International knowledge diffusion and home-bias effect. Do USPTO & EPO patent citations tell the same story?*

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2nd September 2009

Abstract

This paper estimates the international diffusion and obsolescence of technological knowledge by technological field and country using patent citations from the US Patent and Trademark Office (USPTO) and from the European Patent Office (EPO). We control for self-citations and for procedural and legal differences between patent offices in the citation procedures using equivalent patents. We find that: (1) there are clear biases in patent examination processes that generate citations in the two offices; (2) at the EPO we find a strong localization effect at country level, and the size is comparable to that found at the USPTO; (3) technological fields have different properties of diffusion and decay of technical knowledge in the two patent offices that do not depend upon a patent office bias; (4) using EPO data, the USA is not the leading country in terms of citations made and received as occurs at the USPTO.

JEL codes: O31, O33, O34

Keywords: Knowledge flows, Spillovers, Diffusion, Patents, Patent citations

I. Introduction

This paper uses patent citations to estimate the process of diffusion and obsolescence of technical knowledge by countries and technological fields. Patent citations are increasingly used to track knowledge flows between different applicants or inventors and assess the intensity of knowledge spillovers and their geographical and technological scope[1]. Many papers show that patent

*We are grateful to Stefano Breschi, Bruno Cassiman, Dirk Czarnitzki, Dietmar Harhoff, Deepak Hedge, Katrin Hussinger, Adam Jaffe, Nicolas Van Zeebrooeck and two anonymous referees who commented on an earlier draft of this paper. We also thank Gianluca Tarasconi for his valuable assistance with data.

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[1]An enormous number of articles use patents and patent citations. Griliches (1990) provides a path-breaking and renowned survey and OECD (1994) is a highly referenced manual. A set of important papers from the NBER group is collected together in Jaffe and Trajtenberg (2002). Trajtenberg (1990), Harhoff et al. (1999), Lanjouw and Shankermann, (2004), and Hall et al. (2005) are fundamental references on patent citations and the value of innovations. On patent citations and knowledge spillovers, there is a recent survey by Breschi et al. (2005).

citations tend to be geographically localized (Jaffe et al., 1993; Jaffe and Trajtenberg, 1999; Maruseth and Verspagen, 2002; Bottazzi and Peri, 2003; Peri, 2005; Criscuolo and Verspagen, 2008; Breschi and Lissoni, 2009). In particular, Jaffe and Trajtenberg (1999) analyze patent citations at the US Patent and Trademark Office (USPTO) and show the existence of a home-bias in USPTO patent citations: an inventor from one country is much more likely to cite other inventors from the same country compared to inventors from other countries - this is especially true for American inventors. Secondly, they suggest that the USA is the most open and interconnected technological system as US inventors tend to make and receive more citations than inventors from other countries. This paper asks whether these results are generated by the specific organizational characteristics of the USPTO or rather reflect true phenomena. The empirical exercise is based upon the comparison of results from the USPTO and the European Patent Office (EPO).

We study the process of diffusion and decay of technological knowledge and estimate separately at the USPTO and EPO the citation-lag distribution for six different technological fields and five countries. We take into account many features of the citation process. In particular, we underline a "patent office" effect due to the different specific institutional practices and legal rules that generate citations to previous patents. This issue is addressed with a quasi-structural model as proposed by Caballero and Jaffe (1993) and discussed in Jaffe and Trajtenberg (1996) and Hall et al. (2001) in order to address the truncation bias in our data: recent cohorts of patents are less likely to be cited than older ones, because the pool of potential citing patents is smaller.

Controlling for the presence of self-citations and using patent equivalents, we find the following four main results: 1) there are clear biases in the patent examination processes that generate citations in the two offices. Despite these biases, 2) at the EPO we find a strong localization effect at country level, and the size is comparable to that found at the USPTO. 3) Not only are there some differences across technologies in the knowledge diffusion path, but also technological fields have different properties of diffusion and decay of technical knowledge in the two patent offices. These differences cannot be attributed to a patent office bias because using patent equivalents the estimated speed of diffusion and obsolescence of technological knowledge at the sectoral level is very similar in the two offices. Rather, they have to be attributed to differences in the patent activity in the two patent systems. 4) Finally, using EPO data, the USA is not the leading country in terms of citations made and received as occurs at the USPTO. This result reported by Jaffe and Trajtenberg (1999) is affected by the different legal rules and patent examination procedures that generate citations in the two offices. In addition to the four main results, we show on the methodological side that at the USPTO the approximate median lag is twice as large relative to the citations at the EPO and that using patent families generates a selection bias in the direction of patents with a higher value.

The paper is organized into six sections. The following section explains the background and motivation of the paper, Section III describes our data and shows the differences between the USPTO and the EPO data. Section IV describes the model and the econometric specification. Section V shows the results and gives possible interpretations. Section VI provides concluding observations.

II. Background and Motivation

Recent macroeconomic modelling has underlined the importance of knowledge spillovers and externalities, suggesting that the equilibrium path of productivity growth may differ according to the extent of the diffusion of knowledge. In general, endogenous growth is guided by disembodied knowledge spillovers, and the possibility (and ability) to re-use existing knowledge may produce increasing returns and long-run welfare effects. These knowledge-driven macroeconomic models draw attention to the different effects on growth rates of the different types of knowledge flows and push empirical research to inquire more in depth into the processes of knowledge accumulation and decay and the different channels along which ideas may be transferred (Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991; Griffith et al., 2003 and 2004; Piga and Vivarelli, 2004).

In fact, recent works have shown the usefulness of patent citations for exploring knowledge flows across regions, countries and technologies (see footnote 1). In patent documents, citations are used by examiners and applicants to show the degree of novelty and inventive steps of the patent claims. They are located in the patent text, usually by either the inventor's attorneys or by patent office examiners (depending upon national regulations, see below for details about the EPO and USPTO) and, once published, provide a legal delimitation of the scope of the property right. Therefore citations identify the antecedents upon which the invention stands and, for this reason, they are increasingly used in economic research to gauge the intensity and geographical extent of knowledge spillovers and to measure the economic value of innovations (Griliches, 1990, pp. 1688–1689). Typically both citations from USPTO and EPO patents are used in economic analysis[2].

If patent citations are an important track of knowledge spillovers and if forward citations[3] are a relevant indicator of the economic value of innovative activity, the timing of citation flow and, in particular, the citation-lag distribution become extremely relevant. This is because the citation-lag distribution indicates for how long new technical knowledge spills over (identifying therefore a process of knowledge diffusion and obsolescence) and the time needed to observe a sufficient number of forward citations and, consequently, to evaluate the importance of the invention.

Available empirical evidence regarding citation-lag distribution is mainly based on USPTO data and shows that the modal lag is about five years and that intra-industry citations are much more likely than inter-industry ones (Jaffe and Trajtenberg, 1996, 1999). Considerable evidence shows that patent citations tend to be localized[4]. Using the NBER-USPTO data Jaffe and Trajtenberg (1999) show that patents from the same country are 30 to 80 per cent more likely to cite each other than patents from other countries. In the same vein Peri (2005) shows that knowledge flows tend to be geographically localized. He also uses the NBER data on patents and patent citations from the USPTO, for a panel of 113 European and North American

[2]The use of patent citations as an index of knowledge flow has been validated by Jaffe et al. (2000) for the USPTO (with a survey of inventors) and by Duguet and MacGarvie (2005) for the EPO (with Community Innovation Survey data). Jaffe et al. (1993), Verspagen (1997), Maruseth and Verspagen (2002), Malerba and Montobbio (2003) and Malerba et al. (2007) provide evidence on the nature and types of knowledge spillovers using patent citations.

[3]The citations received by a patent are called "forward citations". Forward measures are typically informative of the subsequent impact of an invention. Conversely, "backward citations"are those included in a patent that refer to an antecedent body of knowledge.

[4]The classic reference is Jaffe et al. (1993). They show that citing patents are up to three times more likely than control patents to come from the same state as the cited ones, and up to six times more likely from the same metropolitan area. Their methodology and particularly, the way the control sample is constructed have been challenged by Thompson and Fox Kean (2005). A response can be found in Henderson et al. (2005).

regions over 22 years. Turning to EPO citations, Maruseth and Verspagen (2002) use a cross-section of 112 European regions to show that EPO patent citations are geographically localized. Similar results, also using EPO citations, are obtained by Bottazzi and Peri (2003).

This paper takes its start from the Jaffe and Trajtenberg (1999) results. We ask to what extent the higher propensity of inventors to cite other inventors from the same country means that there are real localized knowledge flows or, alternatively, the result is generated by the specific organizational characteristics of the USPTO. Could it be for example just an artifact of the search process of the citing behaviour of patent attorneys and examiners? Table 1 looks at 657,151 patent families with at least two equivalent patents: one at the EPO and one at the USPTO (the details are explained below in Section V). Column 1 shows the distribution of the citing patents by the first inventor's country (which is the same in the two patent offices). Columns 2 and 3 show the distribution across countries of the cited patents using respectively the USPTO and EPO patent citations.

[Table 1, about here]

Table 1 shows that 41.6 per cent of citing patents are from American inventors. However, the two distributions of cited patents show that at the USPTO, the frequency of American cited patents exceeds 65 per cent, while at the EPO, the same frequency is less than 40 per cent. The more general result is that, while at the EPO the distribution of cited patents approximately reflects those of the citing ones, at the USPTO this is unbalanced toward the American-cited patents. This evidence is affected by the distributions of the potential cited patents in the two datasets (see below Table 2) and suggests that some bias may exist in the USPTO results. In order to isolate the organizational effect and to explore the nature of the home-bias, we use a coherent methodology to test whether, for example, American patents that are granted by the EPO are also more likely to cite other American patents granted by the EPO, under the assumption that the EPO examiners are not biased toward searching relevant American prior art.

Moreover, there are important sectoral variations in the process of diffusion and decay of technological knowledge. In particular, Jaffe and Trajtenberg (1996) and Hall et al. (2001) show that patents in Electronics, Computers and Communications are more highly cited than other sectors of the economy during the first few years after grant and, at the same time, they decay much faster. Jaffe and Trajtenberg (1996) interpret this result in the following terms: "...this field is extremely dynamic, with a great deal of 'action' in the form of follow-up developments taking place during the first few years after an innovation is patented, but also with a very high obsolescence rate"(p. 12676).

Also patents in Drugs and Medical are more highly cited than patents in other sectors, but knowledge, in this case, has a slower pace of decay. This is explained in terms of long lead times in pharmaceutical research (and in approval procedures by the Federal Drug Administration). Therefore, this field is not evolving as fast as Electronics, or Computers and Communications and new products arrive at a slower rate in the market (Jaffe and Trajtenberg, 1996; Hall et al., 2001).

In order to estimate coherently the sectoral and country effects in the citation-lag distribution, it is necessary to control for a set of confounding factors. In particular, the following features of the citation process have to be taken into account: (i) "patent office"effects and (ii) truncation bias and changes over time in the propensity to cite. (i) The modal and average lags between citing and cited patents are deeply affected by the institutional process governing the decision (by inventors, inventors' attorneys or patent examiners) to include a patent citation in the patent document. In fact, there are relevant differences between citation practices at the USPTO and EPO. In the USA there is the 'duty of candor' rule, which requires all applicants to disclose all prior art of which they are aware. Therefore, many citations at the USPTO come directly from inventors, applicants and attorneys and are subsequently filtered by patent examiners[5]. At the European Patent Office the 'duty of candor' rule does not exist and patent citations are added by the patent examiners when they draft their search report[6]. The EPO guidelines for patent examiners suggest including all technically relevant information within a *minimum* number of citations and citations are, with few exceptions, added by the patent office

[5]Alcàcer and Gittelman (2006), using a sample of 442,839 citing patents and 5,434,483 cited patents granted at the USPTO over the period 2001-2003, show that 40 per cent of the cited-citing pairs are generated by patent examiners.

[6]The search report at the EPO is a document, published typically 18 months after the application date, that has the main objective of displaying the prior art relevant for determining whether the invention meets the novelty and inventive step requirements. It represents what is already known in the technical field of the patent application and is a source of additional relevant documentation. Cited documents may be patents or scientific bulletins and publications. Typically cited documents refer to specific patent claims.

examiners (Akers, 2000; Michel and Bettels, 2001; Breschi and Lissoni, 2004; EPO, 2005). As a result, the analysis of diffusion and obsolescence of technological knowledge and knowledge spillovers may reveal different properties according to the patent dataset that is used and, in particular, we expect to observe not only a much smaller number of citations at the EPO but also a shorter lag between citing and cited patents. It is crucial therefore to control for the different properties of the processes of obsolescence and diffusion in the two patent offices.

(ii) Secondly, three issues related to the time dimension need to be considered. First, there is a citing year effect due to an increase, particularly at the USPTO, of the number of citations per patent. This phenomenon of citation inflation is well known at the USPTO and is mainly due to computerization of the search procedures and changes in the behaviour of inventors' attorneys and patent office examiners (for a detailed discussion of this issue, and of the econometric techniques for dealing with it, see Hall et al., 2001). We control also for a cited year effect. This is typically related to the different fertility of different cohorts of patents. Finally, citations data are truncated because recent cohorts of patents are less likely to be cited than older ones, since the pool of potentially citing patents is smaller. These issues are addressed jointly with a quasi-structural model as proposed by Caballero and Jaffe (1993) and discussed in Jaffe and Trajtenberg (1996) and Hall et al. (2001). It is possible with this model to identify separately the contribution to variations in the observed citation rates of changes in the citation-lag distribution, in the propensity to cite and in the fertility of different cohorts of patents.

III. The data

We use the publicly available USPTO Patent and Patent Citations Database, which contains 3,449,478 USPTO (granted) patents from 1963 to 2005 and 37,730,701 citations from (and to) USPTO, together with the European Patent Office dataset, which contains 1,702,652 EPO patent applications from 1978 to 2005 and 1,623,094 citations from (and to) EPO patents from 1978 to 2005[7]. From these datasets we select two samples: the universe of all patents and patent

[7]USPTO data are available on a CD delivered directly from the USPTO and on the ftp USPTO server (ftp://ftp.uspto.gov/pub/patdata/). EPO data come from the Espace Bulletin CD-R produced by the EPO, and patent citations from the REFI tape. PCT citations are also included. Considerable effort has been made

citations between 1978 and 2002 in five countries: France, Germany, Japan, UK and USA. Self-citations are excluded from the samples[8]. Summary statistics are displayed in Table 2. Each patent is characterized by a date, a country (first inventor's address) and a technological field (based on the International Patent Classification for EP-CESPRI and the USPTO classification system for the USPTO-CESPRI). Details for both datasets are provided in Appendix A.

[Table 2, about here]

As expected at the USPTO there are more patents and, in particular, many more citations per patent due to the different institutional processes underlying the citation practices. In Table 2 the institutional, technological and country composition of the EPO and USPTO patent samples are compared: c_c is the number of (forward) citations by technological field and n_c is the number of (potential cited) patents by technological field. Table 2 shows the sectoral and national shares $s_c = c_c/c$ and $p_c = n_c/n$ (in parentheses) by patent office, where c and n are respectively the total number of citations and patents. Moreover, in Table 2 we display an index of citation intensity equal to $cint_c = s_c/p_c$. The value of $cint_c$ is affected by the characteristics of the patents in the different technological fields. Typically, patents in the Mechanical sector cite and receive fewer citations than Biotech patents, mainly because of the different average patent scope in the two fields. As a matter of fact, the Mechanical and Others sectors receive on average fewer citations than, for example, the Drugs and Medical sector in both patent offices.

However, we observe that $cint_c$ ranks differently in the two patent offices. In particular, at the EPO we have Drugs and Medical and Chemicals at the top, and then Electrical and Electronics and Computers and Communications. Conversely, at the USPTO the highest value of $cint_c$ is in Computers and Communication and then Drugs and Medical, Electrical and Electronics and Chemicals follow. This raises the issue, discussed in the previous section, as to which other variables affect the citation intensity of a technological field beyond its technological characteristics. The first possible explanation is that these differences reflect the heterogeneity

to clean up the databases in the CESPRI Research Centre of Bocconi University and therefore we refer to the databases as respectively USPTO-CESPRI and EP-CESPRI.

[8]The ratios between the total number of self- citations and the total number of citations in our sample are 10 per cent at the USPTO and 32 per cent at the EPO. Since we focus on spillovers we present all our results excluding self-citations. We comment briefly below on some of the results found including also the self-citations.

of patents and companies in the two patent offices: the sets of patenting firms at the two patent offices are different and, as long as the value of their patent stock differs, we observe different levels of citation intensity at the level of the patent office. The second possibility is that this depends upon the different legal and administrative procedures related to patent citations at the EPO and at the USPTO.

Likewise, Table 2 shows the geographical composition of the patents in the two patent offices by country of the first inventor. If the share of total (forward) citations of a country (s_p) is higher than its fraction of total patents (p_p in parentheses), this indicates an above average citation intensity ($cint_p$) for that country. It's worthwhile noting that, only at the USPTO the USA has a higher share of citations relative to their share in the patent sample. At the EPO Japan and the UK display the highest values of $cint_p$. Of course $cint_c$ and $cint_p$ are confounded by all the factors mentioned in the previous section. The propensity to be cited is then properly estimated in the following sections.

IV. Model specification and econometric framework

We describe the random process underlying the generation of citations with a quasi-structural approach. The model follows the specification in Jaffe and Trajtenberg (1996, 1999), and Hall et al. (2001). The diffusion process is modelled as a combination of two exponential processes, one for the knowledge diffusion and the other for the process of obsolescence. The general formulation of the model is

$$\begin{aligned} p(k,K) &= \alpha(k,K)\exp\left[-\beta_1(k,K)(T-t)\right] \\ &\quad \times\left(1-\exp\left[-\beta_2(k,K)(T-t)\right]\right) \qquad (1) \end{aligned}$$

where $p(k,K)$ is the likelihood that any particular patent k, granted at time t, is cited by some particular patent K, granted at time T. The parameters β_1 and β_2 represent the rate of obsolescence and diffusion, respectively, and both exponential processes depend on the citation lag $(T-t)$. The coefficient α does represent a multiplicative factor, as the constant term in a simple linear regression model. However, as indicated by the dependence of α from (k,K), such a proportionality factor $\alpha(k, K)$ is allowed to vary with attributes of the citing and cited patents. The estimate of a particular $\alpha(k, K)$, indicates the extent to which a patent k is more or less likely to be cited, with respect to a base characteristic patent, by a patent K.

From the formulation above, β_1 and β_2 single out the main features of the diffusion process. The lag at which the citation function is maximized, i.e. the modal lag, is approximately equal to $1/\beta_1$, while the maximum value of the citation frequency is approximately equal to β_2/β_1. Such features of the model have important implications for both the estimation and interpretation of the results. In fact, an increase in β_1 simply shifts the citation function to the left, while an increase in β_2, leaving β_1 unchanged, increases the overall citation intensity, at every value of $(T - t)$. As a consequence, variations in β_2 with β_1 unchanged are not separately identified from variations in the constant term α. Following Jaffe and Trajtenberg (1996), thus, we prefer to allow variations in α, leaving β_2 constant for all observations.

The constant term α and the structural parameter β_1 depend on k and K. This indicates that they depend upon particular features of both cited and citing patents. From the empirical point of view, however, modelling single pairs of patents (citing and cited), might lead to dealing with very small expected values. Therefore, we aggregate patents in homogeneous groups and model the number of citations to a particular group of cited patents by a particular group of citing patents. We wish to have a finer understanding of the statistical properties of the citations received (forward citations), since this is the usual way of assessing the value of patents. The following characteristics of the cited patent k might affect its citation frequency[9] (see Appendix A for relative details of USPTO-CESPRI and EP-CESPRI): the application or priority date t; the first inventor's country p and, finally, the technological field c. Moreover, for the citing patent K we consider the application or priority date T, and the first inventor's country P.

The number of citations to a specific group of cited patents by a specific group of citing patents is: c_{tpcTP}. Hence, a treatable formulation of the model, where the various different

[9]Bacchiocchi and Montobbio (2009) use this model only for EPO data to estimate the citation lag distribution of university patents vs. corporate patents.

effects enter as multiplicative parameters, becomes

$$\begin{aligned} E(c_{tpcTP}) &= (n_{tpc})\,(n_{TP})\,\alpha_t\alpha_c\alpha_T\alpha_{pP}\exp\left[-(\beta_1)\,\beta_{1c}\beta_{1pP}\,(T-t)\right] \\ &\quad \times\left(1-\exp\left[-\beta_2\,(T-t)\right]\right) \end{aligned} \tag{2}$$

or equivalently, in the estimable form

$$\begin{aligned} p_{tpcTP} &= \frac{c_{tpcTP}}{(n_{tpc})\,(n_{TPG})} = \alpha_t\alpha_c\alpha_T\alpha_{pP}\exp\left[-(\beta_1)\,\beta_{1c}\beta_{1pP}\,(T-t)\right] \\ &\quad \times\left(1-\exp\left[-\beta_2\,(T-t)\right]\right)+\varepsilon_{tpcTP} \end{aligned} \tag{3}$$

where n_{tpc} and n_{TP} represent the total amount of potentially cited and citing patents for each of the particular (tpc) and (TP) groups, respectively. The model (3) can thus be estimated by nonlinear least squares under the well-known hypotheses on the residual terms ε_{tpcTP}.

Variations in any particular $\alpha\,(k)$ (i.e. the multiplicative coefficients related to cited patents) should be interpreted as differences in the propensity to be cited, with respect to the base category[10]. Equivalently, estimates of multiplicative coefficients related to citing patents, $\alpha\,(K)$, indicate differences in the propensity to cite compared to a base category. All fixed effects have been estimated relative to a base value of unity; for each effect thus, the coefficient associated with the reference group is constrained to unity. Note that following Jaffe and Trajtenberg (1999), we have introduced into the specification the interaction terms α_{pP} between the cited and citing country. In this case, the α_{pP} coefficient indicates the relative likelihood that the average patent granted to country p is cited by a patent granted to inventors in country P. These interaction coefficients are at the core of our analysis because they are able to measure the home bias effect, that is, whether an inventor from one country is more likely to cite other inventors from the same country as compared to inventors from other countries.

A similar interpretation has to be given to variations in β_1 coefficients, which represent differences in the rate of decay across categories of cited and citing patents. Higher values

[10] As an example, let us consider an estimated coefficient α (k=Computers and Communications) = 2.86; this means that patents belonging to the category "Computers and Communications" have a more than double probability (across all lags) to receive a citation in the next few years vis à vis patents belonging to the base field.

of β_1, with respect to the base category, mean a faster obsolescence, which corresponds to a downward and leftward shift in the citation function. Also, in this case we have included the interaction terms β_{1pP} between the citing and cited country.

One more consideration about the specification of the model concerns the difficulties in estimating citing and cited time effects together with the citation lag; in fact, citation lags enter the model non-linearly and the identification of all effects is not precluded a priori. However, due to the great number of parameters to be estimated, we prefer to calculate the fixed effects grouping cited years into five-year intervals, as in Jaffe and Trajtenberg (1996)[11]. Moreover, in estimating the model we faced some problems of convergence due to the contemporaneous presence of technological fields for cited and citing patents for both α and β_1. We thus decided to exclude technological fields for the citing patents on the β_1's.

We estimate the model using weighted non-linear least squares. The weights are needed in order to deal with heteroskedasticity. Since each observation is obtained dividing the number of citations by the product of the total amount of potentially citing and potentially cited patents corresponding to a given cell, it has been weighted by $(n_{tpc}n_{TP})^{1/2}$, following Jaffe and Trajtenberg (1996) and Hall et al (2001).

[Table 3, about here]

Table 3 shows the statistics for the regression variables. The data consist of one observation for each feasible combination of values of t, pP, c and T. For the cited patents we have 25 years, six technological fields, and five countries and for the citing patents we have 25 years and five countries. We consider only citations with a lag between the citing and cited patent greater than or equal to 0. Hence the total amount of observations is: $n\_obs = [(25 \times 26)/2] \times 6 \times 5 \times 5 = 48,750$. In each dataset there are some cells with zero citations. We have zeros when c_{tpcTP} is zero and $(n_{tpc})(n_{TP})$ is positive. In the EP-CESPRI 6015 observations have zero citations (12.3 per cent) while the number of zeros in the USPTO-CESPRI is 863 (1.3 per cent).

[11]Grouping cited year is a reasonable assumption as the fertility of invention does not change substantially over time. Estimated results, not reported in the present paper, confirm such an assumption.

V. Results

In this section we report and comment on the results of the estimation of Equation (3). Significant tests for any particular $\alpha(k)$, being a proportionality factor, focus on the null hypothesis H_0 :*coeff* $= 1$. The null hypothesis for the significance of β_1 and β_2, instead, remains the standard $H_0 : \beta_i = 0$, $i = 1, 2$. The results are presented in a way to facilitate the understanding of the three main points the paper wants to address: a) the presence of a home bias effect at USPTO and EPO; b) a test for different diffusion processes between sectors; and finally c) a test for patent office effect. The complete set of estimated parameters, with related standard errors, is reported in Table 9.

Some general features about the estimated diffusion processes should be preliminarily underlined. The main general result can be observed from Figure 1. The shapes of the two diffusion functions are based upon the estimated β_1 and β_2 coefficients for the two datasets. The rate of decay for the USPTO is $\beta_1 = 0.173$ while the one for the EPO is $\beta_1 = 0.375$. Concerning the β_2 coefficients, we obtain that for the USPTO $\beta_2 = 2.82 \times 10^{-6}$ while for the EPO $\beta_2 = 6.21 \times 10^{-6}$. These results show that patents at the EPO have a higher probability of being cited during the first few years but this probability decreases faster as time elapses with respect to patents at the USPTO. The likelihood that a EPO patent is cited becomes half of its estimated maximum after about 6-7 years while for the USPTO patents, this occurs after 14-15 years. Moreover, after 20 years the estimated probability for an EPO patent to be cited is almost zero, but for a USPTO patent it is still one fourth of its maximum value. This is consistent with the different processes of assigning citations in the different patent offices outlined in Section II.

[Figure 1, about here]

A second general result refers to the estimated time effects for the citing years. The estimated citing year effects at the USPTO do not show any upward trend. All estimated coefficients appear to be greater than one but in many cases they are not significantly different from one. At the EPO on the other hand, the α_T display a steep downward trend. As the number of potential citing and cited patents increases over time in both datasets, the number of citations per patent grows faster at the USPTO than at the EPO. This creates the observed decline in the coefficients for the EPO and the absence of a trend for the USPTO[12]. Finally, for the cited time effects a substantial absence of fertility changes characterizes both datasets. Concerning the goodness of fit of the models, despite the double exponential formulation not forecasting zero probabilities, it is interesting to note that the approximation between actual and forecasted probabilities is extremely high in both cases. The adjusted R^2 for the two models are $\bar{R}^2 = 0.87$ for the USTPO and $\bar{R}^2 = 0.76$ for the EPO. The good approximation is not surprising if one observes that the percentage of zeros is 12.3% for the EPO data while only 1.3% for the USPTO.

Home Bias Effects at USPTO and EPO

In Table 4 we report the estimated coefficients for country interactions in matrix form for both USPTO and EPO data. In particular, we report the α's in the upper part of the table, the lag (expressed in years) at which the citation frequency reaches its maximum value ($1/\beta_1$) in the second panel, and, in the third panel, an estimation of the expected number of citations that a single patent could potentially receive for all future years[13], i.e. $\alpha\beta_2/\left(\beta_1\right)^2$. The estimated α's measure the citation intensity (or "fertility"or "importance") relative to a base category, and the β_1's measure the speed of diffusion. Higher values of β_1 signify a higher rate of decay. Note that higher values of α and higher values of β_1 would generate offsetting effects on the citation lag distribution. To understand which parameter dominates it is therefore necessary to estimate the overall cumulative frequencies $\alpha\beta_2/\left(\beta_1\right)^2$.

Concerning the α's it is possible to look at the data by row and by column. If we look at the data by row the citation intensity varies with the characteristics of the *citing* patents and it has to be interpreted as the probability of making a citation. So we observe variation in the *use* of knowledge. For example, in the case of USPTO data if P=France and p=USA, $\alpha_{pP} = 0.38$ means that the average patent granted to a French inventor is 38% as likely as a patent granted

[12]To substantiate this conjecture we calculated the differences in level and trend of the raw amount of backward citations per citing patent in the two datasets (note that in the two datasets we have the same left truncation bias because we do not consider citations that go to patents granted, or applied for, before 1978). At the EPO backward citations per patent are 1.16 in 1979, they reach a maximum in 1994 at 2.10, declining slightly afterwards. At the USPTO backward citations per patent are 1.26 in 1979 and they grow more steeply reaching a maximum in 1995 at 8.28.

[13]This can be seen as the integral of the citation function from $t = 0$ to infinity.

to a US inventor to cite any given US patent. If we look at the data by column, the citation intensity varies with the characteristics of the *cited* patents and it has to be interpreted as the probability of receiving a citation. So we observe variation in the *importance* or *fertility* of knowledge. Again in the case of USPTO data if P=USA and p=France, $\alpha_{pP} = 0.44$ means that a French patent is 56% less likely to get a citation from an average US patent than is a random US patent.

Table 4 shows that the diagonal coefficients strongly dominate both the rows and columns of the matrix using both EPO and USPTO patents. This reinforces the pattern of geographic localization discussed in Jaffe and Trajtenberg (1999) in two respects: first, because we use more recent USPTO data (they use data up to 1994, we use data up to 2002); second, our results show that also at the EPO, with very different citation practices, domestic citations are more likely relative to citations received from and made to other countries. This is particularly true for the USA (at the USPTO), for the UK (in both patent offices) and for Japan (at the EPO).

Another result of Jaffe and Trajtenberg (1999) that we can generalize using EPO data is the symmetry of the matrices, meaning that the knowledge flows between countries tend to be bidirectional. It is remarkable that the symmetry of the matrices is very similar using citations from the two patent offices. In particular for the USA - both at the USPTO and at the EPO - the highest off-diagonal α's are for the UK citing the USA and the USA citing the UK while the lowest off-diagonal number is for Germany citing the USA and the USA citing Germany. Even if there is not exact correspondence in the symmetry of the two matrices it is important to emphasize that for most countries the highest off-diagonal elements are the same in both matrices and describe bi-directional relationships (e.g. for the UK is also the USA, for Japan is also the USA).

National localization and symmetry are also evident in the β_1 coefficients, or equivalently in the estimated modal lags, as reported in the second panel of Table 4. In this case the diagonal elements are the smallest ones, in particular at the USPTO. The citation frequency reaches its maximum value at shorter lags for domestic citations, relative to citations to and from other countries. For the patents granted at the USPTO, the only exception is in the USA. Japanese, French and British patents cite US patents with a shorter lag than the average US patent. For the EPO data, instead, this pattern is less evident, in particular for the European countries. British, French and German inventors do not seem to have any significantly different behaviour when citing domestic or foreign patents. American and Japanese inventors, instead, are faster to cite domestic patents than they are to cite foreign patents. A common result of the two patent offices is that the fastest citing inventors are the Japanese, and in both cases, to cite domestic patents.

The third panel in Table 4 summarizes the results for the α and β_1 coefficients. In particular, it is shown that for all countries and for both patent offices, the α's dominate the β_1 coefficients. Higher α's in principle could be compensated by the higher obsolescence effects measured by the β_1's. The estimated overall cumulative probabilities, presented in the third panel, instead suggest that such compensation is only partial and that the diffusion effect dominates the obsolescence one[14]. The highest values on the diagonal of the matrix with respect to rows and columns is a common result for both the USPTO and EPO data. All these empirical results reinforce the home bias effect highlighted in Jaffe and Trajtenberg (1999) that is not confined to the USPTO patents, but can also be generalized to the EPO patents.

Looking at the cumulative probabilities, our evidence provides only partial support to the claim by Jaffe and Trajtenberg (1999) that the USA has "the most open and interconnected economic and technological system in the world"(p. 123). If we look at the data by column (i.e. the cumulative frequencies vary with countries of the *cited* patents) the estimated cumulative frequency provides the estimation of the total expected number of citations that a single patent could potentially receive. In this case results are the same in both datasets and confirm the results found by Jaffe and Trajtenberg (1999). In particular, Table 4 shows that an average UK or Japanese patent is more likely to cite a random US patent than to cite another foreign patent. At the same time, the average US and French patents are more likely to cite a random UK patent than to cite other foreign patents. These numbers show that US patents have a relatively big international impact but that UK patents also have a similar impact.

If we look at the results by row (i.e. the cumulative frequencies vary with countries of

[14]For all combinations of countries, the estimated overall cumulative probabilities for the USPTO data are higher than those obtained with the EPO data (the only exceptions are represented by the Japanese patents).

the *citing* patents) the estimated cumulative frequency provides an estimation of the total expected number of citations that a single patent could potentially make. In this case results for the USPTO confirm Jaffe and Trajtenberg (1999) and show that in every row the largest off-diagonal entry is the one from the USA. Hence, at the USPTO the US inventors tend to make more citations than other countries. This is clearly not true at the EPO where the French patents are the ones that have the overall highest probability to cite foreign patents. In sum, even if with USPTO data we replicate the Jaffe and Trajtenberg (1999) results, using EPO data we show that the American technological system cannot be considered unequivocally the most open and interconnected and American patents cannot be considered the leading source of patent citations. However, a question remains open as to whether these differences may be due to differences in the citation practices in the two offices or to a real economic phenomenon. We tackle this issue below, where we discuss the patent office effect.

[Table 4, about here]

In order to verify the robustness of our results, we performed the following other regressions[15]. First of all, we re-estimated the model for both datasets including the self-citations. As expected, the results show an even stronger localization effect. Self-citations also have a shorter modal lag both at the EPO and at the USPTO and with self-citations the rate of decay for the USPTO is $\beta_1 = 0.19$ (instead of 0.173) while the rate for the EPO is $\beta_1 = 0.499$ (instead of 0.375). Moreover, only for the EPO data[16], do we also inquire whether the citations added by the patent examiners and, in particular, the citations that invalidate the patents[17] display different properties. This is suggested by Sampat (2005), Alcàcer and Gittelman (2006) and Criscuolo and Verspagen (2008). Even if the usual assumption is that examiner citations are less localized than inventor citations, we do not find a reduced localization effect at the national level. When we consider all citations added by patent examiners we find results that are very

[15] All the estimates are available from the authors on request.

[16] USPTO data are not available for most of the time period we have used. Alcàcer and Gittelman (2006), however, do not find strong evidence in USPTO data that the geographical distributions of examiner and inventor citations are significantly different (Alcàcer and Gittelman, 2006).

[17] In particular we considered citation category X and citation category Y. X-citations are particularly relevant documents which when taken alone imply that the claimed invention cannot be considered novel or cannot be considered to involve an inventive step. Y-citations are particularly relevant if combined with another document of the same category.

similar to those displayed in Table 4. When we consider only 'invalidating' citations we also find a similar localization effect at the national level. At the same time, these citations have a shorter modal lag ($\beta_1 = 0.499$).

Results by Sectors

Two types of variations relative to the technological fields are considered in the model: variations in the fixed effects α_c and in the obsolescence parameter β_{1c}. The base field is Chemicals for both the USPTO and the EPO databases.

The estimated coefficients α_c partially confirm the results displayed for $cint_c$ in Table 2, particularly for the USPTO data. The propensity to be cited is higher in Computers and Communications, Drugs and Medical and Electrical and Electronics at the USPTO and in Drugs and Medical and Computers and Communications at the EPO.

At the USPTO Electrical and Electronics, Mechanicals and Computers and Communications have the highest rate of decay (β_{1c}) and reach their modal lag earlier with respect to the other technological fields. In fourth place is Chemicals and the lowest β_{1c} is in Drugs and Medical (this broadly confirms the results of Jaffe and Trajtenberg, 1996, and Hall et al., 2001). At the EPO, Chemicals, Drugs and Medical, Electrical and Electronics, Computers and Communications sectors display almost the same obsolescence while Mechanicals and Others display a slightly lower decay rate. In Table 5 we report both the β_{1c} coefficients and the estimated modal lag for all the sectors and for both datasets. The sectoral ranking in the modal lag across sectors is different in the two offices. For example, Drugs and Medical at the USPTO has the largest modal citation lag (7 years) while at the EPO the same sector shows the smallest value.

[Table 5, about here]

As for the previous case, in order to observe the joint result of the diffusion and obsolescence effects, we calculate the overall cumulative probabilities for all the aggregate sectors. All the results are reported in Table 5, in the fourth column of each block. In line with the general results commented on above, the cumulative probabilities for the USTPO are larger than those for the EPO. In particular, the cumulative probability of receiving a citation belonging to the

Drugs and Medical and Computer and Communication sectors are four times higher at the USTPO compared to the EPO. For these two sectors, however, in the USPTO patent office the β_{1c} coefficients dominate the α_c's. Although the Computer and Communication sector presents a higher diffusion coefficient than Drugs and Medical ($\alpha_c = 2.86$ against $\alpha_c = 1.58$), the faster obsolescence of the former makes the overall probability of receiving a forward citation higher for the latter (222.5 against 186.9)[18]. This phenomenon does not appear in the EPO data, mainly because the rates of decay are very close, and in particular, significantly lower than that for the Mechanical and Other sectors only ($\beta_{1c} = 0.92$ and $\beta_{1c} = 0.86$, respectively). The patterns of the diffusion processes for all the technological sectors are shown in Figure 2 for the USPTO, and in Figure 3 for the EPO.

[Figure 2 and Figure 3, about here]

As in the previous section, the problem of identifying the portion of variation coming from real phenomena and the portion of variation coming from the different administrative practices and rules remains unsolved and therefore is addressed in the following section.

Patent Office Effect

In the previous sections we found clear support for a national localization of knowledge flows but we also found some differences between the results based on USPTO and EPO patents. In particular, looking at the EPO data we do not confirm that the USA tends to make more citations than other countries (as in Jaffe and Trajtenberg, 1999) and we do not find exactly the same sectoral ranking in the speed of the diffusion process. It is difficult, however, to identify whether these differences reflect true economic phenomena or depend upon institutional and procedural differences between the two patent offices. Part of the variation comes from the heterogeneity of patents filed in the two offices and part of the variation comes from the procedural differences. In other words, either there is a bias in the citation procedures or there is heterogeneity in the patent population.

[18]It is worth remembering that, due to the very low numbers, all the probabilities in the paper are multiplied by 10^6.

In the first case (where US-invented patents are less prominent at the EPO relative to the USPTO), the results could depend upon the fact that searches by attorneys and examiners at the USPTO are based mainly on USPTO patents. The opposite might occur at the EPO, where patent examiners could have a preference for patents with European priorities. If we consider exactly the same set of citing patent applications in the two patent offices, the differences between the results in the two patent offices should disappear unless results depend upon the specific citation procedures of the two offices. The differences in the distribution of knowledge sources across patent offices observed in the previous sections would reflect that there are different citing patents at the EPO and at the USPTO with different types of knowledge sources.

In the second case, the differences in the estimates relate to the sectoral heterogeneity in the patterns of diffusion and decay of technological knowledge. Also in this case, if we use exactly the same set of citing patents we should produce estimates that rank technological fields the same way in terms of the rates of diffusion and obsolescence between the two offices. As a result, sectoral differences, displayed in the previous section, would not be determined by the procedural differences in the patent offices but rather by real differences in the knowledge diffusion.

The simplest way to eliminate the heterogeneity in the patent population is to exploit an important characteristic of the international patent system. Actually, the current dataset includes some patents filed only in the USPTO, some patents filed only in the EPO, and some patents filed in both offices. Using patents filed in both offices eliminates the heterogeneity in the citing population, and provides the baseline framework against which results based on the full sample could be compared[19]. We have therefore selected from the EPO and USPTO databases all the patent families with at least one USPTO and one EPO patent. We end up with 657,151 families. We therefore have 657,151 patents at the USPTO and 657,151 patents at the EPO that are equivalent, i.e. with exactly the same set of Paris Convention priorities[20].

[19] As suggested by one of the referees, another way to potentially deal with this problem is to include firm-fixed effects in the analysis. The Jaffe and Trajtenberg model could be modified along the lines of Branstetter (2006).

[20] We have used a database of equivalent patents provided by Dietmar Harhoff and colleagues at http://www.inno-tec.bwl.uni-muenchen.de/forschung/forschungsprojekte/patent_cit_project/index.html (see also Harhoff et al., 2007; downloaded June 2008). There are many possible definitions of patent equivalents. It is worthy to underline that they have used the most restrictive definition, that is, those patents that have

We therefore re-estimate the model (3) considering this subset of patents. We now have 473,263 citations at the EPO and 3,457,937 citations at the USPTO. The new regression statistics are displayed in Table 6.

[Table 6, about here]

A complete set of results is reported in the right panel of Table 9, while in Table 7 and Table 8 country interactions and sector effects are compared for the two offices. From the former, we confirm the general pattern of national localization of patent citations. In the upper panel, the α coefficients on the diagonal are higher than those in the corresponding rows and columns. In the middle panel, the modal citation lags are shorter for domestic citations, for both EPO and USPTO offices. As for the general case, however, the diffusion coefficients dominate the obsolescence rate, and this is clearly shown in the lower panel, when considering overall cumulative citations (the only exception at the USPTO is represented by Japanese patents, which receive more citations from US inventors than from Japanese ones). In general, particularly at the USPTO, once controlled for all other factors, the cumulative number of citations received is higher for the equivalents than for the whole set of patents. This reveals that an inventor who strongly believes in the potentiality of his/her invention generally decides to file the patent in both offices and that in the equivalent set, there is a selection bias towards patents with a higher value.

[Table 7 and Table 8, about here]

We confirm also that, according to EPO data, the USA cannot be considered as a leading source of international knowledge flow. Looking at the cumulative probabilities, if we compare Table 7 and Table 4 we also observe very similar results. The important implication is that using a homogeneous set of equivalent patents, some differences do persist between the two patent offices. We interpret this evidence as a bias introduced into the citation procedures of the two offices. However, it should be pointed out that this bias does not affect the other

exactly the same set of Paris Convention priorities. This minimizes the possibility of including two patents incorrectly in the same family. When there is more than one USPTO or EPO patent in the same family we have chosen the oldest one.

main results of the paper outlined above, in particular, the results concerning the localization of knowledge flows and the higher speed of domestic flow of citations in the two offices.

We also show that the patent office bias does not affect sectoral ranking in terms of diffusion and decay. Comparing Table 8 and Table 5, the ranking of the α coefficients is exactly the same in both USPTO and EPO data. Moreover, in this last case, the diffusion coefficient α dominates the β_1's and the ranking concerning the overall cumulative citations strictly reflects the order of the former while in the USPTO the rate of obsolescence of the Computer and Communication sector is much higher than for the other sectors (in particular Drugs and Medical). All these features are graphically represented in Figures 4 and 5. Our estimates, moreover, confirm that the elimination of the heterogeneity in the citing population generates similar sectoral ranking in terms of the rates of diffusion and obsolescence between the two offices. This confirms that the differences we found in the previous section are the results of heterogeneous patenting activity in the EPO and USPTO.

[Figure 4 and Figure 5, about here]

VI. Conclusion

Since the early 1990s, a large body of theoretical research has focused upon the relationship between knowledge spillovers and aggregate growth. The nature and scope of knowledge spillovers play a prominent role in determining the equilibrium path of economic growth and patent citations are increasingly used to explore knowledge flows across regions, countries and technologies. This paper estimates the process of diffusion and obsolescence of technical knowledge by country and technological field using data from two patent offices: EPO and USPTO.

First, we show that a patent office bias exists that depends upon the different legal rules and procedures of patent examination and approval that generate patent citations.

We control for this bias using equivalent patents and, as second result, we also confirm, with new and more recent data, some of the results obtained by Jaffe and Trajtenberg (1996, 1999) and Hall et al. (2001). In particular, we show that also at the EPO there is a remarkable national localization of patent citations. This eliminates the doubts that the Jaffe and Trajtenberg results - obtained solely on USPTO data - may depend on biases in the American examination and patent search procedures.

Third, controlling for the patent office bias, at the EPO (relative to the USPTO) the US technological system is less prominent. While Jaffe and Trajtenberg (1999) found, using USPTO data, that the USA make and receive more citations than other countries, this result does not show up using EPO data.

Fourth, our estimates of the citation-lag distribution confirm that there are some differences across technologies in the diffusion path and show that technological fields have different properties of diffusion and decay of technical knowledge in the two patent offices. Computers and Communications and Electrical and Electronics at the USPTO and Drugs and Medical at the EPO display very high early citations and the most rapid obsolescence. Our paper shows that these differences cannot be attributed to the different citation procedures of the two patent offices considered and therefore reflect real differences in the process of knowledge diffusion at the sectoral level.

This paper also provides some evidence that helps to understand the statistical properties of patent citations in the two offices with consequences for their use as knowledge flow indicators. In particular, we measure the distribution of citation-lags in the two offices with the same methodology and we show that at the USPTO the approximate median lag is twice as large relative to citations at the EPO. Second, we do not find that examiner citations have a different pattern of national localization at the EPO and find that those examiner citations (called X and Y citations) that are more at risk of invalidating a patent have a shorter median lag. Finally, we show that using patent families generates a selection bias towards high quality patents.

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Appendix A: The data

In both datasets *Countries* are defined on the basis of the address of the first inventor in the patent application. We have used five countries: Germany, France, the UK, Japan and the USA.

The *Technological Fields* used are the US NBER categories as in Hall et al. (2001) that can be found in the USPTO database. For the EP-CESPRI database, we used 30 technological classes based on Annex III-A of OECD (1994). This classification aggregates all (primary) IPC codes (version 7 used at the EPO) into 30 technological classes. A concordance table has been created by the authors that re-aggregates the 30 classes into the USPTO fields.

The USPTO fields used are: 1. Chemical; 2. Computers & Communications; 3. Drugs & Medical; 4. Electrical & Electronic; 5. Mechanical; 6. Others. Below we report the 30 classes and, in parentheses, the USPTO field that has been assigned to each class by the authors:

1. Electrical engineering (4); 2. Audiovisual technology (4); 3. Telecommunications (2); 4. Information Technology (2); 5. Semiconductors (4); 6. Optics (5); 7. Control Technology (5); 8. Medical Technology (5); 9. Organic Chemistry (1); 10. Polymers (1); 11. Pharmaceuticals (3); 12. Biotechnology (3); 13. Materials (1); 14. Food Chemistry (1); 15. Basic Materials Chemistry (1); 16. Chemical Engineering (1); 17. Surface Technology (5); 18. Materials Processing (5); 19. Thermal Processes (6); 20. Environmental Technology (6); 21. Machine Tools (5); 22. Engines (5); 23. Mechanical Elements (5); 24. Handling (5); 25. Food Processing (6); 26. Transport (5); 27. Nuclear Engineering (4); 28. Space Technology (5); 29. Consumer Goods (6); 30. Civil Engineering (6).

Finally we have chosen the closest *dates* available to the actual timing of invention for both datasets. These are the priority dates for the EP-CESPRI and the application dates for the USPTO.

Tables and Figures

Table 1: Distribution by country (in %) of Cited and Citing patents at EPO and USPTO for a set of equivalent patents

	Citing[a]	Cited[a]	
		USPTO	EPO
Germany	19.0	7.7	16.7
France	8.0	3.0	7.3
UK	6.2	3.1	8.5
Japan	25.2	20.5	27.9
USA	41.6	65.6	39.6

Notes: [a]In all tables, for “Cited” and “Citing” we intend “cited patent” and “citing patent”, respectively. We consider the country of the first inventor.

Table 2: Statistics for technological and geographical composition of EPO and USPTO patent samples

	EPO	USPTO
Range of cited patents	1978-2002	1978-2002
Range of citing patents	1979-2002	1979-2002
Potential cited patents	1,210,085	2,381,001
Total citations	1,094,301	15,416,292
Citations per potentially citing patent	0.90	6.47
Patents by fields	s_c - (p_c) - $cint_c$	s_c - (p_c) - $cint_c$
Chemicals	25.8 - (19.5) - 1.32	15.2 - (17.2) - 0.88
Computers and Communications	11.3 - (12.3) - 0.92	22.1 - (16.3) - 1.36
Drugs and Medical	14.6 - (11.1) - 1.32	12.6 - (9.8) - 1.29
Electrical and Electronics	12.5 - (12.9) - 0.97	18 - (18.3) - 0.98
Mechanical	29.8 - (34.5) - 0.86	16.7 - (20.2) - 0.83
Others	6.0 - (9.5) - 0.63	15.3 -(18.0) - 0.85
Patents by country	s_p - (p_p) - $cint_p$	s_p - (p_p) - $cint_p$
Germany	18.8 - (25.4) - 0.74	5.4 -(8.5) - 0.64
France	7.5 - (9.6) - 0.78	2.3 - (3.2)- 0.70
United Kingdom	8.6 - (7.5) - 1.14	2.5 - (3.1) - 0.82
Japan	26.6 - (21.9) - 1.21	19.6 -(22.9) - 0.85
United States	38.5 - (35.1) - 1.10	70.2 - (62.1) - 1.13

Notes: $s_c = c_c/c$ and $p_c = n_c/n$, where c_c : number of citations by technological field, n_c : number of (potential cited) patents by technological field, c : total number of citations, n : total number of patents, $cint_c = s_c/p_c$: index of citation intensity. Similar definitions apply for s_p, p_p and $cint_p$.

Table 3: Statistics for the regression model

	EPO			
	Mean	St. Dev	Min	Max
Number of citations	16.98	35.91	0	947
Potential cited patents	1217.10	1273.74	28	9298
Potential citing patents	12058.75	7843.83	620	30548
Citation Frequency (10ˆ6)	1.44	1.90	0	53.80
Regression weights	3296.80	2207.44	131.76	16853.35
	USPTO			
	Mean	St.Dev	Min	Max
Number of citations	281.94	1189.31	0	39873
Potential cited patents	2555.01	3404.04	134	23092
Potential citing patents	22758.55	27364.86	2084	96228
Citation Frequency (10ˆ6)	3.90	3.56	0	81.50
Regression weights	5411.62	5610.57	528.45	47139.12

Table 4: Estimated results: country interaction effects at EPO and USPTO

	USPTO					EPO				
	Citing									
	α coefficients									
Cited	us	uk	fr	ge	jp	us	uk	fr	ge	jp
us	1	0.55	0.38	0.26	0.33	1	0.65	0.41	0.31	0.49
uk	0.55	1.59	0.45	0.33	0.29	0.59	1.48	0.47	0.38	0.38
fr	0.44	0.45	1.46	0.35	0.25	0.37	0.43	0.93	0.33	0.29
ge	0.40	0.46	0.48	1.08	0.35	0.26	0.33	0.29	0.54	0.28
jp	0.40	0.31	0.29	0.30	1.09	0.53	0.44	0.37	0.36	1.52
	Modal Lag									
us	5.78	5.72	5.53	6.00	5.16	2.66	3.05	3.60	3.62	3.05
uk	6.27	4.49	5.19	5.50	4.96	2.98	3.12	3.75	3.66	3.16
fr	6.21	5.99	4.43	5.50	5.15	2.87	3.27	3.48	3.58	3.04
ge	6.16	5.44	4.93	4.54	4.64	3.22	3.43	3.96	3.54	3.11
jp	6.16	5.66	4.98	5.41	4.16	3.02	3.23	3.70	3.57	2.62
	Cumulative Probability									
us	94	50.8	32.6	26.4	24.8	44	37.5	33.1	24.9	28.1
uk	60.8	90.3	34.4	28.1	19.8	32.4	89.8	40.8	31.5	23.8
fr	47.7	45.8	80.6	30.1	18.8	18.9	28.2	69.9	26.3	16.8
ge	42.5	38.5	32.8	62.6	21.1	16.5	23.9	28.7	42.2	16.8
jp	42.6	28.2	20.2	24.5	52.8	30.2	28.3	31.4	28.2	64.7

Notes: The "Modal Lag" is the lag (expressed in years) at which the citation frequency reaches its maximum value and is approximated by $(1/\beta_1)$. The "Cumulative Probability" is the expected number of citations that a single patent could potentially receive for all the future years. It is the integral of the citation function from $t = 0$ to infinity and can be approximated by $\alpha\beta_2/(\beta_1)^2$. The cumulative probabilities are multiplied by 10^5.

Table 5: Estimated results: sector effects at EPO and USPTO

	USPTO				EPO			
	α_c	β_{1c}	M. Lag	Cum. Prob.	α_c	β_{1c}	M. Lag	Cum. Prob.
Chemicals (base)	1	1	5.78	94.2	1	1	2.66	44.0
Comp. and comm.	2.86	1.20	4.81	186.9	1.23	1.00	2.67	54.2
Drugs and med.	1.58	0.82	7.06	222.5	1.54	1.03	2.60	64.6
Electronics	1.55	1.14	5.05	111.1	1.05	1.01	2.63	45.2
Mechanical	1.15	1.10	5.24	89.0	0.75	0.92	2.90	39.1
Others	0.99	0.97	5.97	99.8	0.53	0.86	3.08	31.3

Notes: "M. Lag" and "Cum. Prob." indicate "Modal Lag" and "Cumulative Probabilities" respectively, and are calculated as indicated in the previous table.

Table 6: Statistics for the regression model for equivalent patents

	EPO			
	Mean	St. Dev	Min	Max
Number of citations	9.69	21.99	0	502
Potential cited patents	1217.10	1273.74	28	9298
Potential citing patents	6557.78	4963.38	460	19014
Citation Frequency (10ˆ6)	1.43	2.09	0	72.50
Regression weights	2368.27	1656.83	113.49	12855.48
	USPTO			
	Mean	St.Dev	Min	Max
Number of citations	70.91	227.75	0	5796
Potential cited patents	2555.01	3404.04	134	23092
Potential citing patents	6547.96	4913.17	69	18500
Citation Frequency (10ˆ6)	3.94	3.70	0	54.20
Regression weights	3201.14	2686.37	107.35	20668.87

Table 7: Estimated results: country interaction effects for equivalent patents at EPO and USPTO

	USPTO					EPO				
	Citing									
	α coefficients									
Cited	us	uk	fr	ge	jp	us	uk	fr	ge	jp
us	1	0.45	0.35	0.25	0.32	1	0.69	0.51	0.38	0.55
uk	0.63	1.41	0.45	0.31	0.32	0.62	1.71	0.57	0.45	0.44
fr	0.55	0.43	1.32	0.34	0.30	0.40	0.52	1.16	0.36	0.34
ge	0.50	0.46	0.46	0.98	0.40	0.29	0.38	0.34	0.63	0.33
jp	0.50	0.33	0.34	0.31	1.19	0.59	0.52	0.48	0.47	1.73
	Modal Lag									
us	5.88	5.61	5.38	5.89	4.72	2.85	3.22	3.75	3.79	3.17
uk	6.26	4.25	4.79	5.39	4.45	3.12	3.19	3.73	3.73	3.26
fr	6.02	5.59	4.38	5.38	4.65	3.01	3.16	3.47	3.73	3.15
ge	6.01	5.05	4.75	4.45	4.29	3.33	3.43	4.03	3.64	3.18
jp	5.88	5.03	4.49	5.12	3.58	3.14	3.32	3.74	3.64	2.72
	Cumulative Probability									
us	188.6	77.1	55.8	46.6	39.3	46.3	40.9	41.1	30.8	31.8
uk	134.3	138.9	55.9	48.9	34.3	34.4	99.4	45.6	36	26.9
fr	108.4	72.6	138.3	53.4	35.0	21	30	80.2	28.9	19.3
ge	98.7	64.1	56.3	105.6	39.8	18.1	25.7	31.6	48	19.3
jp	94.4	45.7	37.0	44.4	83.6	33.3	32.6	38.2	35.9	72.8

Notes: The "Modal Lag" is the lag (expressed in years) at which the citation frequency reaches its maximum value and is approximated by $(1/\beta_1)$. The "Cumulative Probability" is the expected number of citations that a single patent could potentially receive for all the future years. It is the integral of the citation function from $t = 0$ to infinity and can be approximated by $\alpha\beta_2/(\beta_1)^2$. The cumulative probabilities are multiplied by 10^5.

Table 8: Estimated results: sector effects for equivalent patents at EPO and USPTO

	USPTO				EPO			
	α_c	β_{1c}	M. Lag	Cum. Prob.	α_c	β_{1c}	M. Lag	Cum. Prob.
Chemicals (base)	1	1	5.88	188.6	1	1	2.85	46.3
Comp. and comm.	2.09	1.28	4.59	240.7	1.33	1.01	2.82	60.4
Drugs and med.	1.59	0.89	6.64	381.9	1.29	1.00	2.85	59.8
Electronics	1.11	1.16	5.08	157.0	1.16	1.04	2.75	50.3
Mechanical	0.78	1.06	5.54	130.1	0.82	0.94	3.02	42.8
Others	0.55	0.91	6.43	124.5	0.47	0.89	3.20	27.8

Notes: "M. Lag" and "Cum. Prob." indicate "Modal Lag" and "Cumulative Probabilities" respectively, and are calculated as indicated in the previous table.

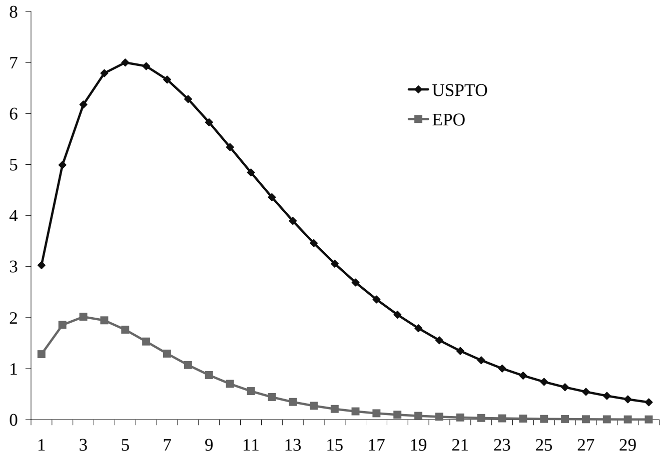

Figure 1: Diffusion processes for EPO and USPTO data

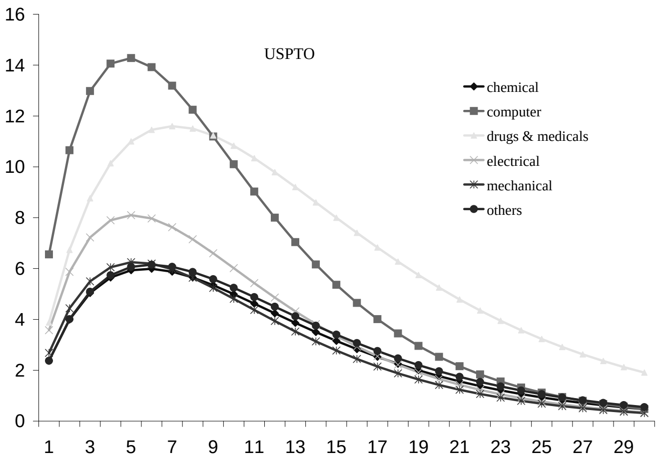

Figure 2: Diffusion processes for different technological sectors - USPTO

Table 9: EPO and USPTO estimated results

	general				equivalent			
	USPTO		EPO		USPTO		EPO	
	coeff	SE	coeff	SE	coeff	SE	coeff	SE
				cited year effects				
q_2	1.07	0.02	0.98	0.02	1.15	0.03	0.96	0.02
q_3	1.05	0.03	0.92	0.04	1.14	0.04	0.91	0.03
q_4	1.06	0.05	0.9	0.05	1.1	0.07	0.92	0.05
q_5	0.86	0.06	0.87	0.07	0.82	0.07	0.83	0.07
				cited class effects				
cl_2	2.86	0.08	1.23	0.04	2.09	0.06	1.33	0.04
cl_3	1.58	0.04	1.54	0.05	1.59	0.05	1.29	0.05
cl_4	1.55	0.03	1.05	0.04	1.11	0.05	1.16	0.04
cl_5	1.15	0.02	0.75	0.02	0.78	0.02	0.82	0.02
cl_6	0.99	0.02	0.53	0.01	0.55	0.01	0.47	0.01
				citing-cited country effects				
pp_{11}	1.08	0.04	0.54	0.02	0.98	0.04	0.63	0.03
pp_{12}	0.48	0.01	0.29	0.01	0.46	0.02	0.34	0.01
pp_{14}	0.46	0.01	0.33	0.01	0.46	0.02	0.38	0.02
pp_{15}	0.35	0.01	0.28	0.01	0.4	0.02	0.33	0.01
pp_{16}	0.4	0.01	0.26	0.01	0.5	0.01	0.29	0.01
pp_{21}	0.35	0.01	0.33	0.01	0.34	0.01	0.36	0.02
pp_{22}	1.46	0.05	0.93	0.04	1.32	0.05	1.16	0.05
pp_{24}	0.45	0.02	0.43	0.02	0.43	0.02	0.52	0.03
pp_{25}	0.25	0.01	0.29	0.02	0.3	0.02	0.34	0.02
pp_{26}	0.44	0.01	0.37	0.02	0.55	0.01	0.4	0.02
pp_{41}	0.33	0.01	0.38	0.02	0.31	0.01	0.45	0.02
pp_{42}	0.45	0.02	0.47	0.02	0.45	0.02	0.57	0.03
pp_{44}	1.59	0.06	1.48	0.06	1.41	0.06	1.71	0.08
pp_{45}	0.29	0.01	0.38	0.02	0.32	0.02	0.44	0.02
pp_{46}	0.55	0.01	0.59	0.02	0.63	0.01	0.62	0.02
pp_{51}	0.3	0.02	0.36	0.02	0.31	0.01	0.47	0.02
pp_{52}	0.29	0.01	0.37	0.01	0.43	0.01	0.48	0.02
pp_{54}	0.31	0.01	0.44	0.02	0.33	0.01	0.52	0.03
pp_{55}	1.09	0.04	1.52	0.06	1.19	0.04	1.73	0.07
pp_{56}	0.4	0.01	0.53	0.02	0.5	0.02	0.59	0.02
pp_{61}	0.26	0.01	0.31	0.01	0.25	0.01	0.38	0.02
pp_{62}	0.38	0.01	0.41	0.02	0.35	0.01	0.51	0.02
pp_{64}	0.55	0.02	0.65	0.03	0.45	0.01	0.69	0.03
pp_{65}	0.33	0.02	0.49	0.02	0.32	0.02	0.55	0.03
				citing year effects				
$t^a_{1978-80}$	1.21	0.15	0.99	0.11	1.07	0.1	0.88	0.1
t_{1981}	1.26	0.15	1.01	0.11	1.14	0.11	0.99	0.11
t_{1982}	1.22	0.14	1.07	0.11	1.02	0.09	1.02	0.11
t_{1983}	1.2	0.13	1.02	0.11	0.97	0.08	0.95	0.1
t_{1984}	1.15	0.13	1.04	0.11	0.93	0.08	0.95	0.1
t_{1985}	1.13	0.12	0.98	0.1	0.9	0.07	0.9	0.1
t_{1986}	1.16	0.13	0.98	0.1	0.89	0.07	0.88	0.09
t_{1987}	1.17	0.13	0.91	0.1	0.9	0.07	0.82	0.09
t_{1988}	1.16	0.13	0.87	0.09	0.88	0.07	0.77	0.08
t_{1989}	1.14	0.12	0.82	0.09	0.82	0.07	0.72	0.08
t_{1990}	1.12	0.12	0.79	0.09	0.81	0.07	0.72	0.08
t_{1991}	1.13	0.12	0.8	0.09	0.79	0.07	0.71	0.08
t_{1992}	1.18	0.13	0.78	0.09	0.8	0.07	0.71	0.08
t_{1993}	1.24	0.14	0.76	0.09	0.83	0.08	0.7	0.08
t_{1994}	1.3	0.15	0.76	0.09	0.83	0.08	0.7	0.08
t_{1995}	1.45	0.16	0.71	0.08	0.89	0.08	0.66	0.08
t_{1996}	1.39	0.16	0.68	0.08	0.89	0.09	0.62	0.07
t_{1997}	1.39	0.16	0.62	0.07	0.87	0.09	0.57	0.07
t_{1998}	1.31	0.15	0.57	0.07	0.82	0.08	0.51	0.06
t_{1999}	1.31	0.16	0.51	0.06	0.83	0.09	0.45	0.06
t_{2000}	1.35	0.16	0.44	0.05	0.86	0.09	0.37	0.05
t_{2001}	1.31	0.16	0.35	0.04	0.84	0.09	0.29	0.04
t_{2002}	1.3	0.16	0.16	0.02	0.86	0.1	0.16	0.02

Table 9: EPO and USPTO estimated results: continued

	general				equivalent			
	USPTO		EPO		USPTO		EPO	
	coeff	SE	coeff	SE	coeff	SE	coeff	SE
β_2	2.82E-06	2.93E-07	6.21E-06	6.43E-07	5.46E-06	4.22E-07	5.72E-06	5.97E-07
β_1	0.17	0	0.38	0.01	0.17	0	0.35	0.01
	obsolescence citing-cited country effects							
β_{1pp11}	1.27	0.02	0.75	0.01	1.32	0.03	0.78	0.02
β_{1pp12}	1.17	0.02	0.67	0.01	1.24	0.03	0.71	0.02
β_{1pp14}	1.06	0.02	0.78	0.02	1.16	0.02	0.83	0.02
β_{1pp15}	1.25	0.03	0.86	0.02	1.37	0.03	0.9	0.02
β_{1pp16}	0.94	0.01	0.83	0.02	0.98	0.01	0.86	0.02
β_{1pp21}	1.05	0.02	0.74	0.02	1.09	0.03	0.76	0.02
β_{1pp22}	1.3	0.02	0.77	0.02	1.34	0.03	0.82	0.02
β_{1pp24}	0.96	0.03	0.81	0.02	1.05	0.03	0.9	0.03
β_{1pp25}	1.12	0.03	0.88	0.02	1.26	0.04	0.9	0.02
β_{1pp26}	0.93	0.01	0.93	0.02	0.98	0.02	0.94	0.02
β_{1pp41}	1.05	0.02	0.73	0.02	1.09	0.03	0.76	0.02
β_{1pp42}	1.11	0.03	0.71	0.02	1.23	0.04	0.76	0.02
β_{1pp44}	1.29	0.03	0.85	0.02	1.38	0.03	0.89	0.02
β_{1pp45}	1.17	0.03	0.84	0.02	1.32	0.04	0.87	0.02
β_{1pp46}	0.92	0.01	0.89	0.02	0.94	0.01	0.91	0.02
β_{1pp51}	1.07	0.03	0.75	0.02	1.15	0.03	0.78	0.02
β_{1pp52}	1.16	0.03	0.72	0.02	1.31	0.03	0.76	0.02
β_{1pp54}	1.02	0.02	0.83	0.02	1.17	0.02	0.86	0.02
β_{1pp55}	1.39	0.03	1.02	0.02	1.64	0.03	1.05	0.02
β_{1pp56}	0.94	0.02	0.88	0.02	1	0.02	0.91	0.02
β_{1pp61}	0.96	0.02	0.74	0.01	1	0.02	0.75	0.02
β_{1pp62}	1.05	0.01	0.74	0.02	1.09	0.02	0.76	0.02
β_{1pp64}	1.01	0.02	0.87	0.02	1.05	0.02	0.88	0.02
β_{1pp65}	1.12	0.03	0.87	0.02	1.25	0.04	0.9	0.02
	obsolescence cited sector effects							
β_{1cl2}	1.2	0.02	1	0.02	1.28	0.02	1.01	0.02
β_{1cl3}	0.82	0.01	1.03	0.02	0.89	0.02	1	0.02
β_{1cl4}	1.14	0.01	1.01	0.02	1.16	0.01	1.04	0.02
β_{1cl5}	1.1	0.01	0.92	0.01	1.06	0.02	0.94	0.01
β_{1cl6}	0.97	0.01	0.86	0.01	0.91	0.01	0.89	0.01

Notes: The results come from the estimation of model (3) through Weighted Non Linear Least Squares. The weights are obtained by multiplying each observation by $(n_{tpc}n_{TP})^{1/2}$.
a: The 25 years reduce to 23 as we aggregate the first three years, because of the reduced number of observations for these years.

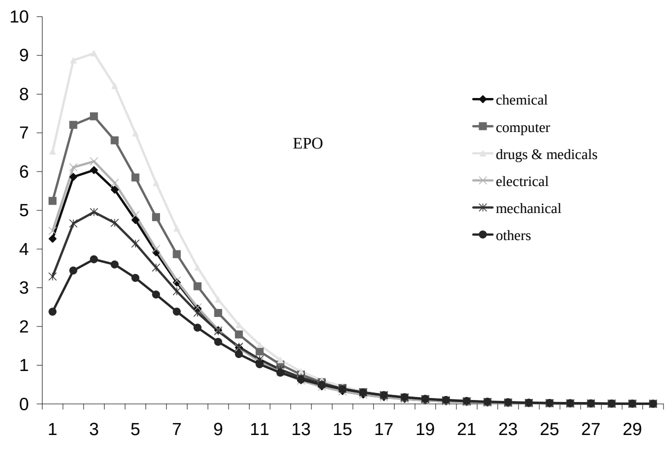

Figure 3: Diffusion processes for different technological sectors - EPO

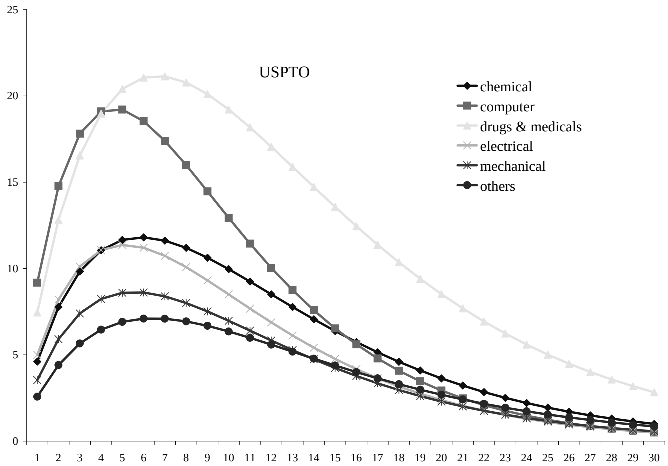

Figure 4: Diffusion processes for different technological sectors - equivalent patents at USPTO

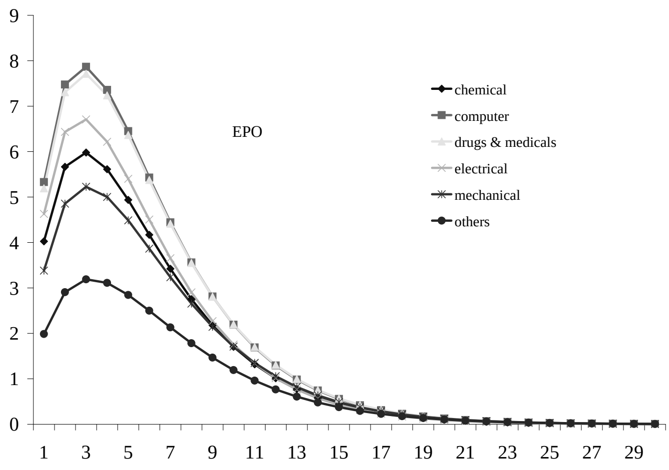

Figure 5: Diffusion processes for different technological sectors - equivalent patents at EPO