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Knowledge Turnover and Innovation Quality: Evidence from the Japanese Patent Database*

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Abstract

With Internet and Communication Technology (ICT) having removed geographical constraints for communication, this study examines how knowledge turnover induced by interregional migration increases the innovation quality in pre-ICT (1980--1995) and ICT periods (1996--2005). We find that the quality of innovation as measured by the number of patent citations was on average high in locations with active interregional migration in the pre-ICT period. Since the late 1990s, however, knowledge turnover at the regional level has played an insignificant role in enhancing quality of innovation within the context of the ICT age. Our results suggest that face-to-face knowledge exchange is selectively localized in the ICT age.

JEL classification: O31, O34, R12, R23
Keywords: Innovation, Patent, Interregional migration, Knowledge turnover

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1 Introduction

Innovation is an important driver of economic growth. Although innovative outcomes rest on individual efforts in research and development (R&D) in firms and scientific organizations, knowledge exchanged with others constitutes important input for the creation of new knowledge. In this regard, location is viewed as an important factor affecting innovation. Marshall (1890) famously described a localized industry: "The mysteries of the trade become no mysteries; but are as it were in the air." This idea was later adopted by Lucas (1988) who points out that cities are best suited to the exploitation of such externalities owing to the density of their populations. For that reason, the association between regional agglomeration and innovation deserves special attention.

The literature of urban economics emphasizes that active knowledge spillovers trigger the geographical concentration of innovative activities (e.g., Carlino and Kerr, 2015). Following the seminal work of Jaffe et al. (1993), many studies have revealed that knowledge transfer and exchange are constrained by geographical distance (e.g., Criscuolo and Verspagen, 2008; Inoue et al., 2013; Murata et al., 2014). It is widely believed that proximity to a greater number of people reduces the cost of face-to-face communication, thereby fostering innovation. For that reason, among others, large cities are viewed more suitable for R&D. Moreover, evidence has been presented that patent production is related to the patent holder's city population (Bettencourt et al., 2007) and its population density (Carlino et al., 2007).[1] As shown in Figure 1, patent production in Japan is concentrated in large cities such as Tokyo, Osaka, and Nagoya.

[Figure 1]

Our main concern in this study is that the concentration of patent production in large cities does not directly support the notion that large cities further enhance innovative activities in the Internet and Communication Technology (ICT) age, as suggested in the original knowledge externality story. ICT enables us to exchange ideas across distant regions. Therefore, the cost saving incentive of face-to-face communication by localizing in regional agglomeration is not necessarily a priority. Moreover, Huber (2012) showed that technological knowledge spillover effects within the Cambridge Information Technology Cluster were extremely weak. Shearmur (2012) provided

[1] According to Bacolod et al. (2009), working in large cities enhances thinking and social interaction, rather than physical abilities. Feldman and Audretsch (1999) find that diversity across complementary economic activities in large cities sharing a common science base is conducive to innovation. See also Audretsch and Feldman (1996) and Audretsch (1998). Carlino and Kerr (2015) provide a more comprehensive literature review on agglomeration and innovation.

a critical review on the roles of cities in innovation, arguing that innovation is not attributed to any particular location.

Our research framework concept has been inspired by Berliant and Fujita (2012) who studied a dynamic process of knowledge exchange in innovation. They analyzed a model based on a trade-off between the necessity of building common knowledge for facilitating communication and the benefit of maintaining the exclusive knowledge of each worker. If knowledge among workers is mutually exclusive with no commonality, it might prove difficult for them to establish any meaningful collaboration. The more common knowledge they have, the easier it is to communicate. However, the more common their knowledge becomes, the less they can learn from their mutually exclusive knowledge. Berliant and Fujita (2012) further demonstrated that the diversity and volume of a knowledge worker determine the production of new knowledge, thereby leading to higher economic growth in the end. This study raises an empirical question regarding how new communication styles in the ICT affect innovation process under a multi-regional innovation system.

This study examines the manner in which knowledge turnover induced by interregional migration increases innovation quality in the pre-ICT (1980–1995) and ICT periods (1996–2005). The focus is on physical movement for knowledge exchange across regions. In the pre-ICT period, physical movement was required for even shallow communication across distant regions. With ICT removing geographical constraints for communication, physical movement has become selectively required for deep communication. The magnitude of interregional knowledge turnovers on the quality of innovation is considered to have changed between the pre-ICT and ICT periods.

To measure the quality of innovation, this study uses the Institute of Intellectual Property Patent Database (IIP-DB), which includes Japanese patent information on applications, registrations, citations, applicants, inventors, and right holders, and we use the number of forward patent citations by examiners.[2] In the Japanese patent system, the Japan Patent Office (JPO) examiners refer to prior art patents when rejecting patent applications. As such, patents frequently cited by the examiners can be perceived as an innovation quality indicator.[3] Patent citation data on examiner rejection

[2]Nagaoka et al. (2014, p. 1086) point out that "not all patents represent innovation, nor are all innovations patented." Although this is beyond the perspective of this study, we should keep in mind that uncodified, tacit knowledge plays an important role in higher productivity in industrial clusters (Audretsch, 1998). See also Griliches (1990) and Nagaoka et al. (2014) for indicators of patent quality.

[3]See also Jaffe and Trajtenberg (1999), Alcácer and Gittelman (2006), Singh (2008), Alcácer et al. (2009), and Cotropia

covers a long period, enabling us to explore how knowledge turnover's effects on innovation have changed over time.

According to the empirical results of the present study, patents invented in areas with active interregional migration of knowledge workers had a higher number of patent citations in the pre-ICT period after controlling for firm and regional fixed effects. However, this causality is not observed in the ICT period. The findings suggest that high-quality innovation activity via face-to-face communication is localized either selectively or strategically, not localized in regional agglomeration by saving face-to-face communication costs. This is also discussed by Shearmur (2012): "It does not make sense to attribute innovation to any particular physical location."

This study contributes to the existing literature by advancing the work of Faggian and McCann (2009), who criticized the literature related to the geography of innovation, remarking that it tends to ignore the role played by human capital mobility. Their analysis demonstrated the simultaneous significance of university graduate human capital inflows and regional innovation performance measured by the number of patent applications. By shedding light on how mobility affects innovation quality, not the quantity, this study finds that promoting human capital mobility does not automatically lead to high-quality innovation in the ICT age.

The remainder of this paper is organized as follows. Section 2 describes the data. Section 3 explains the empirical framework. Section 4 presents a discussion of the estimation results and a robustness check for endogeneity. Finally, Section 5 concludes by discussing the policy implications and future research.

2 Data and Variables

2.1 Patent Database

Our empirical analysis uses the IIP-DB (ver. iipdb20140417) developed by Goto and Motohashi (2007), which contains Japanese patent information on applications, registrations, citation, applicants, inventors, and right holders from 1964. Nakamura (2016) provides detailed information on the recent version of the IIP-DB. To study recent situations of innovation activities in the pre-ICT and ICT periods, our sample focuses on the patents applied between 1980 and 2005 and finally registered; these are further divided into the pre-ICT period (1980–1995) and the ICT period (1996–2005).

et al. (2013) for issues on self-citations of inventors and differences between inventor and examiner citations.

As a proxy for innovation quality, we focus on the forward citation counts of patents. The IIP-DB has two types of patent citation by the JPO examiners (Goto and Motohashi, 2007). The first type of citation relates to examiner rejection. If a patent application is rejected, the patent examiners provide prior art references. The second type is offered in the Patent Gazette when the examiners additionally mention important prior art references, although this is not for the purpose of rejection. As discussed by Goto and Motohashi (2007), citation information in the Patent Gazette is available from 1985 onward and later as year of publication. As a proxy for innovation quality, our analysis primarily focuses on patent citations for examiner rejection.[4]

Furthermore, the IIP-DB is matched with the firm name database offered by the National Institute of Science and Technology Policy (2014), which covers firms with over 100 patent applications between 1970 and 2010 or listed firms with fewer than 100 patent applications. Thus, our sample is limited to relatively large-sized firms.

For highlighting the role of geography in innovation, sole focus is on patents invented in the same municipalities among inventors, enabling us to form a one-to-one correspondence between a patent and a location of invention. The IIP-DB includes basic information on inventors' team size (i.e., number of inverters), their network between establishments, and firms as an applicant. To control for interregional network effects on innovation, we exclude patents whose inventors are located in different municipalities.[5]

Using the International Patent Classification (IPC), we control for technological differences across patents. We use the following eight sections defined in the IPC: A. Human necessities; B. Performing operations, Transporting; C. Chemistry, Metallurgy; D. Textiles, Paper; E. Fixed constructions; F. Mechanical engineering, Lighting, Heating, Weapons, Blasting; G. Physics; H. Electricity.

2.2 Interregional Migration Flows as Knowledge Turnover

Our patent dataset is matched with an interregional migration dataset at the municipal level based on the inventors' addresses. We initially add municipal codes from character strings of inventors' addresses. Using these municipal codes, municipal-level panel data of interregional migration is

[4]In the IIP-DB, we found some patents wherein the application years of the cited patents are newer compared with those of the citing patents. These observations are excluded from the sample.

[5]For example, Ter Wal (2014) studied dynamic inventor network formation from the economic geography perspective and shows triadic closure among inventors dynamically increases in the innovation network with longer distance collaboration.

combined with patent information.[6] However, we do not directly use the municipal-level data in the regression; instead, a distance-based variable is constructed to measure regional knowledge turnover using interregional migration flows.

Figure 2 illustrates how distance-based variables of interregional migration flows were constructed in the case of Chiyoda-ku, Tokyo. The construction of regional knowledge turnover variables comprises two steps. First, this study counts the numbers of in- and-out migrants that have moved further than 30 km. The inter-municipal distance is calculated based on the centroid of municipalities (i.e., represented by dots in Figure 2). In Panel (a) of Figure 2, we count the total migrants of Chiyoda-ku as migrants from municipalities outside of the 30km circle; in other words, short-distance migration less than 30 km is excluded. This step is conducted for each municipality. Second, we consider knowledge turnover of neighboring municipalities. The use of administrative units is not appropriate because regional knowledge spillover also results from inter-municipal commuting. In Panel (b) of Figure 2, we calculate the local sum of migration flows within 30 km as the knowledge turnover in Chiyoda-ku.

The interregional migration data is derived from Japanese population censuses. Interregional migration flows by education level (i.e., university graduates and non-university graduates) are calculated using the micro-data of the population censuses. Japan's population census includes questionnaires on residential mobility every 10 years (i.e., population censuses conducted in 1980, 1990, 2000, and 2010). According to the population census, migration is defined as residential location change from where one lived five years before the census to where one lives during the census. We count the number of people who migrated 30 km or further, where the distance is measured between two centroids of municipalities. Each municipality has in- and out-migration. This paper uses gross migration, calculated as the sum of in- and out-migrants. Linear interpolation for migration variables is implemented between each 10-years interval.

[Figure 2]

2.3 Descriptive Statistics

Table 1 presents the descriptive statistics for the variables used in our regression analysis. The average number of citations is approximately 1, and the median is 0. As displayed in Figure 3, more

[6] The geographical division of municipalities in our analysis is fixed as of April 1, 2011, because approximately 1,500 out of roughly 3,200 municipalities in 1980 experienced municipal mergers in the 2000s. Appendix A provides how this study constructs the municipal-level panel data in the period 1980–2005.

than half the patents applied for in both 1980 and 2000 are never cited; however, a small number of patents are highly cited. In our analysis, the uppermost 0.01 percentile of the distribution of patent citations is excluded from the sample as outliers.

Figure 4 shows the scatterplots between the number of patent citations and gross migration flows of university and non-university graduates in 1980 and 2000, respectively. Patents with a large number of citations are observed in locations where majority of the population is migrants. The upper limit of patent citations becomes higher in locations with a higher turnover of residents. However, it is noted that many uncited patents also exist there; in other words, not all patents in locations with larger migration flows are of a high-quality, but extremely high-quality patents are developed only in those locations.[7]

[Table 1; Figures 3–4]

3 Empirical Framework

3.1 Poisson Regression for Patent Citation

To examine whether regional knowledge turnover increases innovation quality, we estimate the following Poisson regression model for patent citation:

$$\begin{aligned} \Pr(C_{ijkprt} = c_{ijkprt}) &= \frac{\exp\big(-\lambda_{ijkprt}(\boldsymbol{\theta})\big)\big(\lambda_{ijkprt}(\boldsymbol{\theta})\big)^{c_{ijkprt}}}{c_{ijkprt}!}, \quad c_{ijkprt} = 0, 1, 2, \ldots, \\ \lambda_{ijkprt}(\boldsymbol{\theta}) &\equiv \exp\big(\alpha \log(M_{rt}) + \boldsymbol{X}_{ijkprt}\boldsymbol{\beta} + \psi_j + \tau_t + \phi_k + \kappa_p\big), \end{aligned} \tag{1}$$

where c_{ijprkt} is the number of forward citations of patent i applied by firm j with IPC k in municipality r of prefecture p in year t; M_{rt} is the gross migration flows of university graduates or non-university graduates (i.e., sum of in- and out-migrants) in municipality r where inventors are registered in patent i in year t; $\boldsymbol{X}_{ijkprt}$ is the vector of control variables; ψ_j is the fixed effect of firm j that has the right of patent i (applicant); τ_t is the application year effect; ϕ_k is the fixed effect of IPC k; and κ_p is the prefecture fixed effect of location r.[8] Control variables $\boldsymbol{X}_{ijkprt}$ include the logarithm

[7] Appendix B provides supplementary information on our dataset.

[8] It may be criticized that the variable of gross migration does not consider the directions of interregional migration. For example, Duranton and Puga (2001) presented "a nursery city model" wherein diversified cities act as nurseries for firms to find their ideal production processes. They later exit to seek lower costs elsewhere. Such outflow is necessary to reduce congestion and uphold high productivity in innovation in diversified cities. An empirical approach

of geographical area and the number of inventors. Geographical area refers to the total area of municipalities located within the 30 km circle from the centroid of the municipality r. The number of inventors is calculated by aggregating inventors registered in patent i.

Our interest is in the parameter α, which captures the elasticity of innovation quality with respect to knowledge turnover after controlling for firm fixed effects, application year effects, patent classification, and regional fixed effects. The parameter α is expected to be positive under the conventional knowledge spillover hypothesis. This study analyzes how the magnitude of the parameter estimate $\hat{\alpha}$ has changed in the pre-ICT and ICT periods.

Controlling for firm fixed effects ψ_j is important to avoid an omitted variable bias for estimating the parameter α. Innovation quality will be higher for productive firms with bigger investment in R&D activity, as those firms attract more knowledge workers and are located in urban areas with active migration. To control for firm-level factors on innovation, we introduce firm dummy variables relying on the firm name database offered by the National Institute of Science and Technology Policy (2014).

One might further note a reverse causality issue regarding knowledge workers' migration. For example, locations at which firms' R&D centers develop high quality patents attract more knowledge workers. However, our approach using a lag between patent citation and migration can slightly mitigate a bias arising from reverse causality. The JPO patent examiners conduct patent citation after the invention process, and the knowledge workers' interregional migration is measured during the invention process.

Endogenous location choice of R&D centers also leads to a bias for estimating the parameter α. Innovative firms may establish R&D centers in easily accessible locations. These locations originally attract more people, generating a positive bias between knowledge turnover and innovation. In turn, if innovative firms establish R&D centers in rural areas, a negative bias is observed between knowledge turnover and innovation. This endogeneity is controlled though the instrumental variables (IV) method using long-lagged variables

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for dealing with this issue is to decompose the gross migration into in-migration, out-migration, and the cross term of them. However, this approach suffers from collinearity. See Appendix B for correlation matrix of regional variables. For example, the correlation coefficient between in- and out-migrations is 0.997 in 1980.

3.2 Instrumental Variables Method

The endogeneity in migration variable is controlled using the IV method. Owing to the computational limitation in estimating a nonlinear model with a large number of firm dummies, we estimate the following linear model:

$$c_{ijkprt} = \gamma \log(M_{rt}) + \boldsymbol{X}_{ijprkt}\boldsymbol{\delta} + \psi_{jt} + \phi_k + \kappa_p + u_{ijkprt}, \tag{2}$$

where u_{ijkprt} is an error term. Note that the parameter γ is interpreted as the semi-elasticity. Moreover, we introduce firm × application year dummies ψ_{jt} instead of ψ_j and τ_t in the Poisson regression (1).[9]

The candidates of IVs are those that are highly correlated with interregional migration and not correlated with unobserved shocks in innovation quality. This study uses the long-lagged variable suggested by Ciccone and Hall (1996). We construct population density of municipalities located within a 30 km circle of the centroid of municipality r as of 1930. Although large cities with high population density in the past still attract large migrations, unobserved shocks for the innovation are not related to the population density measured as of 1930. Moreover, as used by Combes et al. (2010) and de la Roca and Puga (2017), geologic features can be possible candidates for the IVs. In this study, we use the mean altitude of municipality r, which is calculated based on the 500 meters by 500 meters grid square data on "Altitude and Inclination" in Ministry of Land, Infrastructure, Transport and Tourism (2020). Some missing data on mean altitude are complemented by the data offered by Zaiki et al. (2005). The validity of our IVs is examined by a weak instrument test and an overidentification test.

4 Estimation Results

4.1 Knowledge Turnover Effects on Innovation Quality

Table 2 presents the baseline estimation results of Poisson regression (1). The knowledge turnover impacts of university graduates are shown in Columns (1) and (2) and those of non-university graduates in Columns (3) and (4). In the pre-ICT period (1980–1995), regional knowledge turnover of both types had significant positive impacts on innovation quality. However, in the ICT period (1996–2005), these impacts are not significant, and their magnitude is estimated to be quite small.

[9] We used the Stata command `ivreghdfe` developed by Correia (2019).

These results suggest that the knowledge turnover impacts induced by interregional migration have changed over the two periods. In contrast, innovation quality is increasing as regards team size (i.e., number of inventors) in both periods.

For investigating heterogeneous effects of regional knowledge turnover across types of patent technology, we estimated the Poisson regression (1) by introducing the cross terms of the interregional migration variable and IPC dummies. Table 3 presents the estimation results, and similar to Table 2, the knowledge turnover impacts of university graduates are shown in Columns (1) and (2) and those of non-university graduates in Columns (3) and (4).

As before, regional knowledge turnover of both types has significant positive impacts on innovation quality except for the technology type "E. Fixed construction" in the pre-ICT period (1980–1995). The top two largest impacts of knowledge turnover are observed for the technology type "D. Textiles" and "H. Electricity" in the pre-ICT period. On the other hand, the knowledge turnover effects are insignificant for all technology types in the ICT period (1996–2005).

In sum, our findings complement those of Faggian and McCann (2009), who found that inflows of university graduates promote regional innovation. The only difference is that while we highlight knowledge turnover effects on innovation quality, Faggian and McCann (2009) consider the number of patent application at the regional level. Moreover, this study shows that both university and non-university graduates contributed to innovation activity in the pre-ICT period. More importantly, we find that in the ICT period, regional knowledge turnover does not affect innovation quality. As deep knowledge exchange via face-to-face communication plays an integral role in enhancing innovation quality, it is suggested that ICT facilitates interregional knowledge spillover, and the location for face-to-face communication is not attributable to regional agglomeration in the ICT period, as stated by Shearmur (2012).

[Tables 2–3]

4.2 Robustness Check for Endogeneity

Table 4 presents the OLS and IV estimation results of regression model (2), which corresponds to the Poisson estimation results in Table 2. The basic statistical results are almost identical to those of the Poisson regression, despite the parameter estimates being interpreted differently.

The IV estimate in Column (3) of Table 4 is larger than the OLS estimate in Column (1) of Table 4, whereas its tendency is not observed for non-university graduates in Columns (5) and (7) of Table 4.

This implies that unobserved shocks in innovation are correlated with the migration of university graduates.

Tables 5 and 6 present the OLS and IV estimation results for the heterogeneous effects across technology types, which correspond to the Poisson estimation results in Table 3. Here, again, regional knowledge turnover effects are significant in the pre-ICT period and not significant in the ICT period. A notable difference from the comparison between OLS and IV estimation results is that the knowledge turnover effects on innovation quality in technology class "A. Human necessities" become insignificant through the IV estimation. Despite slight quantitative differences between the OLS and IV estimation, the robustness check for the endogenous migration variable supports our baseline findings.

[Tables 4–6]

5 Conclusion

Knowledge spillover in agglomeration is believed to foster the creation of new knowledge. However, because ICT removed geographical constraints on communication across distant regions, the cost saving incentive of face-to-face communication by localizing in regional agglomeration is no longer a priority. To investigate how regional knowledge turnover induced by interregional migration enhances innovation quality between the pre-ICT and ICT periods, we constructed our original dataset on interregional migration flows and paired it with Japan's patent database.

According to the empirical analysis of this study, after controlling for firm and regional fixed effects, patents invented in areas with active interregional migration of knowledge workers had a higher number of patent citations in the pre-ICT period (1980–1995). However, this causality disappears in the ICT period (1996–2005). Although deep knowledge exchange via face-to-face communication remains pertinent, it is implied that deep knowledge exchange is internalized in firms, regardless of agglomeration. Our findings suggest that the conventional knowledge spillover story in agglomeration is not evident in the ICT period. In fact, Huber (2012) notes that technological knowledge spillover effects within the Cambridge Information Technology Cluster are extremely weak.

The empirical findings of the present study have important implications for regional innovation policy. According to Faggian and McCann (2009), human capital mobility increases innovation quantity; however, our study suggests that a simple policy for promoting human capital mobility at the regional level does not automatically lead to high-quality innovation in the ICT age. Thus, future research should investigate how knowledge turnover at the firm or laboratory level affects innovation quality by distinguishing between internal and external face-to-face communication.

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Appendix A Constructing the Municipal Panel Data of 1980–2005

The 1980–2005 municipal panel dataset on inter-municipal migration flows, population density, share of university graduates, and industrial diversity index is constructed by integrating data from the 1980 to 2005 Japanese population censuses. Municipal data on population and share of university graduates are publicly available. However, migration flows of university graduates are unavailable online and, therefore, were calculated using the micro-data of the 1980, 1990, 2000, and 2010 population censuses.

The reference date for geographical information is April 1, 2011, at which date the total number of municipalities was 1,747 (not counting the Northern Territories). The 23 wards of Tokyo are counted individually. The cities designated by a government ordinance (*Seirei Shitei Toshi*) are counted as cities (*shi*), rather than subcategories *ku*. The corresponding cities are Sapporo-shi, Sendai-shi, Saitama-shi, Chiba-shi, Yokohama-shi, Kawasaki-shi, Sagamihara-shi, Niigata-shi, Shizuoka-shi, Hamamatsu-shi, Nagoya-shi, Kyoto-shi, Osaka-shi, Sakai-shi, Kobe-shi, Okayama-shi, Hiroshima-shi, Kitakyushu-shi, and Fukuoka-shi. In addition, we excluded Miyake-mura and Ogasawara-mura from the sample. As such, the number of municipalities is 1,745.

Since some municipalities merged between 1980 and 2011, municipal values are re-aggregated based on the information for these merged municipalities.[10]

Appendix B Supplementary Information on Dataset

Table B.1 shows the correlation matrix of regional variables. The in- and out-migration flows are highly correlated. To avoid collinearity problems in regression analysis, we use gross migration flows. Furthermore, migration flows of university and those of non-university graduates are highly correlated. To avoid collinearity problems, we do not include both variables in the same regression. Table B.2 presents the breakdown of our sample by application year. Firms and municipalities duplicate in different years. Table B.3 presents the breakdown at the IPC section level.

[Tables B.1–B.3]

[10]Changes in statistical area codes are available on the portal site for Japan's official statistics, e-Stat (URL: `http://www.e-stat.go.jp/SG1/hyoujun/initialize.do`).

Table 1: Descriptive Statistics of Variables

Variables	Obs.	Mean	S.D.	Min	p25	p50	p75	Max
Period: 1980–2005								
Number of Patent Citation	1,769,143	0.949	1.676	0.000	0.000	0.000	1.000	32.000
Log(Gross Migration Flows of University Graduates)	1,769,143	12.788	1.409	5.469	12.093	13.170	14.005	14.277
Log(Gross Migration Flows of Non-University Graduates)	1,769,143	13.068	1.178	6.759	12.425	13.448	14.057	14.398
Log(Area)	1,769,143	7.855	0.201	4.286	7.754	7.870	7.985	8.456
Number of Inventors	1,769,143	2.148	1.399	1.000	1.000	2.000	3.000	28.000
Log(Population Density in 1930)	1,769,143	6.884	0.957	1.642	6.009	7.285	7.819	7.988
Log(Altitude)	1,769,027	3.293	1.321	−2.181	2.463	3.316	4.131	7.017
Period: 1980–1995								
Number of Patent Citation	893,034	1.013	1.729	0.000	0.000	0.000	1.000	32.000
Log(Gross Migration Flows of University Graduates)	893,034	12.706	1.417	6.496	11.993	13.082	13.899	14.212
Log(Gross Migration Flows of Non-University Graduates)	893,034	13.167	1.173	8.343	12.521	13.513	14.179	14.398
Log(Area)	893,034	7.844	0.202	6.171	7.740	7.853	7.955	8.456
Number of Inventors	893,034	2.133	1.360	1.000	1.000	2.000	3.000	28.000
Log(Population Density in 1930)	893,034	6.894	0.947	1.642	6.034	7.122	7.819	7.988
Log(Altitude)	892,989	3.246	1.297	−2.181	2.586	3.395	4.077	7.017
Period: 1996–2005								
Number of Patent Citation	876,109	0.883	1.617	0.000	0.000	0.000	1.000	32.000
Log(Gross Migration Flows of University Graduates)	876,109	12.871	1.396	5.469	12.254	13.271	14.100	14.277
Log(Gross Migration Flows of Non-University Graduates)	876,109	12.968	1.174	6.759	12.319	13.331	13.986	14.278
Log(Area)	876,109	7.867	0.199	4.286	7.754	7.889	7.996	8.456
Number of Inventors	876,109	2.163	1.438	1.000	1.000	2.000	3.000	20.000
Log(Population Density in 1930)	876,109	6.873	0.968	1.642	5.953	7.343	7.845	7.988
Log(Altitude)	876,038	3.341	1.344	−1.117	2.463	3.240	4.140	7.017

Note: The uppermost 0.01 percentile of the distribution of patent citations is excluded from the sample as extreme outliers.

Table 2: Poisson Estimation Results for Turnover Effects on Quality of Innovation

	Dependent Variable: Number of Patent Citations			
	Period: 1980–1995	Period: 1996–2005	Period: 1980–1995	Period: 1996–2005
Explanatory Variables	(1)	(2)	(3)	(4)
Log(Gross Migration of Univ.)	0.0528***	0.0040		
	(0.0133)	(0.0153)		
Log(Gross Migration of Non-Univ.)			0.0615***	0.0082
			(0.0164)	(0.0184)
Log(Area)	0.0193	0.0809	0.0226	0.0760
	(0.0931)	(0.0592)	(0.0933)	(0.0595)
Number of Inventors	0.0643***	0.0709***	0.0643***	0.0709***
	(0.0050)	(0.0041)	(0.0050)	(0.0041)
International Patent Classification Dummy	Yes	Yes	Yes	Yes
Prefecture Dummies	Yes	Yes	Yes	Yes
Firm Dummies	Yes	Yes	Yes	Yes
Application Year Dummies	Yes	Yes	Yes	Yes
Number of Observations	893,034	876,109	893,034	876,109
Number of Firms	3,037	3,651	3,037	3,651
Pseudo $\bar{R}^2$	0.0556	0.0661	0.0556	0.0661

Note: Heteroskedasticity-consistent standard errors clustered by firms are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 3: Poisson Estimation Results for Heterogeneous Turnover Effects on Quality of Innovation by International Patent Classification

	Dependent Variable: Number of Patent Citations			
	Period: 1980–1995	Period: 1996–2005	Period: 1980–1995	Period: 1996–2005
Explanatory Variables	(1)	(2)	(3)	(4)
Log(Gross Migration of Univ.) × D(IPC A)	0.0351**	−0.0195		
	(0.0179)	(0.0242)		
Log(Gross Migration of Univ.) × D(IPC B)	0.0585***	−0.0070		
	(0.0157)	(0.0169)		
Log(Gross Migration of Univ.) × D(IPC C)	0.0455***	0.0188		
	(0.0151)	(0.0181)		
Log(Gross Migration of Univ.) × D(IPC D)	0.0698**	0.0014		
	(0.0281)	(0.0350)		
Log(Gross Migration of Univ.) × D(IPC E)	0.0232	−0.0360		
	(0.0249)	(0.0224)		
Log(Gross Migration of Univ.) × D(IPC F)	0.0401**	−0.0133		
	(0.0163)	(0.0190)		
Log(Gross Migration of Univ.) × D(IPC G)	0.0465***	0.0151		
	(0.0143)	(0.0172)		
Log(Gross Migration of Univ.) × D(IPC H)	0.0717***	0.0011		
	(0.0188)	(0.0171)		
Log(Gross Migration of Non-Univ.) × D(IPC A)			0.0415*	−0.0110
			(0.0231)	(0.0292)
Log(Gross Migration of Non-Univ.) × D(IPC B)			0.0700***	−0.0050
			(0.0190)	(0.0205)
Log(Gross Migration of Non-Univ.) × D(IPC C)			0.0580***	0.0231
			(0.0188)	(0.0216)
Log(Gross Migration of Non-Univ.) × D(IPC D)			0.0960***	0.0079
			(0.0353)	(0.0432)
Log(Gross Migration of Non-Univ.) × D(IPC E)			0.0355	−0.0341
			(0.0300)	(0.0272)
Log(Gross Migration of Non-Univ.) × D(IPC F)			0.0402**	−0.0138
			(0.0203)	(0.0226)
Log(Gross Migration of Non-Univ.) × D(IPC G)			0.0570***	0.0222
			(0.0179)	(0.0206)
Log(Gross Migration of Non-Univ.) × D(IPC H)			0.0748***	0.0022
			(0.0227)	(0.0212)
Log(Area)	0.0217	0.0788	0.0230	0.0739
	(0.0910)	(0.0575)	(0.0913)	(0.0582)
Number of Inventors	0.0644***	0.0709***	0.0644***	0.0709***
	(0.0050)	(0.0041)	(0.0050)	(0.0041)
International Patent Classification Dummy	Yes	Yes	Yes	Yes
Prefecture Dummy	Yes	Yes	Yes	Yes
Firm Dummies	Yes	Yes	Yes	Yes
Application Year Dummies	Yes	Yes	Yes	Yes
Number of Observations	893,034	876,109	893,034	876,109
Number of Firms	3,037	3,651	3,037	3,651
Pseudo $\bar{R}^2$	0.0557	0.0661	0.0556	0.0661

Note: Heteroskedasticity-consistent standard errors clustered by firms are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level. The regression uses the following eight sections defined in the IPC: A. Human necessities; B. Performing operations, Transporting; C. Chemistry, Metallurgy; D. Textiles, Paper; E. Fixed constructions; F. Mechanical engineering, Lighting, Heating, Weapons, Blasting; G. Physics; H. Electricity.

Table 4: Robustness Check for Turnover Effects on Quality of Innovation

	Dependent Variable: Number of Patent Citations							
	Estimation Method: OLS		Estimation Method: IV		Estimation Method: OLS		Estimation Method: IV	
	Period: 1980–1995	Period: 1996–2005	Period: 1980–1995	Period: 1996–2005	Period: 1980–1995	Period: 1996–2005	Period: 1980–1995	Period: 1996–2005
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Gross Migration of Univ.)	0.0587***	0.0060	0.0657***	0.0049				
	(0.0145)	(0.0155)	(0.0214)	(0.0249)				
Log(Gross Migration of Non-Univ.)					0.0723***	0.0103	0.0752***	0.0055
					(0.0173)	(0.0186)	(0.0241)	(0.0284)
Log(Area)	−0.0007	0.0764	−0.0121	0.0783	−0.0034	0.0718	−0.0074	0.0791
	(0.0876)	(0.0551)	(0.0874)	(0.0677)	(0.0872)	(0.0554)	(0.0867)	(0.0661)
Number of Inventors	0.0711***	0.0713***	0.0711***	0.0713***	0.0711***	0.0713***	0.0711***	0.0713***
	(0.0058)	(0.0049)	(0.0057)	(0.0048)	(0.0058)	(0.0049)	(0.0057)	(0.0048)
International Patent Classification Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Dummies × Application Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	893,034	876,109	890,231	871,194	893,034	876,109	890,231	871,194
Number of Firms	3,037	3,651	2,550	3,107	3,037	3,651	2,550	3,107
Adjusted $\bar{R}^2$	0.0723	0.0716			0.0723	0.0716		
First stage			Endogenous Var.: Log(Gross Migration of Non-Univ.)				Endogenous Var.: Log(Gross Migration of Non-Univ.)	
Log(Population Density in 1930)			0.8055***	0.7789***			0.6999***	0.6792***
			(0.0692)	(0.0545)			(0.0500)	(0.0405)
Log(Altitude)			−0.0317	−0.0268			−0.0357**	−0.0283*
			(0.0218)	(0.0201)			(0.0162)	(0.0155)
Weak Instruments (F-statistic)			86.1177	107.3504			132.3106	153.5769
Overidentification Test (p-value)			0.7246	0.5105			0.7591	0.5089

Note: Heteroskedasticity-consistent standard errors clustered by firms are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level. Weak instruments indicate a weak identification test based on Kleibergen-Paap Wald rk F statistic. Overidentification test is based on Hansen J statistic.

Table 5: Robustness Check for Turnover Effects of University Graduates on Quality of Innovation by Patent Class

	Dependent Variable: Number of Patent Citations			
	Estimation Method: OLS		Estimation Method: IV	
	Period: 1980–1995	Period: 1996–2005	Period: 1980–1995	Period: 1996–2005
Explanatory Variables	(1)	(2)	(3)	(4)
Log(Gross Migration of Univ.) × D(IPC A)	0.0444**	−0.0117	0.0405	−0.0158
	(0.0215)	(0.0250)	(0.0292)	(0.0307)
Log(Gross Migration of Univ.) × D(IPC B)	0.0547***	−0.0079	0.0607***	−0.0083
	(0.0148)	(0.0169)	(0.0215)	(0.0263)
Log(Gross Migration of Univ.) × D(IPC C)	0.0517***	0.0209	0.0495*	0.0069
	(0.0167)	(0.0188)	(0.0254)	(0.0277)
Log(Gross Migration of Univ.) × D(IPC D)	0.0707***	0.0124	0.0851***	0.0107
	(0.0222)	(0.0285)	(0.0263)	(0.0350)
Log(Gross Migration of Univ.) × D(IPC E)	0.0238	−0.0224	0.0425*	−0.0189
	(0.0201)	(0.0173)	(0.0247)	(0.0259)
Log(Gross Migration of Univ.) × D(IPC F)	0.0406***	−0.0088	0.0500**	−0.0079
	(0.0144)	(0.0169)	(0.0236)	(0.0262)
Log(Gross Migration of Univ.) × D(IPC G)	0.0568***	0.0176	0.0753***	0.0193
	(0.0159)	(0.0175)	(0.0234)	(0.0253)
Log(Gross Migration of Univ.) × D(IPC H)	0.0801***	0.0047	0.0758***	0.0076
	(0.0187)	(0.0180)	(0.0238)	(0.0280)
Log(Area)	0.0025	0.0759	−0.0039	0.0824
	(0.0853)	(0.0536)	(0.0873)	(0.0659)
Number of Inventors	0.0713***	0.0713***	0.0712***	0.0713***
	(0.0058)	(0.0049)	(0.0058)	(0.0048)
International Patent Classification Dummy	Yes	Yes	Yes	Yes
Prefecture Dummy	Yes	Yes	Yes	Yes
Firm Dummies × Application Year Dummies	Yes	Yes	Yes	Yes
Number of Observations	893,034	876,109	890,231	871,194
Number of Firms	3,037	3,651	2,550	3,107
Adjusted $\bar{R}^2$	0.0724	0.0716		
Weak Instruments (F-statistics)			23.2190	26.6272
Overidentification Test (p-value)			0.7373	0.3847

Note: Heteroskedasticity-consistent standard errors clustered by firms are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level. Instrumental variables include cross terms between logarithm of population density in 1930 and altitude and dummies of IPC. Weak instruments indicate a weak identification test based on Kleibergen-Paap Wald *rk F* statistic. Overidentification test is based on Hansen *J* statistic. The regression uses the following eight sections defined in the IPC: A. Human necessities; B. Performing operations, Transporting; C. Chemistry, Metallurgy; D. Textiles, Paper; E. Fixed constructions; F. Mechanical engineering, Lighting, Heating, Weapons, Blasting; G. Physics; H. Electricity.

Table 6: Robustness Check for Turnover Effects of Non-University Graduates on Quality of Innovation by Patent Class

	Dependent Variable: Number of Patent Citations			
	Estimation Method: OLS		Estimation Method: IV	
	Period: 1980–1995	Period: 1996–2005	Period: 1980–1995	Period: 1996–2005
Explanatory Variables	(1)	(2)	(3)	(4)
Log(Gross Migration of Non-Univ.) × D(IPC A)	0.0530**	−0.0088	0.0442	−0.0196
	(0.0262)	(0.0289)	(0.0341)	(0.0358)
Log(Gross Migration of Non-Univ.) × D(IPC B)	0.0711***	−0.0074	0.0702***	−0.0105
	(0.0179)	(0.0205)	(0.0244)	(0.0303)
Log(Gross Migration of Non-Univ.) × D(IPC C)	0.0674***	0.0273	0.0564*	0.0072
	(0.0204)	(0.0223)	(0.0293)	(0.0321)
Log(Gross Migration of Non-Univ.) × D(IPC D)	0.1048***	0.0197	0.0994***	0.0120
	(0.0265)	(0.0354)	(0.0315)	(0.0415)
Log(Gross Migration of Non-Univ.) × D(IPC E)	0.0391	−0.0237	0.0483*	−0.0229
	(0.0249)	(0.0207)	(0.0284)	(0.0299)
Log(Gross Migration of Non-Univ.) × D(IPC F)	0.0539***	−0.0088	0.0571**	−0.0092
	(0.0177)	(0.0200)	(0.0270)	(0.0303)
Log(Gross Migration of Non-Univ.) × D(IPC G)	0.0708***	0.0254	0.0867***	0.0221
	(0.0191)	(0.0209)	(0.0264)	(0.0290)
Log(Gross Migration of Non-Univ.) × D(IPC H)	0.0897***	0.0088	0.0871***	0.0082
	(0.0229)	(0.0222)	(0.0271)	(0.0322)
Log(Area)	−0.0020	0.0714	−0.0005	0.0834
	(0.0854)	(0.0540)	(0.0865)	(0.0648)
Number of Inventors	0.0712***	0.0713***	0.0712***	0.0713***
	(0.0058)	(0.0049)	(0.0058)	(0.0048)
International Patent Classification Dummy	Yes	Yes	Yes	Yes
Prefecture Dummy	Yes	Yes	Yes	Yes
Firm Dummies × Application Year Dummies	Yes	Yes	Yes	Yes
Number of Observations	893,034	876,109	890,231	871,194
Number of Firms	3,037	3,651	2,550	3,107
Adjusted $\bar{R}^2$	0.0724	0.0716		
Weak Instruments (F-statistics)			28.8135	30.3458
Overidentification Test (p-value)			0.7458	0.3819

Note: Heteroskedasticity-consistent standard errors clustered by firms are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level. Instrumental variables include cross terms between logarithm of population density in 1930 and altitude and dummies of IPC. Weak instruments indicate a weak identification test based on Kleibergen-Paap Wald *rk F* statistic. Overidentification test is based on Hansen *J* statistic. The regression uses the following eight sections defined in the IPC: A. Human necessities; B. Performing operations, Transporting; C. Chemistry, Metallurgy; D. Textiles, Paper; E. Fixed constructions; F. Mechanical engineering, Lighting, Heating, Weapons, Blasting; G. Physics; H. Electricity.

Table B.1: Correlation Matrix of Regional Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Application Year: 1980								
(1) Log(Gross Migration Flows of University Graduates)	1.000							
(2) Log(In-Migration Flows of University Graduates)	0.999	1.000						
(3) Log(Out-Migration Flows of University Graduates)	0.999	0.997	1.000					
(4) Log(Gross Migration Flows of Non-University Graduates)	0.996	0.995	0.996	1.000				
(5) Log(In-Migration Flows of Non-University Graduates)	0.996	0.996	0.995	0.999	1.000			
(6) Log(Out-Migration Flows of Non-University Graduates)	0.993	0.991	0.995	0.998	0.994	1.000		
(7) Log(Population Density in 1930)	0.917	0.913	0.919	0.929	0.919	0.936	1.000	
(8) Log(Altitude)	−0.449	−0.452	−0.446	−0.483	−0.476	−0.488	−0.493	1.000
Application Year: 2000								
(1) Log(Gross Migration Flows of University Graduates)	1.000							
(2) Log(In-Migration Flows of University Graduates)	0.999	1.000						
(3) Log(Out-Migration Flows of University Graduates)	0.999	0.995	1.000					
(4) Log(Gross Migration Flows of Non-University Graduates)	0.998	0.997	0.996	1.000				
(5) Log(In-Migration Flows of Non-University Graduates)	0.997	0.998	0.994	0.999	1.000			
(6) Log(Out-Migration Flows of Non-University Graduates)	0.996	0.994	0.996	0.999	0.995	1.000		
(7) Log(Population Density in 1930)	0.924	0.926	0.919	0.932	0.928	0.934	1.000	
(8) Log(Altitude)	−0.580	−0.579	−0.580	−0.594	−0.584	−0.601	−0.609	1.000

Note: Gross migration flows are defied as the sum of in-migration and out-migration.

Table B.2: Numbers of Patents Registered, Firms, and Municipalities in Sample

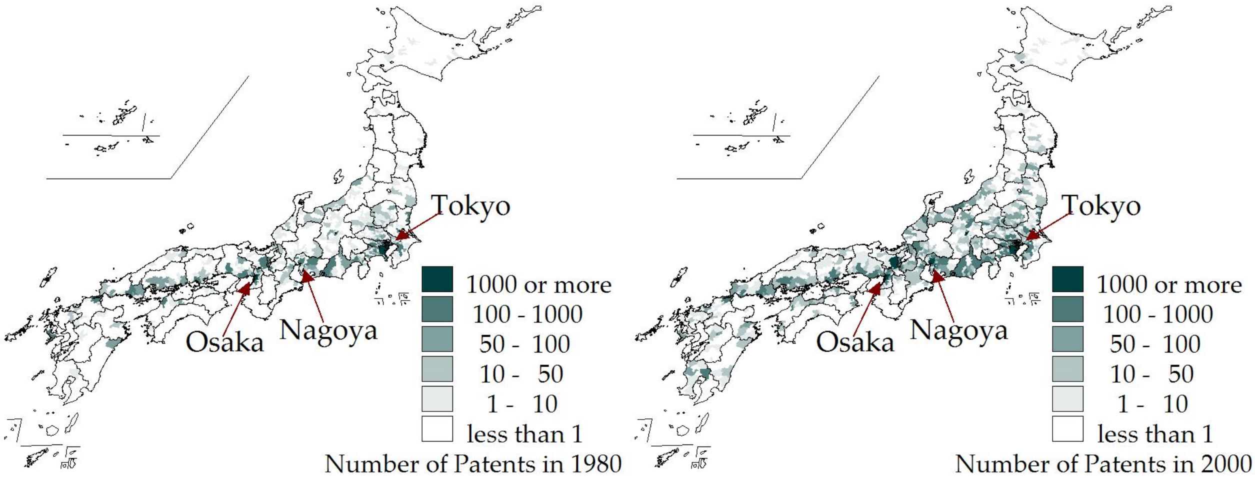
Application Year	Number of Patents	Number of Firms	Number of Municipalities
1980	30,302	345	445
1981	35,668	351	459
1982	37,510	351	470
1983	39,709	345	472
1984	43,306	345	479
1985	45,326	350	473
1986	48,557	349	459
1987	51,291	353	473
1988	53,174	356	468
1989	56,921	355	468
1990	60,880	803	532
1991	78,062	2,062	680
1992	77,900	2,148	705
1993	79,829	2,247	715
1994	75,509	2,359	713
1995	79,090	2,331	709
1996	78,195	2,361	699
1997	80,536	2,368	700
1998	82,014	2,424	719
1999	80,750	2,451	720
2000	82,415	2,533	716
2001	87,631	2,567	716
2002	95,219	2,582	728
2003	95,791	2,592	716
2004	91,393	2,544	782
2005	102,165	2,583	734
Total	1,769,143	3,803	1,087

Note: This presents the breakdown of sample in Table 1. Firms and municipalities duplicate in different years.

Table B.3: Section in International Patent Classification

IPC	Explanation	Obs.
A	Human necessities	121,968
B	Performing operations; Transporting	325,420
C	Chemistry; Metallurgy	172,232
D	Textiles; Paper	25,153
E	Fixed constructions	62,318
F	Mechanical engineering; Lighting; Heating; Weapons; Blasting	166,737
G	Physics	442,498
H	Electricity	452,817
Total		1,769,143

Note: This shows the breakdown at the section level of International Patent Classification.

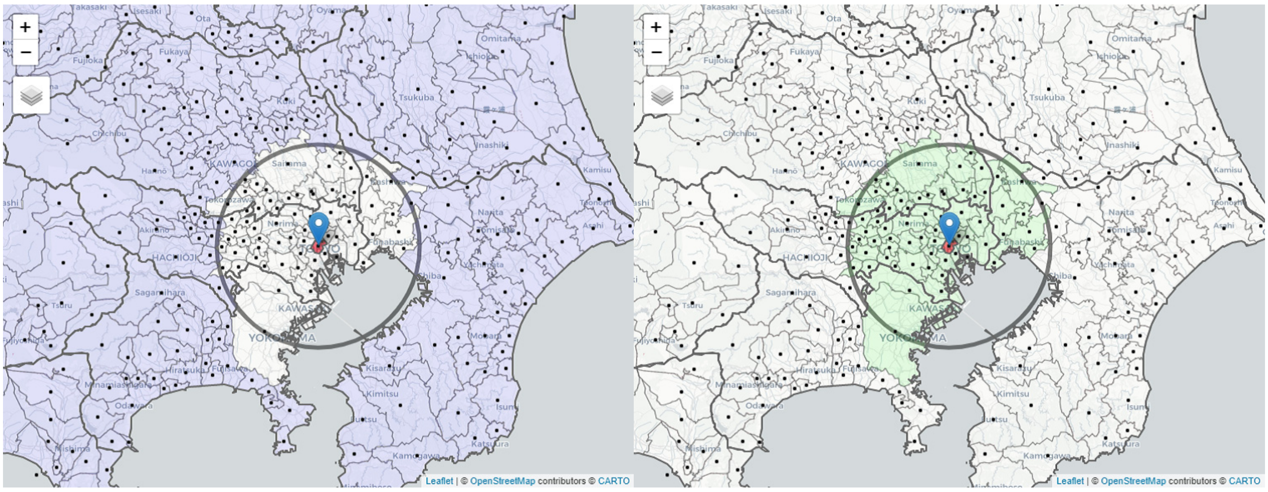


(a) 1980 (Application Year)

(b) 2000 (Application Year)

Figure 1: Geographical Distribution of Patents

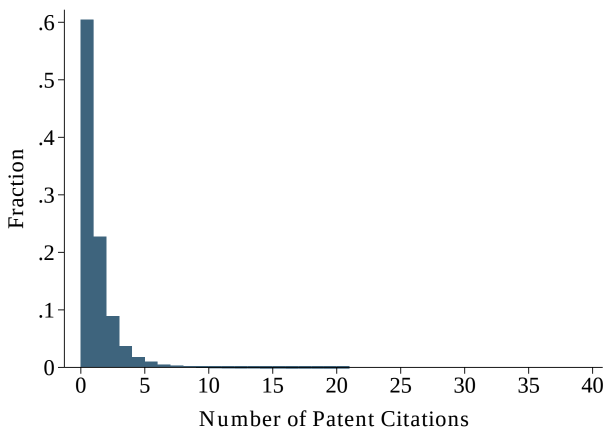
Note: Created by the authors from the IIP-DB. Patents used in our sample are limited to those in which all inventors are in the same municipalities. Patents that were applied in 1980 and in 2000 and finally registered are 30,302 and 82,415 in our sample, respectively. Some patents in the IIP-DB with garbled characters in inventors' addresses are excluded from the data. We assigned location to each patent based on the inventors' address.



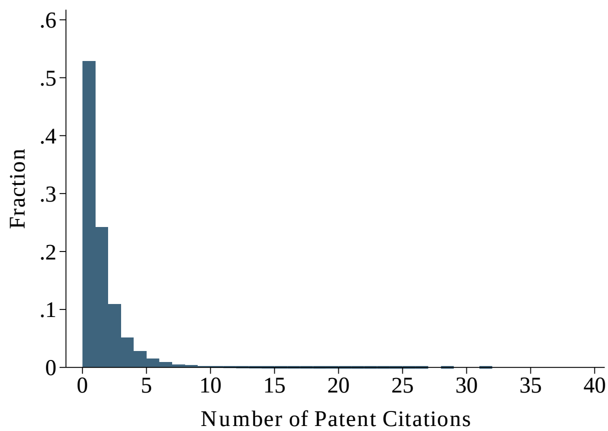
(a) Step 1: Geographical Range of Interregional Migration (b) Step 2: Local Sum of Interregional Migration Flows

Figure 2: Measuring Regional Knowledge Turnover using Interregional Migration Flows

Note: Created by the authors. Figure 2 shows the case of Chiyoda-ku, Tokyo. The knowledge turnover is measured as interregional migration flows. In this study, we consider gross migration flows as sum of in- and out-migration flows. The construction of gross migration flows includes two steps. First, this study counts the numbers of in- and out-migrants that move farther than 30 km. The interregional distance is calculated based on the centroid of municipalities. In Panel (a), we count total migrants of Chiyoda-ku as migrants from municipalities outside the 30 km circle, meaning that short-distance migration less than 30 km is excluded. The markers in this figure indicate the centroid of each municipality polygon. This step is conducted for each municipality. Second, we consider knowledge turnover of neighboring municipalities because administrative units are not appropriate. We assume that knowledge creation of firms is affected by knowledge turnover in surrounding areas via inter-municipal commuting. In Panel (b), we calculate the local sum of gross migration flows within 30 km as the knowledge turnover in Chiyoda-ku.



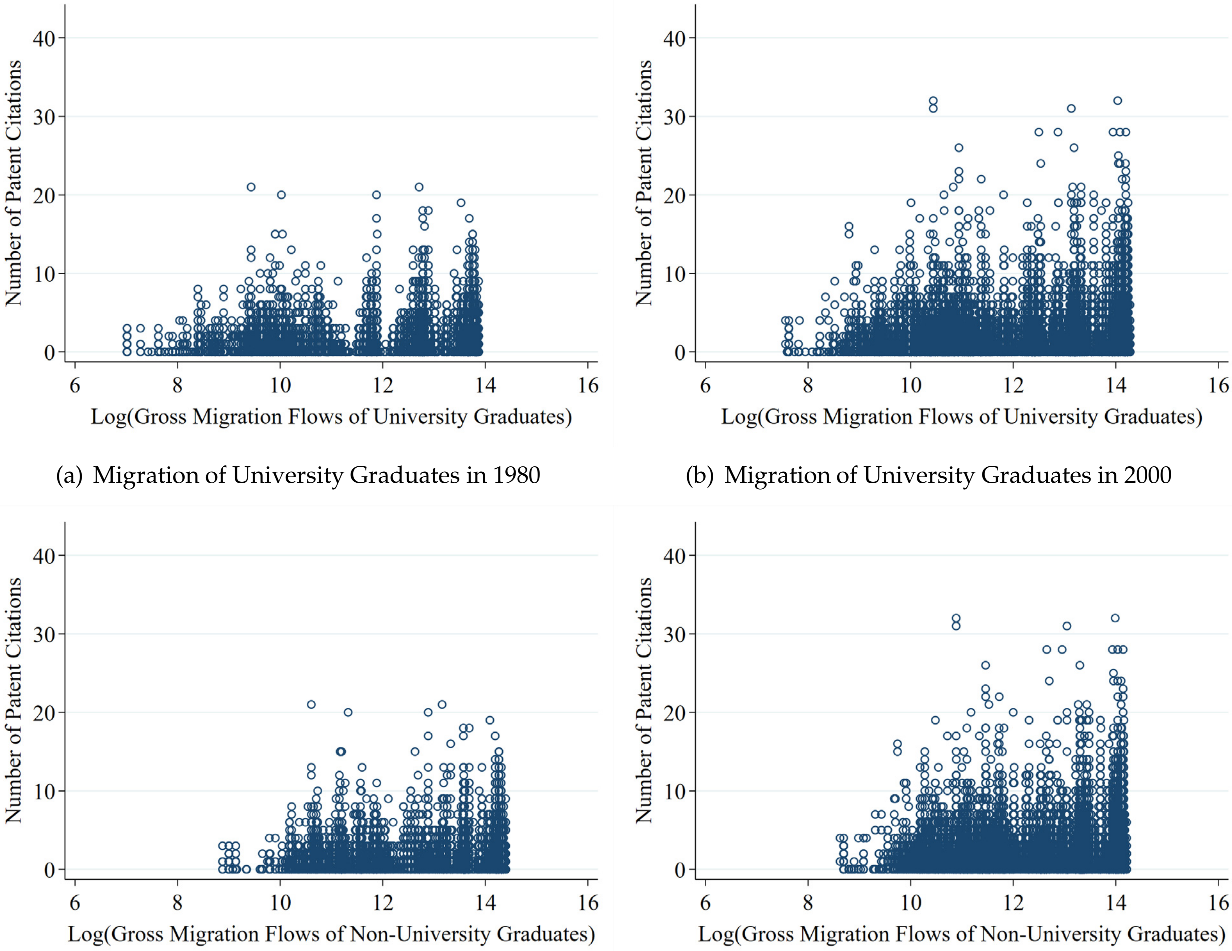
(a) 1980 (Application Year)



(b) 2000 (Application Year)

Figure 3: Number of Patent Citations

Note: Created by the authors from the IIP-DB. Sample in Table 1.



(a) Migration of University Graduates in 1980

(b) Migration of University Graduates in 2000

(c) Migration of Non-University Graduates in 1980

(d) Migration of Non-University Graduates in 2000

Figure 4: Number of Patent Citations and Gross Migration Flows

Note: Created by the authors from the IIP-DB. Sample in Table 1. Number of patent citations represents number of examiner citations of patents applied in 1980 or 2000. Gross migration flows represent sum of in-migrants and out-migrants in 1980 and 2000 in location of inventors.