Technological opportunities or absorptive capacity? An estimation of the rate of diffuson and decay of technical knowledge using patent citations.

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Abstract

This paper estimates the diffusion and obsolescence of technological knowledge by technological field, country and type of institution using patent citations. We estimate patent citation-lag distributions from the U.S. Patent and Trademark Office (USPTO) and from the European Patent Office (EPO). We show that absorptive capacity, and not only technological opportunities, is an important determinant of the rate of diffusion and decay of technical knowledge. Moreover we show that the citation-lag distribution is crucially affected by the different rules governing citation practices at the USPTO and EPO.

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

JEL Classification: O30, O33, O34

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. The empirical research on R&D spillovers 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 ? 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 technological fields. 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. A higher level of absorptive capacity

[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 knolwledge 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. (2003) provide evidence on the nature and types of knowledge spillovers using patent citations.

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.

The empirical exercise is based upon patent citations from two distinct datasets from the US Patent and Trademark Office (USPTO) and the European Patent Office (EPO). In order to study the process of diffusion and decay of technological knowledge we estimate the citation-lag distribution for six different technological fields and eight 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.

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. On the methodological side our results show that the choice of the patent office deeply affects the distribution of the citation lags: at the USPTO there are more citations per patent due to the different rules governing citation practices and that their approx. median lag is twice as large relatively to the citations at the EPO.

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 explores possible explanations. 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 enquire 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 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.

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).

If patent citations are an important track of knowledge spillovers and if forward citations[2] are an

[2] 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.

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 is 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, that intra-industry citations are much more likely then inter-industry ones and that citations tend to be localized but the degree of localization fades away over time (Jaffe and Trajtenberg, 1996, 1999). This evidence suggests also that there are important technological and country variations.

Jaffe and Trajtenberg (1996) and Hall et al. (2001) show that obsolescence and diffusion of technical knowledge vary across technological fields. In particular they 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.

The first explanation of the sectoral differences in the observed citation-lag distribution points at the properties of the knowledge base of a technological field and, in particular, at the technological opportunities to quickly create new product and process developments. Technological opportunities are defined as the likelihood of innovating conditional to the amount of money invested in research (Breschi et al. 2000). With high technological opportunities we expect potential innovators to reach frequent and important discoveries[3]. We call this hypothesis 'technological opportunity' (TO) hypothesis.

Moreover knowledge flows more quickly if companies are able to absorb it more quickly. Economists have shown that the use of external knowledge is costly and depends on the firms' learning and absorptive capacity (Cohen and Levinthal, 1989, 1990; Griffith et al. 2003 and 2004; Kneller Stevens, 2006). 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. Firms' absorptive capacity is the result of the value of the stock of accumulated prior knowledge, which, in turn depends upon relative past R&D expenditures and the level of human capital. This paper argues that a higher level of absorptive capacity generates faster spillovers, and smaller average and median values of the citation-lag distribution. This is because in case of higher absorptive capacity, less time is needed to learn from external sources and the entire innovative process is quicker[4]. We assume as in many diffusion models that diversity between firms in their learning and absorptive abilities is a fundamental characteristic of industries undergoing technical change (Silverberg et al. 1988). We call this hypothesis 'absorptive capacity' (AC) hypothesis.

This paper tries to assess the weight of the TO and AC hypotheses, that may coexist because they do not provide alternative explanations, using data from two different patent offices: the USPTO and the EPO. Writers in the economics of innovation field have emphasized that within each industry the nature of the knowledge base and the level of technological opportunities are similar across the advanced countries (Dosi, 1988 and 1997). As a result, if the TO hypothesis is correct, and the process of technological diffusion and decay depends only upon the nature of the technology, 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. If this is not the case, we expect 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

[3] We are aware that technological opportunities may vary considerably along products and industries life cycles. As in Jaffe and Trajtenberg (1996) in this paper we will estimate the citation lag distribution over very broad industries. At the aggregate industry level we expect that this issue does not affects dramatically our results.

[4] We may expect both the level of technological opportunity and absorptive capacity to be related to the intensity of competition at the industry level.

(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.

In doing so 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, (ii) country effects, (iii) university and public laboratories effects and, finally, (iv) 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 is 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[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 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) This paper controls for citing and cited country effects because firms' patenting practices may change according to the nationality of the inventors. For example Jaffe and Trajtenberg (1996

[5] 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.

[6] The search report at the EPO is a document, published typically 18 months after the application date, 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 bullettins and publications. Typically documents cited refer to specific patent claims.

and 1999) show that USPTO patents granted to US inventors are more likely to cite US patents than patents granted to inventors of other countries. In general they show a pattern of geographical localization with higher domestic citation rates. Moreover they also show that Japanese patents at the USPTO tend to get more citation with a lower rate of decay than European ones. Finally country specificities may emerge because of different institutional practices in writing and licensing patents: in Japan, for example, patents contain less claims and have a narrower scope than US and European ones (Ordover, 1990; Sakakibara and Branstetter, 2001).

(iii) Recent empirical evidence suggests that patents granted to universities and public research laboratories tend to be more cited than companies' patents (Henderson et al. 1998; Mowery et al. 2004; Bacchiocchi and Montobbio, 2006) Therefore it is important to control for the different institutional types of applicant. In particular we distinguish between government and non government (corporate) patents.

(iv) Finally 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 NBER U.S. Patent Citations Data, which contains the 2,923,922 USPTO (granted) patents from 1963 to 1999 and 16,522,438 citations from (and to) USPTO patents from 1975 to 1999 (Hall et al., 2001), and the EP Cespri dataset, which contains the 1,391,350 EPO patent applications from 1978 to 2001 and 1,119,761 citations from (and to) EPO patents from 1978 to 2001[7]. From these datasets (from now on USPTO and EPO) we select two samples: the universe of all patents and patent citations between 1978 and 1998. In particular we consider all the citations from patents granted between 1979 and 1998 to patents granted between 1978 and 1997 (in the EP - CESPRI we use patent applications) in order to have the same right and left truncation biases in the two datasets. Summary statistics are displayed in Table 1. Each patent is characterized by a date, a country (first inventor's address) a technological field (based on the International Patent Classification for EP - CESPRI and the USPTO classification system for the NBER - USPTO) and the institutional type of the applicant (government or non government) (Details for both datasets are provided in the Appendix).

[Table 1, 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 1 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 1 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 1 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.

However we observe that $cint_c$ ranks differently in the two patent offices. In a particular at the EPO we have Drugs&Medical at the top and then Chemicals, Computers and Communications and Electrical and Electronics. 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. In line with the literature

[7] NBER-USPTO data are avilable from http://www.nber.org/patents/ and the EP-CESPRI Bibliographic data come from the Espace Bulletin CD-R produced by the EPO, patent citations come from the REFI tape.

that associates patent citations to the value of patents, we interpret this index as the relative value of the stock of accumulated knowledge of the patenting firms. Of course the meaningful comparison is for the same technological field between 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.

Likewise Table 1 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 reflects 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 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) 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 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 (see the Appendix for relative details of the NBER - USPTO and EP - CESPRI):

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

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

- T, the application or priority date,
- g, 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_{tpicTg}. Hence a treatable formulation of the model, where the various different effects enter as multiplicative parameters, becomes

$$\begin{aligned} E(c_{tpicTg}) &= (n_{tpic})\,(n_{Tg})\,\alpha_t\alpha_p\alpha_i\alpha_c\alpha_T\alpha_g \exp\left[-(\beta_1)\,\beta_{1p}\beta_{1i}\beta_{1c}\beta_{1g}\,(T-t)\right] \\ &\quad \times (1-\exp\left[-\beta_2\,(T-t)\right]) \end{aligned} \tag{2}$$

or equivalently, in the estimable form

$$p_{tpicTg} = \frac{c_{tpicTg}}{(n_{tpic})(n_{Tg})} = \alpha_t \alpha_p \alpha_i \alpha_c \alpha_T \alpha_g \exp\left[-(\beta_1)\beta_{1p}\beta_{1i}\beta_{1c}\beta_{1g}(T-t)\right] \times (1-\exp[-\beta_2(T-t)]) + \varepsilon_{tpicTg} \quad (3)$$

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

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

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, means a faster obsolescence, which corresponds to a downward and leftward shift in the citation function.

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)[9]. 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 $(n_{tpic}n_{Tg})^{1/2}$, following Jaffe and Trajtenberg (1996) and Hall et al (2001).

[Table 2, about here]

[8] As an example, let consider an estimated coefficient α (k=Computers and Communications) = 2.094; 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.

[9] 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 2 shows the statistics for the regression variables. The data consist of one observation for each feasible combination of values of t, p, i, c and L and g. For the cited patents we have 20 years, 3 institutional types, 6 technological fields, and 8 countries and for the citing patents we have 20 years and 8 countries. We consider only citations with a lag between the citing and cited patent greater than or equal to 1. Hence the total amount of observations is: n_obs=[(20*21)/2]*8*8*6*3=241920. In each dataset there are some cells with zero citations and some cells with missing values. We have zeros when c_{tpicTg} is zero and $(n_{tpic})(n_{Tg})$ is positive. Missing values are generated when also $(n_{tpic})(n_{Tg})$ is zero. In the EP - CESPRI 144481 observations have zero citations (59%) and there are 15360 missing (6.3 %). These are due to the scarcity of patents by universities or public research centres in Germany and Italy between '78 and '82 and Sweden and Finland mainly between '78 and '86. In the NBER - USPTO 81454 obs. have zero citations (33%) and 24616 observations are missing (10.1%). Missing values come from the scarcity of patents by universities or public research centres in Germany, Italy and Sweden and Finland.

5 Results

The results from the estimation of equation (3) are reported in Table 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 the estimates of any particular $\alpha(k)$, being a proportionality factor, focus on the null hypothesis $H_0 : coeff = 1$. The null hypothesis of significant tests for both β_1 and β_2, however, remains the standard $H_0 : \beta_i = 0$, $i = 1, 2$.

Results show that citations at the EPO have shorter life and the rate of decay is twice the one observed for USPTO ($\beta_1 = 0.396$ and $\beta_1 = 0.189$ for the EPO and USPTO respectively). The modal lag is approx. 5.3 for the USPTO[10] and 2.7 for the EPO. For the two datasets average fitted values of equation (3) are plotted in Fig. 1. The likelihood that a EPO patents 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 one fourth of its maximum value.

The goodness of fit of the model, measured as adj-R^2, highlights the difficulty of such double-exponential model to fit zero probabilities. The adj-R^2 for the USPTO and EPO datasets corresponds

[10] This confirms approximately the results of Jaffe and Trajtemberg (1996 and 1999) even if our estimated $\beta_1 = 0.189$ is slightly lower.

to 0.45 and 0.22 respectively. The low goodness of fit for the European data can be easily explained by observing that the percentage of zeros is almost double with respect to the US data (59% against 33%).

Technological Fields. Two types of variation relative to the technological fields are considered in the model: variations in the fixed effects α_c and in the obsolescence parameter β_{1c}(see Table 3, Figure 2 and Figure 3). The base field is 'Chemicals' for both the USPTO and the EPO database. The estimated coefficients α_c confirm the results displayed for $cint_c$ with two small exceptions [11]. The propensity to be cited is higher in Computers and Communications, Electrical and Electronics and Drugs and Medical at the USPTO and in Drugs and Medical, Chemicals 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 confirm the results of Jaffe and Trajtenberg 1996 and Hall et al. 2001). At the EPO the Chemicals sector displays the most rapid obsolescence and then in order we have Drugs and Medical, Electrical and Electronics, Computers and Communications, Mechanicals and, finally, Others.

According to the TO hypothesis we would expect the same relative sectoral patterns of diffusion and decay in the two patent offices. In fact on the one hand we observe a positive correlation of the estimated α_c in the two patent offices. This would suggest that some invariant technological attributes affect the likelihood to be cited across all lags. On the other hand we observe a negative correlation between the estimated β_{1c}[12] and, accordingly, relative sectoral diffusion paths are different for the two datasets (see Table 3, Figure 2 and Figure 3). As a result even if there are common technological characteristics that affect the overall number of forward citations, invariant technological opportunities as such cannot be the only explanation for the relative pace of knowledge diffusion and obsolescence of one sector vis à vis the other sectors in the economy.

Therefore we suggest that firms in the two patent offices have different absorptive capabilities. Consider for example Computers and Communication at the USPTO. Since we control for a number of confounding factors as indicated above, it is possible to claim that these patents receive

[11] The two small exceptions are at the USPTO: Electrical and Electronics have a higher propensity to be cited than Drugs and Medical and the Mechanical sector has a higher estimated α_c than Others.

[12] The linear and rank correlations between the coefficients in the two patent offices (6 obs.) are respectively equal to 0.29 and 0.54 for the $\alpha_c$and equal to -0.27 and -0.14 for the β_{1c}.

coeteris paribus more citations (relative to the same sector at the EPO, note that $\alpha^{USPTO}_{computer\&comm} > \alpha^{EPO}_{computer\&comm}$) because of a their relatively higher quality. As a consequence, we claim that firms patenting at the USPTO in Computers and Communication have a relatively higher absorptive capacity that, in turn, affects positively the relative rate of obsolescence of technological knowledge in this sector. This is particularly evident also looking at Electrical and Electronics at the USPTO and at Chemicals and Drugs and Medical at the EPO. These sectors display very high early citations and the most rapid obsolescence and are the sectors in the respective patent offices with the highest (relative) values of α_c (and $cint_c$) These same results can be expressed also in the following terms: let α^{EPO}_c,α^{USPTO}_c, β^{EPO}_{1c},β^{USPTO}_{1c} be the sectoral estimated coefficients α_c and β_{1c} in the two patent offices. Assume that the difference ($\alpha^{EPO}_c - \alpha^{USPTO}_c$) indicates the relative quality/value of the stock of sectoral patents between the two patent offices. It can be noted that there is a strong positive correlation between ($\alpha^{EPO}_c - \alpha^{USPTO}_c$) and β^{EPO}_{1c} (0.64) and a strong negative correlation between ($\alpha^{EPO}_c - \alpha^{USPTO}_c$) and β^{USPTO}_{1c} (-0.49). As a result the rate of obsolescence and decay at the sectoral level is related to the relative qualities of the stock of patents that we take as an indicator of the absorptive capacity of the applicant firms[13].

In sum previous work (Jaffe and Trajtenberg; 1996 and Hall et al. 2001) shows that obsolescence and diffusion of technical knowledge vary across technological fields. This can be interpreted as a result of given technological opportunities that enhance the possibility of potential innovators to reach frequent and important discoveries. However in this case 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. We have shown that this is only partly the case. So the TO interpretation has to be complemented with another interpretation. The evidence proposed here does not contradict the intuition that a quicker process of diffusion and faster obsolescence may be determined by a higher level of absorptive capacity that is the ability to imitate and exploit new research findings to quickly develop new processes and products[14]. Few other results can be emphasized in relationship to the following features of the citation process we have controlled for: (i) country effects, (ii) university and public laboratories effects and, finally, (iii) time effects.

[13] Note that we are considering differences in the quality of the stock of patents at the sectoral level. R&D expenditure is the main determinant of the values of these stocks and, in turn, is the main determinant of firms' absorptive capacity.

[14] In principle there may be some noise due to the different patent classifications on which the technological fields are built. As explained in the Appendix, differences between the two datasets may emerge because the matching between the US NBER categories and the reaggregation of 30 technological classes based on European IPC codes may be imperfect. However we do not think this can be the only explanation of these diverging sectoral patterns.

Country Effects. For what concerns the country effects (Tab. 3 and Figure 4 and 5) we observe the highest propensity to be cited (α_p) for the US and Japanese patents. It's remarkable that at the EPO the lowest propensity to be cited is for patents originating in continental Europe: Germany, France and Italy. Consistently with what we observed above US and Japanese patents display very high early citations and the most rapid obsolescence (β_{1p}). At the USPTO patents granted to American inventors are more likely to be cited at every lags and the gap with respect to the other countries is in the order of 30% and more. At the EPO Japanese patents have the highest probability to be cited and the highest rate of decay. This might also reflect the country specific patenting and citing practice as emphasized by Ordover (1991) among others. Before recent reforms the so called "Sashimi system" was characterized by a narrower patent scope and limited number of claims (one single independent claim before 1988). This patent structure increases the number of patents and the number of citations.

Institutional Types. For the European data, patents assigned to Universities or Public Institutions and to Companies are respectively 40% and 18% more likely to be cited than the 'Not Assigned' patents. For the US data instead (as in Jaffe and Trajtenberg, 1996), non government patents are cited significantly more than government ones, although they have a slightly higher rate of decay. These differences are probably affected by the different classifications in the two datasets. For example a relevant role is played by university patents that seem to have higher likelihood to be cited according to Jaffe and Trajtenberg (1996). These patents at USPTO belong to the non government group while at the EPO they are in the non firm group. In a companion paper we show that at the EPO the higher likelihood of citations to university patents is mainly due to US patents in the Chemical and Drugs & Medical fields (Bacchiocchi and Montobbio, 2006).

Time Effects. 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 the EPO. This creates the observed decline in the coefficients for the EPO and the absence of a trend for the USPTO. 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. Finally for the cited time effects a substantial absence of fertility changes characterizes both datasets.

6 Conclusion

There is a large empirical and theoretical literature on knowledge spillovers and growth. However important 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 ? remain largely unexplored. This paper constitutes an attempt to fill this gap in the literature building upon the established literature that uses patents and patent citations as economic indicators. This paper therefore focuses solely on patents and patent citations and estimates the process of diffusion and obsolescence of technical knowledge by country and technological field using data from two patent offices: EPO and USPTO.

Our estimates of the citation-lag distribution show that there are remarkable differences across technologies in the diffusion path. In parallel technological fields have different relative 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 play a prominent role. Computers and Communications and Electrical and Electronics at the USPTO and at Chemicals and Drugs and Medical at the EPO display very high early citations and the most rapid obsolescence

On the methodological side we show that at the USPTO there are more citations per patent due to the different rules governing the citation practices. Moreover, citations at the USPTO have longer life and a lower rate of decay. The approximate median lag is twice as large relatively to the citations at the EPO.

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Appendix

In both datasets *Countries* are defined on the basis of the address of the first inventor in the patent application. We have used 8 countries and country groups: 1. Germany, 2 France, 3. Italy, 4. United Kingdom, 5. Japan, 6. United States, 7. Sweden and Finland, 8.others.

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 reaggregates 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).

The *institutional nature* of the assignee could not be built exactly in the same way for the two datasets. In particular in the EP - CESPRI the group called 'firms' includes just companies while in the USPTO this group includes 'non government organization'. The group called 'non firm' in the EP - CESPRI includes university and public research centres while in the USPTO dataset is just 'government'.

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.

Table 1: Statistics for EP and US patent and citation samples

	EP-CESPRI Dataset	NBER-USPTO Dataset
Range of cited patents	1978-1997	1978-1997
Range of citing patent	1979-1998	1979-1998
Potentially cited patents	906,792	1,766,075
Potentially citing patents	984,148	1,734,687
Total citations	959,852[a]	8,080,276[a]
Citations per potentially citing patent	0.98	4.66
Citations per citing patent	1.86	5.59
Cited patents by fields,%[b] and citations intensity	s_c - (p_c) - $cint_c$	s_c - (p_c) - $cint_c$
(potentially cited patents in parenthesis)		
Chemicals	27.45 - (22.1) - 1.24	17.93 - (19.3) - 0.93
Computers and Communications	10.58 - (10.1) - 1.05	17.60 - (12.6) - 1.40
Drugs and Medical	12.92 - (9.5) - 1.36	10.8 - (9) - 1.2
Electrical and Electronics	12.72 - (13) - 0.97	18 - (17.5) - 1.03
Mechanical	29.89 - (35.3) - 0.85	18.05 - (21.2) - 0.85
Others	6.43 - (9.8) - 0.66	17.62 - (20.2) - 0.87
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	16.06 - (20.1) - 0.8	5.99 - (7.8) - 0.77
France	6.59 - (7.9) - 0.83	2.34 - (3) - 0.78
Italy	2.73 - (3.2) - 0.85	0.83 - (1.2) - 0.69
United Kingdom	7.57 - (6.5) - 1.16	2.64 - (2.9) - 0.91
Japan	21.82 - (18.5) - 1.18	19.6 - (19.9) - 0.98
United States	31.76 - (29.1) - 1.09	61.09 - (54.7) - 1.11
Sweden and Finland	2.17 - (2.5) - 0.87	0.94 - (1.2) - 0.78
Others	11.29 - (12) - 0.94	6.56 - (9.1) - 0.72
Cited Patents by institutional field,%[c] (potentially cited patents in parenthesis, %)		
not assigned	9.14 (10.6)	14.62 (16.8)
firms	87.46 (86.3)	83.93 (81.5)
non firms	3.40 (3.1)	1.45 (1.6)

a. Cells with the lag $T - t < 1$ have been removed (T: date of the citing patent, t: date of the cited patent),

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

c. in the EP - CESPRI the group called 'firm' includes just companies while in the NBER - USPTO this group includes 'non government organization'. The group called 'non firm' in the EP - CESPRI includes university and public research centres while in the NBER - USPTO dataset is just 'government'.

Table 2. Statistics for regression variables

	EP-CESPRI			
	Mean	St. Dev	Min	Max
Number of citations	3.97	18.95	0	776
Potentially cited patents	262.36	579.7	1	6626
Potentially citing patents	7414.97	5843.27	277	25813
Citation Frequency (10^6)	2.61	12.58	0	1632.65
Lag in years[a]	7.33	4.82	1	20
Regression weights	907.84	1111.34	16.64	13078.11
	NBER - USPTO			
	Mean	St.Dev	Min	Max
Number of citations	33.4	233.86	0	13661
Potentially cited patents	588.77	1335.22	1	13433
Potentially citing patents	11903.73	17359.69	320	76976
Citation Frequency (10^6)	4.86	15.25	0	1619.43
Lag in years[a]	7.33	4.82	1	20
Regression weights	1442.3	2232.51	17.89	29690.93

a. Cells with the lag $T - t < 1$ have been removed.

Table 3: Estimated results

	USPTO		EP-CESPRI	
	coeff.	$t-statistic$ $_{H_0:\ coeff=1}$	coeff.	$t-statistic$ $_{H_0:\ coeff=1}$
citing year effect $_{(base=1979)}$				
1980	1.191	3.28	0.859	-2.28
1981	1.233	4.04	0.872	-2.19
1982	1.178	3.27	0.878	-2.14
1983	1.139	2.66	0.776	-4.44
1984	1.095	1.89	0.755	-5.02
1985	1.077	1.56	0.717	-6.09
1986	1.093	1.86	0.705	-6.44
1987	1.107	2.12	0.646	-8.42
1988	1.102	2.03	0.607	-9.93
1989	1.083	1.68	0.576	-11.23
1990	1.068	1.38	0.552	-12.29
1991	1.081	1.63	0.556	-12.04
1992	1.131	2.51	0.547	-12.40
1993	1.183	3.36	0.532	-13.09
1994	1.226	3.97	0.524	-13.44
1995	1.344	5.51	0.480	-15.89
1996	1.249	4.27	0.434	-19.02
1997	1.125	2.36	0.375	-24.02
1998	0.882	-2.80	0.292	-34.75
cited time effect $_{(base=1978-1982)}$				
1983-1987	1.049	8.36	0.986	-1.24
1988-1992	1.040	4.31	0.948	-3.06
1993-1997	0.967	-2.76	0.972	-1.16
institutional nature $_{(base=not\ assigned)}$				
companies	1.348	34.17	1.181	8.37
Univ. or public	0.839	-7.72	1.397	10.12
technological field $_{(base=chemical)}$				
computer & communication	2.094	65.75	0.836	-12.46
drugs & medical	1.336	27.98	1.243	14.04
electrical & electronic	1.407	32.89	0.771	-19.43
mechanical	0.990	-1.01	0.592	-53.61
others	0.943	-6.35	0.395	-54.67

Table 3: Estimated results, continued

cited patent country *(base=United States)*				
Germany	0.505	-66.47	0.544	-49.38
France	0.517	-43.71	0.602	-27.98
Italy	0.453	-30.16	0.643	-15.35
Great Britain	0.600	-36.99	0.980	-1.16
Japan	0.700	-60.55	1.281	18.70
Sweden and Finland	0.604	-21.89	0.749	-8.92
Other	0.615	-52.76	0.796	-14.86
citing patent country *(base=United States)*				
Germany	0.433	-156.02	0.717	-51.83
France	0.492	-88.97	0.784	-26.73
Italy	0.417	-66.31	0.711	-24.65
Great Britain	0.633	-61.14	1.052	5.62
Japan	0.607	-178.27	1.089	13.98
Sweden and Finland	0.584	-47.71	0.735	-19.74
Other	0.537	-150.18	0.873	-18.37
β_1	0.189	121.67	0.396	71.77
β_2	3.29E-06	21.86	9.27E-06	15.12
rate of obsolescence				
by technological field *(base=Chemical)*				
computer & communication	1.045	7.61	0.878	-12.91
drugs & medical	0.812	-33.54	0.977	-2.48
electrical & electronic	1.140	19.89	0.924	-8.16
mechanical	1.064	8.89	0.863	-18.52
others	0.970	-4.54	0.797	-13.26
by institutional nature *(base=not assigned)*				
companies	1.105	16.82	1.008	0.69
univ. or public	1.052	2.88	1.069	3.40
by cited patent country *(base=United States)*				
Germany	0.974	-2.54	0.875	-12.56
France	0.965	-2.32	0.893	-7.51
Italy	0.964	-1.25	0.900	-4.42
Great Britain	0.940	-4.92	0.974	-2.26
Japan	1.037	6.88	1.074	8.87
Sweden and Finland	0.949	-2.42	0.902	-4.15
Other	0.984	-1.84	0.924	-7.11

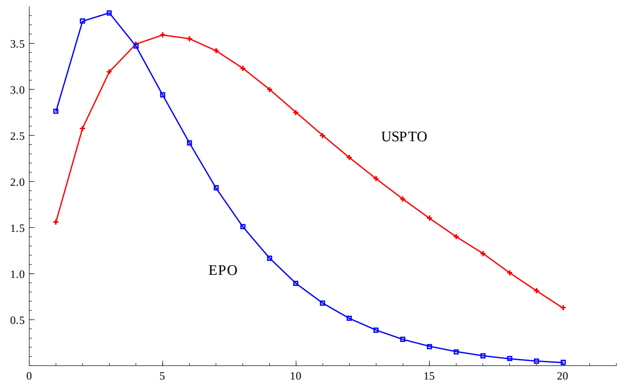

Figure 1: Fitted frequency ($\times 10^6$) of citation from EPO and USPTO.

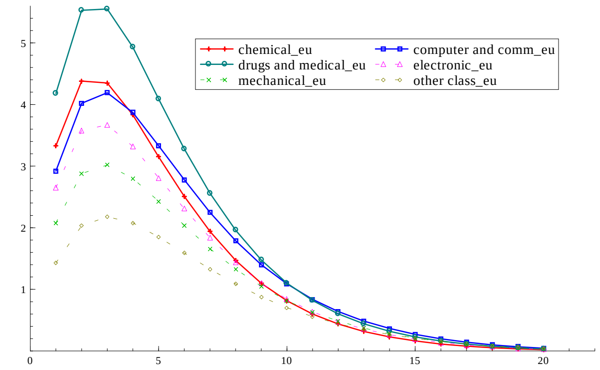

Figure 2: Fitted citation function for class of patents from the EPO dataset.

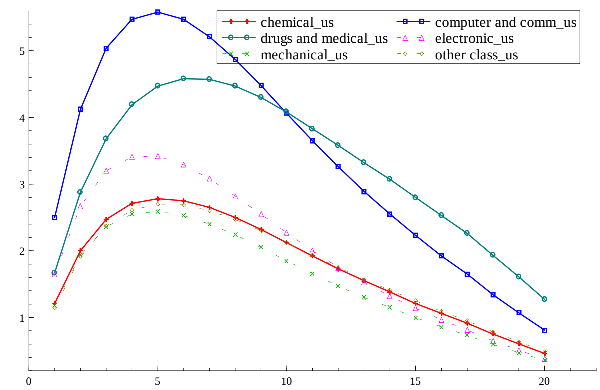

Figure 3: Fitted citation function for class of patents from the USPTO dataset.

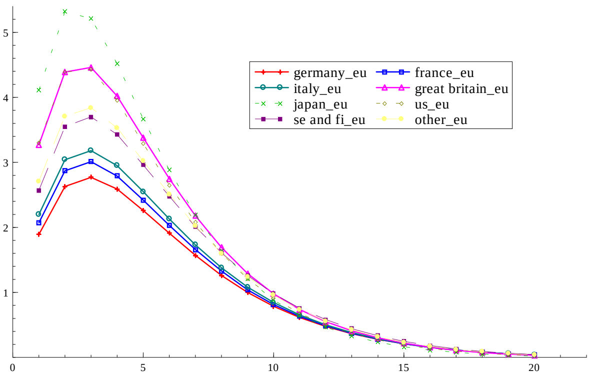

Figure 4: Fitted frequency of citation to patents originating in different countries; resuts from the EPO dataset.

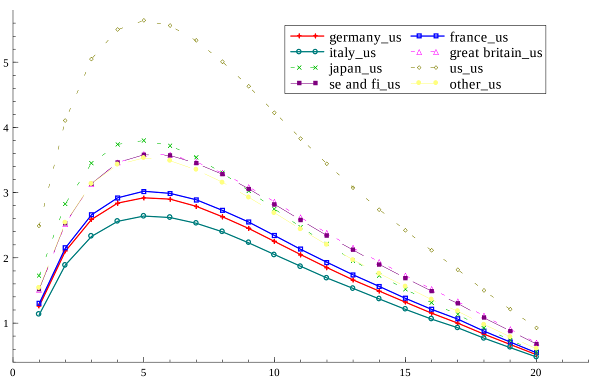

Figure 5: Fitted frequency of citation to patents originating in different countries; results from the USPTO dataset.