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## Two decades of academic invention in France : scope and driving forces

Elodie Carpentier

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Par Elodie CARPENTIER

**TWO DECADES OF ACADEMIC INVENTION IN  
FRANCE: SCOPE AND DRIVING FORCES**

Sous la direction de  
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Soutenue le 29 mars 2022

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## ABSTRACT IN ENGLISH

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Since Bush, (1945), governments of advanced economies have become aware of the importance of science for technical progress and economic growth. However, it is only very recently that researchers start being able to quantify the knowledge flows between academia and the private sector. In this thesis, I first measure the direct contribution of academics to invention, and then I go further by evaluating the impact of different public policies on academics' incentives to invent. All the chapters are based on the French case, for which we have collected quasi-exhaustive data on the population of academics and their inventions over around twenty years.

In the first chapter, I quantify academic invention in France and explore its individual and social drivers. I find that more than 11% of the patented inventions for the years 1995–2012 stem from academia, revising upwards prior estimations. Every year increase not only the number of academic inventions, but also the propensity of professors to invent (by 75% between 1995 and 2012). Given that the drivers of this diffusion remain unclear, I study the contribution of micro and meso level characteristics. I explore age and cohort effects: are young people trained in a more entrepreneurial culture more likely to invent, or less likely than older ones for their focus on advancing their career first? I find support for the latter, that is a life-cycle effect rather than a cohort effect. But invention is also a social phenomenon, so I wonder whether being surrounded by fellow inventors (in the lab or in the university) affects one's own propensity to invent. My results indicate that a professor patents four times more inventions when colleagues in the lab invent one more patent per year on average.

In the second chapter, I evaluate the impact of the university ownership regime on academic invention. This regime has been introduced in many advanced economies following the US pioneering Bayh-Dole Act. It consists in assigning intellectual property rights over academic inventions to universities, rather than to professors, companies or federal agencies, with the aim of encouraging academic invention and its transfer to society. France introduced its Innovation and Research Act in 1999. How does the effective implementation of the university ownership regime affect professors' incentives to invent? I find that only some universities effectively implement the corresponding policy recommendations, and at different times. I use a Coarsened Exact Matching on universities followed by a difference-in-differences regression to

compare academics in universities that took the step and increasingly managed their intellectual property to other similar academics in universities that have not taken the step. I find that, upon the implementation of the regime in their university, professors patent up to 20% more inventions. I conclude that it is efficient to allocate the intellectual property rights to universities, and suggest that negative effects observed in other countries may result from a lack of flexibility towards universities in the practical implementation of the regime.

In the third chapter, I assess the impact of competitive science funding on academic invention. The French government introduced competitive funding for scientific research in 2005. A national research agency was created to support the production of higher quality fundamental knowledge. I merge to our previous database on professors and patents the data on the projects they submitted in 2005-2009 and the funding decisions of the selection committees. In a Heckman probit regression, I find that academics with experience or who have contributed to innovation have a higher propensity to apply but are less likely to be selected by the agency. I show that the former effect dominates the latter, as several hundred researchers have applied for and received funding because of the particular characteristics shared by academic inventors and researchers whose research is cited in patents. But once I match researchers on the characteristics that affect their chances of applying and being selected and estimate the impact of receiving a grant in a difference-in-difference regression, I find no significant impact of research grants on academic invention. This means that the positive correlation between public funding and academic invention initially observed is entirely due to selection effects.

## RÉSUMÉ EN FRANÇAIS

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Depuis Bush, (1945), les gouvernements des économies avancées ont pris conscience de l'importance de la science pour le progrès technique et la croissance économique. Cependant, ce n'est que très récemment que les chercheurs ont commencé à pouvoir quantifier les flux de connaissances entre le monde universitaire et le secteur privé. Dans cette thèse, je mesure d'abord la contribution directe des universitaires à l'invention, puis je vais plus loin en évaluant l'impact de différentes politiques publiques sur les incitations des universitaires à inventer. Tous les chapitres sont basés sur le cas français, pour lequel nous avons collecté des données quasi-exhaustives sur la population des universitaires et leurs inventions sur une vingtaine d'années.

Dans le premier chapitre, je quantifie l'invention académique en France et j'explore ses facteurs individuels et sociaux. Je trouve que plus de 11% des inventions brevetées pour les années 1995-2012 proviennent du milieu universitaire, révisant à la hausse les estimations précédentes. Chaque année, non seulement le nombre d'inventions académiques augmente, mais aussi la propension des professeurs à inventer (de 75% entre 1995 et 2012). Étant donné que les déterminants de cette diffusion restent peu clairs, j'étudie la contribution des caractéristiques aux niveaux micro et méso. J'explore les effets de l'âge et de la cohorte : les jeunes formés dans une culture plus entrepreneuriale sont-ils plus enclins à inventer, ou moins enclins que leurs aînés en raison de la priorité qu'ils accordent à l'avancement de leur carrière ? Je trouve des arguments en faveur de cette dernière hypothèse, c'est-à-dire un effet de cycle de vie plutôt qu'un effet de cohorte. Mais l'invention est aussi un phénomène social, et je me demande donc si le fait d'être entouré de collègues inventeurs (dans le laboratoire ou à l'université) a une incidence sur la propension à inventer. Mes résultats indiquent qu'un professeur dépose quatre fois plus d'inventions lorsque ses collègues du laboratoire déposent un brevet de plus par an en moyenne.

Dans le deuxième chapitre, j'évalue l'impact de l'implémentation du régime de propriété universitaire sur l'invention académique. Ce régime a été introduit dans de nombreuses économies avancées à la suite de la loi pionnière américaine Bayh-Dole. Il consiste à attribuer les droits de propriété intellectuelle sur les inventions universitaires aux universités, plutôt qu'aux professeurs, aux entreprises ou aux agences fédérales, dans le but d'encourager l'invention universitaire et son transfert à la so-

ciété. La France a introduit sa loi sur l'innovation et la recherche en 1999. Comment le régime de propriété universitaire affecte-t-il les incitations des professeurs à inventer ? Je constate que seules certaines universités mettent effectivement en œuvre les recommandations politiques correspondantes, et ce à des moments différents. J'apparie les universités qui franchissent le pas et gèrent de plus en plus activement leur propriété intellectuelle à d'autres universités qui n'ont pas franchi le pas et j'effectue une régression de différence de différences sur les inventions que leurs professeurs font breveter et transfèrent par la suite. Je constate qu'après la mise en œuvre du régime dans leur université, les professeurs font breveter jusqu'à 20% d'inventions supplémentaires. Je conclus qu'il est efficace d'attribuer les droits de propriété intellectuelle aux universités, et je suggère que les effets négatifs observés dans d'autres pays peuvent résulter d'un manque de flexibilité envers les universités dans la mise en œuvre pratique du régime.

Dans le troisième chapitre, j'évalue l'impact du financement compétitif de la science sur la contribution des universitaires à l'innovation. Le gouvernement français a introduit le financement compétitif de la recherche scientifique en 2005. Une agence nationale de recherche a été créée pour soutenir la production de connaissances fondamentales de meilleure qualité. Je fusionne à notre base de données précédente sur les professeurs et les brevets les données sur les projets qu'ils ont soumis en 2005-2009 et les décisions de financement des comités de sélection. Dans une régression probit de Heckman, j'observe que les universitaires ayant de l'expérience ou ayant contribué à l'innovation ont une plus grande propension à soumettre une demande mais ont moins de chances d'être sélectionnés par l'agence. Je montre que le premier effet domine le second, puisque plusieurs centaines de chercheurs ont demandé et obtenu un financement grâce aux caractéristiques particulières que partagent les inventeurs académiques et chercheurs dont les recherches sont cités dans les brevets. Mais une fois que j'apparie les chercheurs sur les caractéristiques qui affectent leur chances de candidater et d'être sélectionné et estime l'impact de la réception d'une subvention dans une régression en différence de différences, je ne trouve pas d'impact significatif des subventions de recherche sur l'invention académique. Cela signifie donc que la corrélation positive entre financement public et invention académique initialement observée est entièrement due aux effets de sélection.

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## ACRONYMS

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ANR	Agence Nationale de la Recherche
CAGR	Compound Annual Growth Rate
EPO	European Patent Office
GDP	Gross Domestic Product
HHMI	Howard Hughes Medical Institute
INPI	Institut Nationale de la Propriété Intellectuelle
IP(R)	Intellectual Property (Rights)
IPC	International Patent Classification
ISI	Institute for Scientific Information
NIH	National Institute of Health
NSF	National Science Foundation
OST	Observatoire des Sciences et Techniques
PATSTAT	Patent Statistical Database
PIA	Plan d'Investissements d'Avenir
PRO	Public Research Organization
RTA	Revealed Technological Advantage
SAIC	Service des Activités Industrielles et Commerciales
SATT	Société d'Accélération du Transfert de Technologies
TTO	Technology Transfer Office
USPTO	United States Patent and Trademark Office





## GENERAL INTRODUCTION

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Innovation is the engine of technical progress and economic growth. It largely relies on the new ideas and knowledge that are produced by science (Jaffe, 1989; Mansfield, 1991; Mowery and Nelson, 1999). Many large U.S. companies have operated their own research laboratories for most of the twentieth century, conducting extensive scientific research that often led to new products and technologies. They were aware that, as much as applied research is important to bring innovations to market, basic research broadens the knowledge base required to make breakthrough scientific advances. As for many other major innovations, scientists have built upon decades of accumulated knowledge in various fields to develop mRNA vaccines, which in addition to saving millions of lives helped advance the reopening of many economies. Yet this idea that science is critical to innovation was not obvious a century ago. Public opinion had (and remain) to be convinced that investing in science is beneficial to all.

The first research laboratories were established in Europe by wealthy professors in their own homes back to the fifteenth or sixteenth century. With time, these eventually migrated into universities, making research the second official mission of academics (Schmidgen, 2021). But until the late nineteenth century, these structures did not yet exist in the United States. American researchers were sent to Europe to be trained in research, and the only basic research undertaken was in private sector laboratories, while universities were entirely devoted to teaching. The outbreak of World War II created many tactical and logistical challenges for the military. The United States invested heavily in science to develop bigger bombs, faster airplanes, better medical treatments, and more precise communications. In light of the technological advances made during this period, Vannevar Bush wrote a now-famous report encouraging the U.S. government to maintain the investment effort in basic research after the war in order to foster economic growth (Bush, 1945).

These recommendations were taken seriously by the American government, which in 1950 established the National Science Foundation. This foundation was responsible for the distribution of public funding for science in all non-medical disciplines, along-

side the already existing National Institutes of Health. It should be noted that the competitive approach to research funding that these agencies implement and which dominates the U.S. research landscape, differs significantly from the approach taken by other advanced countries. Indeed, most European countries, as well as some Asian ones, predominantly distribute block funding to universities, rather than grants to individual researchers or projects.

Whether in universities, research centers, or companies, the scientific pursuit results in discoveries that sometimes have commercial potential. But while in the private sector the profit motive naturally leads companies to patent and commercialize their inventions, universities rather operate under the Mertonian norms of communism (free sharing of knowledge) and disinterestedness (Merton, 1942).

When the first inventions arose in academia at the very beginning of the twentieth century, it was not clear whether universities and academics should engage into commercial activities, and there were no legal provision as to which entity could and should claim ownership of these inventions. The federal government decided to take on this responsibility in the 1920s. The primary intention was to avoid unrest between universities when great licensing revenues accrue to one institution which retained intellectual property rights (IPR) while other decided not to commercialize. It was also in the spirit of optimization and fair redistribution of revenues from licenses across universities (Etzkowitz, 1994). But in the 1970s it became apparent that the federal government was in fact distributing very few licenses (less than 5%) and that potentially many inventions were underused. On the contrary, some universities were very willing to take on this duty, which at the end of a long institutionalization process led them to gain ownership over academic inventions with the passage of the U.S. Bayh-Dole Act in 1980 (Popp Berman, 2008).

The transfer of scientific advances to the private sector is precisely Europe's self-perceived weakness. In a 1995 Green paper, the conjecture that EU countries are world leaders in generating high-quality scientific output, but lag behind in the ability to convert this strength into marketable innovations was called the "European Paradox" (European Commission, 1995). Subsequent work has questioned the empirical validity and alleged causes of this paradox (Dosi, Llerena, and Labini, 2006). In fact, academic technology transfer is a difficult phenomenon to measure, because the data collection related to this transfer (patents, licensing agreements, spin-offs) is often non-standardized, operated by each institution involved in a one-sided manner rather than centralized at the national or supra-national level, and above all, the confiden-

tiality of the data often limits access to it, even for research purposes. Yet there is a prolific body of research on the subject, and over time these difficulties are being overcome.

Recent work has managed to systematically measure the indirect contribution of researchers to innovation, through the citation links between scientific articles and patents (Ahmadpoor and Jones, 2017; Marx and Fuegi, 2020; Poege et al., 2019). For instance, Ahmadpoor and Jones, (2017) show that in the U.S. 80 percent of scientific papers are used directly or indirectly to develop an innovation, while 61 percent of patented innovations are based on a previously published scientific discovery. On the other hand, some work has attempted to estimate the level of academics' direct contribution to innovation, via academic patents. In the KEINS research project, Lissoni et al., (2008) collect samples of academic patents in France, Italy and Sweden, and re-estimate upwards the level of technology transfer in these countries. However, to the best of my knowledge, there is no work that exhaustively measures academic patenting, at least on the scale of a large European country. The empirical validity of the European paradox therefore remains to be verified or refuted.

Since the first warning signs at the end of the twentieth century, European governments have initiated a series of legislative changes affecting the organization and funding of academic research and that converges towards the American model. These reforms aim at legitimizing university-industry interactions and the commercialization of science, and at fostering the interest and involvement of researchers and universities in commercial issues. The ultimate goal is to improve the return on investment in science and to foster technology transfer.

*Did these reforms have the intended effect on academic invention and technology transfer?* The first observation is that some European countries indeed recorded a positive trend in academic patenting since the beginning of the 21st century (Lissoni et al., 2008).

The cohort the professor belongs to reflects instead the norms regarding commercialization that prevailed during the researcher's training (Azoulay, Ding, and Stuart, 2007; Thursby and Thursby, 2007). Both factors showed some correlation with academic patenting, but it has been difficult to conclude with regard to their effect because of their mutual entanglement.

Another set of factors relates to peer effects and local norms. The entrepreneurial culture in some university campuses (e.g. MIT or Stanford) was highlighted as critical

to commercial engagement (Grimaldi et al., 2011; Tartari, Perkmann, and Salter, 2014), as well as the influence that professors have on each other in their immediate work environment (Bercovitz and Feldman, 2008; Krabel and Schacht, 2014; Louis et al., 1989). This branch of the literature does not address academic patenting specifically, but rather commercialization activities as a whole, and rely on very small and particular samples.

At the macro level, the growth in the number of U.S. academic patents in the late twentieth century was first attributed to the Bayh-Dole Act (Mowery et al., 2001). The subsequent end of the professor's privilege in some European countries, which also consisted in the assignment of academic patent ownership to universities, had more of a negative effect on the propensity of academics to patent, at least immediately after the passage of the reform (Ejermo and Toivanen, 2018; Hvide and Jones, 2018). It is therefore unclear whether giving ownership of academic patents to universities promotes academic invention.

Rather than the Bayh-Dole Act, Mowery et al., (2001) suggest that the growth in federal financial support for basic biomedical research and the increased patentability in this field better explain the positive trend in academic patenting. The only studies that have established a causal link between public funding and academic invention are Payne and Siow, (2003) and Tabakovic and Wollmann, (2019), who focused on the U.S. case at the university level, and examined federal or university funding. It remains to be seen whether this causal link persists in other countries, at a more meso or micro scale, and when funds are distributed in different ways.

### *Thesis purpose and outline*

In this thesis, I contribute to these different branches of the literature by investigating the extent of academic invention in France and its determinants at different levels. More specifically, I address the following research questions: Are there peer effects in academic patenting, and at what scale do they operate? How does the allocation of patent intellectual property rights to universities affect the involvement of universities and researchers in academic invention and its transfer? Does the allocation of competitive public funding promote academic invention and how?

To answer these questions, I use a large database on the French case covering the two past decades (1995–2016). I first contributed to build an employment database of more than 140,000 professors and researchers that includes the name of the employ-

ing laboratory and university, as well as personal information such as year of birth, gender, academic position and scientific discipline, and use different versions of it according to the chapter. I then use this information to collect patents whose inventor has the same (or similar) name as one of the researchers, and disambiguate the results using machine learning techniques that rely on scores for similarity between names, frequency of name, consistency between age and year of patent application, consistency between discipline and technology class, and finally the presence, if any, of the employing university among the patent applicants. In this way, I end up with a highly reliable set of over 44,000 academic patents filed between 1995 and 2012, and following an intermediate update over 77,000 between 1995 and 2016. Finally, I merge this database with another one containing their publications (previously disambiguated) and related indicators such as H-index and citations, as well as funding applications and awards by the French National Research Agency (ANR) between 2005 and 2009. It is thus a large database that provides a wealth of detail allowing to investigate the phenomenon of academic invention in many aspects, at several levels (individual, laboratory, university), while having a remarkable control over potential endogeneity or selection biases.

In the following outline, I describe the precise objective of each chapter, with the methodology employed and the main results.

**CHAPTER 1.** Given that the transfer of technology between science and industry is not well quantified, I develop in the first chapter a methodology to identify academic inventions in France over two decades. It relies on machine learning techniques and by the end of the disambiguation, we find at least 44,759 academic patents over the years 1995–2012 (more when using different filtering parameters).

I then describe extensively the phenomenon and its evolution over time. I show, in particular, that 11% of all patented inventions in France actually stem directly from academia, and up to 9% as of year 1999, thus casting serious doubt on the existence of the European paradox in this country. I further find that as much as 20% of professors and researchers invented at least once, and this engagement level is observed in almost all hard and life sciences fields. Hence, academics are pretty well aware of and involved in the commercialization their scientific discoveries.

Finally, I contribute to prior investigation on the individual and social drivers of academic invention by investigating specifically the existence of life-cycle and cohort effects, as well as local peer effects at the laboratory and university levels. Are young people trained in a more entrepreneurial culture more likely to invent, or less likely

than older ones for their focus on publishing to advance their career first? Using linear regressions with many levels of fixed effects, I find evidence in support of a life-cycle effect whereas cohort effects are insignificant. Since invention is also a social phenomenon, I wonder whether being surrounded by fellow inventors (in the lab or in the university) affects one's own propensity to invent. The results indicate that a professor invents four times more when colleagues in the lab invent one more patent per year on average.

CHAPTER 2. In the second chapter, I study how universities' effective ownership of academic patents affects researchers' incentives to invent. The French Innovation and Research Act introduced in 1999 aimed of incentivizing universities to retain the ownership of their inventions. I develop a methodology that captures whether and when universities make the move toward retaining their patent Intellectual Property Rights. The first observation is that only about half of them eventually made it over the entire period (although this varies with a threshold that we set), with a higher likelihood around years 2008, after some other legislations were introduced, and 2012, coinciding with the regionalization of technology transfer offices.

This great heterogeneity offers an idea setup to perform an original impact evaluation exercise. Since universities and business and engineering schools do not have the same propensity to jump on the bandwagon, we match those that did it with other similar institutions that did not. I then run difference-in-differences regressions on the number of patents their professors and researchers file and find that professors and researchers employed at institutions that have adopted the university ownership regime, have raised their propensity to invent by 20.7% on average.

CHAPTER 3. In the third and final chapter, I explore the relationship between competitive research funding and researchers' contributions to innovation. Here I use both the experience in innovation, proxied by the number of academic patents, and the contribution to innovation, measure by the number of publications that are subsequently cited in patents. In France, a national project-based funding agency was created in 2005, following a similar operating model to the NSF in the United States. The goal of this public policy is to support the production of higher quality basic knowledge. In a first exploratory analysis, we find out that funded applicants file on average more patents than non-funded ones, and these last still file more patents than non-applicants. Are academics with a potential for invention more attracted to grant funding, are they more likely to be selected, and/or is the grant receipt increasing their propensity to contribute to innovation?

First, we use a Heckman probit model to investigate the likelihood of inventors and researchers cited in patents to apply and receive a grant. I find that researchers who contribute to innovation are more attracted to project funding than their respective counterparts. However, controlling for their observable differences, I find that they are significantly less likely to be selected by the agency. The combination of the two effects is still beneficial, as several hundred researchers have applied for and received grants solely thanks to some specific characteristics shared by inventors and researchers cited in patents. It could be for instance a greater ability to identify the potential impacts of a research project, or an entrepreneurial mindset.

Second, I use a matching to restrict the sample to a set of similar candidates that are funded and unfunded. In a set of difference-in-differences regression, I observe that project-based funding does not significantly affect researchers' contribution to innovation overall. This leads me to conclude that the positive correlation previously recorded between the two phenomena is therefore mainly the result of a selection effect.



## THE SPREAD OF ACADEMIC INVENTION: A NATIONWIDE CASE STUDY ON FRENCH DATA (1995-2012)<sup>1</sup>

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### 1.1 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; Jones, 1995; Nelson, 1959; Romer, 1990). 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 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 define academic patents as being those patents invented by professors and researchers employed in universities and research institutes. The nice feature of such a definition is that it is independent of the patent assignee and thus immune to the transfer strategies of the professors and universities. The flip side is that this definition is much more demanding in terms of data collection and data treatments. Rosters of professors and researchers need be collected and matched with patent inventors. The main originality of our approach with respect to previous attempts<sup>2</sup> is that we systematize the matching and filtering procedures on a large scale thanks to machine learning techniques that avoid time-consuming, painstaking checking procedures performed by humans. Our method requires a reliable benchmark though, to ensure that false positives and negatives are 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 apply

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<sup>1</sup> This paper is co-authored with N. Carayol and has been published in the Journal of Technology Transfer (DOI: 10.1007/s10961-021-09888-9. [Access here](#)). Although the dataset of academic patents presented in this chapter has been updated subsequently to include more recent years (2013-2016) and a broader list of individuals, this chapter still uses the first version ending in 2012 that offers details at the laboratory level that are no longer available in the most recent dataset.

<sup>2</sup> e.g. Lissoni et al., (2008), Meyer, (2003), and Thursby, Fuller, and Thursby, (2009).

this method to France, the seventh country in the world in terms of GDP, sixth for scientific articles, and fourth for patents granted in this period of time.

Over the eighteen-year period under scrutiny, academic patents are found to account for more than 11% of all patents invented in the country. This is well above prior estimates and therefore provides a new insight into the real direct contribution of science to technological inventions. As our data provide interesting covariates on professors and researchers extending beyond those who might have a patent, we are able to characterize their involvement in technology transfer. We find 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 field of science. Obviously, faculty members do not operate in some “ivory tower” and are much more directly involved in technological invention than is often assumed.

Is this a recent phenomenon potentially entirely due to increasing incentives to patent and commercialize academic research? We find 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 1999 Innovation Act.<sup>3</sup> 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 find that faculty members’ propensity to invent increased by 75% between 1995 and 2012. To control for a potential trend affecting patenting behavior (improvements in communication technology or instrumentation, for instance), we use non-academic patents as a reference point and show that academic inventors increase 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 consider 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 find that more recent cohorts are not more likely to engage in patenting. Age plays positively on academic patenting at the individual level, a result which 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

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<sup>3</sup> In France, public universities were entitled to retain the intellectual property rights over inventions from publicly funded research since 1984, but it is the 1999 Innovation Act that started providing an institutional design allowing them to commercialize their research outcomes.

than traditional incentives to publish. However, the propensity to patent of professors is shown to increase significantly over time, controlling for age and cohort effects.

To further understand how patenting behavior spreads through the academic community, we explore the influence of local social factors. 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 (Bercovitz and Feldman, 2008; Krabel and Schacht, 2014; Louis et al., 1989). We proxy 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 find that local diffusion within the lab plays 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 2.2 reviews the literature on the extent of academic patenting and its drivers. Section 1.3 exposes data collection and the methodology. Section 1.4 proposes descriptive statistics on academic patenting in France. Section 1.5 assesses how the propensity to invent varied over the period in academia, as compared to non-academic inventor profiles. Section 1.6 discusses the factors explaining the spread of patenting behavior within the academic community. Section 1.7 concludes.

## 1.2 LITERATURE ON ACADEMIC PATENTING

### 1.2.1 *The extent of academic patenting*

At least since 1980, with the passage of the Bayh-Dole Act in the US<sup>4</sup> attracting policy makers' and researchers' attention to this phenomenon, the number of patents invented by professors and researchers has been increasing over time in most advanced economies (Henderson, Jaffe, and Trajtenberg, 1998; Mowery and Ziedonis, 2002).

The early 2000's data on university patenting pointed to an underperformance of UK and European universities as compared to their US counterparts, given the nations'

<sup>4</sup> The Bayh-Dole Act allowed universities to retain the intellectual property rights over inventions stemming from federally funded research.

investment in fundamental research (Geuna and Nesta, 2006). Based on this prior and the belief that the growth in US university patenting was driven by the Bayh-Dole Act, several European countries voted similar reforms (Mowery and Sampat, 2004).

But counting university patents hardly reflects the true contribution of academia to innovation in Europe (Geuna and Nesta, 2006). Considering university-owned patents leads to bias downward the estimations of academic patenting because of cultural, regulatory and managerial differences regarding the attribution of intellectual property rights of professors and researchers employed in universities and public research institutes. Whereas US universities may strongly enforce the ownership of their inventions, their European counterparts often left the rights to their professors (the so-called “professor’s privilege” in German and Nordic countries), or simply did not have the resources to manage it, and thus inventions were owned by the private sector or the individual inventor herself (Lissoni et al., 2008; Thursby, Fuller, and Thursby, 2009). International comparisons become meaningless simply because data are contaminated by the choice of a transfer strategy. Carayol and Sterzi, (2021) even show that promising technologies are likely to be cherry-picked and transferred without the involvement of the university TTO.

In such a context, an appropriate methodology for measuring the contribution of academia to invention is to find and count in those patents invented by professors employed at universities and not assigned to their institution. Following this methodology, in what is probably the most comprehensive national study, Meyer, (2003) found that 8% of all patents invented in Finland the years 1986-2000 stem from academia. Another great advantage of such an approach is that it also allows the analyst to appreciate the engagement of professors and researchers in patenting. In six European countries, Lissoni, (2012) finds that 2 to 5% of professors have filed a patent. This approach is however sensitive to potential underevaluation if the lists are incomplete or if academic patents are difficult to retrieve.

Another approach based on surveys has also been used to appreciate faculty participation in patenting. This literature provides very heterogeneous results, ranging from 2 to 40%. Gulbrandsen and Smeby, (2005) provide a figure of 7% in Norway, considering all scientific fields, including the social sciences and humanities. When focusing on hard and life sciences, Landry et al., (2010) find 22% of academic inventors in Canada, Klofsten and Jones-Evans, (2000) 26% and 12% in Ireland and Sweden, and Walsh and Huang, (2014) 26% and 32% in the US and Japan. For the hard sciences only, D’Este and Perkmann, (2011) find 31% inventors among professors in the UK. Finally, the share goes up to 40% among life scientists in the UK and Germany combined (Haeussler and Colyvas, 2011). Selection bias may explain some of these highest

figures, as inventors may be more likely to answer such surveys about their transfer or commercial activities. Heterogeneity may be explained by field, institutional and national differences.

In this paper, we introduce a methodology (Section 1.3) to build large datasets of academic patenting. We use it to set up a longitudinal dataset covering all scientific fields at a national level. Among other benefits, this allows us to extend the above mentioned lines of investigation in a more systematic way.

### 1.2.2 *The drivers of academic patenting*

Even though the extent of academic engagement was not yet fully appreciated, considerable concern was expressed in the 90's that the move towards commercialization in the university community may be coming at the expense of the production of fundamental knowledge (Dasgupta and David, 1994; Stephan and Levin, 1996). A stream of work investigated the nature of the relationship between patenting and publishing (Azoulay, Ding, and Stuart, 2007; Carayol, 2007; Czarnitzki, Glänzel, and Hussinger, 2007; Stephan et al., 2007), and concluded that both activities are complement rather than substitutes.

Once this concern was essentially dismissed, scholars became interested in the drivers of academic patenting. In the US, the positive trend in academic patenting was first attributed to the Bayh-Dole Act, although Mowery et al., (2001) suggest that the growth in federal financial support for basic biomedical research and the increased patentability in this field may better explain this positive trend than the Act itself. Conversely and on a similar level, Ejeremo and Toivanen, (2018) and Hvide and Jones, (2018) find that the end of the Professor's Privilege had a negative impact on academics' propensity to invent.

At the individual level, the type of research performed, the degree of collaboration with the private sector as well as relevance of intellectual property rights protection varies greatly among scientific fields, making the discipline another important driver to consider (Carayol, 2007; Stephan et al., 2007). Tenure was also found to be relevant in the US context (Azoulay, Ding, and Stuart, 2007; Stephan et al., 2007). The literature also identifies age as a key characteristic in explaining academic productivity. The life-cycle effect indicates that a scientist productivity grows up to a certain (biological) age before decreasing towards the end of the career. It is usually observed in scientists' publishing patterns, but also in their patenting activity. Carayol, (2007) finds that

patenting increases with age whereas Stephan et al., (2007) finds little evidence of such an effect. Those results need to be taken with caution as the cross-sectional nature of the data prevented these studies from accounting for cohort effects. Different generations of scientists may have a different productivity pattern because of the varying contexts in which they were trained and are working (Stephan, 2010).

Based on longitudinal data, Azoulay, Ding, and Stuart, (2007) and Thursby and Thursby, (2007) find that, once controlling for cohorts, patenting decreases over the life-cycle. However, while the authors of the former paper argue that newer cohorts are more likely to patent than are earlier cohorts, the latter finds opposite results. We contribute to this debate by studying the age and cohort effects on our longitudinal dataset covering all scientific fields and almost all universities at a national level.

Finally, the literature 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; Tartari, Perkmann, and Salter, 2014). 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 highlight the importance of “local group norms” in predicting active involvement in commercialization. Krabel and Schacht, (2014) highlight the influence of Max Plank research institute leaders in disclosing inventions. Considering peer effects in faculty engagement in technology transfer activities, Bercovitz and Feldman, (2008) show that faculty members of two US medical schools were more likely to disclose inventions when their peers did so in the previous year.

We investigate the influence of university recent involvement in patenting as well as similar effects within research labs.

### 1.3 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.

### 1.3.1 *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 and Ziedonis, 2002; Mowery et al., 2001), 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 to find university research personnel. 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 (Ejeremo 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 (Balconi, Breschi, and Lissoni, 2004; Hvide and Jones, 2018; Iversen, Gulbrandsen, and Klitkou, 2007; Lissoni et al., 2008; Meyer, 2003; Thursby, Fuller, and Thursby, 2009). 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 use large lists of professors and researchers and develop a filtering procedure which simultaneously avoids performing time-consuming manual checking and controls for merge quality.

### 1.3.2 *Data sources*

Our data come from the French Ministry for Higher Education and Research. We know, each year, the full name, gender, age, field of science, employing university and status of all the professors employed in France. Besides, we know precisely in which laboratory each person works. This is important because the French research system, as in most continental European countries, is organized in research laboratories (see

Azagra-Caro, Llerena, and Carayol, 2006; Carayol and Matt, 2004). These laboratories are the elementary units structuring research activity in nearly all higher education and research institutions. In France, labs host both professors employed by the universities (or higher education schools) and researchers employed by research institutes. They vary in size from a few professors and researchers to several hundreds. Lab information is available as labs provide their staff lists when surveyed by the ministry every four to five years. As most labs were surveyed this way at least twice over the period, we can observe movements in time. 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.<sup>5</sup>

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 or INPI (the French national office) for which at least one inventor had a home address in France. We obtained 427,891 French-invented patents from 1995 to 2012.

### 1.3.3 *Filtering academic patents*

Professors or researchers’ first and last names are first matched with those of the inventor (using exact and fuzzy matching techniques to allow limited variation in spelling). This returns almost 91,000 patents and 148,000 professor-inventor pairs on a given patent that remain to be filtered out. We use a statistical model to estimate the probability that each match is correct. Our filtering process takes four stages.

In the first stage, we estimate 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 is made up of almost 1,200 professor-inventor pairs.<sup>6</sup> Explanatory variables include 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 are performed per patent office as Hausman tests showed that logit coefficients are significantly dif-

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<sup>5</sup> Carayol and Lanoë, (2019) used a very similar dataset to estimate the impact of project-based funding.

<sup>6</sup> This benchmark includes 31 pairs for the USPTO, 236 for the EPO and 945 for the INPI. There were too few USPTO pairs for the algorithm to perform well on this subset so we removed them from the data.

ferent across offices. Results for each patent office are presented in Table 6 in the Appendix.

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

In the third step, we consider 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 compute precision as

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

and recall as

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

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

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

with  $\beta$ , 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 do not want our results to be sensitive to a particular value of  $\beta$ , all our statistics are computed for  $\beta = 0.5$ ,  $\beta = 1$  and  $\beta = 2$ . In Figure 3 in the Appendix, we display the computed values of those indicators for the different threshold probability values  $p$ .

The fourth and last stage consist in finding the optimal  $p$  threshold value, for each  $\beta$  and patent office  $i$ . That is, we want to find

$$p_{\beta,i}^* = \arg \max_p \{F_{\beta,i}(p)\}, \quad (4)$$

for all  $\beta$  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 consider two offices and three different values of  $\beta$ , we end up with a series of six optimal threshold values to be calculated. Optimal thresholds presented in Table 7 are significantly different for each considered office. Table 7 also indicates the precision and recall values for each pair  $(\beta, i)$ . We compute these indicators on the benchmark pooling patents from each office. As expected, recall increases with  $\beta$  whereas precision decreases with  $\beta$ . 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  $\beta$  equals 1. Recall and precision rates for EPO patents are found to be simultaneously satisfactory when  $\beta$  equals 1 or 0.5.

For an external assessment of the quality of our data filtering, we use a more limited sample of faculty inventions which have been identified via a combination of web searches, emails and phone calls.<sup>7</sup> Having created faculty-inventor-patent tables in both datasets and excluded homonyms born in the same year, those tables are merged on prof name, first name, birth year and patent identifier code. This essentially leads us to restrict data to the benchmark, obtaining 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  $F_\beta$  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 preferentially in the rest of the paper, when applications at another office is 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 two offices (EPO and INPI).

#### 1.3.4 *Estimating the number of academic patents*

By definition, a patent is academic if at least one of its inventors is an academic staff member. In our framework, this translates as 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  $N_{\beta,i}^1$  be the set of these validated patents, the cardinal of that set is  $n_{\beta,i}^1$  and the number of candidate but non-validated patents is  $n_{\beta,i}^0$ . Assuming that

<sup>7</sup> We thank F. Lissoni for giving us access to those data (Lissoni et al., 2008).

$n_{\beta,i}^1$  reflects the expected number of academic patents would be slightly misleading, as some patents counted in the underlying set ( $N_{\beta,i}^1$ ) are considered as such (because of false positives) while some patents in the complement set ( $N_{\beta,i}^0$ ) are 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:

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

for all  $\beta \in \{0.5, 1, 2\}$ ,  $i \in \{EPO, INPI\}$ . We multiply the number of already validated academic patents by precision rate (true positives among positives), and add this number to the number of rejected patents multiplied by the rate of false negatives among negatives. This leads to Table 8 in the Appendix.

We make another correction to those numbers because the data cover only universities and public research organizations recognized by the Ministry for Higher Education and Research. Some higher education or research institutions are funded by other ministries (defense, industry, agriculture) and not at all by Ministry for Higher Education and Research. Table 1 reports the new calculations. The gain from this correction is 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 or 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  $\beta$ ) actually provide very similar numbers, ranging from 44,759 to 45,637 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  $\beta$  values (from 1995 to 2012) – Alternative method.

Office	$\hat{x}'_2$		$\hat{x}'_1$		$\hat{x}'_{0.5}$		All French-invented patents
EPO	19786	(11.1%)	21034	(11.8%)	21039	(11.8%)	177286
INPI	24973	(10%)	24604	(9.8%)	24273	(9.6%)	250605
Total	44759	(10.5%)	45637	(10.6%)	45312	(10.6%)	427891

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 public research organization (exclusively or in joint ownership with companies).
- This table displays fractional counts.
- The shares of academic patents - by office and overall - over all patents invented in France are placed into parentheses.

#### 1.4 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.

##### 1.4.1 *Strength and specialization of academic patents*

Table 1 shows that academic patents represented 11.1% of all patented inventions generated in France between 1995 and 2012<sup>8</sup>. Although it should be remembered that this is a floor value (as some academic patents owned exclusively by the private sector are still missing for the reasons mentioned above), it is way above previous estimates which reported that 3.4% of EPO patents from 1995 to 2001 stemmed from academia (Lissoni et al., 2008). Restricting our analysis to a similar period (1995-2002), we estimate the share of academic inventions in France to be as much as 9.3%<sup>9</sup>. Academic inventions were thus much greater than previously estimated by a factor of more than 2.5.

<sup>8</sup> Recall that for the rest of the paper, we only interpret statistics and results for EPO patents validated according to  $\beta = 2$  (see Subsection 1.3.3).

<sup>9</sup> This calculation was performed separately from Table 1 and thus does not appear on it.

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.<sup>10</sup> 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 51% less specialized in fixed constructions and 45% more specialized in chemistry and metallurgy than France. To a lesser extent, academia is more specialized than the country in the physics and electricity fields (respectively 13% and 5% more specialized). In all other technology classes, academia shows a technological disadvantage.

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

Technology class	Academic patents		All patents		A/B	RTA
	# (A)	%	# (B)	%		
Human necessities	3,358	(17.2%)	30,458	(17.2%)	11%	1
Performing operations; transporting	1,936	(10%)	28,674	(16.2%)	6.8%	0.61
Chemistry; metallurgy	4,039	(20.7%)	25,367	(14.3%)	15.8%	1.45
Textiles; paper	210	(1.1%)	2,231	(1.2%)	9.3%	0.86
Fixed constructions	353	(1.7%)	6,610	(3.7%)	5.3%	0.49
Mechanical engineering; lighting; etc.	1,493	(7.6%)	17,428	(9.8%)	8.6%	0.77
Physics	4,626	(23.7%)	36,813	(20.7%)	12.6%	1.13
Electricity	3,432	(17.6%)	29,533	(16.7%)	11.6%	1.05
Total	19,449	(100%)	177,114	(100%)	11%	1

Notes:

- For a technology class  $i$ , the revealed technological advantage is  $RTA = \frac{A_i}{B_i} \times \frac{\sum_i B_i}{\sum_i A_i}$ .
- A patent may belong to more than one technology class so we use fractional counts.

<sup>10</sup> Separate calculation based on EPO patents for the period 1995-1999. This share is similar on patents from other offices.

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 rapidly in general.<sup>11</sup> Table 9 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 14 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 5.4) which is also the most dynamic sub-field (growth ratio of 5.5), but this sub-class gathers only 0.2% of all patents. We can thus conclude that the technological specialization of academia may not explain a positive variation in overall academic patenting.

#### 1.4.2 *Who is patenting in academia?*

In the previous subsection, we looked at the importance of academia with respect to all national inventions. Let us now reverse the viewpoint to investigate 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 consider patents from all patent offices. To appreciate to what extent professors and researchers are concerned by invention, we calculate the share of inventors among professors and researchers<sup>12</sup>. Table 3 displays this information by scientific discipline (social sciences and humanities are not considered here).

<sup>11</sup> 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).

<sup>12</sup> A professor is counted as an inventor only once in a field, independently of its number of inventions or offices where her patents were applied for.

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, using  $\beta = 0.5$  at the filtering stage, and verified that it did not significantly alter the results (Table 10 in the Appendix). 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 11 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).

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, 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<sup>13</sup>.

Those findings are in line with previous research that consider similar scientific fields (D'Este and Perkmann, 2011; Hughes et al., 2016; Klofsten and Jones-Evans, 2000; Landry et al., 2010; Walsh and Huang, 2014) even though they are using a very different methodology. Other studies however display important differences with our results (Gulbrandsen and Smeby, 2005; Haeussler and Colyvas, 2011).

<sup>13</sup> Hughes et al., (2016) recently performed a large-scale survey in the UK and find half our shares in biology and chemistry (just under 15%), a third in physics and mathematics (between 7 and 8%) and a fifth only in health sciences (just under 5%), but they only consider patents filed in the three prior years and not the entire career, or at least 15-20 years.

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:

- The scientific field is part of the employment data collected from the French Ministry of Higher Education and Research and follows the OST classification (Observatoire des Sciences et Techniques).
- 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.

A gender gap in academic patenting has been evidenced in several papers (Ding, Murray, and Stuart, 2006; Frietsch et al., 2009; Whittington and Smith-Doerr, 2005). Our data show that 16% of the nearly 12,000 women in our dataset (again excluding human and social sciences) are patenting, which is 64% of the rate for men. Universe science 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 4,000 life science faculty members.

We now consider the distribution of academic invention over the population of professors and researchers and its trends over the period. There are 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 are active in each sub-period, we find that 3.9% of them are inventors in the 1995-1999 period, 7.9% in 2000-2006 and 10% in 2007-2012. This means that patenting is adopted increasingly widely within our population<sup>14</sup>. However, the most prolific inventors

<sup>14</sup> This trend would result from a composition effect if the numerator (number of inventors) was increasing and the denominator (number of professors) was shrinking simultaneously. This is not the case here, since the denominator is always increasing or stable over the period (see Figure 4 in the Appendix).

tend to maintain or even increase their role: the top 10% most prolific inventors invent 24, 28 and 30% of academic patents in the three periods respectively. The top 5% invent 14, 17 and 19% of academic patents in the three periods. At the same time, the 4 most prolific inventors among them represent a decreasing share over time: 1.11%, 0.56% and 0.67% respectively.<sup>15</sup> 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.

## 1.5 THE TREND IN PROPENSITY TO INVENT IN ACADEMIA

In this section, we aim to appreciate how the probability of inventing varies 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.<sup>16</sup>

### 1.5.1 *The spread within academia*

We create an unbalanced panel dataset using the repeated time observations presented above. When someone was observed 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. The model is of the form:

$$y_{it} = \sum_{t=1995}^{t=2012} \alpha_t \text{Year}_t + \sum_{j=1}^{j=35} \delta_j \text{IPC}_{jit} + \theta_i + \varepsilon_{it}, \quad (6)$$

<sup>15</sup> 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.

<sup>16</sup> Figure 4 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.

where  $y_{it}$  is the outcome variable (number of EPO patent applications),  $\text{Year}_t$  is a year dummy, and  $\theta_i$  is the individual fixed effect.  $\text{IPC}_{j_{it}}$  is a set of 35 dummy variables (one per technological field) controlling for the different dynamics in some fields between academia and the private sector. It equals to one if individual  $i$  invented at least one patent in the class  $j$  in year  $t$ . We are interested in estimating the coefficients of the year fixed effects  $\alpha_t$  for each year  $t$ . A positive trend in the estimated  $\alpha_t$  would indicate an increasing propensity to patent over the years.

Some other factors may influence patenting but do not offer sufficient variation to be properly accounted for in a fixed effects framework. We thus estimate the following equation

$$y_{it} = \sum_{t=1995}^{t=2012} \alpha_t \text{Year}_t + \sum_{j=1}^{j=35} \delta_j \text{IPC}_{j_{it}} + \phi X_{it} + \varepsilon_{it}, \quad (7)$$

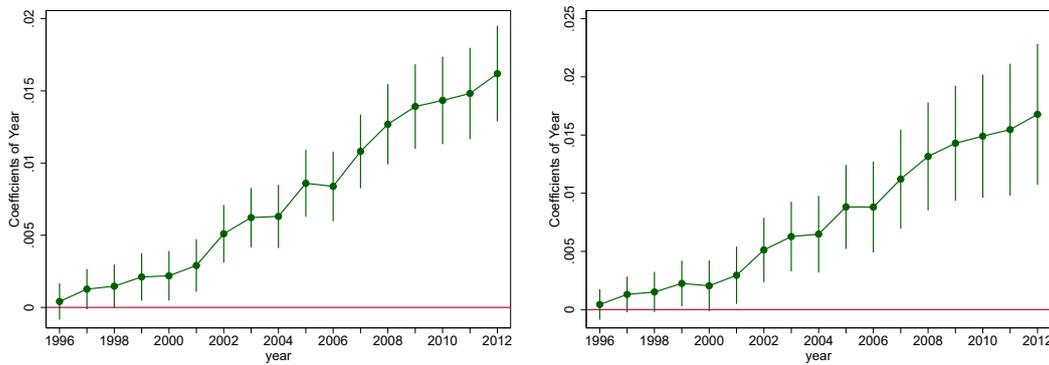
where  $X_{it}$  stands for a vector of control variables, such as age and age squared, and a number of dummies for professional status, gender, field of science, university, and cohort.

Figure 1 displays the estimated  $\alpha_t$  coefficients in Equations 6 and 7 obtained via OLS regressions, allowing for many fixed effects and the clustering of standard errors. The left panel was obtained when we use individual fixed effects (Equation 6), whereas the right one does not and includes the vector of control variables instead (Equation 7). The two regressions provide very similar results concerning the year fixed effects that we aim to estimate. We see that the coefficients of year fixed effects rise significantly over the period. In 2012, academic professors and researchers invented an average of 0.015 patents more than in 1995. As the average number of patents per capita in 1995 was 0.02, this means they actually increased their propensity of 75% over the period.

### 1.5.2 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 in the productivity of all inventors (not just academic ones) increasing under the effects of improvements in communication technology or instrumentation, for instance. We thus need 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.

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  $\alpha_t$  in Equation (6)). In the left graph, the individual scientists fixed effects (the  $\theta_i$ ) are not included whereas they are included in the regressions leading to the right panel. Standard errors are clustered at the individual level.

We create 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 1.3.3) is used to identify potential “academic” PSNIDs. A PSNID inventor profile is academic if at least one of its patents has been validated as academic and thus attached to an academic profile in our dataset of professors and researchers. Otherwise it is not academic. This clearly shows that the academic character of PSNIDs is dependent on the parametrization of the filtering stage (the choice of the  $\beta$ ). All inventors are assumed to be in the dataset from year 1995 to 2012 so that we have a balanced panel dataset. Making the alternative assumption according to which inventors enter the dataset in the year of their first patent and leave it at 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 run fixed effects regressions on the yearly number of inventions. The model is of the form:

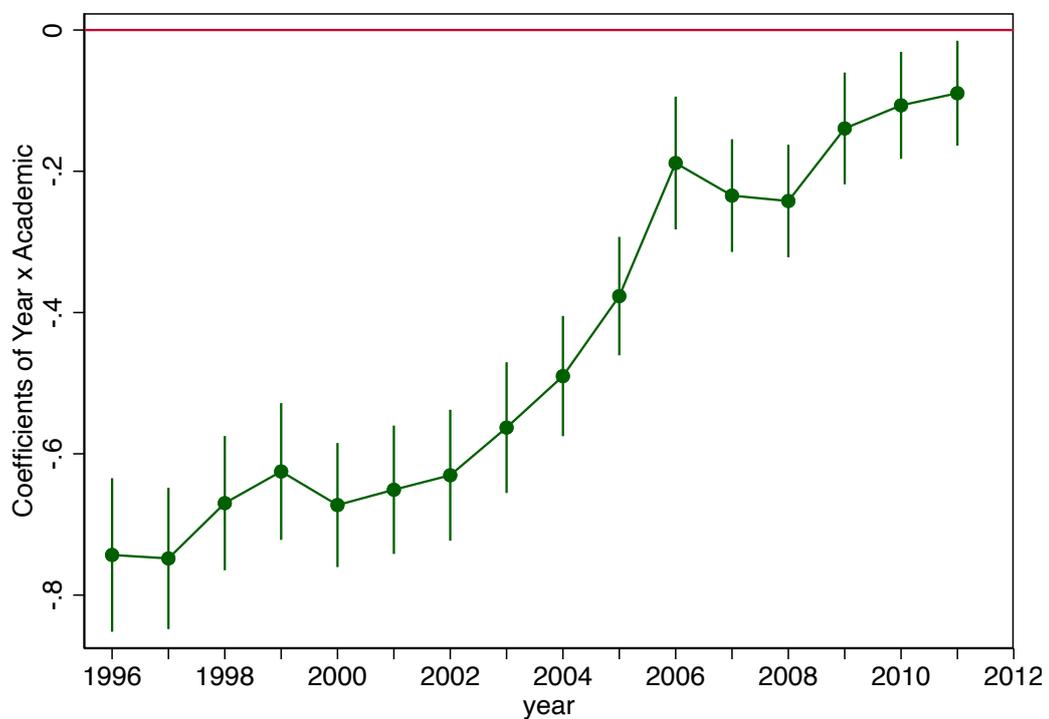
$$y_{it} = \sum_{t=1995}^{t=2012} \alpha_t \text{Year}_t + \sum_{t=1995}^{t=2012} \gamma_t \text{Academic}_i \times \text{Year}_t + \sum_{j=1}^{j=35} \delta_j \text{IPC}_{j_{it}} + \theta_i + \varepsilon_{it}, \quad (8)$$

where  $y_{it}$  is the outcome variable (number of EPO patent applications),  $\text{Year}_t$  is a year dummy, and  $\text{Academic}_i$  is a dummy equal to one if the inventor profile is academic.

The  $\text{Academic}_i$  variable is not introduced directly into the regression as its effect is fully captured via the individual fixed effect  $\theta_i$ .  $\text{IPC}_{j_{it}}$  is a set of 35 dummy variables (one per technological field) controlling for the different dynamics in some fields between academia and the private sector. It equals to one if individual  $i$  invented at least one patent in the class  $j$  in year  $t$ . The main goal of this model is to estimate the coefficient of the interaction term between the academic profile dummy and the time fixed effect,  $\gamma_t$ , for each year  $t$ . A positive trend observed on the  $\gamma_t$  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  $\gamma_t$  coefficients in Equation 8 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  $\beta$  (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 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.

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  $\gamma_t$  in Equation (8)). Standard errors are clustered at the individual level.

## 1.6 FACTORS IN THE SPREAD OF ACADEMIC PATENTING

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

### 1.6.1 *Individual factors*

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

$$y_{it} = \alpha_1 \text{Age}_{it} + \alpha_2 \text{Age}_{it}^2 + \alpha_3 \text{Cohort}_i + \alpha_4 \text{Status}_{it} + \alpha_5 \text{Gender}_i + \gamma X_{it} + \eta_t + \varepsilon_{it}, \quad (9)$$

where  $\eta_t$  is the year fixed effect and  $y_{it}$  the number of EPO patent applications. Individual fixed effects are not introduced, so that time-invariant factors of academic patenting can now be considered. In particular age and cohort effects can now be estimated. The four cohorts are defined as follows: cohort 1 (the reference) groups professors born before 1950, cohort 2 groups the ones born in the 50's, cohort 3 in the 60's, and cohort 4 in the 70's or later. There are four professional statuses: associate professor, (full) professor, associate researcher, or (full) researcher. Vector  $X_{it}$  accounts for a number of controls such as scientific field and university dummies. The latter account for a number of other dimensions affecting patenting behavior, which may be correlated with the explanatory variables of interest. This model is close to the one presented in Equation 7, with some differences, but focuses on different explanatory variables.

Table 4 summarizes the regression results, again using linear regressions with many levels of fixed effects. Controlling for the cohorts, we find that age plays positively on patenting. This confirms previous research evidencing a life-cycle effect in patenting (Azoulay, Ding, and Stuart, 2007; Carayol, 2007; Stephan et al., 2007; Thursby and Thursby, 2007).

When age is not included among regressors (column 1), the second, third and fourth cohort dummies are positively correlated with the outcome variable. However, when

age is controlled for, cohort dummies are not significantly correlated with patenting anymore. This contrasts with Thursby and Thursby, (2007) who find that more recent cohorts are in fact less likely to disclose inventions, controlling for tenure and age, or Azoulay, Ding, and Stuart, (2007) who evidenced the opposite. Professional status makes significant differences. Full professors invent almost twice as many patents per year as associate professors (the reference), junior researchers 67% more, and full researchers invent more than three times more often. Lastly, gender is also an important driver of patenting as women invented 50% fewer patents for equivalent years, ages, disciplines, cohorts, universities and statuses.

### 1.6.2 *Local diffusion effects*

None of the individual factors examined above can fully account for 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 7 and thus, as shown in the right panel of Figure 1, cannot explain the phenomenon. Therefore, we now investigate the role of local culture within the university site and the lab.

We create 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. Note that, as previous years are used to calculate some explanatory variables, observations from the first three years (1995-1997) are not considered.

We rely upon fixed effects regressions of the form

$$y_{it} = \alpha \text{UnivExp}_{it} + \beta \text{LabExp}_{it} + \phi X_{it} + \eta_t + \theta_i + \varepsilon_{it}, \quad (10)$$

where  $\eta_t$  is the year fixed effect. The error terms may be correlated for a given professor, a given research lab and a university, so we cluster standard errors with respect to these three identifiers (multi-way). We include time-varying controls via  $X_{it}$  such as the number of professors and researchers in the lab (LabSize) and in the university excluding those from the focal person's lab (UnivSize).

Table 4: The individual factors of academic patenting.

	(1)	(2)	(3)	(4)	(5)
Age		0.003*** (0.000)	0.003*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Age squared		-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Cohort 2	0.006*** (0.001)		0.002* (0.001)		0.002 (0.001)
Cohort 3	0.007*** (0.001)		0.003 (0.002)		0.001 (0.002)
Cohort 4	0.004*** (0.001)		0.003 (0.003)		0.003 (0.003)
Professor				0.011*** (0.001)	0.011*** (0.001)
Associate Researcher				0.008*** (0.001)	0.008*** (0.001)
Researcher				0.028*** (0.002)	0.028*** (0.002)
Female	-0.014*** (0.001)	-0.014*** (0.001)	-0.014*** (0.001)	-0.013*** (0.001)	-0.013*** (0.001)
Observations	827031	822032	822032	820068	820068
Adjusted R <sup>2</sup>	0.011	0.012	0.012	0.013	0.013
Mean dep variable	0.021	0.021	0.021	0.021	0.021
F-statistics	169.756	268.484	136.962	164.378	113.066

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

The fixed effect framework allows us to capture variation for a given professor or researcher. Therefore the estimated  $\alpha$  and  $\beta$  are likely close to capturing peer effects at the university and laboratory levels respectively. However, professors are not assembled in labs and universities randomly, so correlated effects may still explain both past patenting variation of peers and contemporary variation in the patenting of the focal professor.

A number of other controls could not be introduced as they do not offer sufficient variation. We thus perform similar regressions as in Equation 10 but without individual fixed effects and introducing instead a number of supplementary control variables :

$$y_{it} = \alpha \text{UnivExp}_{it} + \beta \text{LabExp}_{it} + \phi X_{it} + \eta_t + \varepsilon_{it}, \quad (11)$$

where  $X_{it}$  stands for a vector of control variables, that includes LabSize and UnivSize as in Equation 10, but also the age, age squared, and a number of dummies for professional status, gender, field of science, and cohort.

Table 5 presents the fixed effect regression results (Equation 10). We find that although both variables are positively related to academic patenting, only LabExp coefficients are significant. When lab peers each produced one more patent per year on average in the previous years, the average faculty member invents almost 4 times more patents<sup>17</sup>. 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, and potentially through local “peer effects”. This is reminiscent of what Bercovitz and Feldman, (2008) and Tartari, Perkmann, and Salter, (2014) previously found for invention disclosure and academic engagement.

Table 12 in the Appendix exposes the regressions results of the specification introduced in Equation 11. Results are very similar to the fixed effects for LabExp and also very similar to those presented in Table 4 regarding individual factors. The only significant difference is that the university recent experience UnivExp is now positive and significant.

<sup>17</sup> As professors and researchers invented 0.023 patents per year on average, a coefficient of 0.065 means that productivity increases by a factor of 3.8.

Table 5: The social factors of academic patenting.

	(1)	(2)	(3)	(4)	(5)	(6)
UnivExp	0.037 (0.033)		0.034 (0.032)	0.027 (0.033)		0.025 (0.033)
LabExp		0.066*** (0.017)	0.066*** (0.017)		0.064*** (0.017)	0.065*** (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	667590	670805	666822	667590	670805	666822
Adjusted R <sup>2</sup>	0.130	0.130	0.131	0.130	0.130	0.131
Mean dep variable	0.023	0.023	0.023	0.023	0.023	0.023
F statistic	54.353	62.690	41.588	30.139	33.967	27.017

Notes: Standard errors into parentheses are clustered at the individual level. Significance levels:

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01.

## 1.7 CONCLUSION

Since a few decades, academic patenting has been a growing phenomenon in most advanced economies worldwide, and the subject of a longstanding stream of investigation. Policy makers as well as the academic community have raised various concerns about this new practice in academia. National governments voted several reforms in order to shape universities' and professors' involvement in the phenomenon, but they often lacked reliable and consistent scientific information. Most prior literature relied on interviews or small samples of a few hundred professors at best, were cross-sectional in nature, and thus generally covered a short time period.

In this article, we attempt to fill this gap by investigating academic patenting including all scientific fields and several thousands of professors and researchers. We develop 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 estimate that, among the 428,000 patents filed at the EPO and INPI and invented in France over the years 1995-2012, more than 44,000 stemmed from academia. The involvement of professors in technology transfer is found to be larger than expected, with one professor or researcher out of five having invented at least one patent, and widespread across most fields of the hard and life sciences (social sciences and humanities being excluded).

Even if academic patenting is strong before reforms favoring technology transfer were passed, professors and researchers are increasingly likely to invent after such reforms. An aging population of professors or simple cohort effects can not explain this phenomenon. Our results rather indicate that local diffusion, in particular within laboratories, plays a key role in the diffusion of academic patenting. A given professor is up to four times more likely to invent when her colleagues in the laboratory are more involved in patenting in the recent years (controlling for year and individual fixed effects). Though we cannot identify the extent of their exact influence, this suggests that peer effects may actually play a central role in fostering technology transfer.

## 1.8 APPENDIX OF CHAPTER 1

Figure 3: Precision, recall et  $F_\beta$  (when  $\beta = 0.5$ ,  $\beta = 1$  or  $\beta = 2$ ) for different threshold probability values.

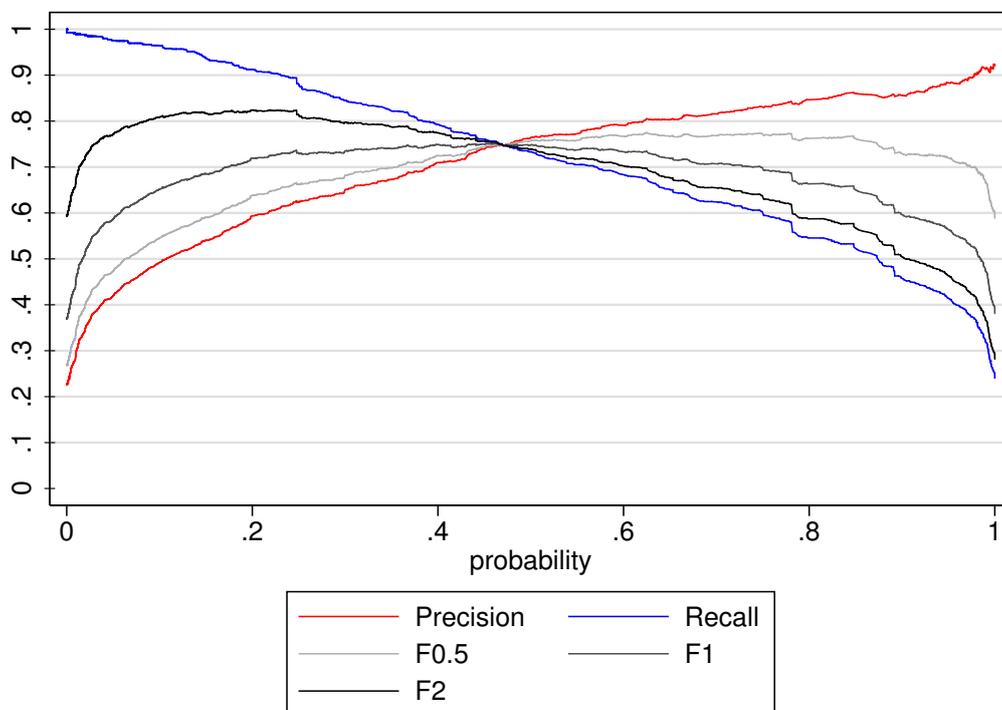
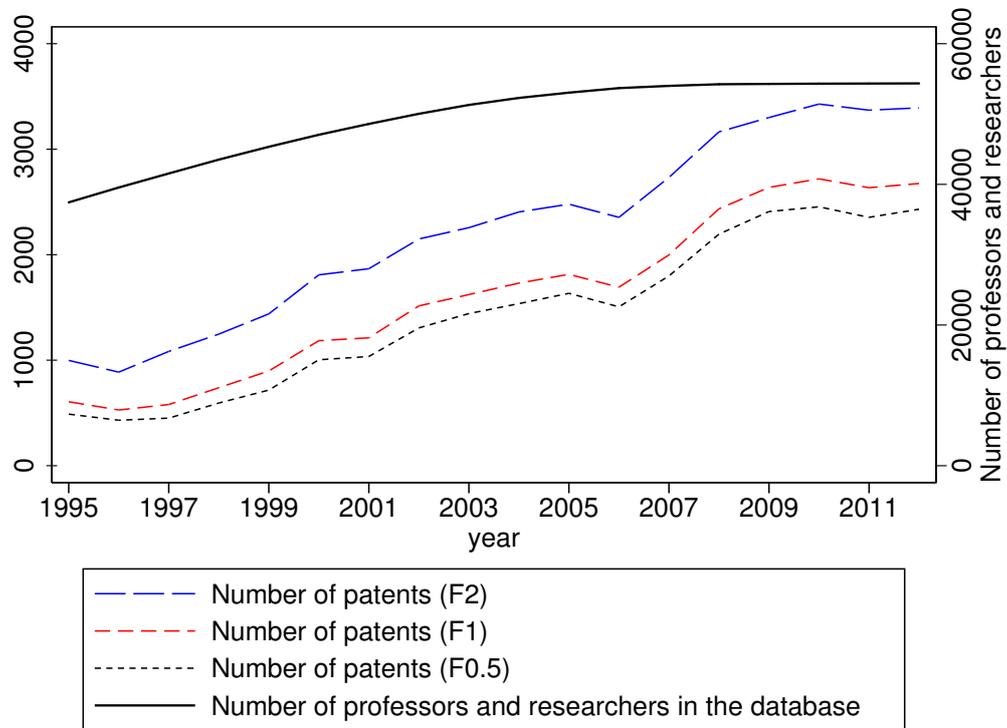


Figure 4: The evolution of academic patenting in France, with respect to the reference population.



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 F0.5 and F2) relates to  $\beta = 1$  (respectively  $\beta = 0.5$  and  $\beta = 2$ ).

Table 6: Logistic regressions on the benchmark, per office

	(1) EPO	(2) EPO	(3) INPI
Name similarity	22.427*** [3.635]	21.834*** [3.117]	12.740*** [2.002]
Inventor's name frequency	1.234*** [0.165]	1.239*** [0.169]	0.645*** [0.055]
Assignee/employer consistency	6.244*** [0.675]	6.231*** [0.662]	1.273*** [0.455]
Tech/discipline consistency	0.566** [0.193]	0.591*** [0.202]	0.425*** [0.087]
Age/year consistency	0.666 [0.554]		1.245*** [0.244]
Constant	-32.188*** [5.046]	-29.189*** [3.618]	-21.841*** [2.392]
Observations	682	682	2829

Notes:

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

Table 7: Optimal thresholds for each office and  $\beta$  values (0.5, 1, 2)

Patent office	$\beta$	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

## 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.

Table 8: Expected number of academic patents for several  $\beta$  values (from 1995 to 2012)

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
Total	22245	(5.1%)	23123	(5.4%)	22798	(5.3%)	427891

Notes:

– This table displays fractional counts.

– The shares of academic patents - by office and overall - over all patents invented in France are placed in parentheses.

Table 9: RTA and CAGRs for patents in 35 technology classes (1995-2012)

Technology class	RTA	CAGR	Growth ratio	Share
Micro-structural and nano-technology	5.40	-1.5%	5.5	0.2%
IT methods for management	0.41	-1.9%	3.5	0.5%
Digital communication	0.53	-0.0%	2.0	3.7%
Semiconductors	2.76	4.1%	1.8	2%
Engines, pumps, turbines	0.81	-3.2%	1.7	3.7%
Computer technology	0.86	1.5%	1.7	5.3%
Analysis of biological materials	3.40	2.6%	1.6	0.8%
Transport	0.34	-2.4%	1.5	8.7%
Measurement	1.99	-0.6%	1.1	4.5%
Thermal processes and apparatus	0.73	1.5%	1.1	1.5%
Surface technology, coating	1.64	0.8%	1.1	1.4%
Environmental technology	1.43	-1.2%	1.1	1.6%
Electrical machinery, apparatus, energy	0.96	1.4%	1.0	5.5%
Food chemistry	0.76	-3.9%	1.0	1%
Civil engineering	0.47	-4.3%	0.9	4.1%
Other consumer goods	0.32	0.4%	0.9	2.6%
Telecommunications	0.82	0.8%	0.8	2.8%
Control	0.65	0.4%	0.8	1.7%
Medical technology	0.89	2.3%	0.8	4.1%
Audio-visual technology	0.77	-1.7%	0.8	2.6%
Machine tools	0.65	-2.6%	0.8	2%
Other special machines	0.57	-1.4%	0.7	3.5%
Handling	0.38	-1.1%	0.7	3.4%
Biotechnology	3.16	-0.5%	0.6	2.7%
Mechanical elements	0.42	-2.6%	0.6	3.8%
Pharmaceuticals	1.57	1.1%	0.6	4.8%
Furniture, games	0.23	3.1%	0.6	2.6%
Materials, metallurgy	1.41	0.7%	0.6	1.9%
Basic materials chemistry	1.52	-1.0%	0.6	2.1%
Macromolecular chemistry, polymers	1.03	1.2%	0.6	1.9%
Basic communication processes	1.32	4.8%	0.6	1%
Chemical engineering	1.71	-1.0%	0.5	2.7%
Optics	1.61	1.2%	0.5	1.9%
Organic fine chemistry	0.82	1.5%	0.4	6.1%
Textile and paper machines	0.44	0.7%	0.0	1.3%
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. A patent may belong to more than one technology class so we use fractional counts.

Table 10: 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
<b>Total</b>	<b>7,503</b>	<b>(21.8%)</b>	<b>34,439</b>

## Notes:

- The scientific field is part of the employment data collected from the French Ministry of Higher Education and Research and follows the OST classification (Observatoire des Sciences et Techniques).
- 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 11: 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
<b>Total</b>	<b>8,441</b>	<b>(24.5%)</b>	<b>34,439</b>

Notes:

- The scientific field is part of the employment data collected from the French Ministry of Higher Education and Research and follows the OST classification (Observatoire des Sciences et Techniques).
- 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%.

Table 12: The social and individual factors of academic patenting.

	(1)	(2)	(3)	(4)	(5)	(6)
UnivExp	0.086*** (0.019)		0.063*** (0.015)	0.084*** (0.020)		0.062*** (0.016)
LabExp		0.151*** (0.017)	0.148*** (0.017)		0.151*** (0.017)	0.148*** (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)
Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	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)	-0.000* (0.000)	-0.000* (0.000)
Cohort 2	0.003** (0.001)	0.003** (0.001)	0.003** (0.001)	0.003** (0.001)	0.003** (0.001)	0.003** (0.001)
Cohort 3	0.003 (0.002)	0.002 (0.002)	0.002 (0.002)	0.003 (0.002)	0.002 (0.002)	0.002 (0.002)
Cohort 4	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)
Professor	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)
Associate Researcher	0.003*** (0.001)	0.003*** (0.001)	0.002*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.002*** (0.001)
Researcher	0.011*** (0.001)	0.011*** (0.001)	0.011*** (0.001)	0.011*** (0.001)	0.011*** (0.001)	0.011*** (0.001)
Observations	658415	661645	657662	658415	661645	657662
Adjusted R <sup>2</sup>	0.450	0.451	0.452	0.450	0.451	0.452
Mean dep variable	0.023	0.023	0.023	0.023	0.023	0.023
F statistic	16.824	17.555	20.664	14.657	15.430	18.886

Notes: All regressions also control for university, field of science, technological specialization and cohort fixed effects. Standard errors into parentheses are clustered at the individual, laboratory and university levels. Significance levels: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

## ASSIGNING INTELLECTUAL PROPERTY RIGHTS TO UNIVERSITIES: THE “LAST MILE” EFFECT<sup>1</sup>

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### 2.1 INTRODUCTION

Universities and public research organizations are constantly feeding society with new ideas and technologies, but beyond fundamental knowledge, professors and researchers also generate inventions whose efficient and rapid transfer to markets is extremely valuable to society. The tremendous growth in academic patents recorded in the United States was largely attributed to a key policy reform, the 1980 Bayh-Dole Act (Henderson, Jaffe, and Trajtenberg, 1998; Mowery and Ziedonis, 2002), that transferred the ownership of academic inventions from the federal government to universities. This reform subsequently inspired many advanced economies to adopt such a “university ownership regime”. However, several recent studies have highlighted that the implementation of a similar reform in Northern European countries has had disappointing impacts. Indeed, ending the so called “professor privilege” and introducing university ownership in Germany, Norway and Finland, has had a significantly negative impact (Czarnitzki et al., 2015; Ejeremo and Toivanen, 2018; Hvide and Jones, 2018). How can it be that a successful reform implementation in one country has a radically opposed impact when implemented in other countries?

In this chapter, we use the French case to provide some answers to this question. In this country, university ownership has been established by law since 1984, but it was not until the introduction of the Innovation and Research Act in 1999 that most universities began to take ownership of their inventions. This reform is quite similar to the Bayh-Dole Act also in the way the regime was introduced. Universities were encouraged, rather than required, to take ownership and manage their intellectual property rights. We leverage this unique setting to elucidate the role of a key dimension in technology transfer under the university ownership regime: an effective involvement of the university in applying the reform. Our empirical strategy is based on the revealed actions of institutions with respect to their management of intellectual property.

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<sup>1</sup> This chapter is based on a paper co-authored with N. Carayol.

We identify which universities actually implement the university ownership model, and if so when, by a kink in the share of university ownership of its research staff inventions. When this share increases sharply and consistently, we infer that the institution has made the decision to follow the policy recommendations that year. Following this procedure, we find that 31 universities implemented the university ownership regime at different points in time between 1999 and 2006, while 48 other institutions did not implement it at all over the entire period (1995-2016). We then match universities that made the move with others that never did. We then estimate the impact of this university implementation on the individual propensity of researchers to invent. We make use of a unique panel dataset of over 118,000 professors and researchers employed by those universities for whom we have collected all articles they published and all their inventions, using the Web of Science and PASTAT databases respectively.

We find that professors employed by universities which made the move towards implementing the university ownership regime, produce significantly more inventions after that move: they increase their propensity to invent by 20.7% on average (32.5% in hard sciences). A number of robustness checks confirm this conclusion. This supports the idea that the “last mile” of university ownership regime may be key to the success of the reform and may thus explain the puzzle faced by the literature. Besides, we also show that companies collaborating with researchers from treated universities were not crowded out. They keep retaining ownership of academic patents after the university move. To the contrary, implementing the reform raises the number of inventions owned by at least one company. This leads us to highlight a second factor shared by the French and the American cases, and which has been largely overlooked by the literature, namely the provision of alternative transfer channels thanks to a pragmatic approach to applying university ownership regime. The use of alternative pathways prevents TTOs from having a monopoly power over the transfer of inventions, which may harm technology transfer (Carayol and Sterzi, 2021), in particular at a time universities are likely not yet efficient in managing those processes whereas professors have their own transfer networks in place.

The rest of the chapter is organized as follows: We start by synthesizing the results from the literature on the impact of the university ownership regime on academic inventions in Section 2.2. In the next section, we describe the methodology we developed to split French universities into two groups according to their implementation or not of the regime (Section 2.4). We then assess the impact of the regime in France in Section 2.5 and discuss the implications of our results in Section 2.6.

## 2.2 LITERATURE REVIEW

### 2.2.1 *The adoption of the university ownership regime*

In his famous report to the President of the United States, Bush, (1945) called for an expansion of government support for science, maintaining that basic research is “the pacemaker of technological progress”. In contrast, the private sector is known for lacking incentives to invest in fundamental research, as it has difficulty appropriating the economic value of the resulting discoveries (Arrow, 1962; Nelson, 1959). All of the world’s advanced economies have invested heavily in basic research since then.

While seeking a fundamental understanding of scientific problems, some research projects falling in Pasteur’s quadrant also have an immediate use for society (Stokes, 1997). It is in the society’s best interest to ensure that the inventions resulting from these projects and other more applied research projects are transferred to the private sector in an efficient and timely manner.

As early as the 1970’s, the number of patents filed for academic inventions has been increasing drastically in the US. Conversely, in Europe emerged a perception that the institutional context was relatively unsuccessful in converting scientific and technological discoveries into commercial success (Commission of the European Communities, 1993), especially considering the level of investment in basic research. Such perception was later labelled the “European Paradox”<sup>2</sup>.

The US trend in university patenting and licensing was largely attributed to its 1980 Bayh-Dole Act, which entitled universities the IPR over technologies stemming from federally funded research (Henderson, Jaffe, and Trajtenberg, 1998; Jaffe and Lerner, 2001). In contrast, the “professor’s privilege” regime, in which the professor-inventor owns the IPR over her discoveries, still applied in most European countries until the end of the 1990’s. In an attempt to end the European paradox, several countries terminated this privilege in the early 2000’s and adopted the Bayh-Dole university ownership regime.

Almost two decades later, the efficiency of the university ownership regime remains questioned. Mowery and Sampat, (2004) early sensed a potential unsuitability of this

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<sup>2</sup> The recent availability of large-scale data in France allowed us to investigate in a prior work (Carayol and Carpentier, 2021) whether such a paradox existed. We find that even prior to any policy change more than 9% of the patents invented in the country stemmed from academia, thus invalidating its existence, at least for this country.

regime in countries characterized by a different higher education system. Hence, the main policy debate still remains open: If one were to maximize faculty incentives to invent, and simultaneously foster the dissemination of the inventions, how should IPR over academic inventions be allocated?

### *2.2.2 Impact of university ownership regime on academic patenting*

Empirically, two historically well identified models of university technology transfer can bring some insights into the debate: the Bayh-Dole US model and the German and Nordic “professor’s privilege” model. In the US, the Bayh-Dole Act contributed to an increase in academic patenting (Mowery et al., 2001), and despite some initial concern (Henderson, Jaffe, and Trajtenberg, 1998), the importance of inventions did not decrease (Mowery and Ziedonis, 2002).

More recently, a few studies investigated the consequences of terminating the professor’s privilege in West and Northern Europe countries towards adopting the university ownership model. Czarnitzki et al., (2015) find that in Germany, for professors who had existing industry connections, the 2000 policy change decreased patenting, but for those without prior industry connections, it increased patenting. The overall balance is negative, though. In Norway, a similar reform introduced in 2003 resulted in a 50% decline in patenting, along with a decline in patents’ quality (Hvide and Jones, 2018). For Finland, abolishing the professor privilege in 2007 resulted in a 27 to 46% decrease in patenting (Ejeremo and Toivanen, 2018). Thus, the introduction of the university ownership regime in Europe had a rather negative impact on academic invention.

According to this prior evidence, the same regime implemented on both sides of the Atlantic had apparently opposite consequences on academic invention. We identified a few characteristics that differ between the two continents: the direction of change in the involvement of researchers in the transfer of their inventions, whether or not the possibility of transferring inventions without going through the TTO is maintained, and whether or not the university is involved in implementing the patent ownership regime.

### 2.2.3 Sources of heterogeneity in the regime implementation

**THE INVOLVEMENT OF THE INVENTOR** The Bayh-Dole Act was motivated by the idea that, due to insecurity regarding their ownership, patents resulting from federally funded research were unexploited (Eisenberg, 1996; Mowery et al., 2015). Prior to the Act, agreements between the government and universities started to be made to allow the latter to manage the IPR on a case-by-case, and then university-by-university, basis (Popp Berman, 2008). These agreements made it easier for inventors to be involved in the future of their inventions.

Then in the early 2000s, when several countries already ended the professor's privilege, a stream of literature strongly criticized the performance of university TTOs (Greenbaum and Scott, 2010; Kenney and Patton, 2009; Litan, Mitchell, and Reedy, 2007). While TTOs are expected to have access to a larger network of companies as potential business partners than inventors, and could save researchers' time by handling the patenting and licensing processes for them, empirical investigation show a rather different reality. They are described as bureaucracies with ineffective incentives. Information asymmetries and conflicting objectives of the different parties involved in the process argue against the university ownership regime (Kenney and Patton, 2009).

On the other side, although they have fewer financial resources and less bargaining power than a TTO, faculty members usually have strong incentives to transfer their inventions, as they often get research funding from the private sector in exchange. In addition, because of the tacit knowledge that surrounds an invention, the professor's involvement in the licensing process is crucial to its commercial success (Agrawal, 2006). Siegel, Veugelers, and Wright, (2007) evidence that the inventor's royalty share is important to secure researchers' cooperation in the licensing process. Finally, many academics are likely to have better opportunity recognition skills, both scientific and entrepreneurial, than the TTO staff (Litan, Mitchell, and Reedy, 2007).

From an empirical stand, while in the United States the federal government was initially responsible for IP management, the reform brought IP management closer to the inventor, at the university level. It made it easier for the inventor to be involved in the technology transfer process. Conversely, the end of the professor's privilege has moved IP management away from the inventor, clearly decreasing her involvement.

**THE POSSIBILITY TO BYPASS THE TTO** The university ownership regime is *highly* enforced in a country when all universities and public research organizations take

a monopoly position over the new technology transfer function, whether interested, skilled and resourceful to perform it or not. Under such framework, professors are not allowed to maintain alternative technology transfer pathways at a time. They must end all prior pathways and can only pass through the university TTO. Conversely, when the regime is *weakly* enforced, it displays a greater flexibility in the technology transfer pathways available to the inventors. Only interested universities develop the new function, invest the resources to become skilled, expand their collaboration network with firms while other less interested universities leave their professors at their prior pathways.

In the US, the debate surrounding the desirability of university patenting was supplanted by the governmental passage of the Bayh-Dole Act. It alerted faculty and administrators who were still operating under the Mertonian norms that conditions were changing, and that it was now socially desirable for universities to patent inventions (Kenney and Patton, 2009). The Act provided incentives for universities to establish a TTO and to engage into the formal transfer of professors' inventions (Link and Hasselt, 2019), thus only weakly enforcing the legislation. On the other hand, the end of the professor's privilege has been characterized by a high level of enforcement. In countries affected by this change, the introduction of the university ownership regime was applied to all universities in a systematic way. This lack of flexibility may have prevented a smooth transition from the old regime to the new one and thus led to an overall negative effect, at least in the short run.

THE INVOLVEMENT OF THE UNIVERSITY To the best of our knowledge, the only work that considers the involvement of the university in the implementation of the patents ownership regime is Link and Hasselt, (2019). They argue that the US Bayh-Dole Act mostly provided incentives for universities to invest in a technology transfer office (TTO), which in turn resulted in increased university patenting.

### 2.3 THE OWNERSHIP OF ACADEMIC INVENTIONS IN FRANCE

In order to shed light on which difference prevails over the others, we estimate the impact of universities' implementation of the ownership regime on academic invention in France. In this section, we first describe the relevant historical and legislative background related to academic inventions' ownership in France, then present our dataset, and finally describe the evolution in the ownership structure of academic inventions over the past two decades.

### 2.3.1 *Historical and legislative background*

The university ownership regime was first introduced in France in 1984. However, since very few universities were actually managing their IPR until the end of the 1990s, the major policy reform regarding the ownership of academic patents, that is comparable to the US Bayh-Dole Act, is the Innovation Act introduced in 1999. This reform introduced the possibility for universities to open a technology transfer office called SAIC<sup>3</sup>. These structures were in charge of the management of research contracts, patenting and licensing activities and the commercialization of the outcomes of professors' and researchers' activities.

Since then, the government voted several other pieces of legislation to incentivize university toward managing industrial relations and the IPRs over the inventions of their professors and researchers. For instance, the introduction of the first national research funding agency, the Agence Nationale de la Recherche (ANR), in 2005 provided competitive funding to collaborative research projects between universities and private firms, sponsored industrial chairs and delivered labels of excellence (label Carnot) along with a substantial funding to universities that actively develop partnerships with the private sector.

A 2007 piece of legislation aimed at increasing universities' administrative autonomy through providing them with greater freedom to hire temporary staff, including for their TTO, and to manage these structures<sup>4</sup>. Three years later, the government voted a reform to regionalize TTOs. The universities' internal services (SAICs) were grouped at a regional level to become SATTs<sup>5</sup>. These SATTs are in charge of managing and commercializing the intellectual property of several universities. In case of joint ownership among multiple universities, a single representative is appointed in order to ease the patenting process. Although these SATTs were meant to replace all other forms of IP management structures such as the SAICs, private subsidiary of universities, or associations, all of these forms still coexist.

The university mission of seeking IPR and commercializing academic inventions was first explicitly stated in 2006, specifically regarding research results stemming from ANR sponsored research, and later extended to inventions from all public civil

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<sup>3</sup> SAIC stands for Services d'Activites Industrielles et Commerciales.

<sup>4</sup> See the 2007 Pecesse Law or LRU.

<sup>5</sup> Societe d'Acceleration des Transferts de Technologie in French, or technology transfer acceleration company.

servants in 2013, and at the same time restrained to commercially valuable discoveries<sup>6</sup>.

### 2.3.2 Data

We first built a panel dataset of tenured professors and researchers employed at French universities, engineering and business schools, and PROs by merging two pre-existing panels. All raw data were provided by the French Ministry of Higher Education and Research. The first panel was built from several lists of professors and researchers employed in universities and public research organizations (PROs) that we compiled and disambiguated. It includes 82,955 professors and researchers observed over the years 1995-2017. The second panel was collected more recently and already had its panel structure, but it only includes professors (and not researchers). It comprises 89,264 professors for the years 2000-2018. We merged the two panels together and disambiguated entries. The resulting unbalanced panel contains 115,885 professors and researchers, associate or full, over the years 1995-2016<sup>7</sup>, for whom we have first and last name, birth year, gender, scientific field, academic position each year, and the name of the employing institution, among other information.

For this list of professors and researchers, we collected in the PATSTAT database (Fall 2019 edition) all patents on which the name of at least one inventor matches that of one of the academics. We limited the search to patents filed with the French and European patent offices (INPI and EPO) between the years 1995 and 2016. The method of disambiguation of the researcher-inventor-patent triplets is that described in Carayol and Carpentier, (2021). As the current list of academics is larger than in the previously cited paper, we had to increase the weight of precision in the calculation of the  $F_\beta$  measure<sup>8</sup>, which is used to define the confidence threshold of the disambiguation, in order to improve the performance of the algorithm. The three thresholds selected are  $\beta = 0.3, 0.5$  and  $1$ , where the weight of precision (versus recall) is decreasing with beta. All statistics and results in the rest of the paper are computed using the threshold  $\beta = 0.5$  and EPO patents, to make comparability with other studies easier, and robustness checks are performed on the two other values of  $\beta$ , and using

6 See the Goulard law in 2006 and the Fioraso Law, or Enseignement Supérieur et Recherche Law in 2013.

7 We trimmed the time-window to 2016 because patent data were not available for more recent years at the time of the data collection.

8 Precision is the fraction of relevant instances among the retrieved instances, while recall is the fraction of relevant instances that were retrieved. The  $F_\beta$  measure combines precision and recall in a single indicator:  $F_\beta = (1 + \beta^2) \times \frac{\text{precision} \times \text{recall}}{\beta^2 \times \text{precision} + \text{recall}}$ .

INPI patents as well. They are available upon request to the authors. By the end of the patent disambiguation procedure, we find that 16,908 professors and researchers have invented 77,353 academic patents from 1995 to 2016, which is consistent with our prior statistics on a smaller dataset and a shorter period (Carayol and Carpentier, 2021).

Finally, we collected and disambiguated publication data of these professors and researchers from ISI Web of Science, including in particular the number of publications adjusted for the number of co-authors, number of citations and H-Index.

### 2.3.3 *Evolution of academic patents ownership*

The ownership structure of academic patents takes three main modalities: either they are owned by universities and other public research organizations, or they belong to the private sector, or else they are co-owned by these two types of entities. Figure 5 shows the temporal evolution of the respective share of academic patents for each modality.

In a first time, before the Innovation Act, academic institutions usually owned less than 5% of their inventions, co-owned around 35% with companies, and left the remaining 60% in exclusive ownership of the private sector. The second phase appears from the passage of the Innovation Act until the introduction of the ANR (2000-2006). It may be called the *transition* phase. Universities and PRO are increasingly retaining ownership of their inventions, both exclusively (from 5 to 20%) and in joint property with firms (up to 55%), leaving as little as 25% in exclusive ownership of the private sector as of 2006. The third and final period, which we call the *stabilization* period, starts after 2007. The ownership structure of academic inventions appears stable, with around 20% of IPRs in exclusive ownership of universities and PRO, 20% in exclusive companies' ownership, and 60% in joint property between these entities.

Far from trivial, filing applications for patents is a long, complex and costly process. The significant development of joint ownership in the transition phase suggests that the French unexperienced and underfunded universities may have used this co-ownership regime as a strategy to learn the patenting process, and possibly rely on their business partners to cover the patenting costs until they could afford it themselves. Moreover, the persisting heterogeneity in ownership after 2007 confirms that the French model is still characterized by some flexibility in IP management.

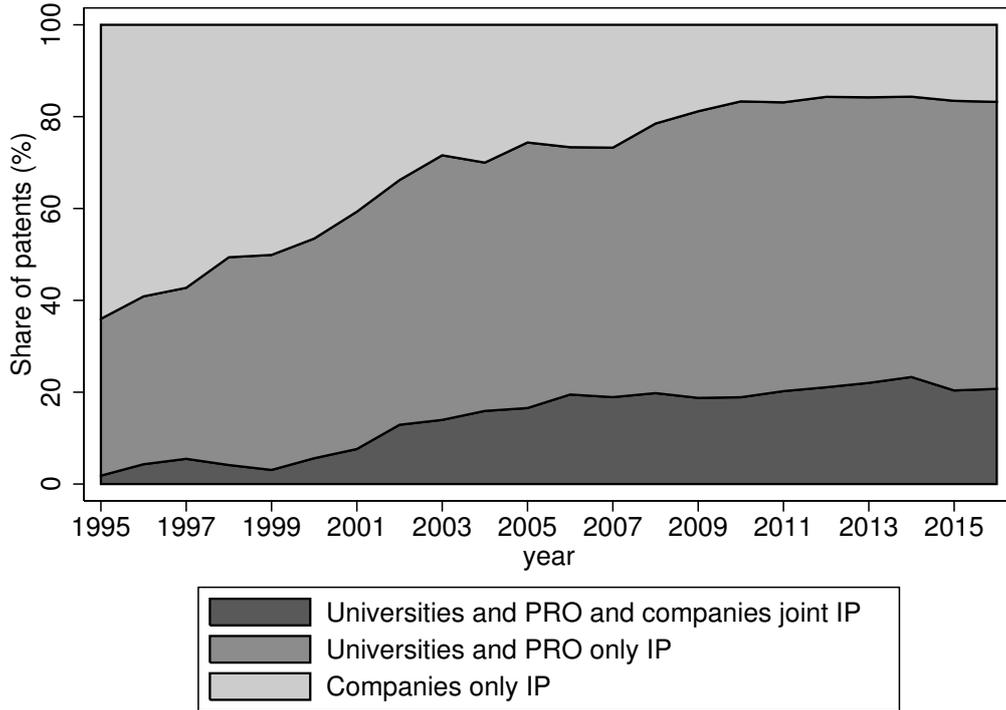


Figure 5: The evolution in the ownership of academic patents (1995-2016)

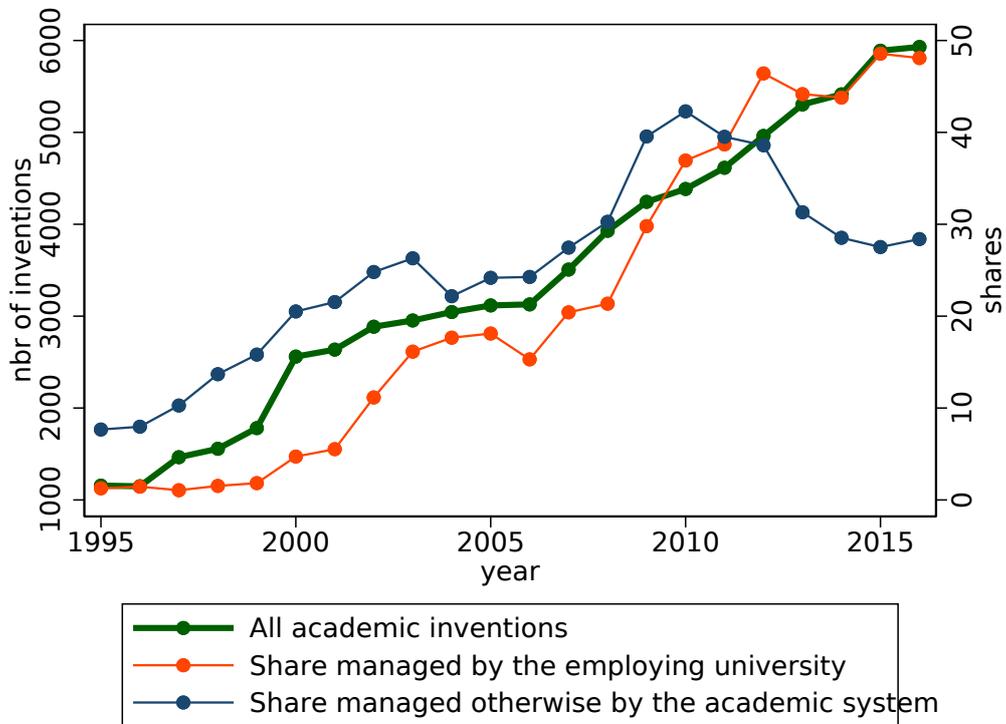


Figure 6: The involvement of universities in the ownership of academic patents (1995-2016)

If we distinguish between patents that are owned by the university that employs the focal researcher and those that are owned by other institutions, such as co-inventors' universities or public research organizations, we see in Figure 6 that the number of universities applying the ownership regime increased significantly after 2006. This movement occurred jointly with PROs until 2011, before somehow substituting for them after that date. Examining very closely, one might wonder whether the increase we see after 1999 and after 2006 (red line, which refers to the right vertical axis) does not better explain the sustained increase in the number of academic inventions (bold green line, which refers to the left vertical axis). Of course, behind these aggregate numbers are individual universities, each of which has a specific strategy and implements the ownership regime at different times.

## 2.4 METHODOLOGY

### 2.4.1 *Identifying the institutions adopting the regime*

We use an empirical approach that exploits heterogeneity across universities and schools in the implementation of government recommendations towards academic patent ownership. Our first step is to identify which universities actually implement the policy recommendations, and when. For this, we use a “revealed strategy” approach based on the share of patents owned by the institution each year: a structural upward break in its time trend is interpreted as a signal of effective implementation of the university's ownership regime.

More in detail, we use the panel dataset presented in Subsection 2.3.2, which we aggregate to the institutional level, and then calculate for each of the 62 universities and 17 business and engineering schools the total number of patented inventions each year<sup>9</sup>, and the share of these for which the institution has retained the intellectual property rights (either alone or in co-ownership with a firm)<sup>10</sup>. We then study the

<sup>9</sup> We removed from the study 19 universities and 25 schools where less than 150 inventions were made over the 22 years.

<sup>10</sup> First, note that we calculate the share retained over the previous, current, and next year to reduce the high temporal variability. Second, since institutions are technically managing as many patents as they fill applications for in each office, this treatment variable is built on the whole set of patents applications (both filed at the EPO and INPI). For instance, one strategy for an institution could be to increase the number of patents filed at the EPO while decreasing in the same proportion the number of patents filed at the INPI. In that case, if the treatment variable is built on EPO patents only, it would allocate the institution to the treated group (by mistake), while built on INPI patents the same institution would be allocated to the control group. Since the volume of patents managed remained constant, in this example the correct allocation is to the control group.

temporal evolution of this share in each institution in search of a notable evolution. For each year in the panel, we calculate the difference in slopes between the three previous years and the three following years. When it is positive in a given year and greater than a threshold (which we will define and then play with to check the robustness of our analysis), we assign the value 1 to the indicator variable *Treated* that signals the observed implementation of the university's ownership regime. If several years are validated for the same institution, we keep only the one with the highest difference in slopes, and if several years have exactly the same maximum difference in slopes we keep only the first year. All universities and years combined, these differences are on average zero (-1%) with a standard deviation of 16.57%, a minimum of -117% and a maximum of +75%. Such a large variance results from the sometimes very low volume of inventions in some institutions. We set the threshold value at 20 percent for the main analysis and run robustness checks on the 15 percent and 25 percent values<sup>11</sup>. With this parameter, there are 31 institutions that pass the threshold while the other 48 are used as potential controls.

Figure 7 illustrates the gradual progression in the implementation of the regime in France: five institutions changed their strategy around the passage of the innovation act in 1999, and then more and more institutions followed until reaching two peaks in 2008 and 2012. This pattern is robust to a change in the threshold value (see Figures 8 and 9 in Appendix). It is possible that legislations introduced in 2005 and 2007 that increased funding for university-industry collaborations and university autonomy explain the first peak, while a reform passed in 2012 initiated the regionalization of TTOs and could explain the revival of institutional involvement that year.

#### 2.4.2 *Identification strategy*

**MATCHING** Because the implementation of government recommendations is a decision made by each institution, presumably based on its needs and expectations, we match universities with each other on a (limited) set of observable characteristics to reduce the effect of potential selection bias. We use a Coarsened Exact Matching (Iacus, King, and Porro, 2012; King and Nielsen, 2018), and match institutions on the number of patents resulting from research within the institution (regardless of patent

<sup>11</sup> Setting lower values increases the number of institutions that pass the threshold, but values that are too low are more likely to include false positives (variations that do not actually signal a change in university strategy), while setting higher values increases precision but significantly reduces the number of institutions that pass the threshold. For example, setting the threshold at 30 percent would leave only 6 institutions.

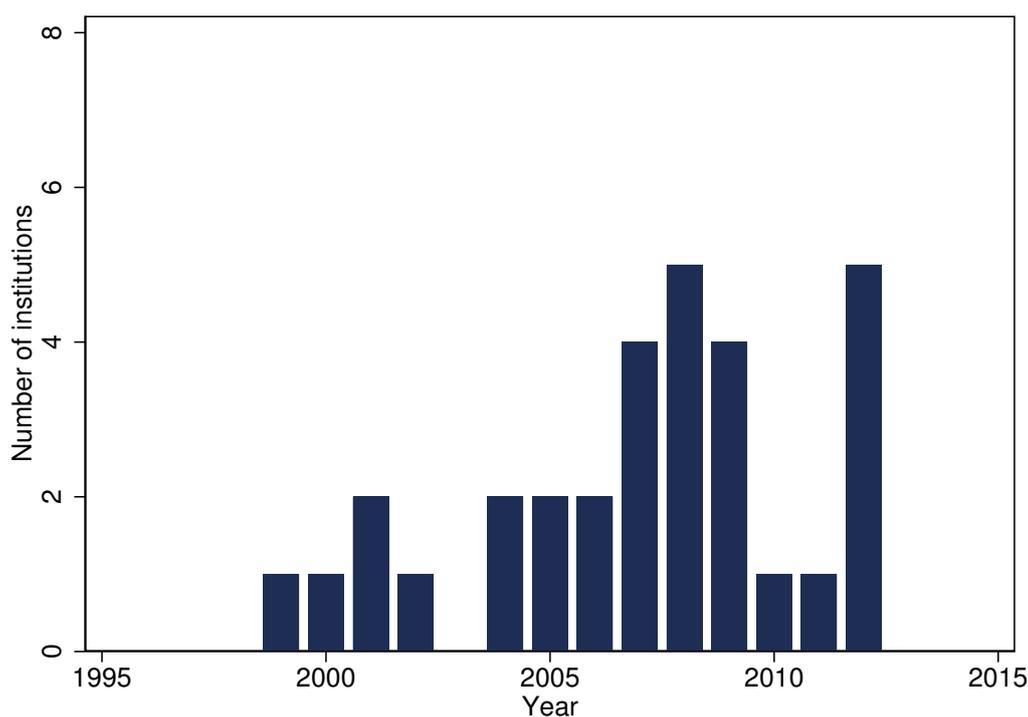


Figure 7: Number of institutions implementing the policy recommendations each year.

ownership) in the three years prior to implementation, the trend in share of patents managed by the institution itself over the same period, the type of institution (public university or business/engineering school) and the year of implementation.

Table 13 shows the mean and standard deviation for each of these matching variables as well as ex-post variables (on which we did not match) for the group of institutions implementing the reform (treated) and the group not implementing it (control)<sup>12</sup>. In the last column, it reports the t-tests of difference in means between groups. The first panel reports these statistics before matching, while the second panel refers to the statistics after matching. We managed to find at least one control institution for three quarters of the treated universities, and the t-tests of the second panel confirm that these two groups are no longer statistically different on observable characteristics.

**ECONOMETRIC SPECIFICATION** We now use the individual-level panel that we restrict to the previously matched institutions and recompute weights (which correct for strata size) to account for the varying number of scientists within institutions. Table 14 summarizes, at the time of the employing institution's adoption of the regime,

<sup>12</sup> There are 665 observations in the pre-matching control group because, unlike treated institutions for which the treatment year is identified, the control group includes several years for each institution in which they may be a counterfactual for a treated institution.

Table 13: Difference in means on observable characteristics between treated and control groups.

	<i>Before matching</i>					
	Treatment group		Control group		Difference t-test	
	mean	sd	mean	sd	b	p
Number of patents <sup>Pre</sup>	66.03	68.70	152.62	187.54	86.59	(0.00)
Share of patents managed <sup>Pre</sup>	-0.01	0.04	0.28	0.66	0.28	(0.00)
Share of universities (vs schools)	0.74	0.44	0.80	0.40	0.06	(0.48)
Year	2007.03	3.69	2007.00	5.48	-0.03	(0.96)
Share of patents managed <sup>Post</sup>	0.29	0.08	0.03	0.06	-0.26	(0.00)
Number of patents <sup>Post</sup>	94.94	100.51	179.73	209.52	84.79	(0.00)
Number of univ-owned patents <sup>Post</sup>	44.94	61.04	84.85	116.33	39.92	(0.00)
Number of firm-owned patents <sup>Post</sup>	28.74	25.23	67.65	62.36	38.91	(0.00)
Number of co-owned patents <sup>Post</sup>	21.26	28.13	27.23	45.39	5.97	(0.28)
Number of cit-weighted patents <sup>Post</sup>	3773.71	10270.78	12842.41	24282.53	9068.70	(0.00)
Number of patent families <sup>Post</sup>	65.35	62.26	124.48	144.90	59.13	(0.00)
Observations	31		665		696	
	<i>After matching</i>					
	Treatment group		Control group		Difference t-test	
	mean	sd	mean	sd	b	p
Number of patents <sup>Pre</sup>	70.21	76.94	80.03	104.51	9.83	(0.68)
Share of patents managed <sup>Pre</sup>	0.01	0.04	0.00	0.07	-0.00	(0.80)
Share of universities (vs schools)	0.79	0.41	0.79	0.41	-0.00	(1.00)
Year	2006.92	3.99	2006.92	3.93	-0.00	(1.00)
Share of patents managed <sup>Post</sup>	0.28	0.06	0.03	0.05	-0.25	(0.00)
Number of patents <sup>Post</sup>	106.25	111.85	106.31	130.01	0.06	(1.00)
Number of univ-owned patents <sup>Post</sup>	48.21	68.82	48.10	67.08	-0.11	(1.00)
Number of firm-owned patents <sup>Post</sup>	32.71	27.08	44.72	43.60	12.01	(0.27)
Number of co-owned patents <sup>Post</sup>	25.33	30.81	13.49	27.66	-11.85	(0.09)
Number of cit-weighted patents <sup>Post</sup>	4641.58	11575.31	5078.74	13557.83	437.16	(0.88)
Number of patent families <sup>Post</sup>	72.29	69.16	76.37	90.93	4.08	(0.85)
Observations	24		71		95	

their demographics, scientific field, productivity (number of publications on the past three years and H-index) and prior patenting experience. This sample is representative of the overall population of professors and researchers in France.

Table 14: Summary statistics on the sample of scientists at matched institutions

	mean	sd	min	max
Gender	0.65	0.48	0	1
Age	47.16	10.32	23	79
Fundamental Biology	0.23	0.42	0	1
Medicine	0.21	0.40	0	1
Applied bio. Ecology	0.12	0.32	0	1
Chemistry	0.13	0.33	0	1
Physics	0.14	0.35	0	1
Universe Science	0.04	0.20	0	1
Engineering Sciences	0.18	0.39	0	1
Mathematics	0.09	0.29	0	1
Social Sciences	0.40	0.49	0	1
Humanities	0.40	0.49	0	1
Nb of publications	0.32	0.65	0	24
H-index	3.79	6.64	0	120
Inventor	0.00	0.00	0	0
Treatment year	2007.33	3.45	1999	2012
Observations	70462			

Note: All variables are measured at the time of the treatment. Gender equals 0 for female, and 1 for male. The number of publications is weighted by the number of co-authors, and averaged on the three previous years.

We run the following difference-in-differences linear regression to assess the impact of the university's implementation of the regime on the propensity to invent of its professors and researchers:

$$y_{iut} = \alpha + \delta \text{Post}_{ut} + \Delta \text{Treated}_{ut} \times \text{Post}_{ut} + X'_{iut} \phi + \theta_i + \Theta_u + \eta_t + \varepsilon_{iut}, \quad (12)$$

where  $y_{iut}$  is the logarithm of the number of EPO patents (for patent disambiguation threshold 0.5<sup>13</sup>) of scientist  $i$  employed by institution  $u$  in year  $t$ ;  $\text{Treated}_{ut}$  is equal to one if entity  $u$  has engaged in the transfer policy (treated) before year  $t$ , and zero otherwise.  $X'_{iut}$  is a vector of individual-level controls including the scientific field, number of publications, and H-index. We also introduce year, individual, and institution fixed

<sup>13</sup> See Carayol and Carpentier, (2021) for more information.

effects ( $\eta_t$ ,  $\theta_i$ ,  $\Theta_u$  respectively). The main coefficient of interest is  $\Delta$ , reporting the average treatment effect of the university ownership regime on academic invention at the individual level.

## 2.5 THE IMPACT OF THE UNIVERSITY OWNERSHIP REGIME ON ACADEMIC INVENTION

### 2.5.1 *Main results*

We report the main results of interest in Table 15 below, and the full version including coefficients for all control variables is available in Appendix Table 17. The first column includes all academics, while the second and third columns split them between hard scientists and life scientists respectively (social scientists and humanities are not reported), and the fourth and fifth columns divide them between professors (associate and full) and researchers (junior and senior). Coefficients are to be interpreted as the average number of supplementary patents per capita obtained each year thanks to implementing the new regime of university ownership at the university level. Those numbers need to be compared to the actual mean numbers of patents invented within each considered set so that policy effect can be perceived as percentage changes.

We find that professors and researchers employed at institutions that have adopted the university ownership regime, have raised their propensity to invent due to their university implementing the new policy by 20.7% on average. To obtain that number, we divide .006 by .029, which is the average number of patents invented each year in the overall population. This effect is significant at the 5% level.

Comparing columns (2) and (3), we see that impact is much larger in hard sciences as compared to life sciences. Relative to the means in each subset, we get a 32.5% impact in the hard sciences (.013/.04) against a 13.5% impact in life sciences (.005/.037). The effect in the hard sciences is significant at the 5% level whereas the one in the life sciences is not significant.

It is also interesting to compare the impact of university involvement on personnel invention propensity, depending on status. In France most scientists are either researchers employed by national research institutes, or professors (including assistant professors) employed by universities. Both work in research units that are most

of the time staffed by the two types of personnel.<sup>14</sup> We find that the impact is positive and significant for professors and assistant professors only with a 29.2% increase (.007/.024). The impact is negative and non significant for researchers. This result is consistent with the idea that most researchers can benefit from the transfer facilities of their research institutes that are coordinated at the national level. Therefore they are less sensitive to the implementation of the university transfer policy.

Table 15: Impact of university participation in the ownership regime on academics' number of patents (partial table)

	(1)	(2)	(3)	(4)	(5)
	All	Hard Scientists	Life Scientists	Professors	Researchers
Treated $\times$ Post	0.003** (0.001)	0.005** (0.002)	0.003 (0.003)	0.004** (0.001)	-0.006 (0.006)
Observations	451746	172296	127430	375588	67293

Note: we present the results of the estimation of  $\delta_t$  from Equation 12. The dependent variable is the logarithm of the yearly number of EPO patents disambiguated with threshold  $\beta = 0.5$ . In column (1), we include the full matched sample. We restrict the sample to scientists in hard sciences in column (2), and those in life sciences in column (3). We divide the sample between professors (including associate professors) in column (4) and researchers (either full or associate) in column (5). In all regressions, we include individual, university and time fixed effects as well as the following control variables: post, age, gender, number of publications (past three years), H-index, and share of patents managed by the academic system (excluding the employing institution). The standard errors are clustered at the individual and university levels. Significance level are: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

One concern that may have accompanied this type of reform is the possibly lesser ability of the private sector to exploit academic inventions. We report in Table 16 the regressions according to the type of patent ownership (see Appendix Table 18 for the complete results). The first column shows the number of patents for which at least one applicant is a firm, in the second column all applicants are firms, in the third all applicants are universities and/or PROs, and in the fourth applicants are both firms and universities or PROs. Note that the first column is the sum of the second and fourth ones. Our results contradict the belief described above, and instead indicate that firms benefit significantly from the reform in the sense that they partially own the additional inventions, but do not manage to capture more of them under sole ownership.

<sup>14</sup> The cut between researchers and professors is career consistent as most assistant researchers are promoted as researchers whereas most assistant professors are promoted as professors.

Table 16: Impact of university participation in the ownership regime on academics' choice of transfer pathway (partial table)

	(1)	(2)	(3)	(4)
	1+ company	Companies only	Universities only	Comp. & univ.
Treated $\times$ Post	0.003*** (0.001)	-0.000 (0.001)	0.000 (0.001)	0.003*** (0.001)
Observations	452331	452331	452331	452331

Note: we present the results of the estimation of  $\delta_t$  from Equation 12, but the dependent variable is the logarithm of the yearly number of EPO patents disambiguated with threshold  $\beta = 0.5$  that are given in ownership to the private sector (not exclusively in column 1, exclusively in column 2), to the university and PRO system exclusively (column 3), or in co-ownership between these two types of entities (column 4). In all regressions, we include individual, university and time fixed effects as well as the following control variables: post, age, gender, number of publications (past three years), H-index, and share of patents managed by the academic system (excluding the employing institution). The standard errors are clustered at the individual and university levels. Significance level are: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

### 2.5.2 Robustness checks

We perform a set of robustness checks by first varying the threshold for disambiguation of academic patents, then the patent office considered, and finally the threshold for the treatment variable.

**PATENT DISAMBIGUATION** The main results presented were performed on EPO patents with the threshold value  $\beta = 0.5$  at the patent disambiguation stage. Alternatively, we repeat the analysis with two other values of  $\beta$ . When we give even more importance to precision than recall ( $\beta = 0.3$ ), there are more institutions in the treated group, but fewer find an appropriate match (Appendix Table 19). The main result remains consistent and become even more significant, while the effects on subgroups of discipline or researchers vs professors become inconsistent (Appendix Table 20). The effect on patent ownership is robust (Appendix Table 21). In turn, when recall is weighted equally to precision ( $\beta = 1$ ), we find much fewer institutions in the treated group so that only 10 finally find an appropriate match (Appendix Table 22). The main result remains robust (Appendix Table 23), while the effect on private sector ownership is consistent but becomes insignificant (Appendix Table 24).

**PATENT OFFICE** We carried the main analysis on patents filed at the EPO to ease comparison between studies. But it could be the case that universities decreased the number of patents filed at the INPI in favor of a more ambitious strategy at the Eu-

ropean level by filing them directly with the EPO. In this case, substitution between patent offices would imply that there is no real increase in the total number of inventions. We verify this hypothesis in Appendix Tables 25 and 26, where the results are replicated on the number of patents filed at the INPI this time. It appears that the coefficients are positive although not significant, but not negative. Thus we can discard the hypothesis of a substitution effect between patent offices.

**THRESHOLDS TO DEFINE THE TREATMENT VARIABLE** Finally, to define the treatment variable, we set the threshold for the difference in slope at 20%. This value may seem arbitrary, so we study how the results are affected when we vary this threshold up and down. Setting it lower, at 15 percent, we find more treated units and more matched control units (Appendix Table 27), but all results are robust (Appendix Tables 28) and 29). Setting it higher, at 25 percent, the number of treated institutions decreases significantly (Appendix Table 30), but the main effect remains robust (Appendix Tables 31), while the hypothesis of a crowding out effect on firms remains unverified in our results (Appendix Tables 32).

## 2.6 DISCUSSION AND CONCLUSION

What is the impact of the university's ownership regime of patents on academic invention? This question is difficult to answer, mainly because of the divergence in its observed effects between the United States and Northern and Eastern European countries. In this chapter, we assess how the effective involvement of universities in the patent ownership regime affects academics' propensity to invent in France. We find that professors in universities that took the step file on average 20.7% more inventions. This supports the idea that the "last mile" of university ownership regime, i.e. the effective implementation by actors, may be the key to the success of the reform and may thus explain the puzzle faced by the literature.

Indeed, the first difference we identified between continents is the variation (positive or negative) in the involvement of the academic inventor in the transfer and commercialization of her invention. In the United States, the reform increased her involvement by bringing the management of technology transfer within the university from the federal government. In contrast, the implementation of the regime in Northern and Eastern European countries caused a reduction of her involvement by adding an additional intermediary between her and her industrial partners, namely the TTO. In France, universities' implementation of the patent ownership regime has also led

to a reduction in her involvement, since before the year 2000 around two third of inventions were transferred directly from researchers to companies. If this determinant had been preponderant in the impact of universities decision to make a move towards adopting the ownership regime, we would have observed a negative impact in France, which is not verified in our results. Thus, it appears that the degree of involvement of the researcher in the transfer of her inventions plays only a secondary role (if any) in determining the performance of the university's ownership regime.

The second difference we observe is that researchers may (or may not) continue to use old technology transfer pathways (such as direct transfer between the inventor and the commercial partner), without passing by the TTO. In this sense, the French case is closer to the American one in terms of the flexibility in the patent ownership structure that we have observed, and further away from that of Northern and Eastern Europe where the abolishment of the professor's privilege rather implied an obligation for inventors to go through the TTO and put an end to the alternative transfer pathways (Czarnitzki et al., 2015). The positive effect observed in France thus suggests that this factor affects more significantly the performance of the university's ownership model. It seems important, then, that researchers can use various transfer pathways: using their network with industry and transferring themselves when relevant, while having the option of relying on their TTO in other situations. This idea echoes the discussion of Litan, Mitchell, and Reedy, (2007) who suggest that the limitations of technology transfer performance in the US can be attributed to the monopolistic position that many TTOs have taken. They suggest possible modifications to the university ownership model, such as a "free agency". The researcher would be required to pay a percentage of the revenues back to her university, and would be free to select the third party that would handle the technology transfer of her invention, the university TTO being simply one of them.

This study has a major limitation that should be addressed in future research. Both the dependent (number of academic inventions) and the main independent (implementation of the university's ownership regime) variables are constructed from the academic patents of professors and researchers affiliated with the university. Alternative approaches to making these two variables independent would be to use as an independent variable the year the TTO creation (or any other transfer structure), or the number of full-time equivalent employees within the TTO. Unfortunately, these data are not available in France. In addition, we have relatively little information on the determinants of universities' decisions to follow policy recommendations. We have considered patent management trends and the number of past inventions, but there are likely many other relevant factors. For example, is there an imitation effect

between universities? Did the industrial partners of the researchers use their bargaining power to delay or even prevent the implementation of the policy reform in some institutions? How important are the financial and human resources available to the institution? Technology transfer seems to be a complex activity, which requires skills, human and financial means, and the construction of a network of industrial partnerships in order to function efficiently. Is there a learning period after the opening of the TTO, and how long does it last before the structure is efficient? These are all avenues that future research can explore.

## 2.7 APPENDIX OF CHAPTER 2

*Complementary tables (main results)*

Table 17: Impact of university participation in the ownership regime on academics' number of patents (complete table)

	(1)	(2)	(3)	(4)	(5)
	All	Hard Scientists	Life Scientists	Professors	Researchers
Treated $\times$ Post	0.003** (0.001)	0.005** (0.002)	0.003 (0.003)	0.004** (0.001)	-0.006 (0.006)
Post	-0.002 (0.001)	-0.002 (0.002)	-0.003 (0.003)	-0.002 (0.001)	-0.002 (0.004)
Outside options	0.005** (0.002)	0.013*** (0.004)	0.004 (0.003)	0.007** (0.003)	-0.006 (0.009)
Nb of publications	0.007*** (0.002)	0.008** (0.004)	0.013*** (0.003)	0.005** (0.002)	0.020*** (0.007)
H-index	0.001*** (0.000)	0.002*** (0.000)	0.001 (0.001)	0.001** (0.000)	0.001 (0.001)
Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (.)
gender	-0.003 (0.005)	-0.003 (0.003)	-0.019 (0.024)	-0.003 (0.005)	0.000 (.)
Observations	451746	172296	127430	375588	67293

Note: we present the results of the estimation of  $\delta_t$  from Equation 12. The dependent variable is the logarithm of the yearly number of EPO patents disambiguated with threshold  $\beta = 0.5$ . In column (1), we include the full matched sample. We restrict the sample to scientists in hard sciences in column (2), and those in life sciences in column (3). We divide the sample between professors (including associate professors) in column (4) and researchers (either full or associate) in column (5). In all regressions, we include individual, university and time fixed effects. Control variables include *outsideoptions*, which is the share of patents managed by the academic system (excluding the institution of the focal scientist) and reflect her possibility to transfer the invention through the university system but without going through her own TTO. The standard errors are clustered at the individual and university levels. Significance level are: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 18: Impact of university participation in the ownership regime on academics' choice of transfer pathway (complete table)

	(1)	(2)	(3)	(4)
	1+ company	Companies only	Universities only	Comp. & univ.
Treated $\times$ Post	0.003*** (0.001)	-0.000 (0.001)	0.000 (0.001)	0.003*** (0.001)
Post	-0.002** (0.001)	-0.001* (0.001)	0.001 (0.001)	-0.001** (0.000)
Nb of publications	0.002 (0.001)	-0.000 (0.001)	0.006*** (0.002)	0.002*** (0.001)
H-index	0.000 (0.000)	-0.000 (0.000)	0.001*** (0.000)	0.000 (0.000)
Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
gender	-0.004 (0.005)	-0.000 (0.000)	0.001 (0.001)	-0.004 (0.005)
Observations	452331	452331	452331	452331

Note: we present the results of the estimation of  $\delta_t$  from Equation 12, but the dependent variable is the logarithm of the yearly number of EPO patents disambiguated with threshold  $\beta = 0.5$  that are given in ownership to the private sector (not exclusively in column 1, exclusively in column 2), to the university and PRO system exclusively (column 3), or in co-ownership between these two types of entities (column 4). In all regressions, we include individual, university and time fixed effects as well as the following control variables: post, age, gender, number of publications (past three years), H-index, and share of patents managed by the academic system (excluding the employing institution). The standard errors are clustered at the individual and university levels. Significance level are: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

*Results using patent disambiguation threshold 0.3*

Table 19: Difference in means on observable characteristics between treated and control groups (patent disambiguation threshold 0.3).

	<i>Before matching</i>					
	Treatment group		Control group		Difference t-test	
	mean	sd	mean	sd	b	p
Number of patents <sup>Pre</sup>	38.97	40.18	117.13	132.37	78.16	(0.00)
Share of patents managed <sup>Pre</sup>	-0.02	0.10	0.25	0.61	0.27	(0.00)
Share of universities (vs schools)	0.82	0.39	0.82	0.39	-0.01	(0.94)
Year	2004.59	4.11	2007.00	5.49	2.41	(0.00)
Share of patents managed <sup>Post</sup>	0.36	0.12	0.05	0.08	-0.32	(0.00)
Number of patents <sup>Post</sup>	73.62	68.60	142.77	145.74	69.16	(0.00)
Number of univ-owned patents <sup>Post</sup>	44.18	50.31	93.63	96.23	49.45	(0.00)
Number of firm-owned patents <sup>Post</sup>	13.06	10.79	18.79	14.21	5.73	(0.01)
Number of co-owned patents <sup>Post</sup>	16.38	17.55	30.35	46.85	13.97	(0.00)
Number of cit-weighted patents <sup>Post</sup>	1857.18	2937.51	6826.72	12692.31	4969.55	(0.00)
Number of patent families <sup>Post</sup>	55.41	51.63	105.23	104.64	49.82	(0.00)
Observations	34		209		243	
	<i>After matching</i>					
	Treatment group		Control group		Difference t-test	
	mean	sd	mean	sd	b	p
Number of patents <sup>Pre</sup>	43.32	47.81	64.63	113.80	21.32	(0.28)
Share of patents managed <sup>Pre</sup>	0.03	0.05	0.04	0.05	0.01	(0.49)
Share of universities (vs schools)	0.89	0.32	0.89	0.31	0.00	(1.00)
Year	2004.42	4.25	2004.42	4.21	0.00	(1.00)
Share of patents managed <sup>Post</sup>	0.39	0.11	0.04	0.07	-0.35	(0.00)
Number of patents <sup>Post</sup>	89.11	83.41	95.93	143.71	6.82	(0.80)
Number of univ-owned patents <sup>Post</sup>	58.42	62.12	60.34	85.73	1.92	(0.92)
Number of firm-owned patents <sup>Post</sup>	14.21	12.69	12.57	10.40	-1.64	(0.62)
Number of co-owned patents <sup>Post</sup>	16.47	16.66	23.02	53.82	6.54	(0.45)
Number of cit-weighted patents <sup>Post</sup>	2441.11	3458.41	5455.71	14207.44	3014.61	(0.17)
Number of patent families <sup>Post</sup>	67.84	62.76	72.09	100.62	4.25	(0.83)
Observations	19		29		48	

Table 20: Impact of university participation in the ownership regime on academics' number of patents (patent disambiguation threshold 0.3)

	(1)	(2)	(3)	(4)	(5)
	All	Hard Scientists	Life Scientists	Professors	Researchers
Treated $\times$ Post	0.002** (0.001)	0.004** (0.001)	0.001 (0.001)	0.001 (0.001)	0.007** (0.003)
Post	-0.001* (0.001)	-0.003 (0.002)	-0.002 (0.001)	-0.001 (0.001)	-0.006 (0.003)
Outside options	0.002** (0.001)	0.005*** (0.002)	0.001 (0.001)	0.001 (0.001)	0.011* (0.006)
Nb of publications	0.000 (0.001)	0.002** (0.001)	-0.002 (0.002)	0.000 (0.001)	0.000 (0.002)
H-index	0.001*** (0.000)	0.001 (0.001)	0.001*** (0.000)	0.001** (0.000)	0.001 (0.001)
Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (.)
gender	0.001 (0.001)	0.003** (0.001)	-0.001 (0.002)	0.000 (0.001)	0.000 (.)
Observations	321753	152228	121721	247891	64242

Note: we present the results of the estimation of  $\delta_t$  from Equation 12. The dependent variable is the logarithm of the yearly number of EPO patents disambiguated with threshold  $\beta = 0.3$ . In column (1), we include the full matched sample. We restrict the sample to scientists in hard sciences in column (2), and those in life sciences in column (3). We divide the sample between professors (including associate professors) in column (4) and researchers (either full or associate) in column (5). In all regressions, we include individual, university and time fixed effects. Control variables include `outsideoptions`, which is the share of patents managed by the academic system (excluding the institution of the focal scientist) and reflect her possibility to transfer the invention through the university system but without going through her own TTO. The standard errors are clustered at the individual and university levels. Significance level are: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 21: Impact of university participation in the ownership regime on academics' choice of transfer pathway (patent disambiguation threshold 0.3)

	(1)	(2)	(3)	(4)
	1+ company	Companies only	Universities only	Comp. & univ.
Treated $\times$ Post	0.001** (0.000)	0.000 (0.000)	0.000 (0.001)	0.001** (0.000)
Post	-0.001** (0.001)	-0.000 (0.000)	-0.000 (0.001)	-0.001** (0.000)
Nb of publications	0.001 (0.001)	-0.000 (0.000)	-0.001 (0.001)	0.001 (0.001)
H-index	0.000 (0.000)	-0.000 (0.000)	0.001*** (0.000)	0.000 (0.000)
Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
gender	0.001** (0.000)	0.000 (0.000)	-0.000 (0.001)	0.000** (0.000)
Observations	321851	321851	321851	321851

Note: we present the results of the estimation of  $\delta_t$  from Equation 12, but the dependent variable is the logarithm of the yearly number of EPO patents disambiguated with threshold  $\beta = 0.3$  that are given in ownership to the private sector (not exclusively in column 1, exclusively in column 2), to the university and PRO system exclusively (column 3), or in co-ownership between these two types of entities (column 4). In all regressions, we include individual, university and time fixed effects as well as the following control variables: post, age, gender, number of publications (past three years), H-index, and share of patents managed by the academic system (excluding the employing institution). The standard errors are clustered at the individual and university levels. Significance level are: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

*Results using patent disambiguation threshold 1*

Table 22: Difference in means on observable characteristics between treated and control groups (patent disambiguation threshold 1).

	<i>Before matching</i>					
	Treatment group		Control group		Difference t-test	
	mean	sd	mean	sd	b	p
Number of patents <sup>Pre</sup>	56.07	39.45	156.71	207.41	100.64	(0.00)
Share of patents managed <sup>Pre</sup>	-0.02	0.08	0.27	0.66	0.29	(0.00)
Share of universities (vs schools)	0.60	0.51	0.84	0.37	0.24	(0.09)
Year	2006.73	3.81	2007.00	5.48	0.27	(0.79)
Share of patents managed <sup>Post</sup>	0.28	0.06	0.02	0.05	-0.26	(0.00)
Number of patents <sup>Post</sup>	85.13	50.61	180.94	230.22	95.81	(0.00)
Number of univ-owned patents <sup>Post</sup>	34.53	22.88	66.67	108.02	32.14	(0.00)
Number of firm-owned patents <sup>Post</sup>	27.80	27.08	92.01	95.37	64.21	(0.00)
Number of co-owned patents <sup>Post</sup>	22.80	23.38	22.27	41.47	-0.53	(0.93)
Number of cit-weighted patents <sup>Post</sup>	1922.20	3210.45	15048.06	34937.77	13125.86	(0.00)
Number of patent families <sup>Post</sup>	64.73	42.05	130.76	165.22	66.03	(0.00)
Observations	15		1159		1174	
	<i>After matching</i>					
	Treatment group		Control group		Difference t-test	
	mean	sd	mean	sd	b	p
Number of patents <sup>Pre</sup>	54.40	33.15	83.02	97.74	28.62	(0.15)
Share of patents managed <sup>Pre</sup>	0.02	0.05	0.02	0.05	0.01	(0.80)
Share of universities (vs schools)	0.80	0.42	0.80	0.40	-0.00	(1.00)
Year	2006.10	3.96	2006.10	3.78	0.00	(1.00)
Share of patents managed <sup>Post</sup>	0.29	0.07	-0.01	0.05	-0.29	(0.00)
Number of patents <sup>Post</sup>	82.30	50.21	106.31	120.84	24.01	(0.38)
Number of univ-owned patents <sup>Post</sup>	32.20	19.72	29.69	43.16	-2.51	(0.80)
Number of firm-owned patents <sup>Post</sup>	32.60	32.41	66.43	66.55	33.83	(0.04)
Number of co-owned patents <sup>Post</sup>	17.50	19.00	10.19	15.32	-7.31	(0.29)
Number of cit-weighted patents <sup>Post</sup>	1456.10	2046.31	5115.18	13101.33	3659.08	(0.07)
Number of patent families <sup>Post</sup>	58.60	38.09	82.43	89.52	23.83	(0.27)
Observations	10		75		85	

Table 23: Impact of university participation in the ownership regime on academics' number of patents (patent disambiguation threshold 1)

	(1)	(2)	(3)	(4)	(5)
	All	Hard Scientists	Life Scientists	Professors	Researchers
Treated $\times$ Post	0.004** (0.002)	0.006 (0.004)	0.004 (0.004)	0.006** (0.003)	-0.007 (0.007)
Post	0.001 (0.003)	-0.001 (0.004)	0.006 (0.007)	-0.002 (0.002)	0.013 (0.008)
Outside options	0.005 (0.004)	0.008 (0.008)	0.000 (0.009)	0.004 (0.003)	-0.002 (0.010)
Nb of publications	0.006*** (0.002)	0.008** (0.004)	0.001 (0.003)	0.007** (0.003)	0.005** (0.003)
H-index	0.001 (0.000)	0.000 (0.001)	0.001** (0.000)	0.001*** (0.000)	-0.000 (0.001)
Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (.)
gender	-0.019 (0.021)	0.001 (0.003)	-0.156 (0.117)	-0.017 (0.022)	0.000 (.)
Observations	308775	106296	65847	253021	47338

Note: we present the results of the estimation of  $\delta_t$  from Equation 12. The dependent variable is the logarithm of the yearly number of EPO patents disambiguated with threshold  $\beta = 1$ . In column (1), we include the full matched sample. We restrict the sample to scientists in hard sciences in column (2), and those in life sciences in column (3). We divide the sample between professors (including associate professors) in column (4) and researchers (either full or associate) in column (5). In all regressions, we include individual, university and time fixed effects. Control variables include *outsideoptions*, which is the share of patents managed by the academic system (excluding the institution of the focal scientist) and reflect her possibility to transfer the invention through the university system but without going through her own TTO. The standard errors are clustered at the individual and university levels. Significance level are: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 24: Impact of university participation in the ownership regime on academics' choice of transfer pathway (patent disambiguation threshold 1)

	(1)	(2)	(3)	(4)
	1+ company	Companies only	Universities only	Comp. & univ.
Treated $\times$ Post	0.002 (0.002)	-0.001 (0.001)	0.003 (0.002)	0.003* (0.002)
Post	-0.001 (0.001)	-0.001 (0.001)	0.002 (0.002)	0.000 (0.001)
Nb of publications	0.003** (0.001)	0.002* (0.001)	0.003* (0.001)	0.001* (0.001)
H-index	0.000 (0.000)	-0.000 (0.000)	0.001 (0.000)	0.000 (0.000)
Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
gender	-0.020 (0.021)	0.001 (0.001)	0.001 (0.001)	-0.021 (0.021)
Observations	308775	308775	308775	308775

Note: we present the results of the estimation of  $\delta_t$  from Equation 12, but the dependent variable is the logarithm of the yearly number of EPO patents disambiguated with threshold  $\beta = 1$  that are given in ownership to the private sector (not exclusively in column 1, exclusively in column 2), to the university and PRO system exclusively (column 3), or in co-ownership between these two types of entities (column 4). In all regressions, we include individual, university and time fixed effects as well as the following control variables: post, age, gender, number of publications (past three years), H-index, and share of patents managed by the academic system (excluding the employing institution). The standard errors are clustered at the individual and university levels. Significance level are: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

### *Results using INPI patents*

Note that the treatment variable, Treated, is built upon patents filed at both the EPO and INPI, so that the results of matching remain unchanged.

Table 25: Impact of university participation in the ownership regime on academics' number of INPI patents

	(1)	(2)	(3)	(4)	(5)
	All	Hard Scientists	Life Scientists	Professors	Researchers
Treated $\times$ Post	0.002 (0.002)	0.005 (0.003)	-0.001 (0.003)	0.002* (0.001)	-0.001 (0.007)
Post	-0.001 (0.002)	-0.004 (0.003)	0.001 (0.003)	-0.002 (0.002)	0.005 (0.005)
Outside options	0.004 (0.003)	0.011** (0.005)	-0.008 (0.005)	0.003 (0.003)	0.007 (0.006)
Nb of publications	0.005** (0.002)	0.007* (0.004)	0.002 (0.003)	0.004** (0.002)	0.008 (0.006)
H-index	0.001 (0.000)	0.001 (0.001)	-0.001 (0.000)	0.001 (0.000)	-0.000 (0.001)
Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (.)
gender	0.001 (0.001)	-0.001 (0.002)	0.004* (0.002)	0.001 (0.001)	0.000 (.)
Observations	451746	172296	127430	375588	67293

Note: we present the results of the estimation of  $\delta_t$  from Equation 12. The dependent variable is the logarithm of the yearly number of INPI patents disambiguated with threshold  $\beta = 0.5$ . In column (1), we include the full matched sample. We restrict the sample to scientists in hard sciences in column (2), and those in life sciences in column (3). We divide the sample between professors (including associate professors) in column (4) and researchers (either full or associate) in column (5). In all regressions, we include individual, university and time fixed effects. Control variables include *outsideoptions*, which is the share of patents managed by the academic system (excluding the institution of the focal scientist) and reflect her possibility to transfer the invention through the university system but without going through her own TTO. The standard errors are clustered at the individual and university levels. Significance level are: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 26: Impact of university participation in the ownership regime on academics' choice of transfer pathway (INPI patents)

	(1)	(2)	(3)	(4)
	1+ company	Companies only	Universities only	Comp. & univ.
Treated $\times$ Post	0.001 (0.001)	-0.000 (0.001)	0.001 (0.001)	0.001 (0.001)
Post	-0.001 (0.001)	-0.001* (0.001)	-0.000 (0.001)	0.000 (0.000)
Nb of publications	0.000 (0.001)	0.000 (0.001)	0.005** (0.002)	0.000 (0.000)
H-index	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000** (0.000)
Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
gender	-0.000 (0.000)	-0.000 (0.000)	0.001 (0.001)	-0.000 (0.001)
Observations	452331	452331	452331	452331

Note: we present the results of the estimation of  $\delta_t$  from Equation 12, but the dependent variable is the logarithm of the yearly number of INPI patents given in ownership to the private sector (not exclusively in column 1, exclusively in column 2), to the university and PRO system exclusively (column 3), or in co-ownership between these two types of entities (column 4). In all regressions, we include individual, university and time fixed effects as well as the following control variables: post, age, gender, number of publications (past three years), H-index, and share of patents managed by the academic system (excluding the employing institution). The standard errors are clustered at the individual and university levels. Significance level are: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

*Results using different threshold values to define the treatment variable*

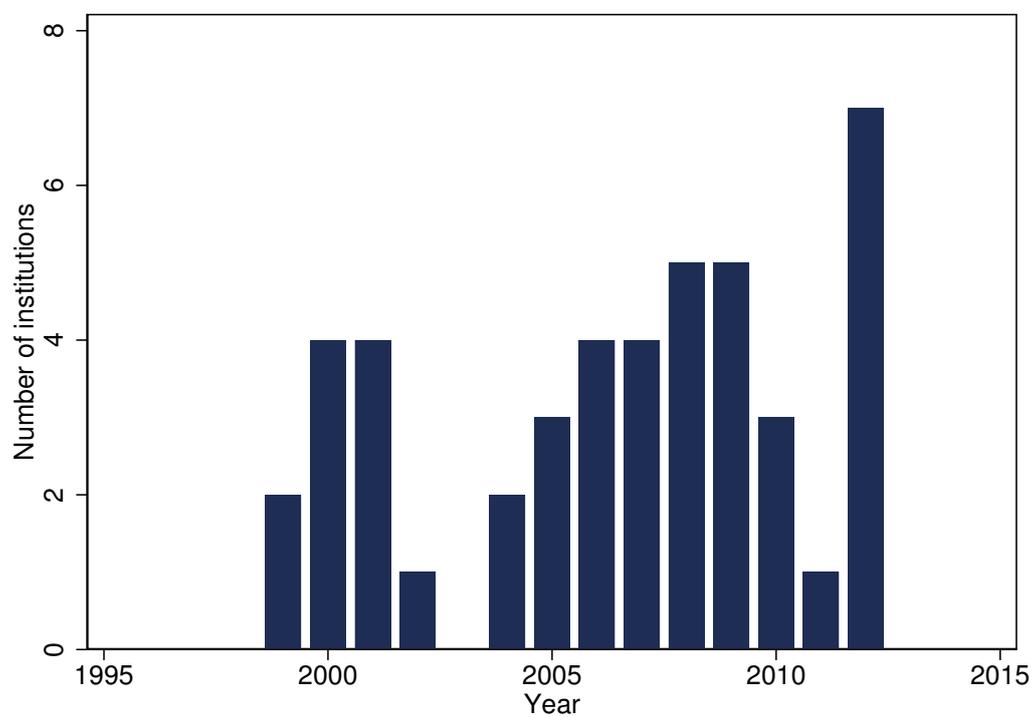


Figure 8: Number of institutions adopting the regime each year (threshold 15%).

Table 27: Difference in means on observable characteristics between treated and control groups (threshold 15%).

	<i>Before matching</i>					
	Treatment group		Control group		Difference t-test	
	mean	sd	mean	sd	b	p
Number of patents <sup>Pre</sup>	80.69	92.54	152.62	187.54	71.94	(0.00)
Share of patents managed <sup>Pre</sup>	-0.01	0.05	0.28	0.66	0.29	(0.00)
Share of universities (vs schools)	0.76	0.43	0.80	0.40	0.04	(0.51)
Year	2006.42	4.14	2007.00	5.48	0.58	(0.38)
Share of patents managed <sup>Post</sup>	0.26	0.08	0.03	0.06	-0.23	(0.00)
Number of patents <sup>Post</sup>	117.11	143.41	179.73	209.52	62.62	(0.01)
Number of univ-owned patents <sup>Post</sup>	55.27	85.24	84.85	116.33	29.59	(0.03)
Number of firm-owned patents <sup>Post</sup>	38.40	41.61	67.65	62.36	29.25	(0.00)
Number of co-owned patents <sup>Post</sup>	23.44	32.34	27.23	45.39	3.79	(0.47)
Number of cit-weighted patents <sup>Post</sup>	6837.29	19386.87	12842.41	24282.53	6005.12	(0.06)
Number of patent families <sup>Post</sup>	81.20	95.73	124.48	144.90	43.28	(0.01)
Observations	45		665		710	
	<i>After matching</i>					
	Treatment group		Control group		Difference t-test	
	mean	sd	mean	sd	b	p
Number of patents <sup>Pre</sup>	83.14	100.77	91.81	127.48	8.67	(0.70)
Share of patents managed <sup>Pre</sup>	-0.00	0.05	-0.00	0.06	-0.00	(0.92)
Share of universities (vs schools)	0.78	0.42	0.78	0.42	-0.00	(1.00)
Year	2006.58	4.21	2006.58	4.17	-0.00	(1.00)
Share of patents managed <sup>Post</sup>	0.25	0.07	0.03	0.05	-0.22	(0.00)
Number of patents <sup>Post</sup>	121.14	151.62	118.03	164.90	-3.11	(0.92)
Number of univ-owned patents <sup>Post</sup>	56.69	93.32	57.18	96.98	0.48	(0.98)
Number of firm-owned patents <sup>Post</sup>	37.89	36.72	45.45	46.05	7.56	(0.41)
Number of co-owned patents <sup>Post</sup>	26.56	35.20	15.40	31.42	-11.15	(0.08)
Number of cit-weighted patents <sup>Post</sup>	7486.86	21298.96	7262.00	20804.26	-224.86	(0.96)
Number of patent families <sup>Post</sup>	82.17	98.47	83.42	111.89	1.26	(0.95)
Observations	36		113		149	

Table 28: Impact of university participation in the ownership regime on academics' number of patents (threshold 15%)

	(1)	(2)	(3)	(4)	(5)
	All	Hard Scientists	Life Scientists	Professors	Researchers
Treated × Post	0.003** (0.001)	0.003 (0.002)	0.005** (0.002)	0.003** (0.001)	0.001 (0.004)
Post	-0.001 (0.001)	0.000 (0.002)	-0.004 (0.002)	-0.001 (0.001)	-0.000 (0.002)
Outside options	0.006** (0.003)	0.012** (0.005)	0.005 (0.003)	0.007** (0.003)	-0.001 (0.009)
Nb of publications	0.006*** (0.002)	0.006** (0.003)	0.009*** (0.003)	0.004*** (0.002)	0.010** (0.004)
H-index	0.001** (0.000)	0.001 (0.001)	0.001 (0.001)	0.001*** (0.000)	0.000 (0.001)
Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (.)
gender	-0.003 (0.003)	-0.003 (0.002)	-0.014 (0.017)	-0.003 (0.003)	0.000 (.)
Observations	797766	325057	235826	639059	137346

Note: we present the results of the estimation of  $\delta_t$  from Equation 12. The dependent variable is the logarithm of the yearly number of EPO patents disambiguated with threshold  $\beta = 0.5$ . In column (1), we include the full matched sample. We restrict the sample to scientists in hard sciences in column (2), and those in life sciences in column (3). We divide the sample between professors (including associate professors) in column (4) and researchers (either full or associate) in column (5). In all regressions, we include individual, university and time fixed effects as well as the following control variables: post, age, gender, number of publications (past three years), H-index, and share of patents managed by the academic system (excluding the employing institution). The standard errors are clustered at the individual and university levels. Significance level are: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 29: Impact of university participation in the ownership regime on academics' choice of transfer pathway (threshold 15%)

	(1)	(2)	(3)	(4)
	1+ company	Companies only	Universities only	Comp. & univ.
Treated $\times$ Post	0.002** (0.001)	0.000 (0.001)	0.001 (0.001)	0.002** (0.001)
Post	-0.001* (0.001)	-0.001 (0.001)	0.000 (0.001)	-0.001* (0.000)
Nb of publications	0.001 (0.001)	-0.000 (0.001)	0.005*** (0.001)	0.002*** (0.001)
H-index	0.000 (0.000)	-0.000 (0.000)	0.001** (0.000)	0.000** (0.000)
Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
gender	-0.003 (0.003)	-0.000 (0.000)	0.000 (0.001)	-0.003 (0.003)
Observations	798351	798351	798351	798351

Note: we present the results of the estimation of  $\delta_t$  from Equation 12, but the dependent variable is the logarithm of the yearly number of EPO patents disambiguated with threshold  $\beta = 0.5$  that are given in ownership to the private sector (not exclusively in column 1, exclusively in column 2), to the university and PRO system exclusively (column 3), or in co-ownership between these two types of entities (column 4). In all regressions, we include individual, university and time fixed effects as well as the following control variables: post, age, gender, number of publications (past three years), H-index, and share of patents managed by the academic system (excluding the employing institution). The standard errors are clustered at the individual and university levels. Significance level are: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

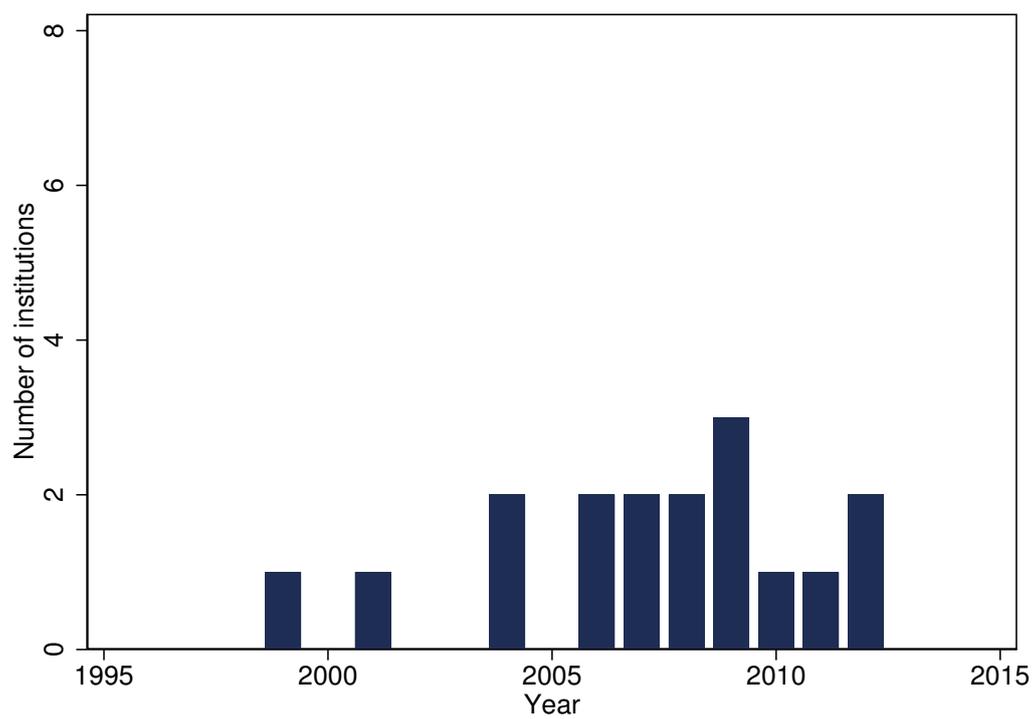


Figure 9: Number of institutions adopting the regime each year (threshold 25%).

Table 30: Difference in means on observable characteristics between treated and control groups (threshold 25%).

	<i>Before matching</i>					
	Treatment group		Control group		Difference t-test	
	mean	sd	mean	sd	b	p
Number of patents <sup>Pre</sup>	62.29	78.01	152.62	187.54	90.33	(0.00)
Share of patents managed <sup>Pre</sup>	0.00	0.04	0.28	0.66	0.28	(0.00)
Share of universities (vs schools)	0.65	0.49	0.80	0.40	0.15	(0.22)
Year	2007.18	3.61	2007.00	5.48	-0.18	(0.85)
Share of patents managed <sup>Post</sup>	0.34	0.06	0.03	0.06	-0.32	(0.00)
Number of patents <sup>Post</sup>	95.71	109.79	179.73	209.52	84.02	(0.01)
Number of univ-owned patents <sup>Post</sup>	50.29	75.27	84.85	116.33	34.56	(0.08)
Number of firm-owned patents <sup>Post</sup>	24.41	25.36	67.65	62.36	43.24	(0.00)
Number of co-owned patents <sup>Post</sup>	21.00	22.22	27.23	45.39	6.23	(0.29)
Number of cit-weighted patents <sup>Post</sup>	4188.06	12936.43	12842.41	24282.53	8654.35	(0.02)
Number of patent families <sup>Post</sup>	64.82	60.67	124.48	144.90	59.66	(0.00)
Observations	17		665		682	
	<i>After matching</i>					
	Treatment group		Control group		Difference t-test	
	mean	sd	mean	sd	b	p
Number of patents <sup>Pre</sup>	71.83	91.81	73.36	110.10	1.53	(0.96)
Share of patents managed <sup>Pre</sup>	0.02	0.03	0.02	0.04	0.00	(0.73)
Share of universities (vs schools)	0.75	0.45	0.75	0.44	0.00	(1.00)
Year	2006.83	3.93	2006.83	3.80	-0.00	(1.00)
Share of patents managed <sup>Post</sup>	0.33	0.05	0.04	0.05	-0.29	(0.00)
Number of patents <sup>Post</sup>	114.25	127.17	96.87	140.70	-17.38	(0.67)
Number of univ-owned patents <sup>Post</sup>	58.33	89.04	44.17	70.21	-14.16	(0.61)
Number of firm-owned patents <sup>Post</sup>	29.50	28.47	37.10	38.44	7.60	(0.43)
Number of co-owned patents <sup>Post</sup>	26.42	24.46	15.61	37.66	-10.81	(0.19)
Number of cit-weighted patents <sup>Post</sup>	5674.33	15335.30	4958.92	16239.69	-715.41	(0.88)
Number of patent families <sup>Post</sup>	76.00	69.33	66.57	98.29	-9.43	(0.68)
Observations	12		48		60	

Table 31: Impact of university participation in the ownership regime on academics' number of patents (threshold 25%)

	(1) All	(2) Hard Scientists	(3) Life Scientists	(4) Professors	(5) Researchers
Treated $\times$ Post	0.005** (0.002)	0.009** (0.004)	0.000 (0.003)	0.006** (0.002)	-0.004 (0.006)
Post	-0.000 (0.001)	-0.004 (0.002)	0.006** (0.003)	-0.000 (0.001)	0.000 (0.005)
Outside options	0.002 (0.002)	0.012** (0.004)	0.001 (0.005)	0.003 (0.002)	-0.002 (0.010)
Nb of publications	0.005*** (0.001)	0.003 (0.002)	0.010*** (0.003)	0.005*** (0.002)	0.006 (0.004)
H-index	0.002*** (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	0.002*** (0.001)
Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (.)
gender	0.002* (0.001)	-0.000 (0.002)	0.006** (0.002)	0.002** (0.001)	0.000 (.)
Observations	317236	123188	95995	254296	55330

Note: we present the results of the estimation of  $\delta_t$  from Equation 12. The dependent variable is the logarithm of the yearly number of EPO patents disambiguated with threshold  $\beta = 0.5$ . In column (1), we include the full matched sample. We restrict the sample to scientists in hard sciences in column (2), and those in life sciences in column (3). We divide the sample between professors (including associate professors) in column (4) and researchers (either full or associate) in column (5). In all regressions, we include individual, university and time fixed effects as well as the following control variables: post, age, gender, number of publications (past three years), H-index, and share of patents managed by the academic system (excluding the employing institution). The standard errors are clustered at the individual and university levels. Significance level are: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 32: Impact of university participation in the ownership regime on academics' choice of transfer pathway (threshold 25%)

	(1)	(2)	(3)	(4)
	1+ company	Companies only	Universities only	Comp. & univ.
Treated $\times$ Post	0.002 (0.001)	-0.001 (0.001)	0.003** (0.001)	0.003** (0.001)
Post	-0.001 (0.001)	-0.000 (0.001)	0.001 (0.001)	-0.001* (0.000)
Nb of publications	0.001 (0.001)	-0.000 (0.001)	0.003*** (0.001)	0.002*** (0.001)
H-index	0.000 (0.000)	0.000 (0.000)	0.002*** (0.000)	0.000 (0.000)
Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
gender	-0.000 (0.000)	-0.000 (0.001)	0.002** (0.001)	0.000 (0.001)
Observations	317470	317470	317470	317470

Note: we present the results of the estimation of  $\delta_t$  from Equation 12, but the dependent variable is the logarithm of the yearly number of EPO patents disambiguated with threshold  $\beta = 0.5$  that are given in ownership to the private sector (not exclusively in column 1, exclusively in column 2), to the university and PRO system exclusively (column 3), or in co-ownership between these two types of entities (column 4). In all regressions, we include individual, university and time fixed effects as well as the following control variables: post, age, gender, number of publications (past three years), H-index, and share of patents managed by the academic system (excluding the employing institution). The standard errors are clustered at the individual and university levels. Significance level are: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .



## RESEARCH GRANTS AND ACADEMICS' CONTRIBUTION TO INNOVATION: A TWO-WAY RELATIONSHIP?<sup>1</sup>

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### 3.1 INTRODUCTION

Whereas scholars have long hypothesized that fundamental research has a much higher social value than its private one (Arrow, 1962), empirically evidencing knowledge flows from academic research to markets is more recent. Some studies tend to show that those flows may be greater than expected. Studying the citation links between 4.8 million U.S. patents and 32 million research articles, Ahmadpoor and Jones, (2017) found 80% of cited articles refer (directly or indirectly) to a future patent and 61% of the patents refer to a prior research article. Li, Azoulay, and Sampat, (2017) found that 31% of the 365,000 NIH-funded projects lead to articles that are cited by patents in the biomedical sector and that about 8% directly lead to a patent.

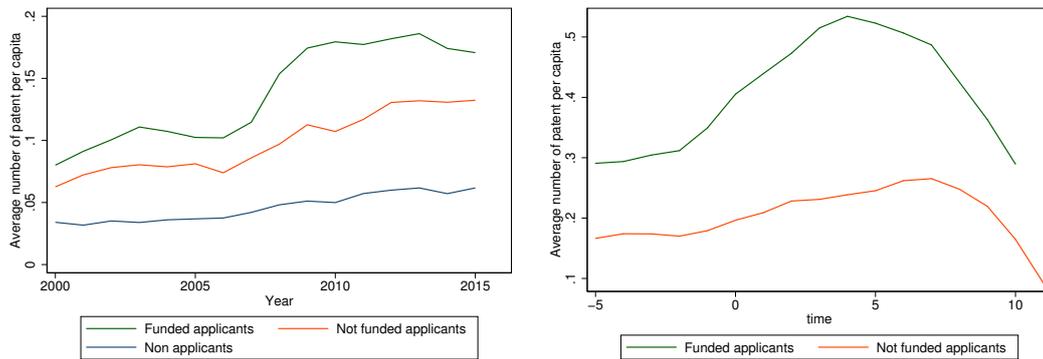
If science does not seem to be this “ivory tower” that has often been portrayed and criticized, it remains unclear how public research policy influences the contribution of academic research to technological innovation. In this paper, we focus on public funding of research projects (namely grants to research projects provided through competitive schemes by a dedicated national agency) and its influence on both invention by researchers or professors, and their published knowledge that is used to produce innovations. Academic invention (usually measured by patent applications in which at least one inventor is a researcher or a professor) has been increasing sharply over the last few decades (Carayol and Carpentier, 2021; Hall, 2004).

In the French case, I computed the average number of patents per capita each year, split into three groups according to their grant application and funding status and reported the statistics in the left panel of Figure 10. After the national funding agency (ANR) was created in 2005, grant applicants who received funding patented more inventions on average than those who were not funded, and those who were not funded themselves patented more inventions than professors and researchers who

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<sup>1</sup> This chapter is based on a paper co-authored with N. Carayol and P. Roux.

Figure 10: Number of patents per capita by application and funding status.



never applied for ANR grants. Since grants were distributed in different calendar years, the right panel of Figure 10 focuses on grant applicants and plots the average number of patents per capita around the year of application to control for possible cohort effects. It leads to a similar conclusion: funded applicants file more patents on average than non-funded applicants. These two figures thus suggest that there is a positive correlation between research grants and academic invention.

In this chapter, we explore whether (and how) academic invention and publications cited in patents can be the direct result of research supported by an identified public policy. A number of previous papers have considered the causal impact of funding on scientific outcomes at the individual (Azoulay, Graff-Zivin, and Manso, 2011; Banal-Estanol, Macho-Stadler, and Perez-Castrillo, 2019; Carayol and Lanoë, 2019; Jacob and Lefgren, 2011), group (Carayol, Henry, and Lanoë, 2020) or university levels (Carayol and Maublanc, 2020). To the best of our knowledge, Payne and Siow, (2003) and Tabakovic and Wollmann, (2019) are the only studies assessing the impact of public funding on academic invention.

Indeed, several mechanisms could explain the positive relationship previously observed between public funding and invention. Funding would have a causal direct effect on invention simply because invention would be a by-product of fundamental research funded by the ANR. But it could also be that project-based funding more likely fund researchers who already have a “taste” for invention. This would not be a direct effect of funding but instead an indirect one through self-selection and/or selection effect. Finally, the design of grant funding could mediate these two mechanisms.

We use individual-level data on the French case, for which we have a panel dataset of 54,024 tenured professors and researchers over the years 2000-2016. We add their publication and patenting records over the same period, collected from ISI Web of Science and PASTAT, respectively, and their applications and funding decisions pro-

vided by the French grant funding agency (ANR) for the years 2005-2009. We take advantage of the quasi exhaustivity of our data to study specifically the characteristics of scholars who apply for and receive funding, rather than merely controlling for the bias that these differences may introduce.

We first investigate the application behavior of academics contributing to innovation and whether the selection committees favor or dislike their projects. Using a probit model, we find that inventors and researchers cited in patents are more likely to seek grant funding, but controlling for this self-selection bias and other observable characteristics in a Heckman probit model, we evidence that the agency is less likely to select their projects. We further notice that projects stemming from a competitiveness cluster are significantly more likely to receive grant funding.

We then assess the impact of receiving an ANR grant on academics' contribution to innovation, controlling for selection bias. We match funded applicants with similar, but unfunded, applicants, and run difference-in-differences regressions on the number of inventions they subsequently patent and the number of papers they publish that are subsequently cited in patents.

We do not find a causal impact, so that positive correlation we initially observed between grant funding and academic invention seems to be entirely driven by selection mechanisms. We find that ANR grants do not affect in a significant way the contribution of researchers to innovation overall, although it has a positive impact on researchers in hard sciences in terms of academic patents and on inventors in directed programs in terms of citations in patents. We also find a puzzling effect on researchers whose project is labelled by a competitiveness clusters, who seem to be negatively affected by a grant receipt.

The rest of the chapter is organized as follows: we first identify the strands of literature to which this article is related in Section 3.2, and describe the background and data for the study in Section 3.3. We investigate the application and selection factors for research grants in Section 3.4, and assess the impact of such grants on academics' contributions to innovation in Section 3.5. We finally discuss the implications of our results and conclude in Section 3.6.

## 3.2 PRIOR LITERATURE

### 3.2.1 *Impact of science funding on research outputs*

Science drives innovation, technological progress and economic growth. The more an economy invest in basic science, the faster its pace of innovation. Although this intuition was born at least a century ago (Bush, 1945), the scientific evidence to prove it has been long in coming. Moreover, measuring the return on investment is still an active area of research, not least because responses are very context-specific, because large-scale data on funding and outputs are not always easy to obtain, and because the science production function varies over time (Wuchty, Jones, and Uzzi, 2007).

One of the first works in this direction is Jaffe, (1989), who initiated a research line that investigates empirically the “real effects” of academic research on private-sector patenting (Acs, Audretsch, and Feldman, 1992; Azoulay et al., 2019; Henderson, Jaffe, and Trajtenberg, 1998; Kantor and Whalley, 2014). It explores how scientific knowledge is used by private sector firms in developing new technologies. At that time when publication data were difficult to obtain, Jaffe, (1989) proxied the production of scientific knowledge by the amount of private R&D funding and universities' research expenditures and showed that private patenting reacts positively to increases in both funding sources. Much more recent studies have finally established the causality of public funding on private patenting. Tabakovic and Wollmann, (2019) exploited the intra-season performance variation of U.S. universities' soccer team as an exogenous shock on university funds and estimate the cost of generating a patentable idea at \$2.59 million, which is well below the \$4.35 million figure that Azoulay et al., (2019) previously arrived at. Azoulay et al., (2019) exploited idiosyncratic rigidities in the NIH funding rules to generate exogenous variation in funding across research areas and estimated that a \$10 million boost in NIH funding leads to a net increase of 2.7 patents.

In addition, there is a much more prolific literature that measures the impact of research funding on scientific output (usually publications), hence focusing on a particular piece of the causal chain. The question addressed by these studies is: how many (valuable) outputs would not have been produced in the absence of funding? Except for a few cases (Ayoubi, Pezzoni, and Visentin, 2019; Benavente et al., 2012; Lawson, Geuna, and Finardi, 2021), the literature converges toward a positive number of publications and citations, both in developed (Azoulay, Graff-Zivin, and Manso,

2011; Carayol and Lanoë, 2019; Hussinger and Carvalho, 2021; Jacob and Lefgren, 2011) and developing countries (Chudnovsky et al., 2008; Ganguli, 2017).

Nevertheless, the magnitude of the impact seems to differ greatly depending on the context. The observed effect may be quite small. In Argentina, Chudnovsky et al., (2008) find that researchers receiving a grant produced one additional publication in a 5-year window, a result that holds when the number of publication is weighted by the journal impact factor. Similarly, Jacob and Lefgren, (2011) find that scholars receiving an NIH grant generate only one additional publication over the next five years, corresponding to a 7% increase. For 230 professors at the university of Luxembourg, Hussinger and Carvalho, (2021) report a 20% increase in publication output upon reception of a grant (corresponding to 0.4 more publications) but the effect drops after five years. However, they show that the increase in quality lasts beyond the term of the grant. In a study evaluating a Swiss funding program sponsoring interdisciplinary collaborations, Ayoubi, Pezzoni, and Visentin, (2019) report that researchers who apply to the program experience a 43% increase in publications and that their average impact factor increases by 7%, but whether the researcher receives the grant seems to have no additional effect on her scientific productivity. For chemistry and physics researchers at the University of Turin, Lawson, Geuna, and Finardi, (2021) do not find that competitive research funding is associated with a higher research productivity.

Conversely, in other contexts, public funding appears to be essential. Carayol and Lanoë, (2019) report a 15% increase in articles' citations upon reception of a grant from the French Research Funding Agency, a higher impact than Jacob and Lefgren, (2011) that they attribute to the lesser availability of alternative funding sources in the French context. Ganguli, (2017) explores the impact of a historic grant program that substituted government R&D funding shortly after the end of USSR. She shows that in a developing country where funding levels are low, the program more than doubled publications on the margin, and significantly induced scientists to remain in the science sector. In the Chilean context, Benavente et al., (2012) also evidence a large increase in the number of publications, between two and six, upon reception of a grant. However, the grant program had no effect on researchers' number of citations, a result they attribute to the small amount of grants as compared to the international standards and to the incentive scheme of the program that does not account for outputs quality. One explanation for these variations could be that funding is critical at times and/or places where few alternative sources of funding exist.

Finally, public funding could favor the production of innovative and patentable knowledge by academics. To our knowledge, there are few if any systematic evidence about the effects of publicly funded science on academic invention. The only study

that addressed this question is Payne and Siow, (2003) who measured at an aggregate level, the impact of federal research funding on university patenting. Their identification strategy is based on instrumenting funds by alumni representation on U.S. Congressional appropriations committees. On a panel of 68 U.S. research universities, they find a positive result: a \$1 million increase in research funding leads to 0.2 more patents.

These observations will lead us to carefully consider the design of research grants in our analysis.

### 3.2.2 *Impact of funding design*

Even when alternative funding sources are available, the origin of the funding has an impact on the *nature and quality* of scientific outputs. Much of the literature that explores the consequences of private sector funding of basic research on the nature and direction of scientific pursuit, initiated by Rosenberg and Nelson, (1994), suggests that research funded by the private sector is more likely to be applied than basic (David, Hall, and Toole, 2000; Geuna, 2001; Gulbrandsen and Smeby, 2005; Perkmann et al., 2013). While private funding tends to decrease the number of articles published and citations received, it has a positive impact on the patentability of research results (Hottenrott and Lawson, 2017; Hottenrott and Thorwarth, 2011). Research teams receiving funding from a variety of sources (including non-federal) are more likely to patent than those with only federal funding, and those who do patent are more likely to produce disruptive inventions (Funk et al., 2019).

Furthermore, the way science funding is administered also has consequences for the knowledge produced. Azoulay, Graff-Zivin, and Manso, (2011) compare the Howard Hughes Medical Institute (HHMI) funding program, that ties the grant to individuals, to NIH grants allocated to projects. They find that HHMI-funded investigators produce high-impact articles at a much higher rate than NIH-funded scholars: the HHMI program increases their overall publication output by 39%, and the magnitude jumps to 96% when focusing on the number of publications in the top percentile of the citation distribution. Their results suggest that the design of NIH grants discourages academics from producing novel results.

Finally, in the process of science funding, national agencies usually define relevant areas of investigation in consultation with socio-economic actors (government, business, academia) and then issue calls for projects for each targeted priority research

area (directed programs), and generic calls that let researchers define the research topic themselves (non-directed programs).<sup>2</sup> For instance, at the UK Medical Research Council, directed and non-directed programs are called *MRC Strategic* and *Researcher-led* respectively, at the US National Institute of Health these are *NIH-Requested research* and *Unsolicited Research*, and at the French Research National Agency, *programmes dirigés* and *programmes blancs*. The underlying rationale of directed programs is that the traditional academic incentives for investigating new or interdisciplinary research areas are not strong enough. Indeed, it is often argued that risk-taking, novelty, and interdisciplinarity are not sufficiently rewarded because the peer-review system, primarily organized within disciplines, does not encourage truly transformative ideas (Braben, 2004; Wang, Lee, and Walsh, 2018; Wessely, 1998). (Wang, Lee, and Walsh, 2018) show that competitive schemes fund more novel research on average than block funding, unless applicants are junior or female researchers. In the French case, Carayol and Lanoë, (2019) show that grants awarded by non-directed programs have much larger scientific impact but cannot find a causal effect of directed programs on the research novelty of the granted.

### 3.2.3 Selection effects in grant funding

One of the benefits of distributing public money for science in a competitive manner is that it allows funds to be directed to the most excellent research projects and thus to maximize the return on investment for government and society. However, if the selection process does not properly identify the most excellent projects, then the competitive scheme cannot fully achieve its objective.

Temporally, the sequence of events is as follows. To apply for funding, researchers respond to calls by submitting a project. From there, although it may vary slightly from one agency to another, a basic selection procedure is the following: first, the agency screens out projects that are not meeting the basic criteria; second, the projects are sent to external peers for evaluation; and third, based on the reviewers' report and the projects themselves, the agency's internal selection committee gathers to decide which projects will be funded. Applicants are subsequently notified of this decision (Ismail, Farrands, and Wooding, 2009).

In this process, how do peers judge which projects are excellent enough to be funded and which are not? By Merton's norm of impartiality in science, the judgment of the quality of knowledge should rely entirely on scientific criteria and with-

<sup>2</sup> Many funding agencies deploy both approaches implemented in separate programs.

out interference from the personal or social background of both the reviewed and the reviewers (Merton, 1973). While the criteria officially stated by the agencies appear consistent with this norm, many of the factors identified in the literature are not.

In principle, the decision is based on criteria defined by the agency. In the case of the United States and continental Europe, these are quality of research (originality; academic and extra-academic relevance; quality, appropriateness, rigor, coherence/justification), quality of description (clarity, completeness), personal qualities (motivation, traits; diversity) and feasibility (Hug and Aeschbach, 2020). But in practice, it is common for reviewers and jury members to rely on heuristics to assess the quality of projects, exploiting, for example, bibliometric indicators of the applicant's publication record or other observable and quickly interpretable characteristics.

While the number of publications does not appear to be a reliable predictor of grant selection, the number of citations, or the impact factor of the journals where the applicant's work was published are more consistent indicators (Arora and Gambardella, 2005; Neufeld, Huber, and Wegner, 2013; Van den Besselaar and Leydesdorff, 2009). Applicants with a past grant experience have also been found more likely to receive grant funding (Bol, Vaan, and Rijt, 2018; Park, Lee, and Kim, 2015), while those producing more novel (Ayoubi, Pezzoni, and Visentin, 2021; Boudreau et al., 2016) or interdisciplinary research (Banal-Estanol, Macho-Stadler, and Perez-Castrillo, 2019; Bromham, Dinnage, and Hua, 2016; Lanoë, 2018) were less likely to be receive it. Political factors such as the applicant's Ph.D. granting institution (Kim and Kim, 2016), network connections (Wennergren and Wold, 2010), academic and departmental status (Bazeley, 1998; Cole, Cole, and Simon, 1981; Jayasinghe, Marsh, and Bond, 2003; Viner, Powell, and Green, 2004), current university size (Murray et al., 2016), research field (Laudel, 2006) and type of research (Porter and Rossini, 1985) can further affect the chances of obtaining funding. In some instances, demographic factors such as the applicant's age (Guthrie, Ghiga, and Wooding, 2017; Lanoë, 2018), gender (Bornmann, Mutz, and Daniel, 2007; Jaggi et al., 2009; Pohlhaus et al., 2011; Van der Lee and Ellemers, 2015; Wennergren and Wold, 2010), and ethnicity (Ginther et al., 2011) have also been identified as affecting the likelihood of receiving funding.

These characteristics of the applicant and the project seem to determine only about half of the allocation of grants, while luck determines the other half (Cole, Cole, and Simon, 1981). The chance factor is partly related to subjectivity in the review process and in the definition of excellence (Lamont, 2009; Van Arensbergen and Van Den Besselaar, 2012). For example, Boudreau et al., (2016) show that reviewers consistently give lower scores to research proposals that are closer to their own areas of expertise. Nevertheless, it appears that the benefits of expertise still dominate the costs of bias

(Li, 2017). Overall, these results suggest that reviewer characteristics and selection committee composition also influence selection.

If we now focus on the efficiency of the selection process, are the selected applicants and projects indeed the most excellent ones and result in the highest quality knowledge compared to those that are not selected? On the one hand, Van den Besseelaar and Leydesdorff, (2009) and Neufeld, Huber, and Wegner, (2013) look at the past performance of applicants and compare it to the results of the selection. They both report that, on average, funded applicants have slightly fewer publications than many rejected applicants, especially those just below the selection threshold. On the other hand, Li and Agha, (2015) and Park, Lee, and Kim, (2015) instead look forward and assess the predictive power of review scores in terms of future performance. Both studies use the NIH case and agree that higher peer-review scores are associated with better outcomes in terms of publications, citations and patents.

Even if the selection process was fully effective and efficient, it remains dependent on the pool of researchers it attracts. A misalignment between the researchers who apply and those whom the agency seeks to attract would reduce the ability of project-based funding to maximize the return on investment. Yet, there is remarkably little empirical research on self-selection in competitive funding (Ayoubi, Pezzoni, and Visentin, 2021; Lanoë, 2018; Lawson, Geuna, and Finardi, 2021; Neufeld, Huber, and Wegner, 2013).

Neufeld, Huber, and Wegner, (2013) bibliometrics analysis reports that the candidates applying to the 2009 edition of ERC grants have greater publication records as compared to the potential applicants. Ayoubi, Pezzoni, and Visentin, (2021) rely on a sample of 717 applicants to a Swiss funding program and define the population of scientists eligible to the program as all actively publishing scientists with a Swiss affiliation. While they confirm that the funding agency is biased against novelty, they further evidence that novel scientists are 14% more likely to apply for a grant than less novel ones. They attribute this surprising result to either an imperfect information of novel candidates when applying regarding the true selection criteria or the absence of intrinsic motives to bring recognition to unconventional ideas and projects. They further find that more senior scientists, those with a stronger scientific profile, those with a broader network and who are holding active funds at the moment of application have a higher probability to apply for a grant.

Analyzing the French national funding program in its early years, Lanoë, (2018) finds that novel and interdisciplinary scientists are more likely to apply for a grant, despite the selection bias against them. She adds that male, more senior scientists,

those with a stronger scientific profile, those who already applied for a grant, and those from a better ranked department have a higher propensity to apply, while holding active funds at the moment of application decreases the likelihood to apply. In contrast, if Ayoubi, Pezzoni, and Visentin, (2021) confirm that novel scientists are more likely to apply for a grant in the Swiss context, they rather find that holding active funds increases the probability to apply, and add that scientists with a broader network are also more likely to apply. More specifically, potential applicants with a connection to a committee member may be more likely to apply if they anticipate a premium at the evaluation stage (Bagues, Sylos-Labini, and Zinovyeva, 2019). In the Italian case, Lawson, Geuna, and Finardi, (2021) find that women are initially not less likely to apply for grants than men, which contrasts with Lanoë, (2018)'s finding.

#### 3.2.4 *Individual drivers of academic patenting*

If research grants are preferentially obtained by researchers who exhibit specific individual characteristics that are also those that favor academic invention, then we might incorrectly attribute an impact on invention to research grants. Therefore, we need to correctly identify the determinants of academic patenting that might also affect the likelihood of being funded, either through a selection mechanism or a self-selection mechanism. What are these factors?

Many studies have questioned the nature of the relationship between academic patenting and the production of scientific articles (Azoulay, Ding, and Stuart, 2007; Carayol, 2007; Czarnitzki, Glänzel, and Hussinger, 2007; Stephan et al., 2007), concerned that patenting may have a negative impact on publication. They conclude that researchers who produce patents typically also produce more and higher quality research articles. Moreover, the type of research performed, the degree of collaboration with the private sector as well as relevance of intellectual property rights protection varies greatly among scientific fields, making the discipline another important driver to consider (Carayol, 2007; Stephan et al., 2007). The to patent also vary with past experiences in patenting activities (Kordal et al., 2016), either directly through learning effects and/or indirectly because these individuals are typically highly creative and productive, able to foster collaborative projects in their research groups and through collaborations with companies or to obtain funding for their projects.

The literature also identified age and career stage as keys characteristics in explaining academic productivity in general. It has been observed that a scientist's productivity grows up to a certain (biological) age before decreasing towards the end of the

career. This effect is much more mixed in academics' patenting activity. For instance, Carayol, (2007) found that patenting increases with age whereas Stephan et al., (2007) found little evidence of such an effect. Different cohorts of scientists may also have heterogeneous productivity pattern because of the varying contexts in which they were trained and are working (Stephan, 2010). Based on longitudinal data, Azoulay, Ding, and Stuart, (2007) and Thursby and Thursby, (2007) find that, once controlling for cohorts, patenting decreases over the life-cycle. However, while the authors of the former paper argue that newer cohorts are more likely to patent than are earlier cohorts, the latter finds opposite results. Finally, tenure was also found to affect the incentives towards invention in the US context (Azoulay, Ding, and Stuart, 2007; Stephan et al., 2007).

In this paper, we contribute to the literature on the effects of research funding in three different ways that correspond to each stage (self-selection, selection, and impact) of competitive science funding. First, we examine the characteristics of researchers who decide to apply for funding by adding a new attribute: the researcher's past contribution to innovation, either directly via academic invention or indirectly via the publication of articles that are subsequently cited in patents. Second, controlling for differences between actual and potential applicants for funding, we study the characteristics of applicants and projects that affect the chances of being selected by the agency. In particular, we look at how past contributions to innovation affect the agency's selection decision. Third, controlling for the selection bias and for the design of the programs, we analyze the causal impact of grants on researchers' contribution to innovation.

### 3.3 CONTEXT AND DATA

#### 3.3.1 *The French funding landscape*

While historically in the United States, project-based funding has been the main mode of budget allocation for basic science, France, like many other European and Asian countries, has long relied on recurrent funding of research laboratories and universities. In 2005, the country initiated a change in direction with the creation of the *Agence Nationale de la Recherche* (ANR). The agency has since been responsible for implementing project-based funding on a national scale. Its functioning is very similar to that of the National Institutes of Health or the National Science Foundation in the United

States. The agency is organized into eight departments that cover all scientific fields. Within these departments, there are dozens of directed programs, each corresponding to a research topic deemed a priority by the agency, as well as an undirected program open to any research topic proposed by scientists.

To request funding, researchers must write a research project that may involve collaboration between universities and possibly in partnership with a company, and send it to one of the programs (directed or not) in response to a call for projects. Projects submitted undergo a standard single-blinded peer review procedure, and then the agency's evaluation committee selects the most promising projects<sup>3</sup>. If the selected project involves more than one partner, the scientist designated as responsible in each institution receives his or her share of the budget to manage it autonomously. The overall research budget allocated to projects has gradually increased from 540 million euros in 2005 to 650 million in 2009<sup>4</sup>. This represents an average budget per project ranging from about 100,000 euros in the social sciences and humanities to nearly 800,000 euros in the hard sciences (Agence Nationale de la Recherche, 2005, 2006, 2007, 2008, 2009).

On another front, the French government has taken a position in favor of university-industry interactions with the passage of the Innovation Act in 1999. In order to further concretize this support, in 2004 it created structures that associate companies, research centers and educational institutions in a given geographical area. The members of these so-called "competitiveness clusters" are meant to work in partnership to generate synergies and encourage industrial competitiveness. Researchers applying for an ANR grant whose institution belongs to a competitiveness cluster can report this information in the project, thereby bringing additional funding from the ANR to their project.

### 3.3.2 *Data*

The data collection began with grant applications to the ANR during the years 2005-2009.<sup>5</sup> These data, provided by the ANR, are exhaustive over the period and include

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<sup>3</sup> In the year of the agency's creation, the selection procedure was relatively unpolished. It was subsequently modified to reach the international ISO 9001 standards as of 2007.

<sup>4</sup> We only provide statistics for years 2005-2009 because our dataset on funding applications and decisions only covers these years

<sup>5</sup> Funding data for subsequent years were not available at the time of this study, and scientific output data are available up to seven years after the most recent awards, which provides sufficient depth to estimate the relationship of interest.

a lot of information such as the name of the projects, the full name of the scientific coordinator but also of each scientific leader at each partner institution within the project, the department to which the project was submitted, the corresponding call for projects and the final funding decision. On the other hand, the evaluators' scores and the amounts requested by and awarded to each project were unfortunately not correctly recorded in the agency's database and are therefore not usable in this study. Moreover, the names of the other researchers involved in the project beyond those of scientific leaders have not been recorded at all by the agency, which prevents us from observing the composition of the team, for instance.

Since a researcher can apply for several grants over time, and even several grants within the same year (as coordinator of one project and partner on other projects), we define the statistical individual  $i$  in the study as a researcher on a project, or applicant-application. Over the period, 23,846 applications were submitted, corresponding to 67,407 applicant-applications. We matched the first and last names, as well as scientific field and institution, of all project scientific leaders to those of 83,721 professors and researchers employed in universities or research organizations in France between 2000 and 2018.<sup>6</sup> We found a match for 17,901 applications (75% of all projects) and 31,501 applicant-applications (47% of all pairs). Since project partners are not necessarily academics, this explains the relatively low level of partners retrieval.

We complemented the database with the individual-level scientific outcomes. First, publication data were extracted from the Web of Science and disambiguated using an automated procedure implemented by Lanoë, (2018). At the end of the process, publications from 63,131 researchers were retrieved. The data include the raw count of publications, the number of publications corrected for the number of co-authors, the number of publications in the top 10% and top 5% most cited in its field, as well as other quality indicators such as the total count of citations, the H-index, and indexes of novelty (maximum and average, based on pairs of keywords) from Carayol, Lahatte, and Llopis, (2019) and interdisciplinarity (maximum and average, based on the list of references using Shannon and Herfindhal indexes). It further indicates whether the publications of the researcher have been cited in patents in all years forward until 2020 (*Cited in patent(s)*). Second, we extracted patents from the PATSTAT 2019 database and disambiguated following the method described in the first chapter. We use the disambiguation threshold  $\beta = 1$  that gives equal importance to precision and recall in the main analysis, and perform robustness checks on the thresholds  $\beta = 0.5$  and  $\beta = 0.3$  that are increasingly favoring precision over recall. This data covers all 83,721

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<sup>6</sup> Further information of the academic employment panel data is available in Carayol and Carpentier, (2021).

academics, of which 13,575 patented at least one invention between 1996 and 2016. This dataset includes the number of patented inventions each year at the EPO and the French INPI separately.

The final panel dataset consists of 54,024 professors and researchers over the years 2000–2016 for whom all funding, employment, publication and patent information is available. For the 17,901 applications, there are on average 2.4 academic partners (min 1, max 15), and 7% are labeled by a competitiveness cluster. Approximately half of the projects were submitted to the agency's non-directed department (52%), with the other half spread across the remaining seven directed departments. The success rate is 30% overall and varies over time. The year the agency was created, this rate was higher (69%) because researchers were either unaware of the funding opportunity, suspicious of or opposed to this research funding system. In subsequent years, the rate dropped to a more typical 30%, before dropping again to 18% in 2009 due to a particularly high number of applications.

### 3.4 DETERMINANTS OF APPLICATION AND SELECTION IN GRANT FUNDING

In this section, we use a probit model to investigate faculty propensity to apply for grant funding, and implement a Heckman probit model (Amemiya, 1978) to study the factors affecting their chances of being selected by the agency, accounting for academics' different propensity to apply. Because we defined the statistical individual as an applicant on a project, researchers appear in the panel as many time as they apply for grants. To avoid the overrepresentation of serial applicants, we define fractional weights that we include in all regressions.

#### 3.4.1 *Econometric specification*

**PROBIT MODEL FOR SELF-SELECTION** We use the following model of academics' propensity to apply for a grant:

$$A_{i,t} = \alpha + \beta_1 \text{Inventor}_{i,t} + \beta_2 \text{Cited in patent}(s)_{i,t} + \sum_{j=3}^m \beta_j X_{i,t} + \sum_{k=m+1}^n \beta_k Z_{i,t} + \gamma_t + \varepsilon_{i,t} \quad (13)$$

where  $A_{i,t} = 1$  if researcher  $i$  applies for a grant in year  $t$ , and our two main independent variables of interest are  $\text{Inventor}_{i,t}$  which is equal to one if researcher  $i$  has invented at least one patent in the five years preceding to application and  $\text{Cited in patent}(s)_{i,t}$  which is one if her papers published in the five years prior to application are cited in patents.  $X_{i,t}$  is a set of individual variables including the age, gender, H-index, and *fundraising profile*, which is a categorical variable that takes value 0 if the applicant never applied for an ANR grant, 1 if she already applied but were never granted, and 2 if she were granted at least once. Finally,  $Z_{i,t}$  is a set of control variables including the academic position and scientific field dummies, and  $\gamma_t$  is a year fixed effect. Standard errors are clustered at the individual and project levels. Table 40 in Appendix provides further details on the construction of these variables. We do not include the count of publications nor citations because they are strongly correlated with the H-index (0.63 and 0.84 respectively).

**HECKMAN PROBIT MODEL FOR SELECTION** We observe if the agency selects a project only if the project has been submitted beforehand. To address the impossibility of observing projects that have not been submitted to the ANR and thus control for systematic differences between potential and actual applicants and projects, we use a two-step Heckman probit model in which the first step estimates the probability to apply for a grant and the second step estimates the conditional likelihood to be selected by the agency. Our exclusion-restriction condition is academic position, since the time an academic must devote to teaching and administrative duties varies from one position to another, and the more time one can devote to research, the more likely one is to apply for a grant. At the same time, and despite some work that finds otherwise in some countries, we still think it is reasonable to assume that the agency does not select projects based on the position of the applicants.

Equation 13 corresponds to the first step, while we model the second step as follows:

$$S_{i,t} = \alpha + \beta_1 \text{Inventor}_{i,t} + \beta_2 \text{Cited in patent}(s)_{i,t} + \sum_{j=3}^m \beta_j X_{i,t} + \sum_{k=m+1}^n \beta_k V_p + \sum_{l=n+1}^r \beta_l Z_{i,t} + \gamma_t + \varepsilon_{i,t} \quad (14)$$

where  $S_{i,t} = 1$  if the project is selected, and  $X_{i,t}$  is a set of individual  $i$  variables including the age, gender, and H-index, and *fundraising profile*.  $V_p$  is a set of project  $p$  time-invariant variables including a dummy equal to one when it is labeled by a competitiveness cluster (Cluster) and the number of partner institutions.  $Z_{i,t}$  controls for the department of the agency to which the application is submitted and the re-

searchers' scientific field and  $\gamma_t$  is a year fixed effect. Standard errors are clustered at the individual and project levels. Report to Appendix Table 40 for further details on these variables.

### 3.4.2 Selection results

**DETERMINANTS OF GRANT APPLICATION** We start with a simple test of differences in average between applicants and non applicants and report the results in Table 33. Professors and researchers who contributed to innovation are significantly over-represented among applicants: 10% of applicants have patented an invention against 2% among non applicants, and 47% of applicants have published articles that are cited in patent(s) against 11% among non applicants. There are different mechanisms that could be at work behind this overrepresentation of inventors and researchers cited in patents among applicants. For instance, applicants could be those academics that are older, or more advanced in their career, which happen to invent more often than their younger counterparts. It could also be that more prolific academics, who also are more often inventors, are more attracted to grant funding than the less-prolific ones. Although it appears that the first hypothesis is not supported by the statistics, since applicants are on average younger than non-applicants, the second one is plausible: applicants are over-performing non-applicants in all metrics of scientific performance (number of publications, citations, publications in top 10% and top 5%, H-index, interdisciplinarity and novelty). Controlling for these variables, we run a regression to identify the effect of contributing to innovation on the likelihood to apply for grant funding.

Table 34 shows the marginal effects from the probit regression results. Coefficients are available in Appendix Table 41<sup>7</sup>. The first column includes all programs, while the second and third columns focus specifically on non directed and directed programs. Considering all programs together, we find that inventors and researchers cited in patents are significantly more attracted to grant funding. The probability to apply increases by 2.4 percentage points when candidates are inventors, and by 3.1 percentage points when their research is cited in patents. In comparison with the probability to apply of the average French researcher in our database (14.8%), it represents a 16%

<sup>7</sup> In the Table 34 presented here and the second and third columns of Table 41, we include among the potential candidates for one type of program (directed or non-directed) all researchers, including those who applied to the other type of program (non-directed or directed, respectively), since it is perfectly possible that researchers apply to both types of programs. Alternatively, in the last two columns of Table 41, we exclude applicants to the other type of program from the potential applicants and observe that the results remain unchanged.

Table 33: T-tests among applicants and non applicants to ANR funding

	(1)		(2)		(3)	
	Applicants		Non Applicants		Difference t-test	
	mean	sd	mean	sd	b	p
Inventor	0.10	0.27	0.02	0.12	-0.08	(0.00)
Cited in patent(s)	0.47	0.42	0.11	0.25	-0.36	(0.00)
Age	33.50	14.17	36.33	16.05	2.82	(0.00)
#Pubs	2.95	3.48	2.09	3.02	-0.86	(0.00)
#Cites (3-y)	20.94	38.35	14.10	38.84	-6.84	(0.00)
Total #Cites	89.74	152.41	60.49	148.02	-29.25	(0.00)
# top 10% Pubs	4.51	7.35	2.98	6.11	-1.53	(0.00)
# top 5% Pubs	2.29	4.41	1.55	3.83	-0.75	(0.00)
H-index	7.54	6.21	5.63	6.12	-1.91	(0.00)
Interdisciplinarity	0.49	0.25	0.41	0.27	-0.09	(0.00)
Novelty	-1.10	1.11	-1.04	1.15	0.06	(0.00)
Observations	27758		172672		200430	

higher probability of applying for inventor scientists, and 21% higher probability of applying for researchers cited in patents. The bulk of the effect occurs in directed programs, where the probability is 13% higher for inventors and 18% higher for researchers cited in patents, against a smaller but not significant probability and a 2% higher one respectively in non directed programs.

As for the other determinants of application, we find a U-inverted relation between age and the likelihood to apply for grant funding, men are more attracted to grant funding with a 7% higher probability to apply, researchers who have a 1 point higher H-index than the average researcher have a 1% higher probability to apply, researchers who applied for ANR funding in the past are almost three times more likely to reapply when they did not receive funding, and 85% more likely when they did.

Considering that the selection may vary greatly across fields (Van Arensbergen and Van Den Besselaar, 2012), we investigate whether the propensity to apply also varies across disciplines. We report regression results by group of disciplines in Table 42 in Appendix, where the first column corresponds to researchers in hard sciences (HS), the second to those in life sciences (LS), and the last column to those in social sciences and humanities (SSH). Interdisciplinary researchers are counted once in each group of discipline where he or she is affiliated. The determinants are very similar, both in direction and effect size, across hard sciences and life sciences. A prior experience

Table 34: Probability to apply for a grant (marginal effects)

	(1)	(2)	(3)
	All Programs	Non Directed Programs	Directed Programs
Inventor	0.024*** (0.003)	-0.001 (0.002)	0.019*** (0.002)
Cited in patent(s)	0.031*** (0.002)	0.003** (0.001)	0.026*** (0.001)
<b>Individual variables</b>			
Age	0.010*** (0.001)	-0.000 (0.001)	0.009*** (0.001)
Age squared	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Male	0.011*** (0.002)	0.004*** (0.001)	0.005*** (0.001)
H-Index	0.002*** (0.000)	0.001*** (0.000)	0.000*** (0.000)
<b>Fundraising profile</b>			
Never applied before			
<i>Applied w/o success</i>	0.261*** (0.005)	0.120*** (0.004)	0.117*** (0.004)
<i>Applied with success</i>	0.127*** (0.004)	0.036*** (0.002)	0.082*** (0.003)
Number of obs	200430	200430	200430

Notes: Robust standard-errors in parentheses, clustered at the individual and project levels. The control variables academic position, scientific field and application year are included in the model but the marginal effects at the mean are not reported.

in ANR grant application is more important for researchers in SSH as compared to those in hard and life sciences, while the effect of age turns insignificant. We do not interpret the coefficients for inventors and researchers cited in patents in SSH because first, there are very few such individuals in the database and second, most of them have a particular profile (they are in large part professors and co-affiliated to either LS or HD).<sup>8</sup>

**DETERMINANTS OF GRANT SUCCESS** Once a researcher applied, what factors affect her chances of success with the ANR? This paragraph focuses on researchers who are applicants for funding. Table 35 reports the tests of differences in average between funded and unfunded ones. Inventors and researchers cited in patents are again over-represented among funded applicants, although this does not control for potential omitted variables biases. We report the marginal effects of the Heckman probit two-step regression results in Table 36, that also controls for the first-stage self-selection bias, and Appendix Table 43 reports the coefficients and other relevant statistics.

Table 35: T-tests among funded and non funded applicants to ANR funding

	(1)		(2)		(3)	
	Funded		Non Funded		Difference t-test	
	mean	sd	mean	sd	b	p
Inventor	0.11	0.29	0.10	0.26	-0.02	(0.00)
Cited in patent(s)	0.52	0.44	0.44	0.41	-0.08	(0.00)
Age	37.16	13.27	31.81	14.26	-5.34	(0.00)
#Pubs	3.45	3.85	2.72	3.27	-0.73	(0.00)
#Cites (3-y)	26.21	43.36	18.51	35.53	-7.71	(0.00)
Total #Cites	109.30	174.15	80.70	140.32	-28.60	(0.00)
# top 10% Pubs	5.80	8.36	3.92	6.75	-1.88	(0.00)
# top 5% Pubs	3.03	5.17	1.95	3.97	-1.08	(0.00)
H-index	8.66	6.88	7.02	5.81	-1.64	(0.00)
Interdisciplinarity	0.55	0.24	0.46	0.24	-0.09	(0.00)
Novelty	-1.26	1.20	-1.02	1.06	0.23	(0.00)
Observations	8777		18981		27758	

All programs considered (column 1), academic inventors have a 5% lower probability of being selected than the average applicant in our database (53.1%), and researchers cited in patents have a 7% lower probability. The bias against inventors is

<sup>8</sup> For instance, 90% of inventors are also affiliated to life sciences, and 52% to hard sciences.

only observed in directed programs (column 2), while the bias against researchers cited in patents is only observed in non-directed programs (column 3).

We find that older scientists are significantly less likely to be selected than younger ones, an applicant one year older than the average one has a 0.4% lower probability of success, and consistent with much previous research, we find that gender does not affect the chances of success. Regarding the researcher's publication profile, a one point higher H-index than the average applicant results in a 0.6% higher probability of being selected. Applicants' fundraising profile only matters when they were not successful: those candidates have a 14% lower probability to be selected. The determinant with the strongest effect that we observe is the affiliation to a competitiveness cluster. Applicants from these structures have a 89% higher probability of being selected than the average candidate, up to 146% higher in non directed programs (the success probability of the average applicant to this program being 50.2%) . Finally, projects involving a greater number of academic partners are more likely to be selected: the involvement of an additional institution increases the probability of success by 7%.

Table 44 in Appendix reports the regression coefficients by field. The stronger bias against inventors and researchers cited in patents is observed in the hard sciences. Age does not affect chances of being selected in the life sciences, while previous failures with the ANR most affect the probability of being selected in the life sciences. The number of institutions does not matter in the hard sciences, unlike in the life sciences. For the reasons discussed above, and also because of the small number of observations in these fields, we do not interpret the regression results on SSH researchers.

**HOW THE INVENTOR AND RESEARCHER CITED IN PATENT STATUSES AFFECT THE SELECTION OVERALL?** While researchers who contribute directly or indirectly to innovation are more likely to apply, they are also less likely to be selected by the agency conditional on having applied. We wonder about the balance of these two effects.

We start with the case of academic inventors. The probability of applying increases by 2.4 percentage points when the individual is an inventor. This means we may estimate that 685 ( $0.024 \times 28,528$ ) more applications were made solely because of inventor status of applicants. How many of them were selected? The probability of being selected conditional on having applied for an average researcher is 53.1%, so 364 of them should be selected, but in fact being an inventor decreases the conditional probability of being selected by 2.8 percentage points so that 20 of them were discriminated against because they are inventors. All in all, being an inventor still has a positive ef-

Table 36: Probability to receive a grant (marginal effects)

	(1)	(2)	(3)
	All prog.	Non directed	Directed
Inventor	-0.028*** (0.010)	-0.020 (0.014)	-0.029* (0.015)
Cited in patent(s)	-0.038*** (0.009)	-0.032*** (0.010)	-0.018 (0.015)
<b>Individual variables</b>			
Age	-0.002*** (0.000)	-0.001 (0.001)	-0.003*** (0.001)
Male	0.009 (0.008)	0.017* (0.010)	-0.002 (0.012)
H-Index	0.003*** (0.001)	0.003*** (0.001)	0.004*** (0.001)
<b>Fundraising profile</b>			
Never applied before <i>Applied w/o success</i>	-0.074*** (0.019)	-0.073*** (0.015)	-0.061** (0.027)
Constant	-0.005 (0.015)	-0.002 (0.014)	0.006 (0.025)
<b>Project variables</b>			
Cluster	0.474*** (0.019)	0.731*** (0.119)	0.493*** (0.025)
Number of institutions	0.013** (0.006)	0.025*** (0.007)	0.004 (0.008)
Number of selected obs	27758	13289	14469

Notes: Robust standard-errors in parentheses, clustered at the individual and project levels. The control variables Scientific field, Department of the agency and Application year are included in the model but the marginal effects at the mean are not reported. There is no fixed effect on the department of the agency for non directed programs because they all belong to the same department.

fect as it allowed an additional 1.2% of inventors, and an additional 7.7% of inventors who applied, to receive funding.

Turning to the case of researchers cited in patents, we observe that the probability of applying increases by 3.1 percentage points when their research is cited in patents. This implies we may estimate that 3,924 ( $0.031 \times 126,600$ ) more applications were made solely because of researcher cited in patents status of applicants. How many of them were selected? The conditional probability of being selected is 53.1%, so 2,084 of them should be selected, but in fact publishing research that receives patent citations decreases the conditional probability of being selected by 3.8 percentage points do that 79 of them were discriminated against because their research is cited in patents. All in all, being cited in patents allowed an additional 1.6% of cited researchers, and an additional 11.1% of cited researchers who applied, to receive a grant.

In conclusion, past experience or contribution to innovation is beneficial to the project-based funding of researchers, driving in some 344 inventors and 2,005 researchers cited in patents into grant funding.

### 3.5 THE IMPACT OF PUBLIC COMPETITIVE FUNDING ON INVENTION

We have discussed how *past* contributions to innovation impacts researchers' participation in the competition for research funding. Now we investigate the consequences of obtaining a grant on researchers' *future* contributions to innovation.

#### 3.5.1 Empirical Strategy

We use a two-step econometric specification to estimate the impact of grant funding on academic invention. First, we match funded applicants to other unfunded applicants who are similar to them in order to control for the selection bias. We use the results from the previous section to define the relevant variables to match. Second, we run linear regressions in a difference-in-differences to further control for the effect of unobserved, time-invariant characteristics.

**MATCHING PROCEDURE** We implement a coarsened exact matching (CEM) procedure (Iacus, King, and Porro, 2012; King et al., 2010) and report the variables used and

a balancing measure in Table 37. The first four columns show the means and standard deviations of funded and unfunded candidates separately<sup>9</sup>. The fifth column reports the Student's t test of difference in means. The first panel displays the values before the CEM, while the second panel refers to the results after the CEM. For the dummies inventor, cited in patents, gender, year of application, fundraising profile, competitiveness cluster, and non-directed program, the match is exact. In contrast, we coarsened the values for the continuous variables as follows: four or less, between four and 10, between 11 and 17, and 18 or more for the H-index; 40 or younger, between 41 and 50, and more than 50 years old for age at application; hard sciences, life sciences, and social sciences and humanities for disciplines; and one, two, or more than two for the number of partner institutions in the project.

Because grants are not randomly assigned to researchers, we observe in Table 37 (first panel, before matching procedure) that the variables measured before application differ significantly between funded and non-funded applicants. Funded applicants are on average more likely to be inventors and cited in patents than non-funded applicants. They are also more often men, have a higher H-index, less often submitted ANR applications in the past but were more often funded, are more likely to apply in a directed program than a non directed one, more frequently belong to a competitiveness cluster, and involve a greater number of institutions in their project. Since all these characteristics can influence the propensity of researchers to contribute to innovation, we ensure that these differences are no longer significant after matching (second panel of the table). We were able to match half of the applicant-applications (4,657 out of 9,281) with at least one other applicant similar on all these characteristics that was not funded. Although the matched sample is fairly representative of the population of funded applicants, we note that it still contains a lower proportion of inventors, women, high-H index researchers and applications from competitive clusters.

**DIFFERENCE IN DIFFERENCES** The linear regression with multiple levels of fixed effects estimated on the matched sample of funded and unfunded applicants is the following:

$$Y_{i,t} = \beta_0 + \beta_3 \text{Funded}_i \times \text{Post}_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \quad (15)$$

<sup>9</sup> When a researcher has submitted several projects in the same year and at least one has been awarded, we remove from the sample the other unsuccessful applications so that the group of unfunded applicants does not contain researchers funded on other ANR projects.

Table 37: Difference in means on observable characteristics between treated and control groups.

	<i>Before matching</i>					
	Funded applicants		Unfunded applicants		Difference t-test	
	mean	sd	mean	sd	b	p
Inventor	0.17	0.37	0.15	0.35	-0.02	(0.00)
Cited in patent(s)	0.62	0.49	0.60	0.49	-0.02	(0.00)
Age	44.43	8.03	44.55	8.15	0.12	(0.25)
Male	0.79	0.41	0.76	0.43	-0.03	(0.00)
H-Index	10.27	8.07	9.71	7.49	-0.56	(0.00)
Application Experience	0.44	0.50	0.51	0.50	0.07	(0.00)
Funding Experience	0.23	0.42	0.22	0.41	-0.01	(0.03)
Hard sciences	0.64	0.48	0.65	0.48	0.01	(0.03)
Life sciences	0.42	0.49	0.42	0.49	-0.01	(0.22)
Social sciences and humanities	0.07	0.26	0.08	0.27	0.00	(0.14)
Non Directed Programs	0.38	0.49	0.53	0.50	0.15	(0.00)
Cluster	0.20	0.40	0.02	0.15	-0.17	(0.00)
Number of institutions	2.52	1.16	2.36	1.04	-0.17	(0.00)
Observations	9281		17761		27042	
	<i>After matching</i>					
	Funded applicants		Unfunded applicants		Difference t-test	
	mean	sd	mean	sd	b	p
Inventor	0.10	0.30	0.10	0.30	-0.00	(1.00)
Cited in patent(s)	0.59	0.49	0.59	0.49	-0.00	(1.00)
Age	43.95	8.05	44.03	8.03	0.08	(0.88)
Male	0.84	0.36	0.84	0.36	-0.00	(1.00)
H-Index	9.84	7.95	9.59	7.63	-0.25	(0.19)
Application Experience	0.43	0.50	0.43	0.50	-0.00	(1.00)
Funding Experience	0.21	0.41	0.21	0.41	-0.00	(1.00)
Hard sciences	0.66	0.48	0.66	0.47	-0.00	(1.00)
Life sciences	0.36	0.48	0.36	0.48	-0.00	(1.00)
Social sciences and humanities	0.04	0.19	0.04	0.19	-0.00	(1.00)
Non Directed Programs	0.39	0.49	0.39	0.49	-0.00	(1.00)
Cluster	0.05	0.22	0.05	0.22	-0.00	(1.00)
Number of institutions	2.50	1.00	2.53	1.11	0.03	(0.44)
Observations	4657		8863		13520	

Notes: We removed 55 funded applicants-applications for which entry into the panel coincides with the funding application. In addition, age is missing for 546 funded AAs, gender for an additional 4, and discipline for an additional 22, so that only 9,281 of the 9,908 funded AAs remain in this table before matching.

$Y_{i,t}$  is either the number of patented inventions or the number of articles cited in patents of researcher  $i$  in year  $t$ ,  $Funded_i$  indicates whether the individual was funded or not<sup>10</sup>, and  $Post_{i,t}$  is a binary variable that is set to 0 for the three years prior to the application (excluding the application year) and 1 for the four years after application. Finally, we introduce an individual fixed effect  $\gamma_i$ , and a year fixed effect  $\delta_t$  to control for annual shocks.

### 3.5.2 *Impact results*

**ACADEMIC PATENTS** We report in the first column of Table 38 the regression results on all matched applicants, and the remaining columns correspond to results for subsamples that we split according to the applicant's scientific field (columns 2–3), age group (columns 4–6), inventor status (columns 7–8), funding program type (columns 9–10), and project labeling by a competitive cluster (columns 11–12). Overall, we find that once we control for selection bias grants do not affect academic invention. The coefficient is nearly null in all subsamples, except for inventors where it is significantly negative. It is positive (although insignificant) for projects labelled by a competitiveness cluster and for non inventors (for whom the significance is not robust to changes in patent disambiguation thresholds: see Appendix Tables 45 and 46 for all results on thresholds 0.5 and 0.3 respectively).

We include an event study on applicant-applications labelled by clusters (Figure 11, left panel) and non labelled (right panel). We do not observe any pre-trend in both groups, but there seem to be positive trend in clusters. This observation is robust to changes in the disambiguation threshold (see Appendix Figures 16 and 17 for events studies on thresholds 0.5 and 0.3 respectively). However, this result must be interpreted with caution considering the small number of observations in this sample.

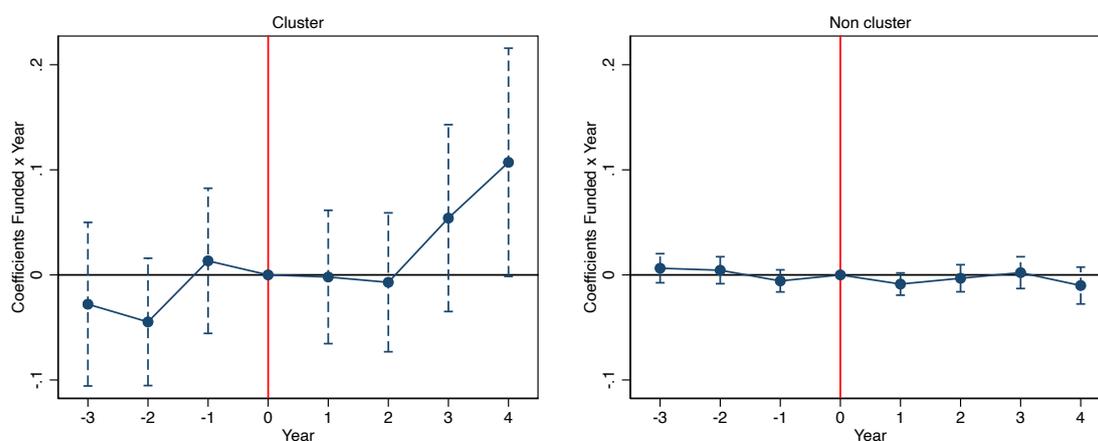
<sup>10</sup> Since the regression is in fixed-effects and the variable is time-invariant, it is not included alone in the regression.

Table 38: The impact of grant funding on academic invention (threshold 1, main results)

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Hard sc.	Life sc.	40 and younger	40 to 50	50 and older
Funded × Post	-0.00 (0.01)	0.01 (0.01)	-0.02 (0.01)	0.00 (0.01)	-0.00 (0.01)	-0.01 (0.01)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	93728	63052	31872	35692	39963	18073
Adj. R-squared	0.29	0.30	0.30	0.23	0.32	0.31
Log-likelihood	-4.6e+04	-2.7e+04	-1.9e+04	-1.4e+04	-2.1e+04	-1.0e+04
	(7)	(8)	(9)	(10)	(11)	(12)
	Inventors	Non inventors	Directed	Non directed	Cluster	Non cluster
Funded × Post	-0.10* (0.06)	0.01* (0.00)	-0.00 (0.01)	0.00 (0.01)	0.04 (0.03)	-0.01 (0.01)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	7474	85566	50396	43332	3134	90594
Adj. R-squared	0.27	0.15	0.29	0.30	0.34	0.29
Log-likelihood	-1.0e+04	-6669.67	-2.9e+04	-1.4e+04	-1717.51	-4.4e+04

Notes: Robust standard-errors in parentheses, clustered at the individual and project levels. The dependent variable is the number of patents using threshold 1. In this model, the pre-treatment window includes the three years prior to grant application. The post-treatment window includes the four years post-treatment (grant reception year excluded).

Figure 11: The impact of grant funding on faculty propensity to invent (disambiguation threshold 1).



Note: The dependent variable is the number of patents using threshold 1.

**PUBLICATIONS CITED IN PATENTS** Turning to the impact of grant funding on academics' indirect contribution to innovation, we report in Table 39 the results on the number of publications that are subsequently cited in patents. Similarly to the previous table, we investigate the effect on samples divided by applicant's field, age group, (absence of) inventorship, funding program design, and (absence of) project labelling by a competitiveness cluster. There is more variation in coefficients estimates than for academic patents. The coefficients are positive (albeit insignificant) on the overall regression, and for hard scientists, applicants aged 50 or older, applicants in directed programs, and those whose project is not labelled by a cluster. We find a weakly significant, but robust, negative effect of grant funding on applicant-applications labelled by a cluster (see Tables 47 and 48 for results on thresholds 0.5 and 0.3 respectively). The same warning as above applies: the number of observations in the clusters is relatively small compared to other samples so this result should be interpreted with caution.

We find in a set of event studies a positive and significant impact on hard scientists (Figure 12, second and fourth year post grant, see Appendix Figures 18 and 19 to check the robustness on the other thresholds), and on inventors in directed programs (although the coefficient for the year prior to funding is significantly different from zero, see Figure 13 and Appendix Figures 20 and 21 on other thresholds).

In addition, the exploration by age groups in Table 39, columns (4) to (6) and Figure 14 uncovers an interesting pattern: the effect and its trend are rather negative on younger researchers (aged 40 or younger, left panel), null to weakly positive on middle age ones (40 to 50 years old, middle panel), and positive on older scientists (those age

50 or older). This suggests a positive correlation between the impact of grant funding and the applicant's age. But focusing on the older group in Figure 15, we notice that those who are funded in directed programs were on a negative pre-trend, as opposed to those funded in directed program who were on a rather positive one, casting some doubt on the effect of the policy on this age group.

Table 39: The impact of grant funding on papers' citations in patents (main results)

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Hard sciences	Life sciences	40 and younger	40 to 50	50 and older
Funded × Post	0.02 (0.16)	0.17 (0.11)	-0.21 (0.39)	-0.18 (0.18)	-0.02 (0.30)	0.50 (0.41)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	93725	63051	31871	35691	39960	18073
Adj. R-squared	0.30	0.32	0.27	0.21	0.34	0.26
Log-likelihood	-3.3e+05	-1.9e+05	-1.2e+05	-1.1e+05	-1.4e+05	-6.9e+04
	(7)	(8)	(9)	(10)	(11)	(12)
	Inventors	Non inventors	Directed	Non directed	Cluster	Non cluster
Funded × Post	-0.19 (1.09)	-0.00 (0.14)	0.19 (0.22)	-0.26 (0.29)	-0.50* (0.29)	0.04 (0.17)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	7471	85564	50394	43331	3133	90591
Adj. R-squared	0.37	0.25	0.27	0.31	0.23	0.29
Log-likelihood	-3.0e+04	-2.9e+05	-1.8e+05	-1.5e+05	-8069.09	-3.2e+05

Notes: Robust standard-errors in parentheses, clustered at the individual and project levels. The dependent variable is the number of papers cited in patents. Academic patents from disambiguation threshold 0.3 are used to encode the inventor dummy included in the matching. In this model, the pre-treatment window includes the three years prior to grant application. The post-treatment window includes the four years post-treatment (treatment year excluded).

Figure 12: The impact of grant funding on hard scientists' propensity to publish articles subsequently cited in patents (disambiguation threshold 1).

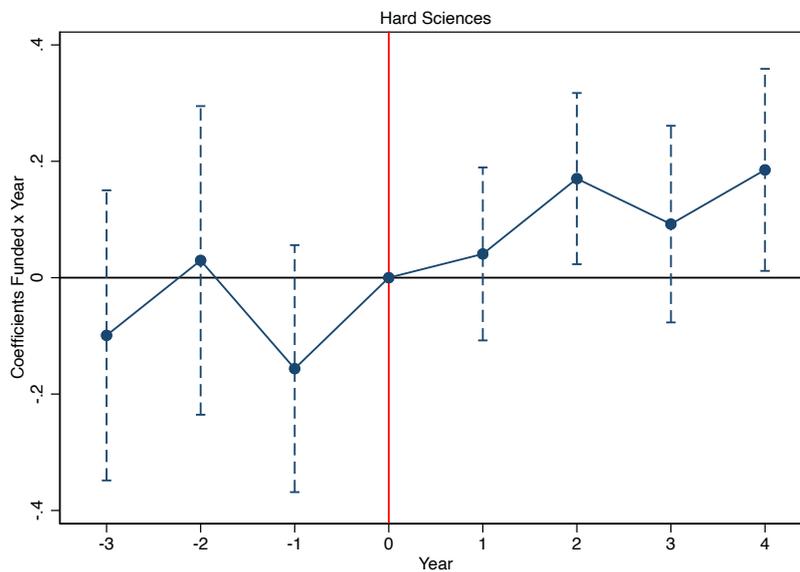
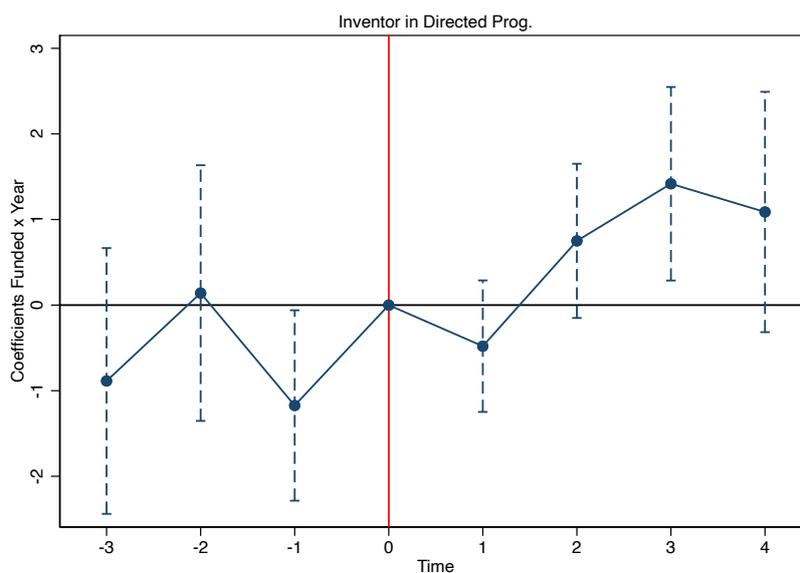
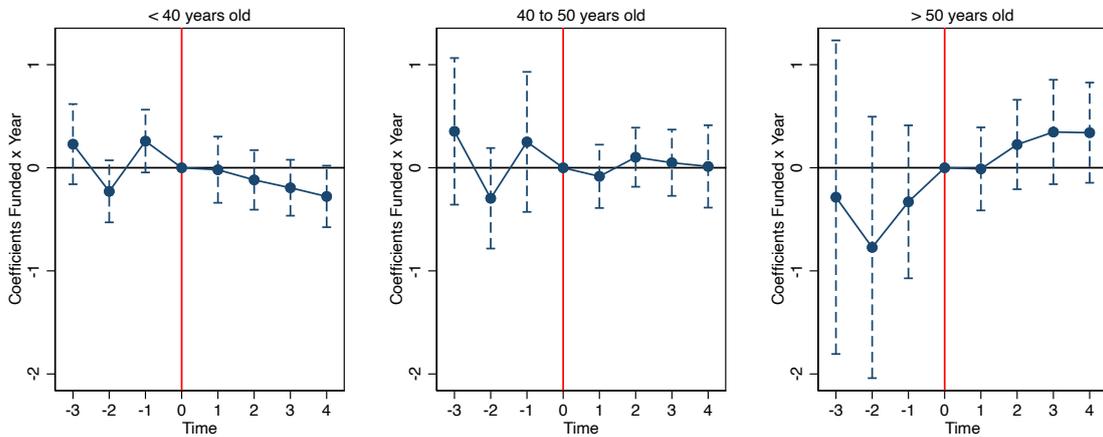


Figure 13: The impact of grant funding on **inventors'** propensity to publish articles subsequently cited in patents in directed programs (disambiguation threshold 1).



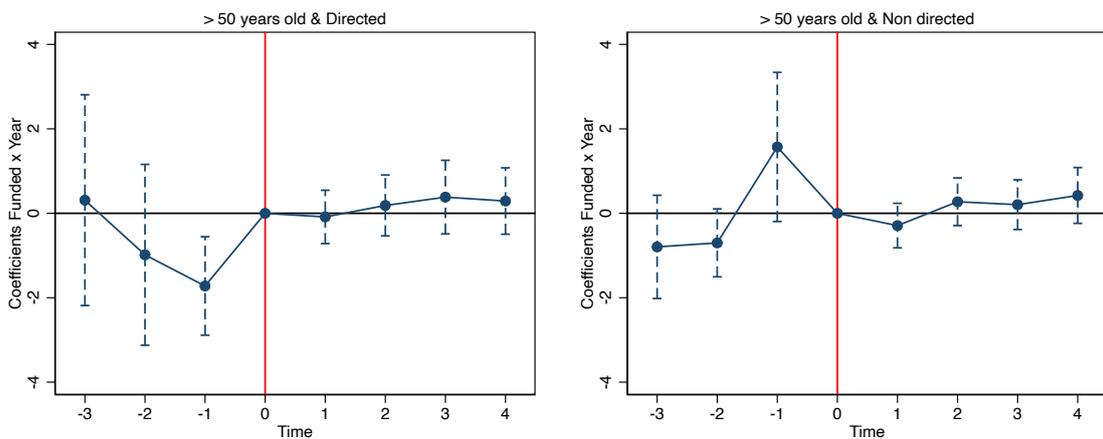
Note: The dependent variable is the number of articles cited in patent(s) using threshold 1.

Figure 14: The impact of grant funding on academics' propensity to publish articles subsequently cited in patents by age group (disambiguation threshold 1).



Note: The dependent variable is the number of articles cited in patent(s) using threshold 1.

Figure 15: The impact of grant funding on academics' aged 50 or more propensity to publish articles subsequently cited in patents by program type (disambiguation threshold 1).



Note: The dependent variable is the number of articles cited in patent(s) using threshold 1.

### 3.6 DISCUSSION AND CONCLUSION

In this chapter, we sought to explore the causal impact of project-based funding on academic invention. Controlling for the self-selection and selection biases, we find that grant funding does not in fact affect overall patent and patent-cited article production, meaning that the positive correlation recorded between funding status and academic invention is entirely due to a selection effect.

At the first stage, we find quite expectedly that male, older scientists, those at higher academic positions, and those with a stronger scientific profile are more confident in applying for ANR grants. But we also discover that academic inventors and researchers cited in patents are more attracted to grant funding than their counterparts, with a 16% and 21% higher probability to apply for these profiles. However, they are subsequently 5% and 7% less likely to be selected by the agency respectively. This resonates with a similar pattern observed by Ayoubi, Pezzoni, and Visentin, (2021) on scientists producing novel research in a Swiss funding program. Furthermore, we estimate that the attraction effect is more powerful than the selection bias: an additional 1.2% of inventors and 1.6% patent-cited researchers applied for and received funding solely thanks to their prior experience and contribution to innovation. We highlight that the results vary between directed and non-directed programs, as well as between scientific fields.

While the literature had not yet explored the role of past experience or involvement in innovation as determinant in the selection for grants, inventing or producing research that supports innovation may be related to the novelty of researchers. Several possibilities have been suggested to counter the bias against novelty, and some of them can be adapted to also reduce the one against researchers who contributed to innovation. One of these options is to use different kind of peers for different purposes (e.g. targeting specifically specialists in translational or high risk, innovative research) (Langfeldt, 2001). Another one is to relax the levels of stringency and degrees of selectivity in the review process to reward the most visionary research for instance (have a dedicated program) or use a different process for innovative projects (Holliday and Robotin, 2010). It could also be possible to make 'innovation' a criteria for assessment in peer review, although evidence of effectiveness is mixed Guthrie, Ghiga, and Wooding, 2017, p. 5. While a consensus among peers is currently desired to confirm the validity of a funding decision, authors have suggested that, conversely, disagreement among reviewers could be perceived as a signal of innovation and that projects with a high disagreement could be prioritized (Kaplan, 2005; Linton, 2016). Finally, it was suggested to fund researchers on their merits regardless of what they

plan to do (Azoulay, Graff-Zivin, and Manso, 2011; Guthrie, Ghiga, and Wooding, 2017).

Our second set of results focuses on the impact of competitive funding on the future contribution to innovation. We find that grant funding does not affect patent and patent-cited article production overall. However, we find a positive impact on the production of patent-cited articles by hard science researchers, and a puzzling negative effect of grant funding of projects labelled by a competitiveness clusters on academic inventions and research cited in patents. One plausible phenomenon would be that the positive bias in favor of these projects leads to a poor selection, so that the funds do not lead to expected results in terms of research quality.

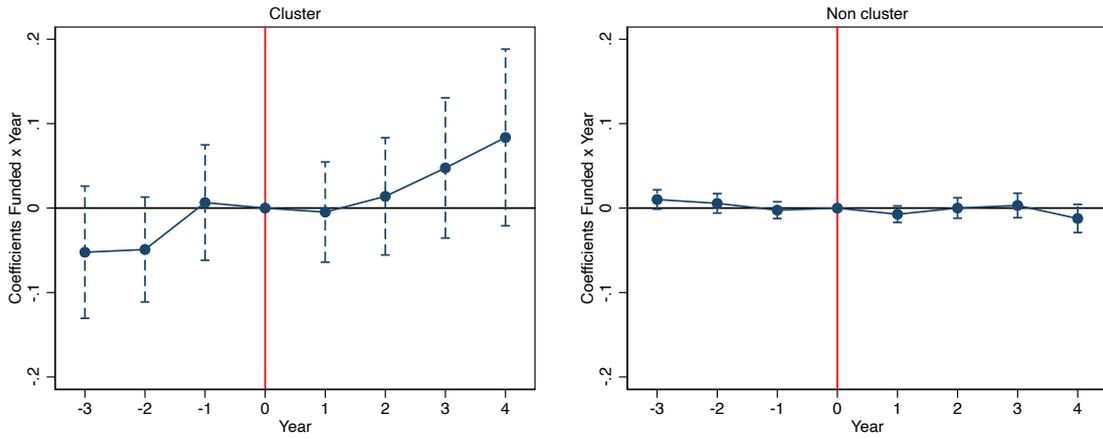
This chapter has several limitations that future work could address. Collecting evaluation scores from both internal and external peers would allow one to explore the particular stage in the process where the bias emerges and thus better identify which intervention is most relevant to reducing this bias. It would also allow to adopt a Regression Discontinuity Design in assessing the impact of grant funding (Lee and Lemieux, 2010). Another important data that we missed is the identification of industrial partners on the projects, which may have influenced both the content of the project, the chances of being selected and the propensity of researchers to patent. The lack of information on project members beyond the scientific leaders, as well as on the content of the project itself, limited our ability to explore the role of project-level factors in this relationship between contribution to innovation and project funding. For instance, it would be interesting to identify whether the bias against researchers who contribute to innovation results from a judgment of the project or the researcher. Finally, in the absence of information on alternative funding sources (in particular ERC funding), we are probably underestimating the real impact of ANR funding on contribution to innovation.

## 3.7 APPENDIX OF CHAPTER 3

Table 40: Description of variables.

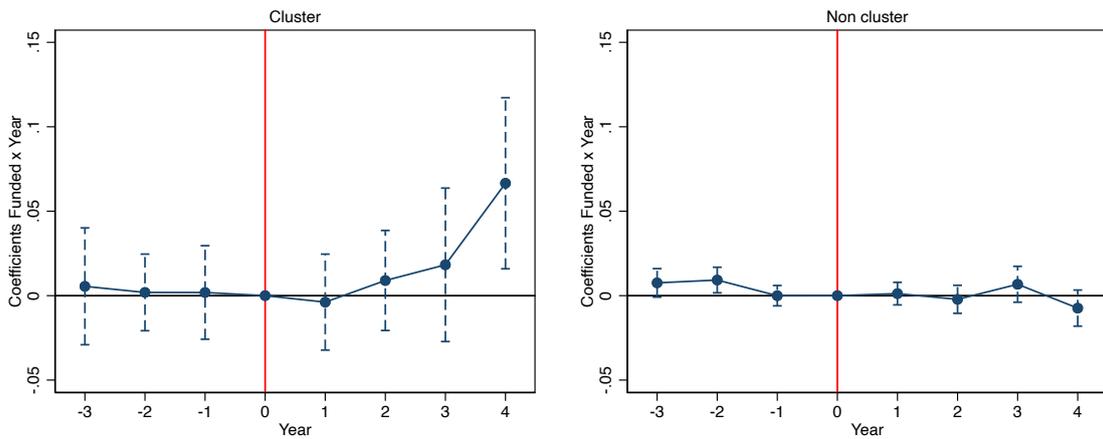
Variable	type	Description
<b>Number of patents</b>	count	Number of EPO patent applications for which at least one inventor is an academic. The threshold for disambiguation is 1 in the main analysis, robustness checks for thresholds 0.5 and 0.3. See Chapter 1 for more information
<b>Number of articles cited in patent(s)</b>	count	Number of articles published in the year with at least one lifetime citation in patent(s) (anywhere in the document, since grant until 2020)
<b>Inventor</b>	dummy	=1 if the researcher patented at least once in the 5 years prior to grant funding application
<b>Cited in patent(s)</b>	dummy	=1 if the researcher's publications are cited in patent(s) at least once in the 5 years prior to grant funding application
Age	continuous	Biological age of the individual
Gender/Male	dummy	=1 if male, and =0 if female
Academic position	categorical	Position at the application year : Associate professor, Full professor, Junior researcher or Senior researcher
Scientific field	dummies (one by field)	Field of affiliation in employment data: biology, physics, chemistry, universe sciences, engineering sciences, mathematics, or social sciences and humanities.
# Pubs	continuous	Average number of publication divided by the number of co-authors in the past 5 years
#Cites (3-y)	continuous	Average number of citations received within 3 years by articles published in the past 5 years
Total # Cites	continuous	Cumulated number of citations received by articles published in the past 5 years
# top 10% Pubs	continuous	Number of articles in the top 10% most cited in its field published in the past 5 years
# top 5% Pubs	continuous	Number of articles in the top 5% most cited in its field published in the past 5 years
Novelty	continuous	Average pairwise keyword novelty of articles published in the past 5 years
Interdisciplinarity	continuous	Average Herfindahl index of interdisciplinarity of articles published in the past 5 years
H-index	continuous	H-index at the application year
Fundraising profile	categorical	=0 if never applied for an ANR grant before, =1 if applied but never received the funding before, and =2 if applied and received at least one ANR grant in the past
Application year	discrete	Year of grant application
Cluster	dummy	=1 if at least one partner on the grant application belongs to a competitiveness cluster
Nb of partners	continuous	Number of academic partner institutions on the project
Coordinator	dummy	=1 if the individual is coordinator of the project
Non Directed Program	dummy	=1 if the application is submitted to a non directed program
Department	categorical	Department of the agency to which the application is submitted: Biology and Health (BH), Ecosystems and Sustainable Development (ESD), Sustainable Energy and Environment (SEE), Engineering, Processes and Security (EPS), Matter and Information (MI), Non-Directed Programs (NDP), Social Sciences and Humanities (SSH), Information and Communication Sciences and Technologies (ICST)

Figure 16: The impact of grant funding on faculty propensity to invent (disambiguation threshold 0.5).



Note: The dependent variable is the number of patents using threshold 05.

Figure 17: The impact of grant funding on faculty propensity to invent (disambiguation threshold 0.3).



Note: The dependent variable is the number of patents using threshold 03.

Table 41: Probability to apply for a grant (coefficients)

	Full sample			Restricted sample	
	(1) All Programs	(2) Non Directed	(3) Directed	(4) Non Directed	(5) Directed
Inventor	0.14*** (0.02)	-0.01 (0.02)	0.19*** (0.02)	0.03 (0.02)	0.20*** (0.02)
Cited in patent(s)	0.18*** (0.01)	0.03** (0.01)	0.26*** (0.01)	0.07*** (0.01)	0.26*** (0.01)
<b>Individual variables</b>					
Age	0.06*** (0.01)	-0.00 (0.01)	0.09*** (0.01)	0.01 (0.01)	0.10*** (0.01)
Age squared	-0.00*** (0.00)	-0.00*** (0.00)	-0.00*** (0.00)	-0.00*** (0.00)	-0.00*** (0.00)
Male	0.07*** (0.01)	0.05*** (0.01)	0.05*** (0.01)	0.06*** (0.02)	0.06*** (0.01)
H-Index	0.01*** (0.00)	0.01*** (0.00)	0.00*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
<b>Fundraising profile</b>					
Never applied before					
<i>Applied w/o success</i>	1.02*** (0.02)	0.84*** (0.02)	0.77*** (0.02)	0.99*** (0.02)	0.91*** (0.02)
<i>Applied with success</i>	0.61*** (0.02)	0.37*** (0.02)	0.61*** (0.02)	0.45*** (0.02)	0.65*** (0.02)
Constant	-2.90*** (0.13)	-1.92*** (0.16)	-4.13*** (0.16)	-2.17*** (0.16)	-4.19*** (0.16)
Academic position	Yes	Yes	Yes	Yes	Yes
Scientific field	Yes	Yes	Yes	Yes	Yes
Application year	Yes	Yes	Yes	Yes	Yes
Number of obs	200430	200430	200430	185961	187141

Notes: Robust standard-errors in parentheses, clustered at the individual and project levels. The control variables academic position, scientific field and application year are included in the model but the coefficients are not reported.

Table 42: Probability to apply for a grant by discipline group (coefficients)

	(1)	(2)	(3)
	Hard Sciences	Life Sciences	Social Sc. and Humanities
Inventor	0.14*** (0.02)	0.15*** (0.02)	0.06 (0.07)
Cited in patent(s)	0.22*** (0.01)	0.16*** (0.02)	0.04 (0.04)
<b>Individual variables</b>			
Age	0.06*** (0.01)	0.08*** (0.01)	0.03 (0.02)
Age squared	-0.00*** (0.00)	-0.00*** (0.00)	-0.00** (0.00)
Male	0.04** (0.02)	0.07*** (0.02)	0.11*** (0.03)
H-Index	0.01*** (0.00)	0.01*** (0.00)	0.00* (0.00)
<b>Fundraising profile</b>			
Never applied before			
<i>Applied w/o success</i>	1.00*** (0.02)	0.99*** (0.03)	1.21*** (0.06)
<i>Applied with success</i>	0.56*** (0.02)	0.63*** (0.03)	0.79*** (0.06)
Constant	-2.81*** (0.15)	-3.67*** (0.21)	-2.97*** (0.44)
Academic position	Yes	Yes	Yes
Scientific field	Yes	Yes	Yes
Application year	Yes	Yes	Yes
Number of obs	117189	76590	33498

Notes: Robust standard-errors in parentheses, clustered at the individual and project levels. Among potential applicants, 1,545 belong to two field groups simultaneously and 148 belong to all three groups. The control variables academic position, scientific field and application year are included in the model but the marginal effects at the mean are not reported.

Table 43: Probability to receive a grant (coefficients)

	(1)	(2)	(3)
	All prog.	Non directed	Directed
Inventor	-0.08*** (0.03)	-0.07 (0.05)	-0.07* (0.04)
Cited in patent(s)	-0.11*** (0.02)	-0.11*** (0.03)	-0.05 (0.04)
<b>Individual variables</b>			
Age	-0.00*** (0.00)	-0.00 (0.00)	-0.01*** (0.00)
Male	0.02 (0.02)	0.06* (0.03)	-0.00 (0.03)
H-Index	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
<b>Fundraising profile</b>			
Never applied before			
<i>Applied w/o success</i>	-0.21*** (0.05)	-0.24*** (0.07)	-0.15** (0.07)
<i>Applied with success</i>	-0.01 (0.04)	-0.01 (0.05)	0.02 (0.06)
<b>Project variables</b>			
Cluster	1.35*** (0.06)	2.57*** (0.25)	1.24*** (0.06)
Number of institutions	0.04** (0.02)	0.09*** (0.02)	0.01 (0.02)
Constant	1.48*** (0.12)	3.84*** (0.29)	1.05*** (0.22)
Department of the agency	Yes	No	Yes
Scientific field	Yes	Yes	Yes
Application year	Yes	Yes	Yes
Number of obs	200430	200430	200430
Number of selected obs	27758	13289	14469
Rho	-.340372	-.4660877	-.2306733
Prob chiz	0.00	0.00	0.01

Notes: Robust standard-errors in parentheses, clustered at the individual and project levels. The control variables Scientific field, Department of the agency and Application year are included in the model but the marginal effects at the mean are not reported. Prob chiz represents the p-value associated with the Wald test of independence; Ho: The selection equation and the structural equation are independent. There is no fixed effect on the department of the agency for non directed programs because they all belong to the same department.

Table 44: Probability to receive a grant by discipline group

	(1)	(2)	(3)
	Hard Sciences	Life Sciences	Social Sc. and Humanities
Inventor	-0.09** (0.04)	-0.07* (0.04)	0.31** (0.15)
Cited in patent(s)	-0.10*** (0.03)	-0.09** (0.04)	-0.09 (0.10)
<b>Individual variables</b>			
Age	-0.01*** (0.00)	-0.00 (0.00)	-0.01 (0.00)
Male	0.02 (0.03)	0.03 (0.03)	0.04 (0.09)
H-Index	0.01*** (0.00)	0.01** (0.00)	0.01* (0.01)
<b>Application experience</b>			
Never applied before			
<i>Applied w/o success</i>	-0.14** (0.07)	-0.28*** (0.07)	-0.36 (0.25)
<i>Applied with success</i>	-0.02 (0.05)	0.06 (0.06)	-0.27 (0.19)
<b>Project variables</b>			
Cluster	1.38*** (0.06)	1.29*** (0.10)	1.04*** (0.23)
Number of institutions	0.03 (0.02)	0.05** (0.02)	0.02 (0.04)
Constant	1.03*** (0.16)	2.20*** (0.17)	2.25*** (0.52)
Department of the agency	Yes	Yes	Yes
Scientific field	Yes	Yes	Yes
Application year	Yes	Yes	Yes
Number of obs	117189	76590	33498
Number of selected obs	18150	11824	1680
Rho	-.2709038	-.407277	-.3638638
Prob chiz	0.00	0.00	0.12

Notes: Robust standard-errors in parentheses, clustered at the individual and project levels. The control variables Scientific field, Department of the agency and Application year are included in the model but the marginal effects at the mean are not reported. Prob chiz represents the p-value associated with the Wald test of independence; Ho: The selection equation and the structural equation are independent. There is no fixed effect on the department of the agency for non directed programs because they all belong to the same department.

Table 45: The impact of grant funding on academic invention (threshold 0.5, first alternative)

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Hard sc.	Life sc.	40 and younger	40 to 50	50 and older
Funded × Post	-0.00 (0.01)	0.01 (0.01)	-0.02** (0.01)	0.00 (0.01)	-0.00 (0.01)	-0.01 (0.01)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	94805	63792	32237	36036	40500	18269
Adj. R-squared	0.26	0.24	0.29	0.18	0.29	0.28
Log-likelihood	-4.1e+04	-2.3e+04	-1.8e+04	-1.1e+04	-1.9e+04	-9025.99
	(7)	(8)	(9)	(10)	(11)	(12)
	Inventors	Non inventors	Directed	Non directed	Cluster	Non cluster
Funded × Post	-0.09* (0.05)	0.01 (0.00)	-0.00 (0.01)	0.00 (0.01)	0.05* (0.03)	-0.01 (0.01)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	7139	87666	50885	43920	3169	91636
Adj. R-squared	0.22	0.14	0.26	0.25	0.28	0.26
Log-likelihood	-9540.12	-5721.37	-2.7e+04	-9913.47	-1588.41	-3.9e+04

Notes: Robust standard-errors in parentheses, clustered at the individual and project levels. The dependent variable is the number of patents using threshold 0.5. In this model, the pre-treatment window includes the three years prior to grant application. The post-treatment window includes the four years post-treatment (grant reception year excluded).

Table 46: The impact of grant funding on academic invention (threshold 0.3, second alternative)

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Hard sc.	Life sc.	40 and younger	40 to 50	50 and older
Funded $\times$ Post	-0.00 (0.00)	0.01* (0.00)	-0.01* (0.01)	0.00 (0.01)	-0.01 (0.01)	0.00 (0.01)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	98759	66441	33773	37128	42147	19484
Adj. R-squared	0.25	0.21	0.31	0.12	0.29	0.32
Log-likelihood	-6533.92	-854.75	-5785.07	-762.04	-4507.70	-971.25
	(7)	(8)	(9)	(10)	(11)	(12)
	Inventors	Non inventors	Directed	Non directed	Cluster	Non cluster
Funded $\times$ Post	-0.17** (0.07)	0.00 (0.00)	0.00 (0.01)	-0.00 (0.01)	0.02 (0.02)	-0.00 (0.00)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	3117	89395	53416	45343	3463	95296
Adj. R-squared	0.30	0.13	0.27	0.15	0.12	0.25
Log-likelihood	-3804.59	21911.12	-8580.16	6533.40	127.09	-6812.00

Notes: Robust standard-errors in parentheses, clustered at the individual and project levels. The dependent variable is the number of patents using threshold 0.3. In this model, the pre-treatment window includes the three years prior to grant application. The post-treatment window includes the four years post-treatment (grant reception year excluded).

Table 47: The impact of grant funding on papers' citations in patents (threshold 0.5, first alternative)

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Hard sciences	Life sciences	40 and younger	40 to 50	50 and older
Funded $\times$ Post	0.04 (0.16)	0.18 (0.11)	-0.19 (0.39)	-0.19 (0.18)	0.01 (0.30)	0.52 (0.41)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	94803	63792	32237	36036	40497	18269
Adj. R-squared	0.29	0.32	0.27	0.21	0.34	0.26
Log-likelihood	-3.3e+05	-1.9e+05	-1.2e+05	-1.1e+05	-1.4e+05	-7.0e+04
	(7)	(8)	(9)	(10)	(11)	(12)
	Inventors	Non inventors	Directed	Non directed	Cluster	Non cluster
Funded $\times$ Post	-0.14 (1.12)	0.01 (0.14)	0.21 (0.22)	-0.25 (0.29)	-0.51* (0.30)	0.06 (0.17)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	7138	87664	50884	43919	3168	91634
Adj. R-squared	0.37	0.25	0.27	0.31	0.24	0.29
Log-likelihood	-2.9e+04	-3.0e+05	-1.8e+05	-1.5e+05	-8196.34	-3.2e+05

Notes: Robust standard-errors in parentheses, clustered at the individual and project levels. The dependent variable is the number of papers cited in patents. Academic patents from disambiguation threshold 0.5 are used to encode the inventor dummy included in the matching. In this model, the pre-treatment window includes the three years prior to grant application. The post-treatment window includes the four years post-treatment (treatment year excluded).

Table 48: The impact of grant funding on papers' citations in patents (threshold 0.3, second alternative)

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Hard sciences	Life sciences	40 and younger	40 to 50	50 and older
Funded $\times$ Post	0.08 (0.15)	0.08 (0.10)	0.07 (0.36)	-0.22 (0.17)	0.18 (0.25)	0.40 (0.42)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	98756	66440	33772	37127	42144	19484
Adj. R-squared	0.29	0.31	0.26	0.20	0.30	0.28
Log-likelihood	-3.5e+05	-2.0e+05	-1.3e+05	-1.1e+05	-1.5e+05	-7.5e+04
	(7)	(8)	(9)	(10)	(11)	(12)
	Inventors	Non inventors	Directed	Non directed	Cluster	Non cluster
Funded $\times$ Post	1.06 (1.60)	0.01 (0.14)	0.21 (0.22)	-0.12 (0.20)	-0.59** (0.27)	0.11 (0.16)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	3117	89393	53414	45342	3463	95293
Adj. R-squared	0.34	0.25	0.27	0.29	0.26	0.28
Log-likelihood	-1.3e+04	-3.1e+05	-1.9e+05	-1.5e+05	-8811.95	-3.4e+05

Notes: Robust standard-errors in parentheses, clustered at the individual and project levels. The dependent variable is the number of papers cited in patents. Academic patents from disambiguation threshold 0.3 are used to encode the inventor dummy included in the matching. In this model, the pre-treatment window includes the three years prior to grant application. The post-treatment window includes the four years post-treatment (treatment year excluded).

Figure 18: The impact of grant funding on hard scientists' propensity to publish articles subsequently cited in patents (disambiguation threshold 0.5).

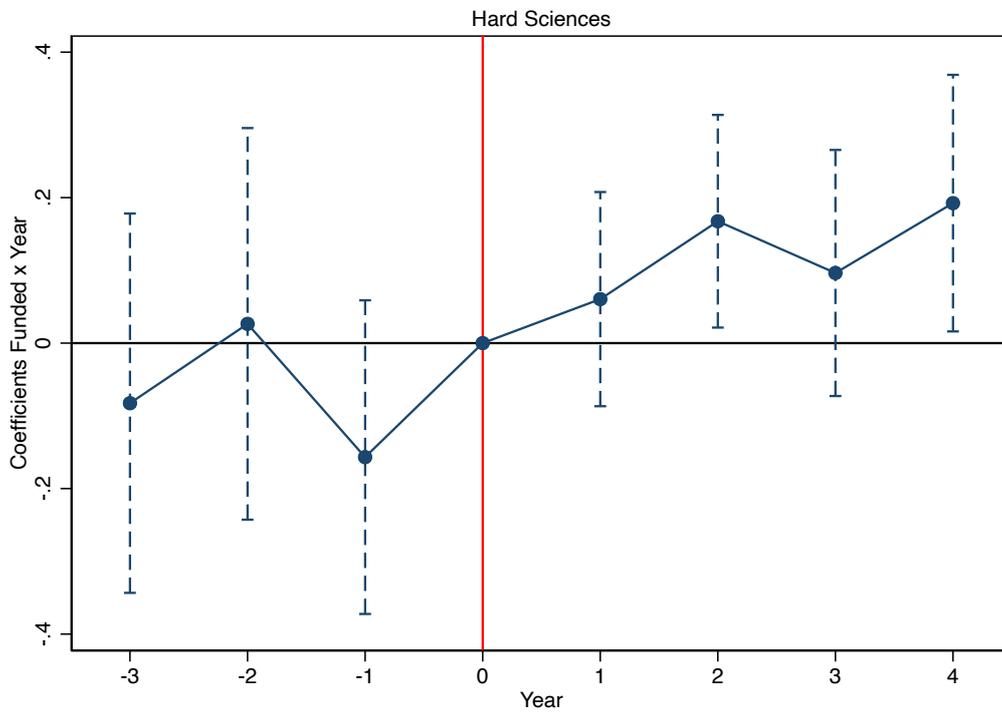


Figure 19: The impact of grant funding on hard scientists' propensity to publish articles subsequently cited in patents (disambiguation threshold 0.3).

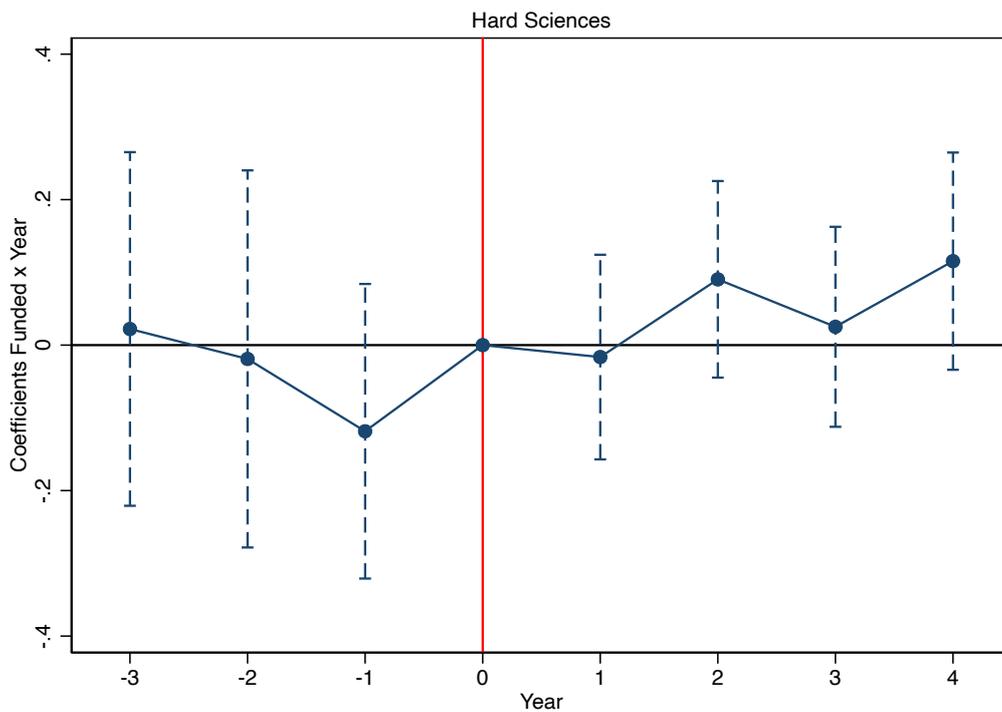


Figure 20: The impact of grant funding on **inventors'** propensity to publish articles subsequently cited in patents in directed programs (disambiguation threshold 0.5).

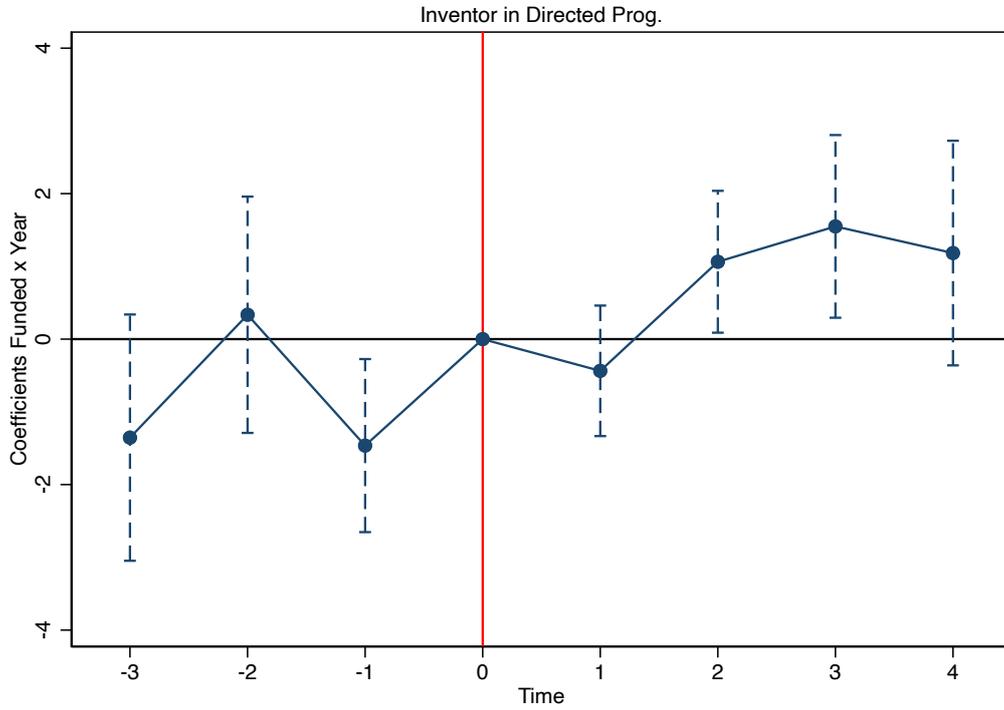
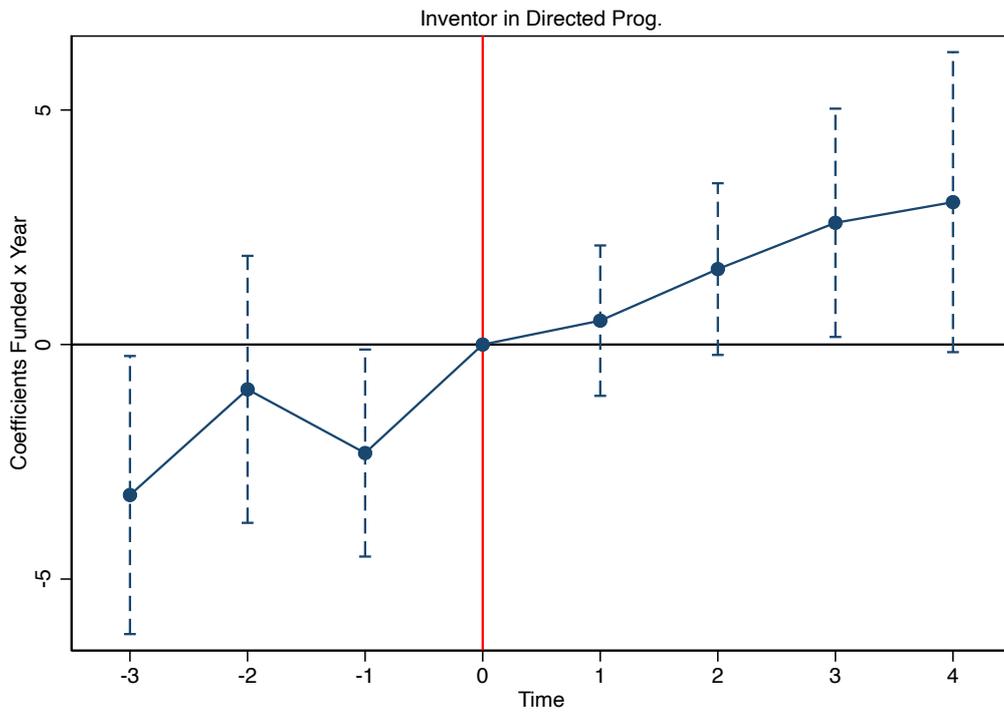


Figure 21: The impact of grant funding on **inventors'** propensity to publish articles subsequently cited in patents in directed programs (disambiguation threshold 0.3).



## GENERAL CONCLUSION

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This thesis aimed at identifying the contribution of different factors to the transfer of knowledge from science to industry, under the form of academic inventions. To this end, a new methodology was developed and implemented to collect a quasi-exhaustive dataset of academic patents at the country level, covering all scientific fields, and spanning two decades. The study focused on France, the seventh greatest country in the world in terms of GDP, sixth in terms of scientific articles, and fourth in terms of patents granted in this period of time. For this country, the first result of this work revealed that over 44,000 academics patents were applied for over the years 1995–2012.

Based on this academic patents dataset, the three chapters of this thesis contributed to: (i) quantify and characterize academic invention on large scale over a long period of time (Chapter 1), (ii) identify the contribution of several factors at individual, laboratory, and university levels (Chapter 1), and (iii) measure the impact of two specific public policies, namely the university ownership regime (Chapter 2) and competitive science funding (Chapter 3), on subsequent incentives to invent. All chapters were empirical studies, with the first and second chapters including a methodological contribution as well. I first detail the contribution, limitation and follow-up research contained in each chapter, and sketch some future avenues of research at the end of this conclusion.

### MAIN RESULTS, LIMITATIONS, AND FOLLOW-UP RESEARCH

**CHAPTER 1.** The first chapter aimed at characterizing the phenomenon of academic invention and its evolution over two decades. After exposing the methodology to collect academic patents, I found that academic patenting is a growing phenomenon over time, and that academia contributes for more than 11% of all inventions patented in the country. One professor or researcher out of five has already transferred knowledge through this channel, which revises upwards prior estimates. I ran logistic regressions to explore which factors most contribute to the phenomenon. First, I found lifecycle effects, whereby patenting is more likely to occur at older ages. However,

changes in norms with regards to commercialization, that would reflect differently across cohorts, appeared to play no significant role in fostering academic invention. Finally, I evidenced for the first time the presence of peer-effects in academic invention at the laboratory level.

These results have important policy implications. The French government has introduced many pieces of legislation over the last decades to support academic patenting and other commercialization activities. The results of this chapter suggest the most efficient levers are the micro (rather than meso or macro) level ones. For instance, legislations could bear greater fruits by accounting for patenting activities in tenure and promotion decisions (Sanberg et al., 2014), or supporting collaborations within laboratories to exploit localized peer-effects and role models. On the contrary, policy efforts to change cultural perceptions in a more diffuse way, or to raise professors' awareness of the commercial potential of their research would appear less efficient.

CHAPTER 2. In the second chapter, I assessed the impact of allocating the intellectual property rights over academic inventions to universities, as opposed to firms or individual inventors, on subsequent incentives to invent. Rather than studying the impact around the year of reform, I developed a new approach to observe if (and when) each institution implemented the policy recommendations. This measure relied on the evolution of the share of inventions the institution took ownership of and managed over time, provided that we showed some percentage often goes straight to firms or the professor-inventor herself. *Treated* universities, i.e. those making the move towards actively managing their intellectual property, were matched to similar *untreated* ones on the same calendar year. A difference-in-differences regression showed professors in treated universities subsequently patent on average 20.7% more inventions.

Comparing with other policy changes in Europe and the US, I suggested that allocating the ownership of intellectual property rights to universities is efficient to support knowledge transfer when the regime implementation is flexible, i.e. in a way that still allows private sector firms to own a share of these inventions. In countries where professors initially owned their inventions and used to transfer them to the private sector through their own network, policy makers could avoid a negative effect on academic invention by allowing professors to maintain these prior transfer pathways while offering the university TTO as a complementary (rather than substitute) transfer pathway.

The main limitation of this study is that the dependent variable was a double-edged sword. It had the benefit of allowing to observe exogenously the strategy of

university in terms of IP management, without allowing them to distort the facts, and the drawback of being built on the independent variable, which raises concerns in case the source for the latter is doubtful. Unfortunately, data on university-level implementation time or date of TTOs' opening were not available. This underlines the importance of government providing access to such data for research purposes. In case these data become available, it would be interesting to study how this constructed variable relates to the timing of TTO opening in universities.

CHAPTER 3. In the third and last chapter, I explored the interplay between competitive grants and academics' contribution to innovation. I merged to the previous database of professors and patents the data on the research projects they submitted to the ANR in 2005–2009 and the funding decisions of the selection committees. The first part examined the relative attraction to grant funding of academics contributing directly (through academic patents) or indirectly (via publications cited in patents) to innovation, and their selection rate by the agency. Using a Heckman probit model to study step-by-step the self-selection and selection into grant funding, I found that contributors to innovation are more likely to apply than non-contributors, but less likely to be selected by the agency. Finally, the attraction effect appeared to be stronger than the selection bias, since a positive number of inventors and researchers cited in the patents applied for and received funding thanks to their prior experience or contribution to innovation.

I assessed the impact of receiving a competitive grant on academic patents and publications cited in patents in the second part of this chapter. After matching funded applicants to similar unfunded ones and comparing their patenting and publishing rates in a difference-in-differences framework, I found that, despite science being an undeniably critical input to innovation, providing funds under a competitive scheme to produce science did not affect its transfer through inventions or publications cited in patents in a systematic way. Despite this, the results unveiled a puzzling effect on researchers whose project is labeled by a competitiveness cluster, which generates a new question: what distinctive features of the professors in these clusters, or the structure and collaboration network they are embedded into, could explain that these grants would be more or less effective at fostering the academic contribution to innovation? Future research could address it by retrieving data on these specific structures that could be combined with the grant funding data, and would ideally include more recent years so that the sample would be large enough to spur more significant insights.

Upon answering this last interrogation, the results will bear important policy implications. Research grants allocated through a competitive scheme have already proved their effectiveness at supporting the creation of new knowledge (e.g. Azoulay, Graff-Zivin, and Manso, 2011, Banal-Estanol, Macho-Stadler, and Perez-Castrillo, 2019, Jacob and Lefgren, 2011, Carayol and Lanoë, 2019). But to the best of my knowledge, there is no literature except for this thesis chapter, evidencing their ability to support the transfer of this new knowledge through academic inventions. The identification of the precise underlying mechanism could help policy makers refine the grant funding model in a way that maximizes the social benefits through supporting both knowledge creation and knowledge transfer.

Finally, these project-based grants are only a share of governmental funds allocated to basic research under a competitive scheme. There exist other programs called “investissements d’avenir” (investments for the future) that distribute research funds to laboratories and universities with the same goal of supporting the creation of cutting-edge knowledge. A relevant extension of this chapter would be to study whether these policies at different levels affect academics’ contribution to innovation.

#### RESEARCH PATHS

One aim of this thesis was to examine the impact of two major policy changes related to academic invention, but other reforms are also relevant for academic invention and equally deserve investigation. For instance, the government introduced in 2004 competitiveness clusters, which are associations of companies, research centers and educational institutions in a given area, working in partnership to generate synergies and foster industrial competitiveness. As these structures are university-industry collaborations and target the industrial competitiveness, further investigation is required to assess whether and how this policy is effective at fostering academic invention. Another key policy change is the regionalization of universities technology transfer offices, called *Sociétés d’Accélération du Transfert de Technologies* (SATTs). This change in the way technology transfer activities are organized, and the introduction of a unique mandate to smooth the process, are expected to further ease academic invention, but this remains to be demonstrated.

Furthermore, this thesis uses the French case to study the existence of the European paradox, i.e., an advanced scientific production but a difficulty in transferring knowledge to the private sector, resulting in a delay in terms of innovation and economic growth. While this phenomenon is not reflected in the data of this thesis, this does

not necessarily imply that the paradox does not exist in other European countries. It would therefore be interesting to study the academic contribution to innovation in neighboring countries, or even to extend the analysis to other continents, such as Asia or Latin America. Moreover, reforms in the organization and funding of science are also being implemented in these nations, and a better understanding of their impact in different contexts might allow to conduct a meta-analysis and draw generic lessons.

While conducting research for this thesis, I have identified some interesting effects on gender that I would like to explore further. I observed in the first chapter that 16% of the nearly 12,000 women in our dataset are patenting, which is 64% of the rate for men, and once controlling for the effect of other variables, I showed that women invented 50% fewer patents than men all else equal. In the third chapter, I note that women are significantly less likely to apply for a grant than men, but once controlling for this self-selection bias, there is no clear evidence of a gender bias in the grant peer-review process. These first elements call for further investigation of the gender bias in academic invention, for instance to examine its evolution in European countries (extending the contributions of Ding, Murray, and Stuart, (2006), Thursby and Thursby, (2005), and Whittington and Smith-Doerr, (2005) on the US case), and studying its determinants both in patenting and grant application behaviors using a nationwide dataset over several decades.

In connection with the prior point, a stream of literature complementary to this thesis investigates the network of academic inventors (Breschi and Catalini, 2010; Forti, Franzoni, and Sobrero, 2013; Lissoni, 2010). This literature, however, does not split the analysis by gender. Neumeyer et al., (2019) investigate the social capital of women entrepreneurs as compared to the one of men, and its impact on entrepreneurship outcomes. Similar investigation focusing on academic invention is required to understand whether women are building different structures of network as compared to men, and whether specific structures are increasing women's likelihood to invent.



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