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The effect of patent grant on the geographic reach of patent trade

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ABSTRACT

This paper examines whether patents increase the geographic reach of the market for ideas. By employing a dataset of 25,127 US patents traded between US located firms, we find that patents sold during application phase are less likely to be traded outside the seller's state than patents that have been issued. To tackle the endogeneity issues we employ coarsened exact matching techniques. We find that patent grant increases the likelihood of a patent to be traded across boundaries of the state. This evidence is stronger for patents originating from the less innovative US states.

1. Introduction

Innovative activity is at the heart of economic growth and the knowledge-based economy. A key driver of innovative activity is the exchange of ideas (Audretsch & Feldman, 1996). Scholars have shown that knowledge flows increase the speed of innovative activity and subsequently the rate of economic growth (Coe & Helpman, 1995; Grossman & Helpman, 1991). As a result, a great deal of attention has been paid to channels that can embody knowledge flows; namely, Foreign Direct Investments (FDI), trade of physical goods, inventor mobility and patent citations.[1]

Recently, the market for patents has received considerable attention as a mechanism through which ideas are exchanged and, therefore, a conduit of knowledge flows. As Ouellette (2012) shows, researchers receive information from studying patent documents in addition to scientific papers, while Bessen (2005) argues that the patent system should operate as a means for the diffusion of technical information disclosed in inventions. Johnson and Liu (2011) show, for the case of Chinese, that technology markets enhance knowledge spillovers and innovation.

Geographic distance has been recognized as one of the most important obstacles for all the aforementioned channels of knowledge diffusion, including patent transactions.[2] Burhop and Wolf (2013) found that geographic distance mitigates patent transactions and

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[1] Branstetter (2006) tested and verified that FDI embodies knowledge flows between Japanese and US firms. Keller (2002) found that accessible R&D from other industries through trade increases the own industry's productivity. Kim & Marschke (2005) showed that hiring high skilled workers increases the knowledge stock resulting in larger innovation output for a given firm. Finally, in the seminal paper Jaffe, Trajtenberg, and Henderson (1993) approximated knowledge flows via patent citations; the large literature stemming from this study has shown that citations approximate knowledge flows with a significant effect on production of innovation (for a recent review consult Autant-Bernard, Fadairo, & Massard, 2013).

[2] For instance Peri (2005) found significant negative effects of distance in the reach of patent citations. For the large literature of the negative effect of distance on trade see Disdier and Head (2008).

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1047-8310/

Drivas and Economidou (2014) came to similar conclusions as regards to patent citations and patent trade. Given the significant role of patents in technology transfer and the importance of geographic distance as a mitigating factor, a key question that emerges is to what extent patents themselves weaken the localization of technology transfer.

In this paper we investigate whether patent applications are less likely to be sold outside the state compared to issued patents. Our focus, therefore, lies on the patent grant, the event in which a patent application is awarded a patent, and on whether it increases the likelihood of a patent to be sold outside a state.

We utilize the recently compiled dataset by the Office of Chief Economist at the United States Patent and Trademark Office (USPTO). From this dataset we isolate a large sample of patents that were traded between US located firms. We compare whether patents traded before patent grant (i.e. during the application phase) are less likely to be sold outside the state than patents traded after patent grant. There is however an inherent endogeneity problem. Patent applications could simply be traded within state borders because they are introduced for a short period of time and, therefore, known only locally. That is, the patent grant could be merely confounded with an aging effect and it could mistakenly be interpreted as the cause of the reach of the transfer.

To tackle this endogeneity issue we perform a coarsened exact matching of patents traded based on the lag of sale since filing date. By matching patents on this lag, we avoid endogeneity issues associated with the age of the patent application or patent. We also match patents based on their citations and the state's patent profile to capture patent quality, and the market opportunity for the patent. We follow the procedure proposed by Iacus, King, and Porro (2012) to match patents based on these characteristics.

Results show that patents originating from similar states in terms of patenting profile with similar trade lags and patent citations are more likely to be traded outside the state compared to patent applications. This indicates that patent grant plays a role in the reach of the market for ideas. Furthermore, we find that the patent grant effect varies across technology fields. Finally, for patents that originate from the forty less innovative states in the US, patent grant has a greater impact than for patents that originate from the top ten innovative states. This finding implies that, the publicity associated with the patent grant is more important in shaping the geographic reach of patent transfers when patents originate from less innovative states.

Our paper relates closely to two streams of literature. The first is the market for patens. This topic was first studied in the economic history literature. Lamoreaux and Sokoloff (1999, 2001) investigated how the patent system contributed to the development of a formal market of trading intangible assets in the US during the 19th century. Burhop and Wolf (2013) examined the market of patents in Germany between 1884 and 1913 and focused primarily on the geographic determinants of patent assignments.[3] While this literature is concerned with the geographic aspect of patent transactions, it has not examined the role of patent grants. Serrano (2010) was the first to use modern day data from USPTO to analyze the determinants of patent trades and focused on the gains from such trades.

The second stream examines the impact of patent grant on licensing. Two recent studies by Elfenbein (2007) and Gans, Hsu, and Stern (2008) concluded that patent grant increases the hazard rate of licensing.[4] However, they did not offer any insights on the geography of the licensing activity and whether this is influenced by the event of patent grant. The only study which examines the impact of patents on the geography of innovative activity is by Moser (2011) which found that an exogenous shift towards patenting chemical inventions enhanced the geographic diffusion of such innovations. However, she did not explicitly examine the market for patents.

We contribute to the aforementioned literature by examining the role of patent grant in the geography for the market of ideas. Geography is one of the most important obstacles of accessing other regions' R&D (Keller, 2002). Therefore, examining whether patents alleviate part of the geographic boundaries in the market of ideas can play a role in our understanding of how patents moderate the role of geography.

The next section describes the data and the empirical setup. In Section 3 we present the results and in Section 4 the paper concludes. Technical details of the coarsened exacting matching are included in Appendix 1.

2. Data description and empirical setup

2.1. Data construction

Data on patent trades have graciously been supplied to us by the Office of Chief Economist at the USPTO.[5] The Office has compiled a dataset which discloses patent assignments (transactions) between entities which are registered at the USPTO.[6] This dataset is called "*Patent Assignment Dataset*". A typical assignment is characterized by a unique identifier (i.e. reel frame), the names of the buyer (i.e. assignee) and seller (i.e. assignor), the date that the transaction agreement was signed (execution date) and the patent numbers or patent applications that are traded per assignment. For detailed information on the dataset see Graham and Marco (2014).

While compiling our sample we faced two main challenges. The first one relates to the fact that entities are not required to report transactions to the USPTO. Hence, it is likely that a number of transactions have not been disclosed to the USPTO either due to negligence, or to strategic behavior of firms. Nevertheless, for legal and perhaps accounting reasons, they have incentives to do so.[7] However, given the question in our paper, as long as this missing information is random for patents sold before (during application) and after grant, it is not likely to bias our results.

3 See Burhop and Wolf (2013) and the references therein for more references concerning the market of patents in a historical context.

4 This finding has also been supported by the theoretical literature (Hellman 2007; Hellmann & Perotti, 2011).

5 As of recently, the data are publicly available at Google bulk downloads: http://www.google.com/googlebooks/uspto-patents-assignments.html.

6 In the US, when entities transfer US issued patents to other entities, they disclose such transactions to the USPTO. The latter are called assignments.

7 For instance, in a potential litigation the courts will need to know clearly which firm or organization holds the intellectual property in question. Thus, parties that are involved in such transactions have incentives to disclose such information to the USPTO.

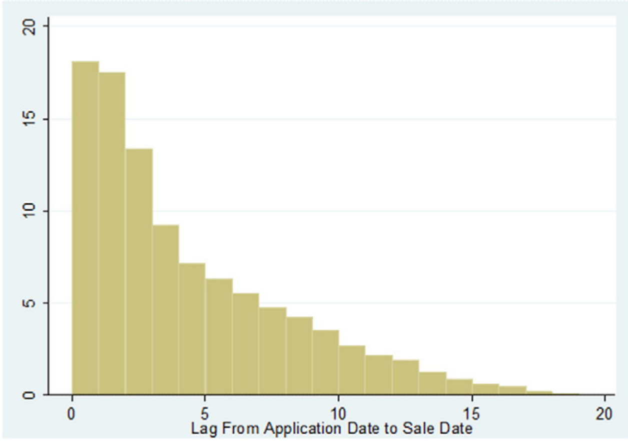

Fig. 1. Distribution of lag from application date to sale date.

The second challenge is associated with excluding "routine" transactions. In the US, only an individual can file for a patent application. Subsequently, this individual may re-assign the patent to the firm or institution where he/she is employed. Such "routine" transactions are also included in the dataset. However, in our case we only consider transactions between firms and we exclude transactions that involve persons; hence we have not included such transactions in our sample.

The concluding sample includes 25,127 patents granted between 1990 and 2003 which have been traded among US located firms for the period 1986 to 2010 and for which location information for both the assignee (buyer) and the assignor (seller) was available. Since our objective is to examine the effect of patent grant on the probability of the patented invention to be sold outside the state of the seller, we distinguish between two groups of patents. The first group is composed by patent applications that have been sold during the application phase. We refer to these patent applications also as "*patents*" throughout the text, as they are eventually patented. We call this group of patents "*group BEFORE*", referring to the fact that they have been sold before patent grant. The second group includes patents that have been sold after patent grant. We name this group "*group AFTER*".

Further, for each patent we collected the number of citations they receive from subsequent patents through 2010. This type of citations is called forward patent citations. We obtained this information from Lai et al. (2010). We collected information regarding the primary US classification of each patent from the NBER data project. Since the latter dataset has the population of patents and location information for each patent owner, we are able to compute the number of patents each state produces each year and the fraction of patents in each technology field.

2.2. Coarsened exact matching procedure

Patent length by and large cannot be influenced by firms[8] (Regibaeu and Rockette 2010). Therefore, from the firms' viewpoint the exact timing of patent grant is exogenous. However, because it takes considerable time for a patent to be issued since its application date,[9] patent grant could just be picking up an age effect of the patented invention. In other words, the longer the time period is since the inception of the patented invention, the longer it takes for firms to become aware of the invention. Hence, the patent grant could be confounded with the age of the patented invention which could be the sole driver of a patent being sold further away.

To tackle this endogeneity problem, we match the patented inventions in *group AFTER* with the patented inventions in *group BEFORE*, based on the lag between the sale date and the application date; we denote this lag as *LAG*. We implement the Coarsened Exact Matching (CEM) procedure by Iacus et al. (2012). By matching the *AFTER group* with the *BEFORE group* based on this lag, we avoid the endogeneity issue of the patent grant being correlated with the age of the patented invention.

The distribution of LAG is displayed in Fig. 1. As can be seen, most of the patented inventions are sold soon after application, a finding consistent with Serrano (2010) and with results from the licensing literature (Elfenbein, 2007). Of note is also the lag of sale date from grant date, which is presented in Fig. 2. The highest likelihood of a patent being sold occurs within a few years before or after grant.

From the above findings we conclude that in order to have a comprehensive match of *AFTER* patents with *BEFORE* patents based on *LAG*, we should consider only patents that were sold within a few years from application date and have an application length of similar or less than that amount of years. Initially, we chose $LAG \leq 6$ and $ApplicationLength \leq 6$. This reduces our sample to 17,780 observations.[10,11] Nonetheless, for robustness, in later specifications i) we also exclude patents sold within one year since the application date, ii) we add patents that were sold within 7 years from the application date and have an application length of less than or equal to

[8] In other jurisdictions, firms can significantly influence patent length via deferral examinations. However, this scheme does not exist in the USPTO.

[9] In this sample the average application length is 2.37 years.

[10] This way, we also avoid a right censoring problem for patents that are granted in 2003 as they would only have 8 years to be sold after grant.

[11] 354 patents were excluded because their application length was larger than 6 years. The additional 6993 patents were rejected as their LAG was larger than 6 years. This implies that 17,780/25,127 = 70.1% of patents are licensed within 6 years.

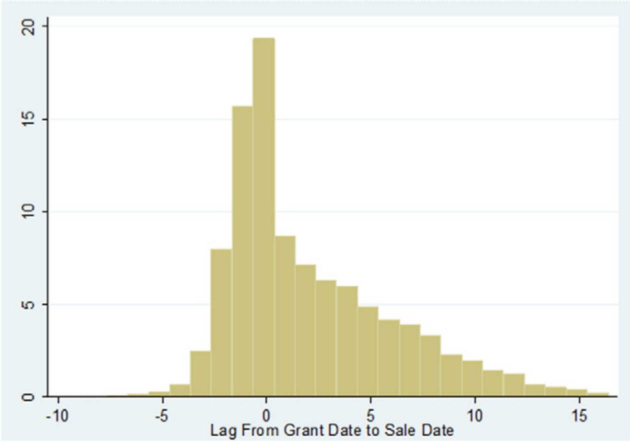

Fig. 2. Distribution of lag from grant date to sale date.

7 years, iii) or only consider patents that were sold within 5 years from the application date and have an application length of less than or equal to 5 years in later specifications.

In addition to the *LAG* variable, we match patents based on two more key variables: the citations that the patent receives through 2010 and the share that the seller's state has in the particular technology field.[12] The first variable (*CITES*) accounts for the quality/importance of the patent (Hall, Jaffe, & Trajtenberg, 2005; Harhoff, Narin, Scherer, & Vopel, 1999). Higher quality patents may become known faster and, therefore, the probability of being sold outside state borders could be higher. The second variable (*SHARE*) accounts for the seller's state innovative activity in the particular field. This way, we control for state bias where technologies that are close to the state's technology portfolio are more likely to be sold within the state regardless of whether they belong in group BEFORE or AFTER. We then coarsen the joint distribution of these three variables into strata and match *BEFORE* with *AFTER* patents. Appendix 1 describes in detail the coarsened matching procedure.

2.3. Summary statistics

Table 1 shows the summary statistics for each group of patents. More specifically, Panel A displays the summary statistics for the two groups prior to the matching procedure, while Panel B post the matching procedure. Note that *SameState* equals to 1 if a patent is sold within the seller's state and equals to zero if it is sold outside the seller's state. In Panel A (raw data), *AFTER* patents are 4% less likely to be sold within the state and they take on average 2.3 years more to get sold. Therefore, as was initially postulated, *AFTER* patents could indeed be sold outside state borders due to an aging effect. Moreover, *AFTER* patents have 1.4 CITES more on average than *BEFORE* patents.

Panel B shows the summary statistics of the coarsened groups. First of all, the matching rate for group *AFTER* is 88% (6499/7385), while for group *BEFORE* is 97.7% (10,158/10,395). Second, a patent in group *AFTER* is 9% more likely to be sold outside a state than a patent in group *BEFORE*. However, unlike Panel A, patents on average now have similar *LAG*, *CITES* and *SHARE*. This is in sharp contrast with the results in Panel A, where the difference in the likelihood of a patent being sold within the state could be attributed to an aging effect. Fig. 3 illustrates the probability of a patent sold within the state in relation to the time it takes to be sold since the application date (i.e. *LAG*). Regardless the time it takes for a patent to be sold, patents sold after grant have lower probability to be sold within the state than patents with similar LAG which are sold before grant.

2.4. Empirical implementation

For the coarsened sample, we estimate the following regression:

$$SameState_i = \alpha_0 + g_1 AfterGrant_i + AppYearDummy + TechnologyDummy \quad (1)$$

As before, $SameState_i$ takes value 1 if patent *i* is sold within the state and 0 if it is sold outside the state. $AfterGrant_i$ is a dummy variable which takes value 1 if patent *i* is sold after grant and 0 otherwise. In other words if patent *i* belongs to the *AFTER* group, then $AfterGrant_i = 1$ and if it belongs to the BEFORE then $AfterGrant_i = 0$. *AppYearDummy* is a group of dummies that cover the application year (overall nineteen dummies) and *TechnologyDummy* is a set of dummy variables representing the thirty seven technology fields (overall thirty six dummies), as defined by Hall, Jaffe, and Tratjenberg (2001) based on the primary US Classification.

[12] We define the technology field in the following way; we obtain the primary US classification of each patent from the NBER patent data project (https://sites.google.com/site/patentdataproject/). Based on Hall et al. (2001) and the NBER update, where they categorize each classification in 37 technology fields, we accordingly assign each patent to one of the 37 technology fields.

Table 1
Summary statistics of original and matched samples. Distinguish between BEFORE and AFTER groups.

	Panel A: prior matching		Panel B: matched patents	
	Group *BEFORE* (N = 10,395)	Group *AFTER* (N = 7385)	Group *BEFORE* (N = 10,158)	Group *AFTER* (N = 6499)
SameState	0.44	0.4	0.50	0.41
	(0.5)	(0.49)	(0.50)	(0.49)
Lag	1.35	3.72	3.43	3.48
	(0.96)	(1.28)	(1.16)	(1.16)
Cites	11.9	13.3	13.07	13.25
	(22.2)	(22.8)	(22.25)	(23.11)
Share	0.06	0.05	0.05	0.05
	(0.04)	(0.04)	(0.04)	(0.04)

Notes: standard errors in parentheses.

We estimate (1) using OLS. While the dependent variable (*SameState*) is binary, we opt for a linear estimation due to the number of dummy variables. Results from a probit model yield qualitatively similar estimates.

3. Results

Table 2 displays the results of the effect of a grant on patent to be sold within the state. Column 1 considers the baseline model which includes patents that were sold within 6 years from application date and have an application length of less than or equal to 6 years. *AFTER* patents are 9% less likely to be sold inside the state compared to *BEFORE* patents. This finding implies that issued patents can stretch the geographic reach of the market for ideas. To check the sensitivity of our results, in Column 2 we only consider patents that were sold within 5 years and have an application length of less than or equal to 5 years. This reduces the sample to 15,360 patents. The matching rate for patents in group *BEFORE* is 97.7% (9,9916/10,153) and for patents in group *AFTER* 92.6% (5444/5881). Results are very similar to Column 1. Next, we consider the baseline sample of Column 1 and add patents that were sold within 7 years from application date and have an application length within 6 and 7 years. This increases our baseline sample to 18,573 observations and the matching rates for *BEFORE* patents and *AFTER* patents are 97.8% (10,307/10,544) and 94.8% (8266/8720) respectively. Column 3 displays these results which are similar to those previously mentioned.

As a last robustness check, we consider the baseline sample but exclude patents sold within one year since the application date in Column 4. We consider this specification, as many patents could be transferred immediately to the parent firms or alternatively to the subsidiary firms. This reduces the sample to 12,459 patents and the matching rate for *BEFORE* patents is 99.7% (5942/5962) while for *AFTER* patents is 88.6% (6517/7354). Results are in agreement with those presented before. Since our findings are overall qualitatively similar and statistically significant at the 1% level, for the remainder we consider patents that were sold within 6 years from the application date and have an application length of less than or equal to 6 years.

Next, in Table 3 we examine whether the role of patent grant varies across technology fields. We classify each patent to a broad technology field per Hall et al. (2001): *Chemical*, *Computer*, *Drug*, *Electronics*, *Mechanical* and *Other*. In each case we first consider each group of patents by their respective technology fields and perform the coarsened exact matching for each technology group separately. Thus, the sample in each procedure was reduced substantially and therefore the matching rate was not satisfactory in certain cases.

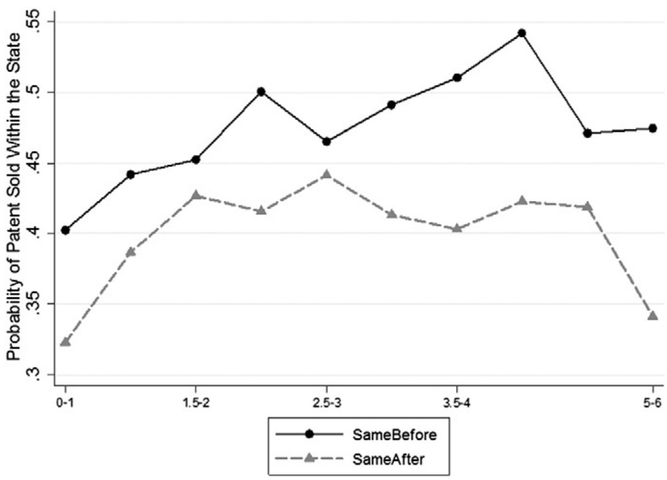

Fig. 3. Probability of a patent sold within the state in relation to the *LAG*.

Table 2
Effect of patent grant on trade within state.

Variables	(1) Baseline (patents sold within 6 years from application date)	(2) Patents sold within 5 years from application date	(3) Baseline + patents sold within 7 years from application date	(4) Baseline without patents sold within 1st year since application date
AFTER	-0.0919^{***}	-0.0963^{***}	-0.105^{***}	-0.110^{***}
	(0.0280)	(0.0201)	(0.0265)	(0.0278)
cons	0.511^{**}	-0.0425	0.407^{***}	0.473^{**}
	(0.217)	(0.0331)	(0.0512)	(0.206)
Observations	16,657	15,360	18,573	12,459
R-squared	0.492	0.511	0.490	0.483

Notes: regressions are estimated via ordinary least squares and they report heteroskedastic robust standard errors (in parentheses). All regressions include application year dummies and technology field dummies. Significance level: *10%, **5%, and ***1%.

Table 3
Effect of patent grant on trade within state across technology fields.

Variables	Chemicals	Computers	Drug	Electronics	Mechanics	Others
AFTER	-0.0741	-0.0366	-0.0473^{*}	-0.155^{**}	-0.150^{**}	-0.124^{**}
	(0.0445)	(0.0237)	(0.0194)	(0.0473)	(0.0465)	(0.0535)
Cons	0.166^{**}	0.976^{***}	0.475^{***}	-0.0177	0.112^{*}	0.165^{***}
	(0.0595)	(0.00861)	(0.0108)	(0.118)	(0.0534)	(0.0215)
Observations	1837	2397	1438	1693	1198	1754
R-squared	0.442	0.441	0.495	0.499	0.544	0.550

Notes: regressions are estimated via ordinary least squares and they report heteroskedastic robust standard errors (in parentheses). All regressions include application year dummies and technology field dummies. Significance level: *10%, **5%, and ***1%.

Column 1 of Table 3 presents the results for the Chemical patents. The matching rate for group *BEFORE* is 94.1% (950/1010) and for group *AFTER* 73.3% (887/1210). While the coefficient of *AfterGrant* is not significant, in absolute size, it is similar as the one in Column 1 of Table 2. This implies that patent grant has almost the same influence in the Chemical patents as in the population of patents.

Column 2 shows the influence of patent grant in Computer patents. The matching rate for *BEFORE* patents is 90.2% (1432/1588) and for *AFTER* patents 72.3% (965/1334). Here the coefficient is both close to zero and insignificant. In Column 3, for *Drug* patents the matching rate is disappointing; for *BEFORE* patents it is 87.4% (789/903) and for *AFTER* patents 60.5% (649/1073). Therefore, for this case results should be interpreted cautiously. While the coefficient is approximately half the size from the baseline specification, it is significant at the 10% level. Further, Columns 4–6 exhibit the results for the Electronics, Mechanical and Other patents respectively. Results are similar to the overall population with the coefficient of AFTER being negative and significant.[13]

Overall, results show that patent grant increases the geographic reach of a sale regardless of the technology field. The weakest results are obtained in the cases of Computers and Drug. While results should be interpreted cautiously, these findings could imply that for these technology fields patent grant may have a smaller impact. Reasons may be that there is a higher concentration in these fields across space for these technologies (Drivas & Economidou, 2014; Maurseth & Björn, 2009); therefore the majority of potential buyers are concentrated in few geographic clusters, and the fact that there may be additional channels though which these types of inventions are diffused across space. This latter reason can decrease the significance of the role of patent grant as a medium of knowledge diffusion.

Our most interesting results are found when we examine whether patent grant plays a differential role in case a patent originates from one of the top 10 innovative states or from a less innovative state. As top 10 innovative states, we consider the states that consistently over the years have spent the most considerable amounts in R&D based on the Science and Engineering State Profiles of the National Science Foundation.[14] These 10 states are CA, IL, MA, MD, MI, NJ, NY, PA, TX and WA.[15] Column 1 of Table 4 considers patents originating from the least innovative states. Overall, of 13,316 patents, 45.2% (6018) originate from these states. The matching rate for *BEFORE* patents is 96.8% (2693/2783) while for *AFTER* patents is 81.1% (2625/3235). The coefficient shows that patent grant decreases the probability of a patent to be sold within the state by 10.6%; the coefficient is significant at the 1% level. Column 2 considers patents that originate from the top 10 innovative states. The matching rate for *BEFORE* patents is 99.8% (3172/3179) while for *AFTER* patents is 83.4% (3434/4119). The coefficient demonstrates that patent grant reduces the likelihood of the patent being sold within the state by 5%. Moreover, the coefficient is significant at just the 10% significance level. This comparison starkly shows that patent grant plays a greater role in the geographic reach of the market for ideas for patents originating from less innovative states than for patents

[13] We should not however that the matching rate for the *AFTER* patents is disappointing in all three sets. Specifically, for Electronics, the rate for *BEFORE* patents is 95.9% (896/934) and for *AFTER* patents 64.7% (797/1232). Mechanical *BEFORE* patents have matching rate of 83.9% (566/675) and *AFTER* patents 57.8% (632/1093). Finally, for the category *Other BEFORE* patents have a matching rate of 93.8% (799/852) and *AFTER* patents a rate of 67.6% (955/1412).

[14] http://www.nsf.gov/statistics/states/.

[15] CA stands for California; IL for Illinois; MA for Massachusetts; MD for Maryland; MI for Michigan; NJ for New Jersey; NY for New York; PA for Pennsylvania; TX for Texas; WA for Washington.

Table 4
Effect of patent grant on trade within state. Distinguish between top innovative and less innovative states.

	(1)	(2)
Variables	Less innovative states	Top innovative states
AFTER	-0.106^{***}	-0.0503^{*}
	(0.0346)	(0.0284)
cons	1.216^{***}	-0.101
	(0.0327)	(0.133)
Observations	5318	6606
R-squared	0.506	0.498

Notes: regressions are estimated via ordinary least squares and they report heteroskedastic robust standard errors (in parentheses). All regressions include application year dummies and technology field dummies. Significance level: *10%, **5%, and ***1%.

originating from the top ten innovative states. Corporations located in the top innovative states are likely to have ties/connections both with the local business environment and with out-of-state corporations. Hence, the patent grant is not as important as in the case of patents originating from the least innovative states.

4. Conclusion

This paper examines whether patents stretch the geographic reach of the market for ideas. Our setting is patent transfers between US located firms. We examine whether patents sold during application phase are less likely to be sold outside the seller's state than patents that are sold after they are issued. In other words, we examine the effect of the patent grant on the probability that the patent will be sold outside the seller's state. Our dataset consists of 25,127 patents granted between 1990 and 2003 and traded among US located firms during the period 1986–2010. Patent grant, however, maybe conflated with merely a timing element; patented inventions may be known for a longer time period and therefore more likely to be sold further way than inventions during the application phase. To deal with this endogeneity problem, we use coarsened exact matching techniques based on the time they take to be sold; in addition we match patents based on quality and state macroeconomic elements.

We find that issued patents that display similar characteristics are more likely to be sold outside the state's boarders, compared to patent applications. This finding indicates that patents play a role in mitigating the geographic distance in the market for ideas. The result is robust to different “cuts” of the data. This result holds across technology fields though it is weaker for Computers and Drug patents. A number of reasons may apply but results should be interpreted cautiously as the matching rates are not satisfactory. Our final important finding is that the aforementioned effect is stronger for patents originating from less innovative states than from top innovative states. Hence, patents may be more necessary to firms that are not located within innovative clusters to stretch the geographic reach of the market for ideas.

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Appendix 1

As the objective is to estimate the effect of patent grant on the probability of a patent to be traded outside the state, we need to address a key endogeneity issue; i.e. patent grant could be correlated with other factors that influence the reach of the trade but cannot be attributed to patent grant itself. As patent grant takes on average years after application date, patented inventions could be traded further away simply because they are known for a longer time and therefore the probability to be traded outside the state increases.

Thus, the first and most important task is to match *AFTER* patents with *BEFORE* patents based on the time they take to be sold since application date (denote this lag as *LAG*).

However, we are also interested in matching patents based on quality. Higher quality patents may be traded further away, as they are more likely to be known by more firms. To proxy for quality we use the variable *CITES*, which is the number of citations the patent has received until 2010.

Lastly, it is important to also match patents based on the state's patent profile. For instance, patents in technology field X are more likely to be sold within a state if the state's concentration of patents in technology field X is high. To proxy for this, we use the variable *SHARE*, which is defined as the share a state has in the technology field of the focal patent. Of 17,780 patents, 7385 belong in the *AFTER* group and 10,395 in the *BEFORE* group. To identify control patents for the *AFTER* patents, we take into account three covariates:

1) LAG
2) *CITES*
3) *SHARE*

Our main concern is the *BEFORE* patents to be matched to the *AFTER* patents based on the *LAG*. Therefore, the distribution of *LAG* is coarsened into six month intervals (except the first year), i.e. 11 strata. With respect to *CITES*, the distribution is coarsened into four quartiles.[16] The distribution of *SHARE* is coarsened into four quartiles as well.[17] Next, we coarsen the joint distributions of these covariates by creating 176 strata ($11 \times 4 \times 4 = 176$).

Finally we match the patents in the *AFTER* group with the patents in the *BEFORE* group based on the strata each patent belongs to. Given that this is a computationally intensive procedure we implement the routine by Iacus et al. (2012).[18]

Finally, there are two issues worth noting. First, in any new sample specification that we may propose (e.g. we include patents sold within 6 to 7 years since application date or keeping only patents from a specific technology field) we repeat the above procedure. We may also include more strata in *LAG* and have different cutoff values for the quartiles of *CITES* and *SHARE*.

Second, ideally we would like to match patents based on other determinants as well; for instance, based on the technology field. However, the number of strata would increase dramatically and therefore we would have a poor matching. This is the so-called "*curse of dimensionality*" where, while we could in theory match a number of dimensions, the matching between units in the one group with the units in the other group would be very poor.[19] Nonetheless, not all is lost since we still control for these variables in the regressions.

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[16] A patent belongs in the first quartile if it has accumulated between 0 and 2 citations; in the second if it has accumulated between 3 and 6; in the third if it has accumulated between 7 and 14 and in the fourth if it has accumulated more than 14 citations.

[17] A patent belongs in the first quartile if its state has less than 2% of its patents in the same technological field (per Hall et al., 2001) as the patent, in the second quartile if its state has between 2% and 4%, in the third if its state has between 4% and 7.5% and in the fourth it has more than 7.5%.

[18] The coarsened exact matching routine can be found in the Stata .do file by Blackwell, Iacus, and King (2009).

[19] For a more detailed discussion consult Azoulay, Graff Zivin, and Wang (2010).