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Knowledge diffusion from university and public research. A comparison between US, Japan and Europe using patent citations

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Abstract This paper estimates the process of diffusion and decay of knowledge from university, public laboratories and corporate patents in six countries and tests the differences across countries and across technological fields using data from the European Patent Office. It finds that university and public research patents are more cited relatively to companies' patents. However these results are mainly driven by the Chemical, Drugs & Medical, and Mechanical fields and US universities. In Europe and Japan, where the great majority of patents from public research come from national agencies, there is no evidence of a superior fertility of university and public laboratory patents vis à vis corporate patents. The distribution of the citation lags shows that knowledge embedded in university and public research patents tends to diffuse more rapidly relative to corporate ones in particular in the US, Germany, France and Japan.

Keywords University patents · Citations · Spillovers · Knowledge diffusion · Public research

JEL Classifications O30 · O33 · O34

1 Introduction: patents from universities and public research in the US and Europe

There is an increased policy interest especially in Europe on how knowledge produced within universities and public research can be efficiently transferred and used by corporations for commercial purposes. University patents are often seen as a possible source of

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commercial technology. In particular university patents, jointly with exclusive licensing, could create the right incentives to develop products and could be a source of extra funds for universities and research centres. A recent set of papers has analyzed university patenting in the US, using data from the US Patent and Trademark Office (USPTO). These papers show that the number of US university patents has increased more rapidly than the total number of US patents in the last 40 years. Moreover some authors have suggested that university patents might be more general and important (measured using patent citations) than corporate ones (Henderson et al. 1998; Jaffe and Trajtenberg 1996). However while the relative number of university patents has increased there is some evidence of a decline in their generality and importance. While this evidence remains in some respect controversial (Mowery et al. 2004; Sampat et al. 2003), the underlying policy issue is whether policy tools (like the Bayh Dole Act) aimed at promoting patenting in universities and public research organizations (PROs) are really creating incentives to generate and disclose important and general inventions.

Conventional wisdom links the increase of university patents in the US to the Bayh Dole Act (BDA). The BDA (1980) gives uniform treatment university and PRO patents derived from research funded with federal funds (Mowery et al. 2004). However some authors suggest that this positive trend in university patenting would have occurred even without the BDA. In parallel to the general expansion of the patentable matter (that includes software, financial services, life forms and biotechnology) there was a change in attitude towards university patenting by some large academic institutions even before the BDA (e.g. Columbia in biomedicine) (Mowery et al. 2004).

Moreover there are wide differences across technological disciplines in the relevance of university patenting. The patent growth is concentrated mainly in biotechnology and pharmaceuticals (Mowery et al. 2004; Mowery and Sampat 2005). This expansion depends upon the federal support to medical research in the US and the expansion of molecular biology at the end of the 70s. Moreover it is only in pharmaceuticals, communications, and electronics that the results of university research are conducive to R&D projects which require clearly identified intellectual property. The question therefore is also whether the importance and value of university patents vary across different technological fields. It may be that reinforcing patenting is beneficial only for some fields and crowds out other technology transfer systems like publications, conferences, workshops and consulting.

In Europe there is also an increase in university patenting even if its magnitude is inferior relative to the US. In addition there are strong national specificities and the available evidence is still weak. In this paper we consider the four largest countries in Europe: France, Germany, Italy and UK. We keep them separate because their institutional features are different. In Germany (like in Denmark, Sweden and Austria) in the period under consideration there was the so called professor's privilege allowing university professors to retain the property right over their research findings. On the contrary in the UK, France and Italy for universities and research centres the standard rule applied according to which the employers retain the property right (e.g. see Sections 39–43 of the Patent Act in the UK). However while in France some universities and in particular the CNRS paid attention to the issue, Italian universities did not worry too much about intellectual property rights and often the ownership of the patent was left to private companies (Balconi et al. 2004).[1] Recent research suggests that also in other countries like

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[1] It's worthwhile noting that in 2000 the German law abolished the professor's privilege (the same occurred in Denmark and Austria) while in Italy in 2001 the professor's privilege was introduced for the first time (Lissoni et al. 2007).

France and Sweden intellectual property rights on the output of university research activity in Europe is often owned by private companies (Lissoni et al. 2006, 2007). As universities do not patent as often as in the US many national agencies and public research institutions have been active patentees (e.g. *Centre National de la Recherche Scientifique* or the *Commissariat a l'Energie Atomique* in France, *Comitato Nazionale per la Ricerca e lo Sviluppo dell'Energia Nucleare* or *Consiglio Nazionale delle Ricerche* in Italy, or, finally, *Max-Planck-Gesellschaft* or *Helmholtz Gemeinschaft - Forschungszentrum Julich* in Germany).

As policy makers move steadily in the direction of stimulating patenting activity of universities and PROs, no evidence is yet available on the relative characteristics of university and PRO patents and on their relative value. One problem arises because the EPO does not register in a separate field the institutional nature of the applicant. Actually there is no comprehensive evidence available yet, apart from specific case studies at the department or university level (OECD 2003; Geuna and Nesta 2006; Sapsalis et al. 2006; Sargossi and Van Pottelsberghe 2003). This paper aims at filling this gap using an original database on patents from universities and PROs. In particular the puzzling question is whether knowledge disclosed in university patents has a larger diffusion than knowledge from corporate patents. This question is studied using patent citations.[2]

This paper using data from the European Patent Office (EPO) compares patents from universities and PROs with corporate patents in six countries: France, Germany, Italy, Japan, UK and US. It studies the different properties of the process of knowledge diffusion and decay, controlling for country, technological field and time effects. In particular we compare the rate of diffusion and obsolescence of technological knowledge using patent citations and estimate the distribution of the patent citation lag. In so doing we deal with changes in the general propensity of different cohorts to cite and to be cited and with the truncation bias: recent cohorts of patents are less likely to be cited than 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).

One of the main results of this paper is that across all time lags university and PRO patents are more cited relatively to company patents. The distribution of the citation lag shows that knowledge embedded in university and PRO patents tends to diffuse more rapidly. At the same time, there is a lot of heterogeneity across countries and technological fields. The results are mainly driven by the Chemical, and Drugs & Medical fields and patents in the US universities.

The paper is organized in five sections. The second section presents our data and some descriptive statistics showing the main differences in the characteristics of university and corporate patents using patent citations. The third section outlines the econometric model used to estimate the different patterns of knowledge diffusion and obsolescence from university and PRO patents. The fourth section presents our results. The last section concludes.

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[2] Patent citations delimit the scope of the property right and, at the EPO, are included in the patent document by the patent examiners that draft their reports trying to include all the technically relevant information within a minimum number of citations (EPO 2005). Recent evidence strongly supports their use to measure the value of innovations and to track knowledge flows from the cited to the citing inventors or applicants (Jaffe and Trajtenberg 2002; Haroff et al. 1999). The differences between citation practices between USPTO and EPO are described in Bacchiocchi and Montobbio (2004), with some implications for their use in economic analysis.

2 Data and descriptive statistics

Each patent is characterized by a date (priority date), a country (first inventor's address), a technological field (based on the International Patent Classification). We use the EP Cespri dataset[3] and select all patent applications and patent citations in six countries (Italy, Japan, France, Germany, UK and US) and six sectors (Chemicals, Computer & Communications, Drugs & Medical, Electrical & Electronics, Mechanical and, finally, Others).[4] We consider the years from 1978 to 1998, this restricts the number of patents to 793040. In particular we consider all the citations from patents between 1979 and 1998 to patents between 1978 and 1997. The sample contains 82571 applicants.[5] Among those we have found 1,707 universities and PROs, 77,181 companies and 3,683 institutions that are 'not assigned'. The numbers of cited and citing patents are respectively 330,335 and 415,621. Moreover in the sample we have 736,548 citations and 1.77 citations per citing patent (cells with the lag $T - t < 1$ have been removed where T is priority date of the citing patent and t the priority date of the cited patent). The share of patents from universities and PROs on the country total number of patents shows that only in the US we observe a steady upward trend over 20 years from 2.57% to 5.61% between the periods 1978–1982 and 1993–1997. In France we have an higher (but declining share) from 9.2% to 5.5%. In Italy and Germany this share is considerably lower (1.58% and 1.28% respectively in the period 1993–1997). Moreover in France, Germany, Italy and Japan national PROs patent much more than universities.[6]

Figure 1 shows the patterns of diffusion and decay of technological knowledge in university and PRO versus corporate patents, using patent citations frequencies. In particular it shows the distribution of forward citation lags for selected cohorts: 1980, 1985, 1990, 1995. University and PRO patents are cited relatively more quickly and, correspondingly, citations to corporate patents come slower. Figure 1 shows that the median lag is smaller for university patents, even though the difference seems to fade away for recent cohorts.

Figure 1 suggests that in general technological knowledge embedded in patents from universities and PROs might diffuse faster. However these raw citation frequencies may be affected by the changing propensity to cite and to be cited over different cohorts of data and by the truncation bias: recent cohorts of patents are less likely to be cited than the older ones, because the pool of potentially citing patents is smaller. Moreover these aggregate frequencies are affected by specific characteristics of both citing and cited patents. In particular it might be the case that an inventor is more likely to cite a patent in the same

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[3] The EP CESPRI database 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. EP-CESPRI Bibliographic data come from the Espace Bulletin CD-R produced by the EPO, patent citations come from the REFI tape. This tape does not contain a field with the type of applicant.

[4] The details on the aggregation between the IPC classes and the six sectors are given in the Appendix.

[5] We have identified universities and publicly owned research centres looking at each one of the 82571 applicants' names in the database.

[6] Among university and PROs the top patentees at the EPO over the whole period are: in France the *Centre National de la Recherche Scientifique*, the *Commissariat a l'Energie Atomique*; in Italy the *Comitato nazionale per la ricerca e lo sviluppo dell'energia nucleare*, the *Consiglio Nazionale delle Ricerche* (CNR); in Germany the *Max-Planck-Gesellschaft* and the *Forschungszentrum Julich;* in the UK the *Secretary of State for Defence*, the *Medical Research Council* and the *Atomic Energy Authority*; in Japan the *Agency of Industrial Science and Technology* and the *Research Development Corporation of Japan*. Conversely in the US we find large universities like the *Massachusetts Institute of Technology*, the *University of California* and the *University of Texas*.

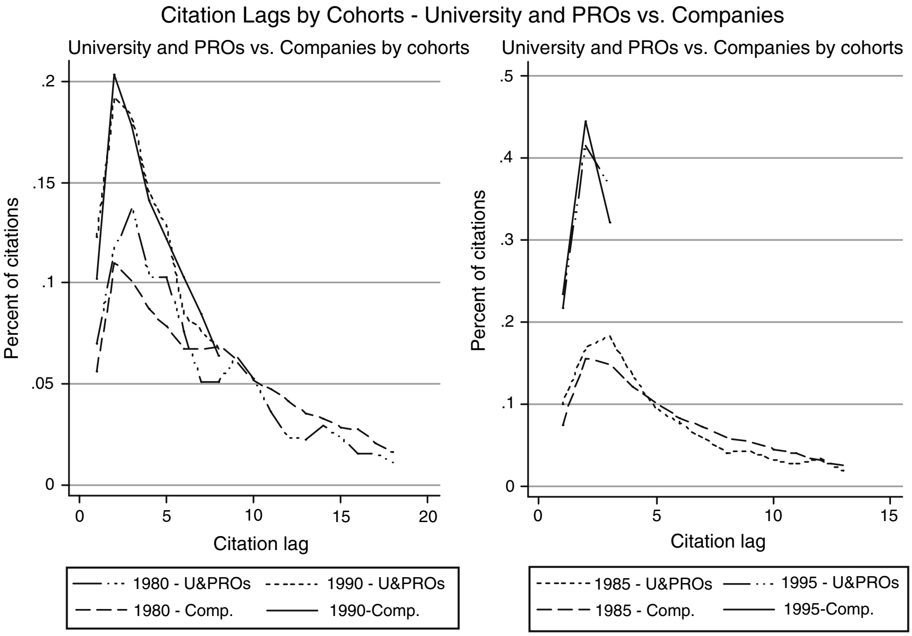

Fig. 1 Observed citation lags by cohorts and institutional types

country and in a related technological field. Therefore this paper estimates a citation lag distribution using the different cohorts and controlling for, technology, country and, finally, cited and citing year effects.

3 Model specification

The random process underlying the generation of citations can be modelled in different ways. The methodology we use is based on the quasi-structural approach originally proposed by Caballero and Jaffe (1993) in which the diffusion process is modelled as a combination of two exponential processes, one for the knowledge diffusion and the other one for the natural process of obsolescence.[7]

The general formulation of the model is

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

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

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[7] There are different reasons for the plausibility of this specification, rather than count data models or selection models. The simplest one relates to the descriptive plot of the citation frequency as a function of time elapsed from the potentially cited patents. Figure 1 shows the gradual diffusion process during the first few years, followed by the natural process of obsolescence. This is particularly evident for the 1980 and 1985 cohorts. A combination of these two processes, thus, can be very useful in describing the citation patterns. Moreover, the particular specification of the model gives the parameters a structural interpretation as explained below.

obsolescence and diffusion, respectively, and both exponential processes depend upon the citation lag $(T - t)$.

The coefficient α is 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.

Coefficients 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 upon k and K i.e. 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 deal with very small expected values from one side, and to enormously increase the computational burden from the other side.[8] 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. In order to have a precise understanding of the statistical properties of the citations received (forward citations), we consider the following characteristics of the cited patents k that affect their citation frequency: t, the 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

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

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.

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, $\alpha(K)$, indicate differences in the propensity to cite compared to a base category.

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[8] With 774,818 potentially cited patents and 838,355 potentially citing patents (Table 1) the expected probability that a single patent will receive a citation by another single patent is very small. This makes very difficult, expecially from the computational point of view, to directly model the propensity of one patent to be cited by another patents using count data models.

[9] As an example, let us consider an estimated coefficient α(k=Universities and PROs) =1.15; this means that patents belonging to the category "University and PROs" have a 15% higher probability (across all lags) to receive a citation vis à vis patents belonging to the base category.

Table 1 Statistics for regression variables

	Mean	St. Dev.	Median	Interq. range	Min	Max
Number of citations (c_{tpicTg})	5.64	24.95	0	2	0	776
Potentially cited patents (n_{tpic})	293.20	645.42	42	235	1	6626
Potentially citing patents (n_{Tg})	8418.60	6167.46	5883	8887	277	25813
Citation frequency (10^6)	2.75	13.1	0	2.04	0	1632.7
Lag in years[a]	7.25	4.78	6.5	8	1	20
Regression weights	1611.06	2751.16	522.8	707.2	16.64	13076.7

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

One coefficient for each category, thus, is omitted from the estimation procedure and is 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.

In this model difficulties arise 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] We estimate the model using weighted non-linear least squares under the well known assumptions on the error terms ε_{tpicTg}.[11]

Table 1 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 T and g. For the cited patents we have 20 years, three institutional types, six technological fields, and six countries and for the citing patents we have 20 years and six 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]*6*6*6*3 = 136080. 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. A total of 71,697 observations have zero citations (52.7%) and there are 5,586 missing (4.1%). These are mainly due to the scarcity of patents by universities or PROs in Germany and Italy between 1978 and 1982.[12]

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[10] Grouping cited year is a reasonable assumption in that we believe that the fertility of invention does not change substantially over time. Empirical results, available from the authors upon request, confirm such assumption.

[11] 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). When estimating the model without weights, a Breusch–Pagan test strongly reject the null of homoskedasticity by a $\chi^2(9)$ = 115945.21, with a p-value = 0.000.

[12] One of the limitations of this model is the impossibility to replicate the great number of zeros in the data. A possible alternative could be to use count data models, which takes the (inflated) zeros as possible response. However, we prefer to use the double exponential approach in that it allows to distinguish between the different diffusion and decay behaviors of knowledge from university, public laboratory and corporate patents.

Table 2 Main results obtained by estimating Eq. 2

	Coefficient	Std. Error	95% confidence interval	
$\alpha(i =$ Companies)	0.94**	0.02	0.90	0.99
$\alpha(i =$ Universities *or PROs*)	1.15***	0.04	1.07	1.24
$\alpha(i =$ not assigned)	1			
β_1	0.433***	0.007	0.419	0.448
$\beta_1(i =$ Companies)	0.94***	0.02	0.92	0.97
$\beta_1(i =$ Universities *or PROs*)	1.01	0.02	0.96	1.05
$\beta_1(i =$ not assigned)	1			
β_2	1.32E-5***	1.02E-6	1.12E-5	1.52E-5

Total observations: 130,494; R-square = 0.245. Base category is ($i =$ not assigned). Results are displayed only for the institutional types ($\alpha(i)$ and $\beta_1(i)$). The estimated α and β_1 (for $k = t,p,c$ and $K = G,T$) are displayed in the Appendix

* Significant at 10%, ** Significant at 5%, *** Significant at 1%

The null hypothesis is H_0: $coeff = 1$ for all coefficients but β_1 and β_2 where H_0: $\beta_i = 0$

4 Results

The results of the estimation procedure are reported in Table 2 (the base category is composed by the patents that are not assigned to a specific institutional type). Results are displayed only for the institutional types ($\alpha(i)$ and $\beta_1(i)$).[13] Table 2 shows that patents form universities and PROs are significantly more likely to be cited across all lags. Patents assigned to universities or PROs are 21% more likely to be cited than patents assigned to companies. Turning to the estimation of the diffusion process we find that β_1 is larger for universities and PROs. This suggests that for these patents the diffusion is more rapid and the rate of obsolescence is also higher relative to corporate ones.[14] Accordingly for universities and PROs the citation lag distribution is shifted to the left relative to the companies. In Fig. 2 we plot the estimated functions and show that knowledge produced from university and PRO patents diffuses more rapidly than corporate ones.[15]

Previous results based on data from the USPTO have shown that university and PRO patents tend to be more important and general patents (Henderson et al. 1998). Our estimated fixed effects $\alpha(i)$ seem to suggest that similar results apply also to universities and PROs of other advanced countries and to European patents.

However there might be some heterogeneity across technological fields and countries. To control for this we re-estimate the model asking whether this result is consistent across sectors and countries of the cited patent. As a result new dummy variables have been created by interacting institutional types with technological fields first, and then with the country of the cited patents. The model has been re-estimated focusing the attention on the $\alpha(i)$ coefficients associated to the interacting dummy variables. Results are displayed in

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[13] The complete table with all estimated coefficients are available from the authors upon request.

[14] A Wald-type test strongly rejects the null H_0:$\alpha_{\text{Univ}} = a_{\text{Companies}}$ by a $\chi^2(1) = 37.55$, with a corresponding p-value = 0.0000. The same holds for the obsolescence coefficients, where the null is rejected by a $\chi^2(1) = 9.23$, with a corresponding p-value = 0.0024.

[15] Some authors suggest that patent examiners tend to identify favorite examples of prior art (Cockburn et al. 2002). As a result they could cite a stable subset of previous patents and publications. Cockburn et al. (2002) claim that many of these preferred documents are university or public sector patents, which may also be written less strategically than those for private firms.

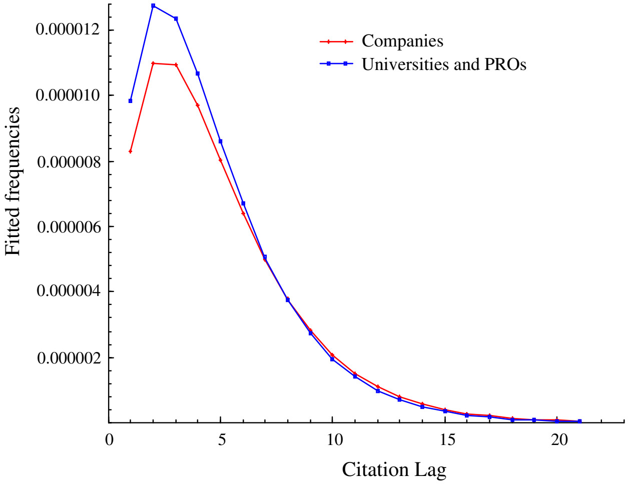

Fig. 2 Estimated citation lag distributions for company and university & PRO patents

Table 3. The base groups are respectively the not assigned patents in the chemical sector and the not assigned patents in the US. Table 3 shows that university and PRO patents are significantly more likely to be cited only in Chemicals, Drugs & Medical, Mechanical and Others. Moreover results across countries show that university and PRO patents are more fertile in particular in the US. There is no evidence of a superior fertility of university and PRO patents vis à vis corporate patents in the UK and Japan. Finally the estimated $\alpha(i)$ are slightly higher for universities and PROs in Germany, France, and Italy, although the difference is not significant from a statistical point of view.

Table 4 shows the ratio between the expected number of citations received by universities and PROs relative to companies at different lags, distinguishing for both technological fields and countries. The expected number of citations has been calculated by simulating the model with the related parameters estimated in the previous steps. In other words, we simulated the model for both public (university and PROs) and corporate patents, distinguishing for technological fields and cited countries, and then made the ratio between the two simulated distributions. Concentrating on the technological field, the common feature in Table 4 is the decreasing pattern of the expected citation ratio for all technological field. The probability for university and PRO patents of being cited is higher in the first years after the patent is granted. After 10 years, however, due to slower obsolescence, corporate patents become more fertile than universities and PRO patents, for all technological fields (even for Chemicals and Drugs & Medical that show higher values of $\alpha(i)$).

We find a more articulated set of results when we calculate the same relative ratio for different countries. The evidence that knowledge incorporated in university patents tends to be used more rapidly is confirmed for the US, Germany and France. One year after the priority date of the patent US, German and French university and PRO patents are respectively 33%, 14% and 6% more likely to be cited relative to corporate patents. However only in the US the ratio remains larger than one for 10 years. These countries show a decreasing relative fertility for university and PRO patents with respect to corporate patents. In Italy and the UK, instead, we observe an opposite behavior; Italian and British university and PRO patents, after twenty years, become 36% and 18% more likely to be cited relative to corporate patents.

Table 3 Estimated $\alpha(i)$ by sector and cited country (std. errors in parenthesis)

	Institutional types			
	Not assigned	Companies	Univ. and PROs	$H_0{:}\alpha_{(Comp)} = \alpha_{(Univ)}\chi^2$ (*p*-value)
Technological field				
Chemical	1	0.93**	1.11***	5.99**
		(0.03)	(0.04)	(0.014)
Computer & Comm.	0.74***	0.73***	0.67***	4.12**
	(0.05)	(0.02)	(0.07)	(0.042)
Drugs & Medical	1.19***	1.11***	1.45***	9.50***
	(0.04)	(0.04)	(0.06)	(0.002)
Electrical & Electronic	0.67	0.74***	.73***	0.04
	(0.04)	(0.02)	(0.05)	(0.835)
Mechanical	0.61***	0.57***	0.68***	8.43***
	(0.02)	(0.02)	(0.04)	(0.004)
Others	45***	0.37***	0.44***	5.18**
	(0.04)	(0.02)	(0.07)	(0.022)
Cited country				
Germany	0.59***	0.49***	0.55***	2.39
	(0.03)	(0.02)	(0.05)	(0.122)
France	0.62***	0.55***	0.59***	1.89
	(0.03)	(0.02)	(0.04)	(0.168)
Italy	0.61***	0.58***	0.62***	0.56
	(0.06)	(0.03)	(0.09)	(0.454)
United Kingdom	1.27***	0.91***	0.89*	0.05
	(0.05)	(0.03)	(0.06)	(0.831)
Japan	1.32***	1.36***	1.22**	2.50
	(0.04)	(0.04)	(0.09)	(0.11)
United States	1	0.97	1.31***	13.26***
		(0.03)	(0.05)	(0.000)

R-square = 0.245 for the Technological Field model and 0.246 for the Cited Country model; number of observations = 130,494 for both models

* Significant at 10%, ** Significant at 5%, *** Significant at 1%

In the first three columns the significance of the coefficients refers to the null hypothesis H_0: *coeff* = 1

In sum two types of results can be underlined. The first one relates to the proportionality factors $\alpha(i)$ and the second one refers to the diffusion parameters $\beta_1(i)$. Even if estimations on the total sample suggests that university and PRO patents have a higher probability to be cited across all time lags, a finer analysis shows that this is confirmed only for the US where university and PRO patents have 30% higher probability to be cited relative to corporate patents. In the other countries we observe a relative higher $\alpha(i)$ only in Italy, France and Germany but the difference cannot be considered statistically different from zero. Therefore we can conclude that for European countries and Japan there is no evidence of a greater importance of these patents relatively to corporate ones. Moreover university and PRO patents have a statistically significant higher probability to be cited in

Table 4 Public/Corporate citation probability ratio by sector and cited country

	Lags				
	1	5	10	15	20
Technological field					
Chemical	1.14	1.07	0.99	0.91	0.84
Computer & Comm.	0.85	0.79	0.73	0.67	0.61
Drugs & Medical	1.30	1.13	0.95	0.80	0.67
Electrical & Electronic	0.92	0.91	0.89	0.88	0.87
Mechanical	1.14	1.07	0.98	0.91	0.83
Others	1.26	1.06	0.84	0.67	0.54
Cited country					
Germany	1.14	0.95	0.76	0.61	0.48
France	1.06	0.96	0.86	0.76	0.68
Italy	0.94	1.02	1.12	1.24	1.36
United Kingdom	0.88	0.94	1.01	1.10	1.18
Japan	0.84	0.82	0.80	0.78	0.76
United States	1.33	1.17	1.00	0.85	0.73

four sectors out of six. In particular the most important ones are the Chemical and Pharmaceutical industries where university patents seem to have had a significant economic impact in the US (Mowery et al. 2004).

The second general result is that it takes less time for the knowledge produced in universities and national agencies to be used by other patents. While this result is quite homogenous across technological fields, considerable differences emerge across countries. Further in depth studies are therefore necessary to disentangle these national specificities.[16]

5 Conclusion

Our goal has been to develop a clearer picture of the diffusion of knowledge from university and public research patents in Europe. Prior work has focused on the US, using patent data from the USPTO and has found that after the BDA there was an increase in the propensity to patent, but less general and important inventions were produced in particular by those universities that entered into patenting after the BDA. We use EPO patent data of four large European countries, US and Japan, and show that, in the period 1978–1998, knowledge incorporated in university and PRO patents is more highly cited than knowledge embedded in corporate patents. However the result is mainly guided by university patents in the US and in the Chemical, Drugs & Medical, and Mechanical sectors. In Europe we do not find evidence that suggests that university and PRO patents have a higher quality. A greater fertility of university and PRO patents emerges only in France, Germany

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[16] Since our data are based on the institutional characteristic of the applicants we are considering only university and PRO owned patents and not all the university and PRO invented patents. In order to single out university invented patents it is required to match databases of university and PRO researchers with the inventors name listed in the patents. Preliminary evidence for Italy, France and Sweden suggests that this paper underestimates the role of universities and PROs in the production of patents in European countries (Balconi et al. 2004; Lissoni et al. 2007).

and Italy, but the difference with corporate patents is not statistically significant. Moreover our results show that knowledge produced in universities and PROs appears to diffuse more rapidly, in particular in the US, Germany and, to a minor extent, France and Japan. However strong national specificities emerge in this respect.

This result raises the question on why, in Europe, universities and PROs do not produce relatively more cited inventions (as it happens in the US in some specific technological fields). We suggest that there are two possible explanations that require further research. The first one is related to the quality of the research activity. Some evidence, both in Europe and in the US, suggests that university patents are positively related to scientific publications at the individual level and reflect the research of the most active researchers and departments (Mowery et al. 2004; Azoulay et al. 2006; Breschi et al. 2007). Therefore a relative lower quality of university patents in Europe could reflect a lower quality of the research activity. If this is the case, one possible policy implication goes in the direction of raising quality in European research institutions (e.g. Dosi et al. 2006). A second reason can be related to the different property regimes of university patents in Europe. Recent research suggests that university-owned patents in Europe are approximately 30% of the patents generated by academic inventors. Most of these university-invented patents belong to companies. Further research should be therefore undertaken to understand whether in Europe these university-invented (but company-owned patents) have a relatively higher quality.

In sum the Bayh–Dole act tried to promote university patenting and technology transfer in the US, where university patents were relatively more general and more important even before the Bayh Dole, however its effects are still controversial. In Europe there is not a strong tradition of patenting and licensing from universities, and some form of technology transfer occurs anyway through patents produced in universities but owned by companies. Finally our results suggest that the quality of European university patents is not higher than the quality of company patents. Taken all these considerations together, we suggest caution in emulating US policy changes in Europe and in pushing European universities to dedicate a big portion of their scarce resources to patent the results of their research activities. This is because university patents may interfere with established patterns of technology transfer (Valentin and Jensen 2007) and there is no evidence that university-owned patents in Europe bring into the market particularly significant technologies.

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Appendix

Data and classifications

Countries are defined on the basis of the address of the first inventor in the patent application. We have used six countries : 1. Germany, 2. France, 3. Italy, 4. United Kingdom, 5. Japan, 6. United States.

The *Technological Fields* are the US NBER categories as in Hall et al. (2001). We first 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 NBER Fields. Further details are available from the authors upon request.

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