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Borders and distance in knowledge spillovers: Dying over time or dying with age?—Evidence from patent citations

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ABSTRACT

This paper explores the effects of distance as well as subnational and national borders on international and intranational knowledge spillovers through patent citations across the 39 most patent-cited countries and 319 metropolitan statistical areas (MSAs) within the U.S. In contrast to previous findings that knowledge localization fades over time, border and distance effects increase over time for the same-age citations. This increasing effect of borders and distance is associated with strengthened knowledge agglomeration over time. Nevertheless, both border and distance effects decrease with the age of patents. Aggregate border effects are often overestimated due to various aggregation bias. Moreover, business travels and knowledge quality effectively attenuate the effect of subnational borders in knowledge flows.

1. Introduction

The degree of localization of knowledge spillovers remains contentious. Recently, Thompson and Fox-Kean (2005a) claimed that only national boundaries restrict knowledge flows and that there is no strong evidence to support significant subnational barriers to knowledge diffusion. In contrast, Henderson et al. (2005) (among others) asserted that knowledge spillovers are localized internationally and intranationally at the state, the consolidated metropolitan statistical area (CMSA), and even the standard metropolitan statistical area (SMSA) levels.[1] These conflicting ideas raise the question of the extent to which knowledge spillovers are localized and further challenge our understanding of the causes of knowledge localization. Are knowledge spillovers restricted more by physical distance or national (and subnational) boundaries? If knowledge spillovers are localized, does knowledge localization truly fade over time, as suggested by the existing

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[1] For example, Peri (2005) found that pooled citations as proxy for knowledge spillovers are strongly localized at the state/province level within one country. Jaffe et al. (1993) reported significant localization of knowledge spillovers at the SMSA level. Thompson (2006) and Alcáer and Gittelman (2006) found that inventor citations and examiner citations are both localized within the U.S.

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literature?[2] The answers to these questions have significant implications for public policy on knowledge dissemination and industrial agglomeration.

To better understand patterns in the localization of knowledge spillovers and their potential sources, this paper tackles three questions. First, how localized is the diffusion of intranational and international knowledge? To address this question, I decompose the frictions affecting knowledge spillovers to national and subnational borders and the effects of average distance and internal distance. Second, if national and subnational borders significantly impede knowledge diffusion, what are the potential sources of border effects in knowledge spillovers? Alternatively speaking, are there any factors which contribute to reducing the effect of borders in knowledge diffusion? Third, how does the pattern of border and distance effects in knowledge diffusion change over time and with age? In this paper, "age" refers to the age of knowledge flows, measured by the time interval between the citing and cited patents.[3]

This definition of "age" highlights two different ways of representing patterns of knowledge flows over time. One approach is to investigate existing knowledge spillovers cross-sectionally and year by year to obtain the temporal trends. Another approach is to track the lifetime of knowledge (embodied in patents) to observe how spillovers change as knowledge gradually ages, which are shown here in the age profiles. The existing literature has not highlighted the difference between the temporal trends and the age profiles,[4] although they may generate completely different patterns of knowledge flows. For instance, one might think that a patent is more likely to receive citations across regions as it ages because of the time required to establish its reputation. In other words, it takes time for the knowledge embodied in this patent to be diffused to other regions. If this hypothesis were true, one would expect new knowledge spillovers to be more localized than old ones. The localization of knowledge would then fade over patents' lifetimes. However, if the proportion of new citations to total citations increases over time, a pattern that has been observed (Hall et al., 2001), it is possible for all knowledge spillovers to become increasingly localized over time. Other mechanisms could also lead to strengthened knowledge agglomeration over time. Therefore, it is necessary to distinguish temporal trends and age profiles of knowledge spillovers.

To answer the three questions stated above, I use a gravity model to estimate the magnitude of and the changes in the border and distance effects of knowledge flows. Following a common approach in the literature of knowledge spillovers, I use patent citations to trace knowledge flows. Patent citations are a good proxy for knowledge flows because patents embody new ideas (or knowledge) and award to inventors the right to exclude others from the unauthorized use of the disclosed invention. The applicant of a patent has the legal duty to disclose any knowledge of the "prior art", and hence, citations to previous patents are included in the patent documents. Intuitively, if patent B cites patent A, patent A then represents a piece of previously existing knowledge upon which patent B builds. When patents generate citations, they leave a paper trail of knowledge flows (Jaffe et al., 1993). Therefore, when patents invented in region i cite patents invented in region j, it is viewed as equivalent to the fact that knowledge flows from region j to i.[5] Here, *patent citations*, rather than the patent stock itself, provide interesting information tracking the direction and intensity of knowledge spillovers (Peri, 2005).[6]

Using different specifications of gravity equations, I estimate the effects of distance and borders on knowledge spillovers at the aggregate level and by different criteria (age, technology category, and time), controlling for technology compatibility between regions and the pre-existing distribution of technological activities by 3-digit patent class. Based on those estimates, I analyze the changing patterns (age profiles and temporal trends) of border and distance effects for knowledge spillovers. I also try to decompose the data along different dimensions to examine the potential sources of border effects.

The main data used in this paper are from the NBER Patent Citations Database, which contains more than 3 million patents and more than 16 million cross-patent citations. Border and distance effects are examined at both the intranational and international levels through patent citations across 319 metropolitan statistical areas (MSAs) within the U.S. and the 38 most cited countries.[7] These regions include more than 93% of patents and citations in the NBER database between 1980 and 1997. I employ the data at the MSA level because a study of the geography of innovation has shown that the majority of innovations are located in major cities, indicating that innovation is mainly an urban activity (Audretsch and Feldman, 2004). This observation raises doubts about the validity of large effect of state borders in the previous literature.[8] The finer data set at the metropolitan level allows for fuller exploration of the sources of subnational border effects and the nature of frictions affecting knowledge flows. In addition, I apply subnational level data regarding business travels, industrial composition and patent quality to tackle relevant factors that could potentially affect subnational border effects.

[2] Jaffe et al. (1993) find that knowledge localization fades over time, but only very slowly.

[3] Citation lag is equal to the grant year of the citing patent – the grant year of the cited patent. For example, if patent A cites patent B which is 20 years old (i.e., B was granted 20 years ago), this is a relatively "old" knowledge flow, and the age of this knowledge flow is 20; if patent A cites patent B which was granted 2 years ago, this is a relatively "new" knowledge flow, and its age is 2.

[4] For example, the finding of that "localization fades over time" in Jaffe et al. (1993) actually means that localization fades over a patent's lifetime.

[5] It should be noted that this paper only addresses the "pure" knowledge flows embodied in patent citations and all knowledge flows studied in this paper refer to those associated with patents and citations since the general concept of "knowledge" contains extensive content and is difficult to quantify.

[6] Measuring knowledge flows in a consistent, systematic way is a difficult task. Peri (2005) provided a concise summary, including some alternative approaches using trade flows or foreign direct investments as proxies for knowledge flows.

[7] These 319 MSAs include 270 typical MSAs, defined by the U.S. Census Bureau in 1990, and 49 phantom MSAs, one for each state (except New Jersey), containing all locations in non-metropolitan areas.

[8] For example, Peri (2005) estimated that knowledge flows will be diminished to 20% when crossing state or province borders within one country. In other words, Peri (2005) reported that around 80% of initial knowledge spillovers will be lost when crossing state/province borders.

I find large subnational border effects at the metropolitan level: overall, approximately 85.7% of subnational border effects are associated with the metropolitan borders. On average, the national border effect is larger than the MSA border effect, and the MSA border effect is significantly larger than the state border effect. This estimate of the national border effect is consistent with the previous literature, though the estimate of the MSA border effect contrasts with the large effects of state borders (blocking approximately 80% of initial knowledge flows) previously reported (Peri, 2005). Furthermore, ignoring MSA borders tends to exaggerate the effect of distance. Combining distance and border effects, the finding suggests the importance of subnational borders at MSA level.

Contrary to previous findings that knowledge localization fades over time, I find that border and distance effects in fact increase over time even for the same-age knowledge flows, and this phenomenon is associated with strengthened knowledge agglomeration over time. The agglomeration analysis of patent citations using EG index (Ellison and Glaeser, 1997) further confirms this result. The increase in border and distance effects over time is robust to different specifications and decompositions, such as by different age cohorts, industries of cited patents, or citing regions. This decomposition exercise alleviates the concern that the increasing distance effect over time is driven by changes in the composition of the sample. The increasing distance effect is also potentially related to the increasing "home bias" in knowledge flows where a reduction in the share of foreign citations at aggregate level is observed. Nevertheless, both distance and border effects decline with the age of knowledge and this age profile is consistent with the previous literature.

I then examine the sources of border effects and find that aggregation bias is a potential explanation. Decomposing data along different dimensions (geography, age, or technological category) contributes to a substantial reduction of aggregate border effects. Moreover, business travels across MSAs and cited MSAs' knowledge quality significantly facilitate knowledge flows and effectively attenuate the effect of subnational borders, while industrial specialization alone does not significantly affect subnational border effect when controlling for knowledge quality in the cited MSAs.

The novel finding that MSA-level border effect estimates have tended to increase over time is intriguing. According to the conventional wisdom, one expects less barriers to knowledge diffusion over time, due to the advancement of information and communication technology in the last few decades. The evidence of "offshoring" and the popular concept that "The World is Flat" are along these lines (Friedman, 2006). However, what might prevent this from happening? First, this could be that the transfer of knowledge works along these lines only for relatively simple processes, not for knowledge intensive ones, such as innovation activities. Keller and Yeaple (2013) suggest in general that the more knowledge intensive a process is, the less likely its knowledge will spatially diffuse. This is because highly knowledge intensive activity requires more non-codified knowledge, and thus incurs the relative high costs of communication. In fact, knowledge can often not fully be codified, and communicating knowledge is prone to errors (Keller and Yeaple, 2013). Therefore, when a region's industrial activity becomes increasingly knowledge intensive over time, the need for geographic proximity might increase, because these innovation activities benefit extraordinarily from face-to-face interaction. Second, with more knowledge intensive activities over time, it might not be possible to separate knowledge intensive activities, such as R&D/design, from regular industrial activities as in Keller and Yeaple (2013), and Levy and Murnane (2004) have a similar argument of why separating R&D from regular production may not be possible. When regular industrial activities are more and more integrated with knowledge intensive activities, one expects overall knowledge diffusion pattern to fall more in line with that of knowledge intensive processes. Last, but not least, innovation might be subject to scale economies and/or agglomeration economies (externalities), especially when knowledge transfer entails substantial fixed costs, more than other economic activities that may be relatively well characterized by perfect competition, constant returns to scale, and no externalities. Thus, one expects increasingly important needs for geographic proximity in knowledge spillovers to be associated with strengthened knowledge agglomeration over time that is confirmed in this paper.

By analyzing the effect of borders and distance in knowledge flows, this paper contributes to the emerging literature that explores the nature of knowledge diffusion using patent citation data. Most prior studies of knowledge flows focus on the geographic or institutional determinants of knowledge localization without explicit distance measures and do not differentiate the contributions of distance and borders (for example, Thompson and Fox-Kean, 2005a; Henderson et al., 2005; Thompson, 2006; Griffith et al., 2011, among others). Therefore, knowledge localization effects in those studies are, in fact, combined effects of geographic distance and borders. Several recent studies have investigated distance explicitly together with borders in knowledge flows (for example, Peri, 2005; Alcáer and Gittelman, 2006; Singh and Marx, 2013), but they either used dummy variables for distance intervals or omitted internal distance, i.e., the distance from one region to itself was set to zero. Rich distance data have not been investigated by the previous studies on knowledge flows. My findings imply that the omitted internal distance is important for examining home bias in knowledge flows. The novel findings of this paper reveal contrasting patterns of age profiles and temporal trends for border and distance effects in knowledge spillovers, which have not been previously reported.

This paper also contributes to studies of the subnational localization of knowledge spillovers. Much of the literature is based on matching methodology, and it can be difficult to reconcile previous quantitative and even qualitative findings (e.g., Thompson and Fox-Kean, 2005a,b; Henderson et al., 2005) due to the different criteria used for control groups.[9] For example, selecting different control groups can yield completely opposite results on whether knowledge spillovers are localized within a country. Hence, this paper uses a gravity framework to avoid selecting control groups and to estimate border and distance

[9] Matching method in knowledge spillovers literature was first used by Jaffe et al. (1993) to study the geography of knowledge flows using patent citations. They matched each citing patent to a non-citing patent, which shares the same location with the citing patent, so as to control for the existing concentration of knowledge production.

effects directly. Closely related work in empirical methodology includes Peri (2005), who used the gravity-like equation with the subnational patent citation data at the state (or province) level to study knowledge flows. Those findings suggest a strong knowledge localization effect at the state level due to large effects of state borders.[10] In contrast, my finding suggests a large subnational border effect at the MSA level.

Finally, the present paper contributes to a large literature on gravity application and border effects. The large border effect remains a key puzzle in international economics: Obstfeld and Rogoff (2000) refer to "McCallum's (1995)" home bias in trade" puzzle as one of the six leading puzzles in modern international macroeconomics. Since their study, many scholars have examined potential biases in estimates of border effects through theoretical and structural models or empirical strategies (Anderson and van Wincoop, 2003). This paper builds on the gravity framework of Anderson and van Wincoop (2003) and presents compelling empirical evidence for the potential resolution of the border puzzle in the context of knowledge flows. Part of the proposed resolution might be extensible and could be linked to border effects in trade flows. For example, when I decompose data from the state to the MSA level, the state border effect is substantially reduced; if I further use disaggregated data at the technological category level, some state border effects are no longer significant. This pattern is consistent with the finding in Hillberry and Hummels (2008): the state-level home bias in trade flows is largely driven by geographic aggregation. This paper also yields insights into the discussion of endogenous border effects in international trade (e.g., Chen, 2004).

The remainder of the paper is organized as follows. Section 2 summarizes the basic framework of analysis and describes the econometric specifications and data. Section 3 presents results, and Section 4 concludes.

2. Empirical specification and data

2.1. Baseline gravity equation

I employ a gravity framework of knowledge flows to disentangle the effects of physical distance and different types of borders on knowledge diffusion, avoiding the confounded "knowledge localization effect". Let c_{ij} denote the number of citations region j receives from region i, i.e., the number of citations by patents in region i of the existing knowledge present in the patents of region j. This measure is a proxy for the quantity of knowledge flowing from j to i. Hence, j is the cited region, and i is the citing region. Let y_i and y_j be the total number of citations region i and j receives, respectively, from all regions in the world, including region i and j themselves. A region's innovation outcome reflects its knowledge production capacity, and in the literature is measured by the total number of patents (weighted by citations received) in this region because the number of citations received captures a patent's importance.[11] Following this idea, I use the total number of citations received in regions i and j, y_i and y_j, to capture the size of the regions' respective knowledge production capacities.

"Region" is defined flexibly in this paper, referring to MSAs within the U.S. and 38 countries outside the U.S. A region-pair specific friction factor prevents the free movement of knowledge flows between region i and region j. Subnational and national borders as well as distance and internal distance serve as a proxy for the friction factor in knowledge flows. Following the gravity literature, I assume that the friction factor is a loglinear function of observables, which mainly include bilateral distance, d_{ij}, and the presence of a national border B^n_{ij} (1 if crossing countries, 0 otherwise), a state border B^s_{ij} (1 if crossing states within the U.S., 0 otherwise), and a MSA border B^m_{ij} (1 if crossing MSAs within the U.S., 0 otherwise). Thus, the basic gravity equation for estimating border and distance effects in cross-sectional knowledge flows is given by

$$\ln\left(\frac{c_{ij}}{y_i y_j}\right) = \alpha \ln d_{ij} + \beta_1 B^m_{ij} + \beta_2 B^s_{ij} + \beta_3 B^n_{ij} + r^i_1 CI^i + r^j_2 CE^j + \varepsilon_{ij}$$

where CI^i is equal to 1 if i is the citing region (destination region of knowledge flows) and 0 otherwise, CE^j is equal to 1 if j is the cited region (source region of knowledge flows) and 0 otherwise, and ε_{ij} is error term. Thus, CE^j and CI^i are origin and destination fixed-effect terms, respectively. In general, the two fixed-effects terms control for those citing- and cited-region-specific characteristics and can replace unobservable, region-specific multilateral resistance terms as in the gravity literature (e.g., Anderson and van Wincoop, 2003).[12] To identify the time trend of border and distance effects, I also conduct the panel estimation where the citing-region-year fixed effects (vis-à-vis importer-year fixed effects) and cited-region-year fixed effects (vis-à-vis exporter-year fixed effects) are used to control for multilateral resistance.

Note that knowledge flows may differ from trade flows, especially in the aspect of technological relations between regions. As the pattern of knowledge spillovers may be partly due to the existing distribution of technological activity, it is reasonable to expect knowledge flows, compared with trade flows, to be more affected by technological similarities between regions. Then, the existence of technological similarity undermines the attempt to identify the true border and distance effects in knowledge flows: do regions cite each other more because ceteris paribus knowledge flows easier between them or because knowledge flows more easily between regions that are likely to be more technologically similar? Therefore, it is

[10] Peri (2005) estimates that only 20% of average knowledge is learned outside the average region of origin, i.e., there is around 80% of initial knowledge flows would be lost when they cross state borders.

[11] Think about a patent granted in one region. If this patent never receives any citations in the subsequent years, it will be treated as a trivial innovation outcome and its impact is negligible.

[12] Anderson and van Wincoop (2003) show that region-fixed effects estimation and structural estimation obtain similar results. Feenstra (2002) also proves that the fixed-effects estimator produces consistent estimates of the average border effect.

of great importance to properly control for technological similarity. The literature has seen contentious debate on how one controls for that and it remains to be a challenge.

To address this issue, I adopt a “technology compatibility” index $TechComp_{ij}$, building upon the one developed by Maruseth and Verspagen (2002) and recently used by the literature in urban and regional economics (e.g., Mukherji and Silberman, 2013). In calculating the technology compatibility index, I use the six one-digit patent technology category in the NBER Patent Citations Database.[13] The index captures technological linkages between different patent classes using the observed pattern of citations between different technology classes and the regions' sectoral specialization in patenting. The precise definition of this index is presented in Appendix A. When two regions are specialized in technology classes that are often observed to cite each other, this region pair receives a high score on the compatibility index, ranging between 0 and 1. This index is not symmetric. For instance, if pharmaceutical patents are often observed to cite chemical patents, while chemical patents rarely cite those pharmaceutical patents, and if region i patents to a relatively large extent in drugs and medical class and region j patents relatively more heavily, among all technology classes, in chemicals, $TechComp_{ij}$ will obtain a high value. $TechComp_{ji}$, on the contrary, will receive a low value. The impact of the index on the knowledge flows between two regions is expected to be positive. To sum up, this index measures the compatibility of the patents of two regions to determine the likelihood that patents of a given region will cite those of another.

To further control for the pre-existing industrial effects of technological activity, I also add the cited- and citing-region-specific 3-digit-patent-class terms to isolate the pre-existing industrial effects of technological specialization. Hence, the empirical gravity equation becomes

$$\ln\left(\frac{c_{ij}}{y_i y_j}\right) = \alpha \ln d_{ij} + \beta_1 B_{ij}^m + \beta_2 B_{ij}^s + \beta_3 B_{ij}^n + \beta_4 TechComp_{ij} + r_1^i CI^i + r_2^j CE^j + \sum_{n=1}^{N} \gamma_n^i T_n^i + \sum_{n=1}^{N} \gamma_n^j T_n^j + \varepsilon_{ij}$$

where n ($n = 1, 2, \ldots, N$) denotes a 3-digit patent class of the total N 3-digit patent classes, and T_n^l ($l = i, j$) represents the proportion of knowledge production accumulation (patent citations received up to the current period) in technological class/industry n to the total knowledge production accumulation in region l.[14]

2.2. Data

Patent and citation data are drawn from the NBER Patent and Citation Database.[15] This database contains all the patents granted by the U.S. patent office (USPTO) and all patent citations since 1975. The inventors' geographic locations are determined by their registered residences. If an inventor is located in a country outside of the U.S., she will be called a “foreigner”. Among all patents and citations, more than 40% of patents have been granted to foreigners and more than 40% of citations have been generated by foreigners. Hence, the database is sufficiently comprehensive to examine international patterns of knowledge spillovers.

I designate the region of a patent as the residence of its first inventor.[16] For a patent invented within the U.S., the region is the MSA of its location. For a patent invented outside the U.S. (i.e., a “foreign” patent), the region is the country of its location. The previous literature using a gravity framework did not use MSA-level information and found very large effects of state (or province) borders. As innovation is mainly an urban activity, knowledge spillovers are expected to be localized at city or metropolitan level. Thus, to better examine the subnational pattern of knowledge spillovers, I compile the data at the MSA level regarding the location of each patent inventor according to the zip code and town/city/place name information (see Appendix B for details). Finally, I match more than 93% U.S. inventors to 319 MSAs.

If the patent of region i (granted in year t) cites a patent of region j (granted in a year prior to year t), it is assumed that there is a single unit of knowledge flowing from j to i in year t. Then, I sum all directed citation flows from region j to i in year t as a measure of knowledge flows from j to i in year t. Thus, I obtain all bilateral knowledge flows between each region pair ij in year t.

The sample contains citations between 1980 and 1997 associated with each citing and cited patent pair whose inventors are residents of 1 of the 357 regions (319 MSAs within the U.S. and 38 other countries). The 38 foreign countries were selected by their rank of knowledge production and the importance of their economy.[17] The time of citation is defined by the grant year of the citing patent. The cited patents in the sample are restricted to patents granted after January 1, 1976. My final sample contains more than 1.6 million patents belonging to more than 400 3-digit patent classes and more than 6.6 million (realized) citations. The final sample covers more than 93% of patents and citations between 1980 and 1997 in the

[13] The six rough categories of patents are the following: chemical, computers and communications, drugs and medical, electronics and electricity, mechanical, and others. I also experimented with two-digit subclass and three-digit patent classes to construct the technology compatibility index and the main results still hold.

[14] Using only $\ln c_{ij}$ as dependent variables and moving $\ln y_i$ and $\ln y_j$ to independent variables does not alter the main results of border and distance effects. I also use Tobit estimation to handle the zero flows of citations between two regions and find that the main results are preserved.

[15] See Hall et al. (2001) for a detailed discussion of this database.

[16] The rule of “location by the first inventor” was designed by the constructor of NBER Patent and Citation Database.

[17] The sample (except for the U.S.) is constructed by the following procedure: (1) rank all countries by the total number of citations production (i.e., citations received) and the total number of patents production (i.e., patents granted), and then choose the 30 largest countries in both ranking list. (2) Use the intersection set of these two groups of 30 largest countries. (3) Add all other OECD countries (except for Slovakia) which are not included in the previous set. (4) Add the OECD Non-Member Economies (China, Russia, Brazil) and India.

original NBER database and therefore is sufficiently comprehensive.[18] Table 1 presents the top 10 most cited regions according to the number of yearly received citations (excluding self-citations).[19] The most cited region is Japan, which received more than 59,000 citations per year during the sample period. This result arises because the most cited country, U.S., has been decomposed to 319 MSAs.[20] Because some representative regions within the U.S. are multi-state MSAs, it is worthwhile to investigate state borders and MSA borders simultaneously after controlling for size effects, physical distance, technology similarities, and pre-existing technological specialization.

Distance data are from CEPII's worldwide geographical database for countries. I use geodesic distances, which are calculated by the great circle formula using latitudes and longitudes of the most important cities/agglomerations (in terms of population). For subnational regions within the U.S., I use coordinates of the largest city (by 1990 population) to locate MSAs. To investigate the intra-regional knowledge flows, I also use the area-based internal distance formula (Mayer and Head, 2002).[21]

To obtain a better understanding of subnational barriers that impede knowledge spillovers, I also apply additional subnational level data in analyzing effects of subnational borders. Those data include *Industrial composition data* from BLS (U.S. Bureau of Labor Statistics) and *Business travel data* from U.S. Department of Transportation (see Section 3.5 and Appendix B for more details).

3. Results

This section presents the main results regarding temporal trends and age profiles of distance and border effects as well as the sources of border effects, in particular, the subnational borders. The key findings are as follows: first, subnational borders significantly impede knowledge flows, and they mainly originate at the MSA level. Second, border and distance effects are interestingly rising over time for the same-age citations, yet decline with the age of knowledge. The increasing effects of borders and distance are associated with strengthened knowledge agglomeration over time. Third, various aggregation bias lead to overestimates of border and distance effects. Lastly, business travels across MSAs and knowledge quality of the cited MSAs significantly facilitate knowledge flows and effectively attenuate the effect of subnational borders.

3.1. Aggregate border and distance effects

Table 2 presents the estimation results of the empirical gravity equation for the whole sample (357 regions and 18 years) on aggregate knowledge flows without controlling for 3-digit patent classes.[22] Different specifications refer to different border combinations or fixed effects combinations. To interpret the economic meaning of those coefficients, take Specification (1) as example. For the whole sample, with controlling for technology compatibility, the distance coefficient is approximately -0.03 over the period 1980–1997, which means that holding everything else constant, a 1% increase in the distance between region i and j decreases patent citation flows by 0.03%. In other words, halving the distance increases knowledge flows by 1.5%. This suggests that knowledge flows are substantially less affected by physical distance than trade flows are: according to Disdier and Head (2008), halving distance increases trade flows by approximately 45%. However, distance still significantly impedes knowledge spillovers.

To interpret border effects, I start with the coefficient (-2.194) on national border dummy B_{ij}^{n} in Specification (1). The percentage difference in the predicted value between cross-nation-border citation flows ($B_{ij}^{n}=1$) and intranational citation flows ($\mathrm{B}_{ij}^{n}=0$) is -88.9% ($=(e^{-2.194}-1)\cdot 100$). Cross-nation-border knowledge flows are thus on average 88.9% less than intranational citation flows. This result is equivalent to the statement that 88.9% of initial knowledge flows are blocked by national borders, holding all other factors constant. In other words, intranational knowledge flows are 8.97 ($=e^{2.194}$) times higher than cross-nation-border knowledge flows, which is referred to as the average national border effect. In general, the average border effect is calculated as the exponent of the (absolute value of the) coefficient of the border indicator (Feenstra, 2002).[23] Correspondingly, the magnitudes of the MSA border effect and the state border effect in Specification (1) are 4.20 ($=e^{1.435}$) and 1.35 ($=e^{0.297}$), respectively. Intra-MSA knowledge flows are thus 4.20 times higher than cross-MSA-border knowledge flows, and intra-state knowledge flows are 1.35 times higher than cross-state-border knowledge flows. My estimate of national border effect is consistent with Peri (2005) who reports that national borders diminish knowledge flows to 9% of their initial level; in my estimate it is 11.1%. My estimates of subnational border effects are also similar to the magnitude of the state border effect in Peri (2005) while Peri (2005) did not report MSA border effect. Thus, both national

[18] The sample sizes of some recent studies of knowledge flows are, for instance, 1456 patents and 16,095 citations by Alcáer and Gittelman (2006), 1.5 million patents and 4.5 million citations by Peri (2005), and about 4 million (realized) citations by Singh and Marx (2013).

[19] Self-citations refer to those citations whose citing patent and cited patent belong to the same assignee and do not capture the true knowledge spillovers. Thus, all self-citations have been excluded from estimations.

[20] To be reminded that "region" is defined as a MSA within the U.S. and a country outside the U.S.

[21] It is an often used measure of average distance between producers and consumers in a country. I follow the formula: $d_{ii}=0.67(area/\pi)^{1/2}$ in the context of flexible "region" to calculate the internal distance. Hence in this paper, the internal distance $d_{ii}\neq 0$.

[22] The results with 3-digit patent classes are qualitatively similar and will be shown in later tables.

[23] Feenstra (2002) proves that this simple method can produce the consistent estimates with the structural estimates.

Table 1
Representative high-cited regions (1980–1997).

Rank	Region	Yearly received citations
1	Japan	59,932
2	Germany	23,095
3	New York–Northern New Jersey–Long Island, NY–NJ–CT–PA (U.S.)	21,058
4	San Francisco–Oakland–San Jose, CA (U.S.)	14,838
5	Los Angeles–Riverside–Orange County, CA (U.S.)	12,619
6	Chicago–Gary–Kenosha, IL–IN–WI (U.S.)	10,705
7	United Kingdom	10,748
8	Boston–Worcester–Lawrence, MA–NH–ME–CT (U.S.)	9193
9	France	9031
10	Philadelphia–Wilmington–Atlantic City, PA–NJ–DE–MD (U.S.)	7269

Table 2
Aggregate border and distance effects

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\ln d_{ij}$	−0.029***	−0.040***	−0.066***	0.003*	−0.011***	−0.039***	−0.030***	−0.040***	−0.067***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
B_{ij}^{m}	−1.435***	−1.644***		−1.925***	−2.289***		−1.427***	−1.633***	
	(0.015)	(0.014)		(0.019)	(0.017)		(0.013)	(0.012)	
B_{ij}^{s}	−0.297***		−0.621***	−0.493***		−0.947***	−0.294***		−0.616***
	(0.008)		(0.008)	(0.011)		(0.010)	(0.007)		(0.007)
B_{ij}^{n}	−2.194***	−2.102***	−1.118***	−3.183***	−3.056***	−1.685***	−2.173***	−2.084***	−1.105***
	(0.016)	(0.016)	(0.012)	(0.018)	(0.018)	(0.011)	(0.014)	(0.014)	(0.010)
Technology compatibility$_{ij}$	0.463***	0.464***	0.529***	0.462***	0.465***	0.533***	0.478***	0.479***	0.544***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
MSA border effect	4.199***	5.177***		6.856***	9.863***		4.165***	5.121***	
	(0.063)	(0.071)		(0.130)	(0.170)		(0.054)	(0.061)	
State border effect	1.346***		1.861***	1.638***		2.578***	1.341***		1.851***
	(0.011)		(0.015)	(0.018)		(0.025)	(0.010)		(0.013)
National border effect	8.971***	8.186***	3.059***	24.131***	21.242***	5.395***	8.789***	8.033***	3.018***
	(0.147)	(0.133)	(0.037)	(0.444)	(0.387)	(0.060)	(0.125)	(0.113)	(0.032)
Citing-region fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
Cited-region fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
Year fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
Citing-region-year fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Cited-region-year fixed effects	No	No	No	No	No	No	Yes	Yes	Yes
No. of observations (ij,t)	467,205	467,205	467,205	467,205	467,205	467,205	467,205	467,205	467,205
F-statistics	1740	1736	1696	13,074	15,738	13,449	151	150	146
Adjusted R^2	0.73	0.73	0.73	0.57	0.56	0.56	0.80	0.80	0.80

Notes: standard errors in parentheses. All regressions include a constant term.
* Significance at 5% level.
** Significance at 1% level.
*** Significance at 0.1% level.

and subnational borders significantly impede knowledge flows. On average, the national border effect is larger than the MSA border effect, and the MSA border effect is larger than the state border effect.

In all specifications in Table 2, the coefficients on borders are all significantly negative, while the coefficients on technology compatibility are significantly positive. If I use only the state border to represent the subnational border effect as in Specification (3), the magnitude of the distance effect becomes much larger, while the national border effect becomes smaller. This pattern suggests that the model ignoring MSA borders compensates by moving part of the border effect into the distance effect, creating an upward bias in estimates of the distance effect. This shift suggests the presence of an geographic aggregation bias at the state level within the U.S. (see Section 3.4 for details). Thus, I include both MSA and state borders as subnational borders.

3.2. *Temporal trends of border and distance effects*

In the recent trade literature, the question of whether distance decays over time has attracted substantial attention. In the knowledge flow literature, only quite recently have economists started to concern themselves with this question (e.g., Griffith et al., 2011), and some conjectures have been proposed that call for more empirical work along the line. Therefore, this paper fills in the gap by examining the temporal trends of both border and distance effects for knowledge flows.

Table 3
Temporal trends of border and distance coefficients for same-age citations.

Age 0 and 1	1980s	1990s	1980–1984	1985–1989	1990–1994	1995–1997
$\ln d_{ij}$	0.011	−0.013	0.022	−0.0002	−0.001	−0.029**
	(0.016)	(0.010)	(0.023)	(0.016)	(0.011)	(0.010)
B_{ij}^m	−0.255*	−0.548***	−0.495**	−0.478***	−0.722***	−0.843***
	(0.119)	(0.076)	(0.168)	(0.119)	(0.084)	(0.079)
B_{ij}^s	−0.115	−0.286***	0.125	−0.227*	−0.263***	−0.177**
	(0.092)	(0.057)	(0.134)	(0.090)	(0.064)	(0.060)
B_{ij}^n	−0.909***	−1.272***	−0.927***	−1.170***	−1.449***	−1.404***
	(0.128)	(0.081)	(0.178)	(0.128)	(0.091)	(0.085)
Age 2 and 3						
$\ln d_{ij}$	−0.022***	−0.028***	−0.018*	−0.021***	−0.027***	−0.028***
	(0.006)	(0.003)	(0.007)	(0.006)	(0.004)	(0.005)
B_{ij}^m	−0.775***	−1.228***	−0.769***	−0.976***	−1.208***	−1.301***
	(0.047)	(0.028)	(0.062)	(0.050)	(0.033)	(0.041)
B_{ij}^s	−0.174***	−0.202***	−0.158***	−0.136***	−0.181***	−0.232***
	(0.032)	(0.018)	(0.043)	(0.034)	(0.021)	(0.026)
B_{ij}^n	−1.412***	−1.866***	−1.381***	−1.572***	−1.856***	−1.935***
	(0.051)	(0.031)	(0.067)	(0.054)	(0.037)	(0.045)
Age 4 and 5						
$\ln d_{ij}$	−0.016**	−0.027***	−0.009	−0.019**	−0.028***	−0.028***
	(0.006)	(0.004)	(0.008)	(0.007)	(0.005)	(0.004)
B_{ij}^m	−0.779***	−1.118***	−0.799***	−0.884***	−1.052***	−1.265***
	(0.052)	(0.033)	(0.066)	(0.058)	(0.042)	(0.040)
B_{ij}^s	−0.133***	−0.209***	−0.144**	−0.156***	−0.195***	−0.234***
	(0.035)	(0.021)	(0.045)	(0.039)	(0.027)	(0.024)
B_{ij}^n	−1.390***	−1.734***	−1.453***	−1.483***	−1.677***	−1.873***
	(0.056)	(0.036)	(0.071)	(0.062)	(0.046)	(0.044)
Age 6 and 7						
$\ln d_{ij}$	−0.016*	−0.020***	−0.009	−0.023**	−0.021***	−0.022***
	(0.006)	(0.004)	(0.008)	(0.007)	(0.005)	(0.005)
B_{ij}^m	−0.700***	−1.025***	−0.775***	−0.748***	−0.947***	−1.179***
	(0.056)	(0.037)	(0.068)	(0.062)	(0.049)	(0.043)
B_{ij}^s	−0.181***	−0.203***	−0.143**	−0.142***	−0.205***	−0.213***
	(0.038)	(0.024)	(0.046)	(0.042)	(0.031)	(0.027)
B_{ij}^n	−1.293***	−1.614***	−1.346***	−1.326***	−1.547***	−1.769***
	(0.059)	(0.040)	(0.072)	(0.066)	(0.052)	(0.048)
Age 8 and 9						
$\ln d_{ij}$	−0.017*	−0.021***	0.004	−0.018**	−0.014	−0.029***
	(0.008)	(0.006)	(0.010)	(0.007)	(0.007)	(0.006)
B_{ij}^m	−0.712***	−0.835***	−0.882***	−0.767***	−0.717***	−1.046***
	(0.069)	(0.051)	(0.088)	(0.061)	(0.067)	(0.051)
B_{ij}^s	−0.193***	−0.191***	−0.0763	−0.162***	−0.226***	−0.143***
	(0.046)	(0.032)	(0.064)	(0.040)	(0.043)	(0.032)
B_{ij}^n	−1.331***	−1.398***	−1.479***	−1.330***	−1.348***	−1.560***
	(0.073)	(0.055)	(0.093)	(0.065)	(0.072)	(0.055)
Age $\in$ [10,15)						
$\ln d_{ij}$	−0.023**	−0.022***	–	−0.023**	−0.018***	−0.031***
	(0.007)	(0.003)	–	(0.007)	(0.004)	(0.004)
B_{ij}^m	−0.820***	−0.986***	–	−0.820***	−0.939***	−1.079***
	(0.068)	(0.033)	–	(0.068)	(0.039)	(0.043)
B_{ij}^s	−0.112*	−0.186***	–	−0.112*	−0.179***	−0.210***
	(0.044)	(0.020)	–	(0.044)	(0.024)	(0.026)
B_{ij}^n	−1.325***	−1.560***	–	−1.325***	−1.541***	−1.620***
	(0.072)	(0.036)	–	(0.072)	(0.042)	(0.047)
Age [15,20)						
$\ln d_{ij}$	–	−0.016**	–	–	−0.017*	−0.011*
	–	(0.005)	–	–	(0.008)	(0.005)
B_{ij}^m	–	−0.837***	–	–	−0.728***	−1.007***
	–	(0.052)	–	–	(0.070)	(0.047)
B_{ij}^s	–	−0.157***	–	–	−0.158***	−0.181***
	–	(0.032)	–	–	(0.045)	(0.028)
B_{ij}^n	–	−1.337***	–	–	−1.240***	−1.526***
	–	(0.055)	–	–	(0.074)	(0.050)

Notes: technology compatibility, the 3-digit patent class effects, and all fixed effects terms (i.e., year, citing-, and cited-region fixed effects) are included. Standard errors in parentheses. All regressions include a constant term.

* Significance at 5% level.

** Significance at 1% level.

*** Significance at 0.1% level.

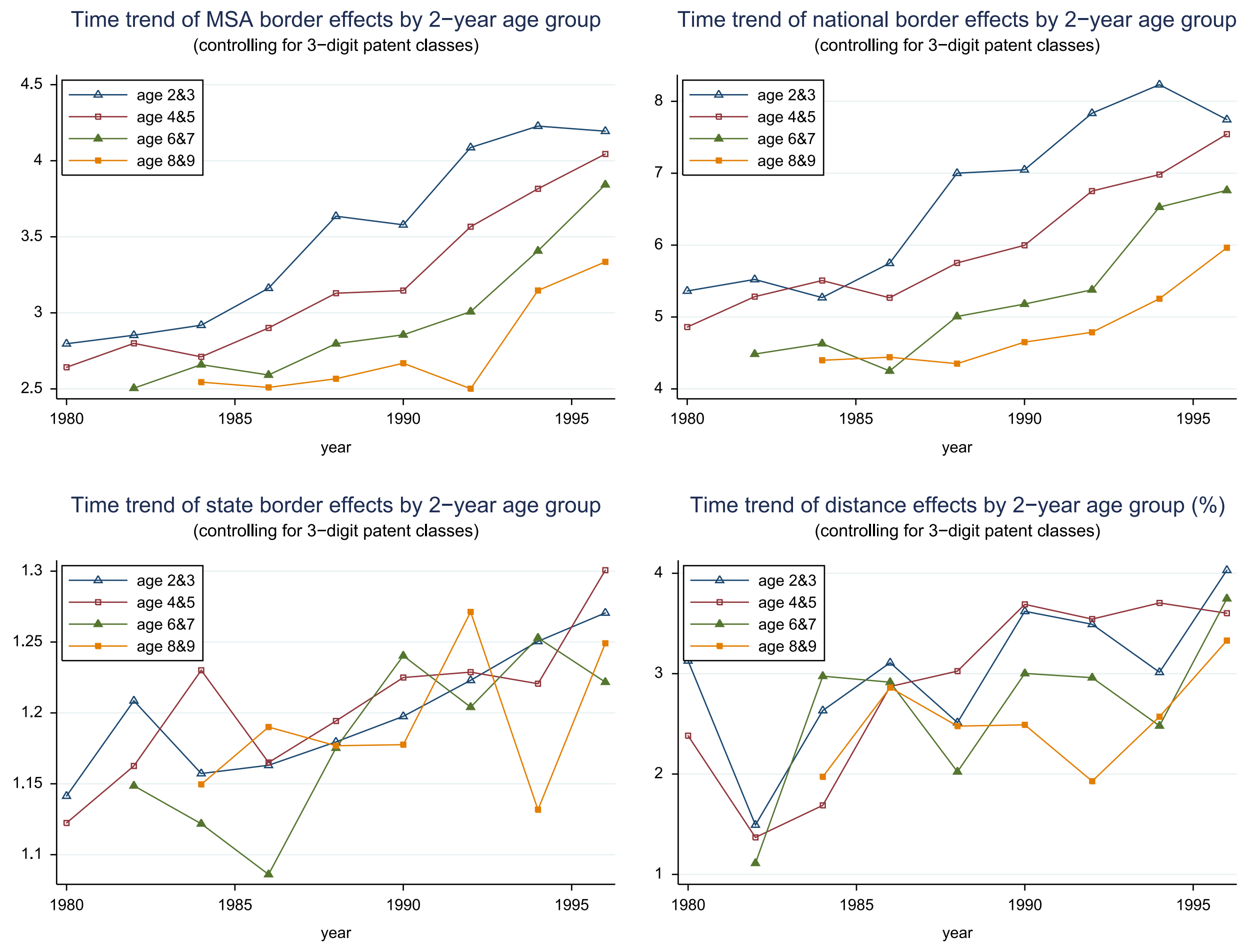

Fig. 1. Increasing border and distance effects over time for each 2-year age group.

3.2.1. Increasing effect of distance and borders

I first run baseline regressions by year and find that both border and distance effects significantly increase over time (i.e., the magnitude of the coefficients on distance and borders increases over time). However, the estimates of aggregate border and distance effects by year are not accurate when large temporal and age heterogeneity exists. Thus, I divide the sample period into several sub-periods, add year fixed effects to capture the time heterogeneity, and run regressions for the same cohort of citations (i.e., the citations with the same age). I use three different time intervals to ensure the robustness of results: (1) 1980s and 1990s; (2) every 5 years; and (3) every 2 years. Table 3 presents the results of (1) and (2) with controlling for technology compatibility; Fig. 1 illustrate the temporal trends of (3) without controlling for technology compatibility, for each 2-year age group.[24]

Table 3 shows that border and distance effects are increasing over time within the same-age citations. This increasing pattern is very robust when one compares 1980s with 1990s, though it is slightly volatile when the sample is decomposed into more disaggregated time intervals. All borders and distance effects are increasing over time, except for the persistent and nearly unchanged distance effect for some very old citations (for instance, citations with age between 10 and 15 years).[25] Even the youngest group (with age less than 1) also preserves increasing MSA and national border effects over time though the distance effect is not significant. Those youngest knowledge flows with very short citation lags are more likely to be added by patent examiners and thus less likely to represent true spillovers (Jaffe et al., 1993).

To further confirm the increasing distance effect, I conduct the following exercise to show the robustness of this result. I restrict the sample to those patents that belong to the same year and the same 3-digit patent class, and further to those that eventually are cited in a particular region in a given year. In other words, I restrict the sample to the citations with the same age, the same 3-digit technology class of cited patents, and the same citing region. Then I compute three statistics: (1) the average

[24] When I use each 5-year age group to depict the temporal trends, the same increasing pattern of border and distance effects is obtained (see Fig. A1 in Online Appendix).

[25] Citations with age 0 and 1 do not see significant distance effects, perhaps because those citations are more likely to be added by examiners rather than inventors.

distance between citing and cited patent, (2) the fraction of patent citations that are from abroad, and (3) the average distance to the cited patent among all foreign citations (average foreign distance hereafter). I vary the parameters of this exercise (the age of citation and the citing region) and report results for 6 representative regions (three countries outside of the U.S. and three MSAs within the U.S.) in Table 4 where the cited patents belong to a certain 3-digit industry. Panel A in Table 4 reports 3-year age group and Panel B reports 5-year age group.

Let me take the first region, Australia, in Panel A as example. For all age-3 citations, the average distance between citing and cited patents for Australia decreases by 7.4% from 1980s to 1990s. Meanwhile, all citations in Australia remain to be foreign citations (i.e., Australian inventors cite patents from abroad), and the average foreign distance reduces by the same proportion, 7.4%. This pattern also holds for regions within the U.S. For instance, the Boston-Worcester-Lawrence MSA sees a 29.7% reduction in average distance and a 4.0% reduction in average foreign distance. Its share of foreign citations also declines by 49.3%. In Panel A, the only region without a reduction in average distance is the Los Angeles-Riverside-Orange County MSA but it also experiences a decline in average foreign distance. In general, all regions experience reductions in either average distance or average foreign distance, which is consistent with the increasing distance effect over time. I repeat this exercise for different industries and different years (see Table A1 in Online Appendix). This exercise alleviates the concern that the increasing distance effect over time is driven by changes in the composition of the sample, such as different age cohorts, industries of cited patents, or citing regions.

Still one compositional change at aggregate level is potentially related to the increase in distance effect and is worth noting. That is the change in the share of foreign citations among all citations. If inventors cite more and more home-country patents which is consistent with the increase in national border effect, the measured average distance between citing and cited patent will be naturally reduced because, on average, distance of domestic citations is much smaller than distance of foreign citations. By computing the fraction of foreign citations for different age group at different periods, I find that all citing regions and, in particular, the regions outside the U.S., clearly experience a reduction in the share of foreign citations over time (see Table A2 in Online Appendix for details). This reduction in foreign share is consistent with the increasing national border effect, and can also partially contribute to the rising time trend of measured distance effect. This increasing "home bias" of knowledge flows is consistent with Singh and Marx (2013) who also find that the country effect in patent citations has strengthened over time.

3.2.2. Strengthened knowledge agglomeration

It is an intriguing phenomenon that border and distance effects increase over time. If it is true, it is expected to be associated with strengthened knowledge localization or knowledge agglomeration over time. To verify this hypothesis that knowledge agglomeration has strengthened over time, I compute the EG index of agglomeration (Ellison and Glaeser, 1997) for knowledge production (by patents granted) at 1-digit, 2-digit, and 3-digit technological class levels in each year.[26] Then I plot the average agglomeration indexes by all regions, foreign regions, U.S. regions, and European Union regions over time in Fig. 2.

In all regions the agglomeration indexes of knowledge production significantly rise over time at all levels of patent classes. Among them, foreign regions outside the U.S. experience the largest increase while the U.S. regions experience a moderate raise in knowledge agglomeration. European regions enjoy higher knowledge agglomeration than the U.S. regions at 1- and 2-digit levels while at the 3-digit level share similar degree of agglomeration as the U.S. regions. I also plot the agglomeration indexes of knowledge production by six patent categories separately for different groups of regions and confirm the same rising pattern (see Fig. A2 in Online Appendix).

The agglomeration analysis confirms that knowledge production indeed increasingly agglomerates over time, which endogenously yields a stronger localization effect and thus generates endogenously larger border and distance effects over time. It will be interesting to analyze what forces contribute to this increasing pattern of knowledge agglomeration. In theory, the potential sources of agglomerative forces could be transport costs (perhaps less relevant to knowledge flows), technological externality, and the pooling of specialized skills, while separating out different sources of agglomeration remains an empirical challenge (Redding, 2010). Disentangling detailed agglomerative forces of knowledge spillovers is even more challenging. Some broadly related questions, such as the impact of skilled emigration on innovation in India (Agrawal et al., 2011) and the role of social connections in facilitating knowledge flows (Agrawal et al., 2006), have been explored by prior research. I will address some complementary aspects such as business travels and industrial composition across MSAs later when analyzing the sources of subnational border effect of knowledge spillovers. Yet a through analysis of why knowledge agglomeration has strengthened over time is out of the scope of the current paper and therefore left for future research.

[26] To compute EG index of agglomeration for patents, I view each citing patent as an individual "knowledge producer" and define its knowledge production as one. The EG index of knowledge agglomeration is given by $\gamma_s = (G_s - (1-\sum_i \chi_i^2)H_s)/(1-\sum_i \chi_i^2)(1-H_s)$, where s and i are index sector and region, respectively; $G_s = \sum_i (p_i - \chi_i)^2$; p_i is the proportion of knowledge production of region i in sector s; χ_i is the share of total knowledge production for region i across all sectors; $H_s = \sum_k z_k^2$ is the Herfindahl index of sector s and z_k is the knowledge production share of a particular patent in sector s. Sector s could be 1-digit, 2-digit, or 3-digit patent class. I also compute the agglomeration index with citations received and obtain the same rising pattern of knowledge agglomeration.

Table 4
Temporal trends: three statistics of distance and share of foreign citations.

Panel A: citation age 3; industry 514							
Citing region: three statistics	1980s	1990s	Growth rate (%)	1980	1985	1990	1994
Australia							
1	16,050.47	14,866.54	−7.38	15,908.26	–	15,625.26	13,584.79
2	1.00	1.00	0.00	1.00	–	1.00	1.00
3	16,050.47	14,866.54	−7.38	15,908.26	–	15,625.26	13,584.79
Canada							
1	4296.55	3908.35	−9.04	6403.35	3725.31	3216.25	4057.18
2	0.91	0.88	−3.23	1.00	0.82	0.88	0.85
3	4485.39	4342.73	−3.18	6403.35	4287.84	3485.89	4562.46
Japan							
1	7091.59	6772.28	−4.50	8799.50	6782.99	7638.96	7545.36
2	0.71	0.67	−5.25	0.90	0.64	0.76	0.76
3	9872.08	9930.56	0.59	9751.40	10,422.24	9941.02	9866.95
San Francisco–Oakland–San Jose (U.S.)							
1	6322.59	4864.82	−23.06	8454.93	7936.54	6860.95	5933.25
2	0.60	0.34	−42.52	0.89	0.86	0.67	0.50
3	8801.92	8510.36	−3.31	9142.07	8602.02	8786.73	8547.27
Boston–Worcester–Lawrence (U.S.)							
1	4821.62	3389.01	−29.71	10,806.93	3824.71	3470.26	4175.99
2	0.51	0.26	−49.29	1.00	0.60	0.25	0.50
3	7549.12	7249.60	−3.97	10,806.93	5797.53	5776.34	6933.77
Los Angeles–Riverside–Orange County (U.S.)							
1	5660.18	5943.77	5.01	3623.77	5907.79	4368.25	7827.22
2	0.51	0.57	12.21	0.00	0.67	0.67	0.79
3	9056.31	8619.83	−4.82	–	8805.63	6315.63	9159.27
Panel B: citation age 5; industry 514							
Citing region: three statistics	1980s	1990s	growth rate(%)	1981	1985	1990	1994
Australia							
1	16,026.16	15,701.66	−2.02	16,460.92	15,557.10	–	14,818.49
2	1.00	1.00	0.00	1.00	1.00	–	1.00
3	16,026.16	15,701.66	−2.02	16,460.92	15,557.10	–	14,818.49
Canada							
1	4547.06	3944.20	−13.26	–	874.07	6222.40	4492.95
2	0.86	0.88	2.14	–	0.60	1.00	0.89
3	4867.60	4297.18	−11.72	–	660.82	6222.40	4881.07
Japan							
1	7607.60	7115.08	−6.47	8741.06	8273.23	7342.26	6793.91
2	0.77	0.70	−7.98	0.86	0.83	0.72	0.67
3	9860.08	10,000.10	1.42	10,159.18	9928.71	10,076.84	10,074.70
San Francisco–Oakland–San Jose (U.S.)							
1	6207.88	5336.84	−14.03	6060.57	5870.59	4415.91	4282.30
2	0.52	0.41	−20.81	0.57	0.39	0.35	0.24
3	8866.52	8696.91	−1.91	8578.63	8955.22	8549.65	8577.17
Boston–Worcester–Lawrence (U.S.)							
1	4812.53	3984.34	−17.21	1675.02	5615.21	4298.37	3680.64
2	0.53	0.37	−30.61	0.00	0.67	0.50	0.18
3	8638.04	7298.56	−15.51	–	8269.61	8419.11	6528.46
Los Angeles–Riverside–Orange County (U.S.)							
1	6913.92	4684.13	−32.25	9250.28	–	3277.17	5967.50
2	0.67	0.33	−49.97	1.00	–	0.13	0.55
3	9237.05	7935.38	−14.09	9250.28	–	3508.54	9122.72

Notes: Three statistics refer to "1 – average distance between citing and cited patent", "2 – the fraction of patent citations that are from abroad", and "3 – average distance to the cited patent among foreign patent citations". Industry 514 is "drug, bio-affecting and body treating compositions".

3.3. Age profiles of border and distance effects

It is expected that different types of knowledge flows (e.g., international and subnational) have different age profiles or age distributions. I draw on the proportion of citations received at each age to total citations received to characterize the age

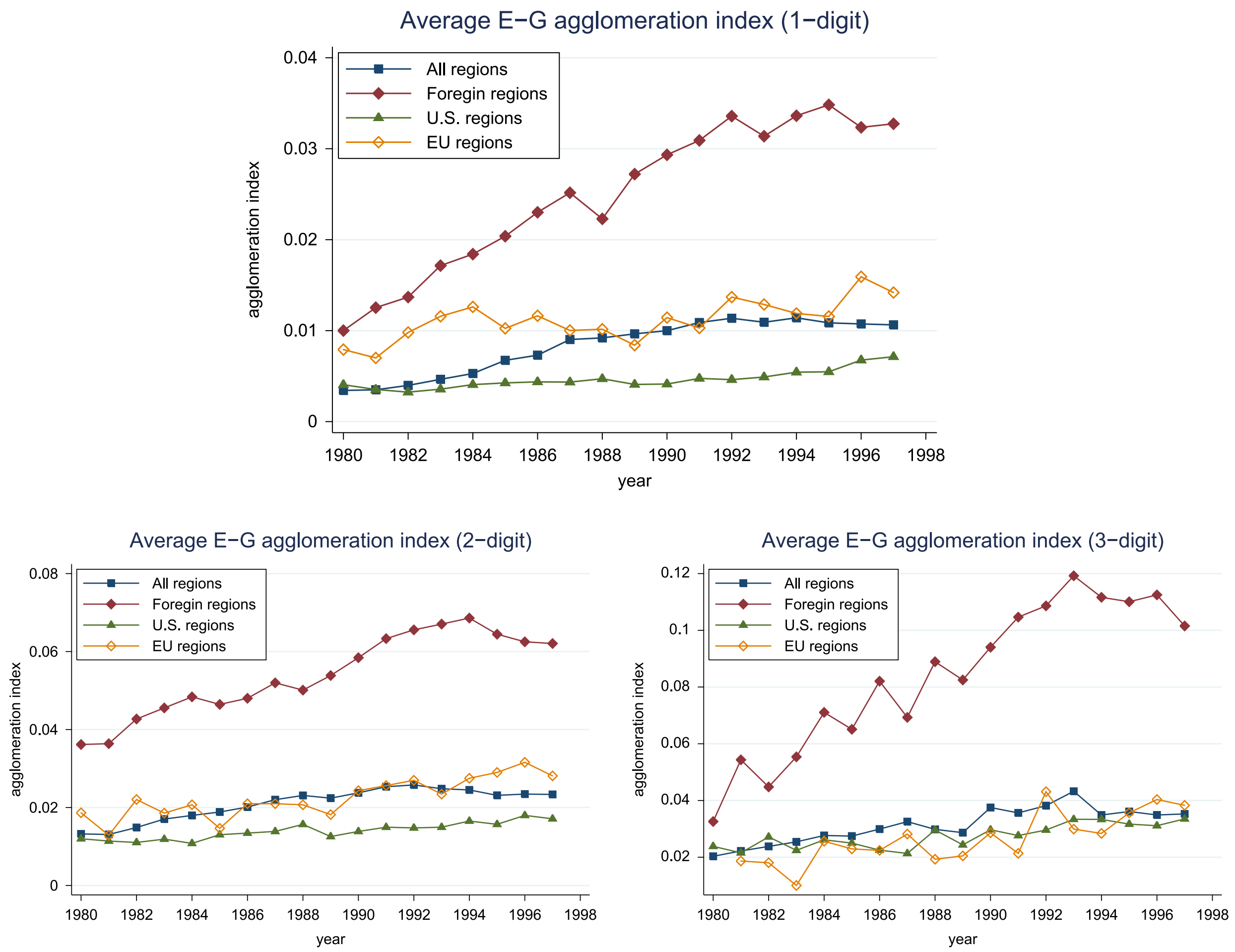

Fig. 2. Agglomeration index for knowledge production (of patents) over time.

distribution for each type of knowledge flows in Fig. 3. It shows approximately a 6-year lag between local vs. non-local knowledge flows and within-MSA vs. cross-MSA flows.[27] It should be noted that as patents age, they are associated with more non-local citation flows than local ones. However, this fact does not contradict the existence of positive border effects because under the gravity framework, the border effect is estimated only after everything else has been controlled, including the region's knowledge capacity, the technology compatibility, the pre-existing distribution of technological activities, and other region-specific characteristics. Thus, although the number of non-local citations is larger than local citations as knowledge flows age, borders still impede knowledge diffusion.

Another message conveyed by Fig. 3 is that border and distance effects are expected to decrease with the age of knowledge because the integrals of the different age distributions converge. To verify this prediction, I decompose the whole sample to 5 subsamples by age groups at 5-year intervals. As expected, the results are very significant and presented in Table 5. Distance and border effects decrease with the age of knowledge, and almost all estimates are significant at 0.1% level. From the age profiles, it can be seen that new knowledge flows face the largest distance and border effects. On average, the effect of national borders is larger than the effect of subnational borders, and this pattern holds true for each age group.

The age profiles of border and distance effects are consistent with the literature that knowledge localization effects become weaker when the same cohort of patents age over their life time (see, Jaffe et al., 1993; Thompson, 2006). In addition, Table 5 shows that age profiles are significant for both intranational and international knowledge spillovers. This result contrasts with the finding of Thompson (2006) that only intranational localization effects decay with the passage of

[27] Local knowledge flows refer to all intra-region flows, i.e., intra-MSA flows within the U.S. and intranational flows within a country outside the U.S. Here within MSA and cross-MSA flows are specific to knowledge flows within the U.S.

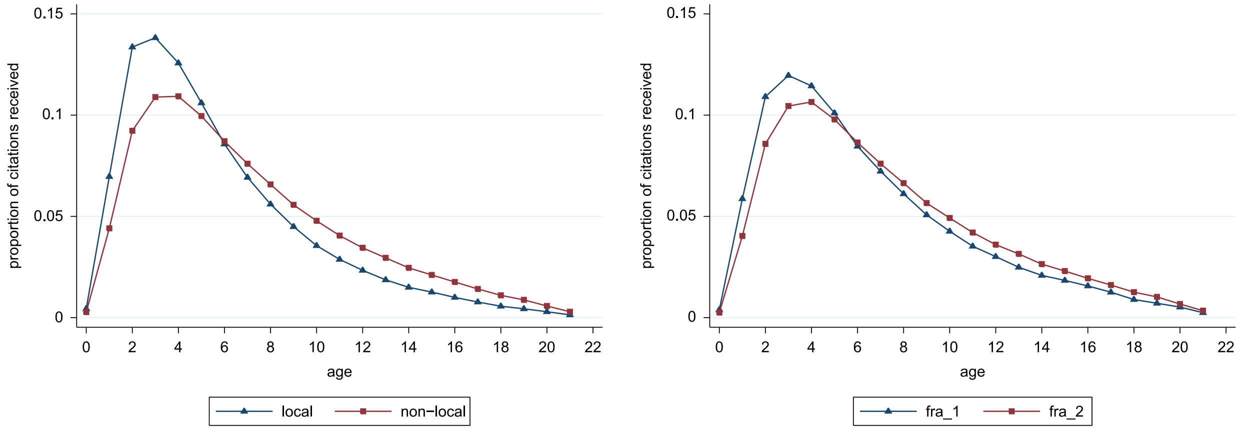

Fig. 3. The age distribution of knowledge diffusion. The blue line represents "within U.S. MSA" and the red line represents "cross U.S. MSA" in the second graph. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

time,[28] but it is consistent with the seminal work by Jaffe et al. (1993).[29] Furthermore, the previous studies use matching methodology and rely on the selection of control groups. The diverse results of previous studies are mainly from different matching controls, for example, Thompson and Fox-Kean (2005a,b) and Henderson et al. (2005). One of the strengths of the current analysis is adopting a different approach of the gravity model that avoids the selection of control groups.

3.4. Aggregation bias as source of border effects

A potential source of aggregate border effect is aggregation bias. There are at least three types of aggregation bias in the context of knowledge flows: geographic aggregation bias, age aggregation bias and industrial aggregation bias.

First, geographic aggregation bias may overestimate border effects. The experiment is to decompose data only to the state level and to compare the result with previous estimates. I find that the magnitude of the state border effect is similar to that of the previous MSA border effect.[30] However, if I further decompose the data into the MSA level as in Table 2, the state border effect declines when including the MSA border into regressions. If I estimate the state border as the only subnational border using the MSA-level data as in Specifications (3), (6), and (9) (compared with Specifications (1), (4), and (7), respectively) of Table 2, the magnitudes of both the subnational and national border effects decrease while the measured distance effects more than double.[31] These results suggest the existence of potential geographic aggregation bias for measuring border and distance effects in knowledge flows.

According to the baseline regression (see Specification (1) in Table 2), approximately 85.7%$(=(1-e^{-1.435})/(1-e^{-2.194}))$ of subnational border effects are associated with the metropolitan borders. The smaller size of state border and the larger size of the MSA border are consistent with the recent gravity literature on border effect, for example, Hillberry and Hummels (2008) demonstrate that the state-level home bias in trade flows is largely driven by geographic aggregation. However, it is worth noting that the measured MSA and state border effects also depend on how one defines the border variables. According to my definition of MSA border and state border, if a citation occurs between different MSAs and different states, both the MSA border B^m and the state border B^s are defined as one. As most citations across states are also across MSAs, including MSA borders largely absorbs the state border effects, yet the state borders remain significant. Incidentally, Singh and Marx (2013) find strong state effects within MSAs, which they view as a puzzle.

Second, decomposing data by age group also reduces the size of border effects (Table 5). This pattern is to some extent surprising because it has been shown that new knowledge faces the largest barriers to diffusion (i.e., border and distance effects). Hence, it should be expected that the magnitude of aggregate border effects ranges between the estimates of newest and oldest age groups. However, the aggregate border effects are always larger than the estimates of each age group, even the newest age group. It is difficult to explain this phenomenon without age-aggregation bias.

Third, decomposing data by technology category also helps to reduce border effects (Table 6). This category aggregation bias might be related to industrial "specialization". If the data on knowledge flows are decomposed by category or by industry, is it possible to attenuate the border effects? To answer this question, one needs to examine the knowledge flows at the industry level. Results from the general category level yield some insights. If the specialization effect also contributes

[28] Thompson (2006) gives the explanation of his result that individual researchers relocate frequently within the U.S. but only infrequently across international borders.

[29] The rate of change in age profiles in my paper is larger than that in Jaffe et al. (1993).

[30] This is also consistent with the reported state/province border effect in Peri (2005).

[31] In some specifications this change would result in an increase in distance effect by more than 10 times.

Table 5
Border and distance effects by age of knowledge.

Specification	Whole sample	Age [0,5)	Age [5,10)	Age [10,15)	Age [15,20)	Age [20,more)
ln d_{ij}	−0.029***	−0.028***	−0.025***	−0.022***	−0.016**	−0.014*
	(0.001)	(0.002)	(0.002)	(0.003)	(0.005)	(0.007)
B_{ij}^m	−1.427***	−1.218***	−1.085***	−0.919***	−0.837***	−0.714***
	(0.015)	(0.019)	(0.023)	(0.033)	(0.052)	(0.062)
B_{ij}^s	−0.297***	−0.237***	−0.228***	−0.179***	−0.157***	−0.144***
	(0.008)	(0.012)	(0.014)	(0.020)	(0.032)	(0.041)
B_{ij}^n	−2.182***	−1.920***	−1.715***	−1.475***	−1.337***	−1.095***
	(0.016)	(0.021)	(0.025)	(0.036)	(0.055)	(0.064)
Technology compatibility$_{ij}$	0.466***	0.424***	0.437***	0.397***	0.364***	0.320***
	(0.006)	(0.008)	(0.009)	(0.013)	(0.021)	(0.026)
3-digit patent class effects	Yes	Yes	Yes	Yes	Yes	Yes
Citing-region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cited-region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations (ij,t)	467,205	283,980	285,081	169,010	83,960	14,258
F-statistics	1125	458	386	220	154	353
Adjusted R^2	0.74	0.72	0.68	0.67	0.74	0.97

Notes: standard errors in parentheses. All regressions include a constant term.
* Significance at 5% level.
** Significance at 1% level.
*** Significance at 0.1% level.

Table 6
Border and distance effects by category.

Specification	Whole sample	Cat 1 Chemical	Cat 2 C.&C.	Cat 3 D.&M.	Cat 4 E.&E.	Cat 5 Mechanical	Cat 6 Others
ln d_{ij}	−0.029***	−0.013	−0.024*	−0.002	−0.006	−0.013**	−0.021***
	(0.001)	(0.007)	(0.012)	(0.011)	(0.007)	(0.004)	(0.003)
B_{ij}^m	−1.427***	−0.762***	−0.380***	−0.532***	−0.748***	−0.880***	−0.918***
	(0.015)	(0.057)	(0.100)	(0.089)	(0.062)	(0.036)	(0.028)
B_{ij}^s	−0.297***	−0.213***	−0.111	−0.120	−0.174***	−0.174***	−0.221***
	(0.008)	(0.041)	(0.069)	(0.067)	(0.043)	(0.023)	(0.018)
B_{ij}^n	−2.182***	−1.404***	−0.908***	−0.962***	−1.281***	−1.570***	−1.613***
	(0.016)	(0.061)	(0.107)	(0.094)	(0.066)	(0.038)	(0.030)
Technology compatibility$_{ij}$	0.466***	0.396***	0.172***	0.129***	0.232***	0.255***	0.167***
	(0.006)	(0.026)	(0.038)	(0.038)	(0.025)	(0.017)	(0.013)
3-digit patent class effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Citing-region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cited-region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations (ij,t)	467,205	128,987	84,978	94,177	123,681	169,061	222,546
F-statistics	1125	189	174	173	212	329	440
Adjusted R^2	0.74	0.56	0.61	0.58	0.59	0.65	0.66

Notes: standard errors in parentheses. All regressions include a constant term.
* Significance at 5% level.
** Significance at 1% level.
*** Significance at 0.1% level.

to border effects, one should expect to see a substantial decrease when data are decomposed by category. I find that border effects do substantially decrease and that the estimates at the category level are much smaller than the aggregate border effects. This result indicates that part of border effects is associated with the "specialization" effect. Splitting the sample by category attenuates the measured border effects by partially ruling out the specialization effect. However, specialization cannot explain all border effects. Even after controlling for the pre-existing distribution of technological activities and technology compatibility, all MSA and national border effects are still significant at the 0.1% level. Additionally, specialization varies by industry. I prefer to call this type of bias "industry aggregation bias", which captures all bias due to the industrial aggregation, and leave more detailed discussion of industrial specialization to the next section.

3.5. Further discussion of subnational border effects

What other factors account for the "border puzzle", especially the subnational borders, in knowledge flows? What are the barriers at the boundary of an MSA that make knowledge flows so much less likely? To provide more complementary answers, I further apply additional MSA-level data regarding business travels, industrial specialization, and knowledge quality to access how they affect subnational border effects.

3.5.1. Business travel

There is a growing literature in international trade and economic growth on the role of international business travel in facilitating international goods trade (e.g., Poole, 2010; Cristea, 2011), foreign direct investment, and innovation (Hovhannisyan and Keller, 2011). As knowledge is embodied in researchers, face-to-face communication may be particularly important for the transfer of technology because knowledge is best explained and demonstrated in person and business travels (Hovhannisyan and Keller, 2011). Then it is fruitful to examine the role of domestic business travel across MSAs in knowledge spillovers.

Hence, to answer whether business travel also matter for subnational border effects, I further construct U.S. MSA level data on domestic business travel using American Travel Survey (ATS) 1995 from the U.S. Department of Transportation.[32] After careful data extracting and mapping, I compute the number of business trips across different MSAs by filtering the information on "reason for trip" and trip destination/origin in ATS. Eventually, I obtain data on the number of business trips across 132 MSAs that account for 87.6% of total citations received among all 319 MSAs within the U.S. in my original sample (see Appendix B for more details).[33]

Accordingly, I construct three travel-related MSA-pair specific variables: trip_{ij}^{O}, the number of business travels from citing region i to cited region j (i.e., citing region as trip origin); trip_{ij}^{D}, the number of business travels from cited region j to citing region i (i.e., citing region as trip destination); trip_{ij}^{T}, the number of two-way business travels between citing and cited MSAs. Then I run the following regressions:

$$\ln\left(\frac{c_{ij}}{y_i y_j}\right) = \alpha \ln d_{ij} + \beta_1 B_{ij}^{m} + \beta_2 B_{ij}^{s} + \beta_4 TechComp_{ij} + \beta_5 \ln trip_{ij}^{O/D/T} + r_1^{i} CI^{i} + r_2^{j} CE^{j} + \varepsilon_{ij} \tag{1}$$

$$\ln\left(\frac{c_{ij}}{y_i y_j}\right) = \alpha \ln d_{ij} + \beta_1 B_{ij}^{m} + \beta_2 B_{ij}^{s} + \beta_4 TechComp_{ij} + \beta_6 B_{ij}^{m} \ln trip_{ij}^{O/D/T} + r_1^{i} CI^{i} + r_2^{j} CE^{j} + \varepsilon_{ij} \tag{2}$$

where β_5 and β_6 are coefficients of interest. The estimation results are presented in Table 7.

There are two findings. First, trips from cited region to citing region or two-way travels significantly facilitate knowledge flows (see columns (3) and (4)) while travel from citing region to cited region alone is not significant (see column (2)). When $trip^{O}$ and $trip^{D}$ are simultaneously included, both become significantly positive (see column (5)) but the effect of trips from cited region is still greater than the effect of trips from citing region. This seems to be consistent with the reality that researchers often go to various places to publicize their studies. When an inventor has more business trips to other metropolitan areas, it is more likely that her invention obtains more attention and thus receives more citations. Second, the coefficients on the interaction term between MSA border and trips ($trip^{D/T}$) are also significantly positive. This suggests that more business travels from cited region to citing region or the two-way travels significantly attenuate the subnational borders at MSA level.

3.5.2. Industrial composition, specialization, and knowledge quality

I use industrial data of real economic activities rather than the data of patent classes to examine whether industrial composition at MSA level relates to knowledge spillovers and how industrial specialization affects the effect of subnational borders. Most often the prior research of knowledge flows adopts the technology class of patents as proxy for industrial classification of real economy due to the imperfect mapping between patent classification and industry classification.[34] But in this paper the gravity model allows for directly adding the industrial economic data at MSA level to control for economic activities.

Thus, I collect the 2-digit NAICS (North American Industry Classification System) industrial employment data from BLS (U.S. Bureau of Labor Statistics) in 1990 (see Appendix B for details) for two reasons. First, 1990 is the earliest year available for MSA-level employment data from BLS website. Second, the MSAs in my sample are defined by the U.S. Census Bureau effective as of 1990. The employment data are assembled either by MSA or by state. Eventually, I obtain 2-digit industrial employment data for 265 MSAs, accounting for 91.7% of total citations received among all 319 MSAs in my original sample.

[32] ATS was only conducted in 1977 and 1995. So I use 1995 survey which is within my sample period. There is another survey, "Nationwide Personal Transportation Survey" (NPTS), conducted in 1969, 1977, 1983, 1990, and 1995. But NPTS more focuses on transportation mode and outbound trips to other countries, and thus is hard to merge with MSA level data.

[33] Note that some small MSAs do not report travel data in ATS 1995 and converting 1995 MSAs to 1990 MSAs also loses some observations.

[34] Unlike the classification systems used to collect and disseminate economic data, the patent classification systems are usually based on the function or structure (e.g., chemical formula, layered product, gear, etc.) of the patented technology and not on the associated industry of manufacture or sector of use.

Table 7
Border and distance effects with business travels.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\ln d_{ij}$	−0.131***	−0.128***	−0.121***	−0.066***	−0.108***	−0.128***	−0.121***	−0.062***	−0.108***
	(0.016)	(0.016)	(0.016)	(0.018)	(0.017)	(0.016)	(0.016)	(0.018)	(0.017)
B_{ij}^{m}	−1.182***	−1.190***	−1.208***	−1.405***	−1.240***	−1.192***	−1.213***	−1.614***	−1.253***
	(0.153)	(0.153)	(0.153)	(0.156)	(0.154)	(0.154)	(0.153)	(0.164)	(0.154)
B_{ij}^{s}	−0.242***	−0.239***	−0.230***	−0.200***	−0.215***	−0.238***	−0.230***	−0.196***	−0.215***
	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)
Technology compatibility$_{ij}$	0.505***	0.504***	0.504***	0.492***	0.501***	0.504***	0.504***	0.491***	0.501***
	(0.045)	(0.045)	(0.045)	(0.044)	(0.045)	(0.045)	(0.045)	(0.044)	(0.045)
$\ln trip_{ij}^{O}$		0.001			0.003**				
		(0.001)			(0.001)				
$\ln trip_{ij}^{D}$			0.003***		0.004***				
			(0.001)		(0.001)				
$\ln trip_{ij}^{T}$				0.075***					
				(0.011)					
$B_{ij}^{m} \ln trip_{ij}^{O}$						0.001			0.003***
						(0.001)			(0.001)
$B_{ij}^{m} \ln trip_{ij}^{D}$							0.003***		0.004***
							(0.001)		(0.001)
$B_{ij}^{m} \ln trip_{ij}^{T}$								0.081***	
								(0.011)	
Citing-region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cited-region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations (ij)	5004	5004	5004	5004	5004	5004	5004	5004	5004
F-statistics	15.9	15.8	15.9	16.2	15.8	15.8	15.9	16.3	15.8
Adjusted R^2	0.356	0.356	0.357	0.362	0.358	0.356	0.358	0.363	0.358

Notes: robust standard errors in parentheses. All regressions include a constant term.
* Significance at 10% level.
** Significance at 5% level.
*** Significance at 1% level.

Following Imbs and Wacziarg (2003), I compute the industrial specialization index S_i for region i at either MSA or state levels:

$$S_i = \sum_s \left(\frac{\sum_k Y_{iks}}{\sum_s \sum_k Y_{iks}} \right)^2 = \sum_s \left(\frac{Y_{is}}{\sum_s Y_{is}} \right) \tag{3}$$

where s indexes sector, i indexes region (either MSA or state), k indexes sub-region within i, and Y denotes economic activity (measured by employment). The numerator sums sectoral activity across all sub-regions; the denominator represents aggregate regional economic activity. A higher value of S implies a high degree of sectoral specialization in that region. Not surprisingly, the industrial specialization index of MSAs is on average higher than that of states.

As the subnational border effect is largely captured by MSA borders, I focus on the MSA-level effect and run the following regressions to test whether the specialization of citing (or cited) MSA affects knowledge flows:

$$\ln c_{ij} = \alpha \ln d_{ij} + \beta_1 B_{ij}^{m} + \beta_2 B_{ij}^{s} + \beta_4 TechComp_{ij} + c_1 \ln y_i + c_2 \ln y_j + \beta_7 PQ_j + \beta_8 S_{i/j} + \varepsilon_{ij} \tag{4}$$

$$\ln c_{ij} = \alpha \ln d_{ij} + \beta_1 B_{ij}^{m} + \beta_2 B_{ij}^{s} + \beta_4 TechComp_{ij} + c_1 \ln y_i + c_2 \ln y_j + \beta_7 PQ_j + \beta_9 B_{ij}^{m} S_{i/j} + \varepsilon_{ij} \tag{5}$$

where i and j index the citing and cited MSAs; PQ_j denotes patent quality of the cited MSA, measured by the average number of citations received (from all over the US) per patent in that MSA[35]; $S_{i/j}$ represents the industrial specialization index of the citing/cited MSA. Eq. (4) explores the effect of citing/cited MSA's industrial specialization and equation (5) examines the interaction between MSA border and industrial specialization.

Eqs. (4) and (5) are both cross-sectional estimation for 1990. As subnational border effects are mainly a cross-sectional pattern, one-year data is sufficient to test the effect of industrial specialization on knowledge flows. Here patent quality of cited MSA is included in the estimation to control for region-specific characteristics because it is reasonable to imagine that a region with better patents should in general receive more citations. Thus, patent quality should be included in the cross-sectional estimation to control for the cited region effect, especially when the variable of interest, $S_{i/j}$, is region specific rather than region-pair specific and therefore it is not possible to add citing- and cited-region fixed effects at the same time.[36]

[35] I also compute the average number of citations received (from all over the world) per patent in that MSA, and the results remain similar.
[36] Note that in all the previous results, both cited-region and citing-region fixed effects are always included when the variables of interest are region-pair specific, for instance, distance ($\ln d_{ij}$), MSA border (B_{ij}^{m}), or the number of business travels between citing and cited regions ($\ln trip_{ij}$). However, when I

Except for directly controlling for cited MSA's patent quality when testing specialization effect, I also expect a potential interaction effect between specialization and patent quality, tested by the following equation:

$$\ln c_{ij} = \alpha \ln d_{ij} + \beta_1 B_{ij}^m + \beta_2 B_{ij}^s + \beta_4 TechComp_{ij} + c_1 \ln y_i + c_2 \ln y_j + \beta_7 PQ_j + \beta_{10} PQ_j S_{i/j} + \varepsilon_{ij} \tag{6}$$

where β_{10} is the coefficient of interest. The estimation results of Eqs. (4)–(6) are reported in Table 8.

There are several observations from Table 8. First, all subnational borders remain to be significantly negative with industrial specialization and patent quality. Second, all control variables are consistent with the theory and the expectation: technology compatibility and the knowledge size of citing and cited MSAs ($\ln y_{i/j}$) are significantly positive; patent quality of cited MSAs positively facilitates knowledge flows. Third, with controlling for patent quality of cited MSAs, specialization of citing or cited MSA is neither significant on its own (see Specifications 1–3) nor has significant interaction effect with MSA border (see Specifications 4–6). This suggests that regional industrial specialization alone cannot directly predict the citation flows between citing and cited regions. This is perhaps because specialization index only points to the degree of sectoral specialization in that region but does not necessarily concentrate on knowledge intensive activities. If a region is specialized in more traditional, labor intensive sectors, it is more remote from the knowledge frontier of the country and would generate less knowledge flows; while if a region is more specialized in knowledge intensive activities, it may be expected to generate more knowledge flows but this effect would be perhaps absorbed by the patent quality of the cited region. Thus, at the aggregate level, the overall effect of specialization is not significant. Further assessment of the potential effect of different factor intensity with different types of sectoral specialization and their relation with subnational border effect requires more detailed sectoral data regarding factor employment and knowledge intensity (e.g., skilled or unskilled labor, physical capital, human capital, R&D expenditure, etc.). This is outside the scope of this paper and thus left for future research.

Specifications 7–9 in Table 8 report the interaction effect between patent quality and regional specialization. The results show that the citing MSA's specialization has negative interaction effect with the cited MSA's patent quality at 10% significance level. In other words, the positive effect of patent quality is weakened for those more specialized citing MSAs. This finding is intuitive: given the patent quality in the cited MSA, a more specialized citing MSA needs to cite more specific patents and this limits the available choices in the cited region for the citing MSA to cite. Note that the marginal effect of patent quality on knowledge flows for the most specialized citing MSA is still positive and in the reasonable range.[37]

Lastly, it is natural to conjecture that better-quality MSAs would be less affected by the MSA-border impediment to knowledge flows. Then I run the following regressions:

$$\ln c_{ij} = \alpha \ln d_{ij} + \beta_1 B_{ij}^m + \beta_2 B_{ij}^s + \beta_4 TechComp_{ij} + c_1 \ln y_i + c_2 \ln y_j + \beta_7 PQ_j + \varepsilon_{ij} \tag{7}$$

$$\ln c_{ij} = \alpha \ln d_{ij} + \beta_1 B_{ij}^m + \beta_2 B_{ij}^s + \beta_4 TechComp_{ij} + c_1 \ln y_i + c_2 \ln y_j + \beta_{11} B_{ij}^m PQ_j + \varepsilon_{ij} \tag{8}$$

where Eq. (7) emphasizes the effect of the cited MSA's patent quality alone and Eq. (8) focuses on the interaction effect between MSA border and patent quality. I expect both coefficients, β_7 and β_{11}, to be significantly positive. The results are consistent with the expectation (see Table 9). A positive coefficient on the interaction between PQ_j and MSA border suggests a lower MSA border effect for relatively better-quality regions. This means that relatively high-quality patent knowledge is relatively likely to move outside the own-MSA, compared to average-quality patent knowledge. One explanation may be that high-quality knowledge may warrant spending the cost to facilitate the communication (e.g., setting up a face-to-face meeting etc.), while this may not be the case for average-quality knowledge.

4. Conclusion

This paper employs a gravity framework to investigate distance and border effects in knowledge spillovers, using evidence from patent citations panel data at the metropolitan level within the U.S. and in the 38 largest patent-cited countries outside the U.S. Strong subnational localization effects at intranational levels are confirmed, and MSA border effects are found to be significantly larger than state border effects. Approximately 85.7% of intranational border effects stem from the metropolitan rather than the state level. This finding contributes to the literature on subnational knowledge localization. I further differentiate between temporal trends and age profiles of knowledge spillovers and find that border and distance effects decrease with the age of cited patents but interestingly increase over time for a given-age group of citations. The increasing border and distance effects suggest that knowledge agglomeration has strengthened over time which is supported by further empirical evidence using agglomeration aalysis. Both age profiles and temporal trends of

(*footnote continued*)
test specialization effect using 1990 data, the region-specific specialization index would absorb the fixed effects of the corresponding regions. Under such consideration, I add patent quality of cited MSA as explanatory variable and also move the size of the citing/cited regions' knowledge capacities $y_{i/j}$ to the right-hand side. It is an usual practice in estimating the gravity equation by treating $\ln y_i$ and $\ln y_j$ as independent variables. I also experiment with this estimation strategy for all the main results in this paper and find that the aforementioned results remain robust.

[37] Taking specification 8 as example, the marginal effect of patent quality on knowledge flows at the maximum level of specialization for the citing MSA is given by $d \ln c_{ij}/dPQ_j = \beta_7 + \beta_{10} S_i = 0.254 - 0.647 \times 0.378 = 0.009$.

Table 8
Border and distance effects with regional industrial specialization and patent quality.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\ln d_{ij}$	−0.027***	0.001	−0.001	−0.027***	0.001	0.001	−0.028***	0.000	−0.001
	(0.006)	(0.010)	(0.010)	(0.006)	(0.010)	(0.010)	(0.006)	(0.010)	(0.010)
B_{ij}^{m}	−1.463***	−1.579***	−1.578***	−1.448***	−1.279***	−1.217***	−1.463***	−1.578***	−1.577***
	(0.085)	(0.085)	(0.085)	(0.138)	(0.292)	(0.321)	(0.085)	(0.085)	(0.085)
B_{ij}^{s}	−0.220***	−0.220***	−0.217***	−0.221***	−0.221***	−0.220***	−0.220***	−0.219***	−0.216***
	(0.035)	(0.043)	(0.044)	(0.035)	(0.043)	(0.044)	(0.035)	(0.043)	(0.043)
Technology compatibility$_{ij}$	0.213***	0.220***	0.219***	0.214***	0.221***	0.220***	0.213***	0.220***	0.218***
	(0.018)	(0.020)	(0.020)	(0.018)	(0.020)	(0.020)	(0.018)	(0.020)	(0.020)
$\ln y_j$	0.391***	0.410***	0.408***	0.392***	0.410***	0.409***	0.390***	0.410***	0.408***
	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
$\ln y_i$	0.361***	0.363***	0.363***	0.361***	0.364***	0.364***	0.361***	0.362***	0.362***
	(0.017)	(0.021)	(0.021)	(0.017)	(0.021)	(0.021)	(0.017)	(0.021)	(0.021)
PQ_j	0.086***	0.070***	0.069***	0.086***	0.070***	0.070***	0.134***	0.254**	0.311***
	(0.014)	(0.016)	(0.016)	(0.014)	(0.016)	(0.016)	(0.046)	(0.105)	(0.117)
S_j	−0.265		−0.424						
	(0.358)		(0.404)						
S_i		−1.281	−1.283						
		(0.914)	(0.914)						
$B_{ij}^{m}S_j$				−0.053		−0.205			
				(0.359)		(0.408)			
$B_{ij}^{m}S_i$					−1.034	−1.039			
					(0.923)	(0.923)			
PQ_jS_j							−0.167		−0.199
							(0.152)		(0.172)
PQ_jS_i								−0.647*	−0.647*
								(0.371)	(0.371)
No. of observations (ij)	13,176	10,711	10,711	13,176	10,711	10,711	13,176	10,711	10,711
F-statistics	571	506	451	571	507	452	570	499	445
Adjusted R^2	0.50	0.51	0.51	0.50	0.51	0.51	0.50	0.51	0.51

Notes: robust standard errors in parentheses. All regressions include a constant term.
* Significance at 10% level.
** Significance at 5% level.
*** Significance at 1% level.

border and distance effects are robust to different specifications and are significant for both intranational and international knowledge spillovers.

This paper also uncovers three types of aggregation bias in explaining sources of overestimated aggregate border effects of knowledge spillovers. Decomposing data into finer levels, e.g., by geographic unit, age group, and category, substantially reduces the magnitude of border effects. In addition, this paper applies business travels across MSAs and patent quality of cited MSAs as well as industrial specialization at MSA level to show that business trips and knowledge quality effectively attenuate the effect of subnational borders. At 10% significance level, the citing MSA's specialization weakens the positive effect of knowledge quality on citation flows. Further analysis of subnational borders and distance effect requires finer data at the resolution of county or zip code level. More assessment of different types of industrial specialization regarding factor intensity and how this would affect subnational border effect are worth exploring with more sectoral data available. It will be also interesting to investigate barriers to knowledge transmission and the scale at which physical distance remains relevant. These analyses are left for future research.

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Table 9
Effect of the cited MSA's patent quality (1990).

Specification	(1)	(2)	(3)	(4)	(5)
$\ln d_{ij}$	-0.026***	-0.027***	-0.026***	-0.027***	-0.026***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
B_{ij}^{m}	-1.460***	-1.463***	-1.461***	-1.663***	-1.537***
	(0.085)	(0.085)	(0.085)	(0.091)	(0.090)
B_{ij}^{s}	-0.224***	-0.221***	-0.224***	-0.221***	-0.224***
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Technology compatibility$_{ij}$	0.215***	0.214***	0.217***	0.214***	0.217***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
$\ln y_j$	0.396***	0.392***	0.393***	0.392***	0.393***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$\ln y_i$	0.361***	0.361***	0.361***	0.361***	0.361***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
PQ_j^{US}		0.086***			
		(0.014)			
PQ_j^{World}			0.021**		
			(0.010)		
$B_{ij}^{m} PQ_j^{US}$				0.087***	
				(0.015)	
$B_{ij}^{m} PQ_j^{World}$					0.022**
					(0.010)
No. of observations (ij)	13,176	13,176	13,176	13,176	13,176
F-statistics	753	650	647	650	646
Adjusted R^2	0.50	0.50	0.50	0.50	0.50

Notes: robust standard errors in parentheses. All regressions include a constant term. PQ_j^{US} denotes patent quality of the cited MSA, measured by the average number of citations received (from all over the US) per patent in that MSA; PQ_j^{World} denotes the average number of citations received (from all over the world) per patent in that MSA.

*Significance at 10% level.

** Significance at 5% level.

*** Significance at 1% level.

Appendix A. Technology compatibility index

Adopting the approach by Maruseth and Verspagen (2002), I compute the index of technology compatibility between two regions (region i and j), $TechComp_{ij}$, in the following way. First, I construct a sector-by-sector matrix Z which describes the sectoral citation relations. Here I use six technology categories in patent classification system as sector. In this matrix, the element Z_{pq} denotes the number of citations received by patents in sector p from patents in sector q (i.e., q is the citing sector and p is the cited sector) and Z_{pq} is a 6×6 matrix. Then I construct a new matrix z by dividing the elements of Z by the column sums, i.e., $z_{pq} = Z_{pq}/\sum_p Z_{pq}$. Now the matrix z describes the share of citations to existing patents in each of the six technology classes to total cited patents granted to all MSAs. For example, the column for chemical patents gives the share of citations made by chemical patents to patents in all six technology categories, including the chemical sector itself.

For each region i, I then calculate the share of sector p in total patenting as $\sigma_{i,p} = P_{i,p}/\sum_p P_{i,p}$, where $P_{i,p}$ is the number of patents in sector p in region i. Then for each region, I compute 6 (i.e., the number of sectors) correlation coefficients $\rho_{i,p}$ between z_{pq} (where $q = 1, \ldots, 6$) and $\sigma_{i,p}$ (where $p = 1, \ldots, 6$). I then calculate the share of a region in patenting of sector p as $\phi_{i,p} = P_{i,p}/\sum_i P_{i,p}$. The technology compatibility between regions i and j is then calculated as the correlation coefficient between the 6 observations on $\rho_{i,p}$ and $\phi_{j,p}$. This correlation coefficient measures to what extent the sectoral patenting structure of region j is likely to be cited by region i, given the technological structure of i and the sectoral citation linkages.

The current technology compatibility index is constructed based on citing patents in 1980–1985, the first six-year panel, to better capture the “prior” distribution of technological similarity. But I also experiment with constructing this index using the whole sample period and all main results remain to be robust.

Appendix B. Data appendix

Location of patent inventors at MSA level: The procedure of matching each patent to MSA level is as follows. Among all inventors, 15% of them reported the zip code of their residence in the U.S., and all inventors reported the town/city or place name of their residence. I first locate inventors to MSAs by zip code and then locate the rest by town/city or place name. The matching is done using correlation files provided by the Office of Social and Economic Data Analysis (OSEDA) of the University of Missouri. However, the definition of MSAs has evolved over time. For example, sometimes a small MSA was combined with another nearby large MSA in a newer version of an MSA definition file. To ensure consistency and because my sample period is 1980–1997, I use MSAs as defined by the U.S. Census Bureau in 1990. I also create 49 phantom MSAs, one for each state (except New Jersey), containing all locations in non-metropolitan areas.[38] In total, I match U.S. inventors to 310 MSAs, including 270 MSAs as defined by the U.S. Census Bureau in 1990 and 49 artificial MSAs.

Industrial composition data by employment at MSA level: The industrial employment data for each MSA in 1990 is collected from BLS and constructed by the following way. As the BLS data set does not provide the MSA code directly, I generate MSA code by combining "State Code" and "County Code". I also drop data of other ownership types and only keep ownership=5 (private sector), since industrial level employment data are only available under private sector. What I am mostly interested in is 2-digit industrial data. In BLS database, industries are classified by NAICS 2002 and include industrial employment data from 2-digit to 6-digit level. Some missing industrial employment data, varying from 6-digit to 2-digit level, increase the difficulty of data cleaning. I solve the problem via the following steps: first, I keep all existing 5-digit level data and use the sum of the belonging 6-digit level data to replace any missing value of the 5-digit data. Next, after I fill in the missing values of 5-digit data, I aggregate up to 4-digit level, and then to 3-digit level, and finally to 2-digit level employment data. Eventually, I obtain the structure of employment data by 2-digit NAICS industry for each MSA.

Business travel data across MSA: I download American Travel Survey (ATS) 1995 from the U.S. Department of Transportation.[39] I keep key variables such as "Metropolitan Area (MA) Code of Trip Origin", "Metropolitan Area (MA) Name of Trip Origin", "Metropolitan Area (MA) Name of Trip Destination", "Metropolitan Area (MA) Code of Trip Destination", "Reason for Trip", and "U.S./International Destination Flag". I define the business trip as "reason" (Reason for Trip)=1 (Business), 2 (Combined Business/Pleasure) or 3 (Convention, Conference, Or Seminar). Then I delete the MSA and foreign country which is not in my original sample of 357 regions. After that, I generate business trip number for every MSA as origin to every other MSA or foreign country as destination.

Appendix C. Supplementary data

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.euroecorev.2014.07.005.

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[38] In my sample, no citations come from non-metro area of New Jersey.

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