Fresh brain power and quality of innovation in cities: Evidence from Japanese patent database

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Making agglomeration 'metabolised' for innovation

Nobuaki Hamaguchi, Keisuke Kondo 07 February 2016

There is no consensus on the effects of agglomeration on innovation. This column presents new evidence on how knowledge turnover impacts the quality of innovation. Agglomerated regions with active knowledge turnover, as measured by interregional migration of university graduates, tend to have a higher number of patent citations, the metric used for quality of innovation. Cluster policy aimed at active innovation may not be effective if interregional migration of knowledge workers is inactive.

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Innovation is an important driver of economic growth. In particular, to acquire global competitiveness, the quality of innovation matters more than the quantity. Although innovative outcomes rest on individual efforts in research and development in firms and scientific organisations, economic research has also paid special attention to the agglomeration economy, which is expected to foster innovation through active knowledge spillovers (e.g. Carlino and Kerr 2015).

It is more likely that high-quality innovations are born in cities. The large number of specialised people in cities is not the only reason for such advantage – the greater diversity of knowledge also matters. It is often pointed out that proximity to a greater number of people facilitates face-to-face

Source: `http://www.voxeu.org/article/making-agglomeration-metabolised-innovation`

Research Questions and Motivation

Does the metabolism of **obese cities** foster innovative activities?

Source: https://en.wikipedia.org/wiki/List_of_metropolitan_areas_by_population

Agglomeration and Innovation

- Recent economic research has paid special attention to the agglomeration economy, which is expected to foster innovation through active knowledge spillovers (e.g., Carlino and Kerr, 2015).
- It is often assumed that proximity to a greater number of people facilitates face-to-face communication and fosters innovation.
- However, repeated interactions would increase common knowledge and reduce diversity of exclusive knowledge, which limit opportunities for learning fresh knowledge from each other.
- *Does agglomeration really make innovation sustainable in the long run?*
- Huber (2012) indicates that technological knowledge spillover effects within the Cambridge Information Technology Cluster are very weak.
- *There must be an important factor for innovation that we are missing.*

Research Questions and Motivation

What Makes Innovation Sustainable?

- Berliant and Fujita (2012) point out that just having a sufficiently large size of knowledge workers is not enough to promote innovation.
- There is a trade-off between the necessity of building common knowledge to facilitate communication and the benefit of maintaining the exclusive knowledge of each worker.
- Berliant and Fujita (2012) emphasize the importance of workers' mobility among institutions to keep knowledge diversity for innovation.
- Faggian and McCann (2009) find the significant positive impact of university graduate inflows on regional innovation performance.
- *Our attempt is to measure how well the knowledge diversity is maintained.*

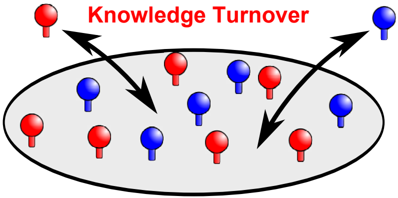


Figure: Concept of Knowledge Turnover

New Perspective of Diversity

- Our measure is different from the standard diversity index (e.g., the inverse of the Herfindahl-Hirschman index).
- The commonly used diversity index might be unchanged if migrants have the same characteristics (e.g. gender, age, education level, and occupation).
- We would like to capture changes in knowledge diversity arisen from interregional turnover of people under the condition in which individuals are heterogeneous.

Research Questions and Motivation

Research Questions

1. *Does the interregional knowledge turnover increases the quality of innovation?*
2. *In which regions are the impacts of knowledge turnover on the quality of innovation bigger?*

Empirical Framework

➻ Research Question ❶

- Regress the number of patent citations on regional factors:

$$\text{CITED}_{ijrkt} = \overbrace{\alpha \log(\text{GM}_{rt})}^{\textit{Migration}} + \overbrace{\beta \log(\text{PD}_{rt})}^{\textit{Density}} + \overbrace{\gamma \text{ED}_{rt}}^{\textit{Education}} + \overbrace{\delta \text{DI}_{rt}}^{\textit{Diversity}}$$
$$+ \underbrace{\boldsymbol{X}_{it}\boldsymbol{\eta}}_{\textit{Controls}} + \underbrace{\pi_j}_{\textit{Technology}} + \underbrace{\tau_t}_{\textit{Year}} + \underbrace{\psi_k}_{\textit{Firm}} + \underbrace{u_{it}}_{\textit{Error}}$$

- CITED_{ijrkt} is the number of forward citations of patent i applied in year.
- GM_{rt} is the average gross migration flows of university graduates (i.e., sum of university graduate in-migrants and out-migrants) in municipalities r where inventors are registered in patent i in year t.
- The vector of $\boldsymbol{X}_{it}$ includes area, team size, dummy for team network, and the cross term of team size and dummy for team network.

Empirical Framework

➼ Research Question ❶

- Introduce the directions of interregional migration into the regression:

$$\mathrm{CITED}_{ijrkt} = \overbrace{\alpha_1 \log(\mathrm{IM}_{rt})}^{In\text{-}migration} + \overbrace{\alpha_2 \log(\mathrm{OM}_{rt})}^{Out\text{-}migration} + \overbrace{\alpha_3 \log(\mathrm{IM}_{rt}) \cdot \log(\mathrm{OM}_{rt})}^{Cross\ \ Term}$$
$$+ \beta \log(\mathrm{PD}_{rt}) + \gamma \mathrm{ED}_{rt} + \delta \mathrm{DI}_{rt} + \boldsymbol{X}_{it}\boldsymbol{\eta} + \pi_j + \tau_t + \psi_k + u_{it}$$

- The cross term of in-migration and out-migration is a key variable to identify whether *interregional knowledge turnover* affects the quality of innovation.
- We would like to examine whether interregional turnover (i.e., not only in-migration but also out-migration) matters for the quality of innovation.
  ↔ Faggian and McCann (2009)

Empirical Framework

➻ Research Question ❷

- Examine the spatial heterogeneous impacts of interregional turnover:

$$
\begin{aligned}
\mathrm{CITED}_{ijrkt} = {} & \alpha \log(\mathrm{GM}_{rt}) + \beta \log(\mathrm{PD}_{rt}) + \gamma \mathrm{ED}_{rt} + \delta \mathrm{DI}_{rt} \\
& + \textstyle\sum_{k=2}^{4} \theta_k \log(\mathrm{GM}_{rt}) \cdot I(\mathrm{PDQTL}_k) \quad \Leftarrow \text{Density} \\
& + \textstyle\sum_{k=2}^{4} \lambda_k \log(\mathrm{GM}_{rt}) \cdot I(\mathrm{EDQTL}_k) \quad \Leftarrow \text{Education} \\
& + \textstyle\sum_{k=2}^{4} \phi_k \log(\mathrm{GM}_{rt}) \cdot I(\mathrm{DIQTL}_k) \quad \Leftarrow \text{Diversity} \\
& + \boldsymbol{X}_{it}\boldsymbol{\eta} + \pi_j + \tau_t + \psi_k + u_{it}
\end{aligned}
$$

- Marginal effects of the interregional turnover are divided into four parts:

$$
\frac{\partial \mathrm{CITED}_{ijrkt}}{\partial \log(\mathrm{GM}_{rt})} = \alpha + \underbrace{\sum_{k=2}^{4} \theta_k I(\mathrm{PDQTL}_k)}_{\substack{k\text{-}th\ Quantile\ Dummy \\ (Density)}} + \underbrace{\sum_{k=2}^{4} \lambda_k I(\mathrm{EDQTL}_k)}_{\substack{k\text{-}th\ Quantile\ Dummy \\ (Education)}} + \underbrace{\sum_{k=2}^{4} \phi_k I(\mathrm{DIQTL}_k)}_{\substack{k\text{-}th\ Quantile\ Dummy \\ (Diversity)}}
$$

Interregional Migration and Knowledge Turnover

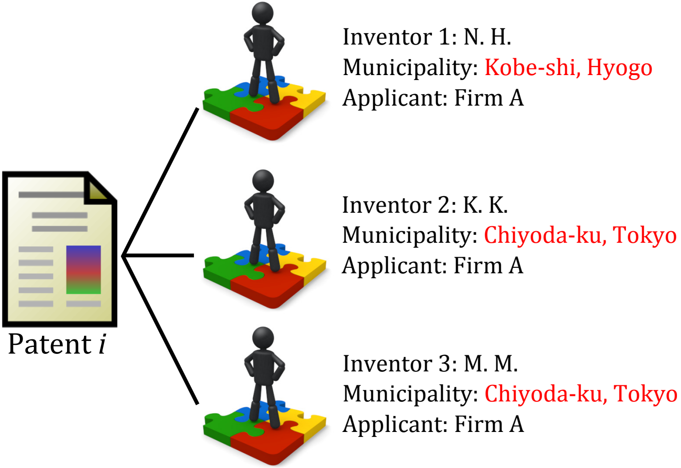
- Data on migration of university graduates across municipalities are available from 1980, 1990, 2000, 2010 population census.
- We count the number of university graduates who migrated more than 30 km across municipalities.
- The municipal panel dataset is constructed between 1980 and 2005.
- Linear interpolation is implemented between each 10 years.

Data

IIP Patent Database (IIPDB20110330)

- Japanese Patent Database constructed by Goto and Motohashi (2007).
- We focus on patents applied between 1980 and 2005 (and registered).
- We use patent citations by the examiners.
- We match regional data with inventors' address registered in patents.
- We control for firm fixed effects using the firm name dictionary built by the NISTEP (2014).

Figure: Correspondence between Patent and Regional Variables



$$X_{r(i)} = \text{mean}\left(X_{\text{Kobe}}, X_{\text{Chiyoda}}, X_{\text{Chiyoda}}\right)$$

Data

Table: Descriptive Statistics

Variables	Mean	S.D.	Min	Max
Number of Patent Citation	0.985	1.808	0.000	68.000
Log(Average Gross Migration Flows of Univ. Grads.)	9.498	1.485	2.633	12.426
Log(Average Gross Migration Flows of Others)	9.931	1.344	3.875	12.450
Log(Average Migration Inflows of Univ. Grads.)	8.780	1.470	0.322	11.761
Log(Average Migration Outflows of Univ. Grads.)	8.804	1.526	2.528	11.703
Log(Av. Migration Inflows) $\times$ Log(Av. Migration Outflows)	79.482	26.014	0.814	137.639
Log(Average Migration Inflows of Others)	9.226	1.348	2.303	11.882
Log(Average Migration Outflows of Others)	9.231	1.363	3.642	11.692
Log(Av. Migration Inflows) $\times$ Log(Av. Migration Outflows)	86.964	24.865	8.386	137.992
Log(Average Population Density)	8.224	1.213	2.081	10.010
Average Share of University Graduates	15.405	6.623	1.575	35.233
Average Industrial Diversity Index	4.092	1.592	0.838	18.446
Log(Area)	4.091	1.182	1.230	6.507
Team Size	2.271	1.467	1.000	38.000
D(1: Invention Network)	0.108	0.311	0.000	1.000
Team Size $\times$ D(1: Invention Network)	0.378	1.202	0.000	38.000

Note: The number of observation is 1,903,672. The uppermost 0.001 percentile of the distribution of patent citations is excluded from the sample as extreme outliers.

Data

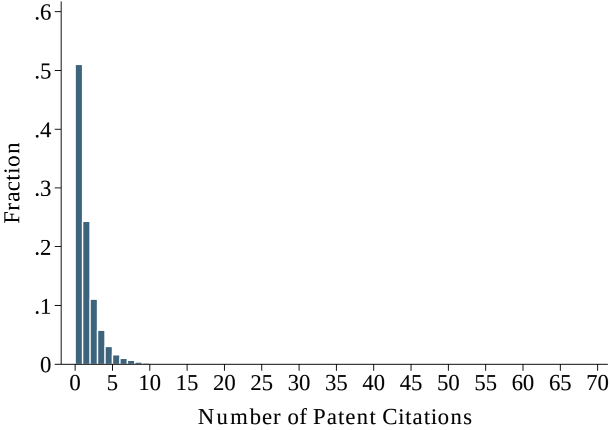


Figure: Number of Patent Citations in 2000 (application year)

Note: Created by the authors from the IIP Patent Database.

Data

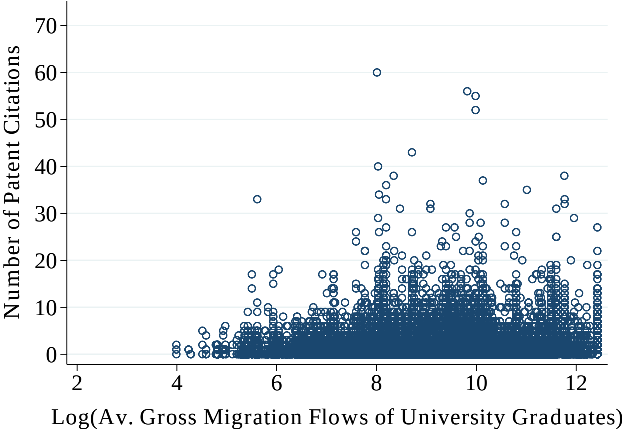


Figure: Number of Patent Citations and Gross Migration Flows in 2000 (application year)

Note: Created by the authors from the IIP Patent Database.

Estimation Results

Table: Knowledge Turnover Effects by Gross Migration Flows in 1980–2005

	Dependent Variable: Number of Patent Citations				
Explanatory Variables	(1)	(2)	(3)	(4)	(5)
Log(Av. Mig. Flows of Univ. Grads.)	0.0388***				0.0486***
	(0.0089)				(0.0109)
Log(Av. Population Density)		0.0274***			−0.0325***
		(0.0084)			(0.0106)
Av. Share of University Graduates			0.0090***		0.0052***
			(0.0018)		(0.0017)
Av. Industrial Diversity Index				0.0023	0.0007
				(0.0056)	(0.0056)
Log(Area)	−0.0392***	−0.0001	0.0062	−0.0060	−0.0475***
	(0.0091)	(0.0055)	(0.0054)	(0.0053)	(0.0134)
Other Controls	Yes	Yes	Yes	Yes	Yes
Application Year Dummy	Yes	Yes	Yes	Yes	Yes
Technology Class Dummy	Yes	Yes	Yes	Yes	Yes
Firm Dummy	Yes	Yes	Yes	Yes	Yes
Number of Observations	1903672	1903672	1903672	1903672	1903672
Adjusted $\bar{R}^2$	0.0697	0.0695	0.0697	0.0694	0.0694
Number of Firms	3900	3900	3900	3900	3900

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

Estimation Results

Table: Turnover Effects by Migration Flows and Directions in 1980–2005

	Dependent Variable: Number of Patent Citations			
Explanatory Variables	(1)	(2)	(3)	(4)
Log(Av. Mig. Inflow of Univ. Grads.)	0.0514***		0.0497**	−0.0367
	(0.0127)		(0.0208)	(0.0288)
Log(Av. Mig. Outflow of Univ. Grads.)		0.0320***	0.0022	−0.0635***
		(0.0082)	(0.0151)	(0.0207)
Log(Av. Inflow) $\times$ Log(Av. Outflow)				0.0097***
				(0.0024)
Log(Av. Population Density)	−0.0325***	−0.0218**	−0.0331***	−0.0442***
	(0.0111)	(0.0105)	(0.0108)	(0.0101)
Av. Share of University Graduates	0.0050***	0.0064***	0.0049***	0.0038**
	(0.0016)	(0.0018)	(0.0017)	(0.0017)
Av. Industrial Diversity Index	0.0005	0.0014	0.0005	0.0036
	(0.0055)	(0.0057)	(0.0056)	(0.0060)
Log(Av. Area)	−0.0516***	−0.0293***	−0.0520***	−0.0775***
	(0.0164)	(0.0098)	(0.0151)	(0.0166)
Control Variables	Yes	Yes	Yes	Yes
Application Year Dummy	Yes	Yes	Yes	Yes
Technology Class Dummy	Yes	Yes	Yes	Yes
Firm Dummy	Yes	Yes	Yes	Yes
Number of Observations	1903672	1903672	1903672	1903672
Adjusted $\bar{R}^2$	0.0698	0.0698	0.0698	0.0699
Number of Firms	3900	3900	3900	3900

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

Estimation Results

Table: Spatial and Temporal Heterogeneity in Turnover Effects

	Dependent Variable: Number of Patent Citations		
	1980–2005	1980–1990	1990–2005
Explanatory Variables	(1)	(2)	(3)
Log(Av. Mig. Flows of Univ. Grad.)	0.0298***	0.0270**	0.0355**
	(0.0107)	(0.0110)	(0.0138)
Log(Av. Mig. Flows of Univ. Grad.) $\times\ I(\mathrm{PDQTL}_2)$	0.0016	0.0026	0.0010
	(0.0020)	(0.0024)	(0.0022)
Log(Av. Mig. Flows of Univ. Grad.) $\times\ I(\mathrm{PDQTL}_3)$	0.0086**	0.0081**	0.0110***
	(0.0032)	(0.0036)	(0.0038)
Log(Av. Mig. Flows of Univ. Grad.) $\times\ I(\mathrm{PDQTL}_4)$	0.0083*	0.0086*	0.0091*
	(0.0046)	(0.0046)	(0.0048)
Log(Av. Mig. Flows of Univ. Grad.) $\times\ I(\mathrm{EDQTL}_2)$	0.0058***	0.0016	0.0110***
	(0.0015)	(0.0026)	(0.0019)
Log(Av. Mig. Flows of Univ. Grad.) $\times\ I(\mathrm{EDQTL}_3)$	0.0058*	0.0039	0.0131***
	(0.0029)	(0.0033)	(0.0030)
Log(Av. Mig. Flows of Univ. Grad.) $\times\ I(\mathrm{EDQTL}_4)$	0.0088**	0.0043	0.0182***
	(0.0033)	(0.0040)	(0.0043)
Log(Av. Mig. Flows of Univ. Grad.) $\times\ I(\mathrm{DIQTL}_2)$	0.0021	0.0049***	0.0016
	(0.0024)	(0.0017)	(0.0031)
Log(Av. Mig. Flows of Univ. Grad.) $\times\ I(\mathrm{DIQTL}_3)$	0.0041*	0.0055**	0.0066**
	(0.0021)	(0.0023)	(0.0030)
Log(Av. Mig. Flows of Univ. Grad.) $\times\ I(\mathrm{DIQTL}_4)$	0.0062**	0.0069*	0.0116**
	(0.0030)	(0.0034)	(0.0046)
Other Controls and Dummies	Yes	Yes	Yes
Number of Observations	1903672	725543	1178129
Adjusted $\bar{R}^2$	0.0697	0.0521	0.0834
Number of Firms	3900	3011	3779

Estimation Results: Robustness Check ❶

Interregional Migration of Non-University Graduates

- We check if the migration of non-university graduates, such as junior high school and high school graduates, also might influence innovative activity.
- To examine which type of people's migration has impact on the quality of innovation, we include both migration flows of university graduates and others

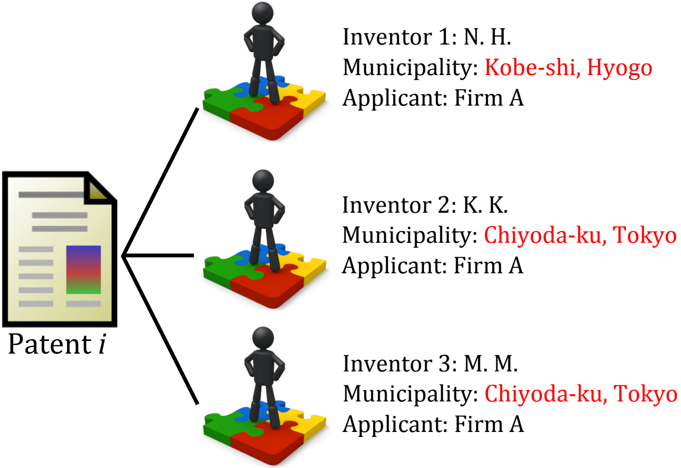
Estimation Results: Robustness Check ❶

Table: Robustness Check by Migration Flows of University Graduates and the Others

Explanatory Variables	Dependent Variable: Number of Patent Citations (1)	(2)
Log(Av. Mig. Flows of Univ. Grads.)	0.0847**	
	(0.0332)	
Log(Av. Mig. Flows of Others)	−0.0447	
	(0.0356)	
Log(Av. Mig. Inflow of Univ. Grads.)		−0.0481
		(0.0420)
Log(Av. Mig. Outflow of Univ. Grads.)		−0.0282
		(0.0489)
Log(Av. Mig. Inflow of Univ.) × **Log(Av. Mig. Outflow of Univ.)**		0.0103**
		(0.0048)
Log(Av. Mig. Inflow of Others)		0.0246
		(0.0686)
Log(Av. Mig. Outflow of Others)		−0.0546
		(0.0758)
Log(Av. Mig. Inflow of Others) × Log(Av. Mig. Outflow of Others)		−0.0006
		(0.0067)
Application Year Dummy	Yes	Yes
Technology Class Dummy	Yes	Yes
Firm Fixed Effects	Yes	Yes
Number of Observations	1903672	1903672
Adjusted $\bar{R}^2$	0.0698	0.0699
Number of Firms	3900	3900

Estimation Results: Robustness Check ❷

Figure: Correspondence between Patent and Regional Variables



➠ $$X_{r(i)} = \max\left(X_{\text{Kobe}}, X_{\text{Chiyoda}}, X_{\text{Chiyoda}}\right)$$

Estimation Results: Robustness Check ❷

Table: Robustness Check by Maximum Values of Regional Variables

	Dependent Variable: Number of Patent Citations		
	1980–2005	1980–1990	1990–2005
Explanatory Variables	(1)	(2)	(3)
Log(Max Mig. Flows of Univ. Grad.)	0.0284***	0.0209**	0.0221**
	(0.0086)	(0.0088)	(0.0106)
Log(Max Mig. Flows of Univ. Grad.) × $I(\mathrm{PDQTL}_2)$	0.0001	0.0018	−0.0012
	(0.0023)	(0.0032)	(0.0021)
Log(Max Mig. Flows of Univ. Grad.) × $I(\mathrm{PDQTL}_3)$	0.0081**	0.0073	0.0112***
	(0.0035)	(0.0048)	(0.0037)
Log(Max Mig. Flows of Univ. Grad.) × $I(\mathrm{PDQTL}_4)$	0.0058	0.0061	0.0083*
	(0.0049)	(0.0054)	(0.0048)
Log(Max Mig. Flows of Univ. Grad.) × $I(\mathrm{EDQTL}_2)$	0.0060***	0.0016	0.0112***
	(0.0017)	(0.0028)	(0.0019)
Log(Max Mig. Flows of Univ. Grad.) × $I(\mathrm{EDQTL}_3)$	0.0069**	0.0046	0.0144***
	(0.0033)	(0.0033)	(0.0037)
Log(Max Mig. Flows of Univ. Grad.) × $I(\mathrm{EDQTL}_4)$	0.0100***	0.0047	0.0193***
	(0.0035)	(0.0039)	(0.0049)
Log(Max Mig. Flows of Univ. Grad.) × $I(\mathrm{DIQTL}_2)$	0.0010	0.0040**	0.0009
	(0.0026)	(0.0018)	(0.0035)
Log(Max Mig. Flows of Univ. Grad.) × $I(\mathrm{DIQTL}_3)$	0.0034	0.0054**	0.0057
	(0.0023)	(0.0024)	(0.0034)
Log(Max Mig. Flows of Univ. Grad.) × $I(\mathrm{DIQTL}_4)$	0.0047	0.0048	0.0114**
	(0.0030)	(0.0032)	(0.0049)
Other Controls and Dummies	Yes	Yes	Yes
Number of Observations	1903672	725543	1178129
Adjusted $\bar{R}^2$	0.0699	0.0521	0.0839
Number of Firms	3900	3011	3779

Concluding Remarks

Main Findings

- Patents invented in areas with active interregional migration have higher number of patent citations.
- Spatial heterogeneous impacts of the interregional knowledge turnover are observed.
  - The knowledge turnover effects are bigger in areas with larger population density.
  - The knowledge turnover effects are indifferent with respect to the share of university graduates in 1980–1990
  - The knowledge turnover effects become bigger in areas with higher share of university graduates in 1990–2005
- Active interregional migration of high-skilled people, not interregional migration of low-skilled people, matters for higher quality of innovation.

Concluding Remarks

Important Messages for Innovation Policy

- Industrial cluster policies aiming at active innovation might not be effective if interregional migration of knowledge workers is inactive.
- Although it is often considered that rural areas have difficulties in enjoying agglomeration benefits for innovation, our empirical findings shed light on the fact that rural industrial clusters also have opportunities for high-quality innovation through active knowledge workers' mobility.
- An important view for industrial cluster policy is mutual cooperation between urban and rural policymakers to facilitate interregional migration without burden, which will make the innovation system sustainable in the long run.