The Spread of Academic Invention: A Nationwide Case Study on French Data (1995-2012)

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Abstract

The direct contribution of professors and researchers employed by universities and public research organizations has been emphasized as being increasingly important in sustaining a nation's technological edge. Although public policies have been introduced to incentivize scholars and researchers employed in universities and public laboratories to generate and transfer inventions, the extent and drivers of any spread in patenting behavior within the academic community have not yet been fully documented. We propose a nationwide empirical investigation of patented academic inventions in France over nearly two decades, which offers a number of new insights. First, the direct contribution of academia to the nation's flow of patented inventions is revised upwards, even before reforms in favor of academic technology transfer were introduced in the country. We also document a significant increase in the propensity of professors and researchers to invent over the whole period. Whereas cohort effects cannot explain this behavioral change, local peer effects within the lab are found to be the main drivers explaining the spread of academic patenting.

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1 Introduction

Economists have long hypothesized that the ever-increasing stock of scientific knowledge has a huge impact on innovation and the pace of economic growth (Arrow, 1962; Nelson, 1959; Romer, 1990; Jones, 1995). Focusing on the direct contribution of academia to innovation, many pieces of public policy have been introduced around the world to encourage scholars to generate academic inventions and support their transfer to society. In this paper, we document the extent to which professors and researchers engaged in academic patenting in France over nearly two decades (1995-2012) and explore the factors leading them to do so.

We defined academic patents as being those patents invented by professors and researchers employed in universities and research institutes. This definition is independent of the patent assignee and the data are thus immune to the transfer strategies of the professors and universities. We collected the data by matching and filtering rosters of professors and researchers at universities and government labs with patent inventors. The main originality of our approach with respect to previous similar attempts[1] is that we systematized the procedure on a large scale thanks to machine learning techniques that avoid time-consuming, painstaking checking procedures performed by humans. Our method did require a reliable benchmark however, to ensure that false positives and negatives were fully controlled and limited. This approach makes it possible to consider i) large lists of professors and researchers which become comparable to the reference population, and ii) sufficiently large time windows. We applied this method to France, the seventh country in the world in terms of GDP, sixth for scientific articles, and fourth for patents granted.

Over an eighteen-year period, academic patents were found to account for more than 10% of all patents invented in the country. This is well above (more than three times) prior estimates and therefore provides a new insight into the real direct contribution of science to technological innovation. As our data provided interesting covariates on professors and researchers extending beyond those who might have a patent, we were able to characterize their involvement in technology transfer. We found that more than one in five professors and researchers is an inventor (excluding social sciences and humanities). This statement applies to nearly all fields in the hard and life sciences, meaning that academic patenting is not specific to a particular discipline. Obviously, faculty members do not operate in some "ivory tower" and are much more directly involved in technological invention than is often assumed.

[1] Meyer (2003); Lissoni et al. (2008); Thursby, Fuller and Thursby (2009).

Is this a recent phenomenon entirely due to the increase in incentives to patent and commercialize academic research? We found that academic patents already accounted for more than 9% of all patents invented in the country prior to the introduction of the first piece of legislation encouraging technology transfer (the Innovation Act). This contradicts the idea of a very low pre-reform level of academic technology transfer, although it does not imply that nothing has changed in the more recent period. On the contrary, we found that faculty members' propensity to invent increased by a factor of two to four between 1995 and 2012. To control for a potential trend affecting patenting behavior (improvements in communication technology or instrumentation, for instance), we used non-academic patents as a reference point. We showed that academic inventors increased their propensity to invent significantly more than non-academic inventors over the same period.

What are the drivers behind the spread of patenting behavior in academia? We considered two series of factors: individual attributes on the one hand, and social and cultural influence on the other. Controlling for a large number of potential confounding factors, such as university, age, gender, status, field and year effects, we found that more recent cohorts were not more likely to engage in patenting. In fact, age plays positively on academic patenting at the individual level. This result is reminiscent of previous findings on smaller datasets (Carayol, 2007; Stephan et al., 2007) and consistent with the idea that incentives to invent are less susceptible to decrease over the life-cycle than traditional incentives to publish. Although the population of tenured professors and researchers under study aged slightly over the period, an age effect cannot explain increasing patenting behavior after controlling for age.

We therefore explored the influence of local social factors to further understand how this new behavior spreads through the academic community. The organizational culture at the individual university level has been emphasized as key to the willingness of faculty members to engage in entrepreneurship (Grimaldi et al., 2011). Other studies have highlighted the importance of norms, role models and peer effects in the research group in explaining faculty engagement in technology transfer (Louis et al., 1989; Bercovitz and Feldman, 2008; Krabel and Schacht, 2014). We proxied community involvement towards patenting using per capita invention rates in the previous years, at the university level (excluding the focal lab staff) and within the laboratory (excluding the focal person). Controlling for year, university and individual fixed effects, we found that local peer effects within the lab played a decisive role. One additional yearly patent invented by the average colleague in the lab in previous years raises the expected number of patents by a factor of four.

The rest of the paper is organized as follows. Section 2 exposes data collection and the methodology. Section 3 proposes descriptive statistics on academic patenting in France. Section 4 assesses how the propensity to invent varied over the period in academia, as compared to non-academic inventor profiles. Section 5 discusses the factors explaining the spread of patenting behavior within the academic community. Section 6 concludes.

2 Identifying academic inventions

In this section, we first discuss the different approaches to identifying academic inventions. We next present our data sources, before exposing our filtering methodology to merge faculty lists with inventors. Lastly, we show how we can estimate the number of academic inventions.

2.1 Academic inventions in the literature

Previous studies of inventions produced in academia have relied on a variety of definitions of what an academic patent is, and on associated data collection methodologies. Scholars initially assumed that academic patents were patents assigned to universities and government labs (Mowery et al., 2001; Mowery and Ziedonis, 2002), but this approach had the drawback of ignoring all patents invented by university personnel but which were not assigned to the university, for whatever reason. Many academic institutions traditionally did not manage their intellectual property rights and thus often did not retain the rights to the inventions their staff were involved in, whether intentionally or unintentionally. To avoid this issue, reference must be to the inventor field rather than to the assignee.

Several strategies can be deployed for the inventor information. Some papers use the title "Prof. Dr." that may be mentioned in the inventor field (Czarnitzki et al., 2016), although this is barely feasible outside Germany. When national statistical institutes provide precise employee data, authors merge them with inventors (Ejermo and Toivanen, 2018). Another way is to merge authors of scientific publications with inventors (Stephane and Martinez, 2014).

Our approach started out with information on the research staff of universities. Several previous studies have used such lists (Meyer, 2003; Balconi, Breschi and Lissoni, 2004; Iversen, Gulbrandsen and Klitkou, 2007; Lissoni et al., 2008; Thursby, Fuller and Thursby, 2009; Hvide and Jones, 2018). The difficulties in this approach are i) collecting large research staff lists over a sufficiently long period of time and ii) performing a reliable and systematic merge of those persons with inventors. In this paper we used large lists of professors and researchers and developed a filtering procedure which simultaneously avoided performing time-consuming manual checking and controls for merge quality.

2.2 Data sources

The French research system, as in most continental European countries, is organized in research laboratories(see Carayol and Matt, 2004; Azagra-Caro, Llerena and Carayol, 2006). These laboratories are the elementary units structuring research activity in nearly all higher education and research institutions. In France, they often host both professors employed by universities or higher education schools and researchers employed by research institutes. They vary in size from a few professors and researchers to several hundreds.

Our data came from the Ministry for Higher Education and Research. Each year, the ministry surveys one-fourth of all labs. Each lab provides the list of tenured staff hosted over the previous four years. For each person on the list, besides their first and last names, information is provided on their status (researcher or professor, junior or senior), research field, date of birth, year of entry in the lab, and gender. We compiled the personnel lists for each lab and each survey from 2005 to 2012 to build a dataset of researchers and professors. Most labs were surveyed this way at least twice over the period. Professors and researchers were thus likely to be listed several times (either in the same lab or in different labs if they moved, for instance) and systematic disambiguation was therefore performed through various automatic and manual procedures. At the end of this task, we had nearly 52,000 faculty members and researchers affiliated to 234 universities and research institutes and more than two thousand laboratories. [2]

Patent data were extracted from the "EPO Worldwide Patent Statistical Database" (PATSTAT Autumn 2017 Edition). We restricted the data to all patents filed at EPO, USPTO or INPI (the French national office) for which at least one inventor had a home address in France. We obtained 562,000 French-invented patents from 1995 to 2012.

2.3 Filtering academic patents

We began by matching the professor or researcher's first and last names with those of the inventor (using exact and fuzzy matching techniques to allow limited variation in spelling). This returned more than 113,000 patents and 185,000 professor-inventor pairs on a given

[2] Carayol and Lanoë (2017) used a very similar dataset to estimate the impact of project-based funding.

patent that remained to be filtered out. We used a statistical model to estimate the probability that each match was correct. The filtering process we used was in four stages.

In the first stage, we estimated a logit model on a set of validated and unvalidated couples. Such a benchmark was already used in Carayol et al. (2019) and was constituted on the basis of experts (mainly professionals of technology transfer employed in the universities) identifying professors as potential inventors. The benchmark was made up of twelve hundred professor-inventor pairs.[3] Explaining variables included Jaccard similarity between names, the inventor name frequency (in log), the distance between the patent technological classification and the professor's scientific disciplines as defined by Magerman et al. (2017) (in log), as well as dummies signaling consistency between the professor's age and the patent application year and between the assignee's name and the professor's employing institution. Regressions were performed per patent office as Hausman tests showed that logit coefficients are significantly different across offices. Results for each patent office are presented in Table A1 in the Appendix.

The second step used the estimated coefficients to predict the probability that potential matches were correct or incorrect over the whole reference population.

In the third step, we considered various thresholds of the probability of accepting or rejecting matches. Let $TP(p)$ denote the number of true positives in the benchmark for a given threshold probability value p, $FP(p)$ is the number of false positives, and $FN(p)$ the number of false negatives. We computed precision as

$$P(p) = \frac{TP(p)}{FP(p) + TP(p)}, \tag{1}$$

and recall as

$$R(p) = \frac{TP(p)}{TP(p) + FN(p)}. \tag{2}$$

Precision and recall varied in opposite directions with threshold p. We thus calculated a synthetic indicator taking both into account:

$$F_\beta(p) = (1 + \beta^2) \times \frac{P(p) \times R(p)}{\beta^2 \times P(p) + R(p)}, \tag{3}$$

with β, a strictly positive parameter weighting precision and recall. If $\beta < 1$, precision gets a lower weight than recall, whereas the reverse holds when $\beta > 1$. As we did not want our

[3]The distribution of pairs among offices is unbalanced: 31 for the USPTO, 249 for the EPO and 970 for the INPI. It explains the underperformance of the filtering on UPSTO patents.

results to be sensitive to a particular value of β, all our statistics were computed for $\beta = 0.5$, $\beta = 1$ and $\beta = 2$. In Figure A1 in the Appendix, we display the computed values of those indicators for the different threshold probability values p.

The fourth and last stage consisted in finding the optimal p threshold value, for each β and patent office i. That is, we wanted to find

$$p^*_{\beta,i} = \arg\max_p \left\{ F_{\beta,i}(p) \right\}, \tag{4}$$

for all β and i, with $F_{\beta,i}(p)$ the indicator defined in Equation 3, but calculated using the patents of office i only. Given that we were considering three offices and three different values of β, we ended up with a series of nine optimal threshold values to be calculated. Optimal thresholds presented in Table A2 are significantly different for each considered office. Table A2 also indicates the precision and recall values for each pair (β, i). We computed these indicators on the benchmark pooling patents from each office. As expected, recall increases with β whereas precision decreases with β. EPO and INPI patents have very good recall rates (above 0.93) when $\beta = 2$. INPI patents have a satisfactory recall rate (above 80%) when β equals 1. Recall and precision rates for EPO patents are found to be simultaneously satisfactory when β equals 1 or 0.5.

We used data produced in Lissoni et al. (2008)[4] for an external assessment of the quality of our data filtering. These data identified faculty inventing EPO patent applications via a combination of web searches, emails and phone calls. We created faculty-inventor-patent tables in both datasets and excluded homonyms born in the same year. Tables were merged on prof name, first name, birth year and patent identifier code. This essentially led to our data being restricted to the benchmark, as it covered a subset of our academic profiles, a shorter time period and considered EPO patents only. We obtained 1,016 faculty-inventor-patent combinations that were present in both datasets, involving 461 distinct scientists inventing 787 distinct patents. Interestingly, the filtering assessment maximizing F_β when $\beta = 2$ on the external dataset led to a 80.7% precision rate and a 83.2% recall. Filtering when $\beta = 1$ or 0.5 led to significant but limited gains in terms of precision at the price of a larger decrease in terms of recall.

This assessment was partially consistent with our own benchmarking exercise on EPO patents: both led to satisfactory recall rates when $\beta = 2$. They diverged slightly, however, with respect to precision. As it is better in principle to rely on external sources to appreciate the quality of a parametrization optimized on a given training set, we will use EPO patents

[4]We thank F. Lissoni for giving us access to the data.

preferentially in the rest of the paper, when applications at other offices are not necessary. This renders comparison with other studies easier and rules out issues concerning institutional differences among patent offices. We will also restrict our sample to EPO patents validated according to $\beta = 2$. This sample performs well on both benchmarks in terms of recall. As our benchmark suggests that a $\beta = 1$ would improve precision significantly, we performed robustness checks of all our results with this parametrization on EPO patent applications. They are available upon request from the authors, as are robustness checks on INPI applications, patent families and the total number of patents at the three offices (EPO, INPI and USPTO).

2.4 Estimating the number of academic patents

By definition, a patent is academic if at least one of its inventors is an academic staff member. This translates in our framework as follows. A patent is academic if at least one of its professor-inventor pairs (if any) has a probability of being a correct match above threshold $p^*_{\beta,i}$. Let $N^1_{\beta,i}$ be the set of these validated patents, the cardinal of that set is $n^1_{\beta,i}$ and the number of candidate but non-validated patents is $n^0_{\beta,i}$. Assuming that $n^1_{\beta,i}$ reflects the expected number of academic patents would be slightly misleading, as some patents counted in the underlying set ($N^1_{\beta,i}$) were considered as such (because of false positives) while some patents in the complement set ($N^0_{\beta,i}$) were also misallocated (because of false negatives). We can however use our own estimations of errors in both directions to correct those numbers and obtain a consistent estimation of the number of academic patents as follows:

$$\hat{x}_{i,\beta} = n^1_{\beta,i} \times \frac{TP(p^*_{\beta,i})}{FP(p^*_{\beta,i}) + TP(p^*_{\beta,i})} + n^0_{\beta,i} \times \frac{FN\left(p^*_{\beta,i}\right)}{FN\left(p^*_{\beta,i}\right) + TN\left(p^*_{\beta,i}\right)}, \quad (5)$$

for all $\beta \in \{0.5, 1, 2\}$, $i \in \{\text{EPO, INPI, USPTO}\}$. We multiplied the number of already validated academic patents by precision rate (true positives among positives), and added this number to the number of rejected patents multiplied by the rate of false negatives among negatives. This led to the results presented in Table A3 in the Appendix.

We made another correction to those numbers because the first staff survey we used was performed in 2005 and we were thus missing patents invented by professors and researchers who were no longer active after 2005. In addition, the data cover only universities and PROs recognized by the Ministry for Higher Education and Research (MHER). Some higher education or research institutions funded by other ministries may host research labs which were not surveyed as they are not recognized by the MHER. We recovered some missing academic patents by including all the patents that did not match at the first step but which were owned by at least one French higher education school, university or research institute[5] in our initial pool of academic patents. We denoted those numbers by $\hat{x}'_\beta$ and they are presented in Table 1. The gain from this last correction was significant in our case. This tells us that our estimation of academic patenting will still be an underestimation as we are missing all the patents invented by professors and researchers who are not in our list but whose assignee is not an academic institution.

We can see in the table that the numbers obtained with different weightings of precision and recall (different values of β) actually provide very similar numbers, ranging from 55,722 to 56,600 academic patents over the period. The fact that those numbers are very close is reassuring in that the estimations are largely unaffected by the weightings of precision and recall.

Table 1: Expected number of academic patents for several β values (from 1995 to 2012)

Office	$\hat{x}'_2$		$\hat{x}'_1$		$\hat{x}'_{0.5}$		All French-invented patents
EPO	19,786	(11.1%)	21,034	(11.8%)	21,039	(11.8%)	177,286
INPI	24,973	(10%)	24,604	(9.8%)	24,273	(9.6%)	250,605
USPTO	10,963	(8.1%)	10,963	(8.1%)	10,963	(8.1%)	134,315
Total	55,722	(9.8%)	56,600	(10.1%)	56,275	(10%)	562,206

Notes:
– For $i = 1, 2, 0.5$ we have $\hat{x}'_i = \hat{x}_i$ + all patents that did not match on names and are owned by French universities and PRO (exclusively or in shared property with companies).
– This table displays fractional counts: if several of its inventors are identified as academic, the patent is counted only once.
– The shares of academic patents - by office and overall - over all patents invented in France are placed in parentheses.
– The share of academic patents filed at the USPTO is smaller than the ones in INPI and EPO because our benchmark is made of fewer patents filed at the USPTO, hence reducing the performance of the filtering algorithm on this specific subset.

3 Academic patenting in France

In this section, we provide descriptive statistics on academic patenting activity in France. Firstly, we discuss the strength and specialization of academic patenting with respect to overall patenting in the country. Secondly, we describe the strength of patenting activity in the academic community.

[5] We made the reasonable hypothesis that a patent invented in the private sector had no reason to be owned by a university or PRO, and that all patents owned by universities and PRO were therefore academic.

3.1 Strength and specialization of academic patents

Table 1 shows that academic patents represented 11% of all patented inventions generated in France between 1995 and 2012, although it should be remembered that this is still a floor value, as some academic patents owned exclusively by the private sector are still missing for the reasons mentioned above. The French case was previously examined in Lissoni et al. (2008), which reported that 3.4% of EPO patents from 1995 to 2001 stemmed from academia. Considering only EPO patents and restricting the analysis to a similar period (1995-2002), we estimated the share of academic inventions in France to be as much as 9.3%. Academic inventions were thus much greater than previously estimated by a factor more than 2.5.

Interestingly, even before the introduction of the Innovation Act in 1999, universities, higher education schools and public research institutes already contributed 9.1% of all patents invented in the country.[6] This number is much larger than expected and this is important in that policy reforms aiming to develop the university ownership model were introduced in France and in other European countries (Geuna and Nesta, 2006; Verspagen, 2006) on the prior that technology transfer was weak in return for the investment made by the nation in fundamental research. It would therefore appear that this prior had no empirical foundations.

Let us now consider the technological specialization of academia, as compared to the country. The first two columns of Table 2 give the number of academic inventions broken down by technology fields. The third and fourth columns provide the same information for all French-invented patents. The fifth column is the absolute specialization of academia in the different technology fields, whereas the sixth column displays the relative specialization (sometimes called "revealed technological advantage") of academia as compared to national invention. Academia is up to 27% more specialized in chemistry and metallurgy than France. To a lesser extent, academia is more specialized than the country in the electricity and physics fields (respectively 11% and 8% more specialized). In all other technology classes, academia shows a technological disadvantage.

Later in this article, we investigate trends in academic patenting and their drivers. A potential confounding factor among these drivers is the specialization of academic patenting. For instance, a positive variation in academic patenting may be due to academia being specialized, or even increasing its specialization, in technological fields that are growing more

[6] Calculation based on EPO patents for the period 1995-1999. This share is similar on patents from other offices.

Table 2: Distribution of French patents and academic patents, by technology class (1995-2012)

Technology class	Academic patents # (A)	%	All patents # (B)	%	A/B	RTA
Human necessities	5,525	(16.5%)	55,646	(17.6%)	9.8%	0.93
Performing operations; transporting	3,931	(11.6%)	48,014	(15.1%)	8.1%	0.76
Chemistry; metallurgy	6,660	(19.8%)	49,132	(15.5%)	13.6%	1.27
Textiles; paper	1,031	(3.0%)	10,563	(3.2%)	9.8%	0.92
Fixed constructions	683	(2%)	8,639	(2.7%)	7.9%	0.75
Mechanical engineering; lighting; etc.	3,810	(11.3%)	41,619	(13.1%)	9.1%	0.86
Physics	6,256	(18.6%)	54,960	(17.2%)	11.3%	1.08
Electricity	5,654	(16.8%)	48,311	(15.1%)	11.6%	1.11
Total	33,550	(100%)	31,6884	(100%)	10.6%	1

Notes:

- For a technology class i, the revealed technological advantage is RTA= $\frac{A_i}{B_i} \times \frac{\sum_i B_i}{\sum_i A_i}$.

- Each patent is counted once in each of its technology class (full counting).

rapidly in general.[7] Table A4 in the Appendix provides descriptive statistics based on the finer-grained classification in 35 technological sub-classes. The first column gives the RTA of academia in each sub-class. The second presents the compound annual growth rate (CAGR) of the revealed technological advantage of each class over the period 1995-2012. The third column (Growth ratio) gives the ratio between the annual growth rate of patents in that sub-class relative to the growth rate of patents in France. The last column (Share) displays the proportion of patents that fall in the corresponding class. Technological sub-classes are ordered in decreasing order relative to the third column, which basically tells us how dynamic the sub-class was in France over the period. The fields that are growing faster than the national average (ratio greater than 1) are listed above the intermediate horizontal line. Of those 16 fast-growing sub-fields, academia has a technological specialization in only 6 of them (RTA greater than 1). Of those 6 sub-fields, academia is reinforcing its specialization in only 3 of them (positive CAGR). It is true that academia is strongly specialized in "Micro-structural and nano technology" (RTA of 5.55) which is also the most dynamic sub-field (growth ratio of 6), but this sub-class gathers only 0.1% of all patents. We can thus conclude that the technological specialization of academia may not explain a positive variation in overall academic patenting.

[7] Using a similar argument, Mowery et al. (2001) suggested that the growth in federal financial support for basic biomedical research and the increased patentability in this field may explain the positive trend in US academic patenting (rather than the Bayh Dole Act).

3.2 Who is patenting in academia?

In the previous subsection, we considered the importance of academia with respect to all national inventions. Let us now reverse the viewpoint to consider how important patenting is for academia, and who is participating. Since the goal here is to characterize the professors who invented at least once and the analysis does not relate to patent characteristics, we used patents from all patent offices. To appreciate to what extent professors and researchers are concerned by invention, we calculated the share of inventors among professors and researchers. Table 3 displays this information by scientific discipline (social sciences and humanities are not considered here). There are two important and somewhat surprising insights that can be drawn from this table.

Firstly, the share of professors and researchers who have been involved in patenting (and thus in technology transfer activities) is significantly high, equal to 22.3%. This means that more than one professor or researcher in five invented at least one patent between 1995 and 2012. We would like to be sure we are not overestimating participation by not being conservative enough in the filtering procedure. Giving too much importance to recall may result in randomly accepting too many patents and therefore wrongly considering many professors and research as inventors. To check for this potential bias, we put more weight on precision and less on recall and verified that it did not significantly alter the results. Table A5 in the Appendix is similar to Table 3 but using a different value for β (0.5), giving more weight to precision over recall at the filtering stage. According to this specification, the share of professors and researchers who invented at least one patent equals 21.8%, which is still large and very close to the main result. When more weight is given to recall over precision ($\beta = 2$ in Table A6 in the Appendix), the share of inventors remains very close (24.5%). Overall, this shows that participation shares are affected by the filtering stage, but to a limited extent which does not modify the results qualitatively. Besides, note that the recorded share of inventors among professors is likely to be less than the share of professors and researchers who have ever invented a patent, as some of those who did not invent over our period may invent in the future or may have invented before 1995 (and are thus not considered here).

Fields of science The second main insight is that the share of inventors in academia is high in almost all disciplines in the life and hard sciences. Professors and researchers in chemistry are the most active, with a share of one inventor for three professors and researchers, and the observed rates in fields such as physics and medicine are above 25%. Even in mathematics,

Table 3: Involvement of professors and researchers in academic patenting, by scientific discipline (1995 – 2012).

Scientific field	professors-inventors		All professors
Chemistry	2,364	(33.3%)	7,093
Applied Bio. Ecology	1,959	(23.1%)	8,469
Fundamental Biology	3,047	(24.1%)	12,639
Medicine	2,938	(25.8%)	11,409
Engineering Sciences	2,693	(24.8%)	10,862
Mathematics	1,586	(21.7%)	7,295
Physics	2,092	(25.2%)	8,309
Universe Science	445	(13.2%)	3,383
Total	7,692	(22.3%)	34,439

Notes:
– 17,347 professors and researchers in Human and Social Sciences are not represented in this table. 754 of them have invented at least one patent over the period (4.3%). If these HSS inventors are included in the full sample (51,786 researchers), the global share of academic inventors goes down to 16.3%.
– 417 have missing scientific field.

more than one professor or researcher in five has been involved in a patent. The lowest rate is in universe science with a 13.2% participation rate and this can be explained by the very fundamental nature of research in that field.

Gender A gender gap in academic patenting has been evidenced in several papers (Whittington and Smith-Doerr, 2005; Ding, Murray and Stuart, 2006; Frietsch et al., 2009). Our data show that 16% of the nearly twelve thousand women in our dataset (again excluding human and social sciences) are patenting, which is 64% of the rate for men. Universe sciences is the most gender biased field with a rate of 40%, whereas chemistry and mathematics (respective rates of 70% and 77%) are best at closing the apparent gender gap. This gender gap is smaller than in Whittington and Smith-Doerr (2005) who reported patenting among women scientists as representing about 40% of that for men in a random sample of four thousand life faculty members.

Concentration We now consider the distribution of academic invention over the population of professors and researchers and its trends over the period. There were $8,863$ academic inventors in our database, defined as those researchers who invented at least one patent over the period under study. Considering the professors and research who were active in each sub-period, we found that 3.9% of them were inventors in the 1995-1999 period, 7.9%

in 2000-2006 and 10% in 2007-2012. This means that patenting was adopted increasingly widely within our population. However, the most prolific inventors tended to maintain or even increase their role: the top 10% most prolific inventors invented 24, 28 and 30% of academic patents in the three periods respectively. The top 5% invented 14, 17 and 19% of academic patents in the three periods. At the same time, the 4 most prolific inventors among them represented a decreasing share over time: 1.11%, 0.56% and 0.67% respectively.[8] This means that although invention behavior tends to be spreading in academia, there are more and more prolific inventors and their role does not seem to be decreasing, but might even be slightly increasing.

4 The trend in propensity to invent in academia

In this section, we aim to appreciate how the probability of inventing varied among professors and researchers over the period. A simple representation of the number of academic patents invented over time may be misleading, as in fact the underlying population of professors and researchers that we consider is likely to be increasing over the period.[9]

4.1 The spread within academia

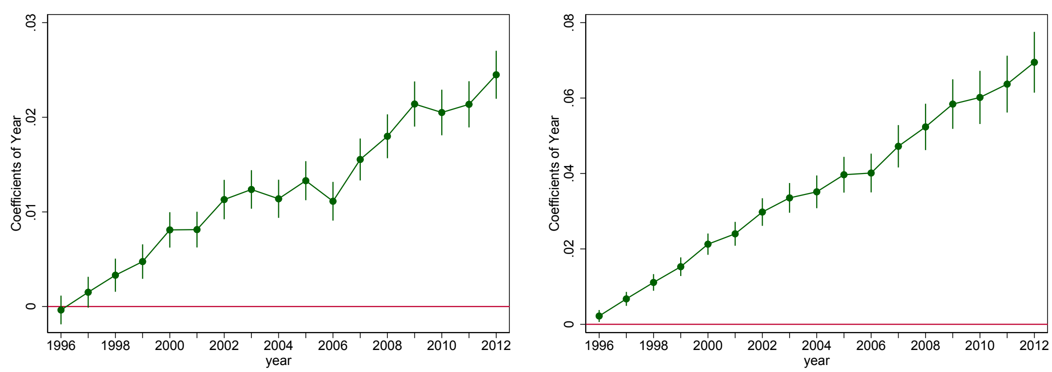
We created an unbalanced panel dataset using the repeated surveys presented above. The entry date in each lab was known in each survey. When someone was surveyed several times, any variation in the data (a promotion for instance) was assumed to occur right in the middle between the two observations. The first entry date naturally determined entry in the panel. When a lab was surveyed several times and a staff member was not listed anymore there and not listed anywhere else, we assumed that they had exited two years after the last observation. Otherwise we assumed the individual was active until the last year considered.

To control simultaneously for all time-invariant confounding factors (such as individual abilities or characteristics), we ran fixed effects regressions on the yearly number of inventions.

[8] This corresponds to the C4 indicator. Similarly, the HHI was 6.61 for 1995-1999, 3.29 for 2000-2006 and 2.89 for 2007-2012.

[9] Figure A2 in the Appendix shows that the number of professors and researchers is increasing over time, meaning that the variation in the propensity to invent is difficult to appreciate just by computing yearly per capita ratios.

Figure 1: How the propensity to invent of academic staff varies over the period 1995-2012.



Note: The graphs present estimated coefficients of the year dummy mentioned in the horizontal axis (the α_t in Equation (6)). In the left graph, the individual scientists fixed effects (the θ_i) are not included whereas they are included in the regressions leading to the right panel. Standard errors are clustered at the individual level.

The model was of the form:

$$y_{it} = \sum_t \alpha_t \,\mathrm{Year}_t + \phi X_{it} + \theta_i + \varepsilon_{it}, \tag{6}$$

where y_{it} is the outcome variable (number of EPO patent applications), Year_t is a year dummy, and θ_i is the individual fixed effect. X_{it} stands for a vector of control variables, such as professional status, university, age and age squared. We were interested in estimating the coefficients of the year fixed effects for each year t. A positive trend in the estimated α_t would indicate an increasing propensity to patent over the years.

Figure 1 displays the estimated α_t coefficients in Equation (6) obtained via OLS, allowing for many fixed effects and the clustering of standard errors. The left panel was obtained when we did not use individual fixed effects, whereas the second includes them. We see that coefficients rose significantly over the period. In 2012, academic professors and researchers invented an average of 0.02 to 0.065 patents more than in 1995. As the average number of patents per capita in 1995 was 0.02, this means they actually increased their productivity by a factor 2 to 4 over the period, depending on the chosen specification.

4.2 Comparison with non-academic inventors

The propensity to invent among academic scientists may be affected by yearly shocks affecting the economy. It could also be affected by changes, with the productivity of all inventors (not just academic ones) increasing under the effects of improvements in communication technology or instrumentation, for instance. We thus needed a reference point outside academia to compare the variation of the propensity to invent of academic profiles with respect to the variation observed for non-academic profiles.

We thus created a panel table of all French inventors from PATSTAT. The only individual identifier available in PATSTAT is "PSNID" (Magerman et al., 2009). This identifier is far from perfect but its flaws are not likely to alter the results qualitatively. The initial merge of inventor names with academic profiles presented above (see Subsection 2.3) was used to identify potential "academic" PSNIDs. A PSNID inventor profile was academic if at least one of its patents had been validated as academic and thus attached to an academic profile in our dataset of professors and researchers. Otherwise it was not academic. This clearly shows that the academic character of PSNIDs is dependent on the parametrization of the filtering stage (the choice of the β). All inventors were assumed to be in the dataset from year 1995 to 2012 so that we had a balanced panel dataset. Making the alternative assumption according to which inventors entered the dataset in the year of their first patent and left the year after their last invention does not change the results qualitatively either.

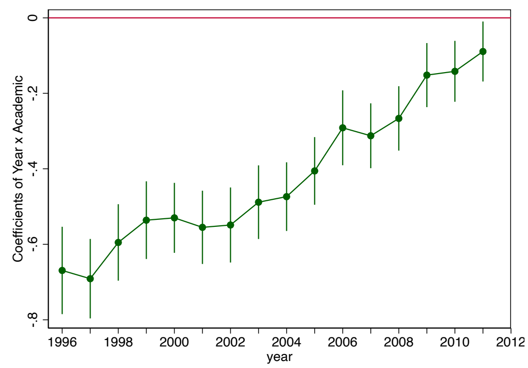
To control simultaneously for all time-invariant confounding factors (such as individual abilities or characteristics), we ran fixed effects regressions on the yearly number of inventions. The model was of the form:

$$y_{it} = \alpha \mathrm{Year}_t + \sum_t \gamma_t \, \mathrm{Academic}_i \times \mathrm{Year}_t + \theta_i + \varepsilon_{it}, \tag{7}$$

where y_{it} is the outcome variable (number of EPO patent applications), Year_t is a year dummy, and $\mathrm{Academic}_i$ is a dummy equal to one if the inventor profile is academic. The $\mathrm{Academic}_i$ variable was not introduced directly into the regression as its effect was fully captured via the individual fixed effect θ_i. The main goal of this model was to estimate the coefficient of the interaction term between the academic profile dummy and the time fixed effect, γ_t, for each year t. A positive trend observed on the γ_t would indicate that academic inventors increased their propensity to patent over the period at a higher rate than non-academic ones (or decreased at a lower rate).

Figure 2 displays the estimated γ_t coefficients in Equation (7) obtained via OLS, allowing us to control for many fixed effects. Profiles are declared here as academic using parameter $\beta = 2$ in the filtering stage, but again, using any of the other two values of β (1 and 0.5) leads to similar results. We can see in the figure that the estimated coefficients of the interaction terms between the year dummies and the academic profile dummy increase over the years. All

Figure 2: How the propensity to invent of academic inventors is affected relative to non-academic inventors over the period 1995-2012.



Note: The graph presents estimated coefficients and confidence intervals of the interaction term between the year dummy mentioned in the horizontal axis and the academic profile dummy (the γ_t in Equation (7)). Standard errors are clustered at the individual level.

coefficients are negative but tend to zero at the end of the period, suggesting that academic inventors were progressively closing the gap with non-academic inventors.

5 Factors in the spread of academic patenting

We have seen that patenting behavior increased over the period in the academic community. We now aim to unveil the drivers of that spread at the micro level. We subsequently considered two series of factors: individual attributes on the one hand, and social and cultural influence on the other hand.

5.1 Individual factors

The spread of patenting was first considered according to individual characteristics. Our main interest at this stage was to disentangle age from cohort factors in patenting, but we also considered other dimensions, such as professional status or gender. We estimated the following model:

$$y_{it} = \alpha_1 \text{Age}_{it} + \alpha_2 \text{Age}_{it}^2 + \alpha_3 \text{Cohort}_i + \alpha_4 \text{Status}_{it} + \alpha_5 \text{Gender}_i + \gamma X_{it} + \varepsilon_{it}. \quad (8)$$

Individual fixed effects were not introduced, so that time-invariant factors of academic patenting could be considered. However, controls (vector X_{it}) such as discipline, year and university dummies were introduced to account for a number of other dimensions affecting patenting behavior, which may be correlated with the explaining variables of interest. We defined four age cohorts: born before 1950, in the 50's, in the 60's, and in the 70's and later. There were four professional statuses: associate professor, (full) professor, associate researcher, or (full) researcher.

Table 4 summarizes the regression results, again using linear regressions with many levels of fixed effects. We found that age always played positively on patenting. When age was not included among regressors (column 1), the second and third cohort dummies were positively correlated with the outcome variable, whereas the most recent cohort dummy had a negative and significant coefficient. However, when age was controlled for, cohort dummies were not significantly correlated with patenting anymore. This contrasts with Thursby and Thursby (2003) who found that newer cohorts were in fact less likely to disclose inventions, controlling for tenure and age. Professional status makes significant differences. Full professors invented almost twice as many patents per year as associate professors (the reference), junior researchers 67% more, and full researchers invented more than three times more often. Lastly, gender was also an important driver of patenting as women invented 50% fewer patents for equivalent years, ages, disciplines, cohorts, universities and statuses.

5.2 Peer effects

None of the individual factors examined above can explain the growing patenting behavior in the French academic community. The fact that the population under study is aging over the years plays in this direction, but age is already controlled for in Equation (6) and thus cannot explain the phenomenon. The literature on academic patenting has emphasized the role of the local culture within the university site and peer effects in embracing a research style that considers innovation and entrepreneurial attitudes (Grimaldi et al., 2011). The entrepreneurial culture in some university campuses (such as MIT, Stanford or the University of Wisconsin at Madison) is often highlighted as critical. The literature also suggests that besides the campus atmosphere, professors influence each other in their immediate work environment. Based on a survey of US life science faculty, Louis et al. (1989) first highlighted the importance of "local group norms" in predicting active involvement in commercialization. Krabel and Schacht (2014) highlighted the influence of Max Plank research institute leaders in disclosing inventions. Considering peer effects in faculty engagement in technology transfer

Table 4: The individual factors of academic patenting.

	(1)	(2)	(3)	(4)	(5)
Age		0.003***	0.003***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)	(0.000)
Age squared		-0.000***	-0.000***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
Cohort 2	0.003***		-0.000		-0.002
	(0.001)		(0.002)		(0.002)
Cohort 3	0.002**		-0.001		-0.001
	(0.001)		(0.002)		(0.002)
Cohort 4	-0.004***		-0.003		-0.003
	(0.001)		(0.003)		(0.003)
Professor				0.011***	0.011***
				(0.001)	(0.001)
Associate Researcher				0.008***	0.008***
				(0.001)	(0.001)
Researcher				0.028***	0.028***
				(0.002)	(0.002)
Female	-0.014***	-0.014***	-0.014***	-0.013***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	827031	822032	822032	820068	820068

Notes: Standard errors into parentheses are clustered at the individual level. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

activities, Bercovitz and Feldman (2008) showed that faculty members of two US medical schools were more likely to disclose inventions when their peers did so in the previous year.

We thus created two variables to capture the influence of these two layers of local social influence: variable UnivExp is the average number of patents per capita in the research community (the university site) in the previous three years ($[t-3;t-1]$), excluding all members of the focal person's lab. It proxies for the university culture towards academic entrepreneurship and patenting. The second variable LabExp is the same per capita average but considering the members of the lab only, excluding the focal person. This variable proxies for the peer effects in the immediate work environment.

We relied upon fixed effects regressions of the form:

$$y_{it} = \alpha \text{UnivExp}_{it} + \beta \text{LabExp}_{it} + \gamma X_{it} + \theta_i + \varepsilon_{it}, \tag{9}$$

where X_{it} stands for a series of time-varying controls, such as age, age squared, professional status and research site (the university). In these regressions, controls could also include the number of colleagues in the lab (LabSize) and the number of colleagues in the university excluding those also in the lab (UnivSize).

Table 5 presents the results. Note that, as previous years were used to calculate some explaining variables, observations from the first three years (1995-1997) were not considered. We found that although both variables were positively related to academic patenting, only LabExp coefficients were significant. When lab peers each produced one more patent per year on average in the previous years, the average faculty member invented 4 times more patents.[10]

This supports the idea that academic patenting behavior is likely to increase in laboratories where such behavior has been pervasive recently. It underlines that academic patenting likely spreads locally thanks to local "peer effects". The coefficients of the control variables are also interesting in themselves, as it appears that both lab and university size play positively on academic patenting.

Table 5: The social factors of academic patenting.

	(1)	(2)	(3)	(4)	(5)	(6)
UnivExp	0.037		0.034	0.027		0.025
	(0.033)		(0.032)	(0.033)		(0.033)
LabExp		0.066***	0.066***		0.064***	0.065***
		(0.017)	(0.017)		(0.017)	(0.017)
UnivSize				0.000**	0.000**	0.000**
				(0.000)	(0.000)	(0.000)
LabSize				0.000**	0.000**	0.000*
				(0.000)	(0.000)	(0.000)
Observations	667552	670805	666784	667552	670805	666784

Notes: Standard errors into parentheses are clustered at the individual level. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

[10]As professors and researchers invented 0.021 patents per year on average, a coefficient of 0.065 means that productivity was increased by a factor of 4.1.

6 Conclusion

In this article we developed a methodology to appreciate the importance of, and trends in, academic patenting in France over nearly two decades. This methodology improves on existing ones as it avoids time-consuming human checking and proves reliable when trained on a benchmark set of only a few thousand professor-inventor pairs. The method is thus tractable to document patenting behavior in large datasets of academic staff and over sufficiently long periods.

We estimated that, among the 560,000 patents filed at the EPO, USPTO and INPI and in- vented in France over the years 1995-2012, more than 55,000 stemmed from academia. The involvement of professors in technology transfer was found to be considerable, with one professor or researcher out of five having invented at least one patent, and widespread across all disciplines (social sciences and humanities being excluded).

The main result of this paper is that local peer effects, rather than individual factors, drove the observed spread of academic patenting over the period studied. Professors' patenting productivity increased significantly when there was previous patenting behavior among colleagues in their lab. This suggests that policies supporting local transitions via peer effects and role models may actually be significantly more efficient in fostering technology transfer than university policies or national reforms.

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Appendix

Figure A1: Precision, recall et F_β (when $\beta = 0.5$, $\beta = 1$ or $\beta = 2$) for different threshold probability values.

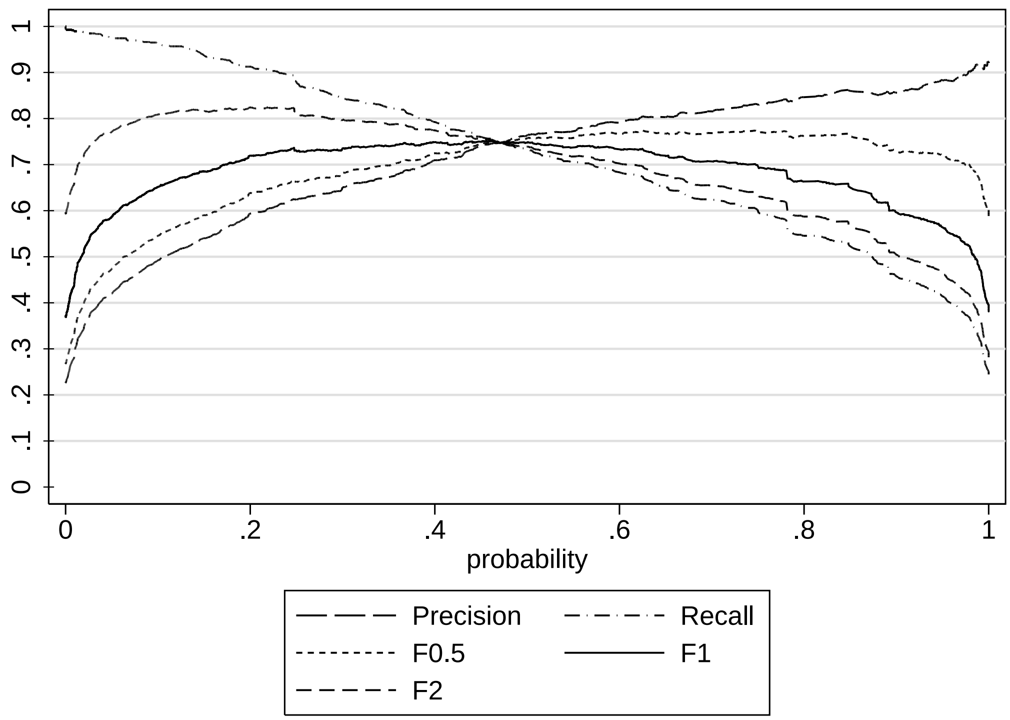
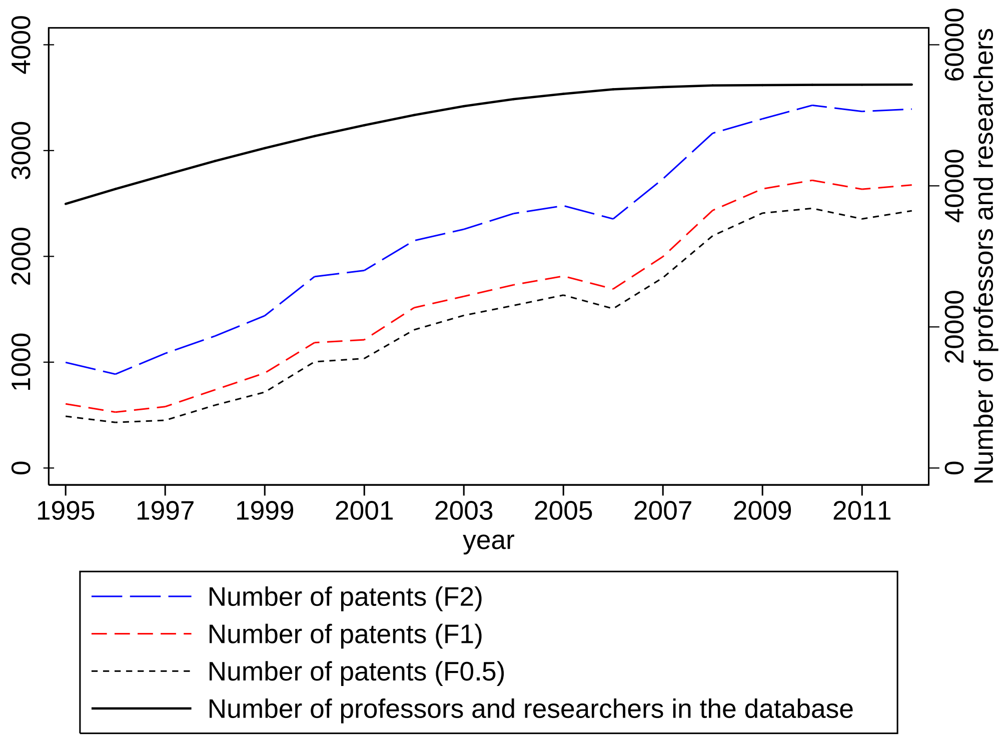


Figure A2: The evolution of academic patenting in France, with respect to the reference population.



Notes:
- This graph displays fractional counts for academic patents.
- The left scale is the number of patents and the right scale the number of professors and researchers in our database.
- The number of patents are computed for each threshold : F1 (respectively F05 and F2) relates to $\beta = 1$ (respectively $\beta = 0.5$ and $\beta = 2$).

Table A1: Logistic regressions on the benchmark, per office

	(1) EPO	(2) EPO	(3) INPI	(4) USPTO	(5) USPTO	(6) USPTO	(7) USPTO
Name similarity	22.427***	21.834***	12.740***	38.788*	38.097***	39.108***	38.022***
	[3.635]	[3.117]	[2.002]	[12.402]	[12.215]	[12.359]	[7.996]
Inventor's name frequency	1.234***	1.239***	0.645***	1.652**	1.680***	1.684***	1.709***
	[0.165]	[0.169]	[0.055]	[0.403]	[0.441]	[0.375]	[0.269]
Assignee/employer consistency	6.244***	6.231***	1.273***				
	[0.675]	[0.662]	[0.455]				
Tech/discipline consistency	0.566**	0.591***	0.425***	0.644	0.720		
	[0.193]	[0.202]	[0.087]	[0.949]	[0.760]		
Age/year consistency	0.666		1.245***	-2.571		-2.646	
	[0.554]		[0.244]	[2.231]		[2.324]	
Constant	-32.188***	-29.189***	-21.841***	-38.773*	-47.578***	-38.619**	-47.231***
	[5.046]	[3.618]	[2.392]	[13.280]	[14.098]	[11.614]	[8.841]
Observations	682	682	2829	115	115	115	115

Notes:
- Bootstrap standard errors into brackets.
- Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table A2: Optimal thresholds for each office and β values $(0.5, 1, 2)$

Patent office	β	Optimal threshold	Precision	Recall	F-measure	Number of validated patents
EPO	2	0.14	0.53	0.95	0.82	20,648
	1	0.44	0.84	0.81	0.82	12,166
	0.5	0.46	0.88	0.80	0.86	11,995
INPI	2	0.20	0.52	0.93	0.80	20,202
	1	0.45	0.66	0.82	0.73	12,620
	0.5	0.74	0.77	0.62	0.74	7,898
USPTO	2	0.24	0.56	1	0.81	7,212
	1	0.24	0.56	1	0.63	7,212
	0.5	0.24	0.56	1	0.51	7,212

Notes:
- Interpretation: For patents filed at the EPO and the when precision is valued the most (thus $\beta = 0.5$), the maximum F-measure is 0.86 for a threshold probability set at 0.46. In the dataset, 11,995 patents have a probability higher than or equal to 0.46 and are thus validated as academic patents.
- In the benchmark, the distribution of professor-patent pairs among offices is unbalanced: 31 for the USPTO, 249 for the EPO and 970 for the INPI. This explains the underperformance of the filtering for UPSTO patents.

Table A3: Expected number of academic patents for several β values (from 1995 to 2012)

Patent office	$\hat{x}_2$		$\hat{x}_1$		$\hat{x}_{0.5}$		All French-invented patents
EPO	11072	(6.1%)	12320	(6.9%)	12325	(7%)	177286
INPI	11173	(4.5%)	10804	(4.3%)	10473	(4.1%)	250605
USPTO	3379	(2.5%)	3379	(2.5%)	3379	(2.5%)	134315
Total	25624	(4.5%)	26502	(4.6%)	26177	(4.6%)	562206

Notes:
– This table displays fractional counts: if several of its inventors are identified as academic, the patent is counted only once.
– The share of academic patents - by office and overall - over all patents invented in France are right-placed in parentheses.
– The share of academic patents filed at the USPTO is smaller than the ones in INPI and EPO because our benchmark is made of fewer patents filed at the USPTO, hence reducing the performance of the filtering algorithm on this specific subset.

Table A4: RTA and CAGRs for patents in 35 technology classes (1995-2012)

Technology class	RTA	CAGR	Growth ratio	Share
Micro-structural and nano-technology	5.55	-1.3%	6.0	0.1%
IT methods for management	0.42	-1.7%	3.8	0.3%
Digital communication	0.54	0.1%	2.2	2%
Semiconductors	2.84	4.4%	2.0	1.1%
Engines, pumps, turbines	0.83	-3.0%	1.8	4.1%
Computer technology	0.88	1.8%	1.8	2.9%
Analysis of biological materials	3.50	2.8%	1.8	0.4%
Transport	0.35	-2.2%	1.6	4.8%
Measurement	2.04	-0.4%	1.3	2.5%
Thermal processes and apparatus	0.75	1.8%	1.3	0.8%
Surface technology, coating	1.69	1.0%	1.2	1.5%
Environmental technology	1.47	-1.0%	1.2	5.3%
Electrical machinery, apparatus, energy	0.99	1.6%	1.1	6.1%
Food chemistry	0.78	-3.7%	1.1	1.1%
Civil engineering	0.48	-4.1%	1.0	2.2%
Other consumer goods	0.33	0.6%	1.0	7.1%
Telecommunications	0.85	1.0%	0.9	3.1%
Control	0.67	0.6%	0.9	0.9%
Medical technology	0.92	2.5%	0.9	4.5%
Audio-visual technology	0.80	-1.5%	0.9	2.8%
Machine tools	0.67	-2.4%	0.9	2.2%
Other special machines	0.58	-1.2%	0.8	7.7%
Handling	0.39	-0.9%	0.8	1.9%
Biotechnology	3.25	-0.3%	0.7	1.5%
Mechanical elements	0.43	-2.4%	0.7	4.2%
Pharmaceuticals	1.61	1.3%	0.7	2.6%
Furniture, games	0.24	3.3%	0.7	1.4%
Materials, metallurgy	1.45	0.9%	0.7	2.1%
Basic materials chemistry	1.56	-0.8%	0.7	2.3%
Macromolecular chemistry, polymers	1.06	1.4%	0.7	1.1%
Basic communication processes	1.35	5.0%	0.6	0.6%
Chemical engineering	1.76	-0.8%	0.5	7.3%
Optics	1.65	1.5%	0.5	2.1%
Organic fine chemistry	0.85	1.7%	0.4	6.6%
Textile and paper machines	0.45	0.9%	0.0	2.8%
Total	1	0%	1	100%

Notes:
- For a technology class i, the revealed technological advantage is RTA= $\frac{A_i}{B_i} \times \frac{\sum_i B_i}{\sum_i A_i}$. Column one displays its average value over the years 1995-2012.
- For column two, we first calculate the RTA of each technological class every year, then we display its Compound Annual Growth Rate between 1995 and 2012.
- We calculate the CAGR of French patents overall ($nCAGR$) and the CAGR of those patents in a technology class i ($nCAGR_i$). Thus, in column three we have the growth ratio = $\frac{nCAGR_i}{nCAGR}$.
- For the fourth and last column, share = $\frac{\#patents_i}{\#patents}$ where $\#patents_i$ is the number of French patents in technological class i, and $\#patents$ the total number of French patents.
- Each patent is counted once in each of its technology class (full counting).

Table A5: Repartition of professors and researchers involved in academic patenting by scientific discipline (1995 – 2012), for a chosen $\beta = 0.5$ at the filtering stage.

Scientific field	professors-inventors		All professors
Chemistry	2,327	(32.8%)	7,093
Applied Bio. Ecology	1,924	(22.7%)	8,469
Fundamental Biology	2,992	(23.7%)	12,639
Medicine	2,892	(25.3%)	11,409
Engineering Sciences	2,626	(24.2%)	10,862
Mathematics	1,545	(21.2%)	7,295
Physics	2,039	(24.5%)	8,309
Universe Science	420	(12.4%)	3,383
Total	7,503	(21.8%)	34,439

Notes:
– 17,347 professors and researchers in Human and Social Sciences are not represented in this table. 670 of them have invented at least one patent over the period (3.9%). If these HSS inventors are included in the full sample (51,786 researchers), the global share of academic inventors goes down to 15.8%.

Table A6: Repartition of professors and researchers involved in academic patenting by scientific discipline (1995 – 2012), for a chosen $\beta = 2$ at the filtering stage.

Scientific field	professors-inventors		All professors
Chemistry	2,500	(35.2%)	7,093
Applied Bio. Ecology	2,121	(25%)	8,469
Fundamental Biology	3,299	(26.1%)	12,639
Medicine	3,174	(27.8%)	11,409
Engineering Sciences	2,923	(26.9%)	10,862
Mathematics	1,742	(23.9%)	7,295
Physics	2,282	(27.5%)	8,309
Universe Science	538	(15.9%)	3,383
Total	8,441	(24.5%)	34,439

Notes:
– 17,347 professors and researchers in Human and Social Sciences are not represented in this table. 1,086 of them have invented at least one patent over the period (6.3%). If these HSS inventors are included in the full sample (51,786 researchers), the global share of academic inventors goes down to 18.4%.