Does inventor mobility affect complexity of inventors' inventions?

Economics of Technology, Innovation and Growth
course term paper

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Abstract

Using patent inventions data, I attempt to investigate if inventor mobility influences the productivity of those inventors. I leverage a database of worldwide urban regions obtained from remote sensing to demonstrate a significant positive correlation between both inter-region mobility and inter-country mobility and future invention productivity of inventors. I discuss two additional approaches to investigate if a causal explanation exists for this relationship but leave empirical analysis for future work. While the empirical results are incomplete, the current work extends prior work on mobility of inventors by attempting to quantify the direct effects of mobility on inventor productivity.

Keywords: Inventor productivity, Inventor mobility, Economic geography

1 Introduction

Scholars have suggested that inventors carry knowledge with them when they move (Almeida and Kogut, 1999). While the literature on knowledge flows has investigated the localized nature of knowledge flow driven by the inter-firm mobility of inventors (Alcácer and Gittelman, 2006; Almeida and Kogut, 1999; Jaffe et al., 1993), we understand very little about the effects of broad mobility of inventors on future inventive productivity. Since firms, regions and countries seek to organize themselves so as to attract the best inventors so as to produce the highest level of innovative output, an understanding of the mobility effects of inventive productivity becomes an important aspect innovation policy. In this paper I ask if the variation in inventor mobility can explain the variation in invention productivity?

Agglomeration economies have been suggested as one reason for localized movement of inventors. These agglomeration economies arise due to labor pooling advantages, economies of specialization of local suppliers, and knowledge spillovers (Krugman, 1991; Porter, 1990). However regions vary in their inventive output (Agrawal et al., 2014) and the nature of knowledge flows in a region may be one source of this variation within regions. In this study therefore, I propose to expand the context to not just localized agglomerations but to all movements of inventors. By doing so, I expect to understand if there is a clear impact of mobility itself on invention productivity. In other words, what is the relationship between the movement of some inventors into or out of a region and the average productivity of inventions from those inventors?

There has been a long and illustrious scholarly tradition highlighting the agglomeration characteristics of economic regions, going back at least as far as Marshall (2009), whose original work was published in 1890. More recently, scholars over the last three decades have demonstrated the paper trail of these knowledge spillovers through the study of patent citations (e.g., Almeida and Kogut (1999); Jaffe et al. (1993)). This tradition of scholarship has further shaped our theoretical understanding of knowledge spillovers through mechanisms such as the effects of inventor mobility (e.g., Almeida and Kogut (1999)), differential Intellectual Property Rights environments across locations (e.g., Zhao (2006)) and of the role of international geography (e.g., Singh (2007)).

The nature and extent of the geographical mobility of inventors observed in practice is highly heterogenous across locations, firms and legal environments. This raises the opportunity to study if a causal effect exists between mobility of inventors and their future productivity. The question is assumes greater significance in the environment surrounding the second machine age (McAfee and Brynjolfsson, 2014) where inventors are expected to influence innovation outcomes in higher proportion.

The innovation policy of emerging countries is influenced with the expectation that the presence of multinational R&D will create value adding spillover effects. Productivity of inventors may provide a richer proxy for value adding innovation. A better understanding of the effects of inventor mobility may therefore help to inform innovation policy. Additionally, work on this line may help to inform managerial decisions about how to organize R&D teams around the world. Current theory seems to suggest both a positive effect due to knowledge spillovers (Almeida and Kogut, 1999) as well as a negative effect due to variation in IPR enforcement ability (Zhao, 2006). I therefore propose the current empirical study to help determine an answer to this question that is not completely explained by theory.

The rest of the paper is organized as follows. The next section explores the motivation of the current study. Hypotheses based on extant literature are then presented. I then describe the data and methods. The preliminary results are then presented, followed by a discussion of the results. I conclude with next steps and open questions for further research.

2 Preliminary Analysis

I motivate this study by demonstrating two broad patterns. First, as Figure 3 suggests, there has been increased mobility of inventors across countries over the years. Not only is the incidence of across-country mobility higher, but there is heterogeneity in the extent across countries and regions. Figure 4 furthers this aspect by depicting the trend in across-region mobility of inventors. Second, Table 3 suggests that about 6% of inventors moved and only about 2% of inventors moved country.

The two broad patterns together provide us both the motivation as well as the variation in the data to be able ask the question of whether the mobility of inventors affects invention productivity. It must be noted at this point that while we have data on inventors who moved and patented in their new location, and data on inventors who did not move and continued to patent at their existing location, the patents data itself does not provide us data on those inventors who moved but did not patent, and those who did not move and did not patent. This may cause us to either overestimate the effect of mobility or underestimate the effect of not moving.

3 Literature Review

4 Inventor Mobility and its Consequences

In this section, I develop three hypothesis building off of prior literature on inventor mobility and knowledge spillovers.

The literature on agglomeration economies and knowledge spillovers suggest that when inventors move across regions, that newer combinations of knowledge now become possible Almeida and Kogut (1999); Jaffe et al. (1993). Literature would therefore predict better and more numerous inventions arising out of the movement of inventors. I therefore propose hypothesis 1 as follows:

Hypothesis 1: An increase in the average mobility of inventors in a region increases the average complexity of innovation generated

Singh (2007) suggests that inventors who were highly productive previously are likely to carry that after the move. I therefore propose hypothesis 2 as follows:

Hypothesis 2: The effect in Hypothesis 1 is moderated positively by the relative strength of the intellectual property rights regime of the region

Finally, the literature of weak and strong IPR suggests that teams within weak IPR locations are likely to integrate their knowledge within global organizations, thus leading to a lower standalone inventive output. I therefore propose hypothesis 3 as follows:

Hypothesis 3: The effect in Hypothesis 1 is moderated negatively by the strength of the prior pool of inventions by the inventing team

5 Method

5.1 Complexity

Fleming and Sorenson (2001) Kauffman (1993) Since patents vary even within technology subclasses, I suggest an additional measure of complexity to capture additional variation in the data. I construct my measure of complexity based interactions between the different patent sub-classes. Since each of the interactions between patent sub-classes may introduce a new interaction, I model interactions on a binomial function. Specifically, when `subclass` represents the number of distinct patent sub-classes, I define `interaction(subclass)` as follows:

$$interaction(subclass) = \begin{cases} 1 & : subclass \leq 2 \\ \binom{subclass}{2} & : subclass > 2 \end{cases}$$

I would expect, from a user perspective that the more number of contexts in which the patent is valuable, the lower should be the complexity. If `complexity` represents my measure of the complexity of the patent, and `usage contexts` represents the number of distinct contexts where the patent is found valuable, I should expect the following relationship to hold:

$$\texttt{Complexity} \propto \frac{1}{usage\ contexts}$$

Similarly, from an inventor perspective, the more the number of contexts that the patent is built on, the higher should be the complexity. A patent that is developed without citing any other patents is an extreme case of lowest complexity, while one that requires to be built upon several `source contexts` is properly understood as being more complex.

The relationship between `source contexts` and `complexity` is therefore a normal one as depicted below.

$$\texttt{complexity} \propto source\ contexts$$

Using the principles above, I therefore develop the following definition of complexity.

$$\texttt{complexity} = \frac{interaction(subclass_{\text{cited}})}{interaction(subclass_{\text{patent}})}$$

By the definition above, a patent that cites no patents (and hence has $subclass_{\text{cited}} = 0$) but is itself assigned to 4 sub-classes (and hence has $subclass_{\text{patent}} = 4$) will have a raw Complexity score of $\frac{1}{\binom{4}{2}} = 0.16$. If the patent itself had been assigned onto to 2 sub-classes, the raw complexity score would have been just 1. Therefore, the more the number of patent sub-classes a patent is assigned to, the lower its complexity score (by a square term). A similar but inverse relationship would hold for sub-classes arising out of cited patents. Here, I take a set union of patent sub-classes assigned to each cited patent, and use that count to determine the value of the `interaction` function.

5.2 IPR Classification

Zhao (2006) has argued that multinational enterprises may benefit from conducting R&D in countries with weak IPR protection by making up for the weaker IPR protection through better internal organization. An alternative specification may therefore be to include IPR score to capture shifts in the data. Scholars (Baldwin and Henkel, 2015; Yayavaram and Ahuja, 2008), have argued that increased interaction with a larger number of components creates organizational impediments to an increase in reusability of prior work. In the presence of a stronger differential in the IPR environments between inventing locations, Zhao (2006) suggests that organizational mechanisms may stand to counter the treat posed by weaker property rights. In a similar vein, I argue that a differential in the IPR rights environment creates the organizational response to increase complexity of the inventions shared across country and IPR boundaries. This may help capture an exogenous variation that may help identify the mobility-productivity relationship.

A review of the academic literature surrounding the construction of IPR indexes indicated that there were several, as was also evident in Zhao (2006) constructing a composite measure for the purposes of her article. Lesser (2010) provides an alternative, composite scoring system that includes the following components: protectable subject matter, membership in convention, enforcement, administration and duration of protection. I have therefore used the scores generated by Lesser (2010) for the purposes of this study. The extensive table of IPR scores has not been presented here, but can be made available on request. The listing has several countries for which scores have not been provided. However none of the top patenting nations were among them, and I therefore chose to go along with this scale.

6 Data and Measures

I derive all patents data for this study from patentsview.org. The dataset considered is for all USPTO patents filed in the period 1976 to 2015. For country definitions, I use the resources provided by Thematic Mapping. To map location data of inventors to regions, I use urban centers data for worldwide locations from Natural Earth Data that uses remote sensing data to determine urban agglomerations (a process developed in Schneider et al. (2003)). While it has been common practice to use Metropolitan Statistical Areas (MSA) for analyses related to economic geography in the U.S., an equivalent measure is unavailable for the rest of the world. For comparability and consistency, I choose to use the urban centers definitions from Natural Earth Data for all regions both within U.S. and outside U.S. Sample region definitions are depicted in Figure 1 and 2.

6.1 Unit of Analysis

The unit of analysis for this study is the `inventor-year`. For each inventor-year, I capture if the inventor moved in that year. As was previously discussed, the nature of our data is that we do not have data for years in which inventors did not patent. However for the years for which patents were applied for, we identify if there was a movement or not.

6.2 Dependent Variable

My primary dependent variable is the productivity of an inventor in a year. I measure `productivity` by the number of patents invented by the inventor in the year and in two years succeeding that year. The dependent variable may be zero, or 1 or a value higher depending on the inventive productivity of the inventor.

6.3 Explanatory Variables

I use two primary explanatory variables - `between-region` mobility, and `between-country` mobility. For each inventor-year, I determine mobility for the inventor in that year by comparing the region of the previous patent to that of the current patent. If the region has not changed, I mark between-region mobility to zero for that inventor-year. Else `between-region` mobility is marked as one for that inventor-year.

Similarly, to determine `between-country` mobility for an inventor-year, I compare the country of the previous patent to that of the current patent. If the country has not changed, I mark `between-country` mobility to zero for that inventor-year. Else `between-country` mobility is marked as one for that inventor-year.

I define two additional explanatory variables.

`Prior patents of inventor` (PPI) is intended to capture the inventor specific aspects and is computed by adding up the number of patents granted to the invented up to but not including the patents granted in the current year. `Prior patents of team` (PPT) is intended to capture the team specific aspects affecting inventor productivity. It is computed by summing up the number of patents granted to the most prolific of the inventors within the team (not including the focal inventor).

6.4 Control Variables and Fixed Effects

I use the technology classification defined by Hall et al. (2001) to control for various technology subcategories. All models also include year dummies so as to account for any year specific effects. Depending on the model run, we cluster standard errors at the region level, the country level or the technology subclass level.

7 Results

The preliminary results from our analysis are presented in Table **??**, Table **??**, Table **??**, Table **??**. Additional results for robustness are provided in the appendix in Table **??**, Table **??**. In each of the tables, Model 1 provides the baseline regression results without secondary explanatory variables; Model 2 provides the results with the primary and secondary explanatory variables but without interaction effects. Model 3 provides the fully specified model with the primary explanatory variable, secondary explanatory variables and interaction effects.

We find that both `between-region` and `between-country` are statistically significantly correlated with inventor productivity. This holds across all specifications. The signs on the coefficient estimates are maintained across specifications, thus indicating that the effects may be stable. Additionally we note that the interaction effect is positive with the priors of the inventor, and negative with the priors of the team.

Overall, we find support in line with each of the three hypotheses proposed. However, due to missing data as well as due to the identification strategy employed, concerns of reverse causality and bias exist. In order to mitigate some of these concerns, I propose two additional dimensions to consider: complexity of inventions, and IPR regime. I discuss them in the following session, but leave the empirical operationalization to future work.

8 Extensions to identify causality

9 Limitations and Looking Ahead

I started this study attempting to understand if inventor mobility affects inventor productivity. While there seems to be theoretical promise to exploring this question, this was a study too big to have been completed within the constraints of a term. Specifically, the endeavor has exposed me to the challenges to demonstrating causal effects in empirical analysis. Primary among the causes of concern are the direction of causality, and the underestimation bias of mobility - effects. The mechanism by which mobility affects productivity has been left out of the current study. Addiitonally alternative measures of productivity could also be considered. However the main contribution of the currents study may be to demonstrate a strong case for mobility and its effect on productivity. I intend to continue to pursue this further and integrate the IPR level data and complexity data and pursue an argument toward a stronger causal effect of mobility on productivity.

10 Conclusion

While still at a preliminary stage, my analysis seem to suggest that inventor mobility has a significant effect on the productivity of inventors produced. Future studies could examine other measures of invention outcomes so as to identify a causal effect. I hope however that the current work spurs has created enough interest to further research in this direction.

Acknowledgements

I am greatly indebted to Chirantan Chatterjee for having helped me with thinking deeply about my research design, level or analysis and causality. While I might have not done as much justice to the causality instruction, I cannot imagine having make as much empirical progress on this project if not for that guidance. I am also indebted to him for having encouraged me to see the theoretical relevance and contribution of empirical work.

I am also grateful to Sai Yayavaram for having introduced me to the literature on innovation, and for having hand held me with working on the patents data. Indeed many of the skills in understanding the data underlying this article owe their origin to him. All mistakes though, remain entirely mine.

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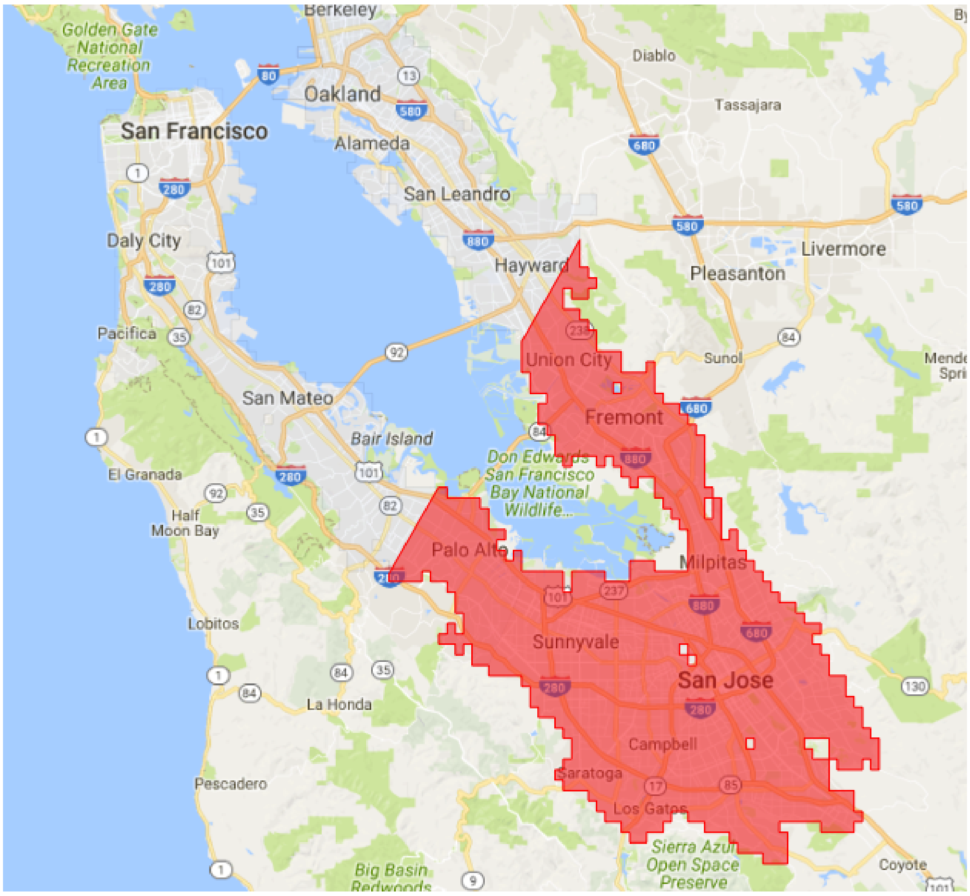

Figure 1: Geographic Definition of San Jose, CA

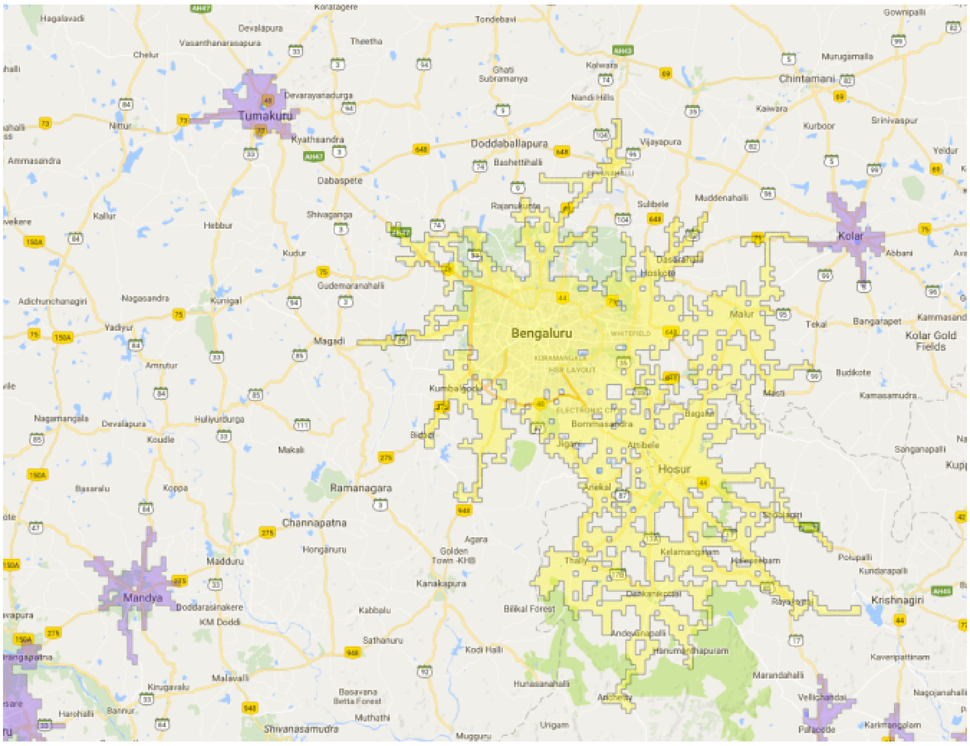

Figure 2: Geographic Definition of Bangalore

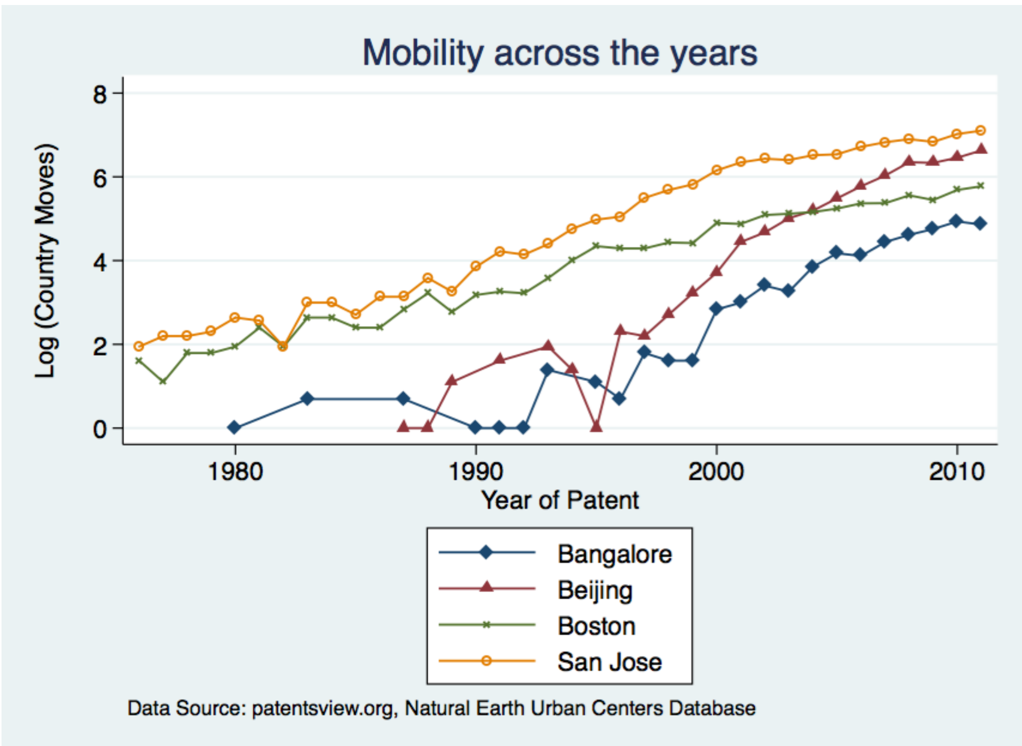

Figure 3: Country moves by year

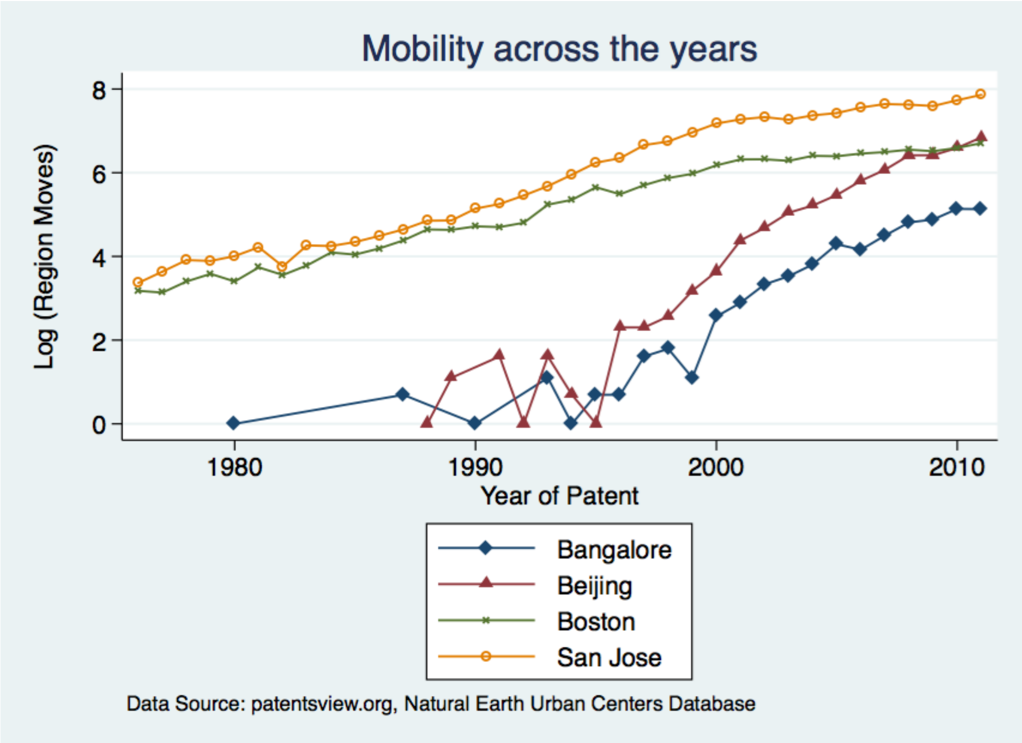

Figure 4: Region moves by year

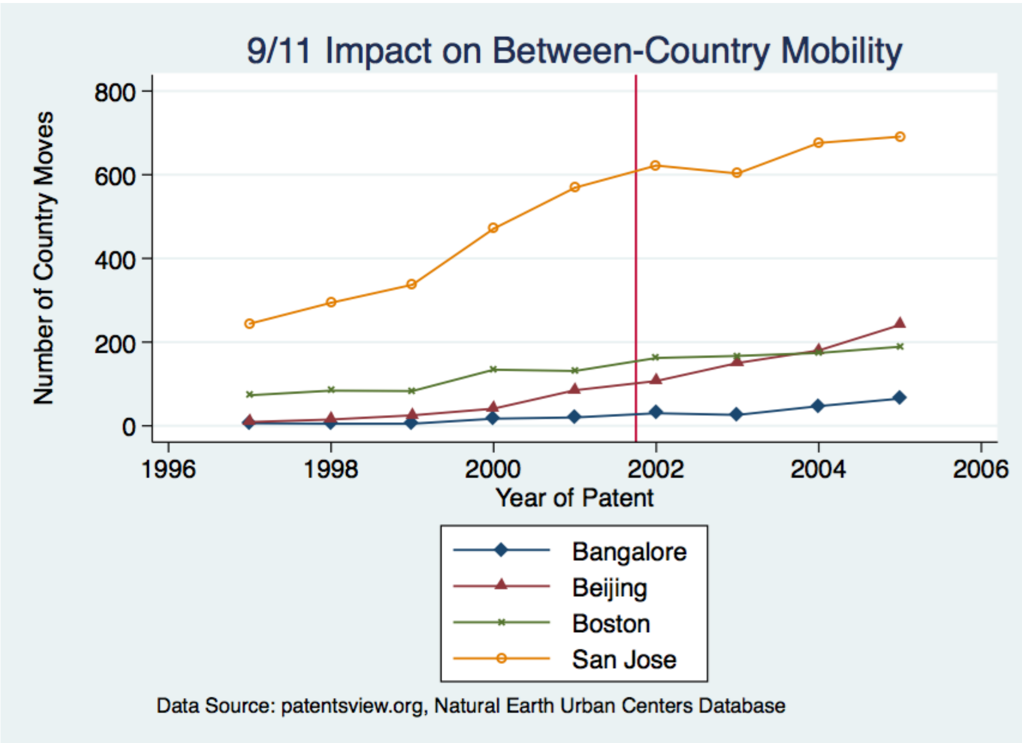

Figure 5: 9/11 impact on country moves by year

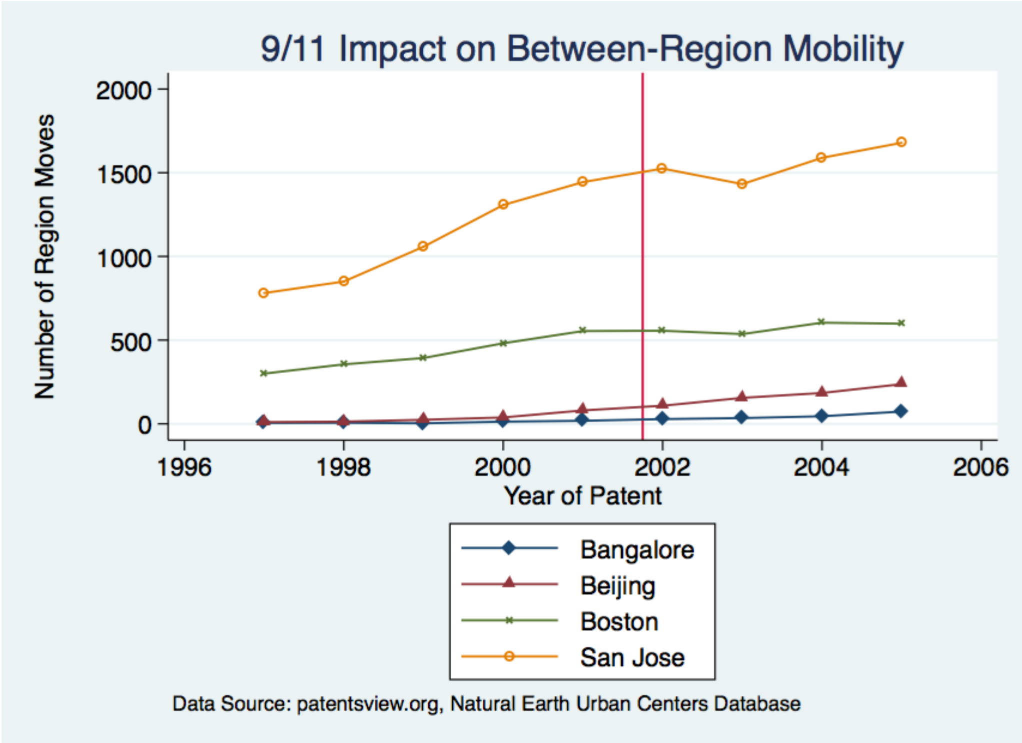

Figure 6: 9/11 impact on region moves by year

Table 1: Summary statistics

Variable	Mean	Std. Dev.	N
moved region	0.08	0.271	8537410
moved country	0.029	0.166	8537410
log(complexity)	-1.004	2.383	7957162
inventor pool	8.542	46.674	8537410
team pool proxy	27.901	112.154	6875208

Table 2: Most complex technology subclasses in 2010

id	Avg Complexity	Technology
32	6.691109	Surgery & Med Inst.
25	6.583521	Electronic business methods and software
24	6.361433	Information Storage
22	5.941292	Computer Hardware & Software
21	5.627072	Communications

Table 3: Least complex technology subclasses in 2010

id	Avg Complexity	Technology
11	2.533947	Agriculture,Food,Textiles
33	3.468262	Genetics
66	3.488879	Heating
52	3.518574	Metal Working
63	3.661588	Apparel & Textile
53	3.667615	Motors & Engines + Parts
55	3.712974	Transportation

Table 4: Preliminary Regression of Mobility of Inventors on Complexity of Inventions

	(1) log(complexity)	(2) log(complexity)	(3) log(complexity)
moved region	0.389***	0.383***	0.957***
	(0.000)	(0.000)	(0.000)
moved country	0.751***	0.736***	1.610***
	(0.000)	(0.000)	(0.000)
IPR index		-0.0371***	-0.0229***
		(0.000)	(0.000)
moved region * IPR index			-0.0601***
			(0.000)
moved country * IPR index			-0.0964***
			(0.000)
Observations	7957162	7918297	7918297
R^2	0.00676	0.00721	0.00757
Clustered SE	No	No	No
Year Dummies	No	No	No
Sample	All Obs	All Obs	All Obs

p-values in parentheses

None of the models include fixed effects, or technology subcategory controls

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: IPR Strength and Mobility of Inventors on Complexity of Inventions

	(1) log(complexity)	(2) log(complexity)	(3) log(complexity)
moved region	0.847***	-0.0635	0.270***
	(0.000)	(0.559)	(0.000)
moved country	1.824***	2.385***	1.255***
	(0.000)	(0.000)	(0.000)
IPR index	-0.0257***	0.0773***	
	(0.000)	(0.000)	
moved region * IPR index	-0.0530***	0.0322**	
	(0.000)	(0.003)	
moved country * IPR index	-0.110***	-0.189***	
	(0.000)	(0.000)	
strong IPR			0.473***
			(0.000)
moved region * strong IPR			-0.0130
			(0.744)
moved country * strong IPR			-0.833***
			(0.000)
Observations	5280190	5280190	5280190
R^2	0.009	0.145	0.146
Clusters	579,806	579,806	579,806
Clustered SE	Region Assignee	Region Assignee	Region Assignee
Year Dummies	No	Yes	Yes
Sample	All Obs	All Obs	All Obs

p-values in parentheses

None of the models include fixed effects, or technology subcategory controls

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: IPR Strength and Mobility of Inventors on Varying Measures of Complexity

	(1)	(2)	(3)	(4)
	log(complexity) 2x	log(complexity) 3x	log(complexity) 4x	log(complexity) 5x
moved region	0.270^{***}	0.269	0.381	0.450
	(0.000)	(0.072)	(0.068)	(0.102)
moved country	1.255^{***}	2.219^{***}	2.847^{***}	3.490^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
strong IPR	0.473^{***}	2.089^{***}	2.823^{***}	3.540^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
moved region * strong IPR	-0.0130	-0.0914	-0.122	-0.106
	(0.744)	(0.562)	(0.579)	(0.715)
moved country * strong IPR	-0.833^{***}	-2.086^{***}	-2.752^{***}	-3.465^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	5280190	537491	460578	391121
R^2	0.146	0.026	0.026	0.026
Clusters	579,806	91,564	80,985	71,085
Clustered SE	Region Assignee	Region Assignee	Region Assignee	Region Assignee
Year Dummies	Yes	Yes	Yes	Yes
Sample	All Obs	All Obs	All Obs	All Obs

p-values in parentheses

None of the models include fixed effects, or technology subcategory controls

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Technology Complexity and Mobility of Inventors on Invention Complexity

	(1) log(complexity)	(2) log(complexity)	(3) log(complexity)
moved region	0.172***	0.183***	0.210
	(0.000)	(0.000)	(0.055)
moved country	1.213***	0.305***	0.0599
	(0.000)	(0.000)	(0.700)
strong IPR	0.408***		
	(0.000)		
moved region * strong IPR	0.0192		
	(0.590)		
moved country * strong IPR	-0.813***		
	(0.000)		
moved region * tech complexity	0.149***	0.250***	0.0448
	(0.000)	(0.000)	(0.734)
moved country * tech complexity	0.00195	-0.123***	0.566**
	(0.927)	(0.000)	(0.002)
Observations	5245466	2599718	32095
R^2	0.169	0.251	0.124
Clusters	575,441	323,620	4,647
Clustered SE	Region Assignee	Region Assignee	Region Assignee
Year Dummies	Yes	Yes	Yes
Technology Controls	Yes	Yes	Yes
Sample	All Obs	US inventions	Indian inventions

p-values in parentheses

None of the models include fixed effects

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Extent of Regional Mobility of Inventors on Invention Complexity

	(1)
	log(complexity)
moved region	-0.0334
	(0.287)
moved country	1.089***
	(0.000)
strong IPR	0.407***
	(0.000)
moved region * strong IPR	0.0503
	(0.103)
moved country * strong IPR	-0.727***
	(0.000)
moved region * tech complexity	0.148***
	(0.000)
moved country * tech complexity	-0.0181
	(0.389)
region moves = 1	-0.0236***
	(0.000)
region moves = 2	0.0167
	(0.058)
3 <= region moves <= 5	0.0517***
	(0.000)
6 <= region moves <= 8	0.120***
	(0.000)
region moves >= 9	0.488***
	(0.000)
Observations	5245466
R^2	0.170
Clusters	575,441
Clustered SE	Region Assignee
Year Dummies	Yes
Technology Controls	Yes
Sample	All Obs

p-values in parentheses

None of the models include fixed effects

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Extent of Country Mobility of Inventors on Invention Complexity

	(1)
	log(complexity)
moved region	0.0584
	(0.073)
moved country	0.864***
	(0.000)
strong IPR	0.409***
	(0.000)
moved region * strong IPR	0.0843*
	(0.012)
moved country * strong IPR	-0.744***
	(0.000)
moved region * tech complexity	0.147***
	(0.000)
moved country * tech complexity	-0.0351
	(0.089)
country moves = 1	-0.0155
	(0.156)
country moves = 2	0.0522***
	(0.000)
country moves = 3	0.0673***
	(0.000)
country moves = 4	0.118***
	(0.000)
country moves >= 5	0.652***
	(0.000)
Observations	5245466
R^2	0.170
Clusters	575,441
Clustered SE	Region Assignee
Year Dummies	Yes
Technology Controls	Yes
Sample	All Obs

p-values in parentheses

None of the models include fixed effects

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Inventor - Technology Class Controls in Mobility of Inventors on Invention Complexity

	(1) log(complexity)	(2) log(complexity)
moved region	0.172***	0.135***
	(0.000)	(0.000)
moved country	1.213***	1.167***
	(0.000)	(0.000)
strong IPR	0.408***	0.382***
	(0.000)	(0.000)
moved region * strong IPR	0.0192	0.0150
	(0.590)	(0.669)
moved country * strong IPR	-0.813***	-0.773***
	(0.000)	(0.000)
moved region * tech complexity	0.149***	0.149***
	(0.000)	(0.000)
moved country * tech complexity	0.00195	0.000912
	(0.927)	(0.966)
inventor-tech class		-5.72e-08***
		(0.000)
Observations	5245466	5245466
r2	0.169	0.169
N_clust	575,441	575,441
Clustered	Region Assignee	Region Assignee
Year	Yes	Yes
Tech	Yes	Yes
InventorClass	No	Yes
Sample	All Obs	All Obs

p-values in parentheses

Unable to add inventor-technology class dummies since there are 4,617,880 unique inventor-technology class tuples

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Using 9/11 Shock to Estimate the effect of Mobility of Inventors on Invention Complexity

	(1) log(complexity)	(2) log(complexity)	(3) log(complexity)
moved region	0.227***	0.0227	0.314***
	(0.000)	(0.165)	(0.000)
moved country	0.151***	0.227***	0.0604
	(0.000)	(0.000)	(0.057)
strong IPR	-0.254***		-0.297***
	(0.000)		(0.000)
moved region * strong IPR	-0.0541**		-0.0808***
	(0.006)		(0.000)
moved country * strong IPR	-0.0544		-0.0774*
	(0.071)		(0.013)
moved region * tech complexity	-0.000520	0.100***	-0.0117
	(0.971)	(0.000)	(0.566)
moved country * tech complexity	0.0219	-0.0444	0.0392
	(0.242)	(0.141)	(0.092)
inventor-tech class	1.78e-08**	3.78e-08***	-9.05e-09
	(0.001)	(0.000)	(0.273)
9/11 Shock	-0.121***	-0.119***	-0.130***
	(0.000)	(0.000)	(0.000)
moved region * 9/11	0.0423***	0.146***	-0.0140
	(0.000)	(0.000)	(0.368)
moved country * 9/11	0.127***	0.0453	0.203***
	(0.000)	(0.111)	(0.000)
Observations	1578946	796535	782411
r2	0.065	0.068	0.072
N_clust	223,041	124,376	98,799
Sample	All Obs	US Inventions	Non-US Inventions

p-values in parentheses
Standard Errors are clustered at the region-assignee level
All models include year dummies and NBER technology subcategory dummies
Control for inventor-technology subcategory included
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Instrumenting with 9/11 Shock to Estimate the effect of Regional Mobility of Inventors on Invention Complexity

	(1) log(complexity)	(2) log(complexity)	(3) log(complexity)
moved region	-23.69***	-6.135***	-16.05***
	(0.000)	(0.001)	(0.001)
strong IPR	-4.212***		-2.777***
	(0.000)		(0.000)
moved region * strong IPR	20.81***		13.32***
	(0.000)		(0.001)
moved country * strong IPR	-2.743***	4.387***	-2.281**
	(0.000)	(0.000)	(0.001)
moved region * tech complexity	5.355***	6.278***	5.778**
	(0.000)	(0.000)	(0.001)
moved country * tech complexity	4.375***	-4.209***	3.530***
	(0.000)	(0.000)	(0.001)
inventor-tech class	-0.000000307***	-8.79e-08*	-0.000000378***
	(0.000)	(0.015)	(0.001)
Observations	1578946	796535	782411
R^2	.	.	.
Clusters	223,041	124,376	98,799
Sample	All Obs	US Inventions	Non-US Inventions

p-values in parentheses

Standard Errors are clustered at the region-assignee level

All models include year dummies and NBER technology subcategory dummies

Control for inventor-technology subcategory included

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$