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Knowledge spillovers and patent citations: trends in geographic localization, 1976-2015

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KNOWLEDGE SPILLOVERS AND PATENT CITATIONS: TRENDS IN GEOGRAPHIC LOCALIZATION, 1976-2015

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Abstract. This paper examines the trends in geographic localization of knowledge spillovers via patent citations, extracting multiple cohorts of new sample US patents from the period of 1976-2015. Despite accelerating globalization and widespread perception of the "death of distance," our matched-sample study reveals significant and *growing* localization effects of knowledge spillovers at both intra- and international levels after the 1980s. Increased localization effects have been accompanied by greater heterogeneity across states and industries. The results are robust to various methods of proxying the existing geography of knowledge production.

Keywords: Innovation, knowledge spillovers, patent citation, agglomeration

JEL Classification: O33, O34, O51, C81

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1. Introduction

Knowledge spillovers are a prevalent and important component of the link between innovation and growth (Griliches, 1992). While numerous studies have found geography to be a barrier to the diffusion of ideas (e.g. Carlino and Kerr, 2015), there is a presumption that place has been becoming less important over time with improvement in communication and transport links, as poignantly echoed by the notion of the "death of distance" (e.g. Cairncross, 2001; Coyle, 1997).

To scrutinize the evolving role of distance in knowledge spillovers, we examine patent citations within and across the US during the period of 1976-2015. Our analysis adopts the matched-sample approach of Jaffe, Trajtenberg, and Henderson (1993) (henceforth JTH) for four separate cohorts of "originating" patents, each consisting of all corporate and institutional utility patents granted by the US Patent and Trademark Office (USPTO) in 1976, 1986, 1996, and 2006, respectively. The corresponding "citing" and "control" patents are found over fixed 10-year window, and multiple measures of technological proximity are considered for control selection *à la* Thompson and Fox-Kean (2005) (henceforth TFK).

The frequency of geographic match between originating and citing patents is compared to the corresponding matching rate between originating and control patents for each pair of geographic boundary (country, state, or metropolitan statistical area) and industry sector (one of 37 sub-categories defined by NBER). The difference in these matching rates gives a measure of how distance matters for the spread of knowledge while accounting for the existing spatial distribution of knowledge production.[1]

The results on the 1976 cohort are similar to those obtained by JTH and TFK. The difference between the two matching rates decreases with the level of disaggregation in defining technological proximity between citing and control patents. In particular, as TFK observe, intra-national (net) localization effects disappear when a match at the nine-digit class level is imposed across each originating-citing-control triad of patents.[2] This reaffirms the importance of the matching process between citing and control patents for the identification of localization effects.

[1]While we follow JTH and others to consider discrete geographic boundaries, Murata, Nakajima, Okamoto, and Tamura (2014) recently adopt the continuous-distance metric of Duranton and Overman (2005) to calculate localization effects. See also Carlino, Carr, Hunt, and Smith (2012) and Kerr and Kominers (2015) who use the method in other related contexts.

[2]One important difference is that our cohort consists of patents granted in all of year 1976, as opposed to just one month (January) taken by TFK. This has mitigated the sample size issue pointed out by Henderson, Jaffe, and Trajtenberg (2005).

In terms of trends, we find that (i) the matching rate between citing and originating patents has grown at all levels of control and spatial boundary since the 1986 cohort; (ii) the matching rate between control and originating patents has increased at intra-national levels but decreased at international level. The latter finding suggests that concentration of innovation activities has intensified within the US, consistent with other observations on the trends of industrial agglomeration (e.g. Moretti, 2012), but international border effect, or "home bias," has deepened only for diffusion of innovation.

More importantly, our data reveal evidence of highly significant localization effects at every unit of analysis since the 1986 cohort; moreover, the extent of such effects has been *growing*. Spread of ideas has indeed become increasingly more localized than production of ideas, contrary to the common expectation otherwise. This finding is robust to further controls, including restriction to most cited patents to account for widely perceived decline in patent quality.

We also compute localization effects across all US states as well as six industry categories. The rise in localization effects has been accompanied by greater heterogeneity in matching rates at both state and industry levels. In particular, we see growing importance of California and few other states as a driving force behind the aggregate trends, in line with others who have also shown stronger localization effects in certain regions (e.g. Almeida and Kogut, 1999).

While a number of recent studies report increasing spatial inequality in the US (e.g. Bishop, 2009; Moretti, 2012; Gyourko, Mayer, and Sinai, 2013), only few have thus far addressed the changing role of geographic proximity in knowledge spillovers. Among these, we are most closely related to Sonn and Storper (2008).

While Sonn and Storper (2008) draw similar conclusions, their analysis is based on patents only up to 1997, and it is precisely around this period when the IT revolution took off and, moreover, we began to see a meteoric rise in both the number of inventions and the diversity of inventors (e.g. Kwon, Lee, and Lee, 2017). Another important difference is that Sonn and Storper select control patents only at the three-digit primary level, but as TFK note, the results are sensitive to the level of disaggregation. This paper finds growing localization effects that persist through the most recent decades and are robust to multiple proxies for the existing distribution of knowledge production.

It is worth emphasizing our empirical contribution at this juncture. Following the debate between JTH and TFK, a number of attempts have been made recently to improve the fidelity of matching citing with control patents. In particular, "coarsened exact matching" allows for multiple covariates beyond just technology class. However, related papers that measure spillover effects (e.g. Singh and Agrawal, 2011; Azoulay, Graf Zivin, and Sampat, 2012) are still based on three-digit level matches; they neither consider nine-digit subclasses nor impose the additional match between control and originating patents. But it is precisely this last method with which TFK, and also this paper, question JTH's result and therefore its application is critical for any robust analysis. To our knowledge, we are the first to fully replicate TFK's methodology, and this is achieved with samples that are far greater than those constructed by TFK (or the aforementioned papers using more sophisticated matching techniques).[3] Our results suggest that the rise of localization effects is indeed a robust finding.

Two papers consider the trends of home bias across national boundaries. Keller (2002) estimates an R&D production function with R&D of other countries as explanatory variable. His results show that the importance of foreign R&D has fallen over the years 1970-1995, suggesting faster diffusion of knowledge across borders. Griffith, Lee, and Van Reenen (2011) examine a panel of USPTO patents granted and citations made to these patents between 1975 and 1999. Using a duration model, they estimate the speed of citations and find evidence of declining "diffusion lag" between domestic and foreign citations.

Regarding intra-national localization trends, Lychagin, Slade, Pinkse, and Van Reenen (2016) examine R&D spillovers into US-based firm productivity over the period 1980-2000 and find no evidence of the "death of distance." Using economics and finance articles published over 1970-2001, Kim, Morse, and Zingales (2009) report evidence of declining local spillover benefits among top US universities.

Our findings stand in sharp contrast to these results. At both intra- and international levels, we observe increasing importance of geographic proximity in knowledge spillovers. One source of the departure may be the measure of diffusion. More importantly, the aforementioned papers (as well as most of the existing literature on knowledge spillovers) are based on datasets that do not include the most recent decades. The surge in patent production during this period makes it particularly important to exploit observations beyond the existing literature.

The rest of the paper is organized as follows. We begin by describing the USPTO data in Section 2 and then our sample patents in Section 3. Our main findings on the trends of localization effects are presented in Sections 4 and 5. Section 6 concludes with

[3] Murata, Nakajima, Okamoto, and Tamura (2014) consider nine-digit matches but only between citing and control patents.

a discussion on potential sources of our findings. Appendices contain materials left out from the main text for expositional reasons.

2. Patent Data

The patent dataset used in this paper is directly extracted from the USPTO bulk data which contain information on all utility patents granted from January 1976 up to, and including, May 2015. The data include patent number, application date, main and additional technology classifications, name of assignee, names and locations of inventors, and patent numbers of cited patents.[4]

Every patent is endowed with a single mandatory "original" (OR) classification and additional "cross-reference" (XR) classifications. The US patent classification (USPC) system is a tree structure consisting of distinct, and mutually exclusive, technology "classes" and "subclasses" that are nested under their parent (sub)classes.[5] For utility patents, classes are identified by a one-, two-, or three-digit integer; each subclass is identified by an additional "indent," indicating its position within a class hierarchy, and a subsequent alphanumeric code. The most disaggregated level of subclasses has nine alphanumeric digits. A group of subclasses are classified as "primary subclasses," and the mandatory original classification must belong to this group.

Our dataset, unsurprisingly, reveals substantial growth in technological diversity. Among all the patents granted between 1976-1985 we found 113729 distinct subclasses, and this number increased to 239233 over the entire sample period.[6] Despite this expansion of technological spectrum, the level of specialization has been relatively stable. On average, a patent granted in 1976 received about 3.6 subclass classification codes. It was about 4 for a patent granted in 2006.

For the purpose of our study, it is necessary to assign a geographic location to each patent, based on inventor location. As in JTH and TFK, our analysis is conducted at three different geographic levels: country, state, and CMSA (consolidated metropolitan statistical area). Since patents report inventor location only in terms of country, state and city, each patent is mapped to one of 17 CMSAs,[7] or a "phantom" CMSA created

[4]We obtained the bulk data for the period 1976-2014 from `https://www.google.com/googlebooks/uspto-patents-grants-biblio.html` and the data for 2015 from `https://bulkdata.uspto.gov/`. The data and replication files that support the findings of this study are available in Harvard Dataverse at `https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/42VDB0`.
[5]See "Handbook of Classification" published by USPTO.
[6]After revisions, USPTO was offering around 160000 subclasses as of June 2015.
[7]We follow TFK and use the method provided by the Office of Social and Economic Data Analysis (OSEDA) of the University of Missouri.

for foreign countries and each state.[8] If a patent is produced by a single inventor or by a group of inventors who reside in the same location, the location of the patent is unambiguously determined. For patents with multiple inventor locations, we randomly assigned a unique location, as done also by TFK.[9]

Table A1 in Appendix A breaks down all utility patents granted by USPTO during the sample period according to their locations, defined as domestic or foreign, and as states.

3. Sample Patents

We adopt the experimental design of JTH to document the trends in geographic localization of knowledge spillovers. This is based on constructing three samples of patents: originating, citing, and control patents. As in TFK, we consider patents assigned to corporation or institution. The USPTO bulk data contain some patents with typographical errors as well as missing information. We remove such patents in obtaining our sample patents.

Originating Patents. A sample of "originating patents" consists of a fixed cohort of patents. Two cohorts of such patents (whose application dates were in 1975 and in 1980) were considered by JTH, and one cohort of patents (granted during January 1976) was used by TFK.

In this study, we construct four cohorts of originating patents: all relevant patents granted in 1976, 1986, 1996 and 2006 with at least one US-located inventor based on the location data before the CMSA mapping. An originating patent must be assigned to a corporation or institution distinct from its inventor.

The 1976 cohort is included to re-examine the previous analyses of JTH and TFK. The sample sizes of the two cohorts of originating patents in JTH were 950 and 1450, respectively, while the corresponding sample size in TFK was 2724. The sample sizes of our four cohorts of originating patents are 44016, 38160, 61581, and 80495, respectively.

Citing Patents. A sample of "citing patents" is constructed for each cohort of originating patents by collecting all patents that cite at least one of the originating patents within a fixed window of periods, excluding self-citations.[10] In JTH, the 1975 and 1980

[8]For a very small number of domestic patents (0.2%), this mapping resulted in two CMSAs. The final CMSA was chosen randomly in these cases.

[9]JTH used a different method based on plurality. Our main message remains unchanged by adopting this rule. See Section 4.3 for a discussion.

[10]A self-citation is defined as a citation from a citing patent whose assignee is the same as that of the corresponding originating patent.

originating cohorts received 4750 and 5200 citations, respectively, by the end of 1989. TFK obtained 18551 citing patents granted between January 1976 and April 2001.

A citing patent has application date within 10 years of each cohort, including the year in which originating patents were granted.[11] This ensures that the citing patents do not overlap across different cohorts. We found 131263 citing patents for the 1976 cohort, 229690 for the 1986 cohort, 928693 for the 1996 cohort, and 684711 for the 2006 cohort.

Table A2 in Appendix B summarizes some descriptive statistics about citations made to our originating patent cohorts. High proportions of patents received citations for all cohorts. The average citation numbers in recent cohorts are substantially larger than in the 1976 cohort.

Control Patents. Key to JTH's experimental design of knowledge spillovers is the construction of a set of "control patents" for each sample of citing patents to mimic the existing geographic distribution of knowledge production. Geographic match of patents may arise as a consequence of agglomeration of research activities in similar fields.

The patent classification system offers possible channels for selecting control patents. The basic idea is to pick, for each citing patent, another patent that (i) has similar application date and (ii) is classified under the same technology (sub-)class as the citing patent, as well as possibly the originating patent. Such a procedure would generate a sample of patents that mirror the sample of citing patents but do not cite the corresponding originating patents.

We consider the following four measures of technological proximity to obtain robust observations. The first control measure, which was originally used by JTH, finds a technology match at the level of "three-digit" class; the next three are the *disaggregated* controls introduced by TFK, with increasing level of disaggregation.

A. [**3-digit**] A control patent has a technology subclass that matches the original classification of the citing patent at the three-digit level.[12]
B. [**Any**] A control patent has a technology subclass that matches the original classification of the citing patent in full.
C. [**Primary**] A control patent has original classification (a primary subclass) that matches the original classification of the citing patent.

[11]One exception is the 2006 cohort, for which the citing patents were collected only up to, and including, May 2015. From June 2015, USPTO began a new system of patent classification, Cooperative Patent Classification (CPC), in an effort to harmonize its classification system with the European Patent Office (EPO). There were total 67576 patents granted between June and December 2015 that cite the 2006 originating patents. This amounts to only a small fraction of all citing patents since 2006.

[12]When two patents are said to match at the "three-digit" level, it means that both patents are given a subclass whose parent class (first one-, two-, or three-digit integer of the classification code) is identical.

D. [**Common**] A control patent has original classification that matches the original classification of the citing patent and a technology subclass that matches any subclass of the corresponding originating patent.

For each measure of technological proximity above, we picked a control patent randomly from all candidate patents whose application dates fell within one-month (30 days) on either side of the application date of the citing patent; if no admissible patent was found, we widened the window to 3 months (90 days) and then to 6 months (180 days). If no control patent was found after three such rounds, a null observation was returned.[13] Our selection procedure was implemented by Python algorithms.

In addition, control patents satisfy the following criteria:

- A control patent has corporation or institution assignee and CMSA information.
- The corresponding citing patent cites an originating patent that has CMSA information, at least one US inventor, is assigned to a corporation or an institution, and has NBER class information.
- The corresponding citing patent has corporation or institution assignee, CMSA information, and USPC class information.

4. Trends in Geographic Localization

4.1. Methodology.

The main idea of JTH is to compare the location of the citing patent with the cited originating patent. However, such geographic match should not necessarily be taken as direct evidence of knowledge spillovers because innovators in particular fields may tend to colocate. If half of the world production of novel semi-conductor technologies hail from Korea then one might also expect half of the citations made to Korean semiconductor patents come from other inventors in Korea. The selection of control patents serves to provide a reference point against which to compare the proportion of citing patents that match the cited patents geographically.

Specifically, for each definition of geographic boundary, we test whether the frequency of geographic match (i.e. identical inventor location) between originating and citing patents is equal to or larger than the matching rate between originating and control patents. Formally, for given geographic boundary (country, state, or CMSA) and for given cohort, let p_{ij}^{citing} denote the matching probability between originating and citing patents in state i and industry sector j, and p_{ij}^{control} denote the matching probability

[13] Appendix C presents the number of control patents found at each round of iteration for each pair of originating and citing patent samples.

between originating and control patents. We consider the 50 US states plus the District of Columbia and the 37 industrial sub-categories under NBER classification.[14]

The overall matching probability can be written as a weighted average of state-sector-level matching rates. This corresponds to

$$p^{\text{ citing}} = \sum_{i=1}^{I}\sum_{j=1}^{J} w_{ij}^{\text{citing}} p_{ij}^{\text{citing}} \quad \text{and} \quad p^{\text{ control}} = \sum_{i=1}^{I}\sum_{j=1}^{J} w_{ij}^{\text{control}} p_{ij}^{\text{control}},$$

where the weight w_{ij}^{citing} (w_{ij}^{control}) is the number of citing (control) patents in state i and sector j divided by the total number of such patents, and I and J are the total numbers of states and sectors, respectively. We can also define the matching rates for each state i, p_i^{citing} and p_i^{control}, and for each sector j, p_j^{citing} and p_j^{control}.

As in JTH and TFK, we are primarily concerned with the difference $p^{\text{ citing}} - p^{\text{ control}}$ in the two matching rates, which will be referred to simply as the *localization effect* (of knowledge spillovers). We test $H_0 : p^{\text{ citing}} = p^{\text{ control}}$ versus $H_1 : p^{\text{ citing}} > p^{\text{ control}}$ for each cohort and for each definition of geographic boundary. The test statistic used in the paper is

$$t = \frac{\widehat{p}^{\text{ citing}} - \widehat{p}^{\text{ control}}}{[\text{SE}(\widehat{p}^{\text{ citing}})^2 + \text{SE}(\widehat{p}^{\text{ control}})^2]^{1/2}},$$

where

$$\widehat{p}^{\text{ citing}} = \sum_{i=1}^{I}\sum_{j=1}^{J} w_{ij}^{\text{citing}} \widehat{p}_{ij}^{\text{citing}},$$

$$\text{SE}(\widehat{p}^{\text{ citing}}) = \left[\sum_{i=1}^{I}\sum_{j=1}^{J} \left(w_{ij}^{\text{citing}}\right)^2 \left(\widehat{p}_{ij}^{\text{citing}} - \widehat{p}^{\text{ citing}}\right)^2\right]^{1/2},$$

and $\widehat{p}_{ij}^{\text{citing}}$ is the sample proportion of p_{ij}^{citing}. We similarly define $\widehat{p}^{\text{ control}}$ and $\text{SE}(\widehat{p}^{\text{control}})$.

Our statistical analysis is conducted at the state-sector level, and this differs from JTH and TFK who treat all individual patents as independent and identically distributed. The key advantage of our group level analysis is that, by doing so, we maintain the effective sample size fixed, at $I \times J$, throughout the cohorts. Replicating the individual level analysis over time could potentially suffer from the effects of increasing sample size. The numbers of our sample patents in 1996 and 2006 are far greater than the corresponding number in 1976. Note also that the clustered standard errors allow for arbitrary dependence within each group.

[14]We employed NBER's mapping table to match each USPC code with an industrial (sub-)category.

4.2. **Main Findings.** In this section, we report the aggregate citing and control matching rates across cohorts. Table 1 presents these findings, together with t-values for the hypothesis testing.[15]

TABLE 1. Frequency of Geographic Match

		citing	3-digit	Any	Primary	Common
1976	TOTAL	104127	104127	97356	81090	34059
	country	66.35	57.78	59.84	59.23	61.34
			(15.49)	(10.87)	(11.43)	(6.38)
	state	9.57	4.68	6.55	6.85	8.71
			(9.73)	(5.71)	(4.87)	(1.31)
	CMSA	8.07	3.47	5.27	5.53	7.34
			(11.7)	(6.72)	(6.01)	(1.36)
1986	TOTAL	185213	185213	176372	153062	67993
	country	71.21	56.62	59.02	58.39	58.48
			(22.02)	(17.67)	(17.24)	(14.84)
	state	10.68	4.72	6.41	6.63	7.62
			(8.8)	(5.93)	(5.49)	(3.88)
	CMSA	8.71	3.4	4.95	5.08	5.92
			(12.56)	(8.35)	(8.19)	(6.03)
1996	TOTAL	709662	709662	700537	656061	236091
	country	76.95	55.18	57.92	58.01	58.1
			(24.24)	(19.54)	(18.8)	(13.96)
	state	15.01	6.7	8.59	8.93	10.73
			(4.72)	(3.49)	(3.25)	(2.12)
	CMSA	11.88	4.5	6.23	6.5	8.06
			(7.05)	(5.14)	(4.83)	(3.26)
2006	TOTAL	551994	551994	547432	525909	236784
	country	77.96	52.84	56.07	56	58.08
			(20.52)	(16.97)	(16.56)	(13.64)
	state	18.31	8.05	10.23	10.47	12.53
			(4.41)	(3.4)	(3.29)	(2.36)
	CMSA	14.06	5.37	7.2	7.4	9.35
			(6.18)	(4.77)	(4.63)	(3.14)

Notes: The numbers in the first row of each cohort represent sample sizes. A number in parenthesis is the relevant t-statistic.

We begin by summarizing our results for the 1976 cohort of patents.

[15]Notice that the sample sizes for citing patents in Table 1 differ from the corresponding numbers appearing in Table A2. For the calculation of citing matching rates, our sample citing patents are taken to be those that allow us to find corresponding control patents according to the 3-digit criterion.

Finding 1. *Localization effects of knowledge spillovers in 1976-1985 are sizable at all location and control levels, except at intra-national (state and CMSA) levels under the most disaggregated level of control.*

In the 1976 cohort of patents, the geographic matching rates between originating and citing patents are considerably higher than the corresponding rates between originating and control patents at all geographic levels (country, state, and CMSA) and for all control measures, except at the two intra-national levels under the most disaggregated control group (Common).[16] These results are consistent with the main findings of TFK: even with large samples, using finer selection criteria increases the matching rate of control patents to the extent that the sizable localization effect disappears altogether (its magnitude is less than 1 percentage point) when we control for technological proximity across all originating-citing-control triads.[17]

Next, considering the trends of geographic localization since 1976, we first observe that the sample size of control patents has increased dramatically. The surge took place most notably between 1986 and 1996, with the numbers tailing off somewhat in 2006. Note that TFK had only 2122 control patents to work with in producing their main result; the corresponding figures for our 1996 and 2006 cohorts are, respectively, 236091 and 236784.

The first trend that we observe is on the citing matching rate.

Finding 2. *The frequency of geographic match between originating and citing patents has increased.*

The matching rate of citing patents has increased at every geographic level and from each decade to the next. Between 1976 and 2006, the gain is about 12% at country level and about 6% at CMSA level; at state level, the matching rate almost doubled from 9.57% to 18.31%. This finding contradicts the widespread belief that geographic proximity has been made less important for the flow of ideas by the advent of internet and other new communication technologies. According to our data, distance still matters, and today it matters even more than before, when one considers diffusion of ideas through patent citations.

We next report the trend of control matching rates.

[16]The matching rates in our sample are generally higher than those reported by TFK. Other than the sample size, one possible reason for this departure is that we consider citations that accrue only for 10 years up to 1985; TFK consider citing patents up to April 2001. The agglomeration effects of both production and diffusion of ideas may decay over time. For related evidence, see Jaffe and Trajtenberg (1999) and Thompson (2006).

[17]The t-statistics are 1.31 (state) and 1.36 (CMSA), which are substantially smaller than those under less disaggregated levels of control. Note that 95% critical value here is 1.645.

Finding 3. *The frequency of geographic match between originating and control patents has increased at intra-national levels but decreased at international level.*

Within each cohort, and for each definition of geographic boundary, the matching rate of control patents increases with the level of disaggregation. This is consistent with the view that producers with similar technologies are more likely to agglomerate.

Across cohorts, the control matching rates fell in almost all cases between 1976 and 1986, but they then trended upward at the two intra-national levels. For example, under the Common criterion, the control matching rate in 1976 was roughly 9% at state level and 7% at CMSA level; the corresponding figures in 2006 were 13% and 9%, respectively.

Interestingly, however, the same trend is not observed at country level: the frequency of control and originating patents simultaneously being domestic dropped monotonically for all measures of control. This suggests that production of knowledge has become increasingly co-located within the US, while the opposite may have been happening across international borders.

Our main results on the trend of localization effects are now summarized.

Finding 4. *Localization effects are substantial and highly significant at all location and control levels in all cohorts of patents since 1986.*

Importantly, we observe significant localization effects in every cohort and for every control measure since the 1986 cohort. This includes even the most disaggregated level of control selection, for which localization effects were not found in the 1976 cohort. The strength of localization effects is also substantial and highly significant (well above the 95% critical value). Despite the intensification of pre-existing geographic distribution of patent production, the increase in localization of citations has indeed been the dominating force.

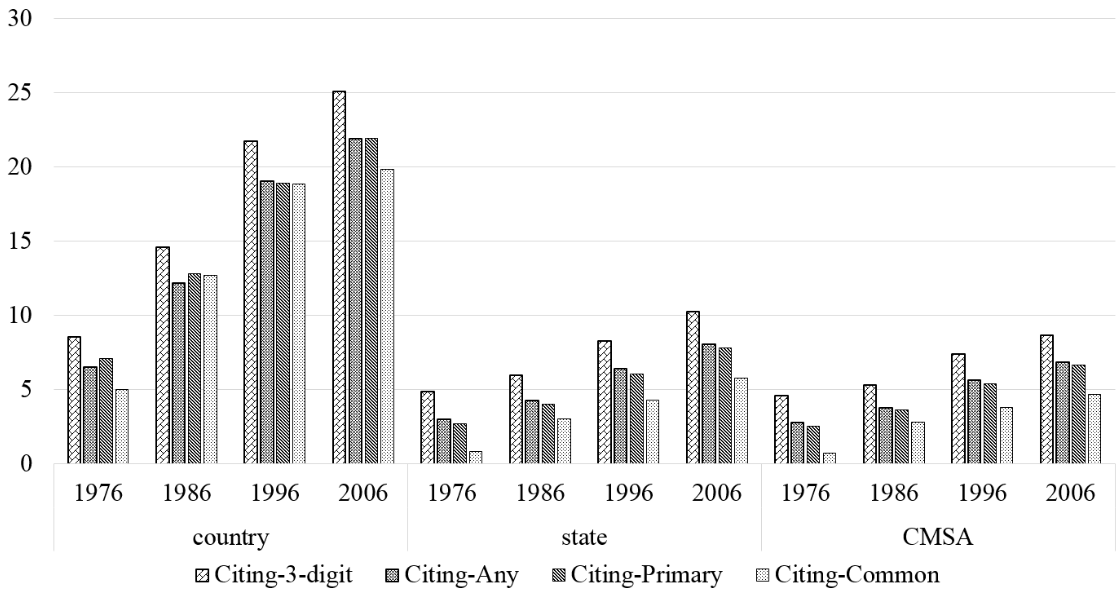
Finding 5. *Localization effects have strengthened.*

Moreover, localization of knowledge spillovers has strengthened over the decades. Figure 1 illustrates the localization effects across cohorts which are also presented by Table 2 in proportional terms. At every geographic level, the difference between citation and control matching rates is greater in 2006 than in 1976, regardless of the selected controls.

Table 2. The Degree of Localization Effects

		3-digit	Any	Primary	Common
1976	country	12.91%	9.81%	10.72%	7.55%
	state	51.08%	31.53%	28.42%	8.91%
	CMSA	57.05%	34.72%	31.49%	9.04%
1986	country	20.49%	17.12%	18.0%	17.87%
	state	55.81%	39.98%	37.94%	28.66%
	CMSA	60.92%	43.21%	41.65%	32.01%
1996	country	28.29%	24.72%	24.61%	24.5%
	state	55.34%	42.75%	40.49%	28.54%
	CMSA	62.11%	47.57%	45.31%	32.19%
2006	country	32.22%	28.08%	28.17%	25.51%
	state	56.03%	44.15%	42.82%	31.59%
	CMSA	61.81%	48.77%	47.35%	33.49%

Figure 1. Localization Trends



This trend appears to be more profound for the cases that had relatively low levels of localization to begin with. Considering the country-level effects, the citing patents were about 13% more localized according to 3-digit controls and 8% more localized according to the most disaggregated controls than the control patents in the 1976 cohort; these figures rose to 32% and 26%, respectively, in the 2006 cohort. When controls were selected under the most stringent criteria, intra-national localization effects leaped from only about 9% in 1976 to over 30% in 2006 at both state and CMSA levels.

4.3. **Other Robustness Considerations.** The aggregate number of patents has grown dramatically in recent decades. Many have argued that this is, at least in part, due to declining standards at the USPTO (e.g. Jaffe and Lerner, 2004). If marginal innovations are more likely to be adopted locally than nationally, declining average quality will be reflected in growing apparent localization.

To address this potential concern, we additionally consider localization trends for "quality-constant" patents. Specifically, from each sample cohort of originating patents, we restrict attention to those which were in the top 10% of the forward citation distribution and retrieve corresponding citing and control patents according to the procedures described above.

Due to ties, the precise distributional cutoff varies slightly from 10%. All other sample selection procedures remain the same. The basic features of the restricted sample of originating patents are given in Table 3, while Table 4 summarizes the localization effects computed for each cohort with new sample patents. Our results turn out to be robust.

Table 3. Most Cited Originating Patents

Cohort	Cutoff	No. of Citations at Cutoff	Sample Size
1976	12.07%	8	3646
1986	10.18%	15	3044
1996	10.14%	37	5346
2006	10.27%	25	6111

Table 4. Aggregate Trends: Most Cited Originating Patents

		citing	3-digit	Any	Primary	Common
1976	TOTAL	39116	39116	37545	32605	14134
	country	66.58	57.45	59.63	58.98	61.09
			(11.96)	(8.13)	(8.62)	(4.9)
	state	9.99	5.1	7.01	7.19	9.17
			(7.53)	(4.32)	(3.92)	(0.98)
	CMSA	8.46	3.69	5.53	5.86	7.66
			(8.5)	(4.95)	(4.4)	(1.1)
1986	TOTAL	71713	71713	69203	62319	27483
	country	74.79	58.5	61.01	60.31	59.33
			(15.8)	(12.9)	(13.03)	(11.52)
	state	11.19	5.38	6.99	7.21	7.69
			(5.3)	(3.65)	(3.44)	(3.07)
	CMSA	9.34	4.11	5.54	5.58	6.01
			(6.31)	(4.42)	(4.62)	(4.32)
1996	TOTAL	342507	342507	342106	329006	109799
	country	81.9	58.15	61.37	61.48	62.65
			(22.81)	(17.63)	(17.19)	(10.08)
	state	17.32	7.94	10.01	10.24	12.75
			(3.58)	(2.65)	(2.55)	(1.42)
	CMSA	13.51	5.36	7.24	7.41	9.47
			(5.27)	(3.84)	(3.73)	(2.18)
2006	TOTAL	286364	286364	285714	278215	125470
	country	83.25	55.59	59.46	59.48	62.53
			(17.94)	(14.49)	(13.99)	(11.55)
	state	20.33	8.67	11.22	11.47	13.76
			(3.87)	(2.95)	(2.87)	(2.05)
	CMSA	15.45	5.77	7.8	8.01	10.26
			(5.4)	(4.17)	(4.06)	(2.66)

Notes: The numbers in the first row of each cohort represent sample sizes. A number in parenthesis is the relevant t-statistic.

Another issue that may have created a bias in our results relates to the method of assigning location to multi-inventor patents. Following TFK, we allocated such patents randomly if inventors are in different geographical locations. However, the average number of inventors per patent has increased over time, and therefore, the random allocation rule may have generated a measurement error that has become more severe.

To check for robustness against this issue, we replicate our results–with all sample patents and with most cited patents, respectively–by adopting an alternative allocation rule based on plurality, as used by JTH. Again, our central message is unaffected. See Appendix D for details.

5. Disaggregate Trends

5.1. **Comparison by State.** Our previous findings on the patterns of knowledge spillovers treat all locations identically. We next explore possible heterogeneity in localization effects across states. Over 60% of all utility patents granted to domestic inventors across the sample period were concentrated in less than 10 states; furthermore, Californian inventors have been by far the most prolific, and they have actually widened their lead in patent production.[18] This raises the question whether our results are driven by disproportionately large localization effects that have taken place in some states.

The observed localization effects across states are summarized in Table 5. For each cohort, we first report the frequency of patents that cite patents originating from a given state and are themselves from the state; we next report the matching rate of control patents selected according to the most disaggregated procedure (Common). The results are also illustrated in Figure 2. In each graph, a point indicates the pair of matching rates for a given state; also, the points vary in size, reflecting their corresponding sample size (as a proportion of the total). The dotted line in each graph represents equal matching rates so that the vertical distance above this line measures localization effect.

For the 1976 cohort, we do not observe substantial differences between the two matching rates for most of the states, similarly to the state-level findings from the aggregate sample. The 1986 cohort displays stronger localization effects across most states. The differences are large in many states including California, New York, Illinois, Minnesota, and Michigan.

An interesting trend that followed concerns the distribution of observations. Through the 1996 and 2006 cohorts, both citing and control matching rates became substantially more dispersed across states. This trend was led by a handful of states, including California, Michigan, Nevada, and Texas. In the 2006 cohort, we also observe a small number of states with large control matching rates that far exceed citing matching rates.

Tables A6 and A7 in Appendix E report detailed breakdown of matching rates for California and the rest of the US, respectively. While Californian inventors have been the key driving force behind greater localization of economic activities reflected in patents, our central findings are also observed for the rest of the country. Albeit in smaller scale,

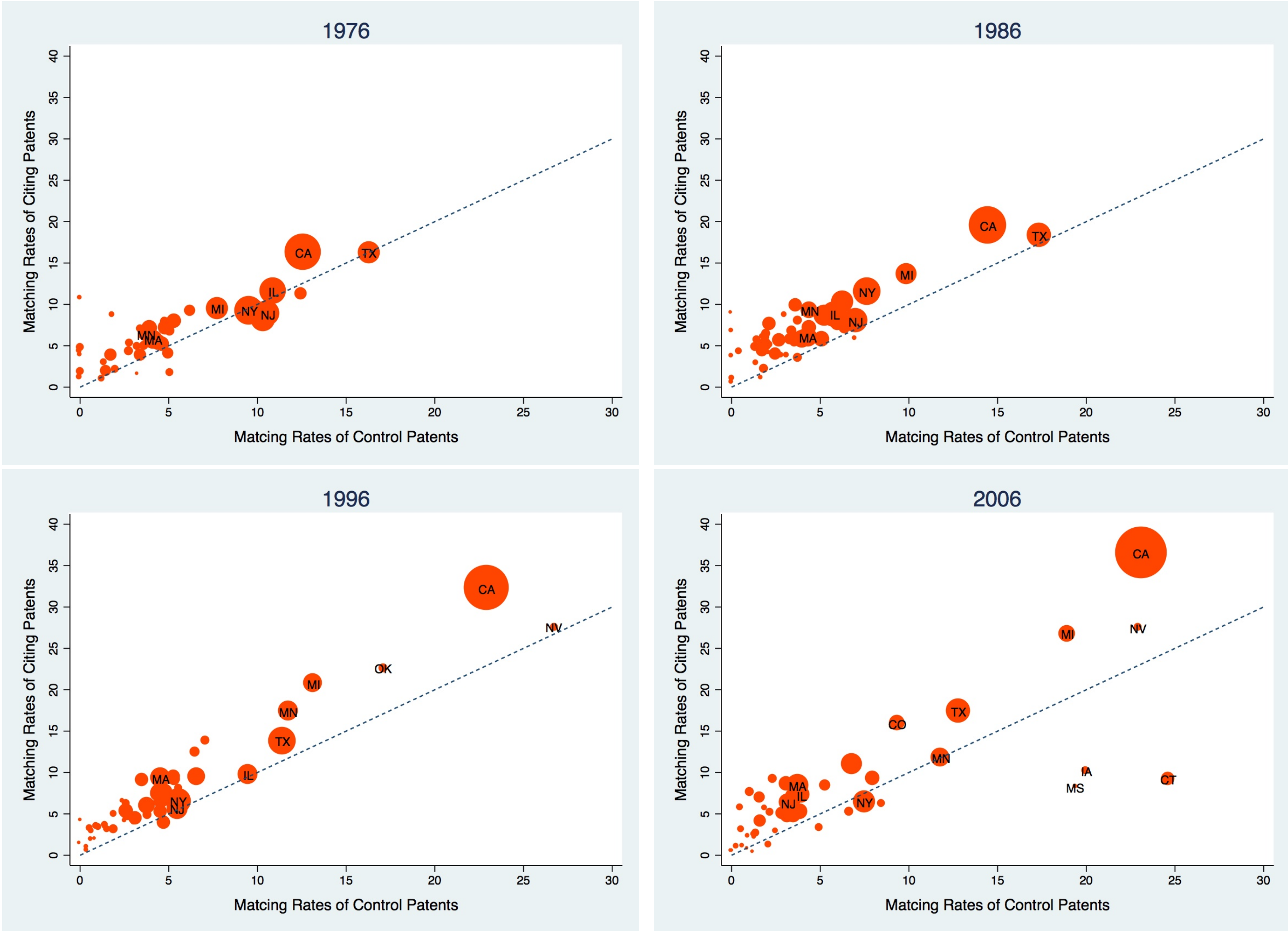
[18]Similar state-wide patterns are observed in the distribution of each of the sample (i.e. originating, citing, and control) patents.

Table 5. Matching Rates by State

State	1976			1986			1996			2006		
	Citing	Control	t-value	Citing	Control	t-value	Citing	Control	t-value	Citing	Control	t-value
California(CA)	16.24	12.59	(4.03)	19.49	14.47	(3.85)	32.20	22.93	(3.04)	36.52	23.09	(6.81)
New York(NY)	9.23	9.56	(-0.24)	11.53	7.65	(1.81)	6.55	5.54	(1.16)	6.41	7.51	(-0.53)
Texas(TX)	16.27	16.29	(-0.0)	18.33	17.37	(0.15)	13.81	11.43	(0.52)	17.41	12.81	(0.67)
Illinois(IL)	11.56	10.9	(0.34)	8.79	5.82	(2.9)	9.75	9.49	(0.07)	7.23	3.96	(2.16)
Michigan(MI)	9.53	7.76	(0.96)	13.65	9.88	(2.18)	20.71	13.17	(2.3)	26.75	18.95	(1.38)
New Jersey(NJ)	8.8	10.61	(-1.01)	7.95	7.01	(0.61)	5.60	5.48	(0.13)	6.28	3.21	(2.45)
Ohio(OH)	9.23	9.72	(-0.42)	10.28	6.30	(4.66)	9.40	6.61	(2.79)	9.20	7.97	(0.61)
Pennsylvania(PA)	8.15	10.34	(-1.37)	8.56	5.24	(2.81)	7.49	4.47	(2.02)	6.35	3.13	(1.93)
Massachusetts(MA)	5.73	4.14	(1.36)	5.99	4.31	(2.71)	9.27	4.56	(3.75)	8.41	3.73	(3.22)
Minnesota(MN)	6.37	3.74	(1.95)	9.22	4.42	(3.47)	17.35	11.75	(1.52)	11.79	11.82	(-0.01)
Washington(WA)	9.23	6.23	(1.28)	7.57	2.18	(4.75)	6.45	4.62	(1.78)	10.98	6.81	(4.96)
Florida(FL)	7.92	5.35	(1.7)	5.67	4.00	(2.75)	5.97	3.79	(2.49)	5.26	3.88	(1.09)
North Carolina(NC)	7.04	4.91	(0.9)	3.93	2.52	(1.83)	9.03	3.53	(2.7)	4.91	3.49	(1.18)
Colorado(CO)	5.43	4.48	(0.57)	9.90	3.64	(3.14)	7.68	4.78	(2.58)	15.88	9.35	(0.72)
Wisconsin(WI)	7.16	4.81	(2.06)	7.59	6.00	(1.17)	9.12	5.36	(1.95)	7.20	3.43	(2.15)
Indiana(IN)	5.39	4.45	(0.85)	7.20	4.40	(2.13)	7.39	4.36	(3.57)	8.45	5.26	(0.97)
Arizona(AZ)	4.1	5.02	(-0.72)	5.10	1.94	(3.59)	5.26	2.65	(2.22)	5.04	2.88	(1.55)
Connecticut(CT)	7.11	3.92	(1.39)	5.78	5.11	(0.42)	5.31	4.52	(0.38)	9.20	24.64	(-1.28)
Maryland(MD)	5.17	4.66	(0.33)	5.59	2.72	(3.08)	4.41	3.13	(1.31)	4.17	1.61	(3.19)
Oregon(OR)	4.91	3.24	(0.9)	6.67	3.41	(1.57)	3.88	4.72	(-0.5)	4.77	3.18	(1.07)
Georgia(GA)	7.87	4.8	(1.5)	5.77	3.31	(1.6)	9.45	5.25	(2.76)	8.62	3.10	(2.57)
Virginia(VA)	3.77	1.75	(2.16)	4.38	1.73	(2.67)	4.82	2.70	(1.71)	6.89	1.59	(5.56)
Missouri(MO)	3.88	3.43	(0.23)	6.27	4.11	(0.97)	5.51	2.52	(2.65)	7.61	1.06	(4.28)
Idaho(ID)	8.16	4.76	(0.64)	8.71	2.99	(2.42)	13.83	7.10	(1.54)	6.53	3.60	(2.15)
Tennessee(TN)	4.21	2.81	(0.63)	6.34	1.98	(3.3)	4.80	3.81	(0.78)	5.24	6.66	(-0.72)
Oklahoma(OK)	11.2	12.47	(-0.29)	7.02	6.38	(0.35)	22.59	17.09	(0.56)	6.27	8.47	(-0.53)
Utah(UT)	4.81	0	(3.81)	7.94	3.80	(2.06)	12.43	6.51	(2.57)	9.13	2.35	(4.12)
Iowa(IA)	6.75	5.11	(0.92)	4.76	1.34	(2.69)	6.23	2.64	(2.56)	10.15	20.01	(-1.3)
South Carolina(SC)	6.94	3.39	(0.9)	5.84	4.32	(0.78)	8.10	5.55	(1.39)	3.30	4.93	(-1.08)
Delaware(DE)	1.9	1.48	(0.47)	3.54	3.73	(-0.11)	5.60	2.54	(2.69)	7.01	1.74	(1.96)
Louisiana(LA)	4.95	3.66	(0.73)	5.41	3.55	(1.37)	4.90	1.89	(1.99)	5.64	1.86	(1.46)
Kansas(KS)	5.3	2.78	(1.12)	4.31	0.45	(2.87)	3.10	1.55	(2.39)	5.20	2.20	(2.41)
Kentucky(KY)	2.11	2.03	(0.08)	2.25	1.81	(0.48)	3.65	1.43	(1.85)	2.50	1.25	(1.12)
Alabama(AL)	1.77	5.08	(-1.44)	5.97	1.93	(1.93)	3.20	0.55	(3.57)	5.73	0.45	(1.9)
New Hampshire(NH)	0.99	1.2	(-0.19)	5.61	1.45	(1.71)	3.18	1.89	(1.3)	2.67	1.37	(0.91)
Nevada(NV)	8.7	1.79	(1.68)	6.08	1.77	(1.25)	27.60	26.72	(0.06)	27.45	22.93	(0.43)
New Mexico(NM)	3.04	1.33	(0.95)	4.66	1.84	(2.07)	3.50	0.94	(3.01)	3.13	0.52	(2.41)
Vermont(VT)	0	0	(-)	2.83	1.39	(1.07)	3.40	1.03	(1.56)	1.27	2.07	(-1.3)
Nebraska(NE)	-	-	(-)	5.12	2.15	(1.48)	4.04	3.03	(0.55)	2.23	1.32	(0.63)
Rhode Island(RI)	1.21	0	(2.01)	3.88	3.12	(0.32)	2.91	0.63	(1.99)	2.90	2.46	(0.19)
West Virginia(WV)	1.88	0	(1.68)	3.77	2.82	(0.46)	4.12	2.50	(1.28)	61.22	1.02	(2.73)
Arkansas(AR)	3.82	1.75	(0.69)	1.11	0.00	(1.28)	3.42	1.41	(1.27)	2.41	0.89	(0.88)
Mississippi(MS)	1.72	0	(1.55)	6.83	0.00	(2.47)	1.95	0.60	(2.18)	8.22	19.38	(-0.8)
Montana(MT)	4.62	0	(1.59)	5.97	6.98	(-0.19)	6.58	2.43	(0.94)	1.16	0.58	(0.73)
Maine(ME)	3.9	0	(3.03)	4.15	2.08	(0.73)	0.62	0.35	(0.55)	0.39	1.18	(-0.65)
Dist. of Columbia(DC)	4.31	0	(2.06)	0.62	0.00	(1.46)	0.92	0.38	(0.75)	1.14	0.27	(1.43)
North Dakota(ND)	1.59	0	(1.23)	3.73	0.00	(2.66)	2.03	0.81	(0.8)	0.47	0.00	(0.91)
Hawaii(HI)	0	0	(-)	2.30	0.00	(1.56)	4.31	0.00	(2.47)	5.45	0.00	(1.34)
South Dakota(SD)	1.59	3.23	(-0.44)	8.93	0.00	(2.7)	1.44	0.00	(1.68)	0.84	0.90	(-0.07)
Wyoming(WY)	10.74	0	(2.78)	1.17	1.64	(-0.3)	4.20	0.00	(1.95)	0.54	0.00	(1.11)
Alaska(AK)	11.76	0	(1.6)	3.85	0.00	(1.29)	0.88	0.00	(0.91)	2.27	0.00	(1.06)

localization effects of knowledge spillovers have strengthened across the US without California.

Figure 2. Matching Rates by State



5.2. **Comparison by Industry.** The results from the aggregate sample of Section 4.2 may contain other types of heterogeneity. Since some states have played a particularly important role in reinforcing the localization effects, and since states often specialize in agglomeration of certain types of industries (e.g. Silicon Valley), it is worth checking the geographic patterns of patent citations across different industries. Another reason to break down localization effects by industry is to explore a potential source of divergence in the "home bias" in localization of patent production.

We report the localization trends in terms of NBER's six industrial categories under which the 37 sub-categories are nested: chemical, computer and communication, drugs and medicine, electronic, mechanical, and others. The detailed results (obtained with Common controls and for each geographic level) are given in Table 6 and also illustrated in Figures A1-A3 of Appendix E.

Let us first examine industry-wide localization trends at country level, where our aggregate analysis showed increasing localization of citations but diminishing localization of controls. Our data clearly reveal growing localization effects across all industry categories (see Figure A1). In each cohort, the magnitude of localization effects is relatively uniform; also, the range of citing matching rates has remained relatively stable. Interestingly, however, the dispersion of control matching rates across industries has steadily widened over the sample decades. The fall in agglomeration of patent production in the "electronic" industry is particularly striking.

At intra-national level, localization effects have grown for all industries in almost all cases. The only exceptions are "mechanical" and "others" in the 2006 cohort at state and CMSA levels, where such effects are statistically insignificant. Again, the distribution of control matching rates has become considerably more scattered, and this is mostly due to greater clustering of research activities in "drugs and medicine," "mechanical," and "others" (see Figures A2 and A3).

Given the importance of California, we in addition break down Californian patents by industries and present the results in Figure A4 in Appendix E. The citing patents from California have increasingly become more localized than the corresponding control patents across all industries, except for "others" in 2006.

Table 6. Matching Rates by Industry

Location	Industry	1976 Citing	1976 Control	1976 t-value	1986 Citing	1986 Control	1986 t-value	1996 Citing	1996 Control	1996 t-value	2006 Citing	2006 Control	2006 t-value
country	Chemical	63.51	60.96	(2.07)	69.36	56.42	(10.0)	76.87	54.26	(18.47)	79.24	52.01	(17.96)
	Cmp&Cm	63.22	55.09	(4.39)	68.35	49.99	(8.66)	77.41	54.04	(17.54)	77.20	57.89	(16.26)
	Drgs&Me	74.40	67.04	(2.53)	80.33	70.80	(5.67)	83.61	70.28	(6.3)	87.97	73.18	(8.78)
	Elec	65.19	58.00	(4.8)	65.75	51.49	(14.32)	71.38	47.87	(24.09)	69.40	39.97	(21.02)
	Mech	63.03	56.10	(3.89)	67.73	54.32	(8.02)	71.25	50.67	(10.99)	78.54	60.50	(3.89)
	Others	72.85	69.10	(2.65)	76.17	65.69	(8.48)	78.53	63.57	(9.91)	80.36	63.53	(6.36)
state	Chemical	8.59	9.20	(-0.46)	10.29	7.69	(2.29)	15.01	9.01	(2.1)	17.95	10.06	(1.6)
	Cmp&Cm	8.81	7.83	(0.46)	9.36	6.45	(1.48)	14.32	10.09	(1.15)	16.73	10.97	(1.48)
	Drgs&Me	9.60	9.39	(0.12)	10.97	8.38	(0.91)	17.61	12.97	(0.72)	22.49	16.13	(0.88)
	Elec	9.06	8.21	(0.8)	10.59	7.38	(2.54)	13.36	8.67	(1.88)	17.50	9.11	(1.91)
	Mech	9.72	8.34	(1.47)	11.51	7.27	(4.35)	14.30	9.45	(2.55)	18.65	17.99	(0.14)
	Others	11.15	9.00	(1.13)	11.34	8.27	(1.28)	15.89	12.69	(0.95)	21.37	19.17	(0.31)
CMSA	Chemical	8.53	9.00	(-0.3)	9.23	7.05	(2.36)	12.64	7.18	(3.1)	13.45	7.28	(2.52)
	Cmp&Cm	7.06	5.86	(1.2)	7.49	4.99	(1.7)	11.04	7.62	(1.43)	12.84	8.03	(1.97)
	Drgs&Me	9.35	9.65	(-0.16)	8.84	5.87	(2.34)	13.39	8.96	(1.31)	15.73	11.26	(1.39)
	Elec	7.29	6.29	(1.55)	7.97	5.32	(3.59)	10.73	6.37	(2.25)	14.41	7.12	(1.91)
	Mech	7.48	6.42	(1.54)	9.60	6.03	(4.97)	11.75	7.93	(2.22)	14.88	14.38	(0.11)
	Others	8.86	7.03	(1.91)	9.07	6.02	(2.55)	12.99	10.23	(1.17)	17.35	16.15	(0.23)

6. Concluding Discussion

This paper reports strong evidence of significant and *growing* localization effects of knowledge spillovers. Our analysis is based on patent citations within and across the US over the period of 1976-2015. The results are robust to multiple methods of proxying the existing geography of knowledge production. Other robustness checks include restricting attention to most cited patents to control for declining average quality.

Since localization of knowledge spillovers is a critical determinant of spatial inequality in long-run growth (e.g. Baldwin and Martin, 2004; Duranton and Puga, 2004), our findings offer important policy implications.[19] They are also surprising given the rapid globalization and development of communication technologies witnessed in recent decades. There is no doubt that information now travels at an unprecedented level of precision and speed. Patents and other scholarly publications are digitized and alerted around the world immediately upon publication. Wasn't the IT revolution supposed to bring down the frictions and usher in a new era of convergence? Why then has the "death of distance" not materialized?

Identifying the source of greater localization of knowledge spillovers is the major outstanding question from the current study. Perhaps high quality ideas have become harder to come by (e.g. Bloom, Jones, Van Reenen, and Webb, 2017), or the increasing use of patents, or patent *thickets*, as a means to deter competitive entry (e.g. Shapiro, 2000; Hall and Ziedonis, 2001) has dampened the intensity of diffusion altogether. Another possibility, as documented by Autor, Dorn, Katz, Patterson, and Van Reenen (2017a,b), is that market concentration has been rising in the US. If a few large firms are generating more of the patents then this could be a reason for why the spillover effects remain localized.[20]

One could also exploit the state-sector variations in localization effects which have indeed intensified over the years. The extensive literature on innovation and knowledge spillovers suggest a number of further directions, from the role of universities (e.g. Jaffe, 1989) to the composition of the stock of knowledge (e.g. Antonelli, Crespi, Mongeau, and Scellato, 2017). If these aspects of knowledge production are becoming more unequal then this could also provide clues as to why we observe increased localization effects.

[19] For the agglomerative forces of knowledge spillovers, see Marshall (1890), Rosenthal and Strange (2001), and Ellison, Glaeser, and Kerr (2010), among others.

[20] Note that we have followed the literature and focused on utility patents. An interesting future research would be to investigate how the spillover effects have evolved for design patents, trademarks, and other non-patented innovations such as open-source software.

Finally, the trends in *inter*national spillover effects turn out to be different from their *intra*national counterparts. In particular, we observe declining frequency of geographic match between control and originating patents within the US, which is consistent with accelerating globalization. However, globalization may have contributed to diffusion of knowledge in ways not captured by patent citations, for instance, via unauthorized piracy and knockoffs in the informal economy.[21]

[21] For evidence of greater knowledge spillovers in the informal sector, see Goel, Saunoris, and Zhang (2016).

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Appendix A. Patent Data

Table A1. Patent Counts

	1976 - 1985		1986 - 1995		1996 - 2005		2006 - 2015		Total	
Number of patents	596983		874190		1444740		2012412		4928325	
US patents	342441		447663		742251		952048		2484403	
Foreign patents	254542		426527		702489		1060364		2443922	
California(CA)	45938	(13.41%)	68384	(15.28%)	159655	(21.51%)	255844	(26.87%)	529821	(21.33%)
New York(NY)	29578	(8.64%)	36753	(8.21%)	52140	(7.02%)	58202	(6.11%)	176673	(7.11%)
Texas(TX)	18853	(5.51%)	30435	(6.80%)	54728	(7.37%)	69549	(7.31%)	173565	(6.99%)
Illinois(IL)	26291	(7.68%)	26302	(5.88%)	33032	(4.45%)	34864	(3.66%)	120489	(4.85%)
Michigan(MI)	19325	(5.64%)	24147	(5.39%)	33502	(4.51%)	35951	(3.78%)	112925	(4.55%)
New Jersey(NJ)	24872	(7.26%)	23496	(5.25%)	28195	(3.80%)	28467	(2.99%)	105030	(4.23%)
Ohio(OH)	21807	(6.37%)	23360	(5.22%)	29066	(3.92%)	27149	(2.85%)	101382	(4.08%)
Pennsylvania(PA)	21653	(6.32%)	22557	(5.04%)	27503	(3.71%)	27005	(2.84%)	98718	(3.97%)
Massachusetts(MA)	11257	(3.29%)	15145	(3.38%)	26790	(3.61%)	38002	(3.99%)	91194	(3.67%)
Minnesota(MN)	8204	(2.40%)	13229	(2.96%)	24734	(3.33%)	32722	(3.44%)	78889	(3.18%)
Washington(WA)	4838	(1.41%)	8329	(1.86%)	18637	(2.51%)	44352	(4.66%)	76156	(3.07%)
Florida(FL)	9019	(2.63%)	15543	(3.47%)	23217	(3.13%)	27593	(2.90%)	75372	(3.03%)
North Carolina(NC)	4396	(1.28%)	7839	(1.75%)	16302	(2.20%)	23336	(2.45%)	51873	(2.09%)
Colorado(CO)	4764	(1.39%)	7840	(1.75%)	17051	(2.30%)	20550	(2.16%)	50205	(2.02%)
Wisconsin(WI)	7202	(2.10%)	10424	(2.33%)	15894	(2.14%)	16010	(1.68%)	49530	(1.99%)
Indiana(IN)	8799	(2.57%)	9429	(2.11%)	12955	(1.75%)	13650	(1.43%)	44833	(1.80%)
Arizona(AZ)	4334	(1.27%)	7721	(1.72%)	14325	(1.93%)	18086	(1.90%)	44466	(1.79%)
Connecticut(CT)	8128	(2.37%)	10210	(2.28%)	12276	(1.65%)	12846	(1.35%)	43460	(1.75%)
Maryland(MD)	6520	(1.90%)	7712	(1.72%)	12459	(1.68%)	13161	(1.38%)	39852	(1.60%)
Oregon(OR)	2805	(0.82%)	5309	(1.19%)	12691	(1.71%)	19012	(2.00%)	39817	(1.60%)
Georgia(GA)	3279	(0.96%)	6118	(1.37%)	12390	(1.67%)	17579	(1.85%)	39366	(1.58%)
Virginia(VA)	5109	(1.49%)	6723	(1.50%)	9522	(1.28%)	12649	(1.33%)	34003	(1.37%)
Missouri(MO)	5395	(1.58%)	6028	(1.35%)	7834	(1.06%)	8378	(0.88%)	27635	(1.11%)
Idaho(ID)	661	(0.19%)	1951	(0.44%)	13144	(1.77%)	10515	(1.10%)	26271	(1.06%)
Tennessee(TN)	3310	(0.97%)	4617	(1.03%)	6999	(0.94%)	7402	(0.78%)	22328	(0.90%)
Oklahoma(OK)	6034	(1.76%)	5674	(1.27%)	4764	(0.64%)	4719	(0.50%)	21191	(0.85%)
Utah(UT)	1876	(0.55%)	3411	(0.76%)	6389	(0.86%)	9068	(0.95%)	20744	(0.83%)
Iowa(IA)	3128	(0.91%)	3621	(0.81%)	5955	(0.80%)	7240	(0.76%)	19944	(0.80%)
South Carolina(SC)	2345	(0.68%)	3630	(0.81%)	4966	(0.67%)	5886	(0.62%)	16827	(0.68%)
Delaware(DE)	3088	(0.90%)	4396	(0.98%)	3994	(0.54%)	3967	(0.42%)	15445	(0.62%)
Louisiana(LA)	3041	(0.89%)	4141	(0.93%)	4234	(0.57%)	3006	(0.32%)	14422	(0.58%)
Kansas(KS)	2082	(0.61%)	2333	(0.52%)	3606	(0.49%)	6366	(0.67%)	14387	(0.58%)
Kentucky(KY)	2437	(0.71%)	2611	(0.58%)	3904	(0.53%)	4525	(0.48%)	13477	(0.54%)
Alabama(AL)	1857	(0.54%)	2677	(0.60%)	3428	(0.46%)	3578	(0.38%)	11540	(0.46%)
New Hampshire(NH)	1032	(0.30%)	2061	(0.46%)	3636	(0.49%)	4226	(0.44%)	10955	(0.44%)
Nevada(NV)	807	(0.24%)	1192	(0.27%)	3001	(0.40%)	5257	(0.55%)	10257	(0.41%)
New Mexico(NM)	1034	(0.30%)	1941	(0.43%)	3180	(0.43%)	3497	(0.37%)	9652	(0.39%)
Vermont(VT)	441	(0.13%)	666	(0.15%)	2704	(0.36%)	3607	(0.38%)	7418	(0.30%)
Nebraska(NE)	759	(0.22%)	1392	(0.31%)	1934	(0.26%)	2268	(0.24%)	6353	(0.26%)
Rhode Island(RI)	843	(0.25%)	1125	(0.25%)	1956	(0.26%)	1929	(0.20%)	5853	(0.24%)
West Virginia(WV)	1297	(0.38%)	1366	(0.31%)	1301	(0.18%)	1040	(0.11%)	5004	(0.20%)
Arkansas(AR)	690	(0.20%)	1001	(0.22%)	1487	(0.20%)	1332	(0.14%)	4510	(0.18%)
Mississippi(MS)	582	(0.17%)	952	(0.21%)	1477	(0.20%)	1293	(0.14%)	4304	(0.17%)
Montana(MT)	432	(0.13%)	747	(0.17%)	1125	(0.15%)	979	(0.10%)	3283	(0.13%)
Maine(ME)	460	(0.13%)	674	(0.15%)	845	(0.11%)	1117	(0.12%)	3096	(0.12%)
Dist. of Columbia(DC)	488	(0.14%)	467	(0.10%)	611	(0.08%)	930	(0.10%)	2496	(0.10%)
North Dakota(ND)	318	(0.09%)	484	(0.11%)	670	(0.09%)	831	(0.09%)	2303	(0.09%)
Hawaii(HI)	296	(0.09%)	539	(0.12%)	594	(0.08%)	783	(0.08%)	2212	(0.09%)
South Dakota(SD)	293	(0.09%)	320	(0.07%)	568	(0.08%)	761	(0.08%)	1942	(0.08%)
Wyoming(WY)	299	(0.09%)	371	(0.08%)	497	(0.07%)	691	(0.07%)	1858	(0.07%)
Alaska(AK)	145	(0.04%)	270	(0.06%)	384	(0.05%)	278	(0.03%)	1077	(0.04%)

Notes: The number in parentheses is the percentage of patents from the state relative to the total number of US patents.

Appendix B. Description of Citing Patents

Table A2. Citation Statistics

year	percent receiving citations	number of citing patents	mean citations received
1976	0.76 (0.79)	131263 (149843)	2.98 (3.40)
1986	0.87 (0.89)	229690 (253989)	6.02 (6.66)
1996	0.94 (0.95)	928693 (1008675)	15.08 (16.38)
2006	0.80 (0.84)	684711 (810919)	8.51 (10.07)

Notes: The numbers in parentheses indicate values including self-citations.

Appendix C. Iteration Results for Control Selection

The table below shows the percentage of control patents selected in each round of iteration for each cohort and each technological match criterion. The final row in each cohort reports the proportions of citing patents for which control patents could not be found within our time frame.

Table A3. Iteration Results for Control Selection

	Class	3-digit	Any	Primary	Common
1976	1-month	99.93	66.46	41.32	16.33
	3-month	0.05	19.70	22.99	9.70
	6-month	0.01	7.16	13.22	6.48
	missing	0.01	6.68	22.47	67.49
1986	1-month	99.87	88.34	50.22	19.10
	3-month	0.11	5.90	21.37	10.54
	6-month	0.01	0.00	10.81	7.02
	missing	0.01	5.76	17.60	63.34
1996	1-month	99.98	95.59	69.87	19.30
	3-month	0.02	2.40	15.34	8.40
	6-month	0.00	0.00	6.43	5.56
	missing	0.00	2.01	8.36	66.74
2006	1-month	99.97	96.06	77.47	26.05
	3-month	0.02	2.18	12.07	9.66
	6-month	0.00	0.12	4.61	6.49
	missing	0.00	1.64	5.85	57.80

Appendix D. Alternative Patent Location Assignment

Here, we consider an alternative assignment rule for patent location based on plurality (see JTH). Whenever a sample patent has multiple inventors, its location is (i) the most frequent location associated with its inventors, and (ii) in case of a tie, randomly chosen among the most frequent locations. Tables A4 and A5 present the corresponding results for all originating patents and for most cited originating patents, respectively.

Table A4. Aggregate Trends: Alternative Location Assignment

		citing	3-digit	Any	Primary	Common
1976	TOTAL	104137	104137	97367	81118	34072
	country	66.36	57.77	59.82	59.21	61.37
			(15.49)	(10.92)	(11.51)	(6.4)
	state	9.57	4.65	6.57	6.85	8.72
			(9.75)	(5.63)	(4.86)	(1.31)
	CMSA	8.12	3.44	5.27	5.54	7.36
			(11.81)	(6.84)	(6.05)	(1.41)
1986	TOTAL	185187	185187	176357	153053	68061
	country	71.27	56.61	58.86	58.45	58.58
			(22.19)	(18.0)	(17.35)	(14.96)
	state	10.75	4.69	6.41	6.63	7.68
			(9.07)	(6.07)	(5.62)	(3.92)
	CMSA	8.75	3.38	4.92	5.07	5.98
			(13.58)	(9.03)	(8.7)	(6.1)
1996	TOTAL	709919	709919	700795	656320	236237
	country	77.16	55.19	57.97	58	58.19
			(23.83)	(19.13)	(18.47)	(13.59)
	state	15.44	6.8	8.77	9.12	10.99
			(4.79)	(3.53)	(3.3)	(2.14)
	CMSA	12.41	4.63	6.45	6.74	8.44
			(6.93)	(5.03)	(4.74)	(3.05)
2006	TOTAL	552741	552741	548204	526639	237062
	country	78.21	52.86	56.04	55.93	58.06
			(20.12)	(16.59)	(16.32)	(13.3)
	state	19	8.22	10.47	10.68	12.85
			(4.43)	(3.42)	(3.34)	(2.39)
	CMSA	14.77	5.53	7.39	7.57	9.67
			(6.17)	(4.83)	(4.73)	(3.2)

Notes: The numbers in the first row of each cohort represent sample sizes. A number in parenthesis is the relevant t-statistic.

Table A5. Aggregate Trends: Alternative Location Assignment & Most Cited Originating Patents

		citing	3-digit	Any	Primary	Common
1976	TOTAL	39115	39115	37544	32610	14144
	country	66.61	57.46	59.57	58.94	61.12
			(11.94)	(8.22)	(8.72)	(4.96)
	state	9.98	5.07	6.98	7.18	9.13
			(7.56)	(4.32)	(3.89)	(1.02)
	CMSA	8.49	3.64	5.48	5.84	7.62
			(8.54)	(5.04)	(4.38)	(1.19)
1986	TOTAL	71671	71671	69184	62300	27516
	country	74.84	58.47	60.59	60.32	59.52
			(15.94)	(13.52)	(13.21)	(11.68)
	state	11.23	5.34	6.97	7.14	7.69
			(5.64)	(3.84)	(3.65)	(3.22)
	CMSA	9.36	4.06	5.47	5.5	6.03
			(7.18)	(5.08)	(5.26)	(4.69)
1996	TOTAL	342773	342773	342360	329254	109883
	country	82.19	58.17	61.45	61.48	62.87
			(22.33)	(17.21)	(16.87)	(9.74)
	state	17.93	8.11	10.26	10.49	13.24
			(3.64)	(2.71)	(2.61)	(1.41)
	CMSA	14.3	5.6	7.56	7.74	10.12
			(5.17)	(3.78)	(3.67)	(1.98)
2006	TOTAL	287263	287263	286626	279110	125856
	country	83.61	55.63	59.44	59.36	62.56
			(17.58)	(14.25)	(13.88)	(11.34)
	state	21.31	8.87	11.49	11.68	14.2
			(3.85)	(2.96)	(2.91)	(2.06)
	CMSA	16.42	5.95	8	8.17	10.63
			(5.29)	(4.17)	(4.11)	(2.71)

Notes: The numbers in the first row of each cohort represent sample sizes. A number in parenthesis is the relevant t-statistic.

Appendix E. Comparison by State and Industry

Table A6. Frequency of Geographic Match: California

		citing	3-digit	Any	Primary	Common
1976	TOTAL	16190	16190	15136	12823	5202
	country	68.29	57.64	60.79	59.92	63.23
			(6.98)	(4.91)	(5.68)	(2.78)
	state	16.24	9.14	11.3	11.64	12.59
			(9.37)	(5.87)	(5.14)	(4.03)
	CMSA	9.38	3.68	5.34	5.69	6.59
			(11.61)	(7.48)	(6.99)	(4.58)
1986	TOTAL	31352	31352	29890	26512	11995
	country	72.49	57	59.55	59.26	59.72
			(6.98)	(5.7)	(5.2)	(4.28)
	state	19.49	10.61	13.08	13.53	14.47
			(7.74)	(5.09)	(4.67)	(3.85)
	CMSA	10.98	4.54	6.5	6.92	7.89
			(10.07)	(5.85)	(5.44)	(4.19)
1996	TOTAL	176073	176073	174567	166264	57989
	country	78.12	56.63	59.59	59.6	59.68
			(8.08)	(6.37)	(6.21)	(4.23)
	state	32.2	16.99	20.17	20.7	22.93
			(7.68)	(5.64)	(5.29)	(3.04)
	CMSA	21.58	9.51	12.26	12.64	13.98
			(8.15)	(6.13)	(5.91)	(3.95)
2006	TOTAL	177003	177003	176642	171202	77966
	country	78.16	52.6	55.44	55.48	56.92
			(7.64)	(6.46)	(6.34)	(5.57)
	state	36.52	17.67	20.91	21.02	23.09
			(10.14)	(8.41)	(8.44)	(6.81)
	CMSA	24.96	10.15	12.74	12.81	14.83
			(9.15)	(7.52)	(7.55)	(6.07)

Notes: The numbers in the first row of each cohort represent sample sizes. A number in parenthesis is the relevant t-statistic.

Table A7. Frequency of Geographic Match: Without California

		citing	3-digit	Any	Primary	Common
1976	TOTAL	87937	87937	82220	68267	28857
	country	65.99	57.81	59.66	59.1	61
			(13.91)	(9.76)	(10.08)	(5.79)
	state	8.34	3.86	5.68	5.95	8.02
			(9.25)	(5.15)	(4.37)	(0.46)
	CMSA	7.83	3.43	5.26	5.5	7.48
			(9.57)	(5.29)	(4.71)	(0.57)
1986	TOTAL	153861	153861	146482	126550	55998
	country	70.95	56.54	58.91	58.21	58.22
			(22.36)	(17.82)	(17.98)	(15.84)
	state	8.88	3.52	5.05	5.18	6.15
			(8.99)	(5.98)	(5.72)	(3.72)
	CMSA	8.25	3.17	4.63	4.7	5.5
			(10.46)	(7.06)	(7.08)	(5.22)
1996	TOTAL	533589	533589	525970	489797	178102
	country	76.56	54.7	57.37	57.47	57.58
			(31.09)	(25.83)	(24.62)	(19.72)
	state	9.34	3.31	4.75	4.94	6.75
			(9.76)	(6.9)	(6.56)	(3.17)
	CMSA	8.68	2.85	4.23	4.41	6.13
			(11.82)	(8.35)	(7.93)	(3.79)
2006	TOTAL	374991	374991	370790	354707	158818
	country	77.87	52.95	56.38	56.26	58.64
			(28.47)	(23.07)	(22.22)	(16.63)
	state	9.72	3.51	5.14	5.38	7.34
			(6.68)	(4.58)	(4.33)	(1.94)
	CMSA	8.92	3.11	4.57	4.79	6.66
			(7.79)	(5.36)	(5.05)	(2.22)

Notes: The numbers in the first row of each cohort represent sample sizes. A number in parenthesis is the relevant t-statistic.

Figure A1. Matching Rates by Industry (Country)

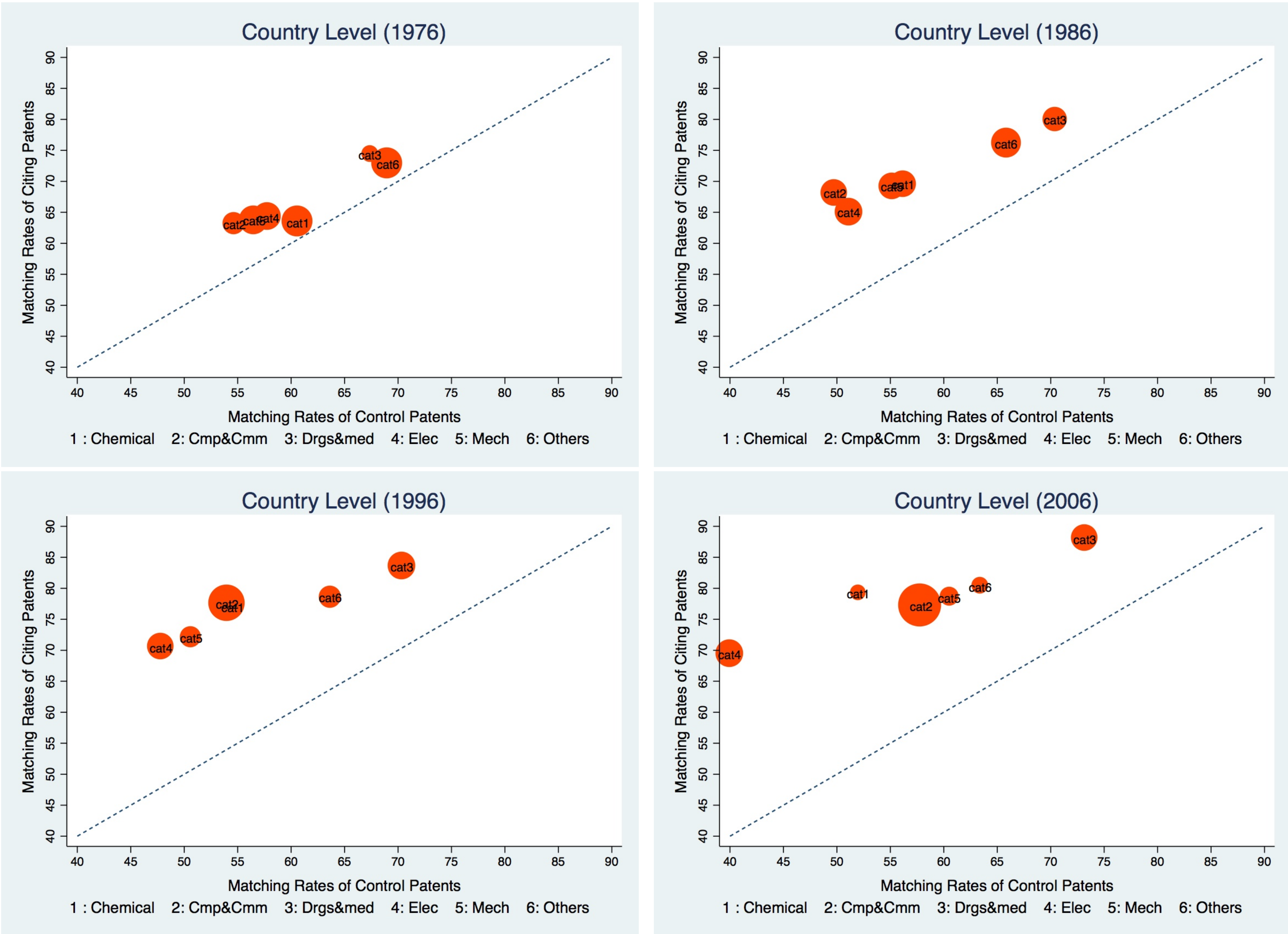

FIGURE A2. Matching Rates by Industry (State)

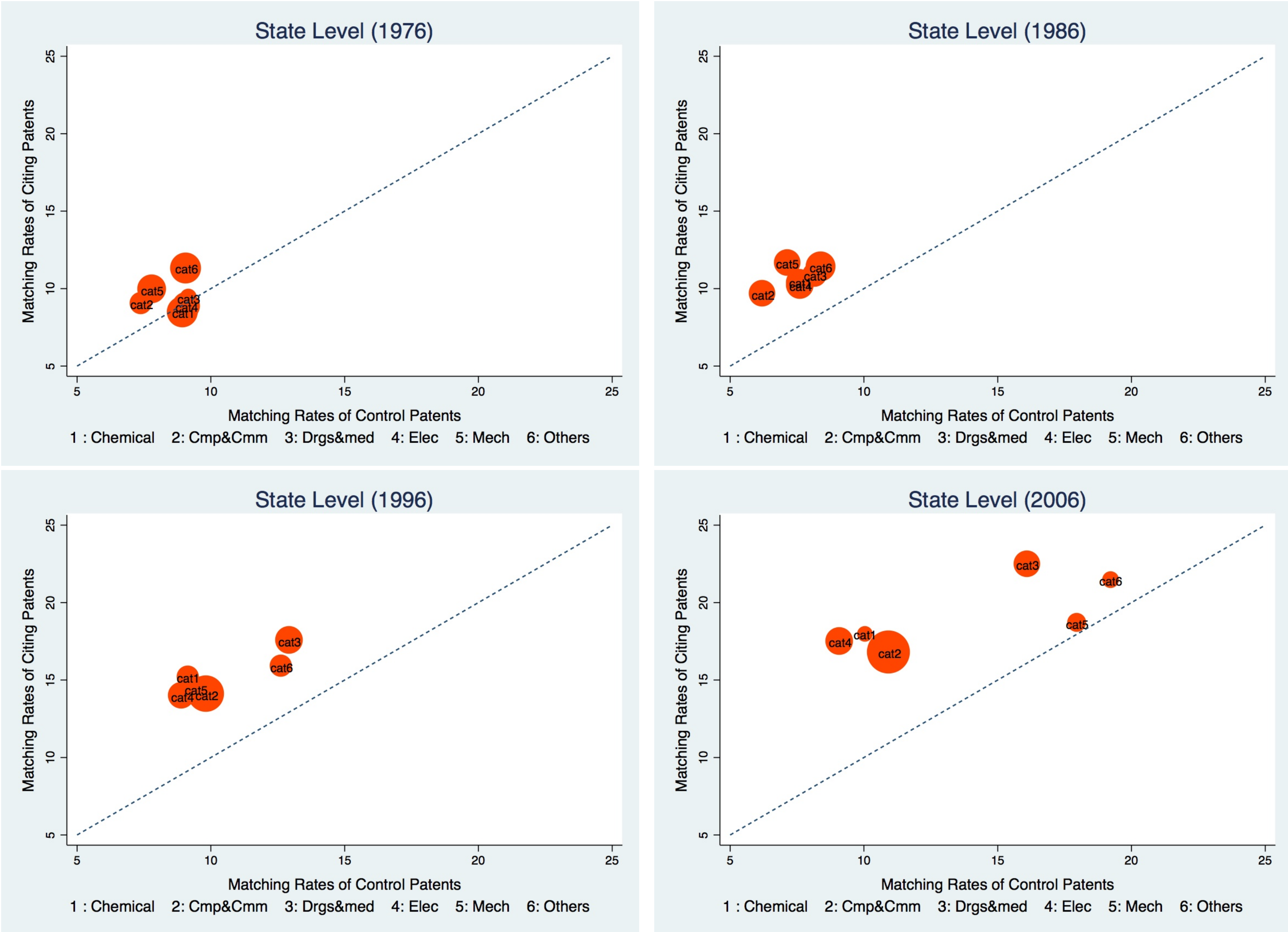

Figure A3. Matching Rates by Industry (CMSA)

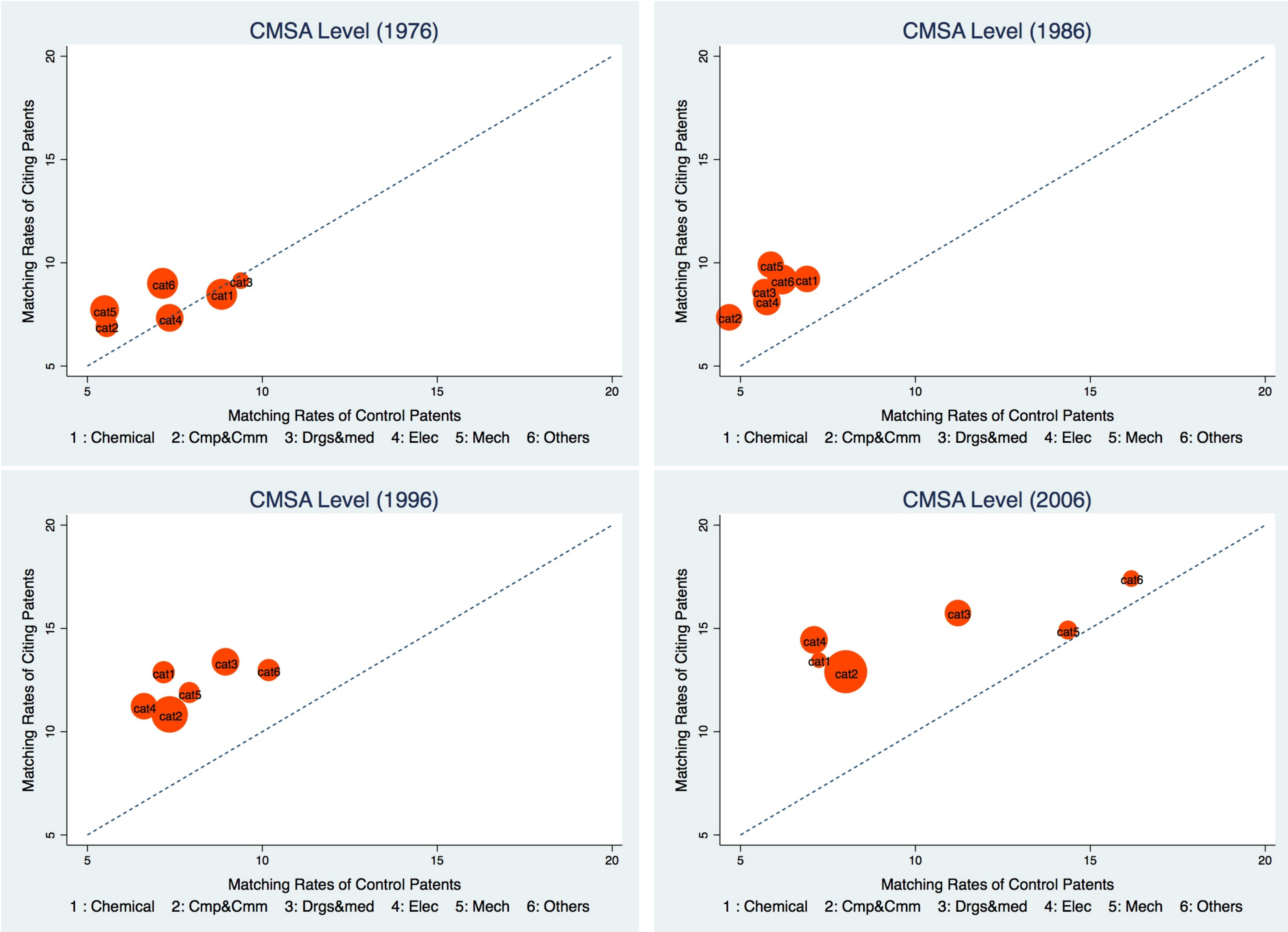

FIGURE A4. Matching Rates by Industry (California)