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Inventors' Mobility and Organizations' Productivity: Evidence from Japanese rare name inventors[†]

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Abstract

This paper investigates the relationship between inventors' mobility and organizations' productivity by constructing a database of patent inventors. We focus on inventors with rare names in order to avoid the problem of identifying distinct inventors with the same name. Tracing the inventors' transfers between organizations, we find the following. First, mobile inventors are more productive than stable inventors who have never transferred. Second, inventors with higher ex ante productivity have a higher frequency of transfers, while the effect of transfers on their ex post productivity for productive inventors is the opposite compared with that of less productive inventors. Thus, ex ante productivity may explain a large part of the higher productivity of mobile inventors relative to stable inventors. Third, the productivity of stable inventors is higher in an organization where inventors have more experience in different organizations. These results suggest the existence of knowledge spillover from mobile inventors to stable inventors, which leads to organizations' high productivity.

Keywords: Knowledge spillover, Inventor, Mobility

JEL classification: O31, O34

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1. Introduction

Since Schumpeter's seminal works, it has been widely perceived that new combinations of knowledge are crucial driving factors of innovation. As observed in North America's Silicon Valley, which is known as a successful region for innovation, many workers originate from different geographical areas and have significant mobility. Thus, many studies examine workers' diversity and mobility as an important element of innovation because these factors are closely related to knowledge diversity.

Those studies empirically examine the relationships between workers' diversity and productivity. Ottaviano and Peri (2005, 2006) find that workers' diversity within a region is related to higher productivity of the region, while Ostergaard et al. (2011) observe the positive effect of researchers' diversity on firms' productivity. Further, Parrotta et al. (2014) find that workers' diversity is related to the diversity of workers' knowledge measured by firms' patent portfolios. However, knowledge diversity tends to decrease over time because workers within a region or an organization come to possess common knowledge through knowledge spillover.

To maintain knowledge diversity, workers' mobility plays an important role. Some studies show empirical evidence of the localization of knowledge due to the geographical friction of knowledge spillover (Jaffe, Trajtenberg, and Henderson, 1993; Inoue et al., 2013).[1] This friction can cause a different pattern of knowledge accumulation in different regions (Berliant and Fujita, 2012). Further, the heterogeneity of knowledge across a region is a source of knowledge transfer by mobile workers from different regions.

In addition, mobile workers are assumed to bring different knowledge from different organizations, thereby increasing the knowledge diversity of workers within an organization. It is driven by the organizational friction of knowledge spillover, observed in Inoue et al. (2013),[2] causing different pattern of knowledge accumulation in different organization. Thus, worker's mobility increases knowledge diversity in a region and in an organization which drives great innovation.

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[1] Jaffe, Trajtenberg, and Henderson (1993) observe the localization of knowledge spillover using patent citation as a proxy for knowledge spillover. Following this, the existence of localized knowledge spillovers is debated by Thompson and Fox-Kean (2005) and Henderson, Jaffe, and Trajtenberg (2005). However, knowledge spillover captured by patent citation can be regarded as codified knowledge spillover. In addition, tacit knowledge spillover through face-to-face communication is indicated as important (Nonaka and Takeuchi, 1995; Hansen, 1999; Hansen et al., 2005). Based on this background, Inoue et al. (2013) observe the localization of knowledge spillover using organizational collaboration in patent data as a measure of tacit knowledge spillover.

[2] Inoue et al. (2013) find that most of the collaboration is generated within organizations, which implies the existence of the organizational friction of knowledge spillover.

In the literature of workers' mobility, researchers try to identify individual inventors and trace mobile inventors by using patent databases. Hoisl (2007) and Yamauchi et al. (2014) find that mobile inventors are more productive than stable inventors who have never transferred. Hoisl (2007) also shows that mobile inventors' productivity increases after transfer by learning from new coworkers. However, the influence of mobile inventors on organizations' productivity is understudied, although Grant (1996) suggests that mobile inventors enhance knowledge spillover and increase organization's productivity. Thus, this paper aims to clarify the impact of mobile inventors on organizations' productivity.

Tracing mobile inventors, however, is difficult. The major difficulty is called the "John Smith problem," which is due to different inventors with the same name. To avoid this problem, we follow the method developed by Yamauchi et al. (2014). We restrict the sample to inventors with unique names in accordance with the Japanese telephone directory provided by Nippon Telegraph and Telephone (NTT). We define such inventors as "rare name inventors." Another difficulty in tracing mobile inventors arises from incomplete information on the inventors' organizations. Following Inoue et al. (2013), we identify inventors' organizations from the "inventor's address" in patent documents, thereby taking advantage of the Japanese convention that inventors register their organizations' addresses as the "inventor's address."

Using this unique Japanese inventors' dataset, we investigate the impact of inventors' mobility on organizations' productivity. Moreover, the originality of this paper lies in the way that we concentrate on the impact of mobile inventors on the productivity of stable inventors who have never transferred rather than focusing simply on organizations' productivity. Thus, we examine whether the productivity of stable inventors varies depending on the proportion of mobile and experienced inventors in organizations. This enables us to evaluate the knowledge spillover effect from mobile inventors to stable inventors. Another advantage of this method is that we can extract the pure effect of inventor mobility by removing the effect of the higher productivity of mobile inventors, given that mobile inventors have higher productivity as observed in prior studies.

We find the following results. First, mobile inventors are more productive than stable inventors who have never transferred, which is consistent with prior studies. Second, inventors with higher ex ante productivity (productivity in their first organizations) have a higher frequency of transfers. In addition, the total effect of transfers on such inventors' ex post productivity (productivity after transfers) is ambiguous because of the opposite effects among productive inventors and less productive inventors; namely, only less productive inventors enjoy the knowledge spillover effect from new organizations. Thus, ex ante productivity may explain to a large extent the higher productivity of mobile inventors relative to stable inventors. Third, the productivity of stable inventors is higher in organizations where inventors have more experience in different organizations. These results suggest the existence of knowledge spillover from mobile inventors to stable inventors, which leads to organizations' high productivity.

The rest of this paper is organized as follows. In the next section, we introduce our dataset and methodology. Section 3 presents a summary of our data and Section 4 presents the results of regression analysis. Section 5 then concludes the paper.

2. Data and Methodology

We construct a patent inventors' dataset from all the patent applications published by the Japan Patent Office from 1993 to 2008. From patent publication documents, we extract each patent application number, application date, and publication date, together with the names and addresses of inventors. The number of patent applications in this dataset is 5,996,881. Using this large dataset, we identify patent inventors and their organizations following Inoue et al. (2013) and Yamauchi et al. (2014).

First, we identify inventors' organizations. We differentiate "establishment" as their organizations; thus, our analysis is based on inventor-establishment level data. Essentially, we follow the method of Inoue et al. (2013), although we make some modifications to improve it. Following a convention in the Japanese patent system, the addresses that inventors register as "inventor's address" in patent documents are those of their establishments.[3] Notably, these establishment addresses typically include the firms' names. Consequently, the inventors' organizations are identified by their firms' names and establishment addresses.[4]

Inoue et al. (2013) assume that when they identify a firm, the names of applicants are the names of the firm's inventors. However, this is not necessarily the case. For example, when an invention is assigned before filing a patent application, the names of

[3] In some companies in our sample, intellectual property activities are centralized to, and managed by, their headquarters; thus, an inventor's address is not the establishment's address but the headquarters' address. Excluding companies that have only one establishment as an inventor's address, in order to avoid this influence, does not change the estimation results.

[4] Because the description format of an address sometimes differs depending on different patents, we use a geocoding system provided by the Center for Spatial Information Science, University of Tokyo to unify the format.

applicants no longer apply to the organization where the invention originated. Thus, we extract a firm's name from "inventor's address" in the patent documents by using a different data source. To achieve this, we compose a list of firms' names from a firm-level dataset provided by Tokyo Shoko Research (TSR), a private credit research company. The dataset includes more than half of the firms in Japan. We then examine which firm's name in the list is included in "inventor's address."

Using this improved identification method for inventors' organizations, we identify an inventor's transfer by the change of organization disclosed in "inventor's address" in different patents generated by the same name inventor. However, a further identification problem, known as the "John Smith problem," remains. In other words, the identified change of organization might relate to different inventors with the same name.

To avoid this problem, we apply the method proposed by Yamauchi et al. (2014). They extract inventors who have unique names in accordance with the Japanese telephone directory provided by Nippon Telegraph and Telephone (NTT), and assume that such inventors are distinctive. We define these inventors with unique names in the telephone directory as "rare name inventors" and restrict our sample to them. The applications filed by rare name inventors cover more than 80% of applications filed by all inventors matched with the telephone directory.

Most of the literature on inventors' identification relies on a computerized matching procedure (Trajteberg et al., 2006; Marx et al., 2009; Nakajima et al., 2010; Lai et al., 2013). They distinguish inventors by using an integrated score based on information disclosed in patent documents such as technology class, assignee, and co-inventors. However, there is a problem when we analyze the differences in the scores as identifiers of inventors' mobility. For example, inventors' mobility is underestimated because mobile inventors tend to join research projects in different technology fields with different co-inventors in new organizations and may then be regarded as different inventors. Focusing only on rare name inventors has the advantage of removing this bias, given that productivity does not differ between rare name inventors and non-rare name inventors.[5]

The main purpose of this paper is to examine the effect of knowledge spillover from

[5] To check any bias due to the restricted sample of inventors with unique names, Yamauchi et al. (2014) compare the productivity of inventors with unique names with that of inventors with non-unique names by matching with a different data source, the RIETI inventor survey, which contains 5,270 identical Japanese inventors, and find no statistically significant difference between them.

mobile inventors to stable inventors. To identify this effect, we investigate whether the productivity of stable inventors is higher in organizations where inventors have more experience in different organizations. If we observe higher productivity among stable inventors, this suggests the existence of a knowledge spillover effect from mobile inventors.

3. Summary Statistics

In our dataset, the number of rare name inventors is 205,046 and the number of organizations is 41,413.[6] Out of 205,046 rare name inventors, 77.6% have never transferred between organizations; 17.0% have transferred once; 4.0% have transferred twice, and 1.4% have transferred no less than three times.

We measure inventors' productivity by the number of applications per year during inventors' lifetimes. The lifetime of an inventor ($lifetime$) is defined by the time between the first application year ($year\_start$) and the last application year ($year\_end$). More specifically, it is defined for each inventor (i) as

$$lifetime_i = year\_end_i - year\_start_i + 1. \tag{1}$$

The productivity of inventors is defined by the total number of patent applications (n_patent_i) divided by lifetime as follows:

$$prod\_lifetime_i = n\_patent_i \,/\, lifetime_i. \tag{2}$$

For mobile inventors, productivity for each organization (o) to which they belong can be defined as

$$prod\_org_{i,o} = n\_patent\_org_{i,o} / \, lifetime\_org_{i,o}. \tag{3}$$

Here, the lifetime of an inventor for each organization ($lifetime\_org_{i,o}$) is similarly defined by the time between the first application year in each organization ($year\_start\_org$) and the last application year in the organization ($year\_end\_org$). In the regression analysis, we regress these inventors' productivities on factors related to

[6] Note that many organizations have single rare name inventors. To control for the influence of a large variation in the number of inventors across organizations, we include organization fixed effect in the regression analysis.

inventors' mobility.

Table 1 presents the summary statistics of the productivity and related variables. Note that more than a quarter of inventors applied only one patent during their lifetimes. If an inventor files only one patent application, his or her lifetime is one and his or her productivity becomes one by definition. Further, since the information on how long it takes for the patent application is not included in patent data, the productivity of inventors with a short lifetime can be overestimated.[7]

Table 1 Summary of productivity and related variables

variable	N	mean	sd	p50	p25	p75
n_patents	205046	9.112	19.174	3.000	1.000	9.000
lifetime	205046	5.540	5.377	3.000	1.000	9.000
prod_lifetime	205046	1.466	1.401	1.000	1.000	1.667

Another concern is the censoring of $lifetime$. If $year\_start$ (the year when a patent is first applied for) is closer to the end year of the sample period, or if $year\_end$ (the year when a patent is last applied for) is closer to the start year of the sample period, the problem might become more severe. Table 2 presents the summary statistics of productivity and related variables for the sample with $year\_start$ later than 2000. We find that the average productivity (*prod_lifetime*) is robust compared with the censored data, although the number of patents and the lifetimes are significantly influenced by the first or last application years.[8]

Table 2 Summary of censored productivity and related variables

variable	N	mean	sd	p50	p25	p75
n_patents	60347	3.701	6.508	2.000	1.000	4.000
lifetime	60347	2.351	2.068	1.000	1.000	3.000
prod_lifetime	60347	1.439	1.228	1.000	1.000	1.500

Table 3 presents the relationship between productivity and inventors' mobility. The table shows the summary statistics of lifetime productivity according to the number of transfers. We find that mobile inventors are more productive in their lifetimes.

[7] As a robustness check for the examination of productivity, we conduct an analysis that restricts the sample to inventors whose lifetimes are longer than one, in addition to the analysis with the full sample, and confirm the robustness of the estimation results in Section 4.

[8] We control start year fixed effect in the regression in Section 4.

Moreover, Table 4 compares productivity in first organizations according to the number of transfers in order to identify the size of the opposite causalities; whether productive inventors have higher propensity to transfer or experience of transfer improves the inventor's productivity. We find that mobile inventors are already productive in the first organization. Interestingly, lifetime productivity for mobile inventors (see Table 3) is lower than productivity in first organizations (see Table 4) except for mobile inventors with no less than three transfers. These results suggest that productive inventors have a higher probability of transfer and become less productive after transfers.

Table 3 Summary of productivity by inventors' mobility

# of transfer	N	mean	sd	p50	p25	p75
0	159115	1.424	1.282	1.000	1.000	1.500
1	34832	1.497	1.684	1.000	0.556	1.875
2	8193	1.849	1.819	1.286	0.750	2.313
3 and more	2906	2.317	1.977	1.778	1.063	2.895

Table 4 Summary of productivity in first organizations

# of transfer	N	mean	sd	p50	p25	p75
0	159115	1.424	1.282	1.000	1.000	1.500
1	34832	1.740	1.605	1.000	1.000	2.000
2	8193	2.009	1.883	1.333	1.000	2.429
3 and more	2906	2.151	2.045	1.500	1.000	2.714

To investigate changes in the productivity of mobile inventors in more detail, we focus on inventors who have only one experience of transfer by comparing productivity in first organizations and that in second organizations (Table 5-1). Similarly, we compare productivity in each organization for inventors who have transferred twice (Table 5-2).

Table 5-1 Change in productivity of mobile inventors (# of transfers = 1)

Organization	N	mean	sd	p50	p25	p75
First	34832	1.740	1.605	1.000	1.000	2.000
Second	34832	1.603	1.521	1.000	1.000	2.000

Table 5-2 Change in productivity of mobile inventors (# of transfers = 2)

Organization	N	mean	sd	p50	p25	p75
First	8193	2.009	1.883	1.333	1.000	2.429
Second	8193	1.844	1.703	1.000	1.000	2.000
Third	8193	1.746	1.650	1.000	1.000	2.000

In Tables 5-1 and 5-2, we observe that mobile inventors' productivity decreases after transfers, which suggests that mobile inventors do not benefit by transferring and learning from inventors in new organizations. However, when we divide the sample into inventors with higher ex ante productivity (productivity in first organizations) and those with lower ex ante productivity, we observe a different situation.

Tables 6-1 and 6-2 present changes in productivity for inventors with original productivity above the median and those with original productivity equal or less than the median, respectively. Here, we limit inventors to those who have transferred only once, as in Table 5-1.

Table 6-1 Change in productivity of productive inventors (# of transfers = 1)

Organization	N	mean	sd	p50	p25	p75
First	16429	2.722	1.893	2.000	1.579	3.000
Second	16429	1.806	1.829	1.000	1.000	2.000

Table 6-2 Change in productivity of less productive inventors (# of transfers = 1)

Organization	N	mean	sd	p50	p25	p75
First	18403	0.864	0.223	1.000	0.750	1.000
Second	18403	1.421	1.149	1.000	1.000	1.500

We can observe that productivity after transfer decreases for inventors who were originally productive, while it improves for ex ante less productive inventors. Thus, less productive inventors can benefit from transfers and the overall negative effect of transfers might be due to the decrease in productivity of productive inventors.

We expect that the knowledge spillover effect from new organizations is larger for inventors with lower productivity because less productive inventors would experience greater benefit from a transfer than productive inventors. This is because the amount of received knowledge would be larger than that of imparted knowledge. This might cause the difference between productive and less productive inventors.

Such a difference, however, might be due to the organizations to which the inventors belong. We observe, for example, a positive correlation between inventors' productivity and organizations' sizes measured by the number of inventors. Tables 7-1 and 7-2 show the differences in organizations' sizes with regard to productive inventors and less productive inventors respectively. The sizes of second organizations are much smaller than those of first organizations, especially for productive inventors, suggesting a lower propensity for patent applications in second organizations. Considering this, we should control for organizations' fixed effect in regression in order to examine changes in mobile inventors' productivity.

Table 7-1 Organizations' sizes of productive inventors (# of transfers = 1)

Organization	N	mean	sd	p50	p25	p75
First	16429	765.8	1439.2	133.0	31.0	583.0
Second	16429	427.2	879.6	64.0	11.0	262.0

Table 7-2 Organizations' sizes of less productive inventors (# of transfers = 1)

Organization	N	mean	sd	p50	p25	p75
First	18403	493.4	1122.9	56.0	8.0	285.0
Second	18403	394.8	903.3	37.0	5.0	201.0

However, an organization can still benefit from a productivity-improving effect because of the knowledge spillover from mobile inventors. In order to examine such a spillover effect on organizations' productivity, Table 8 summarizes stable inventors' productivity by type of organization to which they belong in terms of inventors' mobility. We divide the sample into two groups: organizations with higher inventor mobility and those with lower mobility. To do this, we first calculate the number of transfer experiences for each inventor before arrival at the organization to which he or she belongs ($n\_experience$) and calculate the ratio of inventors with experience greater than zero for each organization ($ratio\_experience$). We define a "high mobility organization" as an organization with a higher ratio of inventors' experiences ($ratio\_experience$) than the median. We find that a stable inventor is more productive in a high mobility organization, which suggests the existence of knowledge spillover from mobile inventors to stable inventors.

Table 8 Summary of stable inventors' productivity by type of organization

Organization	N	mean	sd	p50	p25	p75
All	159115	1.424	1.282	1.000	1.000	1.500
High mobility	79733	1.508	1.406	1.000	1.000	1.750
Low mobility	79382	1.341	1.137	1.000	1.000	1.375

4. Regression Analysis

4.1 Specifications

This paper aims to investigate the effect of inventors' mobility on their productivity and identify the existence of the knowledge spillover effect. First, we estimate the following equation in order to examine the relationships between the number of transfers and inventors' lifetime productivity.

$$prod\_lifetime_i = \beta_0 + \beta_1\, n\_transfer_i + \tau_o + \theta_y + \varepsilon_i. \quad (4)$$

In this equation, i denotes an inventor, o denotes a first organization, and y denotes the first application year. The vector $\boldsymbol{\beta}$ is the coefficient parameter. The variables τ_o and θ_y are organization fixed effect and first application year fixed effect respectively. For the robustness check, we use the average size of the organizations to which the inventors belong measured by the number of inventors during their lifetimes (*mean_size_org*) as a control variable instead of the organization fixed effect τ_o. This is because inventors in large organizations tend to file greater numbers of applications.

We expect that the coefficient of the number of transfers ($n\_transfer_i$) on lifetime productivity ($prod\_lifetime_i$) is positive because it is assumed that productive inventors have a higher propensity to transfer and that transfers give mobile inventors opportunities to learn from new organizations. To identify this effect, we regress the number of transfers on inventors' productivity in first organizations with the following equation.

$$n\_transfer_i = \beta_0 + \beta_1\, prod\_first_i + \tau_o + \theta_y + \varepsilon_i, \quad (5)$$

where the variable $prod\_first_i$ denotes the productivity of inventors in first organizations and τ_o is the fixed effect of such organizations. This equation examines how significantly the original productivity of inventors affects the frequency of transfers during their lifetimes. If $prod\_first_i$ has a positive effect, we find that inventors with higher productivity have a higher propensity to transfer, which causes a positive correlation between the number of transfers and inventors' lifetime productivity.

Another interest of this paper is the knowledge spillover effect. We focus on two channels of knowledge spillover: knowledge spillover from a new organization to mobile inventors and knowledge spillover from mobile inventors to a new organization. First, we investigate whether mobile inventors' productivity increases after transfers because of the knowledge spillover from new organizations. To observe this effect, we regress the productivity of mobile inventors in each organization on the number of prior experiences of working for other organizations.

As discussed in the prior section, we expect that the knowledge spillover effect from new organizations is larger for inventors with lower productivity. Less productive inventors would experience greater benefit from the transfer than productive inventors because the amount of received knowledge would be larger than that of imparted knowledge. To identify the different effect of knowledge spillover from new organizations, we divide the sample into productive inventors in first organizations and less productive inventors. Specifically, focusing on mobile inventors, we estimate the following model.

$$prod\_org_{i\_m} = \beta_0 + \beta_1\, n\_experience_{i\_m} + \tau_o + \theta_y + \varepsilon_{i\_m}, \qquad (6)$$

where the variable $prod\_org_{i\_m}$ is the productivity of mobile inventors and the variable $n\_experience_{i\_m}$ is the number of inventors' prior experiences working for other organizations. We also control for inventors' abilities in this regression in addition to organizations' heterogeneity to capture a change of inventor's productivity. We cannot include both fixed effects in the regression because there are too much dummies for them. Thus, we first include the organization fixed effect and then replace the variable τ_o with inventor fixed effect. Further, we control for both effect of organization and that of inventors' ability, by including the normalized productivity $prod\_org\_n$ which we divide the $prod\_org_{i\_m}$ by means of all inventors' productivity in organizations, in addition to the inventor fixed effect.

Lastly, we investigate whether the productivity of stable inventors increases because of the knowledge spillover effect from mobile inventors. We introduce the index that captures the mobility of organizations in this analysis as in the prior section;

namely, the ratio of inventors who have prior experiences before joining the organization ($ratio\_experience$).

Moreover, we expect that the knowledge spillover effect is larger for smaller organizations because the positive effect of hiring experienced inventors would be larger when stable inventors experience a limited spillover effect from other inventors in an organization. Thus, we include the cross term of the size of organizations ($size\_org$) and the variable $ratio\_experience$. Focusing on the productivity of stable inventors, we estimate the effect of mobile inventor on organizations with the following equation.

$$\begin{aligned} prod\_org_{i\_s} = {} & \beta_0 + \beta_1\, ratio\_experience_o + \beta_2\, size\_org_o \\ & + \beta_3\, (ratio\_experience_o * size\_org_o) \\ & + \theta_y + \varepsilon_{i\_s}, \end{aligned} \qquad (7)$$

where $prod\_org_{i\_s}$ is the productivity of stable inventors. We control for the size of organizations by the number of inventors ($size\_org_o$).

4.2 Baseline results

4.2.1 Inventors' mobility and lifetime productivity

Table 9 presents the estimation results for equation (4). For the robustness check, we also show the results when we restrict our sample to inventors who have never transferred and those who have transferred only once ($n\_transfer \leq 1$). The table shows that the variable $n\_transfer_i$ has positive correlation with the variable $prod\_lifetime_i$ with statistical significance. The results are robust in all circumstances.[9] Thus, inventors with higher mobility have higher lifetime productivity, although this does not necessarily indicate causality.

[9] As a robustness check, we also restrict our sample to the inventors whose lifetime is longer than 1, as discussed in Section 2, and find similar results.

Table 9 Number of transfers and lifetime productivity

	prod_lifetime					
	all inventors			*n_transfer <= 1*		
	(1)	(2)	(3)	(1)	(2)	(3)
n_transfer	0.158***	0.166***	0.172***	0.0303***	0.0390***	0.0470***
	(0.00662)	(0.00659)	(0.00814)	(0.00950)	(0.00949)	(0.0112)
mean_size_org		0.0479***			0.0467***	
		(0.00290)			(0.00291)	
Constant	2.082***	2.036***	1.618***	2.045***	1.999***	1.539***
	(0.180)	(0.180)	(0.0922)	(0.206)	(0.206)	(0.0953)
Organization fixed effect	no	no	yes	no	no	yes
Start year fixed effect	yes	yes	yes	yes	yes	yes
Observations	205,046	205,046	205,046	193,947	193,947	193,947
R-squared	0.030	0.032	0.210	0.023	0.024	0.205

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.2.2 Determinants of transfer frequency

Table 10 presents the results of equation (5) to examine the effect of the original productivity of inventors on the propensity to transfer. Again, we use a limited sample (n_transfer <= 1) in addition to the full sample.

Table 10 Productivity in first organizations and the number of transfers

	n_transfer					
	all inventors			*n_transfer <= 1*		
	(1)	(2)	(3)	(1)	(2)	(3)
prod_first	0.0465***	0.0474***	0.0400***	0.0216***	0.0219***	0.0199***
	(0.00146)	(0.00147)	(0.00147)	(0.000833)	(0.000837)	(0.000869)
size_org_inv		-0.0286***			-0.00923***	
		(0.00116)			(0.000777)	
Constant	0.511***	0.535***	0.434***	0.252***	0.260***	0.203***
	(0.0340)	(0.0339)	(0.0353)	(0.0191)	(0.0190)	(0.0196)
Organization fixed effect	no	no	yes	no	no	yes
Start year fixed effect	yes	yes	yes	yes	yes	yes
Observations	205,046	205,046	205,046	193,947	193,947	193,947
R-squared	0.057	0.060	0.322	0.037	0.038	0.304

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We find that, in all specifications, productivity in first organizations has positive and significant coefficients. This suggests that the originally productive inventors have a higher frequency of transfers. Thus, a significant part of the positive correlation between inventors' mobility and lifetime productivity can be explained by the higher mobility of ex ante productive inventors.

Further, the size of organization is negative, suggesting that inventors do not tend to transfer if they were originally in larger organizations, comparing to inventors with the same productivity in first organizations. Given that inventors in large organizations have higher productivity, relative productivity in organizations rather than absolute productivity may be important in defining the propensity to transfer.

4.2.3 Knowledge spillover effect from new organizations to mobile inventors

Table 11 presents the results of equation (6) to examine the effect of the experience of transfers on inventors' ex post productivity. Here, we restrict our sample to inventors who have transferred only once.[10] We find that the coefficients of the variable $n\_experience_i$ are negative but insignificant when we do not include the organization fixed effect (model (1) in Table 11). However, when we control for the organization fixed effect in model (2), the sign of the coefficient of $n\_experience_i$ is significantly positive. A possible explanation of this result is that mobile inventors tend to transfer to smaller organizations that have a lower propensity for patent applications as shown in Table 7; thus, their absolute productivity decreases but relative productivity increases after transfers.

Table 11 Change in productivity of mobile inventors

	prod_org			*prod_org_n*		
	all inventors			*all inventors*	*productive*	*less productive*
	(1)	(2)	(3)	(4)	(5)	(6)
n_experience	-0.00752	0.0673***	0.0159	0.0267***	-0.297***	0.371***
	(0.0160)	(0.0248)	(0.0201)	(0.00916)	(0.0139)	(0.00910)
Constant	2.544***	2.048***	1.558***	0.878***	1.944***	-0.125
	(0.624)	(0.508)	(0.207)	(0.0924)	(0.135)	(0.0956)
Organization fixed effect	no	yes	no	no	no	no
Inventor fixed effect	no	no	yes	yes	yes	yes
Start year fixed effect	yes	yes	yes	yes	yes	yes
Observations	69,664	69,664	69,664	69,664	34,823	34,841
R-squared	0.021	0.213	0.595	0.574	0.607	0.576

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[10] When we consider the age when inventors transferred, it is better to restrict the sample to inventors who have transferred only once. When we regress the productivity of first organizations on the productivity of second organizations, the size of the coefficient is almost the same even after controlling for *lifetime_first*, the lifetime of first organizations, as a proxy for their age.

Note that the productivity of first organizations and that of second organizations is highly correlated for all inventors because it reflects inventors' ability. In model (3), we control for inventors' fixed effect instead of organizations' fixed effect and find no significant effect, which is similar to model (1). In order to control for both organization effect and inventors' ability effect, we normalize productivity by means of all inventors' productivity in organizations and include inventors' fixed effect. We then observe the positive effect experience on ex post productivity (model (4)).

To check the effect of ex ante productivity on this, we divide the sample into productive inventors and less productive inventors according to the median of ex ante normalized productivity (models (5) and (6)). We find the positive effect of experience solely for less productive inventors, suggesting that these inventors alone benefit from new organizations through knowledge spillover.

Thus, our findings only partially support the results of Hoisl (2007), which indicate that positive knowledge spillover is due to both channels of causality. Another interpretation of the results is that, instead of the knowledge spillover effect from new organizations, higher original productivity of mobile inventors can explain a large part of the differences in productivity between mobile inventors and stable inventors.

4.2.4 Knowledge spillover effect from mobile inventors to new organizations

Table 12 presents the results of estimation equation (7). In addition to productivity of stable inventors in first three columns, we also show the results when we use the full sample of all inventors in the last three columns in Table 12, to show a bias in examining organizations' productivity as knowledge spillover effect.

Table 12 Knowledge spillover effect for new organizations

	prod_org					
	with only stable inventors			with all inventors		
	(1)	(2)	(3)	(4)	(5)	(6)
ratio_experience	0.162***	0.166***	0.215***	0.241***	0.253***	0.314***
	(0.0172)	(0.0172)	(0.0186)	(0.0167)	(0.0166)	(0.0180)
*ratio_experience*size_org_inv*			-0.133***			-0.179***
			(0.0184)			(0.0178)
size_org_inv		0.0359***	0.0497***		0.0436***	0.0618***
		(0.00287)	(0.00354)		(0.00291)	(0.00355)
Constant	1.825***	1.787***	1.780***	1.889***	1.847***	1.840***
	(0.109)	(0.109)	(0.109)	(0.0835)	(0.0835)	(0.0835)
Start year fixed effect	yes	yes	yes	yes	yes	yes
Observations	159,115	159,115	159,115	205,046	205,046	205,046
R-squared	0.021	0.022	0.022	0.028	0.029	0.030

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Examining the results for stable inventors (models (1) to (3)), we find that stable inventors' productivity is higher in organizations with more inventors who have prior experience of working for different organizations. This result provides clear evidence that the knowledge spillover effect from mobile inventors to stable inventors does exist. We also find that the cross term has a negative effect, which indicates that the knowledge spillover effect from mobile inventors on stable inventors is larger in smaller organizations. These results suggest that mobile inventors bring different knowledge to new organizations. This contributes to stable inventors' knowledge creation and increases organizations' productivity, especially for organizations with fewer inventors.

Moreover, comparing the size of the coefficients of the variable $ratio\_experience_o$ between models (2) and (5), where we control for the size of organizations, we find that the effect of mobility is larger for all inventors than for stable inventors. The larger effect in model (5) reflects mobile inventors' high productivity, which indicates the importance of limiting our focus to stable inventors to avoid an overestimation of the knowledge spillover effect. At the same time, this result suggests that, in total, increasing mobility among organizations can significantly contribute to improving organizations' productivity.

4.3 Effect of crossing firms' boundaries with regard to inventors' transfers

This subsection compares the effects of transfers between firms with those of transfers within firms, a comparison that shows the impact of crossing the boundaries of firms.

Table 13 presents the effects of the number of transfers on lifetime productivity for inventors with experience of transfer between firms and for inventors transferred within firms. In Table 13, we focus only on the effects of first time transfer, which means that the coefficients measure the significance of transfer changes to lifetime productivity compared with inventors who have never transferred.

Table 13 Number of transfers and lifetime productivity: between firms vs. within firms

	prod_lifetime					
	between firms			*within firms*		
	(1)	(2)	(3)	(4)	(5)	(6)
n_transfer	-0.0412***	-0.0402***	-0.0581***	0.106***	0.120***	0.176***
	(0.0117)	(0.0117)	(0.0142)	(0.0144)	(0.0143)	(0.0168)
mean_size_org		0.0477***			0.0370***	
		(0.00289)			(0.00288)	
Constant	1.842***	1.795***	1.523***	2.072***	2.033***	1.559***
	(0.0997)	(0.0997)	(0.104)	(0.234)	(0.234)	(0.106)
Organization fixed effect	no	no	yes	no	no	yes
Start year fixed effect	yes	yes	yes	yes	yes	yes
Observations	177,420	177,420	177,420	175,642	175,642	175,642
R-squared	0.022	0.023	0.174	0.023	0.024	0.212

Robust standard errors in p
*** p<0.01, ** p<0.05, * p<0.1

We find that the experience of transfer has a negative correlation with lifetime productivity for inventors who have crossed the boundaries of firms, although the magnitude of coefficients is small. On the other hand, the experience of transfers has a positive correlation for inventors transferred within firms. One reason for these results might be that younger inventors are more likely to cross the boundaries of firms than older inventors.[11] Another reason might be that transfers between firms are more likely to occur for inventors of larger firms for the purpose of training or managing inventors at new organizations. To observe this relation, we examine the determinants of transfer in Table 14.

[11] When we focus on inventors who have transferred only once, the average *lifetime_first* is 9.42 for mobile inventors across firms while the average is 10.22 for mobile inventors within firms.

Table 14 Determinants of transfer: between firms vs. within firms

	n_transfer					
	between firms			*within firms*		
	(1)	(2)	(3)	(4)	(5)	(6)
prod_first	0.0145***	0.0140***	0.0124***	0.0131***	0.0137***	0.0121***
	(0.000713)	(0.000706)	(0.000759)	(0.000688)	(0.000689)	(0.000673)
size_org_inv		0.0116***			-0.0267***	
		(0.000739)			(0.000407)	
Constant	0.130***	0.119***	0.106***	0.160***	0.184***	0.119***
	(0.0166)	(0.0167)	(0.0176)	(0.0174)	(0.0173)	(0.0165)
Organization fixed effect	no	no	yes	no	no	yes
Start year fixed effect	yes	yes	yes	yes	yes	yes
Observations	177,420	177,420	177,420	175,642	175,642	175,642
R-squared	0.023	0.025	0.265	0.023	0.033	0.384

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 14, we find that the magnitude of the coefficients of productivity in first organizations (*prod_first*) is similar for transfers between firms and within firms. However, the size of organization for which inventors are working has opposite effects with regard to the two types of transfer. This table shows that transfers across boundaries are more likely to occur for inventors of larger firms, while transfers within firms are more likely to occur for inventors of smaller firms.

Table 15 presents the effects of transfer on mobile inventors' ex post productivity. We find that the variable *n_experience* has a positive effect when we normalize productivity by means of productivity in organizations and control for the inventor fixed effect. In a similar way to all the transfers observed in Table 11, we find a different effect between productive inventors and less productive inventors. Only less productive inventors experience the knowledge spillover effect from new organizations for transfers between firms and within firms. Thus, the suggestion that more productive inventors decrease their productivity after transfers does not differ depending on whether transfers cross the boundaries of firms.

Table 15 Change in the productivity of mobile inventors: between firms vs. within firms

	prod_org_n					
	between firms			*within firms*		
	(1)	(2)	(3)	(4)	(5)	(6)
	all	productive	less productive	all	productive	less productive
n_experience	0.0292**	-0.336***	0.374***	0.0225*	-0.269***	0.366***
	(0.0131)	(0.0198)	(0.0133)	(0.0129)	(0.0196)	(0.0124)
Constant	0.824***	1.788***	0.0208	0.927***	2.045***	-0.274*
	(0.118)	(0.215)	(0.106)	(0.138)	(0.172)	(0.157)
Inventor fixed effect	yes	yes	yes	yes	yse	yes
Start year fixed effect	yes	yes	yes	yes	yes	yes
Observations	36,610	17,782	18,828	33,054	17,041	16,013
R-squared	0.569	0.610	0.580	0.581	0.606	0.574

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

However, the knowledge spillover effect from mobile inventors to stable inventors shows a large difference depending on whether mobile inventors transfer between firms or within firms. Table 16 presents the effect of mobility between and within organizations on the productivity of stable inventors by the types of mobile inventors' transfers. In this table, we can observe that the coefficient of mobility with regard to organizations (*ratio_experience*) is significantly positive for transfers between firms, whereas it is not significant for transfers within firms. This result suggests that the knowledge spillover effect is larger when mobile inventors come from different firms with different knowledge, which would lead to an increase of knowledge diversity of the new organization. Moreover, we find positive significant effect of the prior experience and negative significant effect of the cross term of the prior experience for both types of transfer. Thus, the knowledge spillover effect exists for both types of transfer for small firms.

Table 16 Knowledge spillover effect for new organizations: between firms vs. within firms

	prod_org: with only stable inventors					
	between firms			*within firms*		
	(1)	(2)	(3)	(4)	(5)	(6)
ratio_experience	0.254***	0.235***	0.271***	0.0187	0.0344	0.0672**
	(0.0288)	(0.0289)	(0.0301)	(0.0263)	(0.0262)	(0.0288)
*ratio_experience*size_org_inv*			-0.0881***			-0.0573***
			(0.0177)			(0.0187)
size_org_inv		0.0346***	0.0435***		0.0357***	0.0417***
		(0.00289)	(0.00351)		(0.00287)	(0.00358)
Constant	1.578***	1.561***	1.524***	1.822***	1.768***	1.733***
	(0.113)	(0.113)	(0.114)	(0.113)	(0.113)	(0.114)
Start year fixed effect	yes	yes	yes	yes	yes	yes
Observations	159,115	159,115	159,115	159,115	159,115	159,115
R-squared	0.021	0.022	0.022	0.021	0.022	0.022

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5. Conclusion

In this paper, we construct a database of rare name inventors and identify inventors' transfers between organizations. We then examine the impact of inventors' mobility on organizations' productivity. This paper also tries to identify the knowledge spillover effect of inventor mobility by focusing on the productivity of stable inventors, instead of looking at the effect solely on organizations' productivity. Such an approach is greatly advantageous because it avoids an overestimation of the knowledge spillover effect by removing the influence of mobile inventors' high productivity and thereby contributes to the literature.

We find the following results. First, mobile inventors are more productive than stable inventors, which is consistent with prior studies. Such a finding is stronger for inventors who transfer within firms. Second, higher productivity of mobile inventors is observed in first organizations. This result suggests that a large part of the positive correlation between inventor mobility and productivity can be explained by the higher mobility of originally productive inventors. Our results also show that productive inventors' productivity decreases after transfers, while for less productive inventors, mobility has a positive effect. This finding indicates the asymmetric effect of inventor mobility on ex post productivity. Third, productivity of stable inventors is higher in organizations where inventors have greater experience in different organizations, especially when mobile inventors originate from outside firms. This result provides clear evidence of the existence of knowledge spillover from mobile inventors to stable inventors, which leads to organizations' high productivity.

In future research, we will investigate whether the impact of knowledge spillover differs between the indirect channel and direct channel, identifying co-invention with mobile inventors. We will also examine the significance of the effect of inventors' transfers on the diversity of knowledge stock in organizations and how changes in diversity affect organizations' productivity. In the literature, knowledge diversity inevitably shrinks to common knowledge over time, although inventors' diversity plays an important role in knowledge creation. This theoretical view is related to the absorptive capacity of organizations. In the literature of organizational collaboration, an inverted U-shape effect is observed for performance in terms of the similarity of knowledge stocks among collaborating organizations. We might see a similar pattern for the relations between mobile inventors and new organizations.

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