0.173***	0.173***	0.172***	0.178***	0.304***	0.173***	0.175***	0.166***	0.149***
	(0.0159)	(0.0150)	(0.0149)	(0.0213)	(0.0245)	(0.0307)	(0.0382)	(0.0403)	(0.0352)	(0.0477)
(10) R^2	0.151					0.184				
(11) Hansen J p-val.		0.928					0.768			
(12) 1st stage F		727.1	2178	1080	509.6		557.6	1590	918.7	471.4
(13) #Obs.	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) IPC class fixed effects are controlled. (*iii*) *** p<0.01, ** p<0.05, * p<0.1.

8.2 Quality/novelty and quantity decomposition

In this section, we decompose the effect of each explanatory variable in (5.1) into the fraction that accrues to the quantity and to the quality/novelty of his or her output, as explained in Section 5.2. We only present the result for the latter here, and that for the former is relegated to Appendix C.2.

The regression results are summarized in Table 5. This table is organized similarly to Table 4, except for the dependent variable. The first-stage of the regression is shared with (5.1). To confirm the exogeneity of the IVs, similarly to (5.1), we used $\ln k_{it}^{\mathrm{IV}_\ell}$ for all $\ell = 3,4$

[44] We obtain qualitatively the same result under alternative quality and novelty measures of inventor productivity in Appendix C (refer to Table 10).

and 5 in columns 2 and 7 for quality- and novelty-adjusted productivities, respectively and conducted Hansen's (1982) J test for overidentifying restrictions. The p-values of the test are 0.419 and 0.314 for quality- and novelty-adjusted productivities, respectively (row 11, columns 2 and 7), meaning that the exogeneity of the IVs cannot be rejected.

Together with the results summarized in Table 4, the results from the present regressions in Table 5 reveal the extent to which each explanatory variable contributes to quality/novelty and to the quantity in collaborative knowledge creation.

As for the differentiated knowledge of collaborators, whereas we find that its contribution is mostly (more than 90%) attributed to increasing the quantity, rather than the quality, of research output under the quality-adjusted productivity measure (compare row 1 and columns 2-5 in Tables 4 and 5),[45] as large as around 65% of the contribution accrues to increasing the novelty, rather than the quantity, of research output under the novelty-adjusted productivity measure (compare row 1 and columns 7-10 in Tables 4 and 5).[46,47]

This result indicates that the collaborators' differentiated knowledge is an especially effective source of technological novelty, and thus, appears to be the key factor for inducing the technological shift of an inventor to a new niche, which is consistent with Berliant and Fujita (2008) as well as Horii (2012).

The decompositions of the effects of other explanatory variables are also worth explanations, although there are no formal theories that account for them.

For both quality and novelty-adjusted productivity measures, the inventor as well as R&D expenditure concentrations exhibit positive significant effect on the quantity but not on the quality of inventions (rows 4 and 5 in Tables 5 and 13). The effects of manufacturing employment and production concentrations are also similar between quality- and novelty-adjusted cases. But, they tend to raise the quality rather than the quantity of inventions (rows 6 and 7 in Tables 5 and 13).

The former result suggests that positive externalities from researcher agglomeration primarily promote starting inventions, whereas the latter result may reflect the tendency that the proximity to the manufacturing concentration and production promotes more targeted inventions with higher quality and novelty.

The results of our regressions so far identified the causal relation suggested by the Berliant-Fujita model behind the correlation between collaborators' differentiated knowledge and the productivity of inventors in Observation 2 in Section 2.3, except for the linkage between the collaborator recombination of an inventor and the amount of differentiated

[45]For the quality-adjusted productivity, the result remains essentially the same even if citations are counted in a five-year, instead of three-year, window (refer to columns 1-5 in Table 12).

[46]For the impacts on the quantity y_{it}^{p} of inventor's output for both quality and novelty-adjusted productivity measures, refer to Table 13 in Appendix C.2.

[47]We find positive significant effects of $\ln k_{it}^{D}$ on the novelty when the productivity is measured by claim count (see columns 6-10 in Table 12), which can be considered as an alternative novelty measure of a patent as discussed in Section 2.1.

knowledge of his or her collaborators that will be established in Section 8.3.[48] It follows that technological shift, Δs_{it}, which was found to be correlated with higher productivity in Observation 2, is in fact intentionally directed toward less explored niches because of inventors' quest for more novel invented technologies. The technological shift caused by utilizing collaborators' differentiated knowledge appears to be a means to overcome the negative effects of the past knowledge stock of inventors pointed out in Observation 1. This part of the result is missing from the Berliant-Fujita model in which all knowledge is assumed to be symmetric. However, this finding agrees with the theoretical result of Horii (2012), who considered a more realistic economy with demand for new technologies.

Table 5: Regression results (Dependent variable: $\ln y^q_{it}$)

	Citations					Novelty				
Variables	(1) OLS	(2) IV3-5	(3) IV3	(4) IV4	(5) IV5	(6) OLS	(7) IV3-5	(8) IV3	(9) IV4	(10) IV5
(1) $\ln k^D_{it}$	0.0273***	0.0264**	0.0269**	0.0154	0.00321	0.119***	0.230***	0.231***	0.221***	0.247***
	(0.00169)	(0.0120)	(0.0119)	(0.0192)	(0.0221)	(0.00278)	(0.0143)	(0.0146)	(0.0168)	(0.0330)
(2) $\ln k_{it}$	0.0104*	0.0106	0.0105	0.0121	0.0138*	0.0364	0.0162	0.0161	0.0179	0.0132
	(0.00578)	(0.00714)	(0.00710)	(0.00832)	(0.00758)	(0.0240)	(0.0274)	(0.0274)	(0.0272)	(0.0272)
(3) $(\ln k_{it})^2$	-0.00549***	-0.00554***	-0.00551***	-0.00616***	-0.00684***	-0.108***	-0.0976***	-0.0976***	-0.0985***	-0.0961***
	(0.00101)	(0.00138)	(0.00136)	(0.00189)	(0.00202)	(0.00520)	(0.00651)	(0.00655)	(0.00653)	(0.00657)
(4) $\ln a^{\mathrm{INV}}_{it}$	-0.0364***	-0.0361**	-0.0363**	-0.0313**	-0.0260**	0.0719**	0.00411	0.00368	0.00967	-0.00596
	(0.0126)	(0.0141)	(0.0142)	(0.0137)	(0.0102)	(0.0318)	(0.0392)	(0.0397)	(0.0383)	(0.0400)
(5) $\ln a^{\mathrm{R\&D}}_{it}$	-0.00252	-0.00251	-0.00252	-0.00236	-0.00220	0.0118*	0.00839	0.00837	0.00868	0.00789
	(0.00414)	(0.00421)	(0.00422)	(0.00409)	(0.00377)	(0.00638)	(0.00570)	(0.00569)	(0.00569)	(0.00598)
(6) $\ln a^{\mathrm{MNF}_e}_{it}$	0.0271***	0.0271***	0.0271***	0.0262***	0.0254***	0.00798	0.0215**	0.0216**	0.0204**	0.0235**
	(0.00559)	(0.00521)	(0.00520)	(0.00531)	(0.00641)	(0.00850)	(0.00929)	(0.00919)	(0.00949)	(0.0112)
(7) $\ln a^{\mathrm{MNF}_o}_{it}$	0.00861	0.00863	0.00862	0.00891*	0.00921*	-0.00636	-0.00728	-0.00729	-0.00720	-0.00742
	(0.00556)	(0.00534)	(0.00535)	(0.00518)	(0.00526)	(0.00458)	(0.00656)	(0.00657)	(0.00637)	(0.00684)
(8) $\ln a^{\mathrm{POP}}_{it}$	-0.582**	-0.580**	-0.581**	-0.562**	-0.541**	0.610	0.163	0.160	0.200	0.0971
	(0.238)	(0.240)	(0.239)	(0.250)	(0.251)	(0.440)	(0.477)	(0.476)	(0.479)	(0.497)
(9) τ_1	0.101***	0.102***	0.101***	0.107***	0.112***	0.151***	0.0699***	0.0694***	0.0765***	0.0578*
	(0.0180)	(0.0223)	(0.0223)	(0.0245)	(0.0200)	(0.0202)	(0.0210)	(0.0209)	(0.0225)	(0.0323)
(10) R^2	0.086					0.140				
(11) Hansen J p-val.		0.419					0.314			
(12) 1st stage F		727.1	2178	1080	509.6		557.6	1590	918.7	471.4
(13) #Obs.	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) IPC class fixed effects are controlled. (*iii*) *** p<0.01, ** p<0.05, * p<0.1.

8.3 Recombinations and the differentiated knowledge of collaborators

This section presents the results for model (5.11), which incorporated the fundamental causality assumed in the Berliant-Fujita model that the collaborator recombination is an effective means to collect novel ideas for innovations. Table 6 summarizes the regression results. This table is organized similarly to Table 4, except that the dependent variable is $\ln \Delta k^D_{it}$, and $\ln \Delta n^{\mathrm{IV}_\ell}_{it}$ for $\ell = 3,4$ and 5 serve as the IVs for an endogenous variable, $\ln \Delta n_{it}$, in this case.

The OLS estimates suggest a positive effect of the collaborator recombination on the size of collaborators' differentiated knowledge (row 1, columns 1 and 6) as expected. The

[48] Although we used inventor productivity, $\bar{y}$, in Section 2 rather than pairwise productivity, y_{it}, these are highly correlated, with correlation coefficients of 0.73 and 0.76 in periods 1 and 2, respectively. Thus, the observations made for $\bar{y}$ in Section 2 basically apply to y_{it} as well.

effect of the knowledge stock on collaborators' differentiated knowledge (rows 2 and 3, columns 1 and 6 of Table 6) turns out to be similar to that on inventor productivity (rows 2 and 3, columns 1 and 6 of Table 4).

However, given the correlations among inventor productivity, collaborators' differentiated knowledge, and collaborator recombinations underlying the innovations, the OLS estimates may be severely biased because of endogeneity. The IV estimates in columns 2-5 and 7-10 indicate that this is indeed the case.

Now, we look at the IV results in detail. For all the different choices of IVs, the first-stage F values are large (row 12, columns 2-5 and 7-10), suggesting that the relevance of the IVs is not weak (see Table 9 in Appendix B for the results from the first-stage regressions). To confirm the exogeneity of the IVs, as in the case of model (5.1), we used $\ln \Delta n_{it}^{\mathrm{IV}_\ell}$ for all $\ell = 3, 4$ and 5 in columns 2 and 7 for quality- and novelty-adjusted productivities, respectively and conducted Hansen's (1982) J test for overidentifying restrictions. The p-values of the test are 0.255 and 0.363 for quality- and novelty-adjusted productivities, respectively (row 11, columns 2 and 7), meaning that the exogeneity of the IVs cannot be rejected.[49] The estimated coefficients for the alternative choices of the IVs are less stable than those for model (5.1), but they agree with each other qualitatively (compare columns 2-5 with columns 7-10).

There is substantial downward bias in the coefficient estimate for $\ln \Delta n_{it}$ for the OLS regression (compare columns 1 and 2 with columns 6 and 7 in row 1). As in the case of model (5.1), for the OLS regression, a part of the effect of the collaborator recombination appears in that of local inventor concentration, since a larger inventor concentration implies a larger pool of potential collaborators. The downsized effect of $\ln a_{it}^{\mathrm{IV}}$ in the IV regression is consistent with this interpretation (compare columns 1 and 2-5 with columns 6 and 7-10 in row 5).

Another source of the bias is reverse causality. A higher productivity for an inventor is on average associated with the larger differentiated knowledge of his or her collaborators as well as a larger stock of knowledge. This bias appears to be reflected in the estimated coefficient of the knowledge stock, $\ln k_{it}$, which has substantial upward bias in the OLS (compare columns 1 and 2-5 with columns 6 and 7-10 in row 2).

Once the endogeneity of $\ln \Delta n_{it}$ is controlled for, we find that the first-order effect of the knowledge stock almost disappears (columns 2-5 and 7-10 of row 2), and instead the second-order effect becomes positive significant (columns 2-5 and 7-10 of row 3); thus, the effect of the knowledge stock exhibits increasing returns. The size of differentiated knowledge is then not necessarily associated with a larger number of new collaborators.

On the one hand, a highly established inventor with a large knowledge stock can attract highly able collaborators selectively even without a large replacement of collaborators. On the other hand, an inventor with only a small stock of knowledge should place a large

[49] The same caveat stated in footnote 41 applies here.

effort to find able collaborators for successful inventions, which in turn results in a large number of new collaborators. Other local factors play relatively minor roles.

We find that the elasticities of average quality- and novelty-adjusted differentiated knowledge of collaborators with respect to the recombination of collaborators for an inventor are around 1.4 and 1.8, respectively. While these estimated elasticities are greater than 1, since the pairwise research productivity exhibits decreasing returns in the input of collaborators' differentiated knowledge, the positive effect of the collaborator recombination on inventor productivity will be diminishing.

Table 6: Regression results (Dependent variable: $\ln k_{it}^{D}$)

	Citations					Novelty				
Variables	(1) OLS	(2) IV3-5	(3) IV3	(4) IV4	(5) IV5	(6) OLS	(7) IV3-5	(8) IV3	(9) IV4	(10) IV5
(1) $\ln \Delta n_{it}$	0.104***	1.372***	1.400***	1.523***	1.236***	0.244***	1.722***	1.718***	1.962***	1.714***
	(0.00626)	(0.0629)	(0.0748)	(0.119)	(0.132)	(0.00792)	(0.0847)	(0.0914)	(0.157)	(0.131)
(2) $\ln k_{it}$	0.131***	-0.0220	-0.0253	-0.0401	-0.00554	0.147***	-0.0313	-0.0308	-0.0601	-0.0303
	(0.0427)	(0.0669)	(0.0653)	(0.0814)	(0.0732)	(0.0338)	(0.0638)	(0.0632)	(0.0786)	(0.0669)
(3) $(\ln k_{it})^2$	-0.0364**	0.223***	0.229***	0.254***	0.195***	-0.0422***	0.261***	0.260***	0.310***	0.259***
	(0.0156)	(0.0197)	(0.0167)	(0.0422)	(0.0392)	(0.0161)	(0.0233)	(0.0223)	(0.0476)	(0.0360)
(4) $\ln a_{it}^{\mathrm{INV}}$	0.387***	0.0138	0.00580	-0.0304	0.0539	0.515***	0.0800	0.0813	0.00957	0.0825
	(0.0916)	(0.0426)	(0.0467)	(0.0461)	(0.0507)	(0.118)	(0.103)	(0.107)	(0.0878)	(0.0939)
(5) $\ln a_{it}^{\mathrm{R\&D}}$	0.0134	0.000705	0.000432	-0.000799	0.00207	0.0320*	0.0172*	0.0172*	0.0148	0.0173*
	(0.0111)	(0.00478)	(0.00487)	(0.00571)	(0.00447)	(0.0165)	(0.00896)	(0.00895)	(0.00939)	(0.00915)
(6) $\ln a_{it}^{\mathrm{MNF}_e}$	-0.0706***	-0.0139	-0.0127	-0.00720	-0.0200	-0.110***	-0.0436**	-0.0438**	-0.0329	-0.0440*
	(0.0220)	(0.0147)	(0.0151)	(0.0183)	(0.0137)	(0.0186)	(0.0219)	(0.0213)	(0.0302)	(0.0239)
(7) $\ln a_{it}^{\mathrm{MNF}_o}$	0.0214	0.00814	0.00786	0.00657	0.00957	0.00221	-0.0133	-0.0132	-0.0158	-0.0132
	(0.0215)	(0.00992)	(0.0101)	(0.0110)	(0.00960)	(0.0265)	(0.00922)	(0.00923)	(0.0107)	(0.00920)
(8) $\ln a_{it}^{\mathrm{POP}}$	1.371	-0.552	-0.594	-0.780	-0.345	3.574***	1.332	1.338	0.968	1.345
	(1.043)	(1.229)	(1.217)	(1.403)	(1.273)	(1.137)	(1.050)	(1.037)	(1.247)	(1.103)
(9) τ_1	0.415***	0.514***	0.517***	0.526***	0.504***	0.698***	0.814***	0.814***	0.833***	0.814***
	(0.0269)	(0.0504)	(0.0525)	(0.0481)	(0.0428)	(0.0373)	(0.0285)	(0.0287)	(0.0310)	(0.0291)
(10) R^2	0.160					0.178				
(11) Hansen J p-val.		0.255					0.363			
(12) 1st stage F		237.7	639.9	338.5	253.9		237.7	639.9	338.5	253.9
(13) #Obs.	94,694	94,694	94,694	94,694	94,694	94,694	94,694	94,694	94,694	94,694

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) IPC class fixed effects are controlled. (*iii*) *** p<0.01, ** p<0.05, * p<0.1.

Taken together, we confirmed that collaborator recombinations are an effective means to acquire differentiated knowledge from new collaborators to facilitate invention, thereby identifying the causal relationship behind Observation 2. Moreover, the results of our regressions also accounted for the mechanism behind Observation 3 in Section 2.4. In other words, we found that the knowledge stock and collaborator recombination remain two effective means for an inventor to improve his or her productivity via collecting differentiated knowledge, even after controlling for the individual fixed effects. More productive inventors attract highly able collaborators with their large knowledge stocks, and thus can collect differentiated knowledge without large replacements of collaborators. Meanwhile, less productive ones depend on relatively large recombination of collaborators to collect differentiated knowledge.

Taken all together, the rather intricate mechanism underlying the churning of inventor productivities in Observation 1 has been disentangled, and explained from the micro-level behavior of individual inventors.

9 Discussion and further research directions

In this section, we summarize our findings and their implications, and discuss possible immediate extensions and further research directions.

9.1 The Berliant-Fujita mechanism and beyond

We have shown evidence consistent with the polyadic collaborative knowledge creation mechanism proposed by Berliant and Fujita (2008). To our knowledge, our work is the first to provide micro-econometric evidence for knowledge creation at the individual inventor level taking into account the endogeneity of collaborations.[50] We have also addressed two major counterfactual aspects of the Berliant-Fujita model, guided by the theoretical model presented by Horii (2012).

One is that that each inventor in their model belongs to a fixed network component in a typical steady state, meaning that polyadic interactions happen only within a given set of collaborators. However, in the data, the set of collaborators evolves for each agent over time, and the inter-temporal recombination of collaborators is found to revise inventors' technological expertise by meeting new agents and adopting their differentiated knowledge.

The other is that inventors in their model face no imitation or obsolescence of their technological knowledge since the number of potential knowledge is infinite and they are symmetric. In reality, however, we found negative significant effects from the knowledge stock of inventors on their productivity. If inventors stick to their past achievement, they most likely lose their present level of creativity in the long run. If, instead, agents are willing to explore new research directions by meeting new collaborators with different backgrounds from theirs, they are more likely to keep their creativity by shifting their technological expertise to unexplored niches. We have explained this more realistic causal relationship by estimating the second and the third regression models, (5.9) and (5.11), in addition to the reduced form of the Berliant-Fujita model (5.1). Specifically, collaborator recombinations are found to be effective in raising the average quality as well as novelty of the collaborators' differentiated knowledge, thereby enhance the quality and novelty of the research output of an inventor.

These additional results reveal a so far overlooked aspect of collaborative knowledge creation. Namely, the active collaborator recombinations are an effective strategy for a fledgling inventor to improve his or her research productivity, as well as for an established inventor to maintain his or her high productivity (although the latter can also utilize his or her large stock of knowledge).

This evidence has an important policy implication: Firms, cities, regions and countries

[50]See Akcigit et al. (2018) for another related attempt at the patent project.

that promote encounters and collaborations among individual inventors across organizations and institutions, despite the possibility of imitations and undesired diffusions, have better chances to foster innovation there. While the lower organizational and institutional barriers for research collaboration are not incompatible with the protection of intellectual property by patents, our finding supports more active coordination than divisions among researchers to encourage innovations.[51]

9.2 Extensions

There are a number of short-run and long-run extensions, among which we touch on three.

First, it is an obvious interest to investigate the role of firms and establishments in R&D activities. Since the financial resources for R&D are typically provided by firms, firm-specific patterns of collaborations and R&D policies could affect the productivity of individual inventors.[52] By matching the addresses of establishments in the patent database with those of the Census of Manufacturers, it is in principle possible to investigate the impact of patent development on firm productivity.[53]

Second, the non-technological diversity among collaborators in terms of, for example, gender, age, education, and cultural background may affect productivity. For example, Østergaard et al. (2011) and Inui et al. (2014) found a positive significant influence of gender diversity in the innovation productivity of Danish and Japanese firms, respectively.

Finally, it is intriguing to explore the differences in the location patterns of R&D activities and industries. It is argued that disproportionately large cities are typically associated with a concentration of knowledge-intensive activities (e.g., Davis and Dingel, 2017, 2018). However, the fundamental distinction between knowledge-intensive activities and those that are less knowledge-intensive has not been made clear thus far.

From our findings, R&D activities – the ultimate knowledge-intensive activities – are expected to be concentrated geographically to better reflect their incentive for frequent collaborator recombinations than industrial activities whose concentrations are typically induced by input/output linkages, demand, and production externalities.

Figure 6(a) plots the aggregate novelty-adjusted patent output and manufacturing output against the population size of a UA in period 1, where all values are expressed by shares in all UAs.[54] The solid and dashed lines indicate the fitted OLS lines for the patent count and manufacturing output plots, respectively. While both plots are super-linear in UA size (i.e., per-capita productivity is increasing in agglomeration size), it is substantially

[51]See Boldrin and Levine (2013) for a related survey of the literature arguing that the patent system hinders rather than promotes innovations.

[52]See Akcigit and Kerr (2018) for an initial attempt in this direction, as they distinguish R&D that is internal and external to firms and study the firm dynamics that arise from this distinction.

[53]In our preliminary attempt, we could match about 70% of establishments that appear in the patent data with those that appear in the Census of Manufacturers.

[54]The location of the patent is identified by the location of the patent applicant who is typically the leader of the patent project. Manufacturing output is obtained from the micro data of the Census of Manufacturers in 2000.

more so for patent output. In fact, doubling the population size of a UA raises R&D productivity by 2.5 times,[55] while raising manufacturing productivity only by 1.2 times.

Figure 6(b) plots the diversity in the primary IPC subclasses of the applied patents as well as the industrial diversity in terms of the number of four-digit Japanese SIC manufacturing industries against the population size of UAs in 2000, where all values are in shares again.[56] Comparing UAs in terms of the diversity in IPC subclass and SIC four-digit industry categories is reasonable, since these two classifications are comparable in the total number of active categories in UAs, which is 608 for the former and 562 for the latter. The solid and dashed lines indicate the fitted OLS lines for the patent class diversity and industrial diversity plots, respectively. While diversity is increasing in the population size of a UA for both patent categories and manufacturing industries, the former is substantially more so: doubling the population size of a UA almost doubles the diversity in the technological category of patents applied in the UA, whereas it only increases the industrial diversity by 55%. Thus, while a larger UA is associated with both larger intensive (i.e., per-capita output) and extensive margins (i.e., diversity) in both R&D and production activities, this tendency is substantial stronger for the former.

These findings are suggestive of a positive association between population concentration and matching externalities promoting collaborator recombinations in large cities.[57] However, the mechanism behind the difference between R&D and industrial location patterns has not been fully explored either theoretically or empirically, and this remains a future research subject.[58]

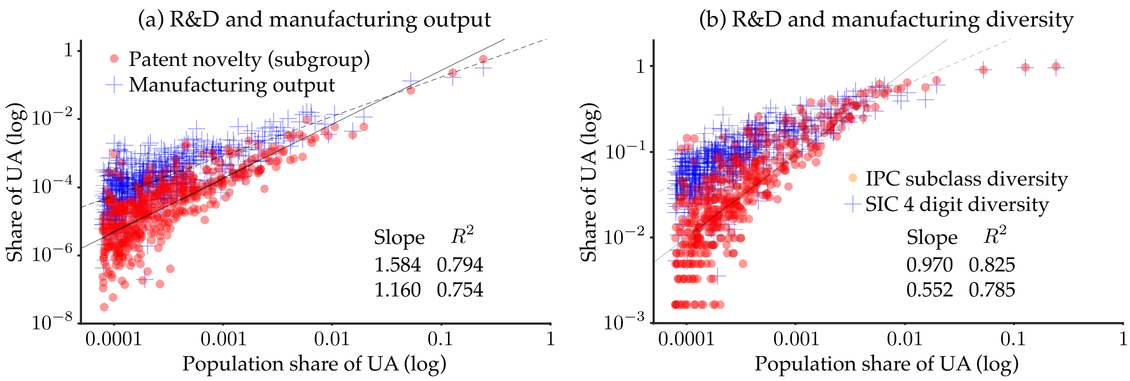


Figure 6: Industrial and research outputs and diversities in UAs in 2000

[55]The estimated elasticity of patent output with respect to UA population size is similar among alternative output measures. Specifically, under IPC subclass and cited count, they are 1.516 and 1.458, respectively.

[56]The industrial diversity of a given UA is defined as the number of four-digit manufacturing industries that have positive employment in the UA.

[57]See, for example, Agrawal et al. (2017); Perlman (2016); Mori and Takeda (2018) for recent empirical studies on geographic agglomeration of R&D activities. In particular, Mori and Takeda (2018) found that the nation-wide development of high-speed railway network had a substantially larger positive impact on the agglomeration of R&D activities than on population agglomeration.

[58]It is also possible to ask if there is any particularly relevant geographic scope of collaborations, e.g., within an establishment, a district, a metropolitan area and an island, and so on. See Gordon (2013) for evidence on the geographic scope of co-authorship in academic research.

References

Abrams, David S., Ufuk Akcigit, and Jillian Popadak, "Patent value and citations: Creative destruction or strategic disruption?," 2013. Discussion paper No. 19647, National Bureau of Economic Research.

Acemoglu, Daron, Ufuk Akcigit, Harun Alp, Nicholas Bloom, and William R. Kerr, "Innovation, reallocation, and growth," November 2017. Discussion Paper No. 12449, Center for Economic Policy Research.

Aghion, Philippe and Peter Howitt, "A model of growth through creative destruction," *Econometrica*, March 1992, *60* (2), 323–351.

Agrawal, Ajay, Alberto Galasso, and Alexander Oettl, "Roads and innovation," *Review of Economics and Statistics*, 2017, *99* (3), 417–434.

Akcigit, Ufuk and William R. Kerr, "Growth through heterogeneous innovations," *Journal of Political Economy*, 2018, *forthcoming.*

_ , Douglas Hanley, and Nicolas Serrano-Velarde, "Back to basic: Basic research spillovers, innovation policy and growth," December 2016. Discussion paper No. 11707, Center for Economic Policy Research.

_ , John Grigsby, and Tom Nicholas, "The rise of American ingenuity: Innovation and inventors of the Golden Age," June 2017. Discussion paper No. 23047, National Bureau of Economic Research.

_ , Santiago Caicedo, Ernest Miguelez, Stefanie Santcheva, and Valerio Sterzi, "Dancing with the stars: Innovation through interactions," 2018. Discussion paper No. 24466, National Bureau of Economic Research.

Arrow, Kenneth J., "The economic implications of learning by doing," *Review of Economic Studies*, 1962, *29* (3), 155–173.

Bartolucci, Cristian and Francesco Devicienti, "Better workers move to better firms: A simple test to identify sorting," August 2013. Discussion paper No. 7601, Institute of Labor Economics (IZA).

Behrens, Kristian, Gilles Duranton, and Frédéric Robert-Nicoud, "Productive cities: Sorting, selection, and agglomeration," *Journal of Political Economy*, 2014, *122* (3), 507–553.

Berliant, Marcus and Masahisa Fujita, "Knowledge creation as a square danc on the Hilbert cube," *International Economic Review*, November 2008, *49* (4), 1251–1295.

_ and _ , "The Dynamics of Knowledge Diversity and Economic Growth," *Southern Economic Journal*, 2011, *77* (4), 856–884.

_ and _ , "Culture and diversity in knowledge creation," *Regional Science and Urban Economics*, 2012, *42* (4), 648–662.

_ and Tomoya Mori, "Beyond urban form: How Masahisa Fujita shapes us," *International Journal of Economic Theory*, February 2017, *13*, 5–28.

Bettencourt, Luís M. A., José Lobo, Dirk Helbing, Cristian Kühnert, and Geoffrey B. West, "Growth, innovation, scaling, and the pace of life in cities," *Proceedings of the National Academy of Sciences of the United States of America*, 2007, *104* (7), 7301–7306.

Boldrin, Michele and David K. Levine, "The case against patents," *Journal of Economic Perspectives*, 2013, *27* (1), 3–22.

Bramoullé, Yann and Bernard Fortin, "Social networks: Econometrics," in Steven N. Durlauf and Lawrence E. Blume, eds., *New Palgrave Dictionary of Economics*, Palgrave Macmillan, 2010.

Bramoullé, Yann and Nicolas Treich, "Identification of peer effects through social networks," *Journal of Econometrics*, 2009, *150* (1), 41–55.

Breschi, Stefano, Francesco Lissoni, and Franco Malerba, "Knowledge-relatedness in firm technological diversification," *Research Policy*, 2003, *32* (1), 69–87.

Caballe, Jordi and Manuel S. Santos, "On endogenous growth with physical and human capital," *Journal of Political Economy*, December 1993, *101* (6), 1042–1067.

Chang, Howard F., "Patent scope, antitrust policy, and cumulative innovation," *RAND Journal of Economics*, 1995, *26* (1), 34–57.

Chu, Angus C., "Effects of blocking patents on R&D: A quantitative DGE analysis," *Journal of Economi Growth*, 2009, *14* (1), 55–78.

Coe, Davit T. and Elhanan Helpman, "International R&D spillovers," *European Economic Review*, May 1995, *39* (5), 859–887.

Comola, Margherita and Silvia Prina, "Do interventions change the network: A panel peer-effect model accounting for endogenous network changes," 2014. IZA Discussion paper No.8641.

Cozzi, Guido and Silvia Galli, "Sequential R&D and blocking patents in the dynamics of growth," *Journal of Economic Growth*, 2014, *19* (2), 183–219.

Dauth, Wolfgang, Sebastian Findeisen, Enrico Moretti, and Jens Suedekum, "Spatial wage disparities – Workers, firms, and assortative matching," 2016. Unpublished manuscript.

Davis, Donald R. and Jonathan I. Dingel, "The comparative advantage of cities," March 2017. Unpublished manuscript.

_ and _ , "A spatial knowledge economy," May 2018. Unpublished manuscript, Columbia University.

Duranton, Gilles and Diego Puga, "Nursery cities: Urban diversity, process innovation, and the life cycle of products," *American Economic Review*, December 2001, *91* (5), 1454–1477.

Eeckhout, Jan and Philipp Kircher, "Assortative matching with large firms," *Econometrica*, 2018, *86* (1), 85–132.

Garcia-Vega, Maria, "Does technological diversification promote innovation? An empirical analysis for European firms," *Research Policy*, 2006, *35* (2), 230–246.

Gaubert, Cecile, "Firm sorting and agglomeration," *American Economic Review*, 2018, *forthcoming.*

Ghiglino, Christian and Nicole Tabasso, "The dynamics of innovations and citations," *Economic Letters*, 2015, *131* (C), 94–97.

Glass, Amy Jocelyn and Kamal Saggi, "Licensing versus direct investment: Implications for economic growth," *Journal of International Economics*, 2002, *56* (1), 131–153.

Goldsmith-Pinkham, Paul and Guido W. Imbens, "Social networks and identification of peer effects," *Journal of Business & Economic Statistics*, 2013, *31* (3), 253–264.

Gordon, Peter, "Thinking about economic growth: Cities, networs, creativity and supply chains for ideas," *Annals of Regional Science*, 2013, *50* (3), 667–684.

Griliches, Zvi, "Research expenditures, education, and the aggregate agricultural production function," *American Economic Review*, 1964, *54* (6), 961–974.

_ , "Issues in assessing the contribution of research and development to productivity growth," *The Bell Journal of Economics*, Spring 1979, *10* (1), 92–116.

Grossman, Gene and Elhanan Helpman, *Innovation and Growth in the Global Economy*, Cambridge, MA: The MIT Press, 1991.

Grossman, Gene M. and Carl Shapiro, "Dynanic R&D competition," *The Economic Journal*, 1978, *97* (386), 372–387.

_ **and Elhanan Helpman**, "Quality ladders in the theory of growth," *Review of Economic Studies*, 1991, *58* (1), 43–61.

Hansen, Lars Peter, "Large sample properties of generalized method of moments estimators," *Econometrica*, 1982, *50* (4), 1029–1054.

Helsley, Robert W. and William C. Strange, "Knowledge barter in cities," *Journal of Urban Economics*, 345 2004, *56* (2), 327.

Horii, Ryo, "Wants and past knowledge: Growth cycles iwth emerging industries," *Journal of Economic Dynamics and Control*, 2012, *36* (2), 220–238.

Hsieh, Chih-Sheng and Lung-Fei Lee, "A social interactions model with endogenous friendship formation," *Journal of Applied Econometrics*, 2016, *31* (2), 1–21.

Huo, Dong and Kazuyuki Motohashi, "Understanding two types of technological diversity and their effects on the technological value of outcomes from bilateral inter-firm R&D alliances," 2015. Discussion paper No. 15-E-06, The Research Institute of Economy, Trade and Industry (RIETI).

Inoue, Hiroyasu, Kentaro Nakajima, and Yukiko Saito Umeno, "Innovation and collaboration patterns between research establishments," 2015. Discussion paper No. 15-E-049, The Research Institute of Economy, Trade and Industry (RIETI).

Inui, Tomohiko, Makiko Nakamuro, Kazuma Edamura, and Junko Ozawa, "Impact of diversity and work-life balance (in Japanese)," December 2014. Discussion paper No. 14-J-055, Research Institute of Economy, Trade and Industry (RIETI).

Jackson, Matthew O., Brian W. Rogers, and Yves Zenou, "The economic consequence of social-network structure," *Journal of Economic Literature*, 2017, *55* (1), 49–95.

Jaffe, Adam B., Manuel Trajtenberg, and Rebecca Henderson, "Geographic localization of knowledge spillovers as evidenced by patent citations," *The Quarterly Journal of Economics*, 1993, *108* (3), 577–598.

Jell, Florian, Joachim Henkel, and Martin W. Wallin, "Offensive patent portfolio races," *Long Range Planning*, October 2017, *50* (5), 531–549.

Jovanovic, Boyan and Rafael Rob, "The diffusion and growth of knowledge," *Review of Economic Studies*, 1989, *56* (4), 569–582.

Kerr, William R. and Scott Duke Kominers, "Agglomerative forces and cluster shapes," *Review of Economics and Statistics*, 2015, *97* (4), 877–899.

Klette, Tor Jakob and Samuel Kortum, "Innovating firms and aggregate innovation," *Journal of Political Economy*, 2004, *112* (5), 986–1018.

König, Michael D., Xiaodong Liu, and Yves Zenou, "R&D networks: Theory, empirics and policy implications," 2014. Discussion paper No.9872, Center for Economic Policy Research.

Kortum, Samuel, "Research, patenting, and technological change," *Econometrica*, November 1997, *65* (6), 1389–1419.

Laboratory, Inc. Artificial Life, "Patent database for research," January 2018.

Lentz, Rasmus and Dale T. Mortensen, "An empirical model of growth through product innovation," *Econometrica*, November 2008, *76* (6), 1317–1373.

Li, Tong and Li Zhao, "A partial identification subnetwork approach to discrete games in large networks: An application to quantifying peer effects," 2016. Unpublished manuscript, Vanderbilt University.

Lucas, Robert E., "On the mechanics of economic development," *Journal of Monetary Economics*, July 1988, *22* (1), 3–42.

Matutes, Carmen, Pierre Regibeau, and Katharine Rockett, "Optimal patent design and the diffusion of innovations," *RAND Journal of Economics*, 1996, *27* (1), 60–83.

Mendes, Rute, Gerard J. van den Berg, and Maarten Lindeboom, "An empirical assessment of assortative matching in the labor market," *Labour Economics*, December 2010, *17* (6), 919–929.

Ministry of Economy, Trade and Industry, *Census of Manufactures* 1995, 2000, 2005.

— , *Corporate Activities Basic Survey* 1995-2010.

Ministry of Internal Affairs and Communications of Japan, *Establishment and Enterprise Census* 1996, 2001, 2006.

— , *Survey of Research and Development* 1997-2010.

— , *Population Census (Tabulation for standard area mesh)* 2010.

Mori, Tomoya and Alessandro Turrini, "Skills, agglomeration and segmentation," *European Economic Review*, January 2005, *49* (1), 201–225.

— **and Kohei Takeda**, "Highways, high-speed railways and the growth of Japanese cities," 2018. Unpublished manuscript, Kyoto University.

Murata, Yasusada, Ryosuke Okamoto Ryo Nakajima, and Ryuichi Tamura, "Localized knowledge spillovers and patent citations: A distanced-based approach," *Review of Economics and Statistics*, 2014, *96* (5), 967–985.

Nicholas, Tom, "Are patents creative or destructive?," *Antitrust Law Journal*, 2014, *79* (2), 405–421.

Olsson, Ola, "Knowledge as a set in idea space: An epistemological view on growth," *Journal of Economic Growth*, September 2000, *5* (3), 253–275.

— , "Technological opportunity and growth," *Journal of Economic Growth*, March 2005, *10* (1), 31–53.

Østergaard, Christian R., Bram Timmermans, and Kari Kristinsson, "Does a different view create something new? The effect of employee diversity on innovation," *Research Policy*, 2011, *40* (3), 500–509.

Panebianco, Fabrizio, Thierry Verdier, and Yves Zenou, "Innovation, pricing and targeting in networks," 2016. Discussion paper No.11398, Center for Economic Policy Research.

Patacchini, Eleonora, Edoardo Rainone, and Yves Zenou, "Heterogeneous peer effects in education," *Journal of Economic Behavior & Organization*, 2017, *134* (C), 190–227.

Perlman, Elizabeth Ruth, "Dense enough to be brilliant: Patents, urbanization, and transportation in nineteenth century America market access, and information flows," January 2016. Unpublished manuscript, Boston University.

Romer, Paul M., "Increasing returns and long-run growth," *Journal of Political Economy*, October 1986, *94* (5), 1002–1037.

— , "Endogenous technological change," *Journal of Political Economy*, October 1990, *98* (5), 71–102.

Scherer, Frederic M., "Inter-industry technology flows and productivity growth," *Review of Economics and Statistics*, 1982, *64* (4), 627–634.

Schotchmer, Suzanne, "Protecting early inventors: Should second-generation products be patentable?," *RAND Journal of Economics*, 1996, *27* (2), 322–331.

Shell, Karl, "Toward a theory of inventive activitgy and capital accumulation," *American Economic Review*, March 1966, *56* (1/2), 62–68.

— , *A model of inventive activity and capital accumulation*, Cambridge, MA: The MIT Press,

Statistics Bureau, Ministry of Internal Affairs and Communications of Japan, *Population Census (Tabulation for standard area mesh)* 1995, 2000, 2005.

— , *Economic Census for Business Frame* 2009.

Tanaka, Hitoshi, "Dynamic analysis of imitation and technology gap," *Journal of Economics*, 2006, *87* (3), 209–240.

__, Tatsuro Iwaisako, and Koichi Futagami, "Dynamic analysis of innovation and international transfer of technology through licensing," *Journal of International Economics*, September 2007, *73* (1), 189–212.

Thompson, Peter and Melanie Fox-Kean, "Patent citations and the geography of knowledge spillovers: A reassessment," *The American Economic Review*, 2005, *95* (1), 450–460.

Trajitenberg, Manuel, "A penny for your quotes: Patent citations and the value of innovations," in Adam B. Jaffe and Manuel Trajtenberg, eds., *Patents, Citations & Innovations*, Cambridge, MA: The MIT Press, 2002, chapter 2, pp. 27–49.

Ulku, Hulya, "R&D, innovation, and growth: Evidence from four manufacturing sectors in OECD," *Oxford Economic Papers*, July 2007, *59* (3), 513–535.

Weitzman, Martin L., "Recombinant growth," *Quarterly Journal of Economics*, 1998, *113* (2), 331–360.

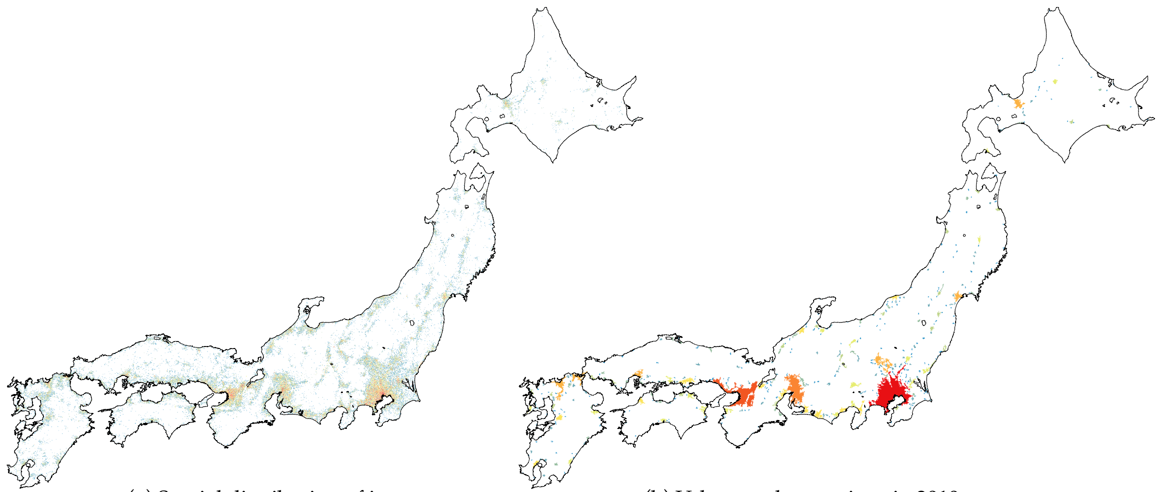
Yang, Guifang and Keith E. Maskus, "Intellectual property rights, licensing, and innovation in an endogenous product-cycle model," *Journal of International Economics*, February 2001, *53* (1), 169–187.

Appendix

A Locational factors

In this section, the description of UAs and precise definitions for the measures of the local factors discussed in Section 6.2 are given.

UAs – Panels (a) and (b) in Figure 7 show the spatial distribution of inventors in I and 453 UAs as of 2010, respectively, where the warmer colors in each panel indicate higher population density. Each inventor is assigned to the closest UA if there is any UA within 10 km of his or her location.



(a) Spatial distribution of inventors (b) Urban agglomerations in 2010

Figure 7: Spatial distribution of researchers and UAs

Inventor population – The local population, a_{it}^{INV}, of inventors within a given distance, $\bar{d}$, of the location of inventor i is defined as

$$a_{it}^{\mathrm{INV}} = \left|\left\{j \in I_t \backslash N_{it} \ : \ d(i,j) < \bar{d}\right\}\right|, \tag{A.1}$$

where $d(i,j)$ represents the great-circle distance between inventors i and j (rows 1-4, Table 7). To evaluate the pure spillover effects, this population excludes the collaborators, N_{it}, of i.

R&D expenditure – Focusing on manufacturing, we first aggregate firm-level R&D expenditure at the industry level according to the three-digit Japanese SIC in each period t. Denote the industry-level R&D expenditure (in million yen) by v_m for each industry $m \in M_t$, where M_t is the set of three-digit manufacturing industries in period t.[59]

[59] Data on R&D expenditure at the firm level are available for firms with at least four employees for every year from 1997 to 2009 from the Survey of Research and Development. Since we do not have data in 1995 and 1996, the total expenditure in 1997–1999 has been inflated by 1.67 times to obtain the value of R&D expenditure in period 0.

Next, from the micro data of the Establishment and Enterprise Census as well as the Economic Census (Ministry of Internal Affairs and Communications of Japan, 1996, 2001, 2006; Statistics Bureau, Ministry of Internal Affairs and Communications of Japan, 2009), we find the set of establishments, E_{mt}, in each industry $m \in M_t$ in period t, and compute the employment share, e_{kt}, of each establishment $k \in E_{mt}$ within industry m.

Table 7: Descriptive statistics of the locational factors

Period		(1) 1	(2) 2
(1) inventor population	1km	5,750 (7,225)	5,629 (7,282)
(2)	5km	31,026 (42,143)	30,158 (42,269)
(3)	10km	70,720 (79,277)	66,011 (77,330)
(4)	20km	140,204 (129,401)	127,470 (120,751)
(5) R&D investment	1km	10,454 (78,020)	18,480 (180,284)
(6)	5km	150,581 (338,668)	278,911 (703,381)
(7)	10km	300,256 (466,130)	520,066 (920,505)
(8)	20km	550,420 (584,891)	899,652 (1,098,091)
(9) Manufacturing employment	1km	2,240 (1,505)	6,676 (7,106)
(10)	5km	52,974 (32,395)	76,491 (74,655)
(11)	10km	182,597 (106,414)	212,371 (166,473)
(12)	20km	551,875 (318,789)	509,703 (322,326)
(13) Manufacturing output (in thousand)	1km	21,801,942 (58,182,730)	20,774,589 (83,883,736)
(14)	5km	158,183,183 (129,167,825)	104,957,604 (129,388,708)
(15)	10km	445,908,195 (255,976,915)	317,846,559 (226,259,080)
(16)	20km	1,213,122,353 (626,842,420)	956,808,207 (532,719,932)
(17) Residential population	5km	595,461 (386,442)	615,722 (399,930)
(18)	10km	2,100,541 (1,388,078)	2,156,271 (1,432,171)
(19)	20km	6,386,959 (4,252,098)	6,573,357 (4,416,168)

Numbers in parentheses are standard deviations.

Assuming that the R&D expenditure of each establishment in each industry is proportional to the employment size of the establishment, the value of R&D expenditure of each establishment in period t is approximated by $v_{mt}e_{mt}$. Assuming that the R&D expenditure in the previous period $t-1$ affects the productivity of inventors in the current period t, the R&D around inventor i in period t is given as follows (rows 5-8, Table 7):

$$a_{it}^{\text{R\&D}} = \sum_{m \in M_t} \sum_{k \in \{j \in E_m : d(i,j) < \bar{d}\}} v_{m,t-1} e_{k,t-1}. \tag{A.2}$$

Manufacturing concentration – Assuming that the employment size and output of an establishment correlate with demand for new knowledge, we proxy the local market size for an invented technology around inventor i by the local manufacturing employment and output around i:[60]

$$a_{it}^{\mathrm{MNF}_j} = \sum_{k \in \{j \in E_t : d(i,j) < \bar{d}\}} e_{kt} \tag{A.3}$$

where $E_t = \cup_{m \in M_t} E_{mt}$, and e_{kt} represents the total output value (employment) of establishment k for $j = o$ ($j = e$) (rows 9-16, Table 7).

Residential population – The local residential population is defined as

$$a_{it}^{\mathrm{POP}} = \sum_{k \in \{j \in R : d(i,j) < \bar{d}\}} r_{kt} \tag{A.4}$$

where R represents the set of 1km-by-1km cells covering the relevant location space in Japan; the centroid of each cell is considered to be the representative location of the cell in measuring the distance from the cell; r_{kt} is the residential population in cell $k \in R$ at the beginning of period t (rows 17-19, Table 7).[61]

B First-stage regressions

This section presents the results of the first-stage regressions for the 2SLS IV regressions corresponding to columns 2-5 and 7-10 in Table 4 and those in Table 6 in Tables 8 and 9, respectively.

[60] Another interpretation of a_{it}^{MNF} is the spillover from the manufacturing concentration around i in period t.

[61] The residential population in the 1 km-by-1 km cells is available from the Population Census of Japan (Statistics Bureau, Ministry of Internal Affairs and Communications of Japan, 1995, 2000, 2005).

Table 8: Regression results (Dependent variable: $\ln k_{it}^{D}$)

	Citations				Novelty			
Variables	(1) IV3-5	(2) IV3	(3) IV4	(4) IV5	(5) IV3-5	(6) IV3	(7) IV4	(8) IV5
(1) k_{it}^{D,IV_3}	0.436***	0.453***			0.340***	0.402***		
	(0.0266)	(0.0169)			(0.0146)	(0.0132)		
(2) k_{it}^{D,IV_4}	0.0235*		0.349***		0.0880***		0.347***	
	(0.0128)		(0.0136)		(0.0149)		(0.0149)	
(3) k_{it}^{D,IV_5}	0.00544			0.249***	0.0411*			0.266***
	(0.0409)			(0.0271)	(0.0225)			(0.0250)
(4) $\ln k_{it}$	0.124***	0.124***	0.131***	0.134***	0.156***	0.156***	0.166***	0.176***
	(0.0212)	(0.0210)	(0.0266)	(0.0304)	(0.0126)	(0.0128)	(0.0130)	(0.0145)
(5) $(\ln k_{it})^2$	-0.0491***	-0.0491***	-0.0524***	-0.0545***	-0.0900***	-0.0892***	-0.0934***	-0.0949***
	(0.00741)	(0.00738)	(0.0107)	(0.0126)	(0.00766)	(0.00777)	(0.00967)	(0.0114)
(6) $\ln a_{it}^{\mathrm{INV}}$	0.359***	0.360***	0.390***	0.402***	0.504***	0.515***	0.538***	0.561***
	(0.0787)	(0.0772)	(0.0845)	(0.0859)	(0.0969)	(0.0988)	(0.108)	(0.115)
(7) $\ln a_{it}^{\mathrm{R\&D}}$	0.00240	0.00259	0.00553	0.00979	0.0140	0.0158	0.0178	0.0252
	(0.00909)	(0.00921)	(0.0104)	(0.0113)	(0.0137)	(0.0142)	(0.0166)	(0.0181)
(8) $\ln a_{it}^{\mathrm{MNF}_e}$	-0.0668***	-0.0663***	-0.0745***	-0.0759***	-0.0954***	-0.0943***	-0.111***	-0.118***
	(0.0196)	(0.0189)	(0.0244)	(0.0266)	(0.0221)	(0.0197)	(0.0238)	(0.0239)
(9) $\ln a_{it}^{\mathrm{MNF}_o}$	0.0227	0.0227	0.0242	0.0242	0.0160	0.0151	0.0149	0.00968
	(0.0207)	(0.0204)	(0.0247)	(0.0246)	(0.0294)	(0.0273)	(0.0320)	(0.0317)
(10) $\ln a_{it}^{\mathrm{POP}}$	1.139	1.143	1.391	1.510	3.041***	3.084***	3.466***	3.699***
	(0.935)	(0.918)	(1.112)	(1.148)	(1.042)	(0.985)	(1.163)	(1.240)
(11) τ_1	0.285***	0.288***	0.333***	0.369***	0.474***	0.504***	0.548***	0.611***
	(0.0211)	(0.0190)	(0.0233)	(0.0288)	(0.0346)	(0.0345)	(0.0382)	(0.0443)
(12) R^2	0.205	0.205	0.183	0.171	0.203	0.201	0.188	0.179
(13) F	443.2	718.4	652.5	84.21	398.6	925.4	541.2	113.2
(14) p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(15) #Obs.	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) inventor, IPC class and period fixed effects are controlled. (*iii*) ***p<0.01, **p<0.05, * p<0.1

Table 9: Regression results (Dependent variable: $\ln \Delta n_{it}$)

	Citations				Novelty			
Variables	(1) IV3-5	(2) IV3	(3) IV4	(4) IV5	(5) IV3-5	(6) IV3	(7) IV4	(8) IV5
(1) $\ln \Delta n_{it}^{\mathrm{IV}_3}$	0.244***	0.278***			0.244***	0.278***		
	(0.0212)	(0.0138)			(0.0212)	(0.0138)		
(2) $\ln \Delta n_{it}^{\mathrm{IV}_4}$	0.00997		0.231***		0.00997		0.231***	
	(0.0321)		(0.0304)		(0.0321)		(0.0304)	
(3) $\ln \Delta n_{it}^{\mathrm{IV}_5}$	0.106***			0.208***	0.106***			0.208***
	(0.0339)			(0.0392)	(0.0339)			(0.0392)
(4) $\ln k_{it}$	0.114***	0.116***	0.117***	0.117***	0.114***	0.116***	0.117***	0.117***
	(0.0268)	(0.0266)	(0.0261)	(0.0255)	(0.0268)	(0.0266)	(0.0261)	(0.0255)
(5) $(\ln k_{it})^2$	-0.202***	-0.202***	-0.203***	-0.204***	-0.202***	-0.202***	-0.203***	-0.204***
	(0.00986)	(0.00962)	(0.00971)	(0.00984)	(0.00986)	(0.00962)	(0.00971)	(0.00984)
(6) $\ln a_{it}^{\mathrm{INV}}$	0.232***	0.237***	0.261***	0.273***	0.232***	0.237***	0.261***	0.273***
	(0.0529)	(0.0542)	(0.0600)	(0.0651)	(0.0529)	(0.0542)	(0.0600)	(0.0651)
(7) $\ln a_{it}^{\mathrm{R\&D}}$	0.00704	0.00845	0.00680	0.00712	0.00704	0.00845	0.00680	0.00712
	(0.00751)	(0.00733)	(0.00840)	(0.00874)	(0.00751)	(0.00733)	(0.00840)	(0.00874)
(8) $\ln a_{it}^{\mathrm{MNF}_e}$	-0.0329	-0.0326*	-0.0412*	-0.0427*	-0.0329	-0.0326*	-0.0412*	-0.0427*
	(0.0200)	(0.0194)	(0.0220)	(0.0240)	(0.0200)	(0.0194)	(0.0220)	(0.0240)
(9) $\ln a_{it}^{\mathrm{MNF}_o}$	0.00479	0.00514	0.00793	0.00868	0.00479	0.00514	0.00793	0.00868
	(0.0142)	(0.0142)	(0.0155)	(0.0170)	(0.0142)	(0.0142)	(0.0155)	(0.0170)
(10) $\ln a_{it}^{\mathrm{POP}}$	1.053**	1.106**	1.210**	1.338**	1.053**	1.106**	1.210**	1.338**
	(0.506)	(0.539)	(0.585)	(0.585)	(0.506)	(0.539)	(0.585)	(0.585)
(11) τ_1	-0.167***	-0.146***	-0.139***	-0.131***	-0.167***	-0.146***	-0.139***	-0.131***
	(0.0206)	(0.0187)	(0.0252)	(0.0263)	(0.0206)	(0.0187)	(0.0252)	(0.0263)
(12) R^2	0.197	0.196	0.190	0.189	0.197	0.196	0.190	0.189
(13) F	142.2	406.1	57.40	28.24	142.2	406.1	57.40	28.24
(14) p-value	0.000	0.000	0.000	3.44e-07	0.000	0.000	0.000	3.44e-07
(15) #Obs.	94,694	94,694	94,694	94,694	94,694	94,694	94,694	94,694

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) inventor, IPC class and period fixed effects are controlled. (*iii*) ***p<0.01, **p<0.05, * p<0.1

C Results for the alternative quality measures of patents

Supplementary regression results for models (5.1) and (5.1)′ in Section 8.1 as well as model (5.11) in Section 8.3 are presented in Sections C.1, C.2 and C.3, respectively.

C.1 Results for model (5.1)

Tables 10 and 11 present the results from the second-stage regressions for model (5.1) based on the four alternative measures are presented, where the output, g_j, of project j in (2.1) is given by (*i*) the cited count within five years of its publication, (*ii*) technological novelty based on the IPC subclass, (*iii*) count of patent claims; or (*iv*) count of patennts, i.e., $g_j = 1$ for all j. The organization of each table is the same as that in Table 4.

Table 10: Regression results (Dependent variable: $\ln y_{it}$)

	(*i*) Citations (5 years)					(*ii*) Novelty (Subclass)				
Variables	(1) OLS	(2) IV3-5	(3) IV3	(4) IV4	(5) IV5	(6) OLS	(7) IV3-5	(8) IV3	(9) IV4	(10) IV5
(1) $\ln k^D_{it}$	0.163***	0.282***	0.283***	0.271***	0.252***	0.176***	0.305***	0.288***	0.351***	0.411***
	(0.0109)	(0.0276)	(0.0280)	(0.0361)	(0.0393)	(0.00867)	(0.0281)	(0.0334)	(0.0311)	(0.0757)
(2) $\ln k_{it}$	0.116***	0.0991***	0.0991***	0.101***	0.103***	0.117***	0.0952***	0.0981***	0.0874***	0.0774***
	(0.0155)	(0.0117)	(0.0115)	(0.0148)	(0.0168)	(0.0217)	(0.0143)	(0.0146)	(0.0131)	(0.0201)
(3) $(\ln k_{it})^2$	-0.0887***	-0.0820***	-0.0820***	-0.0826***	-0.0837***	-0.122***	-0.112***	-0.113***	-0.108***	-0.104***
	(0.01000)	(0.00892)	(0.00888)	(0.00996)	(0.0103)	(0.0143)	(0.0103)	(0.0105)	(0.00944)	(0.0124)
(4) $\ln a^{\text{INV}}_{it}$	0.167***	0.118*	0.118*	0.122**	0.130**	0.246***	0.174**	0.184**	0.148**	0.116***
	(0.0539)	(0.0606)	(0.0608)	(0.0573)	(0.0527)	(0.0658)	(0.0708)	(0.0747)	(0.0701)	(0.0388)
(5) $\ln a^{\text{R\&D}}_{it}$	0.0269***	0.0254***	0.0254***	0.0255***	0.0258***	0.0402***	0.0370***	0.0374***	0.0359***	0.0344***
	(0.00744)	(0.00650)	(0.00651)	(0.00645)	(0.00660)	(0.0130)	(0.0111)	(0.0115)	(0.0102)	(0.00808)
(6) $\ln a^{\text{MNF}_e}_{it}$	0.0188***	0.0269***	0.0269***	0.0262***	0.0249***	-0.00508	0.00844	0.00665	0.0133	0.0196
	(0.00566)	(0.00465)	(0.00463)	(0.00549)	(0.00589)	(0.0112)	(0.0106)	(0.00993)	(0.0114)	(0.0195)
(7) $\ln a^{\text{MNF}_o}_{it}$	0.00857	0.00546	0.00545	0.00575	0.00624	-0.00994**	-0.0108**	-0.0107**	-0.0111*	-0.0115*
	(0.00616)	(0.00835)	(0.00838)	(0.00786)	(0.00733)	(0.00459)	(0.00508)	(0.00489)	(0.00581)	(0.00659)
(8) $\ln a^{\text{POP}}_{it}$	-0.435	-0.626	-0.627	-0.609	-0.578	0.357	0.0202	0.0649	-0.102	-0.257
	(0.527)	(0.494)	(0.494)	(0.502)	(0.489)	(0.507)	(0.438)	(0.458)	(0.413)	(0.325)
(9) τ_1	0.272***	0.214***	0.214***	0.220***	0.229***	0.380***	0.290***	0.302***	0.257***	0.216***
	(0.0175)	(0.0156)	(0.0155)	(0.0237)	(0.0272)	(0.0269)	(0.0350)	(0.0387)	(0.0353)	(0.0524)
(10) R^2	0.165					0.237				
(11) Hansen J p-val.		0.845					0.208			
(12) 1st stage F		712.6	2134	1053	512.4		491.3	1393	801.8	440.7
(13) #Obs.	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) IPC class fixed effects are controlled. (*iii*) *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Regression results (Dependent variable: $\ln y_{it}$)

	(*iii*) Claim count					(*iv*) Patent count				
Variables	(1) OLS	(2) IV3-5	(3) IV3	(4) IV4	(5) IV5	(6) OLS	(7) IV3-5	(8) IV3	(9) IV4	(10) IV5
(1) $\ln k^D_{it}$	0.198***	0.339***	0.337***	0.354***	0.386***	0.163***	0.326***	0.324***	0.347***	0.377***
	(0.0133)	(0.0383)	(0.0391)	(0.0386)	(0.0389)	(0.0112)	(0.0304)	(0.0319)	(0.0298)	(0.0403)
(2) $\ln k_{it}$	0.140***	0.115***	0.116***	0.113***	0.107***	0.0981***	0.0775***	0.0777***	0.0749***	0.0710***
	(0.0135)	(0.0152)	(0.0151)	(0.0165)	(0.0181)	(0.0114)	(0.00723)	(0.00713)	(0.00811)	(0.0125)
(3) $(\ln k_{it})^2$	-0.0953***	-0.0858***	-0.0859***	-0.0848***	-0.0827***	-0.0826***	-0.0742***	-0.0743***	-0.0732***	-0.0716***
	(0.00337)	(0.00338)	(0.00345)	(0.00293)	(0.00318)	(0.00911)	(0.00715)	(0.00712)	(0.00740)	(0.00850)
(4) $\ln a^{\text{INV}}_{it}$	0.212***	0.142**	0.143**	0.135**	0.119**	0.187***	0.109	0.110	0.0992	0.0846
	(0.0559)	(0.0579)	(0.0584)	(0.0540)	(0.0490)	(0.0658)	(0.0734)	(0.0741)	(0.0686)	(0.0525)
(5) $\ln a^{\text{R\&D}}_{it}$	0.0276***	0.0251***	0.0252***	0.0249***	0.0243***	0.0290***	0.0265***	0.0265***	0.0261***	0.0257***
	(0.0101)	(0.00865)	(0.00869)	(0.00833)	(0.00784)	(0.00971)	(0.00767)	(0.00772)	(0.00722)	(0.00663)
(6) $\ln a^{\text{MNF}_e}_{it}$	0.0148**	0.0274***	0.0272***	0.0287***	0.0315***	-0.00502	0.0120**	0.0117**	0.0141**	0.0172*
	(0.00658)	(0.00542)	(0.00541)	(0.00582)	(0.00697)	(0.00639)	(0.00504)	(0.00493)	(0.00673)	(0.0102)
(7) $\ln a^{\text{MNF}_o}_{it}$	0.0127**	0.00860	0.00866	0.00817	0.00726	0.000798	-0.00151	-0.00148	-0.00180	-0.00223
	(0.00508)	(0.00604)	(0.00602)	(0.00627)	(0.00654)	(0.00344)	(0.00586)	(0.00584)	(0.00614)	(0.00635)
(8) $\ln a^{\text{POP}}_{it}$	0.594	0.154	0.161	0.108	0.0105	0.0162	-0.331	-0.326	-0.374	-0.439
	(0.478)	(0.484)	(0.487)	(0.468)	(0.422)	(0.450)	(0.409)	(0.411)	(0.400)	(0.350)
(9) τ_1	0.122***	0.0788***	0.0794***	0.0742***	0.0645**	0.133***	0.0801***	0.0807***	0.0735***	0.0637***
	(0.0236)	(0.0230)	(0.0229)	(0.0249)	(0.0251)	(0.0160)	(0.0155)	(0.0158)	(0.0150)	(0.0170)
(10) R^2	0.105					0.107				
(11) Hansen J p-val.		0.399					0.629			
(12) 1st stage F		889.2	2646	1498	901.9		774.7	2309	1188	648.1
(13) #Obs.	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) IPC class fixed effects are controlled. (*iii*) *** p<0.01, ** p<0.05, * p<0.1.

C.2 Results for model (5.9)

Table 12 presents the second-stage regression results for model (5.9) under the productivity measure based on cited counts in a five-year window (columns 1-5) and on claim counts (columns 6-10). The organization of the table is the same as that in Table 5.

Table 12: Regression results (Dependent variable: $\ln y_{it}^{q}$)

	Citations (5 years)					Claim count				
Variables	(1) OLS	(2) IV3-5	(3) IV3	(4) IV4	(5) IV5	(6) OLS	(7) IV3-5	(8) IV3	(9) IV4	(10) IV5
(1) $\ln k_{it}^{D}$	0.0354***	0.0389***	0.0396***	0.0240	0.0163	0.0739***	0.135***	0.134***	0.143***	0.167***
	(0.00155)	(0.00896)	(0.00897)	(0.0161)	(0.0255)	(0.00316)	(0.00848)	(0.00840)	(0.0172)	(0.0347)
(2) $\ln k_{it}$	0.0160**	0.0155**	0.0154**	0.0176**	0.0187**	0.0433**	0.0325	0.0327	0.0312	0.0269
	(0.00663)	(0.00752)	(0.00749)	(0.00887)	(0.00850)	(0.0210)	(0.0219)	(0.0217)	(0.0241)	(0.0274)
(3) $(\ln k_{it})^2$	-0.00482***	-0.00462**	-0.00458**	-0.00545**	-0.00589**	-0.0126*	-0.00848	-0.00857	-0.00798	-0.00635
	(0.00171)	(0.00183)	(0.00181)	(0.00241)	(0.00287)	(0.00725)	(0.00791)	(0.00781)	(0.00872)	(0.0100)
(4) $\ln a_{it}^{\mathrm{INV}}$	-0.0451***	-0.0466**	-0.0469**	-0.0404**	-0.0372**	0.00711	-0.0231	-0.0224	-0.0267	-0.0386
	(0.0170)	(0.0190)	(0.0191)	(0.0190)	(0.0148)	(0.0477)	(0.0392)	(0.0399)	(0.0341)	(0.0288)
(5) $\ln a_{it}^{\mathrm{R\&D}}$	-0.00304	-0.00308	-0.00309	-0.00289	-0.00279	-0.00182	-0.00288	-0.00286	-0.00301	-0.00343
	(0.00525)	(0.00534)	(0.00535)	(0.00518)	(0.00489)	(0.00483)	(0.00493)	(0.00494)	(0.00489)	(0.00492)
(6) $\ln a_{it}^{\mathrm{MNF}_e}$	0.0321***	0.0323***	0.0324***	0.0313***	0.0308***	0.0257***	0.0312***	0.0311***	0.0318***	0.0340***
	(0.00639)	(0.00609)	(0.00607)	(0.00634)	(0.00748)	(0.00891)	(0.00870)	(0.00866)	(0.00909)	(0.00980)
(7) $\ln a_{it}^{\mathrm{MNF}_o}$	0.00880	0.00871	0.00869	0.00910	0.00930	0.0132**	0.0114**	0.0114**	0.0112*	0.0105*
	(0.00631)	(0.00620)	(0.00620)	(0.00600)	(0.00618)	(0.00585)	(0.00577)	(0.00576)	(0.00586)	(0.00612)
(8) $\ln a_{it}^{\mathrm{POP}}$	-0.594**	-0.599**	-0.600**	-0.576**	-0.563**	0.616	0.426	0.430	0.403	0.327
	(0.269)	(0.269)	(0.268)	(0.280)	(0.284)	(0.448)	(0.455)	(0.453)	(0.471)	(0.499)
(9) τ_1	0.149***	0.147***	0.147***	0.154***	0.158***	-0.0252	-0.0440**	-0.0436**	-0.0463**	-0.0538**
	(0.0209)	(0.0244)	(0.0245)	(0.0261)	(0.0217)	(0.0180)	(0.0173)	(0.0170)	(0.0200)	(0.0241)
(10) R^2	0.109					0.030				
(11) Hansen J p-val.		0.382					0.465			
(12) 1st stage F		712.6	2134	1053	512.4		889.2	2646	1498	901.9
(13) #Obs.	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) IPC class fixed effects are controlled. (*iii*) ***p<0.01, ** p<0.05, * p<0.1.

Tables 13 and 14, the second stage regression results for model (5.9) with $m = p$. Specifically, in Table 13, k_{it}^{D} is based on cited counts in a three-year window (columns 1-5) and on novelty in terms of IPC-subgroup (columns 6-10), whereas in Table 14, it is based on cited counts in a five-year window (columns 1-5) and on claim counts (columns 6-10).

Table 13: Regression results (Dependent variable: $\ln y_{it}^{p}$)

	Citations (3 years)					Novelty (Subgroup)				
Variables	(1) OLS	(2) IV3-5	(3) IV3	(4) IV4	(5) IV5	(6) OLS	(7) IV3-5	(8) IV3	(9) IV4	(10) IV5
(1) $\ln k_{it}^{D}$	0.135***	0.260***	0.259***	0.272***	0.270***	0.0451***	0.114***	0.110***	0.132***	0.130***
	(0.0103)	(0.0283)	(0.0290)	(0.0271)	(0.0373)	(0.00521)	(0.0214)	(0.0246)	(0.0170)	(0.0416)
(2) $\ln k_{it}$	0.0999***	0.0825***	0.0826***	0.0808***	0.0811***	0.111***	0.0982***	0.0989***	0.0949***	0.0952***
	(0.0110)	(0.00729)	(0.00725)	(0.00844)	(0.0125)	(0.0144)	(0.0112)	(0.0106)	(0.0125)	(0.0194)
(3) $(\ln k_{it})^2$	-0.0835***	-0.0765***	-0.0765***	-0.0758***	-0.0759***	-0.0868***	-0.0803***	-0.0807***	-0.0787***	-0.0788***
	(0.00921)	(0.00761)	(0.00759)	(0.00796)	(0.00884)	(0.0104)	(0.00821)	(0.00800)	(0.00869)	(0.0115)
(4) $\ln a_{it}^{\mathrm{INV}}$	0.207***	0.153**	0.153**	0.148**	0.149***	0.238***	0.196***	0.199***	0.185***	0.186***
	(0.0678)	(0.0752)	(0.0755)	(0.0700)	(0.0574)	(0.0651)	(0.0659)	(0.0683)	(0.0612)	(0.0389)
(5) $\ln a_{it}^{\mathrm{R\&D}}$	0.0298***	0.0281***	0.0281***	0.0279***	0.0280***	0.0302***	0.0280***	0.0282***	0.0275***	0.0276***
	(0.0105)	(0.00925)	(0.00927)	(0.00892)	(0.00867)	(0.0112)	(0.0101)	(0.0102)	(0.00967)	(0.00885)
(6) $\ln a_{it}^{\mathrm{MNF}_e}$	-0.0122*	-0.00309	-0.00313	-0.00222	-0.00236	-0.0166**	-0.00823	-0.00872	-0.00604	-0.00626
	(0.00702)	(0.00616)	(0.00611)	(0.00725)	(0.00869)	(0.00772)	(0.00745)	(0.00756)	(0.00718)	(0.00950)
(7) $\ln a_{it}^{\mathrm{MNF}_o}$	-0.000286	-0.00341	-0.00340	-0.00371	-0.00366	0.00274	0.00217	0.00220	0.00202	0.00203
	(0.00354)	(0.00438)	(0.00438)	(0.00435)	(0.00426)	(0.00420)	(0.00344)	(0.00345)	(0.00339)	(0.00343)
(8) $\ln a_{it}^{\mathrm{POP}}$	0.133	-0.0794	-0.0785	-0.0997	-0.0965	0.183	-0.0932	-0.0768	-0.165	-0.158
	(0.461)	(0.420)	(0.420)	(0.409)	(0.387)	(0.535)	(0.509)	(0.517)	(0.495)	(0.458)
(9) τ_1	0.126***	0.0708***	0.0710***	0.0655***	0.0663***	0.153***	0.103***	0.106***	0.0898***	0.0911***
	(0.0183)	(0.0215)	(0.0217)	(0.0199)	(0.0223)	(0.0179)	(0.0236)	(0.0254)	(0.0206)	(0.0342)
(10) R^2	0.102	0.087	0.087	0.084	0.084	0.089	0.078	0.079	0.072	0.072
(11) Hansen J p-val.		0.878					0.177			
(12) 1st stage F		727.1	2178	1080	509.6		557.6	1590	918.7	471.4
(13) #Obs.	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) IPC class fixed effects are controlled. (*iii*) ***p<0.01, ** p<0.05, * p<0.1.

Table 14: Regression results (Dependent variable: $\ln y^{p}_{it}$)

Variables	Citations (5 years)					Claim count				
	(1) OLS	(2) IV3-5	(3) IV3	(4) IV4	(5) IV5	(6) OLS	(7) IV3-5	(8) IV3	(9) IV4	(10) IV5
(1) $\ln k^{D}_{it}$	0.128***	0.243***	0.243***	0.247***	0.236***	0.124***	0.204***	0.203***	0.212***	0.219***
	(0.0103)	(0.0308)	(0.0317)	(0.0281)	(0.0351)	(0.0122)	(0.0329)	(0.0342)	(0.0295)	(0.0267)
(2) $\ln k_{it}$	0.100***	0.0837***	0.0837***	0.0831***	0.0847***	0.0969***	0.0828***	0.0829***	0.0815***	0.0802***
	(0.0110)	(0.00723)	(0.00717)	(0.00874)	(0.0127)	(0.0127)	(0.00986)	(0.00968)	(0.0113)	(0.0152)
(3) $(\ln k_{it})^2$	-0.0839***	-0.0774***	-0.0774***	-0.0772***	-0.0778***	-0.0827***	-0.0773***	-0.0774***	-0.0768***	-0.0763***
	(0.00928)	(0.00767)	(0.00765)	(0.00820)	(0.00905)	(0.00982)	(0.00869)	(0.00863)	(0.00903)	(0.0104)
(4) $\ln a^{\mathrm{INV}}_{it}$	0.212***	0.165**	0.165**	0.163**	0.167***	0.204***	0.165**	0.165**	0.161**	0.158**
	(0.0685)	(0.0773)	(0.0777)	(0.0716)	(0.0596)	(0.0704)	(0.0817)	(0.0823)	(0.0772)	(0.0687)
(5) $\ln a^{\mathrm{R\&D}}_{it}$	0.0299***	0.0285***	0.0285***	0.0284***	0.0285***	0.0294***	0.0280***	0.0280***	0.0279***	0.0278***
	(0.0107)	(0.00964)	(0.00965)	(0.00939)	(0.00925)	(0.0105)	(0.00972)	(0.00975)	(0.00944)	(0.00929)
(6) $\ln a^{\mathrm{MNF}_e}_{it}$	-0.0133*	-0.00542	-0.00542	-0.00514	-0.00590	-0.0110	-0.00381	-0.00388	-0.00315	-0.00251
	(0.00713)	(0.00618)	(0.00614)	(0.00715)	(0.00823)	(0.00726)	(0.00661)	(0.00657)	(0.00737)	(0.00779)
(7) $\ln a^{\mathrm{MNF}_o}_{it}$	-0.000229	-0.00324	-0.00324	-0.00335	-0.00306	-0.000475	-0.00279	-0.00276	-0.00300	-0.00321
	(0.00363)	(0.00425)	(0.00426)	(0.00412)	(0.00412)	(0.00374)	(0.00469)	(0.00470)	(0.00469)	(0.00457)
(8) $\ln a^{\mathrm{POP}}_{it}$	0.159	-0.0266	-0.0265	-0.0330	-0.0152	-0.0225	-0.272	-0.269	-0.295	-0.317
	(0.464)	(0.426)	(0.427)	(0.417)	(0.402)	(0.496)	(0.500)	(0.502)	(0.494)	(0.492)
(9) τ_1	0.124***	0.0673***	0.0673***	0.0654***	0.0708***	0.148***	0.123***	0.123***	0.121***	0.118***
	(0.0188)	(0.0243)	(0.0246)	(0.0217)	(0.0236)	(0.0167)	(0.0183)	(0.0185)	(0.0182)	(0.0182)
(10) R^2	0.100	0.087	0.087	0.086	0.089	0.100	0.093	0.094	0.092	0.091
(11) Hansen J p-val.		0.931					0.905			
(12) 1st stage F		712.6	2134	1053	512.4		889.2	2646	1498	901.9
(13) #Obs.	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928	116,928

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) IPC class fixed effects are controlled. (*iii*) ***p<0.01, ** p<0.05, * p<0.1.

C.3 Results for model (5.11)

Table 15 presents the second-stage regression results for (5.11) with the productivity measure based on cited counts in a five year window (columns 1-5) and novelty in terms of IPC subclass (columns 6-10). Table 16 similarly presents the results under the productivity measures based on claim counts (columns 1-5) and on patent counts (columns 6-10).

Table 15: Regression results (Dependent variable: $\ln k^{D}_{it}$)

Variables	(*i*) Citations (5 years)					(*ii*) Novelty (Subclass)				
	(1) OLS	(2) IV3-5	(3) IV3	(4) IV4	(5) IV5	(6) OLS	(7) IV3-5	(8) IV3	(9) IV4	(10) IV5
(1) $\ln \Delta n_{it}$	0.107***	1.383***	1.413***	1.533***	1.236***	0.171***	1.486***	1.506***	1.630***	1.381***
	(0.00587)	(0.0683)	(0.0781)	(0.118)	(0.133)	(0.00876)	(0.0869)	(0.0891)	(0.139)	(0.152)
(2) $\ln k_{it}$	0.137***	-0.0166	-0.0202	-0.0346	0.00109	0.143***	-0.0154	-0.0179	-0.0328	-0.00278
	(0.0452)	(0.0688)	(0.0675)	(0.0831)	(0.0736)	(0.0502)	(0.0746)	(0.0734)	(0.0867)	(0.0795)
(3) $(\ln k_{it})^2$	-0.0366**	0.225***	0.231***	0.256***	0.195***	-0.0428*	0.226***	0.231***	0.256***	0.205***
	(0.0160)	(0.0191)	(0.0165)	(0.0412)	(0.0372)	(0.0228)	(0.0279)	(0.0250)	(0.0478)	(0.0446)
(4) $\ln a^{\mathrm{INV}}_{it}$	0.365***	-0.00994	-0.0187	-0.0539	0.0332	0.485***	0.0985*	0.0925	0.0560	0.129**
	(0.0965)	(0.0387)	(0.0417)	(0.0467)	(0.0513)	(0.0973)	(0.0537)	(0.0578)	(0.0464)	(0.0546)
(5) $\ln a^{\mathrm{R\&D}}_{it}$	0.0129	0.000127	-0.000170	-0.00137	0.00160	0.0233	0.0102	0.00995	0.00871	0.0112
	(0.0106)	(0.00535)	(0.00545)	(0.00644)	(0.00493)	(0.0155)	(0.00793)	(0.00796)	(0.00762)	(0.00800)
(6) $\ln a^{\mathrm{MNF}_e}_{it}$	-0.0666***	-0.00955	-0.00822	-0.00286	-0.0161	-0.101***	-0.0423**	-0.0414**	-0.0359*	-0.0470***
	(0.0212)	(0.0150)	(0.0154)	(0.0186)	(0.0138)	(0.0213)	(0.0166)	(0.0170)	(0.0207)	(0.0157)
(7) $\ln a^{\mathrm{MNF}_o}_{it}$	0.0221	0.00871	0.00840	0.00715	0.0102	0.00217	-0.0116	-0.0118	-0.0131	-0.0105
	(0.0204)	(0.0112)	(0.0115)	(0.0125)	(0.0104)	(0.0268)	(0.0108)	(0.0107)	(0.0111)	(0.0114)
(8) $\ln a^{\mathrm{POP}}_{it}$	1.238	-0.698	-0.743	-0.925	-0.475	2.153**	0.160	0.129	-0.0591	0.319
	(1.058)	(1.278)	(1.269)	(1.454)	(1.307)	(0.880)	(1.087)	(1.081)	(1.211)	(1.109)
(9) τ_1	0.459***	0.560***	0.562***	0.571***	0.548***	0.678***	0.781***	0.783***	0.792***	0.773***
	(0.0289)	(0.0539)	(0.0560)	(0.0512)	(0.0465)	(0.0279)	(0.0311)	(0.0323)	(0.0338)	(0.0277)
(10) R^2	0.177					0.218				
(11) Hansen J p-val.		0.254					0.261			
(12) 1st stage F		237.7	639.9	338.5	253.9		237.7	639.9	338.5	253.9
(13) #Obs.	94,694	94,694	94,694	94,694	94,694	94,694	94,694	94,694	94,694	94,694

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) IPC class fixed effects are controlled. (*iii*) *** p<0.01, ** p<0.05, * p<0.1.

Table 16: Regression results (Dependent variable: $\ln k^D_{it}$)

	(iii) Claim count					*(iv* Patent count				
Variables	(1) OLS	(2) IV3-5	(3) IV3	(4) IV4	(5) IV5	(6) OLS	(7) IV3-5	(8) IV3	(9) IV4	(10) IV5
(1) $\ln \Delta n_{it}$	0.110***	1.525***	1.538***	1.726***	1.443***	0.0851***	1.318***	1.342***	1.474***	1.193***
	(0.00630)	(0.0540)	(0.0689)	(0.155)	(0.173)	(0.00595)	(0.0512)	(0.0637)	(0.125)	(0.130)
(2) $\ln k_{it}$	0.166***	-0.00414	-0.00578	-0.0284	0.00573	0.116***	-0.0324	-0.0354	-0.0513	-0.0174
	(0.0234)	(0.0526)	(0.0499)	(0.0720)	(0.0644)	(0.0307)	(0.0563)	(0.0543)	(0.0716)	(0.0640)
(3) $(\ln k_{it})^2$	-0.0456***	0.244***	0.247***	0.285***	0.227***	-0.0343***	0.218***	0.223***	0.250***	0.193***
	(0.0103)	(0.0200)	(0.0159)	(0.0495)	(0.0485)	(0.0131)	(0.0200)	(0.0165)	(0.0436)	(0.0405)
(4) $\ln a^{\mathrm{INV}}_{it}$	0.445***	0.0288	0.0248	-0.0303	0.0529	0.450***	0.0876	0.0804	0.0415	0.124**
	(0.131)	(0.0561)	(0.0575)	(0.0695)	(0.0759)	(0.0913)	(0.0534)	(0.0588)	(0.0474)	(0.0534)
(5) $\ln a^{\mathrm{R\&D}}_{it}$	0.0186	0.00446	0.00433	0.00245	0.00528	0.0156	0.00330	0.00306	0.00174	0.00456
	(0.0129)	(0.00568)	(0.00572)	(0.00688)	(0.00566)	(0.0140)	(0.00545)	(0.00555)	(0.00482)	(0.00531)
(6) $\ln a^{\mathrm{MNF}_e}_{it}$	-0.0916***	-0.0283	-0.0277	-0.0193	-0.0320	-0.106***	-0.0505***	-0.0494***	-0.0434**	-0.0560***
	(0.0233)	(0.0203)	(0.0201)	(0.0266)	(0.0219)	(0.0219)	(0.0139)	(0.0140)	(0.0187)	(0.0141)
(7) $\ln a^{\mathrm{MNF}_o}_{it}$	0.0225	0.00768	0.00754	0.00558	0.00854	0.00888	-0.00401	-0.00427	-0.00565	-0.00270
	(0.0257)	(0.0132)	(0.0133)	(0.0142)	(0.0131)	(0.0253)	(0.00891)	(0.00877)	(0.00912)	(0.0101)
(8) $\ln a^{\mathrm{POP}}_{it}$	2.924***	0.778	0.758	0.473	0.903	1.808*	-0.0609	-0.0982	-0.299	0.129
	(0.886)	(1.167)	(1.155)	(1.370)	(1.227)	(0.951)	(1.000)	(0.986)	(1.173)	(1.058)
(9) τ_1	0.287***	0.398***	0.399***	0.414***	0.392***	0.301***	0.398***	0.400***	0.410***	0.388***
	(0.0262)	(0.0322)	(0.0338)	(0.0328)	(0.0289)	(0.0215)	(0.0319)	(0.0338)	(0.0314)	(0.0262)
(10) R^2	0.089					0.111				
(11) Hansen J p-val.		0.245					0.251			
(12) 1st stage F		237.7	639.9	338.5	253.9		237.7	639.9	338.5	253.9
(13) #Obs.	94,694	94,694	94,694	94,694	94,694	94,694	94,694	94,694	94,694	94,694

(i) standard errors clustered by UAs are in parentheses. *(ii)* IPC class fixed effects are controlled. *(iii)* ***p<0.01, ** p<0.05, * p<0.1.

D Results for the alternative radiuses for the locational factors

This section presents the results from the second-stage regressions for (5.1) in Section 8.1 and (5.11) in Section 8.3 for the alternative radius values for the local factors defined in Section 6.2 in Tables 17 and 18 (19 and 20), respectively for quality-adjusted (novelty-adjusted) productivity.

One can see that the choice of radius values for the local factors does not alter the qualitative results obtained in the baseline setup shown in Tables 4 and 6 in Section 8 regarding the effect of collaborators' differentiated knowledge and that of the knowledge stock of an inventor on his or her productivity as well as the role of the collaborator recombination in the size of collaborators' differentiated knowledge. The values of the estimated coefficients for the endogenous variables, $\ln k^D_{it}$ and $\ln \Delta n_{it}$, as well as those for the knowledge stock, $\ln k_{it}$ and $(\ln k_{it})^2$, appear to be stable in all cases.

Table 17: Regression results (Dependent variable: $\ln y_{it}$)

	Citations (IV3-5)						
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) $\ln k^{D}_{it}$	0.293***	0.296***	0.294***	0.286***	0.288***	0.288***	0.286***
	(0.0225)	(0.0193)	(0.0214)	(0.0254)	(0.0239)	(0.0242)	(0.0254)
(2) $\ln k_{it}$	0.0923***	0.0893***	0.0889***	0.0931***	0.0917***	0.0911***	0.0931***
	(0.0124)	(0.0135)	(0.0141)	(0.0119)	(0.0121)	(0.0121)	(0.0119)
(3) $(\ln k_{it})^2$	-0.0814***	-0.0803***	-0.0802***	-0.0820***	-0.0815***	-0.0816***	-0.0820***
	(0.00886)	(0.00903)	(0.00911)	(0.00868)	(0.00879)	(0.00866)	(0.00868)
(4) $\ln a^{\mathrm{INV}}_{it}$							
1km	0.162***						
	(0.0624)						
5km		0.0886					
		(0.108)					
10km			0.127				
			(0.135)				
20km				0.117*	0.126**	0.125*	0.117*
				(0.0633)	(0.0634)	(0.0709)	(0.0633)
(5) $\ln a^{\mathrm{R\&D}}_{it}$							
1km	0.0267***	0.0260***	0.0270***				0.0256***
	(0.00611)	(0.00734)	(0.00838)				(0.00679)
5km				0.0256***			
				(0.00679)			
10km					0.0294***		
					(0.0106)		
20km						0.0314***	
						(0.00865)	
(6) $\ln a^{\mathrm{MNF_e}}_{it}$							
1km	0.0113	0.0176**	0.0209***	0.0240***	0.0277***	0.0202***	
	(0.00825)	(0.00799)	(0.00487)	(0.00438)	(0.00597)	(0.00427)	
5km							0.0240***
							(0.00438)
(7) $\ln a^{\mathrm{MNF_o}}_{it}$							
1km	0.00492	0.00563	0.00650	0.00522	0.00534	0.00588	0.00522
	(0.00863)	(0.00821)	(0.00880)	(0.00804)	(0.00667)	(0.00722)	(0.00804)
(8) $\ln a^{\mathrm{POP}}_{it}$							
1km	-0.624	-0.628	-0.628	-0.660	-0.939*	-0.522	-0.660
	(0.472)	(0.517)	(0.546)	(0.490)	(0.497)	(0.504)	(0.490)
(9) τ_1	0.165***	0.166***	0.163***	0.173***	0.164***	0.166***	0.173***
	(0.0143)	(0.0174)	(0.0190)	(0.0150)	(0.0196)	(0.0117)	(0.0150)
(10) H. J p-value	0.952	0.972	0.974	0.928	0.938	0.878	0.928
(11) F	768.5	775.2	758.3	727.1	734	733.4	727.1
(12) #Obs.	116,928	116,928	116,928	116,928	116,928	116,928	116,928

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) IPC class fixed effects are controlled. (*iii*) ***p<0.01, ** p<0.05, * p<0.1.

Table 17: Regression results continued (Dependent variable: $\ln y_{it}$)

	Citations (IV3-5)						
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) $\ln k_{it}^{D}$	0.284***	0.286***	0.284***	0.287***	0.280***	0.285***	0.280***
	(0.0249)	(0.0248)	(0.0274)	(0.0248)	(0.0280)	(0.0249)	(0.0264)
(2) $\ln k_{it}$	0.0932***	0.0923***	0.0913***	0.0931***	0.0907***	0.0921***	0.0903***
	(0.0115)	(0.0105)	(0.0121)	(0.0119)	(0.0117)	(0.0107)	(0.0117)
(3) $(\ln k_{it})^2$	-0.0822***	-0.0820***	-0.0817***	-0.0821***	-0.0817***	-0.0815***	-0.0809***
	(0.00864)	(0.00848)	(0.00867)	(0.00857)	(0.00861)	(0.00834)	(0.00861)
(4) $\ln a_{it}^{\mathrm{INV}}$							
1km	0.117*	0.124**	0.119*	0.118*	0.115*	0.116*	0.108*
	(0.0634)	(0.0599)	(0.0609)	(0.0608)	(0.0632)	(0.0654)	(0.0598)
(5) $\ln a_{it}^{\mathrm{R\&D}}$							
1km	0.0251***	0.0240***	0.0209***	0.0274***	0.0177***	0.0275***	0.0271***
	(0.00780)	(0.00911)	(0.00498)	(0.00570)	(0.00635)	(0.00634)	(0.00530)
(6) $\ln a_{it}^{\mathrm{MNF_e}}$							
1km			0.0488***	0.0155	0.0283***	0.0218***	0.0217***
			(0.0159)	(0.0157)	(0.00899)	(0.00515)	(0.00695)
10km	-0.0245						
	(0.0165)						
20km		-0.105					
		(0.0783)					
(7) $\ln a_{it}^{\mathrm{MNF_o}}$							
1km	-0.00201	-0.00280				0.00736	0.0102*
	(0.0119)	(0.0129)				(0.00539)	(0.00619)
5km			0.0573***				
			(0.0199)				
10km				-0.0122			
				(0.0481)			
20km					0.137***		
					(0.0483)		
(8) $\ln a_{it}^{\mathrm{POP}}$							
5km						0.0295	
						(0.276)	
10km							0.666
							(0.547)
20km	-0.592	-0.491	-0.217	-0.806	0.232		
	(0.562)	(0.542)	(0.533)	(0.749)	(0.592)		
(9) τ_1	0.177***	0.190***	0.160***	0.178***	0.162***	0.189***	0.203***
	(0.0153)	(0.0173)	(0.0132)	(0.0159)	(0.0162)	(0.0213)	(0.0271)
(10) H. J p-value	0.943	0.944	0.875	0.934	0.846	0.920	0.935
(11) F	721.8	728.7	728.5	728.6	722.6	729.1	709.6
(12) #Obs.	116,928	116,928	116,928	116,928	116,928	116,928	116,928

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) IPC class fixed effects are controlled. (*iii*) *** p<0.01, ** p<0.05, * p<0.1.

Table 18: Regression results (Dependent variable: $\ln k_{it}^{D}$)

	Citations (IV3-5)						
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) $\ln \Delta n_{it}$	1.381***	1.403***	1.404***	1.372***	1.378***	1.372***	1.372***
	(0.0616)	(0.0560)	(0.0571)	(0.0629)	(0.0583)	(0.0634)	(0.0629)
(2) $\ln k_{it}$	-0.0243	-0.0279	-0.0257	-0.0220	-0.0212	-0.0225	-0.0220
	(0.0660)	(0.0671)	(0.0671)	(0.0669)	(0.0673)	(0.0675)	(0.0669)
(3) $(\ln k_{it})^2$	0.226***	0.231***	0.230***	0.223***	0.224***	0.223***	0.223***
	(0.0184)	(0.0200)	(0.0216)	(0.0197)	(0.0207)	(0.0199)	(0.0197)
(4) $\ln a_{it}^{\mathrm{INV}}$							
1km	-0.0460						
	(0.0699)						
5km		-0.287***					
		(0.100)					
10km			-0.338**				
			(0.171)				
20km				0.0138	0.0109	0.0144	0.0138
				(0.0426)	(0.0473)	(0.0418)	(0.0426)
(5) $\ln a_{it}^{\mathrm{R\&D}}$							
1km	0.000665	0.00203	-0.000853				0.000705
	(0.00443)	(0.00617)	(0.00529)				(0.00478)
5km				0.000705			
				(0.00478)			
10km					-0.0150*		
					(0.00821)		
20km						0.00480	
						(0.0109)	
(6) $\ln a_{it}^{\mathrm{MNFe}}$							
1km	-0.0106	0.00436	-0.00815	-0.0139	-0.0161	-0.0144	
	(0.0167)	(0.0151)	(0.0141)	(0.0147)	(0.0175)	(0.0146)	
5km							-0.0139
							(0.0147)
(7) $\ln a_{it}^{\mathrm{MNFo}}$							
1km	0.00833	0.00795	0.00566	0.00814	0.0117	0.00741	0.00814
	(0.00995)	(0.00980)	(0.0111)	(0.00992)	(0.0112)	(0.00973)	(0.00992)
(8) $\ln a_{it}^{\mathrm{POP}}$							
20km	-0.539	-0.458	-0.471	-0.552	-0.688	-0.464	-0.552
	(1.231)	(1.061)	(1.023)	(1.229)	(1.247)	(1.179)	(1.229)
(9) τ_1	0.520***	0.555***	0.557***	0.514***	0.494***	0.520***	0.514***
	(0.0550)	(0.0441)	(0.0358)	(0.0504)	(0.0552)	(0.0471)	(0.0504)
(10) H. J p-value	0.253	0.243	0.251	0.255	0.253	0.254	0.255
(11) F	266	258.3	249.5	237.7	238	239.6	237.7
(12) #Obs.	94,694	94,694	94,694	94,694	94,694	94,694	94,694

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) IPC class fixed effects are controlled. (*iii*) ***p<0.01, ** p<0.05, * p<0.1.

Table 18: Regression results continued (Dependent variable: $\ln k_{it}^{D}$)

	Citations (IV3-5)						
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) $\ln \Delta n_{it}$	1.371***	1.377***	1.379***	1.381***	1.375***	1.366***	1.366***
	(0.0601)	(0.0652)	(0.0631)	(0.0595)	(0.0628)	(0.0614)	(0.0537)
(2) $\ln k_{it}$	-0.0228	-0.0232	-0.0212	-0.0205	-0.0228	-0.0233	-0.0227
	(0.0666)	(0.0661)	(0.0664)	(0.0648)	(0.0659)	(0.0652)	(0.0647)
(3) $(\ln k_{it})^2$	0.223***	0.224***	0.224***	0.225***	0.224***	0.223***	0.223***
	(0.0206)	(0.0194)	(0.0194)	(0.0197)	(0.0192)	(0.0185)	(0.0204)
(4) $\ln a_{it}^{\mathrm{INV}}$							
1km	0.0148	0.0176	0.0124	0.0220	0.0127	0.0117	0.0120
	(0.0421)	(0.0429)	(0.0443)	(0.0440)	(0.0434)	(0.0446)	(0.0491)
(5) $\ln a_{it}^{\mathrm{R\&D}}$							
1km	0.000500	9.21e-05	0.00515	0.0153**	0.000744	0.00240	0.00211
	(0.00483)	(0.00500)	(0.00487)	(0.00729)	(0.00518)	(0.00631)	(0.00686)
(6) $\ln a_{it}^{\mathrm{MNF_e}}$							
1km			-0.0372	-0.0761**	-0.0190*	-0.0183	-0.0154
			(0.0268)	(0.0386)	(0.00986)	(0.0151)	(0.0163)
10km	-0.0345						
	(0.0464)						
20km		-0.0559					
		(0.0614)					
(7) $\ln a_{it}^{\mathrm{MNF_o}}$							
1km	0.00762	0.00926				0.0107	0.0103
	(0.00909)	(0.00726)				(0.00763)	(0.00854)
5km			-0.0337				
			(0.0369)				
10km				-0.152*			
				(0.0809)			
20km					0.0171		
					(0.0579)		
(8) $\ln a_{it}^{\mathrm{POP}}$							
5km						0.135	
						(0.450)	
10km							0.111
							(1.355)
20km	-0.566	-0.524	-0.954	-1.760	-0.529		
	(1.298)	(1.304)	(1.278)	(1.340)	(1.368)		
(9) τ_1	0.516***	0.522***	0.529***	0.553***	0.517***	0.529***	0.529***
	(0.0531)	(0.0574)	(0.0503)	(0.0535)	(0.0512)	(0.0384)	(0.0501)
(10) H. J p-value	0.256	0.252	0.258	0.258	0.256	0.258	0.252
(11) F	238.6	241.1	238.8	239.2	238.4	242.9	230.5
(12) #Obs	94,694	94,694	94,694	94,694	94,694	94,694	94,694

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) IPC class fixed effects are controlled. (*iii*) *** p<0.01, ** p<0.05, * p<0.1.

Table 19: Regression results (Dependent variable: $\ln y_{it}$)

	Novelty (IV3-5)						
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) $\ln k_{it}^{D}$	0.355***	0.358***	0.351***	0.344***	0.344***	0.345***	0.344***
	(0.0290)	(0.0303)	(0.0312)	(0.0310)	(0.0285)	(0.0306)	(0.0310)
(2) $\ln k_{it}$	0.112***	0.108***	0.107***	0.114***	0.113***	0.111***	0.114***
	(0.0227)	(0.0211)	(0.0204)	(0.0228)	(0.0219)	(0.0231)	(0.0228)
(3) $(\ln k_{it})^2$	-0.176***	-0.175***	-0.175***	-0.178***	-0.177***	-0.177***	-0.178***
	(0.00650)	(0.00698)	(0.00731)	(0.00594)	(0.00608)	(0.00621)	(0.00594)
(4) $\ln a_{it}^{\mathrm{INV}}$							
1km	0.256***						
	(0.0789)						
5km		0.223					
		(0.149)					
10km			0.397**				
			(0.155)				
20km				0.200**	0.213**	0.212**	0.200**
				(0.0939)	(0.0957)	(0.104)	(0.0939)
(5) $\ln a_{it}^{\mathrm{R\&D}}$							
1km	0.0381***	0.0366***	0.0395***				0.0364***
	(0.0116)	(0.0124)	(0.0137)				(0.0127)
5km				0.0364***			
				(0.0127)			
10km					0.0399**		
					(0.0189)		
20km						0.0492***	
						(0.0154)	
(6) $\ln a_{it}^{\mathrm{MNF_e}}$							
1km	-0.00656	-0.00148	0.00538	0.0132	0.0181	0.00757	
	(0.00776)	(0.00851)	(0.00928)	(0.00989)	(0.0126)	(0.0110)	
5km							0.0132
							(0.00989)
(7) $\ln a_{it}^{\mathrm{MNF_o}}$							
1km	-0.00532	-0.00412	-0.00151	-0.00512	-0.00445	-0.00496	-0.00512
	(0.00882)	(0.00790)	(0.00931)	(0.00721)	(0.00467)	(0.00493)	(0.00721)
(8) $\ln a_{it}^{\mathrm{POP}}$							
20km	0.112	0.0752	0.0741	0.0701	-0.340	0.361	0.0701
	(0.414)	(0.426)	(0.489)	(0.415)	(0.377)	(0.443)	(0.415)
(9) τ_1	0.158***	0.150***	0.137***	0.173***	0.159***	0.171***	0.173***
	(0.0376)	(0.0377)	(0.0338)	(0.0382)	(0.0366)	(0.0426)	(0.0382)
(10) H. J p-value	0.663	0.619	0.642	0.768	0.823	0.782	0.768
(11) F	588.2	593.8	568.5	557.6	564.3	563.9	557.6
(12) #Obs.	116,928	116,928	116,928	116,928	116,928	116,928	116,928

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) IPC class fixed effects are controlled. (*iii*) ***p<0.01, ** p<0.05, * p<0.1.

Table 19: Regression results continued (Dependent variable: $\ln y_{it}$)

	Novelty (IV3-5)						
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) $\ln k_{it}^{D}$	0.338***	0.344***	0.342***	0.345***	0.340***	0.343***	0.332***
	(0.0300)	(0.0299)	(0.0301)	(0.0313)	(0.0303)	(0.0289)	(0.0302)
(2) $\ln k_{it}$	0.114***	0.113***	0.112***	0.114***	0.111***	0.113***	0.109***
	(0.0225)	(0.0235)	(0.0233)	(0.0226)	(0.0235)	(0.0237)	(0.0229)
(3) $(\ln k_{it})^2$	-0.178***	-0.178***	-0.177***	-0.178***	-0.177***	-0.177***	-0.177***
	(0.00592)	(0.00566)	(0.00622)	(0.00596)	(0.00618)	(0.00549)	(0.00558)
(4) $\ln a_{it}^{\mathrm{INV}}$	0.203**	0.212**	0.202**	0.199**	0.195**	0.198**	0.180**
	(0.0917)	(0.0878)	(0.0912)	(0.0893)	(0.0950)	(0.100)	(0.0886)
(5) $\ln a_{it}^{\mathrm{R\&D}}$	0.0356**	0.0341**	0.0285***	0.0355***	0.0252**	0.0367***	0.0353***
	(0.0147)	(0.0160)	(0.00994)	(0.0107)	(0.0120)	(0.0122)	(0.00869)
(6) $\ln a_{it}^{\mathrm{MNF_e}}$							
1km			0.0557***	0.0182	0.0276***	0.00800	0.0110
			(0.0202)	(0.0382)	(0.0101)	(0.0126)	(0.00690)
10km	-0.0728**						
	(0.0294)						
20km		-0.169					
		(0.106)					
(7) $\ln a_{it}^{\mathrm{MNF_o}}$							
1km	-0.0147**	-0.0128				-0.00360	0.00286
	(0.00740)	(0.00967)				(0.00616)	(0.00574)
5km			0.0767***				
			(0.0259)				
10km				0.00257			
				(0.0890)			
20km					0.168***		
					(0.0404)		
(8) $\ln a_{it}^{\mathrm{POP}}$							
5km						0.248	
						(0.331)	
10km							1.870***
							(0.672)
20km	0.155	0.286	0.803*	0.144	1.293**		
	(0.500)	(0.457)	(0.474)	(0.885)	(0.535)		
(9) τ_1	0.184***	0.199***	0.150***	0.169***	0.153***	0.177***	0.214***
	(0.0398)	(0.0322)	(0.0414)	(0.0358)	(0.0424)	(0.0299)	(0.0355)
(10) H. J p-value	0.776	0.654	0.850	0.729	0.842	0.809	0.767
(11) F	550.6	563.4	555.8	557.7	552.2	562.4	537.2
(12) #Obs.	116,928	116,928	116,928	116,928	116,928	116,928	116,928

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) IPC class fixed effects are controlled. (*iii*) *** p<0.01, ** p<0.05, * p<0.1.

Table 20: Regression results (Dependent variable: $\ln k_{it}^{D}$)

	Novelty (IV3-5)						
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) $\ln \Delta n_{it}$	1.743***	1.764***	1.743***	1.722***	1.730***	1.727***	1.722***
	(0.0748)	(0.0706)	(0.0784)	(0.0847)	(0.0799)	(0.0815)	(0.0847)
(2) $\ln k_{it}$	-0.0355	-0.0397	-0.0359	-0.0313	-0.0310	-0.0342	-0.0313
	(0.0635)	(0.0655)	(0.0659)	(0.0638)	(0.0647)	(0.0654)	(0.0638)
(3) $(\ln k_{it})^2$	0.266***	0.271***	0.266***	0.261***	0.262***	0.262***	0.261***
	(0.0226)	(0.0241)	(0.0243)	(0.0233)	(0.0250)	(0.0241)	(0.0233)
(4) $\ln a_{it}^{\mathrm{INV}}$							
1km				0.0800	0.0820	0.0849	0.0800
				(0.103)	(0.112)	(0.106)	(0.103)
5km	0.0170						
	(0.132)						
10km		-0.208					
		(0.150)					
20km			0.00578				
			(0.208)				
(5) $\ln a_{it}^{\mathrm{R\&D}}$							
1km	0.0177**	0.0186*	0.0177**				0.0172*
	(0.00874)	(0.00989)	(0.00861)				(0.00896)
5km				0.0172*			
				(0.00896)			
10km					-0.00246		
					(0.0159)		
20km						0.0285	
						(0.0177)	
(6) $\ln a_{it}^{\mathrm{MNF_e}}$							
1km	-0.0451***	-0.0307*	-0.0441**	-0.0436**	-0.0442	-0.0464**	
	(0.0172)	(0.0159)	(0.0195)	(0.0219)	(0.0276)	(0.0218)	
5km							-0.0436**
							(0.0219)
(7) $\ln a_{it}^{\mathrm{MNF_o}}$							
1km	-0.0133	-0.0134	-0.0132	-0.0133	-0.00819	-0.0142	-0.0133
	(0.00886)	(0.00828)	(0.00945)	(0.00922)	(0.00928)	(0.0101)	(0.00922)
(8) $\ln a_{it}^{\mathrm{POP}}$							
20km	1.361	1.429	1.365	1.332	0.966	1.594*	1.332
	(1.039)	(0.896)	(1.030)	(1.050)	(1.078)	(0.895)	(1.050)
I2000	0.820***	0.850***	0.821***	0.814***	0.780***	0.821***	0.814***
	(0.0324)	(0.0283)	(0.0333)	(0.0285)	(0.0390)	(0.0280)	(0.0285)
(10) H. J p-value	0.358	0.348	0.363	0.363	0.352	0.363	0.363
(11) F	266	258.3	249.5	237.7	238	239.6	237.7
(12) #Obs.	94,694	94,694	94,694	94,694	94,694	94,694	94,694

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) IPC class fixed effects are controlled. (*iii*) ***p<0.01, ** p<0.05, * p<0.1.

Table 20: Regression results continued (Dependent variable: $\ln k_{it}^{D}$)

	Novelty (IV3-5)						
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) $\ln \Delta n_{it}$	1.719***	1.734***	1.720***	1.724***	1.717***	1.728***	1.711***
	(0.0840)	(0.0892)	(0.0827)	(0.0786)	(0.0817)	(0.0811)	(0.0761)
(2) $\ln k_{it}$	-0.0339	-0.03 49	-0.0293	-0.0278	-0.0305	-0.0333	-0.0337
	(0.0627)	(0.0624)	(0.0647)	(0.0628)	(0.0642)	(0.0618)	(0.0605)
(3) $(\ln k_{it})^2$	0.261***	0.264***	0.260***	0.261***	0.260***	0.262***	0.259***
	(0.0234)	(0.0224)	(0.0235)	(0.0237)	(0.0234)	(0.0232)	(0.0238)
(4) $\ln a_{it}^{\mathrm{INV}}$							
1km	0.0832	0.0902	0.0800	0.0935	0.0811	0.0756	0.0647
	(0.103)	(0.102)	(0.106)	(0.0974)	(0.102)	(0.114)	(0.108)
(5) $\ln a_{it}^{\mathrm{R\&D}}$							
1km	0.0165*	0.0156*	0.0187*	0.0348**	0.0156	0.0143	0.0125
	(0.00931)	(0.00926)	(0.0107)	(0.0154)	(0.0104)	(0.00888)	(0.00974)
(6) $\ln a_{it}^{\mathrm{MNF_e}}$							
1km			-0.0511	-0.114	-0.0338*	-0.0512*	-0.0425*
			(0.0434)	(0.0779)	(0.0192)	(0.0272)	(0.0221)
10km	-0.107*						
	(0.0572)						
20km		-0.148**					
		(0.0729)					
(7) $\ln a_{it}^{\mathrm{MNF_o}}$							
1km	-0.0147*	-0.00892				-0.0138	-0.0108
	(0.00890)	(0.00783)				(0.00843)	(0.0109)
5km			-0.0346				
			(0.0540)				
10km				-0.219			
				(0.156)			
20km					-0.00425		
					(0.0639)		
(8) $\ln a_{it}^{\mathrm{POP}}$							
5km						0.494	
						(0.529)	
10km							1.445
							(1.530)
20km	1.287	1.390	1.178	-0.112	1.461		
	(1.112)	(1.129)	(1.043)	(1.348)	(1.194)		
(9) τ_1	0.819***	0.834***	0.817***	0.856***	0.807***	0.795***	0.809***
	(0.0296)	(0.0348)	(0.0330)	(0.0489)	(0.0301)	(0.0177)	(0.0318)
(10) H. J p-value	0.361	0.359	0.361	0.359	0.362	0.356	0.348
(11) F	238.6	241.1	238.8	239.2	238.4	242.9	230.5
(12) #Obs.	94,694	94,694	94,694	94,694	94,694	94,694	94,694

(*i*) standard errors clustered by UAs are in parentheses. (*ii*) IPC class fixed effects are controlled. (*iii*) *** p<0.01, ** p<0.05, * p<0.1.