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

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Abstract

This paper estimates the international diffusion and obsolescence of technological knowledge by technological field and country using patent citations from the U.S. 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 show that (1) both at the EPO and USPTO domestic citations come sooner and there is a strong localization effect of patent citations at national level; (2) the US technological system is becoming less central in the international web of knowledge flows; (3) some differences across patent offices emerge in the ranking by technological fields in the speed of diffusion and decay of technological knowledge. We support the conjecture that not only technological opportunities but also absorptive capacity plays a role. Finally on the methodological side we show that at the USPTO the median citation lag is twice as large relatively to the citations at the EPO, that some bias is induced by the different institutional practices at the EPO and USPTO and that using patent families generates a selection bias towards high quality patents.

JEL codes: O30, O33, O34

Keywords: Knowledge flows, Spillovers, Diffusion, Patent citations, Technological Opportunities, Absorptive Capacity

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1 Introduction

In the last two decades a large body of theoretical research has focused upon the relationship between knowledge capital, knowledge spillovers and aggregate growth. The nature and scope of knowledge spillovers play a prominent role in determining the equilibrium growth path (Rivera-Batiz and Romer, 1991; Grossman and Helpman, 1991). In parallel the empirical research on R&D spillovers has shown that research productivity of firms and regions depends not only upon intra-muros R&D expenditures but also on external R&D spending of other firms, regions and industries. This research recognizes that patents are a fundamental empirical source to measure research productivity. Moreover patent citations are increasingly used to evaluate the value of patents (e.g. to evaluate companies' patent portfolios) and to track knowledge flows between different applicants or inventors (e.g. intensity and geographical and technological scope of knowledge spillovers)[1].

In order to understand the impact of knowledge accumulation on aggregate and industrial growth it is important to ask questions such as: how long does new technical knowledge spill over for? how much time is needed for a new piece of technical knowledge to become obsolete? How far does new technical knowledge spill over? Are there differences across sectors? Patents and patent citations have been increasingly used to measure knowledge spillovers from R&D activity but relationships have been often assumed contemporary and the time dimension tends to be unexplored (Caballero and Jaffe, 1993). Accordingly this paper focuses on the time dimension of knowledge spillovers and uses patent citations to estimate the process of diffusion and obsolescence of technical knowledge by countries and technological fields.

The empirical exercise is based upon patent citations from two distinct datasets: the US Patent and Trademark Office (USPTO) and the European Patent Office (EPO). In order to

[1]There is an enormous number of articles that use patent 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 in Jaffe and Trajtenberg (2002). On patent citations and the value of innovations Hall et al. (2005), Lanjouw and Shankermann, (2004), Haroff et al. (1999), Trajtenberg (1990) are fundamental references. On patent citations and knowledge spillovers there is a recent survey by Breschi et al. (2005). 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.

study the process of diffusion and decay of technological knowledge we estimate the citation-lag distribution for six different technological fields and five countries using separately the data from the two patent offices. In doing so it's necessary to take into account many features of the citation process. In particular we underline a "patent office" effect due to the different specific institutional practices that generate the citations to previous patents in the two different offices and the truncation bias: recent cohorts of patents are less likely to be cited then the older ones, because the pool of potentially citing patents is smaller. 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). This model provides a flexible empirical tool to adjust raw citation counts.

This paper provides new evidence in three directions. The first result relates to the geographical dimension of international knowledge flows. Many papers in the field show that patent 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). Jaffe and Trajtenberg (1999), in particular, 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 as compared to inventors from other countries – this is especially true for American inventors. We use data from the EPO to test this finding in a coherent methodological setting. Controlling for the presence of self-citation and using patent equivalents we find that also at the EPO there is such a strong localization effect at country level, and the size is comparable to the one found at the USPTO. Moreover we find that in recent years both at the USPTO and EPO the US is no more unequivocally the leading country in terms of citations made and received. This suggests that the US technological system is becoming less central following the process of internationalization of the patenting activity. The third advancement regards how the speed of diffusion and obsolescence of technical knowledge differs across sectors. These differences may depend upon the level of technological opportunities and/or firms' absorptive capacity. Estimating the process of diffusion and decay of technical knowledge both at the EPO and at the USPTO, our results give support to the idea that not only technological opportunities are important for the process of diffusion and decay of technological knowledge but also firms' absorptive capacity play a prominent role.

Finally, on the methodological side our results show that at the USPTO the approx. median lag is twice as large relatively to the citations at the EPO. We show also some evidence of a country bias induced by institutional differences in the citation procedures between the EPO and the USPTO, and finally we show that using patent families generate 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 3 describes our data and shows some of the differences between the USPTO and the EPO data. Section 4 describes the model and the econometric specification and Section 5 shows the results and gives possible interpretations. Section 6 provides concluding observations.

2 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 bring the attention to the different effects on growth rates of the different types of knowledge flows and push the empirical research to inquire more in depth the processes of knowledge accumulation and decay and the different channels along which ideas may be transferred (Rivera-Batiz and Romer, 1991; Grossman and Helpman, 1991; Griffith et al. 2003 and 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 the patent documents citations are used by examiners and applicants to show the degree of novelty and inventive step of the claims of the patent. 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 the details about 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 gouge 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 an important indicator of the economic value of innovative activity, the timing of the flow of citations and, in particular the citation-lag distribution, becomes 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.

The available empirical evidence regarding the 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 then inter-industry ones (Jaffe and Trajtenberg, 1996, 1999). Considerable evidence shows that patent citations tend to be localized. Using the NBER-USPTO data Jaffe and Trajtenberg (1999) show that patents from the same country are 30 to 80% 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 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 have also a propensity to be geographically localized. Similar results, also using EPO citations, are obtained by Bottazzi and Peri (2003).

[2]The use of patent citations as an index of knowledge flow has been validated by a survey of inventors (Jaffe et al. 2000, for the USPTO) and corroborates substantial evidence on the type and nature of knowledge spillovers (e.g. Maruseth and Verspagen, 2002; Jaffe et al. 1993, Piga and Vivarelli, 2004). Moreover patent citations are correlated with the value of patents and, in particular, recent work has shown that patent citations increase the market value of firms (Hall et al. 2005) and that the number of citations is correlated with the reported value of the inventors and with the payment of patent renewal fees (Haroff et al. 1999).

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

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 organization characteristics of the USPTO. Could it be for example just an artifact of the search process of the citing behavior of patent attorneys and examiners? Table 1 takes 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 5.3). 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. The distribution of citing patent, which is common in both offices, suggests that 41.6% of patents are from American inventors. Among the others, 25.2% and 19.0% come from German and Japanese inventors, respectively, while only 8.0% and 6.2% for French and British inventors. The two distributions of cited patents show that at the USTPO, the frequency of American cited patents exceeds the 65%, while at the EPO, the same frequency is less than 40%. 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 suggests that some bias in the USPTO results may exist. In order to isolate the organization 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.

[Table 1 about here]

Moreover there are important sectoral variations on 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 the 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 Drug and Medical are more highly cited than patents in the 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, Computers and Communications and new products arrive at a slower rate in the market (Jaffe and Trajtenberg, 1996 and Hall et al. 2001). These authors, in their interpretative framework, refer to differences in the "technological dynamism" and level of "action" among technological fields. We suggest that there are different explanations of these sectoral differences that are implicit in the interpretation of Jaffe and Trajtenberg. One explanation relates to the intrinsic nature of the knowledge underpinning firms' innovative activity and, in particular, to the exogenously given set of technological opportunities. The second explanation relates to firms' ability to re-use existing knowledge and create new products and processes, and therefore, is related to their absorptive capacity. This paper tries to disentangle these two aspects contrasting the different sectoral profiles of the citation-lag distribution in the two patent offices using the same methodology. Moreover we use patent equivalents to isolate the procedural differences between the two offices.

In order to estimate coherently the sectoral and country effect of the citation-lag distribution, it's 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) the truncation bias and the changes over time in the propensity to cite. (i) The modal and average lags between the citing and the 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 US there is the 'duty of candor' rule, which imposes all applicants to disclose all the prior art they are aware of. Therefore many citations at the USPTO come directly from inventors, applicants and attorneys and are subsequently filtered by patent examiners[4]. 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[5]. The

[4]Alcàcer and Gittleman (2004) using a random sample of 442,839 patents granted at the USPTO over the period 2001-2003 show that 40% of the cited-citing pairs are generated by patent examiners.

[5]The search report at the EPO is a document, published typically 18 months after the application date,

EPO guidelines for patent examiners suggest to include all the technically relevant information within a *minimum* number of citations and citations are, with few exceptions, added by the patent office examiners (EPO, 2005; Michel and Bettels, 2001; Akers, 2000; Breschi and Lissoni, 2004). 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 have to be considered. First, there is a citing year effect due to the increase in particular 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 behaviors of inventors' attorney and patent office examiners (for a detailed discussion of this issue, and of econometric techniques to deal 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 then the 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). This model permits 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.

3 The data

We use the publicly available USPTO Patent and Patent Citations Data, which contains the 3,449,478 USPTO (granted) patents from 1963 to 2005 and 37,730,701 citations from (and to)

that has the main objective to discover 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 documents. Cited documents may be patents or scientific bulletins and publications. Typically documents cited refer to specific patent claims.

USPTO, and the European Patent Office dataset, which contains the 1,702,652 EPO patent applications from 1978 to 2005 and 1,623,094 citations from (and to) EPO patents from 1978 to 2005[6]. From these datasets we select two samples: the universe of all patents and patent citations between 1978 and 2002 in 5 countries: France, Germany, Japan, UK and US. Self-citations are excluded form the samples[7]. 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 and Appendix B.

[Table 2, about here]

As expected at the USPTO there are more patents and, in particular, much 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 (potentially 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 parenthesis) 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 less 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 less citations than, for example, the Drugs and Medical sector in both patent offices.

[6]USPTO data are available from a cd delivered directly from the USPTO and on the ftp USPTO server (ftp://ftp.uspto.gov/pub/patdata/). The EPO data come from the Espace Bulletin CD-R produced by the EPO, patent citations come from the REFI tape. PCT citations are also included. Considerable effort has been dedicated to clean the databases in the CESPRI research center of Bocconi University and therefore we refer to the databases as respectively USPTO-CESPRI and EP-CESPRI.

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

However we observe that $cint_c$ ranks differently in the two patent offices. In particular at the EPO we have Drugs&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, on 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 of patents and companies in the two patent offices: he 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 parenthesis), this indicates an above average citation intensity ($cint_p$) for that country. It's worthwhile noting that, both at the EPO and USPTO, the US have a higher share of citations relatively to their share in the patent sample. This could reflect their position as world wide technological leader. 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.

4 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 modeled as a combination of two exponential processes, one for the knowledge diffusion and the other for the natural process of obsolescence. The general formulation of the model is

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

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 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 allowing 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 conduct 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 want 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[8]

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

(see Appendix A for relative details of USPTO - CESPRI and EP - CESPRI):

- t, the application or priority date,
- p, the first inventor's country,
- c, the technological field,

Moreover the following attributes are considered for the citing patent K:

- T, the application or priority date,
- P, the first inventor's country,

The amount of citations to a specific group of cited patents by a specific group of citing patents is: c_{tpicTP}. Hence a treatable formulation of the model, where the various different effects enter as multiplicative parameters, becomes

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

or equivalently, in the estimable form

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

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[9]. Equivalently, estimates of multiplicative coefficients related to citing patents, $\alpha\,(K)$,

[9] As an example, let consider an estimated coefficient $\alpha\,$(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 years vis à vis patents belonging to the base field.

indicate differences in the propensity to cite compared to a base category. One coefficient for each category, thus, will be omitted from the estimation procedure and will be constrained to unity. Note that following Jaffe and Trajtenberg (1999) we have introduced in 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 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 5-year intervals, as in Jaffe and Trajtenberg (1996)[10]. 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]

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

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, where pP considers all the possible interactions between citing and cited countries. For the cited patents we have 25 years, 6 technological fields, and 5 countries and for the citing patents we have 25 years and 5 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%) while the number of zeros in the USPTO - CESPRI is 863 (1.3%).

5 Results

In this section we report and comment the results of the estimation of equation (3). All fixed effects have been estimated relative to a base value of unity; for each effect thus, one group is omitted from the estimation and constrained to unity. 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, however, 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) presence of a home bias effect at USPTO and EPO, b) test for different diffusion processes between sectors, and finally c) test for patent office effects. The complete set of the estimated parameters, with related standard errors and significant tests, are reported in Appendix B.

Some general features about the estimated diffusion processes have to 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 years but this probability decreases faster as the 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 a EPO patent to be cited is almost zero, 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 2: while at the USPTO there is the 'duty of candor' at the EPO patent citations are added by the patent examiners that select a minimum number of (recent) citations.

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 instead, the α_T display a steep downward trend. As the amount of potentially citing and cited patents increases over time in both datasets, the amount 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 [11]. 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 can not forecast 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 observe that the percentage of zeros is 12.3% for the EPO data while only 1.3% for the USPTO.

5.1 Home bias effect at USPTO and EPO

In Table 4 we report the estimated coefficients for country interactions in matrix form. 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

[11] 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 data sets (note that in the two datasets we have the same left truncation bias because we do not consider citations that goes to patents granted, or applied for, before 1978). At the EPO backward citations per patent are 1.16 in 1979, they reach the 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 the maximum in 1995 at 8.28.

receive for all the future years[12], i.e. $\alpha\beta_2/(\beta_1)^2$. In Table 4 we report the estimated coefficients for both USPTO and EPO data.

Concerning the α's, 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 relatively to citations received from and made to other countries.

This is particularly true for the US (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 US - both at the USPTO and at the EPO - the highest off-diagonal α's are for UK citing US and US citing UK while the lowest off diagonal number is for Germany citing US and US 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 US, for Japan is also the US).

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, relatively to citations to and from other countries. For the patents granted at the USPTO, the only exception is in the US. 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 significant different behavior when citing domestic or foreign patents. American and Japanese inventors, instead, are faster to cite domestic patents then they are to cite foreign patents. A common result of the two patent offices, is that the fastest citing inventors are the Japanese ones, and in both cases, to

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

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 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. 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. What emerges from this last result is that 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). All these empirical results, however, reinforce the home bias effect highlighted in Jaffe and Trajtemberg (1999). This bias, moreover, is not confined to the USPTO patents, but can be generalized to the EPO patents too.

Looking at the cumulative probability, our evidence provides only partial support to the claim by Jaffe and Trajtenberg (1999) that the US are “the most open and interconnected economic and technological system in the world” (p. 123). They base their claim on the evidence that in the cumulative probabilities the US tends to make and receive more citations than other countries. Looking at Table 4 the US row contains the largest figure (other than the diagonal) only for the UK using the USPTO data and only for the UK and Japan using the EPO data. For the EPO data the UK has the highest propensity to be cited by the US, France and Germany. If we look at the results on the cumulative probability by row we observe different results at the USPTO and the EPO. 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 US. 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 France column contains the largest figure in every row.

Taken together our results tend to confirm the results found by Jaffe and Trajtenberg (1999). In particular our evidence gives further support to the idea that knowledge spillovers are geographically localized and domestic citations have a shorter model lag. In particular it can be claimed that the results found, among other, by Jaffe and Trajtenberg are not an artifact of the search process of American patent examiners and attorneys. In fact also at the

EPO where patent examiners are not expected to have biases towards US generated knowledge, American inventors have a higher likelihood to cite other American inventors than inventors from other countries.

Other results are not confirmed. While according to Jaffe and Trajtenberg (1999) American patents seem to be the leading source of patent citations, in our case this is not true in both USPTO and EPO databases. The first question is then why using data from the USPTO we do not find the same results. Considering that Jaffe and Trajtenberg use data up to 1994 and we use data up to 2002 we suggest that the US technological system is becoming less central. This is in line with the expansion of foreign patenting in the US and with the exponential growth of international patenting between 1994 and 2002. The second question is why we find some differences between the EPO and the USPTO estimates. 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 in Section 5.3.

[Table 4, about here]

In order to verify the robustness of our results, we performed the following other regressions[13]. First of all, we have re-estimated the model for both datasets including the self citations. As expected the results show an even stronger localization effect. Moreover self-citations have also 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 one for the EPO is $\beta_1 = 0.499$ (instead of 0.375). Moreover, only for the EPO data[14], we enquire also whether the citations added by the patent examiners and, in particular, the citations that invalidate the patents[15] 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

[13]All the estimates are available from the authors under request.

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

[15]In particular we considered citation category X and citation category Y. X-citations are particularly relevant documents that 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.

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 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 ($\beta_1 = 0.499$).

5.2 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 database.

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. At the fourth place there 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 Medicals at the USPTO has the largest modal citation lag (7 years) while at the EPO the same sector shows the smallest value.

As for the previous case, in order to observe the joint result of the diffusion and obsolescence effects, for all the aggregate sectors we calculate the overall cumulative probabilities. All the results are reported in Table 5, in the fourth column of each block. In line with the general results commented 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 with respect to the EPO. For these two sectors, however, for the USPTO patent office the β_{1c} coefficients do 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)[16]. This phenomenon does not appear in the EPO data, mainly because the rates of decay are very close, and in particular, significantly lower than one only for the Mechanical and Other sectors ($\beta_{1c} = 0.92$ and $\beta_{1c} = 0.86$, respectively). The pattern of the diffusion processes for all the technological sectors are shown in Figure 2 for the USPTO, and in Figure 3 for the EPO.

In order to account for the speed of diffusion and obsolescence of technical knowledge we put forward two explanations. The first one suggests that the level of technological opportunities (i.e. the likelihood of innovating conditional to the amount of money invested in research, Breschi et al. 2000) give the possibility to potential innovators to reach frequent and important discoveries and therefore accelerates the process of diffusion and decay of the related knowledge. The second explanation suggests that the process of diffusion and obsolescence of technical knowledge depends upon the firms' absorptive capacity. Absorptive capacity is a fundamental component of firms' capacity to innovate and includes the firm's ability to imitate new processes and products and to exploit basic and applied research findings (Cohen and Levinthal, 1989, 1990; Griffith et al. 2003 and 2004; Kneller and Stevens, 2006). A higher level of absorptive capacity generates also faster spillovers because less time is needed to learn from external sources. According to the first explanation we should observe that the pace of diffusion and decay mainly varies across technological fields assuming that the variance of technological opportunities is due to the given characteristics of the technology and its knowledge base. According to the second explanation we should observe also variations across geographical areas for the same technology because firms differ in their absorptive capacity, which depends upon the accumulated prior knowledge, which, in turn, depends upon relative past R&D expenditures and the level of human capital.

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

In sum if the process of technological diffusion and decay depends only upon the nature of the technology (technological opportunities), the relative speed of knowledge diffusion and decay in the different technological fields should be the same, independently from whether we use patents and patents' citations at the EPO or at the USPTO. However this is not the case, and consequently, our evidence supports the idea that there is a quicker process of diffusion where there is a higher level of absorptive capacity. In this respect we can qualify the broad interpretation of Jaffe and Trajtenberg (1996) and Hall et al. (2001); 'more action' and 'technological dynamism' at industry level would depend not only upon the existence of technological opportunities but also upon firms' ability to assimilate and re-use the available stock of knowledge.

As in the previous section the problem to identify 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 it is addressed in the following section.

5.3 Patent office effect

In this section we test whether we can identify a patent office effect. In the previous sections we have found clear support for the national localization of knowledge flows but we have found also some differences between the results based on USPTO and EPO patents. In particular looking at the EPO data we do not confirm that the US tend to make more citations than other countries (as in Jaffe and Trajtenberg, 1999) and we do not find 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.

In the first case (that the US invented patents are less central at the EPO relatively 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, patent examiners could have a preference for patents with European priorities. If there is no such a bias in the citation procedures and if we eliminate the heterogeneity in the citing population, the differences between the results in the two patent offices should disappear. As a consequence differences in the distribution of knowledge sources across patent offices would reflect the heterogeneity of patent activity in the two patent offices. Conversely if we find that - eliminating the heterogeneity in the citing population - the differences persist, we can infer that they are determined by procedural differences in the two patent offices.

In the second case the differences in the estimates relate to the sectoral heterogeneity in the patterns of diffusion and decay of technological knowledge. We have conjectured that absorptive capacity may play an important role together with technological opportunities. Again the results that the patterns are due to variation in absorptive capacity and not to institutional differences would be more convincing if the elimination of the heterogeneity in the citing population produced estimates that rank technological fields the same way in terms of the rates of diffusion and obsolescence between the two offices. In fact a similar sectoral ranking across patent offices for an homogeneous set of patents would evidence that sectoral differences are not 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[17]. We have therefore selected from the EPO and USPTO database, all the patent families with at least one USPTO and one EPO patent. We end up with 657,151 families. We have therefore 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 [18]. We therefore re-estimate the model in eq.(3) considering this subset of patents. We now

[17]As suggested by one of the referee, 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).

[18]We have used the database of equivalent patents provided by Dietmar Haroff and colleagues at http://www.inno-tec.de/forschung/forschungsprojekte/patent_cit_project/index.html

have 473,263 citations at the EPO and 3,457,937 citations at the USPTO. The new regression statistics are displayed in Table 6 in Appendix B.

The complete set of results is reported in Table 10 in the Appendix B, while in Table 7 and Table 8 country interactions and sector effects are compared for the two offices. From the former, we confirm as expected the general pattern of national localization of patent citations. In the upper panel, the α coefficients on the diagonal are higher then those in the corresponding rows and columns. In the medium panel, the modal citation lags are shorter for domestic citations, for both EPO and USTPO offices. As for the general case, however, the diffusion coefficients dominates the obsolescence rate, and this is clearly shown in the lower panel, when considering the 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, as expected, that an inventor who strongly believes in the potentiality of its invention generally decides to file the patent in both offices and that in the equivalents set there is a selection bias towards patents with an higher value.

We confirm also that the US are no longer a leading source of international knowledge flow. Looking at the cumulative probabilities, if we compare Table 7 and Table 4 we observe also very similar results. The important implication is that using an homogeneous set of equivalent patents, some differences do persist between the two patent offices. In particular, not only in Table 4 but also in Table 7, for the USPTO we observe that in every row the largest off-diagonal entry is the one from the US. Conversely for the EPO the France column contains the largest figure in every row. We interpret this evidence as a bias introduced in the citation procedures of the two offices. However it has to be pointed out that this bias does not affect the other main results of the paper outlined above. In particular the results concerning the localization of the knowledge flows and the higher speed of the domestic flow of citations in the two offices.

(see also Haroff et al. (2007); download 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 exactly the same set of Paris Convention priorities. This minimizes the possibility to include incorrectly two patents in the same family. When there are more than one USPTO or EPO patent in the same family we have chosen the oldest one.

We show also that the patent office bias does not affect the sectoral ranking in terms of diffusion of decay. Comparing Table 8 and Table 5 the ranking of the α coefficients is exactly the same in USPTO and EPO data. Moreover in this last case, the diffusion coefficients 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 Figure 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 Section 5.2 are the results of heterogeneous patenting activity in the EPO and USPTO. If these heterogeneous patenting activity generates different profile of technological diffusion and obsolescence, technological opportunities cannot be the only explanation. The conjecture advanced in the previous section that absorptive capacity may explain part of the observed variation finds therefore some support.

6 Conclusion

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. We control for differences in the citation procedure of the two patent offices using equivalent patents and underline three results. First we confirm with new and more recent data some of the results found by Jaffe and Trajtenberg (1966, 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 previous results - found solely on USPTO data - may depend on biases in the American search procedures. The second result is that the US together with the increasing internationalization of patents activity is less central in the international web of knowledge flows. While Jaffe and Trajtenberg (1999) have found that the US make and receive more citations than other countries, we find that this result is much weaker at the USPTO. In addition this result does not show up using EPO data.

Finally our estimates of the citation-lag distribution show that there are some differences across technologies in the diffusion path. In parallel, technological fields have different properties of diffusion and decay of technical knowledge in the two patent offices. We propose two complementary explanations. First we suggest that the level of technological opportunities give the possibility to potential innovators to reach frequent and important discoveries and therefore accelerates the process of diffusion and decay of the related knowledge. Secondly we suggest that the process of diffusion and obsolescence of technical knowledge depends upon firms' absorptive capacity. A higher level of absorptive capacity generates faster spillovers because less time is needed to learn from external sources. Our results give support to the idea that not only technological opportunities are important for the process of diffusion and decay of technological knowledge but also firms' absorptive capacity plays a prominent role. 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.

This paper also provides some evidence that helps understanding the statistical properties of the 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 relatively to the citations at the EPO. Secondly 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. Thirdly we show that some bias is induced by the different institutional practices at the EPO and USPTO. 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 5 countries: Germany, France, United Kingdom, Japan, United States.

The *Technological Fields* are the US NBER categories as in Hall et al (2000) that can be found in the USPTO. For the EP - CESPRI we used 30 technological classes based on the 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 are: 1. Chemical, 2. Computers & Communications, 3. Drugs & Medical, 4. Electrical & Electronic, 5. Mechanical, 6. Others. Below we report the 30 classes and, in parenthesis, 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 date for the EP - CESPRI and application date for the USPTO.

Appendix B: Tables and Figures

Table 1: Cited and Citing patents at EPO and USPTO for a set of equivalent patents

	Citing	Cited	
		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
US	41.6	65.6	39.6

a see the Appendix for the sectoral concordance between EP-CESPRI and NBER-USPTO,

Table 2: Statistics for EP and US patent and citation samples

	EP-CESPRI	USPTO-CESPRI
Range of cited patents	1978-2002	1978-2002
Range of citing patent	1979-2002	1979-2002
Potentially 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
Cited patents by fields,%[a] and citations intensity	s_c - (p_c) - $cint_c$	s_c - (p_c) - $cint_c$
(potentially cited patents in parenthesis)		
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
Cited Patents by country,% and citation intensity	s_p - (p_p) - $cint_p$	s_p - (p_p) - $cint_p$
(potentially cited patents in parenthesis)		
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

Table 3: Statistics for the regression model

	EP-CESPRI			
	Mean	St. Dev	Min	Max
Number of citations	16.98	35.91	0	947
Potentially cited patents	1217.10	1273.74	28	9298
Potentially 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-CESPRI			
	Mean	St.Dev	Min	Max
Number of citations	281.94	1189.31	0	39873
Potentially cited patents	2555.01	3404.04	134	23092
Potentially 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: EPO and USPTO cross-countries estimated results

	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

Table 5: EPO and USPTO sector estimated results

	USPTO				EPO			
	α_c	β_{1c}	m.lag	cum. freq	α_c	β_{1c}	m. lag	cum. freq.
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

Table 6: Statistics for the regression model for equivalent patents

	EP-CESPRI			
	Mean	St. Dev	Min	Max
Number of citations	9.69	21.99	0	502
Potentially cited patents	1217.10	1273.74	28	9298
Potentially 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-CESPRI			
	Mean	St.Dev	Min	Max
Number of citations	70.91	227.75	0	5796
Potentially cited patents	2555.01	3404.04	134	23092
Potentially 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: EPO and USPTO cross-countries estimated results for equivalent patents

	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

Table 8: EPO and USPTO sector estimated results for equivalent patents

	USPTO				EPO			
	α_c	β_{1c}	m.lag	cum. freq	α_c	β_{1c}	m. lag	cum. freq.
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

Figure 1: Diffusion processes for EPO and USPTO

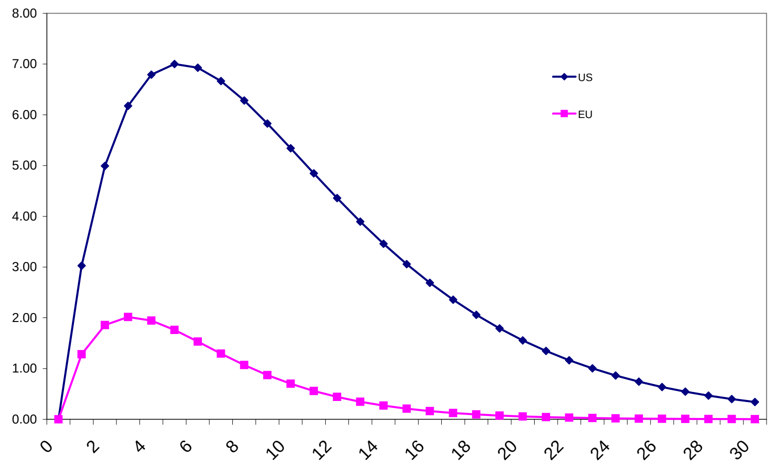

Figure 2: Institutional sectors - USPTO

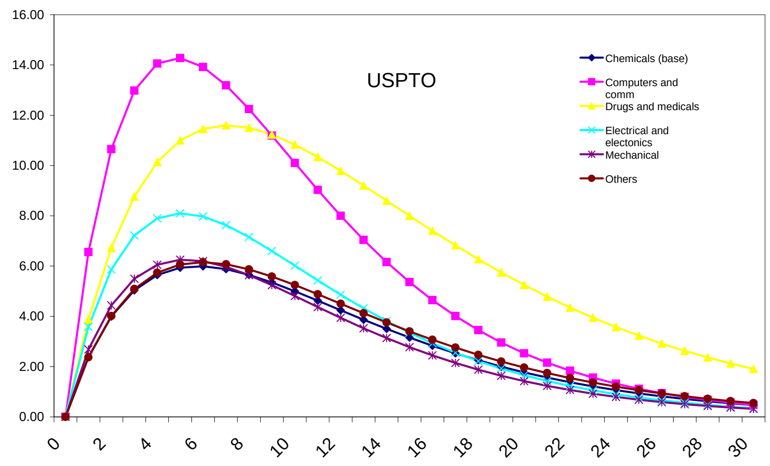

Table 9: EPO and USPTO estimated results

	USPTO			EPO		
	coeff	SE	t stat.	coeff	SE	t stat
			cited year effects			
q_2	1.07	0.02	3.84	0.98	0.02	-1.00
q_3	1.05	0.03	1.63	0.92	0.04	-2.23
q_4	1.06	0.05	1.27	0.90	0.05	-2.10
q_5	0.86	0.06	-2.60	0.87	0.07	-1.90
			cited class effects			
cl_2	2.86	0.08	23.62	1.23	0.04	5.95
cl_3	1.58	0.04	15.35	1.54	0.05	9.95
cl_4	1.55	0.03	19.52	1.05	0.04	1.41
cl_5	1.15	0.02	6.68	0.75	0.02	-15.81
cl_6	0.99	0.02	-0.26	0.53	0.01	-31.92
			citing-cited country effects			
pp_{11}	1.08	0.04	2.11	0.54	0.02	-22.73
pp_{12}	0.48	0.01	-39.63	0.29	0.01	-61.36
pp_{14}	0.46	0.01	-40.61	0.33	0.01	-49.26
pp_{15}	0.35	0.01	-49.26	0.28	0.01	-62.19
pp_{16}	0.40	0.01	-96.94	0.26	0.01	-74.48
pp_{21}	0.35	0.01	-46.90	0.33	0.01	-51.61
pp_{22}	1.46	0.05	10.08	0.93	0.04	-1.96
pp_{24}	0.45	0.02	-26.71	0.43	0.02	-28.32
pp_{25}	0.25	0.01	-66.68	0.29	0.02	-46.71
pp_{26}	0.44	0.01	-65.63	0.37	0.02	-40.71
pp_{41}	0.33	0.01	-49.88	0.38	0.02	-39.77
pp_{42}	0.45	0.02	-32.26	0.47	0.02	-23.98
pp_{44}	1.59	0.06	9.40	1.48	0.06	7.52
pp_{45}	0.29	0.01	-51.50	0.38	0.02	-34.07
pp_{46}	0.55	0.01	-40.87	0.59	0.02	-16.61
pp_{51}	0.30	0.02	-42.22	0.36	0.02	-42.55
pp_{52}	0.29	0.01	-60.33	0.37	0.01	-42.97
pp_{54}	0.31	0.01	-54.44	0.44	0.02	-28.40
pp_{55}	1.09	0.04	2.06	1.52	0.06	8.07
pp_{56}	0.40	0.01	-53.35	0.53	0.02	-24.41
pp_{61}	0.26	0.01	-89.02	0.31	0.01	-59.47
pp_{62}	0.38	0.01	-73.59	0.41	0.02	-34.24
pp_{64}	0.55	0.02	-24.32	0.65	0.03	-12.28
pp_{65}	0.33	0.02	-44.31	0.49	0.02	-22.05
			citing year effects			
$t^a_{1978-80}$	1.21	0.15	1.44	0.99	0.11	-0.13
t_{1981}	1.26	0.15	1.81	1.01	0.11	0.14
t_{1982}	1.22	0.14	1.62	1.07	0.11	0.62
t_{1983}	1.20	0.13	1.51	1.02	0.11	0.17
t_{1984}	1.15	0.13	1.18	1.04	0.11	0.34
t_{1985}	1.13	0.12	1.10	0.98	0.10	-0.22
t_{1986}	1.16	0.13	1.27	0.98	0.10	-0.23
t_{1987}	1.17	0.13	1.36	0.91	0.10	-0.94
t_{1988}	1.16	0.13	1.29	0.87	0.09	-1.45
t_{1989}	1.14	0.12	1.11	0.82	0.09	-2.01
t_{1990}	1.12	0.12	0.97	0.79	0.09	-2.43
t_{1991}	1.13	0.12	1.02	0.80	0.09	-2.30
t_{1992}	1.18	0.13	1.38	0.78	0.09	-2.50
t_{1993}	1.24	0.14	1.76	0.76	0.09	-2.73
t_{1994}	1.30	0.15	2.04	0.76	0.09	-2.68
t_{1995}	1.45	0.16	2.73	0.71	0.08	-3.56
t_{1996}	1.39	0.16	2.44	0.68	0.08	-4.10
t_{1997}	1.39	0.16	2.42	0.62	0.07	-5.17
t_{1998}	1.31	0.15	1.99	0.57	0.07	-6.29
t_{1999}	1.31	0.16	1.97	0.51	0.06	-7.73
t_{2000}	1.35	0.16	2.16	0.44	0.05	-10.36
t_{2001}	1.31	0.16	1.95	0.35	0.04	-14.69
t_{2002}	1.30	0.16	1.84	0.16	0.02	-39.86

Table 9: EPO and USPTO estimated results: continued

	USPTO			EPO		
	coeff	SE	t stat.	coeff	SE	t stat
β_2	2.82E-06	2.93E-07	9.62	6.21E-06	6.43E-07	9.66
β_1	0.17	0.00	51.55	0.38	0.01	60.40
			obsolescence citing-cited country effects			
β_{1pp11}	1.27	0.02	11.35	0.75	0.01	-16.91
β_{1pp12}	1.17	0.02	8.86	0.67	0.01	-22.44
β_{1pp14}	1.06	0.02	3.30	0.78	0.02	-12.50
β_{1pp15}	1.25	0.03	9.76	0.86	0.02	-7.93
β_{1pp16}	0.94	0.01	-6.76	0.83	0.02	-10.50
β_{1pp21}	1.05	0.02	2.11	0.74	0.02	-16.27
β_{1pp22}	1.30	0.02	12.74	0.77	0.02	-14.75
β_{1pp24}	0.96	0.03	-1.28	0.81	0.02	-8.64
β_{1pp25}	1.12	0.03	4.57	0.88	0.02	-5.36
β_{1pp26}	0.93	0.01	-6.00	0.93	0.02	-3.65
β_{1pp41}	1.05	0.02	2.10	0.73	0.02	-16.72
β_{1pp42}	1.11	0.03	4.53	0.71	0.02	-15.86
β_{1pp44}	1.29	0.03	10.45	0.85	0.02	-7.66
β_{1pp45}	1.17	0.03	5.52	0.84	0.02	-7.74
β_{1pp46}	0.92	0.01	-6.99	0.89	0.02	-5.66
β_{1pp51}	1.07	0.03	1.99	0.75	0.02	-14.82
β_{1pp52}	1.16	0.03	5.89	0.72	0.02	-17.67
β_{1pp54}	1.02	0.02	0.87	0.83	0.02	-8.72
β_{1pp55}	1.39	0.03	13.62	1.02	0.02	0.74
β_{1pp56}	0.94	0.02	-4.04	0.88	0.02	-7.37
β_{1pp61}	0.96	0.02	-2.09	0.74	0.01	-17.84
β_{1pp62}	1.05	0.01	3.37	0.74	0.02	-16.03
β_{1pp64}	1.01	0.02	0.55	0.87	0.02	-6.59
β_{1pp65}	1.12	0.03	4.30	0.87	0.02	-6.07
			obsolescence cited sector effects			
β_{1cl2}	1.20	0.02	10.50	1.00	0.02	-0.08
β_{1cl3}	0.82	0.01	-13.05	1.03	0.02	1.39
β_{1cl4}	1.14	0.01	10.51	1.01	0.02	0.76
β_{1cl5}	1.10	0.01	7.46	0.92	0.01	-7.62
β_{1cl6}	0.97	0.01	-2.23	0.86	0.01	-10.04

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: Institutional sectors - EPO

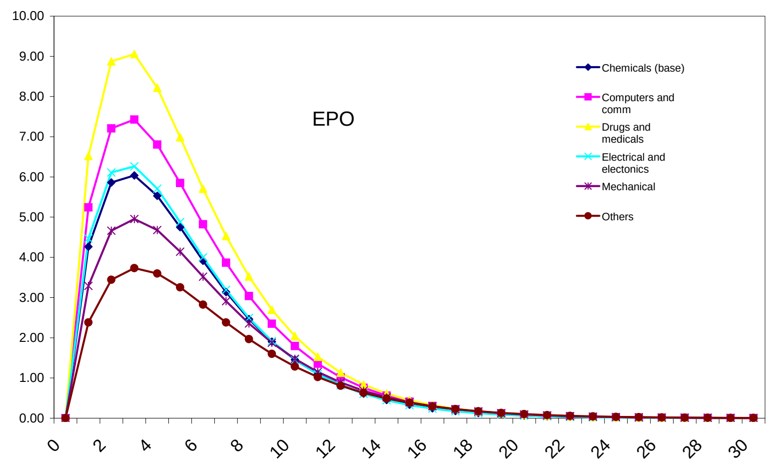

Table 10: EPO and USPTO estimated results for equivalent patents

	USPTO			EPO		
	coeff	SE	t stat.	coeff	SE	t stat
			cited year effects			
q_2	1.15	0.03	6.02	0.96	0.02	-1.69
q_3	1.14	0.04	3.11	0.91	0.03	-2.57
q_4	1.10	0.07	1.51	0.92	0.05	-1.66
q_5	0.82	0.07	-2.58	0.83	0.07	-2.52
			cited class effects			
cl_2	2.09	0.06	17.86	1.33	0.04	7.50
cl_3	1.59	0.05	12.30	1.29	0.05	5.60
cl_4	1.11	0.05	5.19	1.16	0.04	4.07
cl_5	0.78	0.02	-12.66	0.82	0.02	-9.00
cl_6	0.55	0.01	-34.83	0.47	0.01	-40.43
			citing-cited country effects			
pp_{11}	0.98	0.04	2.11	0.63	0.03	-14.28
pp_{12}	0.46	0.02	-36.03	0.34	0.01	-45.38
pp_{14}	0.46	0.02	-35.25	0.38	0.02	-33.30
pp_{15}	0.40	0.02	-35.25	0.33	0.01	-48.96
pp_{16}	0.50	0.01	-52.14	0.29	0.01	-66.22
pp_{21}	0.34	0.01	-46.92	0.36	0.02	-39.42
pp_{22}	1.32	0.05	6.50	1.16	0.05	3.28
pp_{24}	0.43	0.02	-27.69	0.52	0.03	-15.97
pp_{25}	0.30	0.02	-43.00	0.34	0.02	-39.51
pp_{26}	0.55	0.01	-32.24	0.40	0.02	-35.88
pp_{41}	0.31	0.01	-46.60	0.45	0.02	-25.35
pp_{42}	0.45	0.02	-25.25	0.57	0.03	-13.11
pp_{44}	1.41	0.06	6.90	1.71	0.08	8.45
pp_{45}	0.32	0.02	-36.67	0.44	0.02	-27.69
pp_{46}	0.63	0.01	-25.53	0.62	0.02	-15.40
pp_{51}	0.31	0.01	-47.29	0.47	0.02	-23.42
pp_{52}	0.43	0.01	-52.63	0.48	0.02	-24.89
pp_{54}	0.33	0.01	-56.88	0.52	0.03	-18.59
pp_{55}	1.19	0.04	4.47	1.73	0.07	10.40
pp_{56}	0.50	0.02	-32.17	0.59	0.02	-19.47
pp_{61}	0.25	0.01	-84.19	0.38	0.02	-40.85
pp_{62}	0.35	0.01	-59.88	0.51	0.02	-22.34
pp_{64}	0.45	0.01	-39.70	0.69	0.03	-10.07
pp_{65}	0.32	0.02	-38.81	0.55	0.03	-17.75
			citing year effects			
$t^a_{1978-80}$	1.07	0.10	0.66	0.88	0.10	-1.14
t_{1981}	1.14	0.11	1.35	0.99	0.11	-0.09
t_{1982}	1.02	0.09	0.24	1.02	0.11	0.15
t_{1983}	0.97	0.08	-0.36	0.95	0.10	-0.49
t_{1984}	0.93	0.08	-0.92	0.95	0.10	-0.45
t_{1985}	0.90	0.07	-1.29	0.90	0.10	-1.04
t_{1986}	0.89	0.07	-1.43	0.88	0.09	-1.33
t_{1987}	0.90	0.07	-1.41	0.82	0.09	-2.06
t_{1988}	0.88	0.07	-1.70	0.77	0.08	-2.74
t_{1989}	0.82	0.07	-2.64	0.72	0.08	-3.50
t_{1990}	0.81	0.07	-2.69	0.72	0.08	-3.65
t_{1991}	0.79	0.07	-3.13	0.71	0.08	-3.64
t_{1992}	0.80	0.07	-2.74	0.71	0.08	-3.61
t_{1993}	0.83	0.08	-2.25	0.70	0.08	-3.71
t_{1994}	0.83	0.08	-2.15	0.70	0.08	-3.64
t_{1995}	0.89	0.08	-1.35	0.66	0.08	-4.36
t_{1996}	0.89	0.09	-1.25	0.62	0.07	-5.15
t_{1997}	0.87	0.09	-1.57	0.57	0.07	-6.30
t_{1998}	0.82	0.08	-2.20	0.51	0.06	-7.78
t_{1999}	0.83	0.09	-1.96	0.45	0.06	-9.90
t_{2000}	0.86	0.09	-1.53	0.37	0.05	-13.52
t_{2001}	0.84	0.09	-1.70	0.29	0.04	-18.89
t_{2001}	0.86	0.10	-1.33	0.16	0.02	-39.22

Table 10: EPO and USPTO estimated results for equivalent patents: continued

	USPTO			EPO		
	coeff	SE	t stat.	coeff	SE	t stat
β_2	5.46E-06	4.22E-07	12.94	5.72E-06	5.97E-07	9.58
β_1	0.17	0.00	40.21	0.35	0.01	56.08
obsolescence citing-cited country effects						
β_{1pp11}	1.32	0.03	10.95	0.78	0.02	-12.81
β_{1pp12}	1.24	0.03	9.42	0.71	0.02	-16.76
β_{1pp14}	1.16	0.02	6.92	0.83	0.02	-7.34
β_{1pp15}	1.37	0.03	11.48	0.90	0.02	-5.43
β_{1pp16}	0.98	0.01	-1.81	0.86	0.02	-8.48
β_{1pp21}	1.09	0.03	3.30	0.76	0.02	-12.27
β_{1pp22}	1.34	0.03	11.48	0.82	0.02	-9.03
β_{1pp24}	1.05	0.03	1.57	0.90	0.03	-3.51
β_{1pp25}	1.26	0.04	7.06	0.90	0.02	-4.17
β_{1pp26}	0.98	0.02	-1.54	0.94	0.02	-2.77
β_{1pp41}	1.09	0.03	2.94	0.76	0.02	-11.57
β_{1pp42}	1.23	0.04	6.35	0.76	0.02	-10.03
β_{1pp44}	1.38	0.03	11.71	0.89	0.02	-4.53
β_{1pp45}	1.32	0.04	7.77	0.87	0.02	-6.09
β_{1pp46}	0.94	0.01	-4.57	0.91	0.02	-4.65
β_{1pp51}	1.15	0.03	4.76	0.78	0.02	-10.59
β_{1pp52}	1.31	0.03	10.42	0.76	0.02	-12.33
β_{1pp54}	1.17	0.02	7.00	0.86	0.02	-5.91
β_{1pp55}	1.64	0.03	18.66	1.05	0.02	2.25
β_{1pp56}	1.00	0.02	-0.05	0.91	0.02	-5.61
β_{1pp61}	1.00	0.02	-0.14	0.75	0.02	-14.77
β_{1pp62}	1.09	0.02	4.81	0.76	0.02	-13.65
β_{1pp64}	1.05	0.02	2.46	0.88	0.02	-5.54
β_{1pp65}	1.25	0.04	6.84	0.90	0.02	-5.02
obsolescence cited sector effects						
β_{1cl2}	1.28	0.02	12.64	1.01	0.02	0.53
β_{1cl3}	0.89	0.02	-6.37	1.00	0.02	0.00
β_{1cl4}	1.16	0.01	10.64	1.04	0.02	1.98
β_{1cl5}	1.06	0.02	4.05	0.94	0.01	-4.60
β_{1cl6}	0.91	0.01	-6.29	0.89	0.01	-8.00

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 4: Institutional sectors for equivalent patents - USPTO

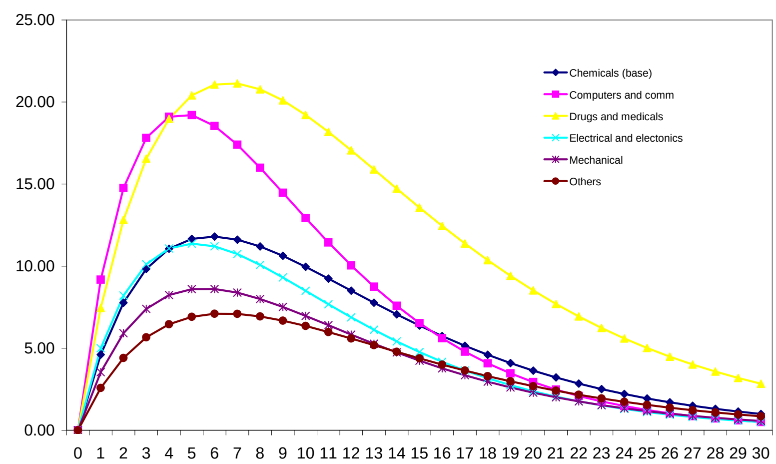

Figure 5: Institutional sectors for equivalent patents - EPO

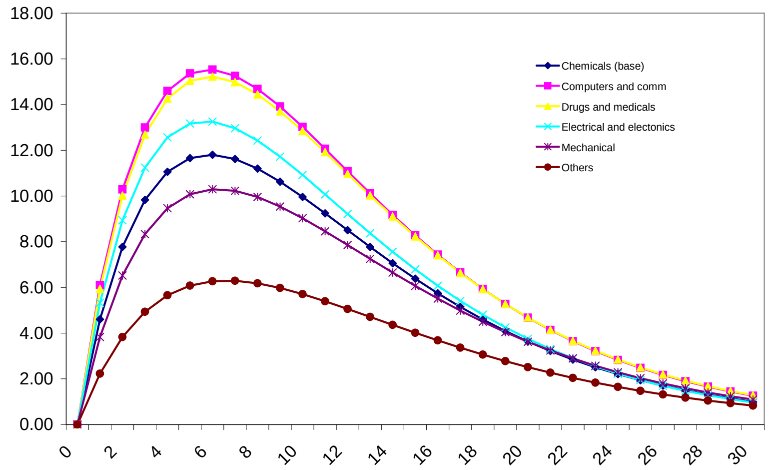

Figure 6: Diffusion processes for all patents and for equivalent patents for EPO and USPTO