DOES LAB FUNDING MATTER FOR THE TECHNOLOGICAL APPLICATION OF SCIENTIFIC RESEARCH? AN EMPIRICAL ANALYSIS OF FRENCH LABS

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RÉSUMÉ

Ce papier s'intéresse à l'effet de l'intensité des financements concurrentiels sur la production de connaissance des laboratoires français de recherche publique. L'analyse empirique est conduite sur 349 laboratoires observés de 2011 à 2015. Pour apprécier la nature de la connaissance produite par les laboratoires, on construit un indicateur de distance à la frontière technologique pour chaque publication du laboratoire. Plus la publication est proche de la frontière et plus la connaissance produite est de nature appliquée. La mesure de l'intensité des financements concurrentiels est basée sur le nombre de financements contractuels nationaux et européens obtenus par le laboratoire pour 1000 chercheurs. Les résultats montrent qu'une intensité plus forte de financements contractuels nationaux est associée à moins de publications proches de la frontière technologique, alors que les financements contractuels européens ont une association positive avec les publications à la frontière. Nous trouvons également que l'association d'un partenaire privé dans le contrat augmente la part des publications qui se situent à la frontière technologique.

MOTS CLÉS

Financement contractuel ; publications scientifiques, frontière technologique, laboratoire français de recherche publique.

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ABSTRACT

This paper investigates how the intensity of competitive grant funding in public research labs affects the type of knowledge produced. The empirical analysis is conducted on 349 French research labs observed over 2011-2015. To assess the type of knowledge produced by labs, we look at the lab publications' distance from the technological frontier: the closer a publication to the technological frontier, the more applied its knowledge content. To measure grant funding intensity within labs, we calculate the number of national and European grants per researcher. We also identify grants in partnership with private companies. We find that a higher intensity of national grants within the lab is associated with fewer publications close to the technological frontier, while European grant intensity has the opposite effect. We also find that companies being partners in the grant increase the share of lab publications at the technological frontier.

KEYWORDS :

Competitive grants; scientific publications; technological frontier; French research labs.

JEL

O31-O32.

Does lab funding matter for the technological application of scientific research? An empirical analysis of French labs

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Abstract: This paper investigates how the intensity of competitive grant funding in public research labs affects the type of knowledge produced. The empirical analysis is conducted on 349 French research labs observed over 2011-2015. To assess the type of knowledge produced by labs, we look at the lab publications' distance from the technological frontier: the closer a publication to the technological frontier, the more applied its knowledge content. To measure grant funding intensity within labs, we calculate the number of national and European grants per researcher. We also identify grants in partnership with private companies. We find that a higher intensity of national grants within the lab is associated with fewer publications *close* to the technological frontier, while European grant intensity has the opposite effect. We also find that companies being partners in the grant increase the share of lab publications *at* the technological frontier.

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1. Introduction

Most research linking science to innovation has adopted the firms' perspective, asking the question: "to what extent do firms rely on basic science in their R&D efforts?" (Marx and Fuegi, 2020). In contrast, less work has been done adopting the perspective of public research labs asking the question: to what extent do public research labs produce knowledge with technological applications? In particular, understanding how lab funding relates to the type of knowledge produced, basic or applied, is a relatively unexplored subject in the extant literature (Babina et al., 2020; Crow and Bozeman, 1987; Gulbrandsen and Smeby, 2005). This paper aims to contribute to the extant literature by assessing how the intensity of competitive grant funding used to support researchers steers the type of knowledge produced within labs.

Historically, the research funding model in Europe evolved from an "institute approach," in which labs are supported with block funding, to a "competitive grant" approach, in which individual researchers write project proposals to obtain funds from national funding agencies (Stephan, 1996; Wang et al., 2018). In the case of France, recent figures suggest that competitive grants amount between 25% and 32% of research funding (*Effective operation of competitive research funding systems*, 2018; Guillou et al., 2022). Although the increasing use of competitive grants to fund research, the "institute approach" is still largely prevalent in Europe. Indeed, labs largely rely on block funding to pay researchers' salaries, lab space, and equipment (Geuna, 2001). In France, block funding is provided to labs by their "*tutelles*", namely public research organizations such as universities and the *Centre National de la Recherche Scientifique* (CNRS), the largest public research organization in France. The amount of funds transferred depends primarily on the size of the lab and, to a lesser extent, on its prestige[1]. Block funding is expected to weakly relate to the basic or applied nature of the knowledge produced, leaving researchers the freedom to choose the type of research conducted (Wang et al., 2018). On the contrary, competitive grant funding is expected to be particularly effective in steering the type of knowledge produced in research labs. Often specific objectives in terms of the type of knowledge produced are declared in grant calls. For instance, the European funding program H2020's stated goal is "*[…] to ensure Europe produces world-class science, removes barriers to innovation and makes it easier for the public and private sectors to work together in delivering innovation.*" According to this

[1] Prestige and size are tightly intertwined. It is essentially via the creation of new positions that prestige enters into play. Additional funding occurs via specific schemes such as, *inter alia*, the organization of conferences, the invitation of foreign prestigious researchers, the participation of the lab to international research consortia, etc.

statement, H2020 grants seem to be particularly oriented toward the production of applied knowledge. Moreover, the stated mission of *Agence Nationale de la Recherche* (ANR), the main French funding agency, is "*To fund and promote the development of basic and targeted research, technological innovation, technology transfer and public-private partnerships*". According to this statement, ANR intends to promote the production of both basic and applied knowledge.

Among the few existing studies relating funds to the type of knowledge produced, Azoulay et al. (2019) find that US *National Institutes of Health* grants stimulate pharmaceutical and biotechnology firms' proliferation of patents in the technological field related to the funded research projects. Crow and Bozeman (1987) report that the labs' funding structure strongly influences the nature of research outcomes. Gulbrandsen and Smeby (2005) find that professors receiving industrial funding do more applied research by analyzing data on 1967 tenured professors at four universities in Norway in 2001.

The contribution of our study to the literature is threefold. First, it contributes to the emerging field of research on "science of science funding," adopting the original perspective of the lab. Although lab characteristics play a crucial role in determining researchers' productivity (Carayol and Matt, 2006), extant funding literature has mainly focused on assessing the effect of individual grants on researchers' productivity, neglecting the lab dimension (Arora and Gambardella, 2005; Ayoubi et al., 2019; Carayol and Lanoë, 2017; Gush et al., 2015; Jacob and Lefgren, 2011). Second, our study contributes to the literature linking lab funding to the type of knowledge produced. Indeed, the vast majority of previous studies links funding only to the quantity and impact of research outcomes. The third contribution regards using an original proxy for the type of knowledge produced. Borrowing from the work of Ahmadpoor and Jones (2017), we measure the distance in the scientific citation network of each lab publication to the closest technological application as represented by a patent citation, i.e., the technological frontier. According to our measure, lab publications close to the technological frontier have a more applied content, while lab publications far from the frontier either lean towards basic science or provide knowledge less relevant to technological innovation. Previous literature has widely used individuals' patenting activity as a proxy for applied knowledge production (Azoulay et al., 2019; Babina et al., 2020). However, this measure has drawbacks. In the context of public research labs, the primary incentive for researchers is to establish priority over their discoveries with publications, while patenting activity is rarer (Dasgupta and David, 1994; Merton, 1957). Therefore, the risk is underestimating the production of applied knowledge if it is embedded in scientific articles (Marx and Fuegi, 2020). Moreover, knowledge produced in university-industry collaborations often results in patents owned by companies, making it difficult to trace the researchers' outcomes using patents (Lissoni et al., 2008). Therefore, looking only at the inventions patented by the lab members might underestimate the lab's contribution to applied research and innovation.

We conduct our empirical analysis over the period 2011-2015 on 349 *Unite Mixte de Recherche* research labs resulting from a collaboration between French universities and CNRS. In these labs, scientists obtain funds for their research in two ways. On the one hand, they are funded by a direct transfer of financial resources from their *tutelles*, i.e., universities and CNRS. On the other hand, lab members respond to competitive calls for projects issued by the French national funding agency (ANR) and the European Union (EU).

Our results show that a higher intensity of national grant funding is associated with a lower share of publications close to the technological frontier and with a higher share of publications not connected to the technological frontier. Vice versa, a higher European grant intensity is associated with a substantial increase in the lab's share of publications close to the technological frontier and a lower share of publications not connected to the technological frontier. Moreover, having a company among the grant partners is associated with a significant increase in the share of lab publications at the technological frontier (science with an immediate technological application) and close to the technological frontier.

Our results are of particular interest from a public policy perspective. Specifically, policymakers can influence the type of knowledge produced within labs by designing different funding programs. For instance, European-like funding programs will lead labs to produce more applied knowledge close to the technological frontier than national-like funding programs. Moreover, encouraging the participation of firms to research projects funded with grants will increase the production of knowledge at and close to the technological frontier.

The remaining of the paper is organized as follows. Section 2 describes the French institutional setting in which the study is conducted. Section 3 describes the data, the estimated econometric model, and the variables used for the empirical analysis. Section 4 shows the results of the regression estimates. Section 5 concludes.

2. Public research funding in France

French research labs went through profound changes during the last two decades. The "institute approach" of distributing funding to public research laboratories was partially complemented with a grant system in which individual scientists are responsible for raising their research funds (OECD, 2014; Stephan, 1996). The practice of funding institutes and the grant system have both advantages and drawbacks. Funding the institute exempts the scientists from devoting considerable time to fundraising activities with uncertain outcomes, distracting them from their research activities. Furthermore, it reduces the strength of the dependence of the institute members' funding on their research outcomes, providing incentives to undertake research projects with more uncertain outcomes and long duration. However, funding the institute gives the lab director more power to influence the lab affiliates' research agenda using funds to promote specific research subjects and disconnects the lab funding from researchers' productivity (Stephan, 1996).

The grant system also has advantages and drawbacks. Among the advantages, the projects proposed by scientists are evaluated by a peer-review system that gives more weight to the proposal's scientific quality during the selection of projects to be awarded. The evaluation by a peer-review system allows scientists to develop research agendas not completely dependent on the prevalent lab's research avenues. Further, policymakers can design calls to attract projects aiming to produce a specific type of knowledge. For instance, in recent years, funding agencies aiming to foster innovation have funded scientific projects close to technological applications, often incentivizing company partnerships. Concerning the drawbacks, the grant system prompts scientists to devote a considerable amount of time to writing proposals that might not be selected for funding. Moreover, it incentivizes scientists to propose short-term, low-risk projects more likely to be funded by risk-averse actors such as funding agencies (Stephan, 1996; Wang et al., 2017).

The main French national funding agency is the *Agence Nationale de la Recherche* (ANR). It was founded in 2005 and endowed with an annual budget of about half a billion euros. The objective of ANR is to finance high-quality research projects proposed by French researchers. ANR has funded more than 1000 research projects per year via various calls for generic projects or projects to research specific topics[2]. These calls are labeled *Appels à projets* (AAP). Around 22% of the project applications by French researchers are awarded a grant. In

[2] Sources: https://anr.fr/fr/actualites-de-lanr/details/news/2005-03-08-lagence-nationale-de-la-recherche-adopte-sa-programmation/ and https://anr.fr/fr/rechercher-un-ancien-appel-a-projets/.

addition, a new granting program, *Programme des investissements d'avenir* (PIA), was created in 2009 aftermath the 2008 economic crisis.[3] Governmental authorities set up this program to finance innovative and promising investments to tighten the link between public research and the technological application of the research outcomes. Among the PIA's sub-programs, three are particularly relevant for public research labs. First is the *Initiative d'excellence* (IDEX), which has, among its multiple goals, fostering innovation and technology transfer between universities and local firms. The second, is LABEX (laboratories of excellence), which aims to provide research units with the means to establish ambitious scientific projects capable of increasing scientific excellence. Third is *Equipements d'excellence* (EQUIPEX), which aims to give the labs the means to acquire cutting-edge scientific equipment to conduct high-quality research[4].

Although the primary source of grant funding for French researchers is the ANR via AAP and PIA programs, another critical source is the European Union (EU). The EU has set up several funding programs over the years. FP7 and Horizon 2020 aimed to fund breakthrough research projects relying on collaboration between scientists in different countries and working in public or private institutions. Horizon 2020 is an EU funding program endowed with 77 billion euros over seven years, of which 13.1 billion euros have been awarded to European scientists' research projects by the European Research Council[5]. According to the *French Ministry of Higher Education, Research, and Innovation* (MESRI), France received 5.2 billion euros from H2020 in 2019 (Guillou et al., 2022). EU funding programs focused on the immediate economic and technological outcomes of projects, promoting SMEs' participation and considering the project's economic implications in terms of economic growth and job creation[6].

3. Model, data, and variables

3.1. Model

The empirical model relates the type of knowledge produced at lab *i* in year *t* ($\mathbf{Y}_{i,t}$) with the intensity of competitive grant funding of lab *i* in year *t-1* ($\boldsymbol{G}_{i,t-1}$) and with the presence of a firm partnership in lab *i* in year *t-1* ($F_{i,t-1}$):

[3] For a description of ANR and PIA, see (Guillou et al., 2022).
[4] Source: https://psl.eu/en/university/investments-future-program
[5] Source: https://erc.europa.eu/projects-figures/facts-and-figures
[6] Source: https://ec.europa.eu/info/funding-tenders/opportunities/portal/screen/programmes/h2020

$$\mathbf{Y}_{i,t} = \beta_0 + \beta_1 \boldsymbol{G}_{i,t-1} + \beta_2 F_{i,t-1} + \beta_3 \mathbf{X}_{i,t-1} + \delta_t + \gamma_i + \varepsilon_{i,t}$$

Equation 1

Vector **Y** represents, in turn, four dependent variables measuring the share of knowledge produced (i) *at* the technological frontier, (ii) *close* to the technological frontier, (iii) *far* from the technological frontier, and (iv) *not connected* to the technological frontier. Hence, vector **Y** is a measure of how useful for innovation publications by public scientists are. Both ***G*** and *F* are lagged by one year to account for the delay in the effect of funding on the lab's knowledge production. Our main interest in Equation 1 relies on estimating the coefficients β_1 and β_2. To avoid biases in the estimates of β_1 and β_2, the model includes a vector $\mathbf{X}_{i,t-1}$ of lab characteristics and a vector δ_t of calendar year dummy variables. Moreover, to proxy for unobservable lab characteristics, the model includes pre-sample mean values of the dependent variable (γ_i). The pre-sample mean estimator is particularly useful in small samples where information on the dependent variable is available for years preceding the observation period covered in the study sample, which is precisely our case. Pre-sample mean is expected to control the historical lab's tendency to produce the knowledge in each of the four classes **Y** and is used as a substitute for the lab's fixed effects (Blundell et al., 2002). Finally, ε represents the idiosyncratic error term.

3.2. Data

Our sample gathers various data sources. First, we collected lab funding data from the *Ministry of Higher Education, Research and Innovation* (MESRI) search engine (ScanR). We complemented these data with additional information about grant starting and ending dates collected from the ANR grant database and the EU grant database (the *Community Research and Development Information Service* - CORDIS). Next, we merged the grant information with the official list of French labs provided by the MESRI using the labs' ID as a unique lab identifier. Once this list was merged with the corresponding grants, we further merged the resulting dataset with the publication data retrieved from the SCOPUS bibliometric database. SCOPUS publications have been attributed to labs using, as matching criteria, the lab name reported in the MESRI list and the authors' affiliation names reported in the SCOPUS publication documents. The quality of matching lab names and publication affiliations has been hand-checked. Last, to calculate our measure of distance from the technological frontier, we identified the position of each lab publication in the scientific citation network by using the publication's *Digital Object Identifier* (DOI). To construct the publication citation network, we used the *Microsoft Academic Graph* citation database[7] (Martín-Martín et al., 2021). Finally, we identify the publications cited by *European Patent Office* and *United States Patent and Trademark Office* patents in the citation network using the *Reliance on Science* database by Marx and Fuegi (2020).

After merging the information collected from the data sources listed above, we select labs that are *Unité Mixte de Recherche*, i.e., labs in which French university researchers collaborate with CNRS researchers. Among these labs, we select those showing a minimum size, i.e., more than ten active researchers in each year during the observation period, and a minimum productivity level, i.e., at least ten publications authored by the lab affiliates in each year of the observation period. We obtained a study sample that includes an unbalanced panel of 349 labs observed for a maximum of 5 years, from 2011 to 2015, in which each lab is observed on average for 4.2 years. Among the 349 labs, 57 labs are classified in chemistry (16.33%), 41 in computer science and math (11.75%), 127 in health and life sciences (36.4%), and 124 in physics and engineering (35.53%)[8].

3.3. Variables

3.3.1. Dependent variables

To measure the share of knowledge produced *at* the technological frontier, *close* to the technological frontier, *far* from the technological frontier, and *not connected* to the technological frontier, we borrow from Ahmadpoor and Jones (2017). Ahmadpoor and Jones define the frontier between science and technology using publication and patent citation networks. Specifically, they reconstruct the citation network of all the publication documents indexed in the Web of Science bibliometric dataset and the whole patent citation network of USPTO patents. Then, they link publication and the patent citation networks by identifying the patents citing publication documents.

[7] As a robustness check, we calculated our variables using *Opencitations* (opencitations.net) as an alternative source of citation data. The advantage of *Opencitations* compared to *Microsoft Academic Graph* is its time coverage. Indeed, *Opencitations* reports citations data until 2020, while *Microsoft Academic Graph* is updated only until 2018. Nonetheless, in our main analysis we decided to use *Microsoft Academic Graph* since *Opencitations* lacks citation information from some important publishers. The regression results reported in Appendix C using *Opencitations* are similar to those reported in Table 5, showing the coherence of our results using the two citation datasets.
[8] To attribute a discipline to each lab, we looked at the most frequent Scopus discipline appearing in the articles published by the lab affiliates over the observation period.

Following Ahmadpoor and Jones (2017), we identify all the 90,226 scientific articles published between 2011 and 2015 by researchers affiliated with the 349 labs considered in our analysis and indexed in the Scopus bibliometric database. Next, we identify the position of these articles in the publication citation network. Finally, we calculate for each of the 90,226 articles the minimum number of edges in the citation network to the closest article cited by an EPO or USPTO patent document[9]. We interpret the number of edges to the nearest article cited by a patent document as the distance of an article from the technological frontier (Appendix A reports an example of distance calculation). Hence, this measure indicates the relevance of a publication in the development of an invention that is worth the cost associated with a patent application. To allow articles published in different years to collect forward citations from other publication documents over the same time span, we consider only citing articles and patents published in a time window ranging from *t* to *t+5*, where *t* is the publication year of the article for which we aim to calculate the distance from the closest article cited by a patent document. For instance, for an article published in 2011, we consider the publications in the citation network and the patents citing publications over the period 2011-2015. For an article published in 2015, we consider the publication in the citation network and the patents citing publications over the period 2015-2019.

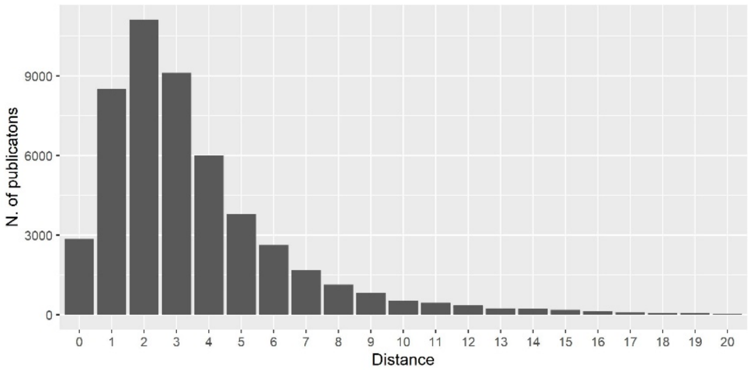
We find that 50,004 of the 90,226 articles (55.4%) published by French researchers affiliated with the 349 labs in our study sample are connected at a finite distance to the technological frontier, while 40,222 are not connected to the technological frontier. Figure 1 shows the distribution of the distances for the 50,004 connected articles. Looking at the distribution, we identify four main categories of articles. The first category represents the articles *at* the technological frontier. These are the articles directly cited by a patent document (distance 0 from the frontier). The second category denotes the articles *close* to the technological frontier. These articles are at a distance of 1, 2, or 3 edges from the technological frontier. The third category denotes articles *far* from the technological frontier. These articles are connected to the technological frontier but at a distance of 4 or greater. Finally, the fourth category denotes the articles *not connected* to the technological frontier. These articles are at an infinite distance from the technological frontier and do not appear in Figure 1. Although articles close to the technological frontier can be viewed as relevant for innovation, qualifying an article far from the frontier is more problematic. Clearly, such a publication exhibits a low level of applicability. But this may be due to two orthogonal reasons: it may either be a publication in

[9] If the article for which we calculate the distance is cited by a patent document, the number of edges from the closest article cited by a patent document equals 0.

basic science with a low level of applicability, or it may simply be an applied research article with a poor level of applicability.

Based on the four types of articles, we calculate four dependent variables to characterize the type of knowledge produced by lab *i* in year *t* (***Y*** in Equation 1). Specifically, we define the variable *Share 0* as the proportion of articles at the technological frontier published at lab *i* in year *t*. *Share 0* is a continuous variable ranging between 0 and 100 percentage points. Similarly, we define the variables *Share 1-3* as the proportion of articles close to the technological frontier, *Share >=4* as the proportion of articles far from the technological frontier, and *Share not connected* as the proportion of articles at infinite distance from the technological frontier.

Figure 1: Distance from the technological frontier for the 50,004 articles connected to the technological frontier at a finite distance



NOTE: We consider 90,226 publications in which at least one author is affiliated with one of the 349 labs included in our study over the period 2011-2015. Among the 90,226 publications, 50,004 (55.4%) are connected to the technological frontier at a finite distance. The distance distribution reported in the figure is for the publications connected to the technological frontier.

3.3.2. Independent variables

We consider three proxies for the grant funding intensity (***G*** in Equation 1). The first proxy is the variable *N. grants per 100 researchers*. It represents the number of lab *i*'s active grants in *t-1* divided by the number of lab *i*'s active researchers in the same year. We define active grants in *t-1* as those grants that started before *t-1* (included) and ended after *t-1* (included)[10]. We define active researchers as those who authored at least one article with the lab *i*'s affiliation in *t-1* or *t-2*[11]. Doing so, we consider all the researchers affiliated with the lab

[10] We have information concerning the awarding date for all the grants. For a limited number of grants, the information on the expiration date is missing. When the expiration date is missing, we calculated it assuming that the grant time length is the average grant time length in our sample.
[11] We tried alternative definitions of active researchers as those who authored at least one article with the lab *i*'s affiliation in *t-1*, in *t-1*, *t-2*, or *t-3*, in *t-1*, *t-2*, *t-3*, or *t-4*. The results of our regression are stable across all the definitions of active researchers.

regardless of their contract status, whereas most studies on technology transfer concentrate on faculty members, which implies ignoring other researchers such as postdocs and Ph.D. students (Choi et al., 2011). The ratio between the number of active grants and the number of active researchers is often of small size; therefore, we multiply the ratio by 100, obtaining the variable *N. grants per 100 researchers*.

The second and third proxies for grant funding intensity (***G***) are calculated to disentangle the effect of national grants and European grants' intensity. The variable aiming to measure the intensity of national grants for lab *i* in year *t-1* is *N. national grants per 100 researchers*. It is calculated similarly to the variable *N. grants per 100 researchers*, but the ratio's numerator considers only grants awarded by the French national funding agency[12]. The variable *N. EU grants per 100 researchers* measure the intensity of European grants for lab *i* in year *t-1*, and it is calculated following the same logic as *N. national grants per 100 researchers*.

To consider the partnership of a private company within the grant (*F* in Equation 1) we calculate the dummy variable *At least one company* that equals one if at least one company is listed among the partners of one of the grants active at lab *i* in year *t-1*, zero otherwise.

3.3.3. Controls

As for controls, we include in all our regressions the lab's publication productivity at time *t-1* (*N. publications per 100 researchers*), the years elapsed since the lab foundation (*Lab age*), the number of researchers who authored at least one paper with the lab affiliation in *t-1* or *t-2* (*Lab size*), and the number of Scopus disciplines in which lab researchers are actively publishing in *t-1* (*N. disciplines*). Moreover, we include the dummy variable *Institut Carnot* that equals one if the lab is part of the Carnot network, zero otherwise. The dummy variable indicates that the lab is oriented toward innovation activities and has received additional funds as such: "Carnot Label is granted to public research structures, Carnot institutes, with proven, high-level R&I competencies dedicated to fostering innovation with industrial partners"[13]. We also control for year fixed effects (δ) with a set of year dummy variables. Finally, we include a pre-sample mean of the dependent variable as a proxy for the time-invariant lab characteristics (γ). If the lab was founded before 2011 (the starting year of our study sample), the pre-sample mean is calculated as the average of the dependent variable's values for the years before 2011. If the lab was founded in 2011 or after 2011, the pre-sample mean takes

[12] These grants include ANR individual grants and PIA grants (Labex, Equipex, and IDEX). PIA grants are observed only starting from 2010 when the French government launched the "Investissements d'avenir" program.
[13] Source: https://www.instituts-carnot.eu/en/carnot-label.

the value of the dependent variable in the lab's foundation year, and the lab's foundation year is not included in the study sample.

Table 1 reports a brief description of the dependent and independent variables.

Table 1: Dependent and independent variables, a brief description

	Description
Dependent variables (Y)	
Share 0	Share of lab *i*'s articles in year *t at* the technological frontier. These articles are cited by a patent document and are at a distance of 0 from the technological frontier in the citation network. The variable is expressed in percentage points with values ranging from 0 to 100.
Share 1-3	Share of lab *i*'s articles in year *t close* to the technological frontier. These articles are at a distance of 1, 2, or 3 edges in the citation network from the closest publication cited by a patent. The variable is expressed in percentage points with values ranging from 0 to 100.
Share >=4	Share of lab *i*'s publications in year *t far* from the technological frontier. These articles are at a finite distance of 4 edges or more from the closest publication cited by a patent. The variable is expressed in percentage points with values ranging from 0 to 100.
Share not connected	Share of lab *i*'s articles in year *t not connected* to the technological frontier. These articles are at an infinite distance from the closest publication cited by a patent. The variable is expressed in percentage points with values ranging from 0 to 100.
Independent variables	
N. grants per 100 researchers *(G)*	Number of grants active in year *t-1* divided by the number of lab members (*Lab size*). The variable's value is rescaled by multiplying by 100, i.e., each unit increase corresponds to 1 additional grant for every 100 researchers.
N. national grants per 100 researchers *(G)*	Number of national grants active in year *t-1* divided by the number of affiliates to the lab (*Lab size*). The variable's value is rescaled by multiplying by 100, i.e., each unit increase corresponds to 1 additional grant for every 100 researchers.
N. EU grants per 100 researchers *(G)*	Number of EU grants active in year *t-1* divided by the number of affiliates to the lab (*Lab size*). The variable's value is rescaled by multiplying by 100, i.e., each unit increase corresponds to 1 additional grant for every 100 researchers.
At least one company *(F)*	Dummy that equals one if at least one firm is listed among the lab's partners in one of the grants active in year *t-1*.
Controls	
Institut Carnot	Dummy that equals one if the lab is part of the Carnot network
N. publications per 100 researchers	Number of lab articles published in year *t-1* divided by the number of affiliates to the lab (*Lab size*). The variable's value is rescaled by multiplying by 100, i.e., each unit increases corresponds to 1 additional paper every 100 researchers.
Lab age	Years that have passed since the lab foundation
Lab size [N. of researchers]	Number of distinct lab affiliates who published a paper in the time window t-1, t-2.
N. disciplines	Number of Scopus disciplines in which the lab affiliates have published in t-1
Year dummies *(δ)*	Set of 5 dummy variables for the calendar years 2011-2015. Each dummy variable equals one during the calendar year. It represents zero otherwise.
Pre-sample means *(γ)*	If the lab was founded before 2011 (the starting year of our analysis), the pre-sample mean variable is calculated as the average of *Y* for the years before 2011. If the lab was founded in 2011 or after 2011, the pre-sample mean takes the value of *Y* in the lab's foundation year, and the lab's foundation year is excluded from the study sample.

Table 2 reports descriptive statistics of the dependent and independent variables. It shows that, on average, 3.31% of the published papers are at the technological frontier (*Share 0*); 34.43% are close to the technological frontier (*Share 1-3*); 20.77% are far from the technological frontier (*Share >=4*); and 41.49% are at an infinite distance from the technological frontier (*Share not connected*). The sum of the four averages equals 100%, and each lab publication is classified in one of the four categories. Concerning the explanatory variables, we observe on average 9.33 grants per 100 researchers for each lab-year pair, 7.95 of which are national grants and 1.38 are European grants.

Table 2: Descriptive statistics

Observations: 1,460 lab-year pairs	Mean	SD	P25	Median	P75	Min	Max
Dependent variables							
Share 0 [%]	3.31	4.27	0	1.91	4.94	0	26.09
Share 1-3 [%]	34.43	20.76	18	30.89	0.5	0	92.31
Share >=4 [%]	20.77	14.03	10.64	17.54	28.21	0	78.05
Share not connected [%]	41.49	24.37	20.31	39.66	60.69	0	100
Independent variables							
N. grants per 100 researchers	9.33	8.49	4.75	7.84	11.85	0	143.4
N. national grants per 100 researchers	7.95	7.43	3.81	6.67	10.15	0	107.55
N. EU grants per 100 researchers	1.38	2.19	0	0.8	2.04	0	35.85
At least one company	0.63 (0.67)	0.48	0	1	1	0	1
Institut Carnot	0.03	0.17	0	0	0	0	1.00
N. publications per 100 researchers	86.34	32.89	64.03	81.25	100.58	25.45	330.12
Lab age	12.83	9.02	5	14	17	2	75
Lab size [N. of researchers]	115.17	73.16	64	96	144	11	482
N. disciplines	11.17	3.69	9	11	13	2	26
Year	2013.12	1.39	2012	2013	2014	2011	2015

NOTE: For the variable *At least one company*, we report in parentheses the average value of the dummy conditional on observing a positive value of the corresponding *N. grants per 100 researchers* variable. Variables *Share 0*, *Share 1-3*, *Share >=4*, and *Share not connected* are expressed in percentage with values ranging from 0 to 100.

Tables 3 and 4 show the average values of the dependent and independent variables by year. The averages of the variables *Share 0*, *Share 1-3*, *Share >=4*, and *Share not connected* reported in Table 3 do not show any specific time trend in 2011-2013. In 2014 and 2015, we observe a decrease in the values of the variables *Share 0*, *Share 1-3*, *Share >=4*, and an increase in the variable *Share not connected*. The decrease of *Share 0*, *Share 1-3*, *Share >=4* can be explained by a truncation in the citation data[14]. The truncation in 2014 and 2015 is expected to be at least partially controlled by the year dummy variables in our econometric models. In Table 4, we observe an increase in the reliance on grant funding of French labs. The increase in grant funding is mainly due to the rise in the national grants, while the average number of European grants remained stable over time. This increase in national grant funding is related to the new PIA funding programs introduced by the French government in 2011.

Table 3: Year average of the dependent variables

Year	Share 0	Share 1-3	Share >=4	Share not connected
2011	3.50	34.60	28.16	33.74
2012	3.53	38.16	24.19	34.12
2013	3.25	37.63	22.61	36.51
2014	3.56	36.55	17.37	42.52
2015	2.79	25.89	13.53	57.79
Overall average	*3.31*	*34.43*	*20.77*	*41.49*

NOTE: The variables are expressed in percentage with values ranging from 0 to 100.

[14] *Microsoft Academic Graph* citation data are available until 2018. The truncation in 2018 does not allow us to reconstruct the full citation network for a 5-year window after 2014 and 2015 (see section 3.3.1 detailing the construction of our dependent variables), while it does not affect 2013, 2012, and 2011. In Appendix C, we report a robustness check where we use *Openciations* as another source of citation data for our analyses. *Openciations* has the advantage of having citation data until 2020, but it does not cover important publishers, decreasing the overall citation data quality (Martín-Martín et al., 2021). The regression results reported in Appendix C using *Opencitations* are similar to those reported in Table 5. Moreover, in Appendix D we report another robustness check where we use *Microsoft Academic Graph* data but consider a 3-year window (instead of a 5-year window) to construct the citation network. By doing so, we avoid any truncation problems for the publications in 2014 and 2015. The results reported in Appendix D using a 3-year window are similar to those reported in Table 5.

Table 4: Year average of the independent variables

Year	N of grants per 100 researchers	N. national grants per 100 researchers	N. EU grants per 100 researchers	At least one company
2011	5.71	4.46	1.25	0.55
2012	9.43	7.89	1.53	0.66
2013	10.03	8.65	1.39	0.64
2014	10.18	8.83	1.35	0.67
2015	10.61	9.23	1.39	0.62
Overall average	*9.33*	*7.94*	*1.38*	*0.63*

4. Results

Table 5 reports the OLS estimates of Equation 1. We run two sets of regressions. In Columns 1, 2, 3, and 4, we consider as dependent variables the log transformation[15] of the variables *Share 0*, *Share 1-3*, *Share >=4*, and *Share not connected*. As explanatory variables, we consider *N. of grants per 100 researchers* and *At least one company*. In Columns 5, 6, 7, and 8, we consider the same dependent variables as in Columns 1-4, but we substitute the variable *N. of grants per 100 researchers* with the variables *N. national grants per 100 researchers* and *N. EU grants per 100 researchers*.

In Columns 1-4, we find no statistically significant association between the intensity of grant funding (*N. of grants per 100 researchers*) and the production of knowledge at the technological frontier (*Share at 0*), close to the technological frontier (*Share 1-3*), far from the technological frontier (*Share >=4*), or not connected to the technological frontier (*Share not connected*). However, when looking at the presence of a company among the grant participants (*At least one company*), we find that it is associated with an increase of 13% and 14% in the share of publications at and close to the technological frontier (Columns 1 and 2). On the contrary, the presence of a company is not significantly associated with the share of publications far and at an infinite distance from the technological frontier (Columns 3 and 4).

[15] The log transformation cannot be calculated when the values of the dependent variables *Share 0*, *Share 1-3*, *Share >=4*, and *Share not connected* equal zero. The variable *Share 0* equals 0 for 543 observations out of 1460 observations in our study sample (~37.2%), while the variables *Share 1-3*, *Share >=4*, and *Share not connected* equal 0 in 2.1%, 2.1%, and 1% of the observations, respectively. To avoid losing observations in our estimations, we adopt the approximation of adding 1 to each dependent variable before applying the log transformation, e.g., we calculate log(1+*Share 0*). This approximation might bias our estimations. Therefore, to check the robustness of our results, in Appendix B, we estimate regression models with the exact specification as in Table 5, but using as dependent variables *Share 0*, *Share 1-3*, *Share >=4*, and *Share not connected* without log transformation. We use OLS and left-censored Tobit estimators. We find substantial coherence between the results presented in Tables B1 and B2 and the results presented in Table 5.

Table 5: Regression results, Ordinary Least Square (OLS) estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log (1+Share at 0)	log (1+Share 1-3)	log (1+Share >=4)	log (1+Share not connected)	log (1+Share at 0)	log (1+Share 1-3)	log (1+Share >=4)	log (1+Share not connected)
N. of grants per 100 res	-0.0034	-0.0039	0.0029	0.0018				
	(0.0035)	(0.0026)	(0.0025)	(0.0023)				
N. of national grants per 100 researchers					-0.0023	-0.0080***	0.0017	0.0054*
					(0.0044)	(0.0031)	(0.0036)	(0.0032)
N. of EU grants per 100 researchers					-0.0092	0.019**	0.0098	-0.019**
					(0.012)	(0.0096)	(0.010)	(0.0092)
At least one company	0.13**	0.14***	-0.063	-0.043	0.14**	0.13***	-0.068	-0.027
	(0.058)	(0.045)	(0.047)	(0.046)	(0.059)	(0.045)	(0.047)	(0.047)
Institut Carnot	0.14	-0.0020	-0.12	0.069	0.14	-0.0043	-0.12	0.072
	(0.12)	(0.076)	(0.080)	(0.075)	(0.12)	(0.077)	(0.081)	(0.077)
log(N. publications per 100 researchers)	-0.23***	-0.13**	-0.062	0.29***	-0.23***	-0.14***	-0.064	0.30***
	(0.071)	(0.056)	(0.063)	(0.066)	(0.071)	(0.055)	(0.063)	(0.066)
log(Lab age)	-0.077**	-0.0066	-0.082***	0.022	-0.078**	-0.0057	-0.081***	0.022
	(0.037)	(0.028)	(0.025)	(0.028)	(0.037)	(0.028)	(0.025)	(0.028)
log(Lab size [N. of researchers])	0.086	-0.089**	-0.054	-0.032	0.089	-0.097**	-0.057	-0.024
	(0.064)	(0.042)	(0.051)	(0.049)	(0.064)	(0.042)	(0.051)	(0.048)
log(N. disciplines)	0.021	0.19**	0.12*	0.083	0.017	0.21**	0.13*	0.067
	(0.084)	(0.088)	(0.070)	(0.065)	(0.085)	(0.087)	(0.070)	(0.064)
Constant	1.09***	1.43***	1.52***	0.18	1.08***	1.48***	1.53***	0.15
	(0.39)	(0.38)	(0.37)	(0.33)	(0.39)	(0.38)	(0.37)	(0.33)
Observations	1,460	1,460	1,460	1,460	1,460	1,460	1,460	1,460
R-squared	0.370	0.666	0.450	0.595	0.370	0.670	0.450	0.597
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-sample means	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

NOTE: Standard errors are clustered at the lab level. The asteriscs represent the following significance levels *** p<0.01, ** p<0.05, * p<0.1

In Columns 5-8, we estimate the coefficients associated with the intensity of national and European grants. We find that increasing by one standard deviation (sd=7.43) the intensity of national grant funding is associated with a 5.9% lower share of publications close to the frontier (*Share 1-3*, Column 6) and a 4% higher share of publications not connected to the frontier (*Share not connected*, Column 8)[16]. Furthermore, the national grant intensity is neither associated with the share of publications at the technological frontier (*Share at 0*, Column 5) nor with the share of publications far from the technological frontier (*Share >=4*, Column 7). Conversely to national grants, increasing by one standard deviation (sd=2.19), the intensity of EU grants is associated with a 4.2% increase in the publications close to the frontier (*Share 1-3*, Column 6) and the same amount of decrease in the share of publications at infinite distance (*Share not connected*, Column 8). Similarly to the national grant intensity, we find no significant association between the intensity of EU grants and the share of publications at (*Share at 0*, Column 5) and far from the technological frontier (*Share >=4*, Column 7). The presence of a company (*At least one company*) as a grant partner is still associated with a 14% and 13% higher share of publications at the technological frontier and close to the technological frontier (Columns 5 and 6).

[16] The values -5.9% and 4% result from -0.008*7.43 and 0.0054*7.43, respectively, where -0.008 and 0.0054 are the coefficients of *N. grants per 100 res, while* 7.43 is the standard deviation of the same variable.

Concerning the control variables, we find that an increase of 1% in lab productivity is associated with a 0.23% decrease in the share of publication at the technological frontier (Column 5), while a 1% increase in the age of the lab is associated with a 0.078% decrease in the share of publication at the technological frontier (Column 5). These results might be driven by the tendency of researchers to do less applied research in productive labs with a long history. Indeed, a 1% increase in lab productivity is associated with 0.30% more publications not connected to the technological frontier (Column 6). Similarly, a 1% increase in lab size is associated with a 0.097% reduction in the share of publications close to the technological frontier (Column 2). Increasing the lab's number of disciplines by 1% is associated with a 0.21% increase in the share of publications close to the technological frontier (Column 6) and a 0.13% increase in the publications far from the technological frontier (Column 7).

4.1 Further results

The primary objective of our analysis is to investigate how public funding affects the type of knowledge produced within research labs. The measure we use to classify the type of knowledge produced relies on the definition of distance from the technological frontier. Indeed, the closer a publication is to the technological frontier, the more applied the knowledge content. The farther a publication is from the technological frontier, the more basic the knowledge content. Our main analysis defines the technological frontier considering the citations to scientific articles from all the EPO and USPTO patents. However, firm-owned patents are expected to be of higher economic value than university-owned patents[17] (Lissoni and Montobbio, 2015; Sterzi et al., 2019). From a policy perspective, we might be more interested in assessing the distance of the knowledge produced by public labs from the most valuable technologies. Therefore, we implement an alternative definition of distance from the technological frontier considering only firm-owned EPO and USPTO patents. These patents are likely to have a highly applied nature.

After recalculating the technological frontier using only citations from firm-owned patents, we find that 53.35% of the 90,226 publications are connected at a finite distance (when considering university-owned patents, this percentage was 55.4%). Then, we calculate the four dependent variables according to the new distance measure, and we run the regression exercises with the same model specification as in Table 5.

[17] We define university-owned patents as all patents owned by universities, hospitals, and public research organizations.

Table 6 shows the results. Concerning our variable of interest, *N. grants per 100 researchers*, *N. national grants per 100 researchers*, and *N. EU grants per 100 researchers*, we find similar results to the ones reported in Table 5. Specifically, Table 6 shows that increasing by one standard deviation (sd=8.49), the intensity of grant funding is associated with a decrease of 4.8% of publications close to the frontier (*Share 1-3*, Column 2) and an increase of 3.4% of the publications far from the frontier (*Share >=4*, Column 3). When we distinguish national and EU grants, increasing by one standard deviation (sd=7.43), the intensity of national grant funding is associated with a 7.4% lower share of publications close to the frontier (*Share 1-3*, Column 6) and a 4% higher share of publications not connected to the frontier (*Share not connected*, Column 8). Increasing by one standard deviation (sd=2.19), the intensity of European funding is associated with a 4.6% increase in the publications close to the frontier (*Share 1-3*, Column 6), a 4.4% increase in the publications far from the frontier (*Share >=4*, Column 7), and a 4% decrease in the share of publications at infinite distance (*Share not connected*, Column 8). Finally, the presence of a company among the grant participants (*At least one company*) is associated with an increase of 9.3% and 12% in the share of publications at the technological frontier and close to the technological frontier (Columns 5 and 6).

Table 6: Regression results. We calculate the distance from the technological frontier considering only patents owned by companies (53.35% of the 90,226 publications are connected at a finite distance)

	(1) log(1+Share at 0)	(2) log(1+Share 1-3)	(3) log(1+Share >=4)	(4) log (1+Share not connected)	(5) log(1+Share at 0)	(6) log(1+Share 1-3)	(7) log(1+Share >=4)	(8) log (1+Share not connected)
N. of grants per 100 researchers	-0.0012	-0.0057*	0.0040*	0.0019				
	(0.0029)	(0.0030)	(0.0023)	(0.0022)				
N. of national grants per 100 researchers					-0.00067	-0.010***	0.0011	0.0054*
					(0.0034)	(0.0035)	(0.0032)	(0.0031)
N. of EU grants per 100 researchers					-0.0041	0.021**	0.020**	-0.018**
					(0.010)	(0.0094)	(0.0091)	(0.0090)
At least one company	0.091*	0.14***	-0.024	-0.041	0.093*	0.12**	-0.036	-0.026
	(0.050)	(0.048)	(0.047)	(0.045)	(0.051)	(0.047)	(0.046)	(0.046)
Institut Carnot	0.13	0.0090	-0.12	0.076	0.13	0.0059	-0.12	0.079
	(0.077)	(0.082)	(0.085)	(0.059)	(0.077)	(0.085)	(0.087)	(0.061)
log(N. publications per 100 researchers)	-0.16***	-0.14**	-0.15**	0.26***	-0.16***	-0.15**	-0.16**	0.27***
	(0.058)	(0.062)	(0.066)	(0.066)	(0.058)	(0.060)	(0.066)	(0.066)
log(Lab age)	-0.085***	-0.034	-0.083***	0.028	-0.085***	-0.033	-0.081***	0.027
	(0.030)	(0.030)	(0.025)	(0.026)	(0.030)	(0.030)	(0.025)	(0.026)
log(Lab size [N. of researchers])	0.053	-0.10**	-0.053	-0.024	0.054	-0.11**	-0.060	-0.015
	(0.051)	(0.052)	(0.055)	(0.048)	(0.052)	(0.052)	(0.055)	(0.047)
log(N. disciplines)	0.041	0.25**	0.15**	0.079	0.039	0.27***	0.17**	0.064
	(0.073)	(0.099)	(0.072)	(0.062)	(0.073)	(0.098)	(0.072)	(0.061)
Constant	0.87***	1.57***	1.86***	0.33	0.86***	1.64***	1.90***	0.30
	(0.31)	(0.38)	(0.42)	(0.33)	(0.31)	(0.38)	(0.42)	(0.33)
Observations	1,460	1,460	1,460	1,460	1,460	1,460	1,460	1,460
R-squared	0.249	0.647	0.432	0.605	0.249	0.651	0.434	0.607
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-sample means	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

NOTE: Standard errors are clustered at the lab level. The asteriscs represent the following significance levels *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7 presents a further analysis disentangling the intensity of France's two most important ANR funding programs during the study period: the AAP (*Appels à projets*) funding program and the PIA (*Programme des investissements d'avenir*) funding program[18]. The variable *N. AAP grants per 100 researchers* is calculated as the number of lab *i*'s active AAP grants in *t-1* divided by the number of lab *i*'s active researchers in the same year, while the variable *N. PIA grants per 100 researchers* is calculated as the number of lab *i*'s active PIA grants in *t-1* divided by the number of lab *i*'s active researchers in the same year. We find a negative association between the intensity of AAP grants and the share of publications close to the technological frontier (*Share 1-3*, Column 2), but no effect of the intensity of PIA grants. This result shows that the negative impact of the variable *N. national grants per 100 researchers* on the share of publications close to the technological frontier in Column 6 of Table 5 is mainly driven by AAP grants. On the contrary, PIA grants show a positive association with the production of basic science, increasing the share of articles not connected to the technological frontier (*Share not connected*, Column 4). This result suggests that the positive coefficient of the variable *N. national grants per 100 researchers* in Column 8 of Table 5 is driven by the intensity of PIA grants.

Table 7: Regression results. We calculate the intensity of AAP and PIA grants separately

	(1) log (1+Share at 0)	(2) log (1+Share 1-3)	(3) log (1+Share >=4)	(4) log (1+Share not connected)
N. AAP grants per 100 researchers	-0.0033	-0.010***	0.0018	0.0022
	(0.0050)	(0.0037)	(0.0038)	(0.0030)
N. PIA grants per 100 researchers	0.0034	0.0054	0.0010	0.023*
	(0.014)	(0.011)	(0.015)	(0.014)
N. of EU grants per 100 researchers	-0.0086	0.021**	0.0097	-0.016*
	(0.012)	(0.010)	(0.010)	(0.0085)
At least one company	0.14**	0.12***	-0.068	-0.032
	(0.059)	(0.045)	(0.047)	(0.046)
Institut Carnot	0.15	0.0035	-0.12	0.082
	(0.12)	(0.078)	(0.081)	(0.077)
log(N. publications per 100 researchers)	-0.23***	-0.15***	-0.064	0.30***
	(0.071)	(0.055)	(0.063)	(0.064)
log(Lab age)	-0.077**	-0.0055	-0.081***	0.022
	(0.037)	(0.027)	(0.025)	(0.028)
log(Lab size [N. of researchers])	0.095	-0.083*	-0.057	-0.0046
	(0.064)	(0.043)	(0.049)	(0.045)
log(N. disciplines)	0.017	0.21**	0.13*	0.068
	(0.085)	(0.087)	(0.070)	(0.063)
Constant	1.06***	1.44***	1.53***	0.087
	(0.39)	(0.37)	(0.37)	(0.33)
Observations	1,460	1,460	1,460	1,460
R-squared	0.370	0.670	0.450	0.599
Year dummies	Yes	Yes	Yes	Yes
Pre-sample means	Yes	Yes	Yes	Yes

NOTE: Standard errors are clustered at the lab level. The asteriscs represent the following significance levels *** p<0.01, ** p<0.05, * p<0.1

[18] AAP and PIA funding programs have different characteristics and goals as explained in Section 2. PIA grants are smaller in number then AAP grants and their effect is maingly related to signaling the participation of the lab in a consortium.

5. Discussion and Conclusion

This paper has examined how grant funding of scientific research affects the type of knowledge produced in French public research labs. We analyze the scientific production of 349 labs over the period 2011-2015, classifying the knowledge produced into four categories: knowledge at the technological frontier, close to the technological frontier, far from the technological frontier, and not connected to the technological frontier. We find that grants awarded by the largest French funding agency (ANR) show a negative association with the production of knowledge close to the technological frontier, while European Union (EU) grants show a positive association. This result could indicate that national grants are more oriented toward basic knowledge, while EU grants favor the production of knowledge of more immediate relevance for innovation. In the same vein, we find that a higher intensity of national grants is associated with a higher share of basic science articles not connected to the technological frontier, while EU grant intensity is associated with a lower share of these articles.

These results are consistent with the EU funding program goals. Indeed, EU programs are primarily oriented toward applied research and university-industry collaboration. For instance, the European Commission report (Commission, 1995) claims that insufficient interaction between firms and universities in the EU has been among the main factors behind the poor commercial and technological performance in high-tech sectors in the EU. Probably this perception has oriented the program towards granting projects more likely to generate applied knowledge. Concerning ANR grants, their mission is to promote both basic and applied research. Our results show that the prevalent effect of obtaining ANR grants is to advance basic research. This effect is probably due to the AAP programs that allow researchers to propose projects without subject constraints (*blanc*) or programs targeting broad research themes. In both cases, French researchers are likely to conduct projects in line with their research avenues that, in research labs, are more oriented toward basic research.

Interestingly, the presence of a company among grant partners is positively associated with the production of knowledge at the technological frontier and close to the technological frontier. This finding complements Arora et al. (2021)'s and Banal-Estañol et al. (2015) results relating university-industry collaborations to research output. Specifically, our results show that university-industry collaborations are the key to favoring public research with more immediate technological applications. Policymakers could use the design of competitive funding programs as a policy tool to drive the type of knowledge produced by public research labs.

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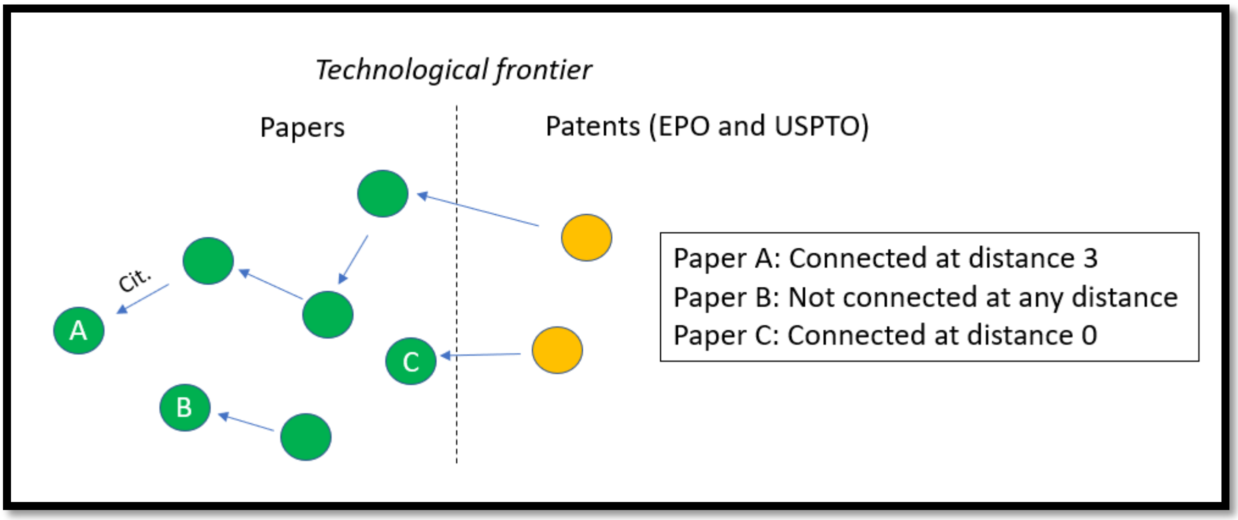
Appendix A

To calculate the distance from the technological frontier, we proceed in three steps. First, we calculate the whole publication citation network. Then, we identify the publications cited by patents as the boundary between science and technology. Finally, we classify the articles published by labs into four categories according to their distance from the technological frontier in the citation network. The four categories include (i) articles at the technological frontier, (ii) close to the technological frontier, (iii) far from the technological frontier, and (iv) not connected to the technological frontier. Compared to the previous literature, measuring the distance from the technological frontier allows for a more fine-grained analysis of the type of knowledge produced within research labs.

Figure A1 shows an example of the distance calculation method. Specifically, publication A is at three edges distance from a publication cited by a patent. Therefore, its distance from the technological frontier equals 3. Publication B is not connected to the technological frontier at any distance. Indeed, although other publications cite B, there is no path in the citation network leading to a publication cited by a patent, i.e., a publication at the technological frontier. Finally, Publication C is cited by a patent document. Therefore, its distance from the technological frontier equals zero.

Figure A1: Example of calculation of the distance from the technological frontier



Appendix B

This appendix includes OLS and Tobit estimations of Equation 1 when using as dependent variables *Share 0*, *Share 1-3*, *Share >=4*, and *Share not connected*.

Table B.1 presents the OLS estimates. The main results regarding the funding effects are in line with those shown in Table 5, except for the coefficient of the variable *At least one company* that is not statistically significant in the regression explaining the share of knowledge produced at the technological frontier (Column 1 and Column 5, *Share 0*). Although not significant, the coefficient keeps the sign of the one estimated in Table 5 despite being insignificant here.

However, in the regression reported in Columns 1 and 5, the variable *Share 0* equals zero for roughly 37% of the observations. We argue that the difference in results here from Table 5 is due to the large number of zero values in the variable *Share 0*. To address this issue, we present the results of Tobit's left-censored at zero estimations in Table B.2.

Table B.1: Regression results, OLS estimates

	(1) Share at 0	(2) Share 1-3	(3) Share >=4	(4) Share not connected	(5) Share at 0	(6) Share 1-3	(7) Share >=4	(8) Share not connected
N. of grants per 100 res	-0.0098	-0.069	0.050	0.012				
	(0.017)	(0.054)	(0.036)	(0.052)				
N. of national grants per 100 researchers					-0.014	-0.14**	0.059	0.037
					(0.020)	(0.068)	(0.047)	(0.067)
N. of EU grants per 100 researchers					0.013	0.34*	0.00039	-0.13
					(0.051)	(0.20)	(0.15)	(0.21)
At least one company	0.41	2.03**	-0.62	-1.95**	0.40	1.73**	-0.59	-1.84*
	(0.28)	(0.81)	(0.69)	(0.98)	(0.28)	(0.80)	(0.69)	(0.99)
Institut Carnot	0.66	-0.50	-1.59	-0.19	0.66	-0.54	-1.58	-0.16
	(0.78)	(1.87)	(0.99)	(2.10)	(0.78)	(1.90)	(0.98)	(2.11)
log(N. publications per 100 researchers)	-1.73***	-2.55**	-1.42	4.92***	-1.74***	-2.76**	-1.41	5.02***
	(0.40)	(1.18)	(0.89)	(1.31)	(0.40)	(1.16)	(0.89)	(1.33)
log(Lab age)	-0.25	0.41	-1.11***	0.87	-0.25	0.43	-1.12***	0.87
	(0.18)	(0.56)	(0.42)	(0.63)	(0.18)	(0.56)	(0.42)	(0.63)
log(Lab size [N. of researchers])	0.58	-0.40	-0.0078	-1.12	0.57	-0.56	0.016	-1.06
	(0.36)	(0.84)	(0.67)	(1.05)	(0.36)	(0.85)	(0.67)	(1.06)
log(N. disciplines)	-0.31	0.83	0.41	0.69	-0.29	1.14	0.37	0.57
	(0.42)	(1.38)	(0.98)	(1.58)	(0.42)	(1.34)	(0.99)	(1.58)
Constant	7.72***	17.5***	17.1***	-14.0**	7.75***	18.3***	17.1***	-14.3**
	(1.87)	(6.17)	(4.62)	(6.89)	(1.88)	(6.20)	(4.59)	(6.95)
Observations	1,460	1,460	1,460	1,460	1,460	1,460	1,460	1,460
R-squared	0.269	0.759	0.618	0.789	0.269	0.761	0.618	0.790
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-sample means	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

NOTE: Standard errors are clustered at the lab level. The asteriscs represent the following significance levels *** p<0.01, ** p<0.05, * p<0.1

Table B.2.1 shows Tobit estimations of left-censored, at zero, dependent variables. The results are in line with those in Table 5. The main differences regard columns 4 and 8, where firms' presence is negatively associated with the share of publications not connected to the technological frontier, and the intensity of national and EU grants is not statistically significant. As in the case of the OLS estimates, although not statistically significant, the estimated coefficients keep the expected sign.

Table B.2: Regression results, Tobit estimates

	(1) Share at 0	(2) Share 1-3	(3) Share >=4	(4) Share not connected	(5) Share at 0	(6) Share 1-3	(7) Share >=4	(8) Share not connected
N. of grants per 100 res	-0.019	-0.076	0.052	0.014				
	(0.029)	(0.055)	(0.036)	(0.052)				
N. of national grants per 100 researchers					-0.015	-0.15**	0.060	0.038
					(0.037)	(0.070)	(0.048)	(0.066)
N. of EU grants per 100 researchers					-0.040	0.37*	0.0032	-0.13
					(0.096)	(0.20)	(0.15)	(0.21)
At least one company	0.94**	2.30***	-0.74	-2.02**	0.95**	1.98**	-0.71	-1.91*
	(0.43)	(0.84)	(0.70)	(0.99)	(0.42)	(0.83)	(0.71)	(1.00)
Institut Carnot	1.12	-0.40	-1.46	-0.19	1.12	-0.44	-1.45	-0.16
	(0.97)	(1.85)	(0.97)	(2.09)	(0.97)	(1.88)	(0.97)	(2.10)
log(N. publications per 100 researchers)	-2.57***	-2.65**	-1.40	5.02***	-2.57***	-2.88**	-1.39	5.11***
	(0.63)	(1.21)	(0.90)	(1.31)	(0.63)	(1.19)	(0.90)	(1.33)
log(Lab age)	-0.45*	0.33	-1.15***	0.86	-0.45*	0.35	-1.16***	0.86
	(0.27)	(0.57)	(0.42)	(0.63)	(0.27)	(0.57)	(0.42)	(0.63)
log(Lab size [N. of researchers])	1.55***	-0.47	0.057	-1.03	1.56***	-0.64	0.081	-0.97
	(0.55)	(0.86)	(0.68)	(1.06)	(0.56)	(0.86)	(0.68)	(1.06)
log(N. disciplines)	0.49	1.38	0.57	0.76	0.48	1.72	0.53	0.65
	(0.70)	(1.50)	(1.00)	(1.58)	(0.70)	(1.45)	(1.01)	(1.58)
Constant	1.51	5.86	2.00	10.5	1.48	7.07	1.90	10.1
	(2.83)	(6.44)	(4.74)	(7.13)	(2.85)	(6.49)	(4.70)	(7.20)
Observations	1,460	1,460	1,460	1,460	1,460	1,460	1,460	1,460
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-sample means	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

NOTE: Standard errors are clustered at the lab level. The asteriscs represent the following significance levels *** p<0.01, ** p<0.05, * p<0.1

Table B.3 reports the marginal effect of regressors using Tobit estimations.

Table B.3: Regression results, Tobit average marginal effects

	(1) Share at 0	(2) Share 1-3	(3) Share >=4	(4) Share not connected	(5) Share at 0	(6) Share 1-3	(7) Share >=4	(8) Share not connected
N. of grants per 100 res	-0.011	-0.073	0.048	0.013				
	(0.018)	(0.053)	(0.034)	(0.050)				
N. of national grants per 100 researchers					-0.0091	-0.15**	0.057	0.037
					(0.023)	(0.068)	(0.045)	(0.064)
N. of EU grants per 100 researchers					-0.025	0.36*	0.0030	-0.12
					(0.058)	(0.19)	(0.14)	(0.21)
At least one company	0.57**	2.22***	-0.70	-1.96**	0.58**	1.91**	-0.66	-1.85*
	(0.26)	(0.81)	(0.66)	(0.96)	(0.26)	(0.80)	(0.66)	(0.97)
Institut Carnot	0.68	-0.38	-1.37	-0.18	0.68	-0.42	-1.36	-0.15
	(0.59)	(1.79)	(0.91)	(2.02)	(0.59)	(1.82)	(0.91)	(2.03)
log(N. publications per 100 researchers)	-1.57***	-2.57**	-1.31	4.86***	-1.57***	-2.78**	-1.30	4.95***
	(0.38)	(1.17)	(0.84)	(1.27)	(0.38)	(1.15)	(0.84)	(1.29)
log(Lab age)	-0.27*	0.32	-1.08***	0.84	-0.27*	0.34	-1.08***	0.83
	(0.16)	(0.55)	(0.40)	(0.61)	(0.16)	(0.55)	(0.40)	(0.61)
log(Lab size [N. of researchers])	0.94***	-0.45	0.054	-1.00	0.95***	-0.62	0.076	-0.94
	(0.33)	(0.83)	(0.64)	(1.03)	(0.33)	(0.83)	(0.64)	(1.03)
log(N. disciplines)	0.30	1.34	0.54	0.74	0.29	1.66	0.50	0.63
	(0.43)	(1.45)	(0.93)	(1.53)	(0.43)	(1.40)	(0.94)	(1.53)
Observations	1460	1460	1460	1460	1460	1460	1460	1460
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-sample means	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

NOTE: Standard errors are clustered at the lab level. The asteriscs represent the following significance levels *** p<0.01, ** p<0.05, * p<0.1

Appendix C

In the analysis reported in Table 5, we use *Microsoft Academic Graph* (MAG) as a data source to calculate the scientific citation network. Although considered a reliable source for citation data (Martín-Martín et al., 2021), MAG was updated only until 2018. This time limit of MAG impacts the calculation of the citation network in recent years, as shown in the descriptive statistics for 2014 and 2015 reported in Table 3. In this appendix, we conduct a robustness check using an alternative source of citation data: *Opencitations* (opencitations.net). The advantage of *Opencitations* compared to *Microsoft Academic Graph* is that its citation data time coverage reaches 2020; however, the drawback of *Opencitations* is the partial coverage of some important publishers, missing a non-negligible share of citation data.

Although the peculiarities of the two data sources in terms of citation data coverage, Table C.1 shows that our main results are robust to the construction of the citation network with *Opencitation*. Indeed, Table C.1 shows results aligned with Table 5 in the main text.

Table C.1: Regression results using Opencitations data, Ordinary Least Square (OLS) estimates

	(1) log (1+Share at 0)	(2) log (1+Share 1-3)	(3) log (1+Share >=4)	(4) log (1+Share not connected)	(5) log (1+Share at 0)	(6) log (1+Share 1-3)	(7) log (1+Share >=4)	(8) log (1+Share not connected)
N. of grants per 100 res	-0.0025	-0.0084***	-0.0040	0.0018				
	(0.0035)	(0.0030)	(0.0043)	(0.0017)				
N. of national grants per 100 researchers					-0.0022	-0.015***	-0.0038	0.0068**
					(0.0041)	(0.0034)	(0.0048)	(0.0028)
N. of EU grants per 100 researchers					-0.0039	0.032***	-0.0047	-0.027**
					(0.012)	(0.012)	(0.015)	(0.013)
At least one company	0.12**	0.14***	0.024	0.034	0.12**	0.11**	0.024	0.055
	(0.058)	(0.051)	(0.057)	(0.034)	(0.058)	(0.048)	(0.058)	(0.035)
Institut Carnot	0.096	0.046	-0.25*	0.11**	0.096	0.042	-0.25*	0.12**
	(0.11)	(0.11)	(0.13)	(0.045)	(0.11)	(0.11)	(0.13)	(0.050)
log(N. publications per 100 researchers)	-0.21***	0.0043	-0.15**	0.040	-0.21***	-0.014	-0.15**	0.052
	(0.069)	(0.064)	(0.072)	(0.057)	(0.069)	(0.060)	(0.072)	(0.053)
log(Lab age)	-0.052	0.039	0.052	-0.012	-0.052	0.040	0.052	-0.012
	(0.036)	(0.032)	(0.039)	(0.015)	(0.036)	(0.031)	(0.039)	(0.015)
log(Lab size [N. of researchers])	0.095	0.010	-0.021	-0.14***	0.096	-0.0043	-0.021	-0.13***
	(0.060)	(0.048)	(0.067)	(0.045)	(0.060)	(0.048)	(0.067)	(0.042)
log(N. disciplines)	0.040	0.0028	0.042	0.22***	0.039	0.032	0.041	0.20***
	(0.079)	(0.087)	(0.095)	(0.062)	(0.080)	(0.085)	(0.095)	(0.055)
Constant	0.88**	0.64**	1.51***	1.62***	0.88**	0.72**	1.51***	1.61***
	(0.37)	(0.32)	(0.42)	(0.50)	(0.37)	(0.31)	(0.42)	(0.48)
Observations	1,460	1,460	1,460	1,460	1,460	1,460	1,460	1,460
R-squared	0.474	0.675	0.422	0.591	0.474	0.684	0.422	0.603
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-sample means	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

NOTE: Standard errors are clustered at the lab level. The asteriscs represent the following significance levels *** p<0.01, ** p<0.05, * p<0.1

Appendix D

In Table 5, we used *Microsoft Academic Graph* (MAG) citation data to construct the scientific citation network and calculate our dependent variables. Specifically, we construct the citation network considering a 5-year time window after the publication date of the articles in our study sample (see section 3.3.1 for a detailed description of the construction of the dependent variables). However, using a 5-year window to construct the citation network for the articles published in 2014 and 2015 causes a truncation problem because *Microsoft Academic Graph* citation data are available only until 2018. Therefore, to avoid truncation problems, in this appendix, we reconstruct the citation network using a shorter time window of 3 years, and we recalculate our dependent variables accordingly.

Table D.1 shows that shortening the time window according to which the citation network is calculated decreases the share of articles at the technological frontier (*Share 0*) and close to the technological frontier (*Share 1-3*) while increasing the share of articles far from the technological frontier (*Share >=4*) and not connected to the technological frontier (*Share not connected*). These figures are expected because shortening the time window to 3 years decreases the size of the citation network and, consequently, the likelihood of reaching the technological frontier for the articles in our study sample.

Table D.1: Descriptive statistics. Dependent variables calculated using a 3-year/5-year window to define the scientific citation network

Observations: 1,460 lab-year pairs	Mean 5-year window (Table 5 regression)	Mean 3-year window (Table D.2 regression)
Dependent variables		
Share 0 [%]	3.31	0.95
Share 1-3 [%]	34.43	11.56
Share >=4 [%]	20.77	24.90
Share not connected [%]	41.49	62.59

Table D.2 reports the results of estimating our econometric models using the dependent variables calculated according to a 3-year time window. Results are similar to those reported in Table 5.

Table D.2: Regression results using a 3-year window to calculate the distance from the technological frontier, Ordinary Least Square (OLS) estimates

	(1) log (1+Share at 0)	(2) log (1+Share 1-3)	(3) log (1+Share >=4)	(4) log (1+Share not connected)	(5) log (1+Share at 0)	(6) log (1+Share 1-3)	(7) log (1+Share >=4)	(8) log (1+Share not connected)
N. of grants per 100 res	-0.0018	-0.0040	-0.0037	-0.000089				
	(0.0020)	(0.0039)	(0.0027)	(0.0014)				
N. of national grants per 100 researchers					0.00080	-0.0043	-0.0095***	0.0031**
					(0.0028)	(0.0046)	(0.0029)	(0.0015)
N. of EU grants per 100 researchers					-0.017**	-0.0025	0.030***	-0.018**
					(0.0084)	(0.014)	(0.0094)	(0.0075)
At least one company	0.086**	0.075	0.092*	0.015	0.097**	0.074	0.063	0.029
	(0.043)	(0.061)	(0.048)	(0.030)	(0.043)	(0.061)	(0.048)	(0.032)
Institut Carnot	0.051	-0.085	-0.16	0.11**	0.051	-0.085	-0.16	0.12**
	(0.13)	(0.10)	(0.16)	(0.044)	(0.13)	(0.10)	(0.17)	(0.046)
log(N. publications per 100 researchers)	-0.16***	0.015	-0.13**	0.097**	-0.15***	0.015	-0.15**	0.11**
	(0.051)	(0.093)	(0.061)	(0.047)	(0.051)	(0.094)	(0.060)	(0.047)
log(Lab age)	-0.049	-0.00087	-0.044	0.018	-0.050*	-0.00081	-0.044	0.018
	(0.030)	(0.039)	(0.031)	(0.015)	(0.030)	(0.039)	(0.030)	(0.015)
log(Lab size [N. of researchers])	0.064	0.068	-0.075	-0.050	0.070	0.067	-0.088*	-0.043
	(0.044)	(0.066)	(0.046)	(0.033)	(0.044)	(0.065)	(0.046)	(0.031)
log(N. disciplines)	0.044	-0.063	0.16**	0.041	0.033	-0.062	0.19***	0.028
	(0.064)	(0.11)	(0.072)	(0.050)	(0.064)	(0.11)	(0.072)	(0.049)
Constant	0.59**	0.56	1.53***	1.65***	0.57**	0.56	1.63***	1.64***
	(0.28)	(0.48)	(0.38)	(0.36)	(0.28)	(0.48)	(0.38)	(0.35)
Observations	1,460	1,460	1,460	1,460	1,460	1,460	1,460	1,460
R-squared	0.140	0.492	0.591	0.548	0.142	0.492	0.597	0.554
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-sample means	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

NOTE: Standard errors are clustered at the lab level. The asteriscs represent the following significance levels *** p<0.01, ** p<0.05, * p<0.1

ABOUT OFCE

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