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Paola Criscuolo & Bart Verspagen

Eindhoven Centre for Innovation Studies, The Netherlands

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Does it matter where patent citations come from? Inventor versus examiner citations in European patents

Paola Criscuolo[*] & Bart Verspagen[**]

[*]Corresponding author, p.criscuolo@imperial.ac.uk, Tanaka Business School, Imperial College, London, South Kensington Campus, London, SW7 2AZ, UK.
Tel: +44-(0)2075941582
Fax: +44(0)2075945915

[**] ECIS (Eindhoven University of Technology) and TIK (University of Oslo)

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Abstract
This paper investigates whether the distinction between patent citations added by the inventor or the examiner is relevant for the issue of geographical concentration of knowledge flows (as embodied in citations). The distinction between inventor and examiner citations enables us to work with a more refined citation indicator of knowledge flows. We use information in the search reports of patent examiners at the European Patent Office to construct our dataset of regional patenting in Europe and in the US states, and apply various econometric models to investigate our research question. The findings point to a significant localization effect of inventor citations, after controlling for various other factors, and hence suggest that knowledge flows are indeed geographically concentrated.

JEL Classification Numbers: O30, O34.
Keywords: Patent citations, local knowledge spillovers.

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1. Introduction

Patent documents contain citations to other patents and references to non-patent literature in order to comply with the legal requirement to supply a complete description of the state of the art upon which the invention described in the patent builds. Thus, citations limit the scope of the inventor's claim for novelty and they represent a link to pre-existing knowledge upon which the invention is built. This latter notion has been used to justify the use of patent citations as indicators of knowledge spillovers. When an inventor cites another patent or a scientific article, this may indicate that the knowledge contained in the cited document has been useful in the development of the citing patent, and therefore the citation might be a proxy for knowledge flows.

A large body of empirical studies has exploited this use of patent citations to assess the spatial nature of technological spillovers (e.g. Jaffe, Trajtenberg et al. 1993; Jaffe and Trajtenberg 1996; Jaffe, Fogarty et al. 1998; Jaffe and Trajtenberg 1999; 2002). Here, the question is whether or not knowledge spillovers between firms, or from (semi-) public knowledge institutes to firms, depend on geographical distance, i.e., whether patent citations are, ceteris paribus, more frequent between two patents that originate from research projects undertaken by inventors that are located closely together. These studies find that both in the US and Europe, such a relationship indeed exists. Thus, knowledge spillovers tend to be more intense between parties that are located close to each other in space.

One of the criticisms of the use of patent citations as indicators of spillovers is that citations are a very noisy indicator of knowledge spillovers (Jaffe *et al.* 1998), i.e., they might be interpreted in different ways than pointing to an actual flow of knowledge from the cited to the citing patent. A crucial factor in this issue is that citations may be added by the applicant (or his/her patent lawyer), as well as by the patent examiner who judges the degree of novelty of the patent. Obviously, when citations are added by the applicant there is more of a case for taking citations as indicators of spillovers, because there is some chance that the inventor actually knew about the cited patent. When the examiner adds the citation, the inventor may never have known about the cited patent, and hence no knowledge spillover has taken place.

Most citation studies are not able to identify precisely those citations chosen by the inventor. Moreover, the role of examiner vs. inventor[1] citations differs somewhat between patent systems. In any case, when the inventor proposes citations, the final decision on which documents to cite in the patent publication lies with the patent examiners, and hence patent documents report the inventor citations as chosen by the examiner. The examiner might decide to accept the ones proposed by the applicant and/or add new references, where the latter leads to the bias already identified above, i.e., that patent citations might not reflect an actual source of knowledge spillovers.

A number of recent studies have investigated this issue in citations appearing in US patents (i.e., patents issued by the US Patent and Trademark Office, USPTO), exploiting the fact that, since 2001, the USPTO provides information on the source of the citations (Alcacer and Gittleman 2004; Sampat 2004; Thompson 2004). In this study we explore the origin of patent citations in European Patent Office (EPO) data, where the source of the citations is available for all patents (i.e., since the start of the EPO in 1979). We are able to discriminate between the citations listed by the examiner, on the one hand, and the ones proposed by the inventor and accepted by the patent examiner, on the other, exploiting the information contained in the search report.

The main objective of this paper is to test whether the references added by the patent examiner are systematically and significantly different from the ones listed by the inventor. In particular, in light of the strong attention to regional spillovers using citations as indicators, this study tries to investigate whether inventor citations and examiner citations are similar with regard to their geographical origin. We draw on a large dataset (all EPO patents originating from a set of 18 European countries), and apply regression analysis to investigate our research question.

2. Theoretical background

It is often assumed that due to the nature of knowledge as only a partial public good, the costs of transferring it depend on distance. Knowledge can in principle be shared without diminishing its value (i.e., knowledge is a non-rival economic good), but there are costs involved in doing so. Face-to-face communication is an efficient way of knowledge transfer, and this is obviously easier at short distances than across the globe. Even with modern information and communication technologies, geographical proximity may be an important factor in transferring knowledge (Morgan 2004).

Often, the tacit nature of knowledge is given as a reason why knowledge is more easily transferred face-to-face, and hence over small distances. Knowledge resides implicitly in the minds of people, and codification into written materials only partially reflects the full knowledge involved. Hence knowledge flows more intensively between people who have opportunities to physically meet on a regular basis.

Jaffe *et al.* (1993) have used this (often rather informal) reasoning as a starting point of their empirical analysis of the geographical concentration of patent citations. Citations are taken as 'paper trails' of knowledge spillovers from the cited inventor to the citing inventor. They find, in an analysis of U.S. patenting at the Metropolitan level, that citations are indeed more intense at the local level, even after taking account of the pre-existing production structure (i.e., if activities of a similar kind tend to be located near to each other, and patents of a similar kind have a higher probability to cite each other, citations will equally tend to be clustered even without localized spillovers). While they take this as an indicator of spillovers, i.e., unintended flows not directly related to any market transaction, Breschi and Lissoni (2001) have argued that citations are often related to research relationships that are somehow institutionalized, either through the market, or through some form of cooperation. In this case, localized patent citations may be an indicator of the localized nature of knowledge flows in a broader sense than just spillovers (i.e., the flows may not be externalities), but the question as to why these flows are so localized remains the same. Face-to-face contact between researchers and institutionalized contacts between organizations may just as well serve to explain why knowledge interaction in general, as opposed to spillovers in particular, is easier between firms and organizations that are located close to each other.

However, even broadening the issue to knowledge interaction rather than spillovers per se, does not solve the problem that citations are primarily legal instruments rather than direct indicators of knowledge flows. Citations are the most important way of limiting a patent's claims, and acknowledging claims made in other (earlier) patents. The fact that a cited patent has implications for the claims in the citing patent does not necessarily imply that spillovers have been going on between the inventors. Jaffe *et al*. (2002) have used a survey instrument to measure spillovers directly (i.e., they asked inventors whether a specific patent had a played a role in the invention described in a patent), and correlated this measure with patent citations. Their conclusion was that "the likelihood of knowledge spillover (...) is significantly greater (...)

than the likelihood without a citation (... but ...) a large fraction of citations, perhaps something like half, do not correspond to any apparent spillover (...) citations are a noisy signal of the presence of spillovers" (Jaffe, Trajtenberg et al. 2002, p. 400).

As was mentioned in the introduction, one way of diminishing the noise is to look at whether patent citations have been added by the examiner or by the inventor (applicant). Examiner citations are less likely to be related to spillovers, because it may be the case that the citing inventor was not aware of the cited patent. This indeed seems to be one of the implications of the survey evidence reported in Jaffe *et al.* (2002). This raises the question whether examiner and inventor citations are of a different (economic) nature, and, if so, whether such differences can be related to the nature of knowledge spillovers/flows (e.g., geographical concentration). These are the questions that we will investigate in this study. Because of differences between the patent systems in the US and Europe (on which we will elaborate below), we expect that our European-based evidence will be complementary to the existing studies, which solely use patent data from the US patent office (USPTO).

3. Data collection and descriptive statistics

Our primary data sources are the EPO database on patent applications (Bulletin CD), patent citations to other patents within the EPO, and patent citations from EPO patents to USPTO patents over the period 1985-2000 (all citations are taken from the EPO REFI database). We also use information contained in the patentability search report that EPO examiners complete during his screening of technically relevant literature. Contrary to other patent office search reports, the one compiled by EPO examiners contains various categories of citation which grade the cited document according to its relevance. As shown in Table 1, the category ‘D’ refers to those citations added by the examiner that were already mentioned in the patent application for which the search is carried out, i.e., were proposed by the applicant. This is our source for inventor citations. Thus, we only observe those citations added by the applicant that the examiner believed relevant with respect to the patentability of the invention.

*************** INSERT TABLE 1 ABOUT HERE *************

We complement this with the information contained in the OECD citations database on patent applications filed under the Patent Cooperation Treaty (PCT) and on equivalent patents (Webb, Dernis et al. 2004). When patent applications are examined under the PCT, they undergo an international search that is carried out by one of the International Search Agencies (ISA), of which the EPO is one. If the EPO is the designated ISA, the cited documents together with the categories of citations are not recorded in the REFI database, but they are in the OECD database.[2]

For each EPO patent the OECD database provides also a list of all patents filed in other patent offices protecting the same innovation (equivalent patents). We use this data to replace citations to national patents with their EPO equivalents in order to increase the sample of within EPO citations for which we have detailed information on inventor's address, technological classes and priority dates.

Our basic sample includes all EPO-to-EPO citations and EPO-to-USPTO citations, but the latter citation type is only included if both citing an cited patent have an inventor located in the US. Table 1 shows, in the last column, the distribution of citations over the citation categories for this sample. Note that cited patents can be classified with up to three categories (e.g., "ADL"). The largest share (62%) of citations is used to describe the state-of-the-art (*A*), followed by particularly relevant documents (*X*, 20% and *Y*, 16%). 9% of all citations are inventor citations

(*D*). All other categories of citations are smaller than 5% of the total. An interesting result is that the predominance of *A* citations is even stronger in the sample of inventor citations in the search report: 72% of all inventor citations has a category *A* attached, vs. 62% for the total sample. Also interesting is the smaller fraction of *X* citations among the sample of inventor citations (11% vs. 21% for the total sample), indicating that inventors have a lesser inclination to cite patents 'particularly relevant if taken alone'. This seems to indicate the (expected) tendency for inventors to not cite patents that may compromise novelty of their own patent. On the contrary, the *Y* category, which similarly points to patents compromising novelty, but only in combination with other patents, occurs as frequent in the sample of inventor citations as in the total sample (both at 16%).

************** INSERT FIGURE 1 ABOUT HERE ***************

Figure 1 shows, for the same sample as in Table 1, the development of the share of inventor citations in the database over time (this includes. We note that this share is (relatively) high initially (around 10%), then declines from the late 1980s to the mid 1990s, and finally remains largely stable for the rest of the period. Because the later years have more patents, these lower numbers contribute a higher weight to the overall count of 9% inventor citations.

The 9% inventor citations in our database is a small percentage compared with the same fraction found in USPTO patents (in the sample of US patents used by Alcacer and Gittelman, 2004, inventor citations represent 60% of all citations). This finding can be explained by the different legal requirements concerning the description of the state of the art in the two patent offices. While in the USPTO the inventor and his/her attorney are obliged to provide a list of those references describing the state of the art which are considered relevant to the patentability of the invention – the so called 'duty of candour' – the EPO has no similar requirement (Akers

2000; Meyer 2000; Michel and Bettles 2001). As a result, in the EPO, examiners rather than inventors or applicants, add the large majority of patent citations. The obvious implication is that in the EPO system, more often than in the case of USPTO, inventors may not be aware of patents (ultimately) cited in their patent. As pointed out by Michel and Bettles (2001), applicants to the USPTO "rather than running the risk of filing an incomplete list of references, (…) tend to quote each and every reference even if it is only remotely related to what is to be patented. Since most US examiners apparently do not bother to limit the applicants' initial citations to those references which are really relevant in respect to patentability, this initial list tends to appear in unmodified form on the front page of most US patents" (p. 197).

Further descriptive statistics are given in Table 2. The top part of the table provides information on the total citations database, while the two bottom panels give information for sub samples that we will use in the regressions below. The reason why we focus on these two sub samples is that we have comparable auxiliary information (such as the IPC class, information on applicant/inventor, etc.) only for EPO and USPTO patents.

The table shows that our two sub samples are slightly different from the total sample. Obviously, the number of citations per patent is lower, but interestingly, this is higher for the EPO-to-USPTO sample of citations that for the EPO-EPO sample. Also the fraction of patents that have only citations added by the examiner is different for the two sub samples. Both sub samples show a higher fraction of patents with only citations added by the examiner, but the fraction of patents with all citations added by the inventor is also higher for both sub samples.

*************** INSERT TABLE 2 ABOUT HERE *************

4. Descriptive findings on the geographical citation patterns

As a first approach to the question whether or not inventor and examiner citations have different geographical profiles, we proceed to analyse the geographical source of inventor and examiner citations at the country and regional (i.e., sub-country) level. We ask whether the inventor citations are more likely to originate in the same country (region) as the cited patent than examiner citations. Our hypothesis is that inventor citations are a more direct indicator of knowledge flows than examiner citations, and hence that inventor citations are more often co-located.

The assignment of patents to a country or a region is based on the inventor address (rather than the applicant address). A single patent may have more than one inventor, and if these inventors are located in different regions (countries), the question whether or not the inventors of a cited and citing patent are located in the same region (country) cannot be answered unambiguously. Throughout our statistical analysis (i.e., also for the regressions below), we approach this issue in the following way. Denote the number of citing inventors by m, and the number of cited inventors by n. We then have $m*n$ combinations of citing and cited locations (countries or regions). We consider all these combinations, and assign them a weight equal to $1/m*n$. Note that if some of the citing or cited inventors are from the same location, the $m*n$ locations will not be unique, but this is taken care of in a natural way by the weighting scheme.

We create a dummy variable that equals to 1 if the citing inventor and cited inventor are resident in the different European regions (variable named *Diff_Regions*), different US States (*Diff_USStates*) or different countries (*Diff_Ctrys*). Note that this variable is defined at the level of inventor locations, not at the level of a patent-citation-pair. At the patent-citation-pair level, there are $m*n$ location-pairs, and hence also $m*n$ values for the geographical dummy variables (these are weighted by the $1/m*n$ weights).

We first consider the *Diff_Ctrys* dummy variable. Figure 2 shows the development of the share of citations where this variable is equal to 1. This rises from 30% in the beginning to 45% in the last year, indicating that the degree of localization of inventor citations decreases over time. We will test for this in a multivariate context below. Table 3 provides some basic statistics on this dummy across 30 technological sub-fields as defined by the *Observatoire des Sciences et des Techniques* (OST) and the *Fraunhofer Institute* (FhG-ISI) (see OST 2002 appendix A5a-1 p. 346). As expected, across all technological classes inventor citations are more co-localized than the examiner citations (that is, the values for inventor citations in the table are smaller). Technology fields in which we find a particularly strong dominance of localized inventor citations (i.e., low values) are information technology, motors-pumps-turbines, thermal processes, and mechanical components (these are the technology fields for which the numbers in the last column of Table 3 are below 30%). Inventor citations are relatively weakly localized (values in Table 3 above 50%) in food & agricultural products.

*********** INSERT FIGURE 2 & TABLE 3 ABOUT HERE *******

We repeat this analysis at a finer level of geographical aggregation. To this end, we use the variable *Diff_Regions* for the European geographical space[3] and *Diff_USStates* for the US geographical space. The European regional breakdown that we use is largely based on the NUTS classification scheme that Eurostat uses. This is based on administrative regions rather than economically coherent regions. Although we would have liked to use the latter, such a classification scheme is not available for the European Union as a whole. We use a mix between NUTS 2- and 3-digit level, and in cases where the NUTS region corresponds to a (large) city or very small area, we combine this with the surrounding or adjacent region in order to arrive at more homogenous spatial units (except for Brussels and Berlin).

The results for this are documented in Figure 3 (time profile) and Table 4a (technology fields) for European regions, and in Figure 4 and Table 4b for US States. Obviously, because of the stricter geographical definition, we now find higher percentages than in Figure 2/ Table 3. In the time profiles, we see somewhat of a contrast between Europe and the US. In Europe, the localization effect seems to weaken over time (a higher fraction of citations with different regions), but in the US the fraction seems to be more or less constant.

****** INSERT FIGURES 3 & 4 & TABLES 4a AND 4b ABOUT HERE **********

In Tables 4a and 4b, inventor citations appear as more co-located than examiner citations, in all technological fields. With regard to the individual technology fields that we identified above as particularly high or low in terms of localization of inventor citations, we now find some differences. Audio-visual (European space, Table 4a), optical instruments (European space, Table 4a), semiconductors (US space, Table 4b), nuclear technology (European space, Table 4a), agricultural machinery and food processing (European space, Table 4a), machine tools (European space, Table 4a), motors-pumps-turbines (European space, Table 4a) and mechanical components (European space, Table 4a) are now highly localized.

Concluding, our descriptive evidence indeed indicates that inventor citations are more indicative of localized knowledge interaction that examiner citations, with variations by technology field, but this needs to be put to a test in a multivariate analysis.

5. Econometric approach

We proceed to investigate the differences between inventor and examiner citations in a broader and more formal context. To this end, we apply a formal econometric model, in which the citation type (examiner or inventor) is the dependent variable. This is a binary variable that takes the value 1 (0) if the citation was added by the examiner (inventor). We interpret this model as a prediction tool for whether a knowledge flow is actually observed (i.e., an inventor citation), or remains a potential linkage of two pieces of knowledge (i.e., an examiner citation).

************** INSERT TABLE 5 ABOUT HERE ***************

The explanatory variables used in the regressions are listed in Table 5. Among them are three variables measuring geographical proximity. The first of these is a standardized measure of regional distance in kilometers (*DistanceKM*) between the region of the citing and cited inventor (but see our explanation of the weighting scheme above). Appendix I explains how this variable was calculated. We calculate this variable both for EU-regions, and for US States (but not between Europe and the US). From the point of view of the localization effect of knowledge spillovers that is observed in the literature, we expect *DistanceKM* to be positively correlated with examiner citations (i.e., the further the distance between two patents, the less likely it is that inventors actually make the citation).

In addition to this, we have the two dummy variables that have been used in Tables 3 and 4. One was coded as 0 if the citing and cited patents originate from the same country (*Diff_Ctrys*), and the other is similarly defined at the regional level (*Diff_Regions*). Along the same lines of reasoning as for *DistanceKM*, we expect these geographical variables to have an odds-ratio greater than 1, i.e., examiners are more likely to add citations to patents originating from distant location than inventors.

Our next variable is the C*itation lag* (in years), which is the time period elapsed between the priority dates of the citing and cited patents. This controls for a potential difference in time scope between inventors and examiners. We have no strong theoretical expectations on the value of the odds-ratios for this variable, but we could hypothesize that examiners, because of their detailed knowledge of patent literature in the specific field they cover, have a 'longer memory' and thus they would have a tendency to add older patents in the search reports.

Technological relatedness is another variable that we wish to control for, and this is why we include a dummy variable that is coded as 0 if the citing and cited patents are classified in the same 4-digit IPC class (*Diff_Tech*). We include this variable in order to be able to account for the potential effect of co-location of similar types of R&D activities. Jaffe *et al.* (1993) have argued that it may be the case that R&D in a certain field tends to be co-located in space (e.g., research on semiconductors may be concentrated in Silicon Valley). Because patent citations are by definition to technologically related patents, this would lead to a geographical concentration of patent citations without necessarily pointing to any additional effect related to stronger knowledge flows at the local level. Our *Diff_Tech* variable, to the extent that its 4-digit IPC level indeed captures the relevant technological linkages, accounts for this. If inventors are more likely to cite local patents for reasons of technological relatedness, we expect this will turn up in the coefficient of the *Diff_Tech* variable. If, on the other hand, we find that the geographical variables are significant in addition to the *Diff_Tech* variable, this is evidence for a localization effect in addition to that of the geographical concentration of R&D activities of a specific kind.

A next set of variables is related to the citation categories that were explained in Table 1 above. We construct three mutually exclusive dummy variables capturing the classes (other than *D*, which defines our dependent variable) that are most frequent (*A*, *Y* and *X*). The remaining categories account for a minor fraction of the patents in our sample (see Table 1), and hence we drop citations classified under one of these categories. This implied excluding from the analysis only 3096 citation pairs. The categories *X* and *Y* pose a serious threat to the novelty of the patent, and hence, as already observed above, we expect that inventors will be less likely to add citations in these categories.

Tables 6 and 7 provide, respectively, descriptive statistics and the correlation matrix for the variables used in the regressions.

*************** INSERT TABLE 6 ABOUT HERE *************

*************** INSERT TABLE 7 ABOUT HERE *************

Our baseline estimation method is the logit model. But as was already indicated, our dependent variable is skewed, i.e., it contains relatively more 1s than 0s. Also, because citation behaviour may be influenced by personal characteristics of the applicant or examiner, as well as the specific technology involved in the patent, we might expect that the error term in our econometric equation is correlated between citation pairs that involve the same citing patent. In order to take account of these special features of the data, we apply a range of specific logit models that address this in various ways.

In order to deal with the correlated error terms, we follow Alcacer and Gittelman (2004) and first apply a random effects panel model, in which the random effects refer to the citing patent, and what is normally the 'time' dimension is represented by the various citations in a given citing patent. We also apply a model with clustered errors on citing patents (Moulton 1990). This assumes that the observations (citations) are drawn from a population with a grouped structure, and that the errors are correlated within the groups. The clustered error structure solves for a downward bias that would result in a model that wrongly assumes no clustered errors.

The skewed nature of the data is addressed by a special logit model, in which the actual logit function that is used in the specification is asymmetric. This is the complementary log-log model (cloglog). The cloglog model fits an asymmetric sigmoid function to the probability between zero and one, unlike the probit and logit models, which are both symmetric around ½.[4] The probability function of the cloglog model approaches zero fairly slowly, but approaches one quite sharply, i.e. the sigmoid function is more elongated in comparison to the logit or probit models (Agresti 2002). For the cloglog model, like the ordinary logit model, we have one version with robust cluster errors, and one version with random effects.

6. Estimation results

We first estimate a number of models for the total sample of within-EPO and within-Europe citations, which are presented in Table 8. All regressions in this table confirm that a greater geographical distance increases the probability of examiner citations (decreases the probability of inventor citations), or, in other words, that inventor citations are more geographically concentrated. This is shown by the odds-ratios for the variable *DistanceKM*, which is always larger than one and significant. The table also confirms that examiners are more likely to add the 'dangerous' citation types *X* than the 'common' citation type *A*, which is the reference category. But contrary to our expectations, examiners are less likely to add citations type *Y* compared to citations type *A*.

******************** INSERT TABLE 8 ABOUT HERE ****************

Examiners have a higher tendency than inventors to cite patents over longer citation (time) lags, however the odds-ratios of this variable (*Citation lag*) is very close to one, pointing to a small difference between inventor and examiner citations in this respect. Finally, examiners tend to cite more outside the technology class (*Diff_Tech*).

Although the various econometric specifications yield the same qualitative results (i.e., signs of the effects), they do differ with regard to the magnitude of the estimated odds-ratios. We choose the logit model with random effects as the preferred model, based on the two information criteria (AIC and BIC). Of the four models, this is the one that has the strongest localization effect (highest odds-ratio). The importance of the individual variance component (within citing patent variation), i.e., the random effects, indeed seems to be quite high (see value and significance of ρ in Table 8). This comes out stronger (higher ρ value) in the random effects logit model than in the random effects cloglog model, and therefore the fact that this model scores higher on the AIC/BIC may indicate that the individual variance component weights is somehow related to the skewness of the data.

******************** INSERT TABLE 9 ABOUT HERE ****************

We use the random effect logit model, in Table 9, to further investigate several issues. The first issue is an alternative definition of 'dangerous' patents (type *X* and *Y*). The alternative definition combines the two types into one, i.e., the dummy variable *Class XY* is 1 only if either one or both of the variables *Class X* and *Class Y* are equal to 1. The result of this regression is documented in the second column of Table 9 (the first column in Table 9 is reproduced from Table 8 as a baseline comparison). The result indicates that examiners are more likely to cite dangerous patents. Other variables are largely unaffected.

The next issue is the possibility of interaction effects between our independent variables, in particular between distance and the other variables. This is documented in the third column in Table 9. All the interaction effects that we investigate are significant at the 1% level, except distance with *Class X*, which is significant at the 10% level. The interactions where *Class X*, *Class Y* and *Diff_tech* are involved yield positive odds-ratios, which points out that these variables reinforce the effect of distance (or, alternatively, distance reinforces the effect of these variables). ‘Dangerous’ patents, or patents outside the own technology class are already less likely to be cited by inventors, and this is ‘worse’ if these patents were invented far away from the citing inventor’s location.

The next two columns in Table 9 investigate the time variance of the parameters. We do this by selecting a sub sample (cohort) of citations on the basis of the year of the citing patent (1985 – 1992 and 1993 – 2000). Both cohorts show a significant geography effect, but in the early cohort, this is somewhat stronger than in the late cohort. We thus find evidence for a slightly weakening impact of distance over time, but this effect is (very) small. In fact, the time-varying effects of the other variables are generally much larger. The *Citation lag* variable changes from a negative impact in the first cohort to a positive impact in the second cohort. The *Diff_tech* variable turns from positive but insignificant to stronger positive and significant. Finally, the impact of the two dangerous citation type variables also grows positively over time.

Finally, Table 9 implements regressions for sub samples in which citing patents with all citations coming from a single source (inventors or examiners) are eliminated. First, we exclude all citing patents for which all citations are examiner citations, next we exclude all citing patents for which the citations are all added by the inventor, and finally we exclude both previous types of citing patents. The reason why we exclude these types of patents is that citations where all citing patents are of one type only, might present cases where unobserved variables (e.g., personal characteristics of the examiner or inventor[5]) dominate the data, rather than a true localization effect. If this is a real feature in our data, the cases where one citing patent contains both examiner and inventor citations are much more reliable indicators for a localization effect (or its absence).

The most important finding from these three regressions is that excluding "all examiner" citations decreases the impact of distance somewhat, but still distance has a significant negative impact on inventor citations. We also see a reversal of the *Citation lag* effect. For the other variables, although the deviations of the odds-ratios from one are smaller for the sub samples, the basic conclusions remain intact. Concluding, what Table 9 shows, is that the overall results in Table 8 are robust to the variations that we apply. Stronger geographical concentration of inventor citations than examiner citations is a strong feature of our dataset, no matter what exact variables we use to indicate such concentration, and whether or not we exclude certain categories of data.

The results obtained so far are only for the European space. We wish to test whether the same results on geography hold for the US. Using our within EPO citation pairs, we can test for this by selecting the EPO patents invented in the US and consider the citations between them. In this case, our geographical units are states (we do not include Alaska and Hawai, which are geographical outliers). These tend to be larger than European regions , and this may affect our results. Specifically, we may expect that the effect of distance is smaller, since we are limiting the regressions to larger (average) distances. For the US geographical space, we stick to the random effects logit model.

******************** INSERT TABLE 10 ABOUT HERE ***************

In Table 10, we repeat the range of logit models of Table 8 for the sample of intra-EPO citations for (EPO) patents invented in the US. The first column again shows a significantly positive effect of distance on the probability of an examiner citation. This confirms that the distance effect also holds for the US space. However, as expected because of the larger average distances, the effect is less strong as in Table 8/9. We find similar results as before for the

European space for the *Diff_Tech* and *ClassX* variables (both positive effects). However, the *Citation lag* and *ClassY* variables now have a reverse effect. The *ClassY* variable now has the expected sign (positive).

In the second column of Table 10, we find the same qualitative results as before for the interaction effects. On the other hand, the results for separate cohorts shows the opposite result as before: over time, the effect of distance becomes slightly larger (rather than smaller as before). Finally, omitting parts of the sample where all citations were added by the examiner and/or inventor, again yields the same result: the effects of distance are slightly weakened by these omissions, but remain significant.

******************** INSERT TABLE 11 ABOUT HERE ****************

It might be the case that the EPO patents invented in the US that we use in Table 11 are a peculiar sub sample of patents originating from the US. We therefore also construct a sample of citations where the cited patent is a US patent invented in the US, rather than an EPO patent invented in the US (the citing patent remains an EPO patent invented in the US).[6] The regression results for this sample are documented in Table 11 (we use the same random effects logit models). Because the USPTO and EPO patents are classified using different classifications that are not easy to match, we can no longer include the *Diff_Tech* variable.

Table 11 again confirms the effect of positive distance on examiner citations. The distance variable is always significant, and has the same order of magnitude as before for the US space (Table 10). The *Citation lag* variable is no longer different from one in the first column. The *ClassX* and *ClassY* variables remain positive and significant, but their effect is stronger than in Table 10. The interaction effects show (again) the same qualitative results as before. For this sample, the two cohorts show exactly the same effect of distance. Omitting patents with all examiner citations or all inventor citations again lowers the odds-ratios on distance a bit, but the distance effect is still significant.

******************** INSERT TABLE 12 ABOUT HERE ****************

In Table 12, we merge the two samples of Table 10 and 11. Hence we have EPO patents invented in the US citing EPO or USPTO patents invented in the US. These results are qualitatively the same as in the two previous tables, hence again confirming the effect of distance on examiner citations.

******************** INSERT TABLE 13 ABOUT HERE ****************

Given our specific interest in the geographical issue, we explore in Table 13 the sensitivity of the results for alternative variables capturing closeness in space. The table presents results for the total time period, for the two cohorts that we applied before, and for the within-EPO/within-Europe sample as well as for the EPO-US sample of Table 12.. The first three columns in this table substitute the *DistanceKM* variable by the *Diff_Region* variable that we applied before. Because we use EU regions here, this is the sample of Table 8. This implies a much stricter definition of the localization effect (whereas the use of *DistanceKM* allows for a smooth decay of the probability of an inventor citation with distance, the effect is dichotomous – within or outside the region – in the case of the region dummy). This is reflected in a sharp increase in the odds-ratio of the region dummy as compared to *DistanceKM*. As before (Table 9), we observe a small decrease of the effect of distance between the two time cohorts.

We repeat in the next three columns of Table 13 the same regressions for a dummy variable that is 1 when the two patents originate from different US states (*Diff_USStates*). Again, we observe the sharp increase in odds-ratios, and, as before in Tables 10/11, a slight increase in the effect of distance over time.

Finally in Table 13, we run regressions where the distance effect is captured by the dummy that is 1 if the two patents originate from different countries (*Diff_Ctrys*). Here we can include both citations pairs from the European space and the US space. For large countries, this dummy does not imply a very strong localization effect, but for small countries it does. In this case, we still find a significant localization effect. The odds-ratios are somewhat smaller than for the regions/states regressions, but still (much) higher than for the *DistanceKM* variable. Overall, the conclusion from Table 13 is that the localization effect for inventor citations is robust for various definitions of localization.

7. A closer look at the effect of distance

So far, we have (implicitly) assumed that the effect of distance is linear, but it might be the case that the relation between the likelihood of examiner citation and distance is nonlinear. In particular, we would expect that at small distances, the increase in distance by a unit (km) would lead to a stronger effect on the likelihood of an examiner citation, than the same increase at longer distance. In order to test for this, we employ a non-parametric method that starts with eliminating the effect of variables other than distance from the likelihood of an examiner citation. To this end, we first estimate a random effects linear probability regression model, with *cits_examiner* as the dependent variable, and independent variables as in Table 9/12. We then calculate a residual from this regression as $r_i = e_i - \hat{e}_i$, where e stands for *cits_examiner*, and $\hat{e}_i = \hat{c} + \hat{\beta} X_i + \delta_i$. Here c and β are the parameters in our linear model, X is the vector of independent variables except *DistanceKM*, δ is the random effect associated with the citing patent, and hats indicate estimated values. Note that the regressions from which we draw $\hat{c}$ and $\hat{\beta}$ did include *DistanceKM* as an independent variable, but we do not include this variable in the calculation of the residual *r*. Hence *r* ‘partials out’ from *cits_examiner* all variables except distance.[7]

Next, we run a locally weighted regression (lowess) of *r* on *DistanceKM* (we use a bandwidth of 0.8). This regression yields a smooth curve, of which each point corresponds the ‘local’ (for the value of *DistanceKM*) effect of distance on the likelihood of an examiner citation. We first document the results of this procedure for the within-Europe/within-EPO sample in Figure 5.[8] Instead of the version of *DistanceKM* that is standardized into units of 173 km, we use on the horizontal axis of this figure a distance variable with units of 1 km.

Figure 5 indeed confirms that the effect of distance is nonlinear. At short distances between the cited and citing patent, the likelihood of an examiner citation quickly increases with distance, but this effect wears off at larger distances. Beyond 1,000 km (which is, say, the distance between the Brussels and Vienna regions, or the Paris and Copenhagen regions), the marginal effect of distance on the likelihood of an examiner citation becomes rather low. The longest distance between two regions in our sample is around 4,000 km (between the northern Scandinavian and Southern Spanish regions) if we do not include the Canary Islands, and approximately 1,500 km more if we include them. This non-linear effect of distance is consistent with the results found in Bottazzi and Peri (2003).

***************** INSERT FIGURES 5/6/7/8 AROUND HERE **********

In the next three figures (6 – 8), we document, respectively, the results for the samples of EPO patents invented in the US citing EPO patents in the US (Figure 6), USPTO patents invented in the US (Figure 7) and EPO or USPTO patents invented in the US (Figure 8). All these figures show the same non-linear shape as in Figure 5. For the US space, the maximum distance is somewhat larger (the horizontal scale extends to 5000 instead of the 4000 of Figure 5, and while this largest distance is a real outlier in Europe, it is not in the US). Despite this, the curvature for the three curves for the US space is rather similar to the one for the European space.

8. Concluding summary

The European patent database allows the identification of whether citations are added by the applicant/inventor (inventor citations) or the patent examiner. This information is available for the complete history of patent citations in the European patent system, and hence provides a rich source of data for assessing whether or not inventor citations indeed tend to be concentrated in geographical space. On the basis of this database, we have provided evidence based both on descriptive statistics and on the basis of multivariate econometrics. Both approaches yield a clear-cut conclusion: citations that originate from inventors/applicants are more concentrated in space than citations that originate from the patent examiners.

In our descriptive analysis, this holds both at the national level (inventor citations are more often to patents invented in the same country where the inventor is resident), and at the regional (i.e., sub-national) level in Europe or in terms of US States (inventor citations are more often to patents invented in the same region/state where the inventor is resident). The econometric analysis controls for a number of other factors, such as the technological relatedness of the cited and citing patent, the citation lag (time elapsed between the cited and citing patent), and the citation type (referring to state-of-the art, or citations that may compromise novelty). We also apply different measures of distance and co-location of cited and citing patent, and we experiment with different sub samples and estimation methods. Finally, we estimate models both for the European and US space.

All econometric evidence points to a significant localization effect of inventor citations. Citations added by the examiner are rarely clustered in the same region or state, and span larger geographical distances between cited and citing patent. This result is completely robust across sub samples, time cohorts, the estimation methods and the various ways in which distance and co-location are measured.

Otherwise, we find that examiner citations more often involve citations that may compromise novelty, which points out that inventors may indeed have a tendency to omit relevant citations that may endanger their patent claims.

By benchmarking inventor citations against examiner citations, we find that knowledge flows (to the extent that they are indicated by patent citations) are indeed localized. We take the patterns of citation in the sample of examiner citations as somehow representative for the potential linkages between global R&D workers, and the inventor citations as the part of these potential flows that have indeed materialized. Interpreted in this way, our evidence suggests that the actual technology flows are more geographically concentrated than the potential flows, or in other words, that knowledge interaction is stronger at small distances than over long distance. Testing for potential non-linearity of this relationship, we find that an increase in distance has a stronger effect when citing and cited patent are close to each other. In other words, the effect of distance is strong initially, but wears off when distance becomes large.

Our econometric analysis also controls for whether or not the technology classes of the cited and citing patent are the same. If the main reason for inventor citations to be more concentrated in geographical space was that patents in the same technology class are more often co-located, we would have expected that the technology class variables would have been positively correlated with inventor citations. But this is not generally the case, and hence we conclude that the localization effect that we find for inventor citations results from a source that is additional to the (potential) tendency of similar R&D activities to co-locate in space. In other words, the distribution of sectoral composition of R&D activities over space is not the prime responsible variable for the localization effect that we observe.

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Appendix I. Distance calculations

A distance table between the European regions in our sample is not readily available. The approach taken here to calculate such a table is based on a computer map of Europe. This map was taken from Eurostat's classification server RAMON[9] but altered to take into account our customized regional breakdown. The map was divided into a dense set of cells (pixels). Each pixel was assigned either to a region or a border between municipalities. This was done on the basis of the borders drawn on the computer image of the map. Pixels assigned to borders were not included in the calculations. The distance between any two pixels on the map was defined as the Euclidean distance between them (the unit of measurement is kilometers). The fact that Euclidean distance on the flat computer map was used implies that no account was taken of the curvature of the globe. Also, no correction was made for the imperfections introduced by the projection of the map onto a flat space. The distance between two regions i and j was defined as the mean of the individual distance between all possible pairs of pixels, with one pixel located in i, and the other pixel located in j.

Because we report odds-ratios in the documentation of regression results, a unit of 1 km is not very useful (it is too small to point out any discernable effect). Thus, we divide the distance in kilometres by 173, which is the distance that is found, on average, between two bordering regions on our map. We arrived at this 173 km distance by first defining a new variable B, in which B_{ij} for regions i and j is defined as the minimum number of borders one has to cross to reach j from i (or vice versa).[10] We then divide the distance in kilometres by the corresponding value of B and take the average over all pairs of regions, which yields 173 km. In cases where the citing and/or cited patents involve more than one inventor, we calculate an average distance value between all combinations of regions involved on the citing and cited side.

Appendix II. The regions

For the following countries/regions, the NUTS classification has been used:

Austria	
AT11	Burgenland
AT12+AT13	Niederösterreich
AT21	Kärnten
AT22	Steiermark
AT31	Oberösterreich
AT32	Salzburg
AT33+AT34	Tirol And Vorarlberg
Belgium	
BE1	Brussels Hfdst.Gew
BE2	Vlaams Gewest
BE3	Region Wallonne
Germany	
DE1	Baden-Württemberg
DE2	Bayern
DE3	Berlin
DE4	Brandenburg
DE5+DE9	Bremen And Niedersachsen
DE6+DEF	Hamburg And Schleswig-Holstein
DE7	Hessen
DE8	Mecklenburg-Vorpommern
DEA	Nordrhein-Westfalen
DEB+DEC	Rheinland-Pfalz And Saarland
DED	Sachsen
DEE	Sachsen-Anhalt
DEG	Thüringen
Spain	
ES11	Galicia
ES12+ES13	Asturias And Cantabria
ES21+ES22+ES23	Pais Vasco, Navarra And Rioja
ES24	Aragon
ES3	Madrid
ES41	Castilla-Leon
ES42	Castilla-La Mancha
ES43	Extremadura
ES51	Cataluna
ES52	Valenciana
ES53	Baleares
ES61	Andalucia
ES62	Murcia
ES7	Canarias

France	
FR1	Ile De France
FR21	Champagne-Ardenne
FR22	Picardie
FR23	Haute-Normandie
FR24	Centre
FR25	Basse-Normandie
FR26	Bourgogne
FR3	Nord-Pas-De-Calais
FR41	Lorraine
FR42	Alsace
FR43	Franche-Comte
FR51	Pays De La Loire
FR52	Bretagne
FR53	Poitou-Charentes
FR61	Aquitaine
FR62	Midi-Pyrenees
FR63	Limousin
FR71	Rhone-Alpes
FR72	Auvergne
FR81	Languedoc-Roussillon
FR82	Provence-Alpes-Cote D'azur
FR83	Corse
Greece	
GR1	Voreia Ellada
GR2+GR3	Kentriki Ellada And Attiki
GR4	Nisia Aigaiou, Kriti
Italy	
IT1	Nord Ovest
IT2	Lombardia
IT31	Trentino-Alto Adige
IT32	Veneto
IT33	Friuli-Venezia Giulia
IT4	Emilia-Romagna
IT51	Toscana
IT52	Umbria
IT53	Marche
IT6	Lazio
IT7	Abruzzo-Molise
IT8	Campania
IT9	Sud
ITA	Sicilia
ITB	Sardegna

Netherlands	
NL1	Noord-Nederland
NL21	Overijssel

NL22	Gelderland
NL23	Flevoland
NL31	Utrecht
NL32	Noord-Holland
NL33	Zuid-Holland
NL34	Zeeland
NL41	Noord-Brabant
NL42	Limburg
Portugal	
PT11	Norte
PT12	Centro
PT13	Lisboa E Vale Do Tejo
PT14	Alentejo
PT15	Algarve
Sweden	
SE01+SE02	Stockholm And Östra Mellansverige
SE03+SE04	Småland And Sydsverige
SE05	Västsverige
SE06	Norra Mellansverige
SE07	Mellersta Norrland
SE08	Övre Norrland
United Kingdom	
UK1	North
UK2	Yorkshire And Humberside
UK3	East Midlands
UK4	East Anglia
UK5	South East
UK6	South West
UK7	West Midlands
UK8	North West
UK9	Wales
UKA	Scotland
UKB	Northern Ireland

For the following countries, a national classification has been used:

Norway	**Based on Fylken**
NO1	Akershus, Oslo
NO2	Hedmark, Oppland
NO3	Østfold, Busekrud, Vestfold, Telemark
NO4	Aust-Agder, Vest-Agder, Rogaland
NO5	Hordaland, Sogn og Fjordane, Møre of Romsdal
NO6	Sør-Trøndelag, Nord-Trøndelag
NO7	Nordland, Troms, Finnmark
Switzerland	**Based on Cantons**
CH1	Jura, Neuchâtel, Fribourg, Vaud, Geneva
CH2	Argovia, Appenzell Inner-Rhodes, Appenzell Outer-Rhodes, Basel-Country-Basel-Town, Berne, Glarus, Lucerne, Nidwalden, Obwalden, St. Gallen, Schaffhausen, Schwyz, Solothurn, Thurgovia, Uri, Zug, Zurich
CH3	Valais, Ticino, Grisons
Denmark	**Based on postal regions**
DK1	Hillerød, Helsingør, København
DK2	Fyn, Sjaelland ex. Hillerød, Helsingør, København
DK3	Jylland
Finland	**Based on municipalities**
FI11_12	Uusimaa+Etelä-Suomi
FI13	Itä-Suomi
FI14	Väli-Suomi
FI15	Pohjois-Suomi

The following countries have been included as a single region:

Ireland

Luxemburg

Figure 1. The share of inventor citations in total citations in the EPO database

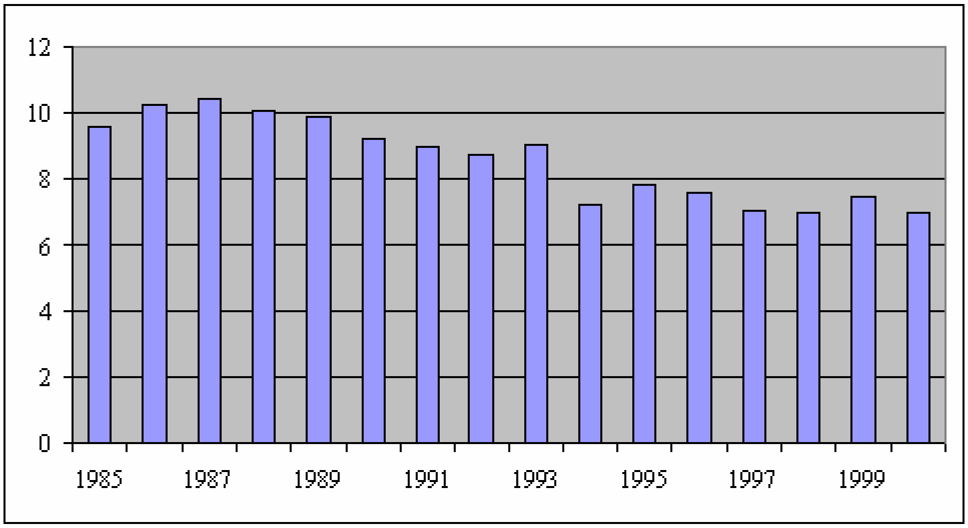


Figure 2. Share of inventor citations where inventors of cited and citing patents are from different countries

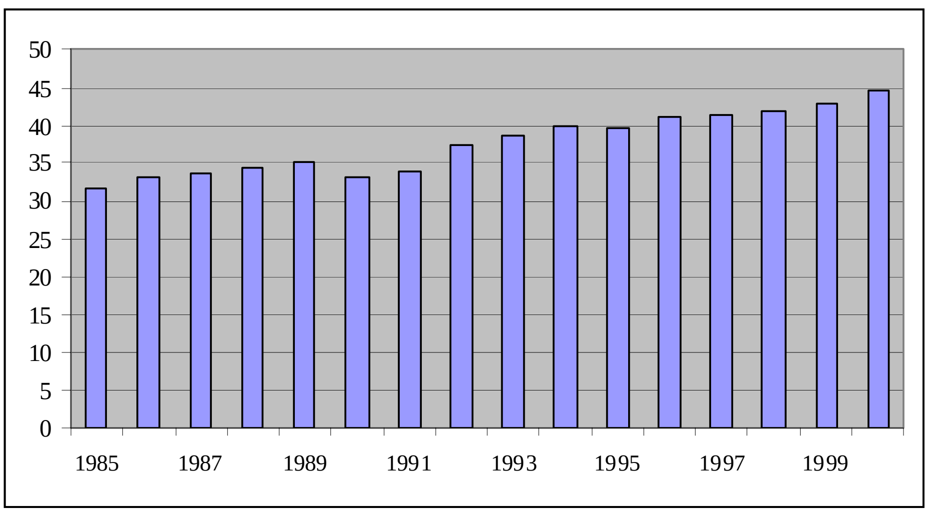


Figure 3. Share of inventor citations where inventors of cited and citing patents are from different European regions

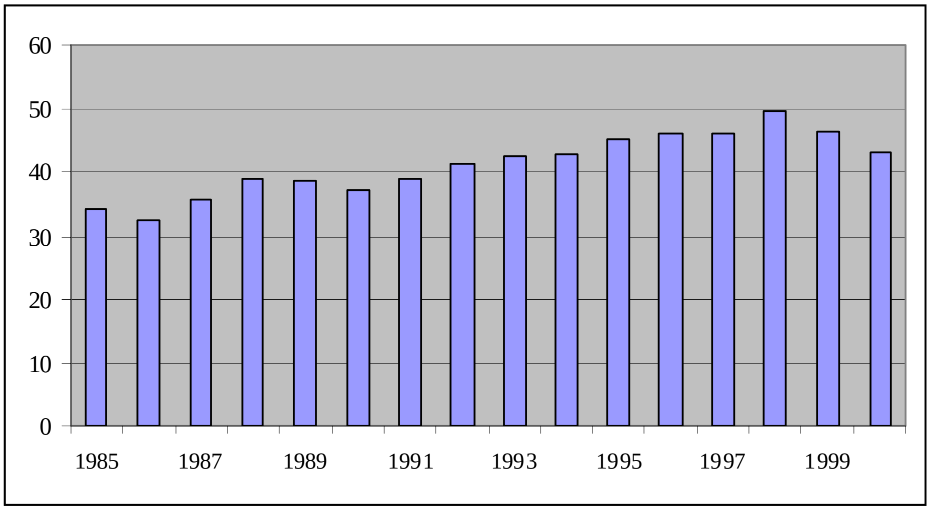


Figure 4. Share of inventor citations where inventors of cited and citing patents are from different countries

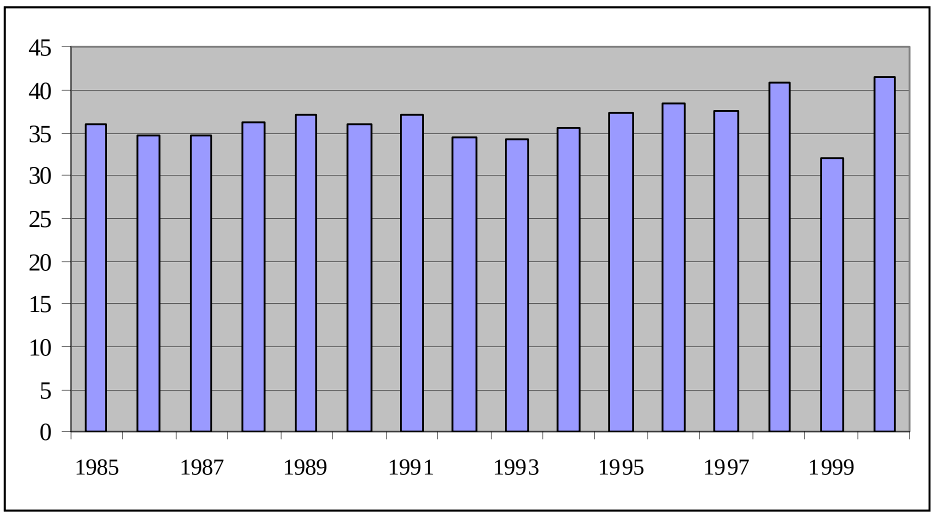
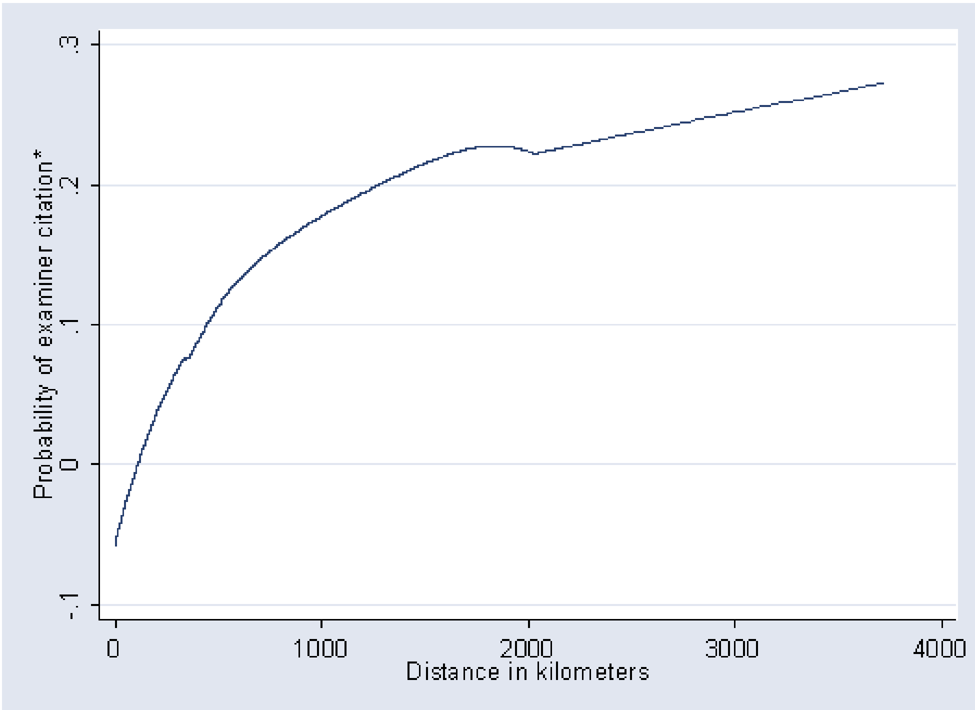
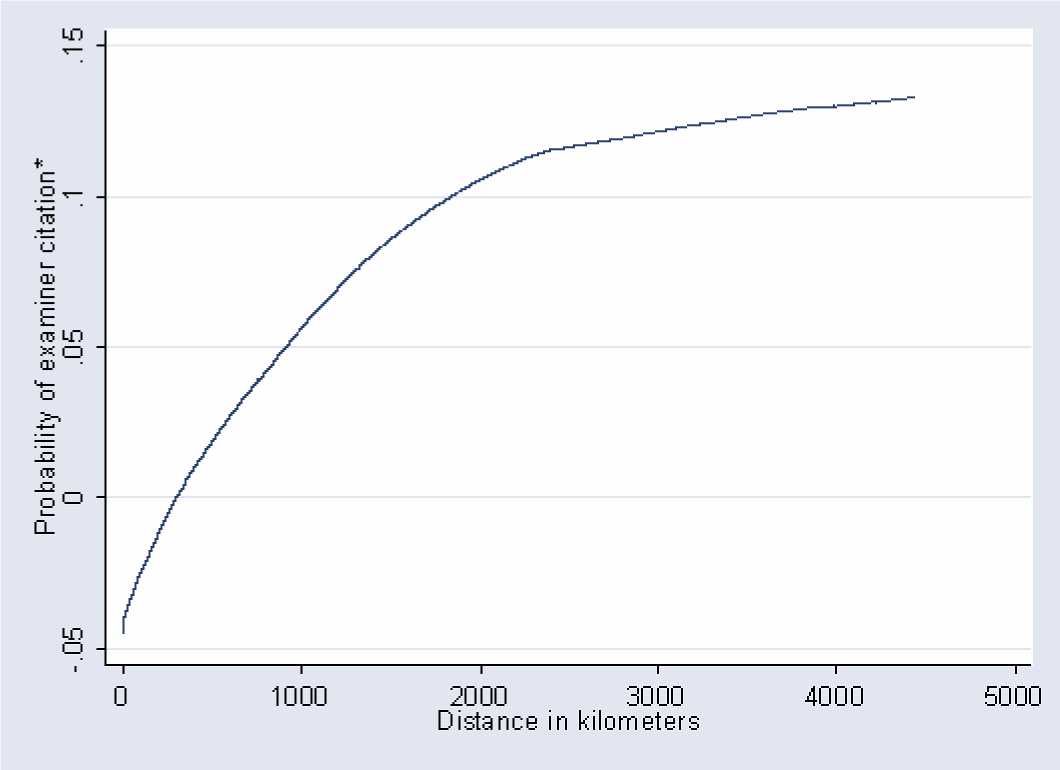


Figure 5. The relationship between distance and the likelihood of an examiner citation, within-EPO and within-Europe sample



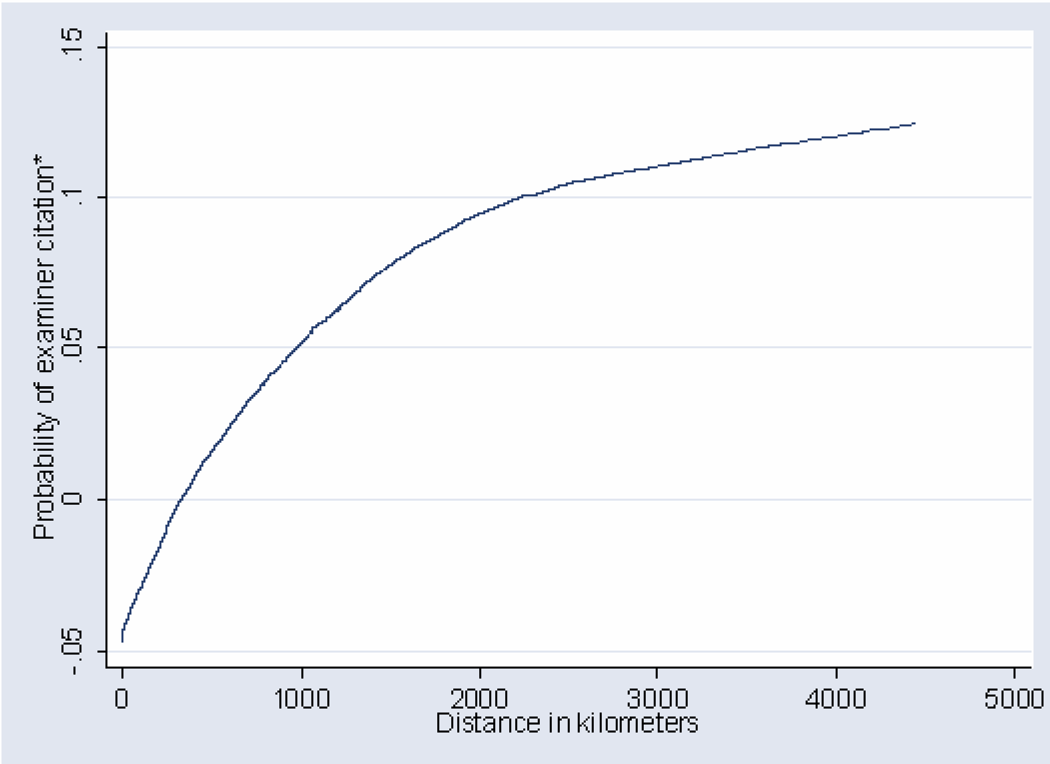
* For definition of probability of examiner citation, see text.

Figure 6. The relationship between distance and the likelihood of an examiner citation, EPO patents invented in the US citing EPO patents invented in the US



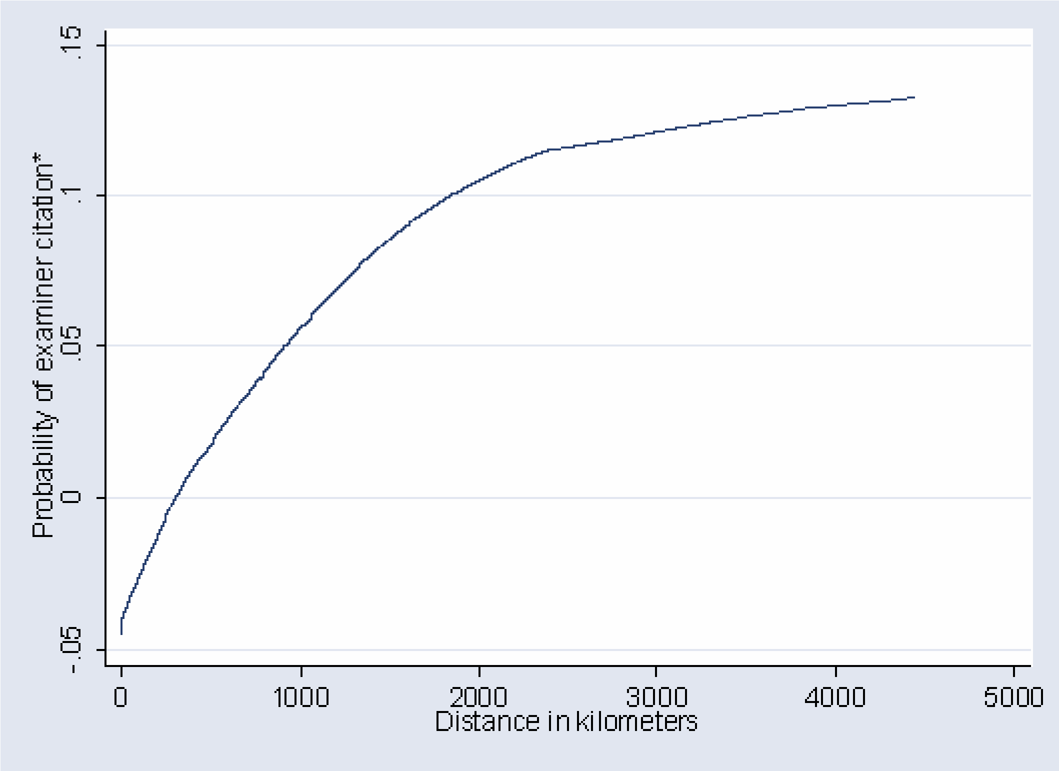
* For definition of probability of examiner citation, see text.

Figure 7. The relationship between distance and the likelihood of an examiner citation, EPO patents invented in the US citing USPTO patents invented in the US



* For definition of probability of examiner citation, see text.

Figure 8. The relationship between distance and the likelihood of an examiner citation, EPO patents invented in the US citing EPO or USPTO patents invented in the US



* For definition of probability of examiner citation, see text.

Table 1. Description of category of citations

Category of citations	Description	Fraction of all citations
X	Particularly relevant documents if taken alone; citations classified under this category are such that when taken alone a claimed invention cannot be considered novel or cannot be considered to involve an inventive step.	0.20
Y	Particularly relevant documents if combined with another document, such a combination being obvious to a person skilled in the art.	0.16
A	Documents defining the state of the art and not prejudicing novelty or inventive step.	0.62
D	Documents cited in the application.	0.09
P	Intermediate documents; Documents published on dates falling between the date of filing of the application being examined and the date of priority claimed.	0.04
E	Earlier patent documents, but published on, or after the filing date.	0.01
O	Documents that refer to a non-written disclosure.	0.00
T	Documents relating to the theory or principle underlying the invention.	0.00
L	Documents cited for other reasons.	0.00

Source: EPO examination guides lines part B chapter X

Table 2. Descriptive statistics

Total Sample	
Number of citing patents	700,674
Number of citations	2,859,714
Citations per patent (mean)	3.25
Number of citing patents with all citations added by the examiner	530,893
Fraction of citing patents with all citations added by the examiner	75.77
Number of citing patents with all citations added by the inventor	16,617
Fraction of citing patents with all citations added by the inventor	2.37
Sample of within EPO citations	
Number of citing patents	490,230
Number of citations	982,826
Citations per patent (mean)	1.91
Number of citing patents with all citations added by the examiner	400,620
Fraction of citing patents with all citations added by the examiner	81.72
Number of citing patents with all citations added by the inventor	34,583
Fraction of citing patents with all citations added by the inventor	7.05
Sample of EPO patents citing USPTO patents	
Number of citing patents	432,776
Number of citations	913,675
Citations per patent (mean)	2.19
Number of citing patents with all citations added by the examiner	379,250
Fraction of citing patents with all citations added by the examiner	87.63
Number of citing patents with all citations added by the inventor	23,262
Fraction of citing patents with all citations added by the inventor	5.38

Table 3. Comparing the geographical distribution of inventor and examiner-citations (share of citations with inventors from different countries)

Technological sub-fields	All observations	Examiner citations	Inventor citations
Electrical Components Electronics	59.05	62.10	34.02
Audio–visual	52.92	53.95	32.76
Telecommunications	66.50	68.08	34.80
Information Technology	55.71	56.81	29.20
Semiconductors	56.41	58.07	30.17
Optical Instruments	50.27	52.18	36.50
Analytical, measurement & control instruments	61.36	64.17	34.69
Medical equipment	58.22	60.45	37.39
Nuclear technology	57.77	62.30	31.47
Organic chemistry	52.90	55.32	44.46
Macromolecular chemistry	52.71	54.91	39.80
Chemical processes: oil	54.97	57.03	43.45
Surface treatment	57.31	59.77	35.62
Materials–metals	56.51	59.70	39.72
Biotechnology	54.87	57.26	40.65
Pharmaceuticals–cosmetics	56.32	58.35	41.13
Food & agricultural products	61.41	62.94	51.85
Technological processes	59.37	62.52	36.18
Product handling printing	57.53	60.33	35.44
Agricultural machinery food processing	61.63	65.78	37.59
Materials handling	58.80	62.50	37.60
Environment–pollution	62.28	65.20	34.39
Machine tools	61.00	65.13	35.36
Motors–pumps–turbines	58.78	61.67	29.25
Thermal processes	62.36	65.97	29.08
Mechanical components	59.98	64.01	29.95
Transport	60.57	63.74	33.24
Space–arms	61.26	65.79	32.78
Household equipment and consumer goods	62.15	65.67	37.09
Building and public works	60.78	65.47	29.83
Overall	**57.63**	**60.24**	**37.47**

Table 4a. Comparing the geographical distribution of inventor and examiner-citations (share of citations with inventors from different European regions)

Technological sub-fields	All observations	Examiner citations	Inventor citations
Electrical Components Electronics	62.34	67.22	35.83
Audio–visual	63.86	67.44	28.07
Telecommunications	73.02	75.42	36.95
Information technology	75.69	78.09	34.48
Semiconductors	62.21	65.58	31.07
Optical Instruments	44.00	49.54	23.52
Analytical, measurement & control instruments	65.24	69.42	36.54
Medical equipment	70.30	73.29	46.43
Nuclear technology	53.56	62.54	22.87
Organic chemistry	48.90	50.83	40.66
Macromolecular chemistry	54.42	57.75	39.14
Chemical processes: oil	55.88	58.52	40.56
Surface treatment	62.57	65.82	38.44
Materials–metals	54.35	58.64	38.57
Biotechnology	60.00	62.74	42.23
Pharmaceuticals–cosmetics	65.79	68.75	43.38
Food & agricultural products	65.56	66.56	58.11
Technological processes	60.17	63.56	40.10
Product handling printing	57.82	63.27	32.49
Agricultural machinery food processing	50.68	62.46	21.49
Materials handling	58.59	62.89	39.86
Environment–pollution	64.67	68.66	42.14
Machine tools	56.57	63.22	25.85
Motors–pumps–turbines	55.36	60.15	23.90
Thermal processes	55.70	59.42	33.18
Mechanical components	46.52	52.86	21.51
Transport	45.97	49.86	28.84
Space–arms	58.00	60.81	40.96
Household equipment and consumer goods	57.94	63.31	31.46
Building and public works	48.25	52.20	31.69
Overall	**67.46**	**72.82**	**44.95**

Table 4b. Comparing the geographical distribution of inventor and examiner-citations (share of citations with inventors from different US States)

Technological sub-fields	All observations	Examiner citations	Inventor citations
Electrical Components Electronics	68.95	75.31	39.81
Audio–visual	66.40	71.80	32.10
Telecommunications	74.33	79.67	32.50
Information technology	72.85	77.81	36.98
Semiconductors	59.92	67.04	23.62
Optical Instruments	61.60	69.02	35.16
Analytical, measurement & control instruments	71.11	77.05	39.02
Medical equipment	74.22	79.76	45.77
Nuclear technology	63.00	71.00	30.22
Organic chemistry	52.60	56.24	43.97
Macromolecular chemistry	58.64	61.63	49.01
Chemical processes: oil	65.52	67.98	55.63
Surface treatment	68.66	74.70	43.75
Materials–metals	65.35	71.03	45.68
Biotechnology	59.00	62.20	45.97
Pharmaceuticals–cosmetics	69.56	75.08	49.05
Food & agricultural products	77.08	80.68	59.60
Technological processes	67.96	73.42	40.57
Product handling printing	70.53	76.27	43.08
Agricultural machinery food processing	70.89	74.94	49.77
Materials handling	65.81	72.22	41.29
Environment–pollution	76.44	80.24	48.36
Machine tools	67.29	73.98	40.34
Motors–pumps–turbines	65.89	71.24	36.05
Thermal processes	72.75	78.68	38.14
Mechanical components	69.43	75.69	36.88
Transport	72.16	77.00	43.21
Space–arms	67.53	76.25	34.38
Household equipment and consumer goods	70.43	76.00	41.30
Building and public works	73.41	79.09	41.55
Overall	**60.97**	**64.94**	**36.38**

Table 5. Variable definitions

Name	Definition
Cits_examiner	1 if examiner citation, 0 if applicant citation
DistanceKM	Average km distance between the citing and cited European region or US State, in units of 173 km
Diff_EURegions	0 if at least one inventor in the citing and cited patent application are resident in the same region, 1 otherwise
Diff_USstates	0 if at least one inventor in the citing and cited patent application are resident in the same US State, 1 otherwise
Diff_Ctrys	0 if at least one inventor in the citing and cited patent application are resident in the same country, 1 otherwise
Citation lag	Priority year of the citing patent application – priority year of cited patent application
Diff_Tech	0 if citing and cited patent application are classified in the same four-digit IPC code
ClassY	1 if the cited patent has been classified under category Y, 0 otherwise
ClassX	1 if the cited patent has been classified under category X, 0 otherwise

Table 6. Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Cits_examiner	251407	0.807	0.394	0	1
DistanceKM	251407	1.962	2.193	0	21.55
Diff_EURegions	251407	0.674	0.468	0	1
Diff_USstates	156623	0.609	0.487	0	1
Diff_Ctrys	949903	0.576	0.494	0	1
Citation lag	251407	5.484	3.838	0	23
Diff_Tech	251407	0.311	0.463	0	1
ClassX	251407	0.192	0.394	0	1
ClassY	251407	0.147	0.354	0	1

Table 7. Correlation matrix for the variables used in the regressions

Variable	*Cits_examiner*	DistanceKM	Citation lag	Diff_Tech	ClassX
Cits_examiner	1				
DistanceKM	0.2106	1			
	(0.000)				
Citation lag	0.0356	0.1351	1		
	(0.000)	(0.000)			
Diff_Tech	0.0221	0.0355	0.0564	1	
	(0.000)	(0.000)	(0.000)		
ClassX	0.1047	0.0349	-0.0419	-0.0032	1
	(0.000)	(0.000)	(0.000)	(0.110)	
ClassY	-0.0359	-0.023	-0.0147	0.0157	-0.2033
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Significance levels of each correlation coefficient are reported below each coefficient.

Table 8. Results of different logit models using the sample of within-EPO, within-Europe citations

	Random effects cloglog	Random effects logit	Logit with robust cluster errors	Cloglog with robust cluster errors
DistanceKM	1.231	1.539	1.437	1.146
	(84.84)***	(93.50)***	(78.75)***	(67.00)***
Citation lag	1.003	1.004	1.003	1.003
	(2.91)***	(2.00)**	(2.04)**	(3.59)***
Diff_Tech	1.071	1.118	1.078	1.047
	(8.68)***	(7.62)***	(6.19)***	(7.62)***
ClassX	1.638	2.556	2.167	1.426
	(46.84)***	(46.16)***	(43.28)***	(45.57)***
ClassY	0.931	0.879	0.932	0.967
	(7.04)***	(7.03)***	(4.71)***	(4.28)***
Observations	251053	251053	251053	251053
Number of citing pats	159799	159799		
Log-likelihood	-112786	-112440	-114305	-115134
AIC	225586.6	224893.9	228622	230279.1
BIC	225659.6	224966.9	228684.6	230341.7
Min cited per citing	1	1		
Avg cited per citing	1.57	1.57		
Max cited per citing	23	23		
Wald χ^2	8609.81	10663.88		
Degrees of freedom	5	5		
ρ	0.25	0.34		
χ^2	4694.52	3730.15		

Absolute value of *z* statistics in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 9. Results of different specifications of the random effects logit model, within EPO and within-Europe citations

	1	2	3	Citing patent in 1985_1992	Citing patent in 1993_2000	All_exam_excl	Allinv_excl	All_exam_allinv_excl
DistanceKM	1.539	1.544	1.554	1.593	1.51	1.261	1.453	1.268
	(93.50)***	(94.43)***	(51.29)***	(59.23)***	(72.08)***	(51.98)***	(68.08)***	(40.85)***
Citation lag	1.004	1.001	1.015	0.978	1.006	0.999	0.995	0.992
	(2.00)**	(0.79)	(6.09)***	(5.43)***	(3.07)***	(0.44)	(2.41)**	(3.33)***
Diff_Tech	1.118	1.108	1.016	1.005	1.194	1.035	1.091	1.037
	(7.62)***	(7.10)***	(0.83)	(0.22)	(9.54)***	(2.02)**	(5.05)***	(1.76)*
ClassX	2.556		2.493	2.18	2.743	1.801	1.946	1.562
	(46.16)***		(35.37)***	(22.76)***	(39.76)***	(26.28)***	(28.03)***	(16.32)***
ClassY	0.879		0.813	0.781	0.957	0.882	0.826	0.799
	(7.03)***		(8.87)***	(8.59)***	(1.83)*	(5.70)***	(9.10)***	(8.74)***
*KM***ClassX*			1.023					
			(1.77)*					
*KM***ClassY*			1.066					
			(5.43)***					
*KM***Citation Lag*			0.992					
			(7.10)***					
*KM***Diff_tech*			1.076					
			(7.82)***					
ClassXY		1.487						
		(27.26)***						
Observations	251053	251053	251053	92620	158428	75475	224091	48513
Number of citing pats	159799	159799	159799	62292	97505	40987	136683	17871
Log-likelihood	-112440	-113403	-112368.76	-43740.8	-68592.2	-47449.3	-66107.3	-32089.9
Min cited per citing	1	1	1	1	1	1	1	1
Avg cited per citing	1.57	1.57	1.57	1.49	1.62	1.84	1.64	2.71
Max cited per citing	23	23	23	11	23	23	23	23
Wald χ^2	10663.88	9690.41	10703.55	3952.92	6636.6	3495.78	5677.14	2067.9
degrees of freedom	5	4	9	5	5	5	5	5
ρ	0.34	0.34	0.34	0.35	0.33	0	0.15	0
χ^2	3730.15	3703.53	3712.19	1373.34	2362.19	0	678.11	0

Absolute value of z statistics in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 10. Results of the random effects logit model, within EPO citations of (EPO) patents invented in the US

	1	2	1985_1992	1993_2000	All_exam_excl	Allinv_excl	All_exam_allinv_excl
DistanceKM	1.131	1.151	1.121	1.14	1.067	1.105	1.065
	(57.41)***	(33.36)***	(37.69)***	(43.31)***	(33.24)***	(39.62)***	(24.74)***
Citation lag	0.997	1.01	0.961	0.992	0.975	0.997	0.975
	(0.97)	(2.66)***	(6.64)***	(2.15)**	(6.60)***	(0.83)	(5.61)***
Diff_Tech	1.129	1.164	1.042	1.193	0.988	1.07	0.957
	(5.60)***	(5.87)***	(1.29)	(5.92)***	(0.52)	(2.71)***	(1.51)
ClassX	2.36	2.356	1.851	2.612	1.668	1.725	1.395
	(30.64)***	(26.08)***	(14.71)***	(25.37)***	(17.28)***	(17.31)***	(9.30)***
ClassY	1.19	1.116	1.043	1.328	0.961	1.095	0.884
	(6.41)***	(3.43)***	(1.10)	(7.49)***	(1.29)	(2.92)***	(3.34)***
*KM*ClassX*		1.001					
		(0.25)					
*KM*ClassY*		1.02					
		(3.78)***					
*KM*Citation Lag*		0.996					
		(6.23)***					
*KM*Diff_tech*		0.991					
		(2.27)**					
Observations	156623	156623	61692	94930	34063	144466	21906
Number of citing pats	96118	96118	39268	56849	18214	85867	7963
Log-likelihood	-57791.2	-57761.9	-26161.5	-31300.4	-21565.2	-33292.9	-14581.6
Min cited per citing	1	1	1	1	1	1	2
Avg cited per citing	1.63	1.63	1.57	1.67	1.87	1.68	2.75
Max cited per citing	17	17	17	15	17	17	17
Wald χ^2	4059.95	4079.54	1602.8	2402.42	1434.09	1866.71	739.73
degrees of freedom	5	9	5	5	5	5	5
ρ	0.48	0.48	0.45	0.49	0	0.25	0
χ^2	3760.16	3760.38	1442.14	2248.53	0	950.12	0

Absolute value of z statistics in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 11. Results of the random effects logit model, EPO patents invented in the US citing USPTO patents invented in the US

	1	2	1985_1992	1993_2000	All_exam_excl	Allinv_excl	All_exam_allinv_excl
DistanceKM	1.122	1.131	1.122	1.122	1.063	1.09	1.058
	(58.42)***	(34.39)***	(43.77)***	(38.54)***	(35.45)***	(40.80)***	(26.70)***
Citation lag	1	1.008	0.989	1	1.007	1	1.007
	(0.16)	(2.92)***	(3.33)***	(0.01)	(3.10)***	(0.08)	(3.04)***
ClassX	3.288	3.113	3.097	3.005	1.777	2.351	1.648
	(34.58)***	(25.91)***	(22.45)***	(23.14)***	(17.51)***	(23.23)***	(12.64)***
ClassY	1.905	1.732	1.616	2.217	1.092	1.638	1.025
	(21.38)***	(14.28)***	(12.04)***	(17.31)***	(2.83)***	(15.50)***	(0.69)
*KM*ClassX*		1.012					
		(2.00)**					
*KM*ClassY*		1.02					
		(3.95)***					
*KM*Citation Lag*		0.998					
		(4.73)***					
Observations	211014	211014	98812	112200	38489	196933	24408
Number of citing pats	107239	107239	52425	54813	19984	95931	8676
Log-likelihood	-67030	-67008.9	-36745.3	-29699.9	-24227.7	-38628.4	-16257.9
Min cited per citing	1	1	1	1	1	1	2
Avg cited per citing	1.97	1.97	1.88	2.05	1.93	2.05	2.81
Max cited per citing	33	33	33	28	13	33	13
Wald χ^2	4515.48	4484.62	2336.05	2050.34	1530.03	2276.04	871.99
degrees of freedom	4	7	4	4	4	4	4
ρ	0.66	0.66	0.65	0.67	0.03	0.39	0
χ^2	10595.15	10579.86	5764.12	4506.89	25.18	2634.76	0

Absolute value of z statistics in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 12. Results of the random effects logit model, EPO patents invented in the US citing EPO or USPTO patents invented in the US

	1	2	1985_1992	1993_2000	All_exam_excl	Allinv_excl	All_exam_allinv_excl
DistanceKM	1.118	1.128	1.115	1.122	1.066	1.102	1.065
	(83.10)***	(50.92)***	(61.43)***	(55.84)***	(56.24)***	(68.64)***	(46.98)***
Citation lag	0.999	1.009	0.984	1	0.993	0.999	0.993
	(0.81)	(4.62)***	(6.93)***	(0.18)	(4.73)***	(0.54)	(4.27)***
ClassX	2.561	2.466	2.272	2.598	1.743	2.138	1.616
	(44.82)***	(35.41)***	(27.87)***	(31.76)***	(28.95)***	(35.28)***	(21.98)***
ClassY	1.411	1.279	1.25	1.597	1.063	1.344	1.006
	(17.64)***	(10.32)***	(8.72)***	(15.61)***	(3.27)***	(14.88)***	(0.29)
*KM***ClassX*		1.01					
		(2.70)***					
*KM***ClassY*		1.025					
		(7.07)***					
*KM***Citation Lag*		0.998					
		(8.68)***					
Observations	367637	367637	173994	193640	88697	350058	71118
Number of citing pats	150338	150338	75843	74494	34773	137377	21812
Log-likelihood	-123571	-123505	-67504	-55236.8	-59252.2	-91955.2	-46545.8
Min cited per citing	1	1	1	1	1	1	2
Avg cited per citing	2.45	2.45	2.29	2.6	2.55	2.55	3.26
Max cited per citing	37	37	37	32	19	37	19
Wald χ^2	8616.98	8578.69	4393.44	4031.03	3903.26	5872.8	2652.65
degrees of freedom	4	7	4	4	4	4	4
ρ	0.54	0.54	0.52	0.56	0	0.36	0
χ^2	17304.89	17256.81	8612.76	8221.54	0	6761	0

Table 13. Results from the random effect logit using within EPO citations with geographical dummies

		1985_1992	1993_2000		1985_1992	1993_2000		1985_1992	1993_2000
Diff_EURegion	3.225	3.381	3.128						
	(108.59)***	(70.48)***	(82.50)***						
Diff_USStates				3.287	3.119	3.475			
				(75.52)***	(49.26)***	(57.55)***			
Diff_ctry							2.536	2.834	2.355
							(129.26)***	(92.48)***	(91.08)***
Citation lag	1.002	0.983	1.005	0.991	0.962	0.986	0.993	0.97	0.99
	(1.53)	(5.22)***	(2.77)***	(3.60)***	(8.22)***	(4.64)***	(7.61)***	(15.31)***	(8.77)***
Diff_Tech	1.065	0.98	1.122	1.086	1.029	1.122	1.153	1.076	1.205
	(5.07)***	(1.00)	(7.21)***	(4.71)***	(1.12)	(4.80)***	(18.23)***	(6.18)***	(18.00)***
ClassX	2.157	1.892	2.289	1.987	1.647	2.147	2.119	1.813	2.252
	(41.86)***	(21.03)***	(35.73)***	(29.82)***	(14.45)***	(24.55)***	(68.69)***	(34.68)***	(57.01)***
ClassY	0.922	0.85	0.978	1.21	1.098	1.312	1.039	0.974	1.098
	(5.33)***	(6.93)***	(1.11)	(8.85)***	(3.09)***	(8.82)***	(3.98)***	(1.88)*	(7.00)***
Observations	1579306	582110	997162	1115867	376975	738888	1280509	475333	805156
Log-likelihood	-105608	-40218	-65316.2	-55668.2	-25333.8	-29974.3	-323810.01	-132255	-190718
AIC	0.13	0.14	0.13	0.1	0.13	0.08	0.51	0.56	0.47
BIC	-22329336.1	-7646653.97	-13642752.87	-22329336.1	-7646654	-13642752.9	-17359796.86	-5948856.31	-10567631.22
Dispersion	0.13	0.14	0.13	0.1	0.13	0.08	0.51	0.56	0.47
Pearson	0.15	0.14	0.15	0.13	0.15	0.12	0.74	0.74	0.74

Absolute value of z statistics in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

[1] We will use the term 'inventor citation' to indicate a citation that was added in the original patent application, i.e., irrespective of whether the actual inventor, a patent lawyer or someone else otherwise involved with the application added the citation.

[2] In the database where we combine information provided by the REFI and the OECD datasets, 2.5% of citing patents have none of their citations classified in any category, and 8.4% of citing patents have at least one of their citations without category of citation. Because this, in principle, corresponds to an omission, we decided to eliminate the citing patents with at least one citation not classified, which results in dropping 15.4% of the total citation pairs.

[3] A full list of the 135 regions we use is provided in the appendix. Our countries include the EU-16 plus Norway and Switzerland.

[4] This model has been used extensively to model grouped survival data (Greenland 1994). The model can be written as $\Pr(Y = 1 \mid x) = 1 - \exp(-\exp(\alpha + \beta x))$, or as $\log(-\log(1-p(x))) = \alpha + \beta x$, where $p(x) = \Pr(Y = 1 \mid x)$.

[5] For example, we might have inventors (applicants) that never cite anything, or examiners who have a very high tendency to scrap inventor citations.

[6] Note that we cannot use USPTO patents as the citing patent, because these citations are not recorded by the EPO, and hence we do not have information on the source of the citation (examiner/inventor).

[7] This method was proposed by Hausman and Newey (1995) and an application can be found in Bandiera and Rasul (2003).

[8] We also applied other methods to assess the potential nonlinear nature of the distance relationship:we estimated a step-function for *DistanceKM*, a linear spline function for

DistanceKM, and we also used kernel regression instead of locally weighted regression in the above procedure. These methods generally pointed in the same direction of the results that we document.

[9] http://europa.eu.int/comm/eurostat/ramon/nuts/home_regions_en.html.

[10] In the geographical literature (e.g. Hagget, Cliff et al. 1977), this is rather common as a direct measure of distance. Note that in order for the distance variable to make sense, the regional map to which it is applied needs to be contiguous, i.e., every region must be reachable from every other region. In our European case, this requires us to deal with a number of sea passages, e.g., between the UK and continental Europe. In those cases, we have assumed that the sea area between our regions can be considered as a separate, artificial region, and so the map of regions becomes contingent. Details of this procedure are available on request, as are the resulting values for this variable.

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