Research Grants and Scientists' Inventions

Nicolas Carayol, Elodie Carpentier and Pascale Roux*

February 20, 2024

*Nicolas Carayol: Univ. Bordeaux, CNRS, INRAE, BSE, UMR 6060, UMR 1441, F-33600 Pessac, France. Email: nicolas.carayol@u-bordeaux.fr. Elodie Carpentier: Univ. Bordeaux, CNRS, INRAE, BSE, UMR 6060, UMR 1441, F-33600 Pessac, France. Email: elodie.carpentier@u-bordeaux.fr. Pascale Roux: Univ. Bordeaux, CNRS, INRAE, BSE, UMR 6060, UMR 1441, F-33600 Pessac, France. Email: pascale.roux@u-bordeaux.fr. We are grateful to participants at the EPIP conference (2017) and the 10th annual European SEI doctoral consortium (2020) for their comments and suggestions. We thank the ANR (no ANR-15-CE26-0005), the French Ministry of Higher Education and Research (grant no 2102928132), and the Fulbright Commission for their financial support.

Abstract

Does competitive funding of public research directly generate inventions (and how)? We use longitudinal data on French researchers and professors, their applications, and grants received from the French National Research Agency (ANR) to document the relationship between public research funding and inventions by grant recipients. We first show that after controlling for various individual characteristics such as age, gender, scientific impact, and field, scientists with a "taste for invention" are significantly more likely to apply for grants, although their chances of being selected are lower. The overall selection effect is positive, particularly for directed programs that strongly attract these profiles. Grants have no significant overall causal impact on the propensity of recipients to generate inventions, but they do favor inventions in hard sciences, from those who have not invented before, and when a "competitiveness cluster" supports the project.

JEL codes: I23; O31; O33; O34

Keywords: Patents; Academic Invention; Research; Policy Evaluation.

1 Introduction

While scholars have long hypothesized that fundamental research conducted by universities may have a high social value (Arrow, 1962), identifying and characterizing its impacts are key empirical questions that have remained open ever since. The literature has mainly focused on identifying externalities of research carried out in universities, using either geographic[1] or research areas coincidence,[2] or by directly observing citation links between research and innovations.[3]

In this paper, we focus on the *direct* contributions of research performed in academia to invention. Our aim is not to quantify the overall impact of university research, but rather to open this black box, i.e. to assess how and to what extent specific scientific funding programs targeting universities and public research laboratories contribute directly to the generation of inventions by individuals (tenured professors and researchers) whose research projects are supported by these programs.

To do so, we rely on an initial dataset of more than 36,000 tenured professors and researchers in the life and hard (or exact) sciences, employed in French academic institutions from 2000-2016, matched with all grant applications and funding decisions provided by the French funding agency (Agence Nationale de la Recherche, from now on ANR) for the years 2005-2009, and with publications and patenting outcomes.[4] We find more than 27,000 indi-

[1]See Jaffe, 1989; Acs, Audretsch and Feldman, 1992; Henderson, Jaffe and Trajtenberg, 1998; Kantor and Whalley, 2014, among many others who use the correlation between academic research spending and patents at the local level.

[2]Azoulay et al. (2019) use research areas coincidence and idiosyncratic rigidities in the rules governing NIH peer review to show that a 1 million increase in NIH funding in the U.S. results in a net increase of .23 patents by pharmaceutical and biotech firms.

[3]Investigating the relationships between U.S. patents and scientific research, Ahmadpoor and Jones (2017) find that 80% of research articles link forward to a future patent and that 61% of patents link backward to a prior research article. Li, Azoulay and Sampat (2017) find that one-third of NIH-funded projects in the U.S. lead to articles that are cited by patents in the biomedical sector and that about 8% directly lead to a patent.

[4]ANR data have been first used in Carayol and Lanoë (2019) and academic patent data in Carayol and Carpentier (2021), but none of those papers study the relation between ANR funding and patenting.

vidual participations to submitted projects, involving 12,000 distinct tenured professors and researchers (i.e. one faculty in three). This suggests self-selection is important whereas it is often ignored in the literature.

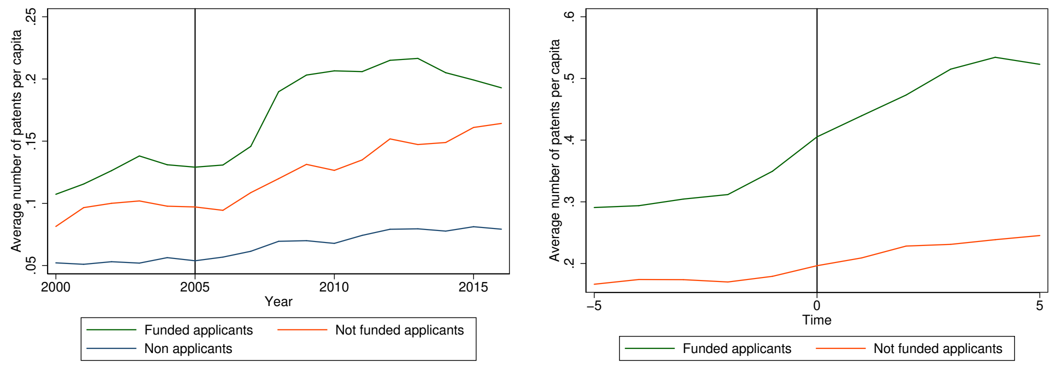
The main originality of our work is that we are able to carefully study the full chain of events, starting from the academics' decision to apply for a grant: self-selection, selection, and causal impact on inventions. We can differentiate between selection and impact effects concerning the specifics of the policy tool for funding projects (such as the use of directed or non-directed programs) or various characteristics of the (potential) applicants (for instance age, past productivity, academic position, or disciplines).

Simply aggregating the data assembled for this paper, we can draw the graphs of Figure 1, which conveniently set the scene for our study. In the left panel, we plot the average number of patents per capita over the years. It is split into three groups of scientists, defined according to their application and funding status in the 2005-2009 period. We observe that funded scientists (green line) patent more inventions on average than the unsuccessful applicants (orange line), who in turn invent more often than those who never applied for ANR grants (blue line). It is also clear that those differences have increased after 2005, the year the funding agency (ANR) was created.

Since grants have been distributed in different calendar years, it is interesting to consider inventions with respect to the funding decision year. The right panel of Figure 1 plots the average number of patents per capita of successful and unsuccessful applicants.[5] We can see that funded applicants file more patents on average than those who were not funded and that such differences become larger after the funding year. This raw data suggests that beyond the selection of scientists who are more likely to invent over time, funding may have a direct causal impact on inventions. But a closer look at this figure may reveal that the widening gap

[5]Note that it then makes it impossible to consider the subset of professors and researchers who have not applied.

Figure 1: Number of patents per capita, by application and funding status.



Notes: Academics are assigned to three groups regardless of year: those who never applied for ANR funding (non-applicants) over the years 2005 to 2009, those who applied at least once but never received an ANR grant (not funded applicants), and those who received at least one grant (funded applicants). In the left-hand non-applicants of these groups, we sum the number of inventions they patented in each calendar year and divide by the number of academics in that year. The graph on the right is not directly comparable since it is centered on the year of application, which varies between individuals. The variation coefficient of those numbers is presented in Figure A1 in the Online Appendix.

precedes funding to some extent. This in turn suggests that selection factors may correlate with variation in the propensity to invent for some other reason than a causal relationship. In this paper, we intend to unravel the chain of causes and consequences between invention and competitive science funding by examining in detail grant application decisions, committee selection, and the causal impact on inventions at the level of individual scientists.

The paper therefore contributes to two specific lines of research. The first one explores the determinants of applicants' selection in funding programs.[6] We contribute to this literature by examining how previous patenting activities or publication of papers related to innovation (which will be cited in patents) may affect the chances of obtaining funding. We show that this role is complex. Scientists who have a "taste" for invention (previous inventors), and

[6]A number of individual or institutional factors have been investigated, such as past applicants' work (Arora and Gambardella, 2005; Van den Besselaar and Leydesdorff, 2009; Neufeld, Huber and Wegner, 2013), past application experiences (Park, Lee and Kim, 2015; Bol, de Vaan and van de Rijt, 2018), research style (Porter and Rossini, 1985; Banal-Estanol, Macho-Stadler and Perez-Castrillo, 2019; Bromham, Dinnage and Hua, 2016; Carayol and Lanoë, 2019), academic and departmental status (Cole, Cole and Simon, 1981; Bazeley, 1998; Jayasinghe, Marsh and Bond, 2003; Viner, Powell and Green, 2004), current university size (Murray et al., 2016), research field (Laudel, 2006), and demographic factors such as the applicant's age (Guthrie, Ghiga and Wooding, 2017; Carayol and Lanoë, 2019), gender (Bornmann, Mutz and Daniel, 2007; Jagsi et al., 2009; Pohlhaus et al., 2011; Van der Lee and Ellemers, 2015; Wenneras and Wold, 2010), or ethnicity (Ginther et al., 2011).

those whose previous research is “close” to inventions (their previously published articles are cited in patents), are more likely to apply to grant funding. As those scientists are also subsequently less likely to be selected by the agency, we argue that they are more “entrepreneurial” (they are more keen to apply even if the selection process is biased against them). Interestingly, the positive attraction effect is significantly more powerful than the negative selection bias, so that the scientists who have already invented, or whose previous research is cited in patents, end out being more likely to obtain ANR grants. We also show that the (self-) selection effect is more prevalent in the directed programs, and therefore directed programs are a very effective policy tool for directing funds to these researcher profiles, essentially through a self-selection mechanism.

Our paper also contributes to a second strand of the literature which aims to uncover the factors and circumstances leading scientists to innovate. This literature explores a large number of factors[7] but does not yet consider the role of competitive project funding in fostering academic patenting. Controlling for selection bias, we find that grant funding does not significantly affect overall patenting rates, implying that the positive correlation recorded between funding status and academic invention could be essentially due to a (self-) selection effect. Looking at specific subsets, we find however that ANR grants have positive and significant effects on invention. If previous inventors, who likely have a richer network of varied connections do not significantly generate more inventions thanks to the grants they obtain, the others, who are way more numerous, do so by 20%. This supports the idea that grant funding has an important byproduct effect on inventions that works at the “extensive margins”, in the sense that it is effective on those who have not invented before. We also show that a specific environment such as that of competitiveness clusters, which usually implies

[7] Academics are more likely to patent when they are engaged in applied research, surrounded by patenting peers, collaborating with the private sector, have previous patenting experience, and are specialized in certain scientific fields that are more likely to result in scientific discoveries with practical use (Azoulay, Ding and Stuart, 2007; Carayol, 2007; Stephan et al., 2007; Stephan, 2010; Kordal et al., 2016; Carayol and Carpentier, 2021).

connections with an (often local) network of companies and research centers, is highly effective in generating inventions from granted research projects, as, in relative terms, a grant in a competitiveness cluster increases inventions by 42%.

The rest of the paper is organized as follows. We describe the French policy and the data we constructed for the study in Section 2. Then, we investigate the factors of application and selection in research grants in Section 3, after which we explore the impact of such grants on academics' contributions to innovation in Section 4. Finally, we summarize our results and discuss the policy implications and limitations of this study in Section 5.

2 Context and Data

2.1 Institutional Context

Whereas 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, long relied on recurrent funding of research laboratories and universities. In 2005, the country initiated a change of 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 Science Foundation in the United States. For the period of interest in this study, the agency is organized into departments that cover all scientific fields. Within these departments are dozens of directed programs, each corresponding to a research topic deemed a priority by the agency. There is also a "non-directed" department that would offer to fund any fundamental research project.

To apply for funding, researchers must write a research proposal that may involve collaboration between research units hosted by distinct universities or public research institutes, and also possibly in partnership with non-academic organizations (such as companies) and send it to one of the programs (directed or not) in response to a call for applications. Submitted proposals undergo a standard single-blind peer review process. Typically, committees are composed of peers and also solicit reviews from external colleagues specialized in the fields of each application. The committees collect evaluations meet and select the most promising projects. The evaluation criteria are the quality and scientific ambition of the project, as well as its organization and expected impact(s). If the selected project involves more than one partner, the scientist designated as coordinator for each institution receives her share of the budget to manage it autonomously. This provides a substantial degree of autonomy between collaborating teams within the same project.

The overall research budget allocated to projects has gradually increased from 540 million euros in 2005 to 650 million in 2009. 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). Those funds do not cover the salaries of tenured personnel in public institutions and involved in the project. Only investments, functioning costs, the wages of doctoral students and post docs working on the project, and subcontracting. Note that over the period of interest (and still today), the financing of research performed in French public academic institutions remains essentially performed via the state recurrent funding of universities and research institutes.

Furthermore, the French government has taken a stand in favor of university-industry interactions with the adoption of the Innovation Act in 1999. In 2004, associative structures bringing together companies, research centers, and educational institutions in a given geographical area were created. The members of these so-called *competitiveness clusters* (*"Pôles de Competitivité"*), are expected to work in partnership to strengthen industrial competitiveness and inventiveness by accelerating the development of new products, services, or processes resulting from research projects. Researchers applying for an ANR grant can ask competitiveness clusters to label their projects and may receive additional funding from the cluster. This information is included in the application files submitted to the ANR, increasing the chances of project selection.

2.2 Data description

Data construction begins with the collection of grant applications to the ANR over the years 2005-2009. We restrict ourselves to the first few years of implementation of this policy, as we wish to have a sufficiently long period of observation of outcomes after the funding date to estimate the relationship of interest. Provided by the ANR, these data are exhaustive over the period and include information such as the full name of the scientific coordinator of each partner institution of the project, the department to which the project was submitted, the corresponding call for projects, and the final funding decision. Over the period, 23,846 projects were submitted to the ANR, having an average of 2.8 partner institutions.

We then use a unique panel dataset of nearly 55,000 tenured researchers and professors employed in French universities or research organizations such as the CNRS between 2000 and 2016.[8] We limit ourselves to the 30,226 individuals for whom we have complete and consistent information (status, institutional employer, laboratory, age, gender, field(s), etc.), excluding those who belong only to the SHS field, as the study of patents is not relevant in this case. We match the first and last names of all scientific coordinators of ANR project partner institutions to this panel. Our final panel dataset of "potential applicants" thus consists of 30,226 faculty and researchers observed during the years 2000–2016, for whom all funding, and employment information is available. 11,314 of those scientists applied at least once to the ANR over the 2005–2009 period, and 6,210 were financed at least once.

[8]Further information on the academic employment panel data is available in Carayol and Lanoë (2019) and Carayol and Carpentier (2021).

Because a researcher can apply for multiple grants over time and even in a given year, and as several individuals may apply in a joint project, we focus on the individual scientist–project pairs. In our dataset, we count 27,309 of such scientists–project pairs that are fully informed, among which 8,633 were funded. The overall success rate is 31.6%. There are 2.4 coordinators/scientists per project on average. 7% of all projects are labeled by a competitiveness cluster. About half of the projects were submitted to the agency's non-directed programs, with the other half distributed among the seven other directed departments.

We then complement this database with individual-level scientific outcomes. We first extract patent inventions of those researchers and professors from the Patstat 2019 database. More precisely, we use patent applications, which is common practice in the literature, since patent applications correspond more to the discovery event, while granted inventions correspond more to a legal event, in specific offices (although we use EPO patents, the entry point may be in another office, as an extension). The disambiguation we have carried out for this matching is fully described in Carayol and Carpentier (2021), which is optimized on a benchmark of scientists-inventors pairs. As recall and precision are opposite targets, the relative importance of minimizing incorrect matches and mismatches can be tuned via a single parameter b. In this study, we base our main analyses on data relying on $b = 1$, which gives equal importance to precision and recall. We then perform robustness checks on $b = .5$, favoring precision over recall, which we report in the Supplementary Appendix.

Secondly, we extract publication data from the in-house XML Web of Science data which is the best-known aggregator of bibliometric data. More precisely, we match our French professors and researchers with the list of authors using names and first name initials. Papers of those researchers and professors are then disambiguated using an automated AI procedure initiated in see Carayol and Lanoë (2019) (see also Carayol, Henry and Lanoe, 2024). The variables used in this paper include individual yearly counts of publications, publications corrected for the number of co-authors, publications in the top 10% and top 5% most cited

Table 1: Descriptive statistics on applications.

	Number of		Gender (%)		Age group (%)			Position (%)				Scientific field (%)	
Year	projects	applications	Women	Men	< 41	$41-50$	51+	AP	FP	JR	SR	LS	HS
2005	1432	2592	18.1	81.9	37.8	40.5	21.6	18.2	31.7	15.6	34.5	34.7	72.3
2006	3694	6381	20.6	79.4	35.1	41.7	23.1	20.1	32.8	18.2	28.9	44.6	64.8
2007	3477	5990	21.6	78.4	33.8	41.6	24.6	21.1	31.8	19.7	27.4	44.6	66
2008	2955	4792	21.9	78.1	33.3	41	25.6	21.1	31.4	21.1	26.5	46.7	64.2
2009	4524	7554	22.8	77.2	33.5	42.1	24.3	20.1	29.1	25	25.7	42	67.7
All years	16082	27309	21.4	78.6	34.3	41.6	24.1	20.3	31.2	20.7	27.8	43.3	66.5

Notes: The column "number of projects" corresponds to the number of projects submitted, potentially involving several institutions and thus several coordinators (one per partnering institution). All other columns refer to the scientist–application unit of observation: there is one "application" and one coordinating scientist per partnering institution in each project. We consider scientists' age, status, and field at the time of application. Coordinators are divided into three groups: 40 years old or younger (denoted <41), 41 to 50 years old ($41-50$), and 51 years old or older (51+). Positions are Associate professor (AP), Full professor (FP), Junior researcher (JR), and Senior researcher (SR). Scientific fields are Life sciences (LS) and Hard sciences (HS). Interdisciplinary projects are counted once in each field, so the percentages of fields may add up to more than 100 percent.

in their field, as well as other quality indicators such as the total count of citations, and the H-index. We are also able to link publication data to patent data, enabling us to identify researchers' publications cited in patents in subsequent years.

Table 1 presents additional statistics regarding the distribution of projects and scientist–applications based on both the application year and the characteristics of coordinators. The percentage of women serving as coordinators shows a gradual increase from 18 to 23 percent. Similarly, scientist–applications are distributed relatively evenly across various age groups, although there is a slightly lower representation of coordinators aged 51 or older. Junior positions, such as associate professors and junior researchers, have seen an increasing trend in coordinating projects over time, but they remain less represented compared to senior positions, including full professors and senior researchers. Lastly, approximately two-thirds or more of the applications involve coordinators from the hard sciences, a third to half involve coordinators from the life sciences, and only 5 percent involve coordinators with a simultaneous affiliation to the social sciences and humanities.

3 Grant Funding: Application and Selection

In this section, we investigate the factors that lead scientists to submit project proposals to the ANR and the selection this institution subsequently performs. In particular, we want to test our hypothesis that those who have a "taste" for invention more often seek and obtain grants.

3.1 Econometric Specification

Consistently with the literature, we expect to observe a biased representation of the population of applicants due to the self-selection of their projects. Indeed, it is likely that a researcher's assessment of her project when she decides to apply will be correlated with the agency's evaluation, implying a correlation between the two outcomes. Since some unobserved covariates could affect both decisions, running two independent probit models would thus produce biased estimates (Heckman, 1976).

We therefore use a two-stage Heckman probit model that accounts for these endogeneity issues to examine the determinants of the decision to submit a project in the first stage (selection equation) and the agency's decision to fund, or not fund, the project in the second equation. The dependent variable in the second equation $Y_{i,p}$ is a dummy variable, which takes value one if the project p involving applicant i is funded, and zero otherwise. The dependent variable of the selection equation $S_{i,p}$ takes value one if the researcher i decides to apply in the project p, and zero otherwise. Note that $Y_{i,p}$ is observed only if $S_{i,p} = 1$.

At the selection stage, we therefore assume that, for each possible application year (2005-2009), all the researchers who do not eventually apply for a grant have one personal project they consider but do not submit. We relax this assumption in robustness checks assuming instead given shares of non-applicants having one non-submitted potential project. In the

Supplementary Appendix, we present results of the same regressions as in the main body of the paper, but having randomly dropped 20 percent of non-applicants each year (they have no potential project). We obtain qualitatively very similar results than in the main regressions. See Tables SA3–SA6. We also tried dropping 15 and 25 percent and obtained similar results.

The selection equation is specified using a probit regression and estimated using maximum likelihood estimation (Greene, 2003) as follows:

$$S^*_{i,p} = \beta_0 + \beta_1 \text{Inventor}_{i,t(p)} + \beta_2 \text{CitedPatents}_{i,t(p)} + \beta_3 X_{i,t(p)} + \beta_4 Z_{i,t(p)} + \varepsilon_{i,p}, \tag{1}$$

with

$$S_{i,p} = \begin{cases} 1 \text{ if } S^*_{i,p} > 0, \\ 0 \text{ otherwise.} \end{cases}$$

$S^*_{i,p}$ is an unobserved latent variable that determines the probability that i submits a project p in year $t(p)$. Our two main independent variables of interest are $\text{Inventor}_{i,t(p)}$ which equals one if researcher i invented at least one patent in the five years before the application[9] and $\text{CitedPatents}_{i,t(p)}$ which is set to one if her papers published in the five years preceding the application are cited in patents. $X_{i,t(p)}$ stands for a vector of individual variables at the time of the project, including age, gender, H-index, and application experience, which is a categorical variable that equals 0 if the scientist has never applied for an ANR grant, 1 if she has already applied but was never granted, and 2 if she was granted at least once.[10] It also includes a number of fixed fixed effects: scientific field interacted with the application year and university fixed effects. This allows us to control for all variation that comes from

[9]Therefore, and throughout the paper, we refer to (previous) inventors as those who have invented at least one patent in previous five years, and non-inventors as those who did not.

[10]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).

university differential capacities to support applications, all that comes from field differences, and all yearly shocks that could be related to the field of study.

Finally, $Z_{i,t(p)}$ is the academic position of the researcher. It is our exclusion-restriction instrument that affects the probability of applying for funding and for which we have no reason to believe that it affects directly the probability that the funding agency will select the project. Note that status is not a discriminating factor in the selection process: committees are expected to rate projects on other dimensions such as scientific quality, organization, and expected impact of the submitted project (see also Subsection 2.1). To support this choice of instrument, we report, in Table A3 of the Appendix, a simple probit regression on the probability of being funded (conditional on applying, without correcting for self-selection effects) adding academic position dummies to the other regressors. If the status is to be directly taken into account by committees, then the selection process would likely be positively biased towards senior applicants. However, we do not find a clear positive relationship between seniority and the likelihood of being funded in the regressions. Being an associate professor does not reduce the chances of being selected compared to being a full professor, actually, it rather increases them overall. We may interpret this effect as indicating greater incentives for assistant professors to apply for grants, which supports the choice of our restriction exclusion variable. Besides, we observe that researchers (both seniors or juniors) are more likely to be selected, which we also interpret as reflecting more self-selection than selection effects (holding constant the quality of their research projects) as a full-time research position goes with more time to write proposals and research-based incentives. In a nutshell, if status correlates with selection, it is likely because it correlates with other factors (such as networks, past patents, funding applications, and publications/impact records of the coordinators) that we control for in the second Heckman step.

Table A1 in the Appendix summarizes all variables used in the paper.

Because we define the statistical individual as a scientist on a given (potential) project, researchers appear exactly one time for each application year they do not apply, but appear several times for the same year if they submit multiple projects that year. To avoid an over-representation of serial applicants, we therefore define fractional weights that sum up to one for each application year, as follows. They are equal to one if the researcher does not apply that year. On the years they do apply, they are equal to one divided by the yearly number of their applications. This leads to a dataset of 178,203 weighted observations. Of course, observations that imply the same individuals, or that concern the same projects, are not independent and thus we cluster standard errors at the individual and project levels.

Table A2 of the Appendix provides some descriptive statistics of individual × submitted projects (Column 1, "Applicants-Projects") and for individuals × application year (equivalent to an individual × potential project) that do not lead to an application (Column 2, "Non-Applicants"). We observe that professors and researchers who contributed to innovation before their application are significantly over-represented in Column (1): 15% of our "Applicants-Projects" have patented an invention and 66% have published articles that are cited in patent(s) against respectively 6% and 27% for non-applicants in Column (2). Different mechanisms could account for this over-representation of inventors and researchers cited in patents among applicants. For instance, it could be that applicants are on average more advanced in their careers, and that simultaneously older scientists invent more often than their younger colleagues. It could also be that more prolific academics, who are also more often inventors, are more likely apply to for competitive grants. Although the first hypothesis does not appear to be supported by the descriptive statistics (applicants are on average younger than non-applicants), the second one remains plausible. Furthermore, applicants over-perform non-applicants in all metrics of scientific performance (count of publications, citations, publications in top 10% and top 5%, and H-index). This requires controlling for scientific profiles when seeking to identify the effect of a previous contribution to innovation (or not) on the likelihood of a grant application.

The second stage estimates the conditional likelihood of being selected by the agency. This regression only concerns submitted projects. It is a simple probit model specified as follows:

$$Y_{i,p}^{*} = \alpha_0 + \alpha_1 \text{Inventor}_{i,t(p)} + \alpha_2 \text{CitedPatents}_{i,t(p)} + \alpha_3 X_{i,t(p)} + \alpha_4 V_p + u_{i,p}, \tag{2}$$

with

$$Y_{i,p} = \left\{ \begin{array}{l} 1 \text{ if } Y_{i,p}^{*} > 0, \\ 0 \text{ otherwise.} \end{array} \right\|$$

$Y_{i,p}^{*}$ is an unobserved latent variable that determines the likelihood that project p submitted by applicant i in year $t(p)$ is eventually funded by the ANR. It stands for the agency's assessment of the project's quality. $X_{i,t(p)}$ is a vector of individual i variables including age, gender, H-index, and application experience. It also includes scientific field interacted with the application year and university fixed effects. As in the previous model, this takes out all variation that comes from university differences, field differences, and all yearly shocks that could be field-related. V_p stands for project variables: a dummy equal to one when it is supported by a competitiveness cluster association, the number of partner institutions, the mean, and the max number of co-authors in the years preceding the application year (network variables) within the team project, the mean and the max H-index within the team. With these project variables, we aim to control for the existence of a richer network of relationships among participants and the quality of the proposed project. V_p also includes fixed effects for the department of the agency to which the application is submitted and the grant application year. Table A1 in the Appendix provides more details on all variables used in the paper.

The Heckman procedure tests whether the error terms in the main and selection equations are correlated ($\rho = corr(u_{i,p}; \varepsilon_{i,p})$), which would imply that the standard probit models produce biased results. In this case, the Heckman-probit procedure will correct for the selection bias.

3.2 Grant Application

Table 2 reports average marginal effects from the probit regression results specified in Equation 1. Considering all programs together (Column 1), we find a positive sublinear relationship between age and the likelihood of applying for grant funding. Besides, being a man increases the probability of applying by 1.2 percentage points. In comparison with the yearly predicted probability to apply of the average scientist, which amounts to 11.7%, it represents a 10.2% higher probability to apply. Using similar calculations, we find that researchers with a 1-point higher H-index than the average researcher have a 1.7% higher probability to apply. Researchers who applied for ANR funding in the past are 2.26 times more likely to reapply when they did not receive funding, and 111% more likely when they did.

Controlling for those factors of self-selection, we further find that inventors and researchers cited in patents are significantly more attracted to grant funding. The probability to apply increases by 2.8 percentage points when candidates are inventors, and by 3.8 percentage points when their research is cited in patents. It represents a 24% higher probability of applying for inventor scientists, and a 32% higher probability of applying for researchers cited in patents. In the second and third columns of the table, we specifically consider submission decisions to directed and non-directed programs as they represent different calls. We find out that the bulk of the effect mentioned above occurs in directed programs where the probability is 47% higher for inventors and 61% higher for researchers cited in patents,[11] against 13% and 23% higher probabilities in non-directed programs.[12]

[11] The average probability to apply to directed programs is 6.2%, and thus 2.9 (resp. 3.8) more percentage points for previous inventors (resp. previously cited in patents) corresponds to a 47% (resp. 61%) increase.

[12] The predicted probability of an average scientist applying in non-directed programs is 5.2%.

Table 2: Probability to apply for a grant (average marginal effects)

	(1) All Programs	(2) Non Directed Programs	(3) Directed Programs
Inventor	0.028***	0.007**	0.029***
	(0.003)	(0.003)	(0.003)
Cited in patent(s)	0.038***	0.012***	0.038***
	(0.002)	(0.002)	(0.002)
Individual variables			
Age	0.013***	0.003***	0.014***
	(0.001)	(0.001)	(0.001)
Age squared	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Male	0.012***	0.007***	0.009***
	(0.003)	(0.002)	(0.002)
H-index	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)
Never applied before (ref.)			
Applied w/o success	0.265***	0.189***	0.182***
	(0.006)	(0.005)	(0.005)
Applied with success	0.130***	0.062***	0.109***
	(0.005)	(0.003)	(0.004)
Number of obs	178078	163637	164838

Notes: Robust standard errors in parentheses, clustered at the individual and project levels. All regressions include control variables for academic position, scientific field interacted with application year, and university, but their average marginal effects are not reported in the table. Applicants on projects of only one type of program (directed or non-directed) in a given year are reported as non-applicants in the other type of program, affecting the number of observations in Columns (2) and (3). There might be slight differences in the number of observations between the Probit and the Heckman models. This is due to the Stata routine for Probit which drops the university fixed effect variable for which there is no cross-sectional variation.

Considering that the selection may also 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 groups of disciplines in Table A4 of the Appendix, where the first column corresponds to researchers in hard sciences (HS) and the second to those in life sciences (LS). The determinants are very similar, both in direction and effect size, across hard sciences and life sciences. Prior experience in ANR grant application is important for researchers in all groups of disciplines.

3.3 Jury Selection

Once a researcher applied, what factors affect her chances of success with the ANR selection process? Table A5 reports some descriptive statistics on individual scientist $\times$ projects submitted to the ANR, broken down with respect to the fact they have, or have not, been funded.

The average marginal effects of the second-stage regression are presented in Table A3. It also reports the ρ coefficient which measures the degree of correlation between the two equations, as well as a Wald test of independent equations. Note that in all cases we reject at the 5% level the null hypothesis of the absence of correlation between the two equations.

In all programs considered, we find that the predicted (weighted) probability of an average participant being selected is 50.7%. Older scientists are significantly less likely to be selected than younger ones: the probability of success of an applicant one year older decreases by 0.2 percentage points. Moreover, consistent with other previous research, we find that gender does not significantly affect the chances of success. Applicants' application experience only matters when they were not successful: those candidates have an 11.4% lower probability of being selected. The strongest effect that we observe is the affiliation to a competitiveness cluster. Applicants from these structures have a 95.1% higher probability of being selected than the average candidate, up to 129% higher in non-directed programs.[13]

Turning to the main variables of interest, we find that academic inventors have a 5.1% *lower* probability of being selected than the average applicant in our database, and researchers cited in patents have a 7.1% *lower* probability. The bias against inventors is observed in both directed programs and non-directed programs (Columns 2 and 3), while the bias against researchers cited in patents is only significant in non-directed programs.

Table A6 in the Appendix reports regression results by large fields. We observe a strong bias against inventors and researchers cited in patents in the hard sciences. Age does not affect the 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 involved in the project does not matter in the hard sciences, unlike in the life sciences.

3.4 The Overall Selection Effects

We have seen that 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 would like to appreciate the "total" selection effect of being a previous inventor or having authored papers cited in patents. That would account for both self-selection and selection, controlling for all other covariates in the right sides of Equation 1 and Equation 2 but the ones related to the projects. Therefore, we regress, on all potential applicants, the (unconditioned on applying) likelihood to receive a grant on the two main explanatory variables.

In column 1 of Table SA1 in the Supplementary Appendix, we observe that the coefficients of the variables "having previously invented" and "having published papers that are eventu-

[13] The success probability of the average applicant to non-directed (directed) programs being 77.9% (52.3%).

Table 3: Probability to receive a grant (average marginal effects)

	(1) All Programs	(2) Non directed Programs	(3) Directed Programs
Inventor	-0.026***	-0.032	-0.022*
	(0.010)	(0.020)	(0.013)
Cited in patent(s)	-0.036***	-0.048***	-0.016
	(0.009)	(0.017)	(0.013)
Individual variables			
Age	-0.002***	-0.001	-0.002***
	(0.000)	(0.001)	(0.001)
Male	0.013	0.021	0.003
	(0.008)	(0.014)	(0.011)
H-index	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)
Application experience			
Applied w/o success	-0.058***	-0.070	-0.069***
	(0.019)	(0.047)	(0.024)
Applied with success	0.005	0.002	-0.006
	(0.015)	(0.020)	(0.020)
Project variables			
Cluster	0.482***	1.004***	0.438***
	(0.018)	(0.301)	(0.018)
Number of institutions	0.011	0.027**	0.002
	(0.007)	(0.013)	(0.009)
Mean H-index	0.004**	0.007**	0.002
	(0.002)	(0.003)	(0.002)
Max H-index	0.002	-0.000	0.003
	(0.001)	(0.002)	(0.002)
Sum network	0.000	0.001	-0.000
	(0.001)	(0.001)	(0.001)
Max network	-0.000	-0.001	0.000
	(0.001)	(0.001)	(0.001)
Number of obs	178203	163980	165117
Number of selected obs	27309	13086	14223
ρ	-.2945494	-.3583593	-.2402792
Prob chi2	0.00	0.00	0.00

Notes: Robust standard errors in parentheses, clustered at the individual and project levels. The control variables scientific field interacted with application year, department of the agency, and university are included in the model but their average marginal effects are not reported. There is no fixed effect on the department of the agency for non-directed programs. Applicants on projects of only one type of program (directed or non-directed) in a given year are reported as non-applicants in the other type of program, affecting the number of observations in Columns (2) and (3).

ally cited" in patents are positive and significant. Similar conclusions hold for the chances of getting a grant in non-directed and directed programs separately (see Columns 2 and 3 of Table SA1) as well as for hard and life sciences separately (see Table SA2).

We conclude that the additional probability of obtaining a grant from researchers with a "taste for invention" (i.e. taking into account the two variables assessing previous links with inventions) is positive. Furthermore, the unreported marginal effects of these variables are larger in directed programs, suggesting that these programs are very effective in directing funds to researchers who are already involved in inventions.

4 The Impact of ANR Funding on Inventions

In the previous section, we have discussed how *past* contributions to innovation impact researchers' participation in the competition for research funding. In this section, we investigate the consequences of obtaining a grant on researchers' *future* contributions to innovation.

4.1 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 to control for selection bias. We use the results from the previous section to define the relevant variables to match. Second, we estimate the average treatment effect on the treated (ATET) relying on linear regressions that further control for time-invariant characteristics.

We implement a coarsened exact matching (CEM) procedure (King et al., 2010; Iacus, King and Porro, 2012) and report the variables used and a balancing measure in Table 4.[14]

[14]See also Table A1 in the Appendix which reports the definition of all variables used in the paper.

The first two columns show the means and standard deviations of funded and unfunded candidates separately at the time of funding.[15] The third 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, application experience, competitiveness cluster, non-directed program, and field of science,[16] the match is exact. In contrast, we coarsened the values for the continuous variables as follows: 40 years old or younger, between 41 and 50 years old, and more than 50 years old for age at application; one, two, or more than two for the number of partner institutions in the project; and below or above the median H-index.

Consistently with the previous section on selection, we observe in Table 4 (first panel, before the 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, submitted fewer ANR applications in the past but were more often funded, are more likely to apply to a directed program, 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 the distance between treated and controls is globally reduced after matching (L1 statistics) and that differences for each variable remain small after matching (second panel of the table).[17]

[15] 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.

[16] We use dummies for hard sciences, life sciences, and social sciences and Humanities. A scholar may be associated with several fields. This is the reason why we still have some scholars associated with social sciences and humanities, though we excluded those who are exclusively in that field. As we have this information, it makes sense to use it for matching.

[17] Differences are still significant for three variables only: age, the number of institutions and the H-index. For the two first variables, differences between treated and controls are very small (less than 1%). For the H-Index, the remaining differences are about 7% which may be considered acceptable given the very dispersed and asymmetric distribution of this variable. Despite differences increasing after matching for this variable, they remain much smaller than when it is not included in the matching procedure. Note that if this variable is not included in the CEM, the results are qualitatively similar.

We were able to match half of the scientists–project (5,985 out of 9,281) with at least one other applicant, similar on all these characteristics, who was not funded. In the bottom part of the same table, we can see that the matched sample is fairly representative of the population of funded applicants.

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

$$Y_{i,t} = \alpha + \beta \,\text{Funded}_i \times \text{Post}_{i,t} + X_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t}, \tag{3}$$

where $Y_{i,t}$ is the number of patented inventions of researcher i in year t, Funded_i indicates whether the individual was funded or not,[18] and $\text{Post}_{i,t}$ is a binary variable that is set to 0 prior to the application, and to 1 for the four years after the application (this ensures the same post-application period for all applicants). $X_{i,t}$ stands for a vector of university and science fields fixed effects, and their interactions with year dummies. This allows us to capture all variation that comes from field differences and universities' capacity to support innovation, as well as any yearly shock that could be related to those two dimensions. Finally, we introduce an individual fixed-effect γ_i, and a year fixed-effect δ_t to control for annual shocks.

Our main goal in this section is to consistently estimate parameter β, which captures the impact of funding in the post-treatment period, as long as the selection effect has been sorted out thanks to the first (matching) stage. The matching stage is taken into account by weighting each observation of the regression specified in Equation 3. Weights are equal to one for treated scientists–project and are equal to $(m^C/m^T) \times (m_i^T/m_i^C)$ for control ones, with m^C and m^T the number of control and treated scientists–projects in the sample, and m_i^T and m_i^C the number of treated and control scientists–project specifically in i's stratum.

[18] In the main regression table, we use the disambiguation parameter $b = 1$ to calculate $Y_{i,t}$ but provide robustness checks in the Supplementary Appendix with $b = .5$. Results remain qualitatively similar.

Table 4: Difference in means on observable characteristics between treated and control groups.

	Before matching					
	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)
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)
H-index	10.27	8.07	9.71	7.49	-0.56	(0.00)
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)
Application year	2006.88	1.37	2007.52	1.27	0.63	(0.00)
Observations	9281		17761		27042	

	After matching					
	Funded applicants		Unfunded applicants		Difference t-test	
	mean	sd	mean	sd	b	p
Inventor	0.12	0.33	0.12	0.33	0.00	(1.00)
Cited in patent(s)	0.62	0.48	0.62	0.48	0.00	(1.00)
Age	44.29	8.05	44.32	8.03	0.03	(0.96)
Male	0.83	0.37	0.83	0.37	0.00	(1.00)
Application Experience	0.45	0.50	0.45	0.50	0.00	(1.00)
Funding Experience	0.23	0.42	0.23	0.42	0.00	(1.00)
Hard sciences	0.64	0.48	0.64	0.48	0.00	(1.00)
Life sciences	0.40	0.49	0.40	0.49	0.00	(1.00)
Social sciences and humanities	0.04	0.19	0.04	0.19	0.00	(1.00)
H-index	10.70	8.19	9.95	7.51	-0.75	(0.00)
Non Directed Programs	0.38	0.48	0.38	0.48	0.00	(1.00)
Cluster	0.06	0.23	0.06	0.23	0.00	(1.00)
Number of institutions	2.50	0.99	2.53	1.10	0.03	(0.37)
Application year	2007.09	1.28	2007.09	1.28	-0.00	(1.00)
Observations	5521		11063		16584	

4.2 Impact Results

In the first column of Table 5, we report the regression results on all matched applicants (Column 1), and the remaining columns correspond to results for sub-samples 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 an industrial cluster (columns 11–12).

Overall, we find that grants are positively but not significantly affecting academic invention. But looking carefully at sub-samples, grant impact is not significantly different from zero in some sub-samples whereas it is positive and significant in some others.

Interestingly, previous inventors are not significantly affected by the grants they obtain. But those scholars (only 509 treated and 666 controls) are very specific. In particular, they are very productive (they produce .47 patents per year on average) and probably have a richer network of varied connections. Therefore, it is likely that, for those individuals, the stable treatment unit hypothesis is not fully verified: they may be able to find alternative sources of funding when one of their projects is not selected by the ANR. We thus cannot fully exclude that our study underestimates the impact on this sub-population.

ANR funding significantly and positively affects the patenting behavior of the (many) other academics who haven't already invented (4,076 treated and 6,080 controls). In relative terms,[19] the effects are of the order of a 20% increase in patents invented each year. Therefore, grant funding seems to have a by-product effect on inventions at an extensive margin, since it attracts researchers to invention behavior.

Effects are significant in the hard sciences: ANR funding raises patents by 15%. In addition, we find that a specific environment such as that of competitiveness clusters is highly effective in generating inventions from ANR-funded research projects. In relative terms, a grant in a

[19] The means of the dependent variable for each regression are reported in the table.

competitiveness cluster increases inventions by 42%. Connections with the specific objectives of an often local network of companies and research centers significantly increase how likely research projects transform into inventions.

Lastly, as the literature previously evidenced that older scientists, in particular when close to retirement, have higher incentives and propensities to invent (Azoulay, Ding and Stuart, 2007; Carayol, 2007; Stephan et al., 2007; Stephan, 2010), we investigate the impact of funding with respect to the age group of the granted. Coefficients are larger as age becomes larger (see columns 4–6), and funding even raises the likelihood of inventing by 7% among the ones who are older than 50. This effect is however not significant at the 10% level.

Table 5: The impact of grant funding on academic invention

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Hard sc.	Life sc.	40 and younger	40 to 50	50 and older
Funded × Post	0.005	0.015**	-0.009	0.004	0.006	0.008
	(0.006)	(0.007)	(0.012)	(0.010)	(0.011)	(0.012)
Observations	112939	75975	42768	40432	48426	24073
Number of Clusters	9065	6175	3399	3720	3915	2009
Mean dep variable	.11	.1	.12	.092	.12	.12
Adj. R-Square	.3	.3	.3	.25	.32	.29
	(7)	(8)	(9)	(10)	(11)	(12)
	Inventors	Non inventors	Directed	Non directed	Cluster	Non cluster
Funded × Post	-0.020	0.009*	0.010	0.002	0.063*	0.000
	(0.043)	(0.005)	(0.009)	(0.008)	(0.038)	(0.007)
Observations	11275	100584	60538	52399	3808	109127
Number of Clusters	909	8325	5587	4912	501	8858
Mean dep variable	.56	.046	.13	.079	.15	.11
Adj. R-Square	.25	.16	.29	.3	.28	.29

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

5 Discussion and Conclusion

In this paper, we provide new evidence on the interplay between researchers' contributions to innovation and competitive research funding. We examine two channels through which this relationship could occur: project-based funding may be more likely to support researchers who already have a "taste" for invention and/or the funding agency may support research that leads directly to patents. To do so, we built a unique dataset that allows us to carefully study the full chain of events, starting from the academics' decision to apply for a grant up to the outcomes of the project, while controlling for a wide range of variables.

We find that scientists who have a "taste" for invention (previous inventors) and those whose previous research is "closer" to invention (their previous articles are cited in patents) are more attracted to grant funding than their counterparts. We interpret this result as a consequence of their more entrepreneurial personality. They are thus more keen to apply even if the selection process is also found to be biased against them. As the overall selection effect is positive for these scientists, we deduce that the positive correlation observed at the beginning of this paper between funding and academic invention is at least partly explained by this selection effect. We also note that directed programs (programs that target specific research areas) are particularly effective tools to attract those researchers, which may be of interest in terms of fine-tuning policy.

Our second set of results focuses on the impact of competitive funding on academic inventions. Controlling for the selection bias, we observe that grant funding does not significantly affect the overall patenting of the grantees, confirming that the positive correlation recorded between funding status and academic invention may essentially be due to a (self-)selection effect.

Whereas the overall effect of funding on invention is not significant, it is comparable to the few studies available on the relationship between funding and academic patenting, though in different countries, examining different funding protocols and relying on different identification methods. We find that one additional million euros in ANR grants leads to .15 patents per capita over 5 years.[20] Li, Azoulay and Sampat (2017) find that 8% of NIH-funded projects directly lead to a patent (one out of 12). Payne and Siow (2003) estimate the effects of federal research funding on the outputs of 68 American universities and finds that a $1 million increase in research funding leads to 0.2 more patents.

Moreover, the absence of a significant overall effect does not mean that subsidies never have a direct impact on inventions. On the contrary, we find that ANR grants have a positive and significant impact in specific sub-samples. In the hard sciences, for instance, both selection and impact effects play in the same direction, so that, in this branch of science, inventors are more likely to get grants, and those grants, in turn, increase their likelihood to further invent.

A positive and significant effect of grants is also observed on non-inventors.[21] This supports the idea that this policy originally designed to increase scientific knowledge may also be beneficial to inventions at the "extensive margin", that is competitive project funding plays a role in leading researchers who have never invented (or who have not invented in recent years) to get their foot in the invention door (again).

Furthermore, we find a strong impact of ANR grants on the inventions of the grantees when their projects are labeled by a competitiveness cluster. We estimate that one million euros leads to 2 additional patents ($.063 \times 5/.16$.) Consequently, the positive selection bias in favor of these projects seems well-founded to encourage academic inventions.

Finally, our study suffers from some limitations that could lead to an underestimation of the impact of competitive grant funding on invention. Firstly, we used a four-year period after

[20] The average ANR grant per partner being .16 million euros, we obtain a total impact over five years of .156 additional patents ($.005 \times 5/.16$) per million euros.

[21] We estimate that 1M euros in average leads .28 additional patents in average for non-inventors ($.009 \times 5/.16$).

the treatment year to record the impact of funding on patent applications. Considering that most research projects last three years, we believe this is consistent for patents as inventors have strong incentives to file patents (in the EU first-to-file regulation) before publishing. Nevertheless, there are potentially long time lags between research and inventions, so we may not have registered some lasting effects. Besides, we do not observe all sources of funding, and some control scientists may actually more intensely search, and more often find, alternative sources of funds for their projects. Last but not least, we only record the direct impact of ANR grants on the inventions of the grantees, whereas their sponsored research may have large externalities on their colleagues, their students, or their readers.

References

Acs, Z. J., D. B. Audretsch and M. P. Feldman. 1992. "Real effects of academic research: comment." *The American Economic Review* 82(1):363–367.

Agence Nationale de la Recherche. 2005. Rapport Annuel 2005. Technical report Agence Nationale de la Recherche.

Agence Nationale de la Recherche. 2006. Rapport Annuel 2006. Technical report Agence Nationale de la Recherche.

Agence Nationale de la Recherche. 2007. Rapport Annuel 2007. Technical report Agence Nationale de la Recherche.

Agence Nationale de la Recherche. 2008. Rapport Annuel 2008. Technical report Agence Nationale de la Recherche.

Agence Nationale de la Recherche. 2009. Rapport Annuel 2009. Technical report Agence Nationale de la Recherche.

Ahmadpoor, M. and B. F. Jones. 2017. "The dual frontier: Patented inventions and prior scientific advance." *Science* 357(6351):583–587.

Arora, Ashish and Alfonso Gambardella. 2005. "The impact of NSF support for basic research in economics." *Annales d'Economie et de Statistique* pp. 91–117.

Arrow, K. 1962. Economic welfare and the allocation of resources for invention. In *The rate and direction of inventive activity: Economic and social factors*. Princeton University Press pp. 609–626.

Azoulay, P., W. Ding and T. Stuart. 2007. "The determinants of faculty patenting behavior: Demographics or opportunities?" *Journal of economic behavior & organization* 63(4):599–623.

Azoulay, Pierre, Joshua S Graff-Zivin, Danielle Li and Bhaven N Sampat. 2019. "Public R&D investments and private-sector patenting: evidence from NIH funding rules." *The Review of economic studies* 86(1):117–152.

Banal-Estanol, A., I. Macho-Stadler and D. Perez-Castrillo. 2019. "Evaluation in research funding agencies: Are structurally diverse teams biased against?" *Research Policy* 48(7):1823–1840.

Bazeley, Pat. 1998. "Peer review and panel decisions in the assessment of Australian Research Council project grant applicants: what counts in a highly competitive context?" *Higher Education* 35(4):435–452.

Bol, Thijs, Mathijs de Vaan and Arnout van de Rijt. 2018. "The Matthew effect in science funding." *Proceedings of the National Academy of Sciences* 115(19):4887–4890.

Bornmann, L., R. Mutz and H.-D. Daniel. 2007. "Gender differences in grant peer review: A meta-analysis." *Journal of Informetrics* 1(3):226–238.

Bromham, Lindell, Russell Dinnage and Xia Hua. 2016. "Interdisciplinary research has consistently lower funding success." *Nature* 534(7609):684–687.

Carayol, N. 2007. "Academic Incentives, Research Organization and Patenting at a Large French University." *Economics of Innovation and New Technology* 16:119–138.

Carayol, N. and E. Carpentier. 2021. "The spread of academic invention: a nationwide case study on French Data (1995-2012)." *The Journal of Technology Transfer* .

Carayol, N., E. Henry and M. Lanoe. 2024. "Stimulating Collaborations? Evidence from a Research Cluster Policy." *The Review of Economics and Statistics* Forthcoming.

Carayol, N. and M. Lanoë. 2019. "The impact of project-based funding in science: Lessons from the ANR experience." *mimeo GRETHA working Paper* .

Cole, Stephen, Jonathan R Cole and Gary A Simon. 1981. "Chance and consensus in peer review." *Science* 214(4523):881–886.

Ginther, D. K., W. T. Schaffer, J. Schnell, B. Masimore, F. Liu, L. L. Haak and R. Kington. 2011. "Race, ethnicity, and NIH research awards." *Science* 333(6045):1015–1019.

Greene, W. H. 2003. *Econometric analysis.* 5th ed. Prentice Hall.

Guthrie, Susan, Ioana Ghiga and Steven Wooding. 2017. "What do we know about grant peer review in the health sciences?" *F1000Research* 6.

Heckman, J. 1976. "The Common Structure of Statistical Models of Truncation, Sample Selection, and Limited Dependent Variables and A Simple Estimator for Such Models." *Annals of Economic and Social Measurement* 5(4):475–492.

Henderson, R., A. B. Jaffe and M. Trajtenberg. 1998. "Universities as a source of commercial technology: a detailed analysis of university patenting, 1965–1988." *Review of Economics and statistics* 80(1):119–127.

Iacus, S. M., G. King and G. Porro. 2012. "Causal inference without balance checking: Coarsened exact matching." *Political analysis* 20(1):1–24.

Jaffe, A. B. 1989. "Real effects of academic research." *The American economic review* pp. 957–970.

Jagsi, Reshma, Amy R Motomura, Kent A Griffith, Soumya Rangarajan and Peter A Ubel. 2009. "Sex differences in attainment of independent funding by career development awardees." *Annals of Internal Medicine* 151(11):804–811.

Jayasinghe, Upali W, Herbert W Marsh and Nigel Bond. 2003. "A multilevel cross-classified modelling approach to peer review of grant proposals: the effects of assessor and researcher attributes on assessor ratings." *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 166(3):279–300.

Kantor, S. and A. Whalley. 2014. "Knowledge spillovers from research universities: evidence from endowment value shocks." *Review of Economics and Statistics* 96(1):171–188.

King, G., M. Blackwell, S. Iacus and G. Porro. 2010. "cem: Coarsened exact matching in Stata." *Stata Journal* 9(4):524–546.

Kordal, Richard, Dexter Cahoy, Beatrix Koev and Eric A Sherer. 2016. "Prevalence of Serial inventorS Within academia." *Technology & Innovation* 17(3):113–126.

Laudel, Grit. 2006. "The 'quality myth': Promoting and hindering conditions for acquiring research funds." *Higher Education* 52(3):375–403.

Li, D., P. Azoulay and B. N. Sampat. 2017. "The applied value of public investments in biomedical research." *Science* 356(6333):78–81.

Murray, Dennis L, Douglas Morris, Claude Lavoie, Peter R Leavitt, Hugh MacIsaac, Michael EJ Masson and Marc-Andre Villard. 2016. "Bias in research grant evaluation has dire consequences for small universities." *PloS one* 11(6):e0155876.

Neufeld, Jörg, Nathalie Huber and Antje Wegner. 2013. "Peer review-based selection decisions in individual research funding, applicants' publication strategies and performance: The case of the ERC Starting Grants." *Research Evaluation* 22(4):237–247.

Park, Hyunwoo, Jeongsik Jay Lee and Byung-Cheol Kim. 2015. "Project selection in NIH: A natural experiment from ARRA." *Research Policy* 44(6):1145–1159.

Payne, AA and A. Siow. 2003. "Does federal research funding increase university research output?" *Advances in Economic Analysis & Policy* 3(1):1–24.

Pohlhaus, Jennifer Reineke, Hong Jiang, Robin M Wagner, Walter T Schaffer and Vivian W Pinn. 2011. "Sex differences in application, success, and funding rates for NIH extramural programs." *Academic Medicine* 86(6):759.

Porter, Alan L and Frederick A Rossini. 1985. "Peer review of interdisciplinary research proposals." *Science, technology, & human values* 10(3):33–38.

Stephan, P. E. 2010. "The economics of science." *Handbook of the Economics of Innovation* 1:217–273.

Stephan, P., S. Gurmu, A. Sumell and G. Black. 2007. "Who's Patenting in the University? Evidence from the Survey of Doctorate Recipients." *Economics of Innovation and New Technology* 16(2):71–99.

Van Arensbergen, Pleun and Peter Van Den Besselaar. 2012. "The selection of scientific talent in the allocation of research grants." *Higher Education Policy* 25(3):381–405.

Van den Besselaar, Peter and Loet Leydesdorff. 2009. "Past performance, peer review and project selection: a case study in the social and behavioral sciences." *Research Evaluation* 18(4):273–288.

Van der Lee, Romy and Naomi Ellemers. 2015. "Gender contributes to personal research funding success in The Netherlands." *Proceedings of the National Academy of Sciences* 112(40):12349–12353.

Viner, Neil, Philip Powell and Rod Green. 2004. "Institutionalized biases in the award of research grants: a preliminary analysis revisiting the principle of accumulative advantage." *Research Policy* 33(3):443–454.

Wenneras, Christine and Agnes Wold. 2010. *Nepotism and sexism in peer-review.* Routledge.

6 Appendix

Figure A1: Variation coefficient of the number of patents per capita by application and funding status.

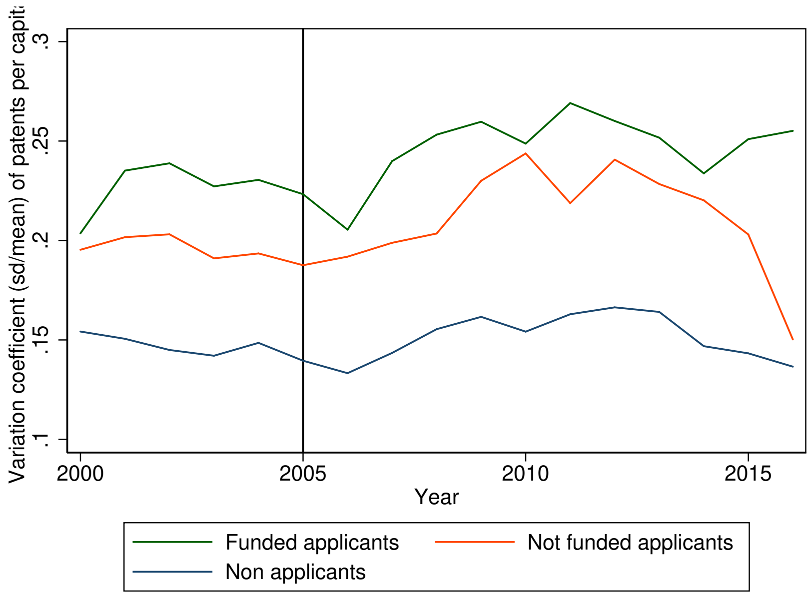


Table A1: Description of variables.

Variable	type	Description
Inventor	dummy	=1 if the researcher patented at least once in the 5 years prior to grant funding application (or potential application)
CitedPatents	dummy	=1 if the researcher's publications are cited in patent(s) at least once in the 5 years prior to grant funding application (or potential application)
Number of patents	count	Number of EPO patent applications for which at least one inventor is academic. The value of the disambiguation parameter is $p = 1$ in the main analysis, and threshold .5 in the robustness checks. See Carayol and Carpentier (2021) for more details
Articles cited in patent(s)	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)
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.
# Pubs	continuous	Average number of publications 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
H-index	continuous	H-index at the application year
Application experience	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
Number of institutions	continuous	Number of academic partner institutions in the project
Coordinator	dummy	=1 if the individual is the 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), Information and Communication Sciences and Technologies (ICST)
Age cat	categorical	=0 if 40 years old or younger, =1 between 41 and 50 years old, and =2 if more than 50 years old
Application Experience	dummy	=1 if applied but never received the funding before
Funding Experience	dummy	=1 if applied and received at least one ANR grant in the past
Number of institutions cat	categorical	=0 if only one institution is in the project, =1 if two partner institutions are in the project, and =2 if more than 2 partner institutions are involved in the project.
Mean H-index	continuous	Mean of the H-indexes of the project coordinators at the application year
Max H-index	continuous	Max of the H-indexes of the project coordinators at the application year
Sum network	continuous	Sum of the coordinators' average number of co-authors over a three-year window (including the application year)
Max network	continuous	Max of the researchers' average number of co-authors over a three-year window (including the application year)

Table A2: Descriptive statistics for submitted individual × projects (“Applicants-Projects”) and for individuals × application year (“Non-Applicants”) to ANR programs over 2005-2009

	(1)		(2)	
	Applicants-Projects		Non-Applicants	
	mean	sd	mean	sd
Inventor	0.15	0.36	0.06	0.23
Cited in patent(s)	0.66	0.48	0.27	0.45
Age	44.67	8.04	44.45	8.93
#Pubs	4.21	4.46	3.05	3.75
#Cites (3-y)	30.30	50.21	20.87	45.46
Total #Cites	131.02	205.21	88.72	176.72
Top 10%	6.35	9.59	4.36	7.78
Top 5%	3.22	5.75	2.23	4.78
H-index	10.68	7.64	8.08	7.05
Applied Biology and Ecology	0.28	0.45	0.26	0.44
Biology and Health	0.40	0.49	0.39	0.49
Chemistry	0.28	0.45	0.23	0.42
Engineering sciences	0.31	0.46	0.30	0.46
Mathematics	0.20	0.40	0.20	0.40
Physics and Universe Sciences	0.32	0.47	0.33	0.47
Social sciences and humanities	0.05	0.21	0.07	0.25
Observations	27309		150894	

Notes: The statistical individual is a scientist on a given (potential) project. Researchers who never eventually apply appear once for each application year. Researchers who apply at least once during the period appear, for each year in which they do not apply, as many times as they apply for a grant over the period. The years they do apply, they appear on each of their projects. To avoid the over-representation of serial applicants, fractional weights are used. They are equal to one if the researcher has never applied. They equal to one divided by the total number of applications for the years they do not apply, and equal to one divided by the number of applications that year, for the years they do apply.

Table A3: Raw probability to receive a grant (average marginal effects), with status variables, without controlling for self-selection effects.

	(1) All Programs	(2) Non directed Programs	(3) Directed Programs
Inventor	-0.05	-0.08	-0.04
	(0.03)	(0.05)	(0.04)
Cited in patent(s)	-0.06**	-0.12***	0.01
	(0.02)	(0.04)	(0.03)
Individual variables			
Age	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)
Male	0.06**	0.08**	0.04
	(0.03)	(0.04)	(0.04)
H-index	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)
Application experience			
Never applied before (Ref)			
Applied w/o success	0.06**	0.10**	-0.03
	(0.03)	(0.04)	(0.04)
Applied with success	0.15***	0.16***	0.10***
	(0.03)	(0.04)	(0.04)
Full Professor (Ref)			
Associate Professor	0.10***	0.18***	0.04
	(0.03)	(0.05)	(0.04)
Junior researcher	0.09***	0.08	0.13***
	(0.03)	(0.05)	(0.04)
Senior researcher	0.21***	0.24***	0.21***
	(0.04)	(0.05)	(0.05)
Other position	0.01	0.41	-0.15
	(0.22)	(0.33)	(0.30)
Number of institutions	0.05***	0.10***	0.02
	(0.02)	(0.02)	(0.02)
Constant	1.22**	-0.60	1.31*
	(0.59)	(0.69)	(0.75)
Number of obs	27272	12427	14177

Notes: Robust standard errors in parentheses, clustered at the individual and project levels. The control variables, Scientific field interacted with application year, Department of the agency, and University are included in the model but their average marginal effects are not reported.

Table A4: Probability to apply for a grant by discipline group (average marginal effects)

	(1) Hard Sciences	(2) Life Sciences
Inventor	0.026***	0.029***
	(0.004)	(0.005)
Cited in patent(s)	0.042***	0.030***
	(0.003)	(0.004)
Individual variables		
Age	0.013***	0.016***
	(0.001)	(0.002)
Age squared	-0.000***	-0.000***
	(0.000)	(0.000)
Male	0.010***	0.016***
	(0.003)	(0.003)
H-index	0.002***	0.002***
	(0.000)	(0.000)
Never applied before (ref.)		
Applied w/o success	0.268***	0.256***
	(0.007)	(0.008)
Applied with success	0.122***	0.137***
	(0.006)	(0.007)
Number of obs	117004	76485

Notes: Robust standard errors in parentheses, clustered at the individual and project levels. The control variables academic position, and scientific field interacted with the application year are included in the model but their average marginal effects are not reported. Potential applicants may belong to two field groups simultaneously. There might be slight differences in the number of observations between the Probit and the Heckman models. This is due to the Stata routine for Probit which drops the university fixed effect variable for which there is no cross-sectional variation.

Table A5: Descriptive statistics for scientist × funded projects by the ANR and scientist × not-funded project applications submitted to ANR (over 2005-2009 period)

	(1) Funded		(2) Not-Funded	
	mean	sd	mean	sd
Inventor	0.15	0.36	0.15	0.36
Cited in patent(s)	0.66	0.47	0.65	0.48
Age	44.50	7.99	44.75	8.06
#Pubs	4.40	4.64	4.12	4.38
#Cites (3-y)	33.87	53.86	28.64	48.34
Total #Cites	141.69	221.22	126.09	197.18
Top 10%	7.48	10.95	5.83	8.84
Top 5%	3.91	6.71	2.91	5.22
H-index	10.84	7.90	10.62	7.52
Applied Biology and Ecology	0.29	0.45	0.28	0.45
Biology and Health	0.40	0.49	0.40	0.49
Chemistry	0.24	0.43	0.29	0.46
Engineering sciences	0.32	0.47	0.30	0.46
Mathematics	0.21	0.41	0.20	0.40
Physics and Universe Sciences	0.32	0.47	0.33	0.47
Social sciences and humanities	0.04	0.20	0.05	0.21
Observations	8633		18676	

Table A6: Probability to receive a grant by discipline group (average marginal effects)

	(1) Hard Sciences	(2) Life Sciences
Inventor	-0.027**	-0.023
	(0.012)	(0.015)
Cited in patent(s)	-0.034***	-0.029**
	(0.011)	(0.014)
Individual variables		
Age	-0.002***	-0.002**
	(0.001)	(0.001)
Male	0.008	0.018
	(0.011)	(0.011)
H-index	-0.000	-0.002***
	(0.001)	(0.001)
Application experience		
Applied w/o success	-0.046*	-0.072***
	(0.024)	(0.026)
Applied with success	-0.012	0.027
	(0.018)	(0.021)
Project variables		
Cluster	0.494***	0.462***
	(0.019)	(0.033)
Number of institutions	0.004	0.029**
	(0.008)	(0.013)
Mean H-index	0.002	0.006***
	(0.002)	(0.002)
Max H-index	0.003	0.001
	(0.002)	(0.002)
Sum network	0.000	-0.002
	(0.001)	(0.002)
Max network	-0.000	0.001
	(0.001)	(0.002)
Number of obs	117189	76590
Number of selected obs	18150	11824
ρ	-.2695966	-.3463473
Prob chi2	0.00	0.00

Notes: Robust standard errors in parentheses, clustered at the individual and project levels. The control variables, Scientific field interacted with application year, Department of the agency, and University are included in the model but their average marginal effects are not reported. Prob chi2 represents the p-value associated with the Wald test of independence.

7 Supplementary Appendix

Table SA1: Probability to apply and obtain a grant

	(1) All Programs	(2) Non Directed Programs	(3) Directed Programs
Inventor	0.117***	0.071**	0.162***
	(0.022)	(0.032)	(0.026)
Cited in patent(s)	0.692***	0.526***	0.822***
	(0.016)	(0.023)	(0.021)
Individual variables			
Age	0.038***	-0.006	0.077***
	(0.007)	(0.009)	(0.009)
Age squared	-0.001***	-0.000	-0.001***
	(0.000)	(0.000)	(0.000)
Male	0.056***	0.061***	0.048**
	(0.016)	(0.022)	(0.020)
H-index	0.006***	0.010***	0.002*
	(0.001)	(0.001)	(0.001)
Application experience			
Never applied before (ref.)			
Applied w/o success	0.386***	0.547***	0.287***
	(0.023)	(0.032)	(0.029)
Applied with success	0.205***	0.178***	0.191***
	(0.022)	(0.031)	(0.027)
Number of obs	177628	161757	164132

Notes: Robust standard errors in parentheses, clustered at the individual and project levels. To simplify the table, the coefficients of the control variables academic position, scientific field interacted with the year of application, and university are not reported. There might be slight differences in the number of observations between the Probit and the Heckman models. This is due to the Stata routine for Probit which drops the fixed effect variables for which there is no cross-sectional variation.

Table SA2: Probability to apply and obtain a grant by discipline group

	(1) Hard Sciences	(2) Life Sciences
Inventor	0.131***	0.104***
	(0.028)	(0.031)
Cited in patent(s)	0.609***	0.879***
	(0.020)	(0.028)
Individual variables		
Age	0.028***	0.066***
	(0.009)	(0.012)
Age squared	-0.000***	-0.001***
	(0.000)	(0.000)
Male	0.040**	0.076***
	(0.021)	(0.024)
H-index	0.004***	0.007***
	(0.001)	(0.001)
Application experience		
Never applied before (ref.)		
Applied w/o success	0.458***	0.215***
	(0.027)	(0.039)
Applied with success	0.204***	0.158***
	(0.026)	(0.036)
Number of obs	116684	75946

Notes: Robust standard errors in parentheses, clustered at the individual and project levels. To simplify the table, the coefficients of the control variables academic position, scientific field interacted with the year of application, and university are not reported. Potential applicants may belong to two field groups simultaneously. There might be slight differences in the number of observations between the Probit and the Heckman models. This is due to the Stata routine for Probit which drops the fixed effect variables for which there is no cross-sectional variation.

Table SA3: Probability to apply for a grant (average marginal effects - 80% of controls)

	(1) All Programs	(2) Non Directed Programs	(3) Directed Programs
Inventor	0.029***	0.006*	0.030***
	(0.004)	(0.003)	(0.003)
Cited in patent(s)	0.040***	0.014***	0.040***
	(0.003)	(0.002)	(0.002)
Individual variables			
Age	0.014***	0.003***	0.015***
	(0.001)	(0.001)	(0.001)
Age squared	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Male	0.013***	0.007***	0.009***
	(0.003)	(0.002)	(0.002)
H-index	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)
Never applied before (ref.)			
Applied w/o success	0.252***	0.184***	0.172***
	(0.006)	(0.006)	(0.006)
Applied with success	0.114***	0.052***	0.100***
	(0.005)	(0.004)	(0.005)
Number of obs	143928	131692	132499

Notes: 20% of non-applicants each year are randomly dropped out. Robust standard errors in parentheses, clustered at the individual and project levels. The control variables academic position, scientific field interacted with the application year, and university are included in the model, but their average marginal effects are not reported. There might be slight differences in the number of observations between the Probit and the Heckman models. This is due to the Stata routine for Probit which drops the university fixed effect variable for which there is no cross-sectional variation.

Table SA4: Probability to apply for a grant by discipline group (average marginal effects - 80% of controls)

	(1) Hard Sciences	(2) Life Sciences
Inventor	0.026***	0.031***
	(0.005)	(0.005)
Cited in patent(s)	0.044***	0.031***
	(0.003)	(0.004)
Individual variables		
Age	0.014***	0.017***
	(0.002)	(0.002)
Age squared	-0.000***	-0.000***
	(0.000)	(0.000)
Male	0.011***	0.017***
	(0.003)	(0.004)
H-index	0.002***	0.002***
	(0.000)	(0.000)
Never applied before (ref.)		
Applied w/o success	0.252***	0.248***
	(0.007)	(0.009)
Applied with success	0.104***	0.125***
	(0.006)	(0.007)
Number of obs	94583	61871

Notes: 20% of non-applicants each year are randomly dropped out. Robust standard errors in parentheses, clustered at the individual and project levels. The control variables academic position, scientific field interacted with the application year, and university are included in the model, but their average marginal effects are not reported. Potential applicants may belong to two field groups simultaneously. There might be slight differences in the number of observations between the Probit and the Heckman models. This is due to the Stata routine for Probit which drops the university fixed effect variable for which there is no cross-sectional variation.

Table SA5: Probability to receive a grant (average marginal effects - 80% of controls)

	(1) All Programs	(2) Non directed Programs	(3) Directed Programs
Inventor	-0.026**	-0.032*	-0.022
	(0.011)	(0.017)	(0.017)
Cited in patent(s)	-0.037***	-0.046***	-0.023
	(0.010)	(0.013)	(0.016)
Individual variables			
Age	-0.002***	-0.001	-0.003**
	(0.001)	(0.001)	(0.001)
Male	0.010	0.015	0.002
	(0.009)	(0.013)	(0.012)
H-index	-0.000	-0.001	0.000
	(0.001)	(0.001)	(0.001)
Application experience			
Applied w/o success	-0.057***	-0.081***	-0.061
	(0.019)	(0.027)	(0.041)
Applied with success	0.007	0.005	-0.006
	(0.015)	(0.020)	(0.020)
Project variables			
Cluster	0.481***	0.973***	0.441***
	(0.019)	(0.112)	(0.169)
Number of institutions	0.010	0.027***	0.000
	(0.007)	(0.010)	(0.009)
Mean H-index	0.004**	0.008***	0.002
	(0.002)	(0.003)	(0.002)
Max H-index	0.001	-0.001	0.003
	(0.002)	(0.002)	(0.002)
Sum network	0.000	0.001	-0.000
	(0.001)	(0.001)	(0.001)
Max network	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)
Number of obs	148170	133947	135084
Number of selected obs	27309	13086	14223
ρ	-.2914854	-.3635438	-.22588
Prob chi2	0.00	0.00	0.00

Notes: 20% of non-applicants each year are randomly dropped out. Robust standard errors in parentheses, clustered at the individual and project levels. The control variables Scientific field interacted with the application year, university, and department of the agency are included in the model but their average marginal effects are not reported. There is no fixed effect on the department of the agency for non-directed programs.

Table SA6: Probability to receive a grant by discipline group (average marginal effects - 80% of controls)

	(1) Hard Sciences	(2) Life Sciences
Inventor	-0.028**	-0.022
	(0.013)	(0.015)
Cited in patent(s)	-0.038***	-0.029*
	(0.011)	(0.016)
Individual variables		
Age	-0.002**	-0.002**
	(0.001)	(0.001)
Male	0.011	0.017
	(0.011)	(0.012)
H-index	0.000	-0.001
	(0.001)	(0.001)
Application experience		
Applied w/o success	-0.058**	-0.063**
	(0.024)	(0.026)
Applied with success	-0.018	0.033
	(0.018)	(0.021)
Project variables		
Cluster	0.484***	0.450***
	(0.020)	(0.034)
Number of institutions	0.003	0.033**
	(0.008)	(0.014)
Mean H-index	0.001	0.007***
	(0.002)	(0.002)
Max H-index	0.002	-0.001
	(0.002)	(0.002)
Sum network	0.000	-0.002
	(0.001)	(0.002)
Max network	-0.000	0.002
	(0.001)	(0.002)
Number of obs	97464	63749
Number of selected obs	18150	11824
ρ	-.2621822	-.34982
Prob chi2	0.00	0.00

Notes: 20% of non-applicants each year are randomly dropped out. Robust standard errors in parentheses, clustered at the individual and project levels. The control variables, scientific field interacted with application year, department of the agency, and university are included in the model but their average marginal effects are not reported. Prob chi2 represents the p-value associated with the Wald test of independence; Ho: The selection equation and the structural equation are independent.

Table SA7: The impact of grant funding on academic invention (alternative parameter $b = .5$)

	(1) All	(2) Hard sc.	(3) Life sc.	(4) 40 and younger	(5) 40 to 50	(6) 50 and older
Funded × Post	0.004	0.013**	-0.011	0.001	0.003	0.008
	(0.006)	(0.006)	(0.011)	(0.008)	(0.011)	(0.012)
Observations	113723	76521	43070	40776	48656	24283
Number of Clusters	9096	6191	3414	3739	3933	2014
Mean dep variable	.095	.084	.11	.078	.11	.1
Adj. R-Square	.27	.25	.29	.2	.29	.28

	(7) Inventors	(8) Non inventors	(9) Directed	(10) Non directed	(11) Cluster	(12) Non cluster
Funded × Post	-0.010	0.006	0.006	0.003	0.068*	-0.001
	(0.040)	(0.005)	(0.008)	(0.008)	(0.036)	(0.006)
Observations	10851	102870	60952	52769	3872	109848
Number of Clusters	875	8453	5594	4938	508	8892
Mean dep variable	.51	.044	.11	.067	.13	.093
Adj. R-Square	.22	.15	.26	.26	.21	.27

Notes: Robust standard errors in parentheses, clustered at the individual and project levels. The dependent variable is the number of patents using the alternative value of the disambiguation parameter $p = .5$. In this model, the pre-treatment window includes the three years prior to a grant application. The post-treatment window includes four years post-treatment (grant reception year excluded).