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Can You Hear Me Now? The Importance of Location for Knowledge Transfer in the Telecommunications Sector

by
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Abstract

This paper examines the evidence on the clustering of innovators within the telecommunications sector, using U.S. patent citation data to trace their locations over time. While clustering is clearly evident, we use multivariate left-censored Tobit regression analysis to control for identifiable factors, showing that the distance between successive innovators has been rising over time, perhaps even exponentially.

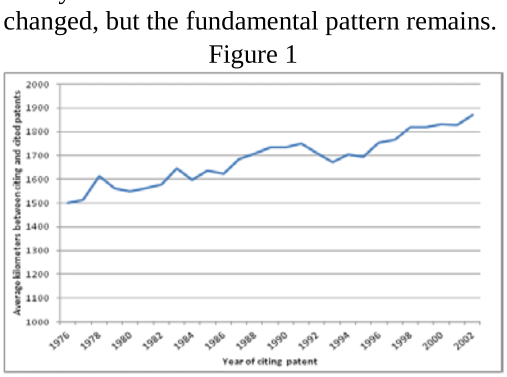
1. Introduction

Firms within an industry often cluster geographically due to localization economies or Marshall-Arrow-Romer externalities that reduce the cost of inputs to firms in the local industry, [1][2]. For some industries, the degree to which knowledge diffuses rapidly or tacitly encourages firms to locate near other firms in the sector [3][4]. To our knowledge no analysis has tested this clustering effect within the telecommunications sector, nor compared its impact across time.

Using all telecommunications patents granted in the U.S. between 1976 and 2002, we show that there is a marked tendency for innovators to cite patents from nearby areas as intellectual background. We statistically test whether this pattern could naturally arise from a tendency to cite other patents listing the same inventor, the same firm assignee, or the same technology class. We conclude that the geographic clustering of citations holds over and above the effects of these other factors, suggesting that there is a local nature to knowledge spillovers (at least insofar as patent citations reflect knowledge flows), but that this tendency is weakening over time.

As Figure 1 shows, the average distance between a citing patent and its bibliographic references has grown by over 350 miles (or twenty percent) between 1976 and 2002. The statistical analysis which follows controls for other factors that have changed, but the fundamental pattern remains.

Figure 1



In section 2 of the paper, we briefly review the relevant literature on energy technology clustering and the geographic nature of knowledge spillovers. Section 3 describes our data set, designed for compatibility with the literature, and Section 4 presents multivariate regression analysis that controls for non-geographic effects in presenting the declining role of distance. Section 5 concludes with implications for policy and further research.

2. Literature Review

Most technical and economics literature suggests that knowledge spillovers cluster geographically, with higher spillovers (more patent citations) occurring locally. The underlying supposition is that inventors are more aware of (or find more use for) inventions located close to them, and therefore build more heavily on local inventions.

Empirical evidence confirms the role of location in the spillover of knowledge from one member of an innovation network to another [5], but some research points out that the importance may differ by technology [6] with location more important for technologies undergoing radical innovation. During technological revolutions, such as telecommunications experienced in the period under study, we expect some large geographic impacts on knowledge flows.

Geographic proximity has already been used to explain the location of R&D-intensive activities [7] due to evidence of localized spillovers within an industry. However, the location of firms is not always a good predictor of the location of innovation [8][9]. Localization of patent citations has been firmly established [10][11][12], with a random sample of patents clearly more likely to cite local patents than patents by parties that are located farther away, an effect prevalent in electronics, optics, and nuclear technology [13]. However, none of these studies examined how that importance changed over time.

On the other hand, there are strong voices in the literature who argue that either distance has never mattered as much as was thought [14], or that the impact of communication technology on productivity or on knowledge transmission across distance will not be that great [15][16].

3. Data

Every patent application must include citations to other patents which were instrumental in the creation of this technology, or which delineate the legal limits of the patent application. Inventors create this citation list to prove the novelty of the patentable product or process, and to provide a record of materials that were consulted during the invention process to protect patent rights in the future. The result is a paper trail of knowledge creation.

Of course, patents records do not reflect the innovation perfectly, as some inventions are never patented and patents vary greatly in importance. However, within the U.S. on a state-by-state level, patents have a high correlation with other measures of innovative activity [8]. Citations themselves do not perfectly reflect the transfer of knowledge, as they may be inserted for a variety of reasons, and perhaps only half show true knowledge transfer [17]. However, if the noisiness of this statistical signal is constant over time, we can use it to compare time periods even with an implied degree of imprecision.

We follow the World Intellectual Property Organization's definition for telecommunications, and our dataset therefore includes all patents granted between 1976 and 2002 that qualify as telecommunications technology, appended with all patents cited by those patents, at least those that were themselves granted between 1976 and 2002. Citing and cited patents from all non-U.S. inventors have been excluded, for reasons of feasibility. However, there is evidence in the literature that international citations are increasing in frequency across a host of technologies [18], evidence which is at least sympathetic to the hypothesis here that citation distances have been increasing over time [19].

Unfortunately, patent citations may cluster for non-geographic reasons, causing a pattern that appears geographic merely through correlation with other phenomena. For example, inventors (or assignees, the firms which retain the patent rights) may be more familiar with their own patents, citing them more frequently than others, which would give a biased impression of the importance of geography. Therefore we include self-citations in the analysis but identify and control for them separately.

Using U.S. patent data from a combination of sources (NBER website as described in [20], in addition to raw data collected by the independent firm MicroPatent), each patent citation's endpoints (citing patent and cited patent) were geo-coded for the primary location of each listed U.S.-based innovator. We identified locations at the geographic center of the city listed as specific addresses are available for less than ten percent of all patent documents.

The result is a dataset of 336,242 citations from U.S.-based telecommunications patent documents to other U.S.-based patent documents. Previous literature [19] indicates that each of the following factors may play some role in the distance of a citation, so this research measured each for every observed citation between citing patent K and cited patent k:

- whether they have the same inventor (hereafter, SI);
- whether they have the same assignee (SA);
- whether they are in the same technology cluster (ST);
- how similar the citing and cited states are in technology types (SC);
- whether the cited patent is also classified as telecommunications (T);
- whether the assignee is a government agency (G);
- whether the assignee is an educational institution (U);
- how old the citation is, in years between citing and cited patent (A), along with its squared term to account for the potentially nonlinear effects of age; and
- year T of citing patent K, to account for citation inflation (Y).

We traced all self-citations, allowing for some flexibility in name spellings (since the United States Patent and Trademark Office, or USPTO, does not standardize name format). These include not only first inventors, but all inventors listed for each patent. Self-citation by inventors accounted for slightly over three percent of all citations, suggesting that while some self-citation is present, there are very strong inter-inventor knowledge spillovers. Self-citation by assignees was slightly more frequent at twelve percent, but both are much lower self-citation rates than have been documented in other sectors like biotechnology [19], suggesting that knowledge transfers between individuals or firms are more common in telecommunications. Unlike academic citations, there is very little reason here to self-cite as a means of advertising, so we can be fairly sure that self-citations are indicators of useful capital or legal protection. Self-citation was coded as a binary variable (SI) for each citation.

It is also possible that patents closer in technological content may have citations that differ from more diverse cited patents. The data are coded so that a binary variable, ST, indicates whether the International Patent Classification (IPC) system places both citing and cited patents in the same technology cluster at the 4-digit level. This system, in global use since 1975, is the standard by which all patents are organized (and thus assigned to examiners for processing, or searched by inventors and lawyers to establish claims). There are 634 clusters at the 4-digit level, so an indicator that the patents share a class is a powerful signal of technological similarity, and a strong indicator that they were both processed by patent examiners with very similar scientific training. In our sample, just under half of all citations saw citing and cited patents sharing a technology class.

The technological correlation between citing and cited states (SC), is included for a similar reason. Each state's technological profile was calculated as the share of patent activity assigned to each of the 634 IPC technology classes. Pair-wise correlations between state vectors then provide a measure of technological similarity between locations. Again, controlling for technological similarity will defuse the power of the data to show an importance of geography that may be superficially the result of two regions sharing the same technological portfolio and hence attracting citation flows. Our sample shows an average correlation of 0.87 between cited and citing state technology profiles.

The analysis also includes an indicator of whether the cited patent is classified as telecommunications (T). Obviously, all citing patents have been defined as such, and there should be a higher probability for them to cite other telecom patents than to cite a random other technology group. In fact, only one-third of patents cited by our telecommunications sample are themselves characterized as telecom.

Because government (G) and university (U) patents may cite knowledge differently than do private sector patents, we include those indicators as controls as well. Only slightly over one percent of our sample falls into each of these categories of assignee.

Linear and squared age terms are included to accommodate nonlinear effects for older knowledge. The average citation is just under 7 years from cited to citing document.

Finally, since the goal of the analysis is to test whether distance changes over time, it is necessary to include indicator variables for each time period.

4. Statistical analysis

Our regression analysis follows the literature [19] in using a simple model [21] with the citation as the unit of analysis. The model recognizes that the distance between a cited patent k granted in year t and a subsequent citing patent K granted in year T, can be explained at least in part as a function of the attributes of patents k and K:

$$\delta_{k,K} = \alpha(k,K) + \varepsilon \qquad (1)$$

where $\delta_{k,K}$ represents the distance between patents k and K, $\alpha(k,K)$ is a vector of the non-geographic attributes of patents k and K that affect the probability of citation, and ε is a randomly distributed error term. We propose a reduced functional form, using the log of distance (or technically the log of [distance plus one] in order to avoid taking the log of a zero distance) because the fit of the equation is better due to the loglinear nature of the data's underlying relationship:

$$\delta_{k,K} = \alpha_0 + \alpha_{SA}SA + \alpha_{SI}SI + \alpha_{ST}ST + \alpha_{SC}SC + \alpha_T T + \alpha_{EC}EC + \alpha_G G + \alpha_U U + \alpha_Y Y + \alpha_{Y2}Y^2 + \sum_{i=1976}^{2002}\alpha_i D_i + \varepsilon_K$$

where the distance δ of each observed citation is explained by the attributes of the citing and cited patents as defined above. Notice that we use a fixed effect specific to the citing patent (ε_K), since there are presumably immeasurable factors specific to the citing patent which might dictate a longer or shorter average citation distance.

Table 1 presents multivariate regression Tobit estimates (left-censored for intra-city citations with a distance of 0 miles), with White-corrected errors to accommodate the presence of heteroskedasticity in the sample, using fixed effects at the level of the citing patent where each individual citations is the unit of analysis. For simplicity, we estimate using only a time trend (and nonlinear versions of it) as an explanatory variable. The average distance unambiguously increases with time, with strong evidence of a non-linear pattern. When considering only inter-city citations (or citations with distances greater than 100 kilometers), the evidence is still very strong that a nonlinear pattern exists, one with distance rising with time.

To permit maximum flexibility to these nonlinearities, and potential nuances in particular years, Table 2 offers the same analysis, using separate year indicator variables. Notice that while increasing, the annual indicator variables do not uniformly increase over time (e.g. 1982-83, 1986-87). Table 3 presents the primary results, confirmed by the ancillary results in Table 4 which use time-based indicator variables instead of a time trend. Both sets of results differ only minimally from the results of a model which uses the citing patent as the unit of analysis (not presented here), where each citation is weighted appropriately according to the number of citations referenced by the citing patent in question.

Sensitivity tests find very similar results if we restrict our consideration to citations of more than 10 kilometers, of more than 50 kilometers, or of more than 100 kilometers. Results for citations spanning more than 100 kilometers, that is, excluding short and intra-city citations, presented in Tables 3 and 4, and tell a very similar story. Alternatively, results omitting citations from the states with the most citations again show the same pattern, with all coefficients of a size and sign similar to those presented here.

Moving to other elements of the regression results, we notice that patents involving electronic communication tend to have a greater distance that those involved in other subsectors. Unsurprisingly, citations with the same assignee or same inventor are more likely to be proximate than are other citations. The effect is especially strong and significant for inventors, suggesting that at least within telecommunications, inventors are not likely to move locations between self-citations. Citations within the same specific technology class appear to reference citing and cited patents that are closer to each other than more dissimilar patents (the ST coefficient is negative), and states that have similar technology sets in their innovative portfolios tend to be close together, a fact captured by the negative coefficient on that variable (SC).

On the other hand, citations that cite other telecom patents average a slightly longer distance than their peers. Apparently distance matters less for the transfer of purely telecom-related knowledge than it matters for the transfer of non-telecom innovations into the telecommunications sector.

Citations from government-assigned patents tend to travel longer transmission distances for the knowledge they cite, a result that is reversed and slightly more pronounced when we consider only long-distance (>100 km) citations. Academic patents tend to be shorter than their peers from the business sector as well, however, this effect is only significantly observed among long-distance citations (>100 km).

The age of the cited patent matters as well: older citations travel longer distances, an effect which other studies [22] have confirmed for an array of technologies. This effect is also reversed and not significantly observed among long-distance citations (>100km).

5. Conclusions

While we are hesitant to draw major conclusions about the nature of technological change in telecommunications from this work, several themes appear relatively obvious and robust to alternative interpretations of the data.

First, citation distances appear to be lengthening over time, whether we model those distances simply as a function of time or as a more complicated function of the attributes of the underlying patents. It appears that telecommunications innovations have potentially benefited from the telecom revolution that they themselves created.

Second, other factors may contribute to the explanation of why one patent cites another. Self-citation is not frequent, but apparently has a strong effect on the probability of a patent citation. Similarly, technology types seem to self-cite in particular ways that often make their citations travel longer distances than their peers.

Might we learn something important about innovation through the study of patent citations? Insofar as they reveal the paths of knowledge transmission, then we can identify the patterns and key actors in a technology such as telecom. As the industry de-clusters, just as other sectors are diffusing, we might expect the key innovators to become increasingly footloose. This is a mixed blessing, as it means they might choose their locations for new reasons (e.g. quality of life, proximity to family) but it may also lead to bidding wars by communities trying to attract productive innovators.

At this point, we can only point to the fact that telecom technology is diffusing more readily than it has in the past, allowing innovators in more widely flung locations to access and cite their predecessors more easily than ever before.

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Table 1: Tobit weighted regressions on log(distance+1), time trend only

	All citations				Only citations with distance > 100 km			
	Time trend		Nonlinear time trend		Time trend		Nonlinear time trend	
	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat
Trend	1.876×10^{-2}	(26.28)***	1.293×10^{-2}	(3.27)**	8.59×10^{-3}	(27.18)***	-1.31×10^{-3}	(0.77)
$Trend^2$	---	---	1.634×10^{-4}	(1.53)	---	---	2.76×10^{-4}	(5.96) ***
Constant	6.125	(391.54)***	6.170	(176.03) ***	7.18	(1037.8) ***	7.254	(481.5) ***
F-stat		690.87***		355.36***		738.73***		396.9***
Obs		336242		336242		280346		280346

Notes: *** indicates 99% confidence, ** 95% confidence, * 90% confidence. Implicit impacts are calculated at the sample mean for the group in question.

Table 2: Tobit weighted regressions on log(distance+1), separate year time dummies

	All citations		Only citations with distance>100km	
Variable	coeff.	t-stat	coeff.	t-stat
Citing year 77	0.079	(0.52)	0.020	(0.31)
Citing year 78	0.001	(0.01)	0.032	(0.50)
Citing year 79	-0.026	(0.17)	0.005	(0.08)
Citing year 80	0.076	(0.53)	0.020	(0.33)
Citing year 81	0.112	(0.80)	0.003	(0.05)
Citing year 82	0.202	(1.46)	-0.016	(0.26)
Citing year 83	0.334	(2.44)**	0.028	(0.48)
Citing year 84	0.256	(1.90)*	0.002	(0.04)
Citing year 85	0.251	(1.87)*	0.020	(0.34)
Citing year 86	0.337	(2.53)**	0.013	(0.22)
Citing year 87	0.433	(3.28)***	0.035	(0.62)
Citing year 88	0.459	(3.47)***	0.058	(1.02)
Citing year 89	0.534	(4.06)***	0.064	(1.12)
Citing year 90	0.490	(3.72)***	0.069	(1.21)
Citing year 91	0.483	(3.67)***	0.082	(1.44)
Citing year 92	0.385	(2.93)***	0.063	(1.11)
Citing year 93	0.263	(2.01)**	0.068	(1.19)
Citing year 94	0.371	(2.84)***	0.092	(1.63)
Citing year 95	0.357	(2.74)***	0.078	(1.39)
Citing year 96	0.445	(3.42)***	0.113	(2.00)**
Citing year 97	0.439	(3.37)***	0.116	(2.06)**
Citing year 98	0.565	(4.35)***	0.122	(2.17)**
Citing year 99	0.545	(4.2)***	0.134	(2.38)**
Citing year 00	0.574	(4.41)***	0.163	(2.89)***
Citing year 01	0.549	(4.21)***	0.162	(2.86)***
Citing year 02	0.635	(4.89)***	0.181	(3.22)***
Constant	6.033	(46.63)***	7.243	(129.33)***
F-stat		38.99***		31.79***
Observations		336242		280346

Notes: *** indicates 99% confidence, ** 95% confidence, * 90% confidence. Implicit impacts are calculated at the sample mean for the group in question.

Table 3: Tobit weighted regressions on log(distance+1), time trend

	All citations		Only citations with distance>100km	
Variable	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Same assignee (SA)	-1.831	(94.57)***	-0.191	(19.14)***
Same inventor (SI)	-2.858	(67.73)***	-0.409	(10.9)***
Same technology (T)	-0.099	(8.51)***	-0.026	(3.92)***
Citing-cited state correlation (SC)	-6.489	(150.48)***	-2.410	(118.34)***
Cited telecommunications (T)	0.044	(3.59)***	0.020	(2.85)***
Electronic communication (EC)	0.062	(6.70)***	-0.021	(3.92)***
Assignee = government (G)	0.058	(1.73)*	-0.053	(2.53)**
Assignee = university (U)	-0.031	(0.84)	-0.058	(2.72)***
Citation age (Y)	0.014	(4.87)***	-3.1×10^{-3}	(1.92)*
Citation age^2 (Y^2)	-2.1×10^{-5}	(0.15)	1.5×10^{-4}	(1.92)*
Trend	-7.8×10^{-5}	(0.02)	5.9×10^{-3}	(2.63)***
Trend^2	-2.5×10^{-5}	(0.23)	2.0×10^{-5}	(0.32)
Constant	12.284	(262.32)***	9.250	(366.46)***
F-stat		4763.2***		1277.9***
Observations		336242		280346

Notes: *** indicates 99% confidence, ** 95% confidence, * 90% confidence. Implicit impacts are calculated at the sample mean for the group in question.

Table 4: Tobit weighted regressions on log(distance+1), separate year time dummies

	All citations		Only citations with distance>100 km	
Variable	**coeff.**	**t-stat**	**coeff.**	**t-stat**
Same assignee (SA)	-1.831	(94.58)***	-0.191	(19.17)***
Same inventor (SI)	-2.856	(67.72)***	-0.409	(10.9)***
Same technology (ST)	-0.099	(8.53)***	-0.026	(3.88)***
Citing-cited state correlation (SC)	-6.488	(150.52)***	-2.412	(118.44)***
Cited telecommunication (T)	0.044	(3.62)***	0.020	(2.79)***
Assignee = government (G)	0.060	(1.80)*	-0.053	(2.53)**
Electronic communication (EC)	0.062	(6.71)***	-0.021	(4.02)***
Assignee = university (U)	-0.030	(0.83)	-0.059	(2.75)***
Citing year 77	-0.005	(0.04)	0.034	(0.51)
Citing year 78	-0.082	(0.77)	0.014	(0.21)
Citing year 79	-0.094	(0.88)	0.007	(0.10)
Citing year 80	-0.057	(0.55)	0.031	(0.48)
Citing year 81	-0.031	(0.31)	0.006	(0.09)
Citing year 82	0.021	(0.21)	0.041	(0.66)
Citing year 83	-0.001	(0.01)	0.034	(0.55)
Citing year 84	-0.059	(0.61)	0.010	(0.17)
Citing year 85	-0.105	(1.10)	0.027	(0.46)
Citing year 86	-0.057	(0.61)	0.029	(0.49)
Citing year 87	0.011	(0.11)	0.046	(0.79)
Citing year 88	-0.095	(1.01)	0.041	(0.71)
Citing year 89	-0.019	(0.20)	0.073	(1.25)
Citing year 90	-0.030	(0.32)	0.082	(1.40)
Citing year 91	-0.019	(0.20)	0.087	(1.49)
Citing year 92	-0.021	(0.22)	0.083	(1.42)
Citing year 93	-0.106	(1.14)	0.111	(1.90)*
Citing year 94	-0.038	(0.41)	0.109	(1.89)*
Citing year 95	-0.040	(0.44)	0.113	(1.96)**
Citing year 96	-0.056	(0.61)	0.132	(2.29)**
Citing year 97	-0.101	(1.10)	0.126	(2.18)**
Citing year 98	-0.032	(0.36)	0.133	(2.31)**
Citing year 99	-0.033	(0.36)	0.139	(2.42)**
Citing year 00	-0.083	(0.89)	0.128	(2.21)**
Citing year 01	-0.080	(0.86)	0.146	(2.51)**
Citing year 02	-0.051	(0.56)	0.151	(2.62)***
citation age (Y)	0.014	(4.86)***	-0.002	(1.49)
square age of citation (Y^2)	-0.001	(0.16)	0.001	(1.52)
Constant	12.320	(127.77)***	9.266	(155.95)***
F-stat		1594.18***		427.87***
Observations		336242		280346

Notes: *** indicates 99% confidence, ** 95% confidence, * 90% confidence. Implicit impacts are calculated at the sample mean for the group in question.