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# DOES GRANT FUNDING FOSTER RESEARCH IMPACT? EVIDENCE FROM FRANCE

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MICHELE PEZZONI

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# Does grant funding foster research impact? Evidence from France\*

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## **Abstract:**

Over the last fifteen years, European countries have increasingly relied on competitive grants to allocate research funding, replacing the more traditional block funding model. Policymakers are interested in assessing the effectiveness of the grant funding model in producing impactful research. However, the literature aiming to quantify the effect of grants on the resulting research's impact is scant. In the French context, we compare the impact of scientific articles resulting from the support of competitive grants from the main national funding agency with the impact of articles not supported by grants. We rely on publication acknowledgments to retrieve funding information and on citation data to assess the articles' impact. We find that articles supported by competitive grants receive more citations than articles not supported by grants in the long run, while the difference is not statistically significant in the short run. We find heterogeneity in the effect of grant funding on citations across fields.

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## 1. Introduction

In the last fifteen years, European countries have supported research institutions introducing the competitive grant model for science funding to replace traditional block funding (Geuna, 2001; Stephan, 2012; De Boer et al., 2017; Wang et al. 2018; Veugelers et al., 2022). The competitive grant funding model echoes the one adopted in the U.S. and consists of public agencies evaluating project proposals to assign funds to researchers through a peer-review process. The block funding model echoes the one historically adopted by European countries and consists of a steady stream of funding, allocated either incrementally or on a formula basis, addressed to universities and research institutions.

Although scientific literature has already attempted to link grant funding and knowledge production at the researcher level (Arora and Gambardella, 2005; Defazio et al., 2009; Gush et al., 2018; Heyard and Hottenrott, 2021), the analysis of the impact of the knowledge produced with grant funding is still scant and relies on selected samples (Wang and Shapira, 2015; Gök et al., 2016; Tonta and Akbulut, 2020; Álvarez-Bornstein and Bordons, 2021). Nonetheless, studying the impact of the knowledge produced with grant funding is crucial because it concerns the effectiveness of governments' spending decisions for advancing science and technology and, ultimately, fostering countries' economic growth (Lane and Bertuzzi, 2011; Oancea, 2019; OECD, 2019). To fill this literature gap, our study aims to answer the question: does grant funding affect the impact of the knowledge produced?

We identified three possible mechanisms through which grant funding influences the impact of the knowledge produced. First, grants provide researchers with additional resources expected to increase the research quality and, ultimately, research impact. Second, grants are delivered by funding agencies whose stated goal is to support promising research ideas. Therefore, agencies are expected to select and fund high-impact research. Nonetheless, this assumption clashes with recent empirical evidence showing that funding agencies tend to be biased against risk and promote less novel and impactful research, contrary to what they claim (Veugelers et al., 2022; Franzoni et al., 2022). Third, grants might hamper impactful research by bounding research ideas and collaborations within the framework of the initially submitted research proposal. Indeed, the lack of flexibility in changing the research subject or the team composition might prevent researchers from following promising research avenues that unexpectedly emerge during the research effort.

Our paper contributes to the literature by shedding light on the effect of grant funding on the impact of the resulting research for a large European country. Moreover, it is the first study considering all the articles supported by public funding across research fields and authors' universities. Finally, unlike the previous literature, we apply a probabilistic matching approach to obtain unbiased estimates of the funding effect.

To assess the effect of competitive grant funding, we identify the articles supported by grants distributed by the *Agence Nationale de la Recherche* (ANR), the French main funding agency. We rely on scientific articles' acknowledgments to distinguish grant-funded articles published between 2009 and 2013 from articles without grant-funding support. Then, we implement a probabilistic matching approach to compare 6,441 ANR grant-funded articles with 6,441 similar non-grant-funded articles (Rubin, 2001; Dehejia and Wahba, 2002). Specifically, we compare the impact of similar publications according to observable authors' and articles' characteristics that differ only in the nature of the funding support. This technique allows us to mitigate the selection bias that arises when comparing the outcome of grant-funded research with the outcome of non-grant-funded research. To assess the articles' impact, we count the yearly citations received by the articles in the short and long run. Being  $t$  the article's publication date, we consider the citations in the short run as those received between  $t$  and  $t+2$ , and the citations in the long run as those received between  $t+3$  and  $t+5$ .

Our main finding is that articles acknowledging competitive grants receive 6.93% more citations than articles without grant support in the long run, while there is no statistical difference in the short run. When breaking down our analysis into four different research fields, we find that articles supported by competitive grants in Life sciences and Medicine, Engineering, and Physical sciences receive 15.06%, 13.87%, and 7.67% more citations in the long run. In addition, articles in Engineering supported by competitive grants are more cited in the short run (+8.15%). Finally, articles in Mathematics follow a different pattern: when supported by grant funding, they receive fewer citations than articles without grant support in the short run (-13.08%), while there is no statistically significant effect of grant funding in the long run.

## 2. Studying the relationship between grant funding and research impact

The empirical literature aiming to quantify the impact of research funding is still limited and far from reaching a consensus (Arora and Gambardella, 2005; Jacob and Lefgren, 2011; Gush et al., 2018; Heyard and Hottenrott, 2021). The vast majority of existing studies look at the change in researchers' publication outcomes when individual researchers are awarded competitive grants. These studies suggest that funding positively affects researchers' productivity. However, the extent to which researchers' productivity benefits from funding is not clear, and not all the empirical evidence confirms the positive impact of funding. Arora and Gambardella (2005) and Gush et al. (2018) evidence a modest positive impact of grant funding on researchers' productivity. Heyard and Hottenrott (2021) find a significant impact of grant funding on researchers' publication quantity, quality, and dissemination for researchers granted by the Swiss National Science Foundation. Mariethoz et al. (2021) claim no correlation between grant funding, researchers' publication, and citation records in Geo-sciences.

Another strand of literature analyzes the effect of funding at the publication level. Some studies find a positive impact of grant funding on publications' citations received and the prestige of the journals where articles are published (Campbell et al., 2010; Zhao, 2010; Wang and Shapira, 2015; Yan et al. 2018; Álvarez-Bornstein and Bordons, 2021). Nonetheless, other studies find a modest effect for selected samples of articles published in specific journals (Rigby, 2013), in specific fields (Haslam et al., 2008), or when focusing on specific funding programs (Langfeldt et al., 2015) or countries (Tonta and Akbulut, 2020).

We expect three possible mechanisms through which competitive grant funding affects the citations received by the articles produced by researchers awarded grants. First, the additional monetary resources provided by grants might increase the likelihood of producing impactful research. Researchers can exploit these resources to bear the cost of state-of-the-art equipment, access to data, and an additional workforce in the lab (Katz and Martin, 1997). Moreover, the grant application guidelines often imply that part of the monetary resources must be contractually devoted to better disseminate the research results to foster the articles' scientific impact<sup>1</sup>. Second, funding agencies claim to support breakthrough research (ANR, 2020; Franzoni et al., 2022).

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<sup>1</sup> See a 2022 ANR *Generic Call for Proposals*, page 20. A part of the budget is foreseen for a “Strategy for disseminating and exploiting results; promoting scientific, technical and industrial knowledge”. Website: <https://anr.fr/fileadmin/aap/2022/aapg-2022-v1.1a-en.pdf>.

Therefore, the selection process conducted by the ANR funding agency is expected to identify breakthrough research projects that lead researchers to produce articles more likely to be cited (Lewison and Dawson, 1998; Wang et al., 2017). Despite what funding agencies claim, a strand of recent literature is skeptical about funding agencies' claim to fund breakthrough research and highlights how funding agencies tend to be risk-averse, selecting safe projects that ensure concrete results in the short-term (Stephan et al., 2017; Veugelers et al., 2022; Franzoni et al., 2022). In this latter case, the support of competitive grants might reduce the articles' impact. Third, grants might bound research ideas within the framework of a submitted research proposal. Grant-funded researchers are forced to pursue their initial idea and must deliver results related to the project proposed to the funding agency. If the project does not develop according to the initial researchers' expectations, its results might be less impactful (Wei et al., 2013). Similarly, research collaborations stated in the project proposed to the funding agency might lead to a lack of flexibility in changing the configuration of the research team, reducing the impact of the project outcomes. Indeed, collaborations stated in the proposed project can also be used for non-scientific purposes. For instance, highly reputed scientists might be included in the project to increase the chances of obtaining the grant (Katz and Martin, 1997).

One original contribution of our study is that we assess the effect of grant funding considering all the articles produced by the awarded researchers across research fields. We expect research funding to affect the publications' impact differently across fields. Research fields differ in research methods, teamwork approach, international vocation, and funding use. For example, researchers in equipment-based fields, such as Engineering or Physical sciences, may benefit more than Mathematics from grants' additional resources by purchasing the state-of-the-art equipment needed to carry out impactful research. Similarly, collaboration-oriented research fields may require additional funding from grants to cultivate broad collaborations and foster researchers' mobility to produce impactful research.

### 3. Empirical framework, data, and methodology

#### 3.1 Empirical framework

We conduct our empirical analysis in France, where researchers are funded in two ways. First, French researchers benefit from block funding through a monthly salary paid by their university of affiliation or by a national public research organization<sup>2</sup> (OECD, 2019). Second, French researchers can apply for research grants. France launched its national funding agency, *Agence Nationale de la Recherche* (ANR), in 2005. ANR distributes funds to individual researchers based on a competitive peer-reviewed process. The main goal of the ANR is to “*promote research in all its forms [...] on the principle of peer review based on scientific excellence*”<sup>3</sup>. Since 2006, it has distributed around 1,100 individual grants per year. In 2019, it awarded 1,157 research projects with an average budget of 400,000 euros per project. Applications from all disciplines are eligible.

#### 3.2 Data

We rely on the funding acknowledgment information reported in scientific articles to identify grant-funded and non-grant-funded publications (Rigby, 2011; Gok et al. 2016; Grassano et al., 2016). Specifically, we retrieve the acknowledgment information from the *Web of Science* (WOS) bibliometric dataset provided by Clarivate<sup>4</sup>. We use *Microsoft Academic Graph* (MAG) citation data to assess the publication impact.

We construct our universe of publications by collecting all the 481,536 scientific articles published between 2009 and 2013, having at least one author affiliated with a French institution and a *Digital Object Identifier* (DOI). We choose 2009 as the starting date of our analysis because WOS acknowledgment data are reliable only starting from that date (Mongeon and Paul-Hus, 2016; Mejia, 2017). We choose 2013 as the end year because MAG citation data are unreliable after 2018 and, for the articles published in 2013, we need a 6-year forward citation window to evaluate their impact. We focus on scientific articles and exclude other types of publications, such as reviews or book chapters. Moreover, we limit our analysis to publications written in English because WOS collects acknowledgments only for those publications. Finally, we exclude journals

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<sup>2</sup> The largest public research organization in France is the *Centre national de la recherche scientifique* (CNRS).

<sup>3</sup> Website: <https://anr.fr/fileadmin/documents/2021/ANR-RA2020-en.pdf>, page 04.

<sup>4</sup> Web of Science (WOS) provides two acknowledgment fields, one reporting the raw text as written in the paper and the other is an artificial field that already extracted the names of the funding organizations from the raw text through an algorithm. The WOS algorithm does not seem to be accurate, thus we rely on the raw text of the acknowledgments.

in Social Sciences and Humanities because, for these disciplines, WOS reports reliable acknowledgments only starting from 2015 (Álvarez-Bornstein et al., 2017; Liu et al., 2020). After applying all the previously mentioned constraints, we obtained a sample of 283,873 scientific articles.

We retrieve articles' and authors' characteristics used for the matching identification strategy from Elsevier's SCOPUS database. We add information on the authors' gender by matching the authors' given names with French<sup>5</sup> and international gender-name databases<sup>6</sup>. We use the QS university ranking<sup>7</sup> to characterize the prestige of the authors' affiliations. Our sample of 283,873 publications can not be promptly matched with the complementary information retrieved from these databases. For instance, when we attribute gender to authors by matching the authors' names with the gender-name datasets, we can not attribute gender to all the authors for 84,943 articles. In this case, we remove the corresponding articles from our dataset. After matching the articles' and authors' characteristics, we end up with a study sample of 195,435 articles.

### *3.3 Identifying grant-funded articles and non-grant-funded articles*

From our sample of 195,435 articles, we select all 23,950 articles acknowledging at least one ANR grant among the funding sources (12.25% of the publications in our sample). To avoid mixing the effects of several funding sources contributing to the research outcome described in an article, we limit the sample of grant-funded articles to the 6,441 publications reporting only ANR grants as the funding source. In other words, we excluded the articles acknowledging other non-ANR grants in addition to an ANR grant<sup>8</sup>.

To identify publications without grant funding, we considered articles that do not report any acknowledgment. The logic is that if no grant acknowledgment is reported in an article, the research outcome described in the article is likely to result from government block funding used to pay the researcher's salary and the lab equipment. Among the 195,435 publications in our sample, we identified 76,615 articles with no acknowledgments. This figure corresponds to 39.2% of our sample, in line with previous studies (Grassano et al., 2016).

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<sup>5</sup> Website: <https://www.data.gouv.fr/fr/datasets/liste-de-prenoms/>

<sup>6</sup> Authors' names non-matched with the French dataset are matched with the *U.S. Census Bureau* gender-name dataset and the WIPO gender-name dataset (website: <https://www.wipo.int/publications/en/details.jsp?id=4125>).

<sup>7</sup> Website: <https://www.topuniversities.com>

<sup>8</sup> See the robustness check section for an empirical analysis in which we consider as ANR grant-funded articles also the articles supported by additional competitive grants other than ANR.

### 3.4 Methodology

Our analysis compares the impact of articles resulting from the support of ANR grants with the impact of articles not supported by any grant. We measure the articles' impact in the short and long run. To measure the impact in the short run, we count the number of yearly citations received by an article in the first three years after its publication, i.e., from year  $t$  to  $t+2$ , where  $t$  is the year of publication. To measure the impact in the long run, we count the number of yearly citations received by an article from year  $t+3$  to  $t+5$ .

A simple comparison between the number of citations received by the 6,441 grant-funded and the 76,615 non-grant-funded articles is likely to be affected by a selection bias (Jaffe, 2002). Indeed, grant-funded and non-grant-funded articles might systematically differ in other aspects than the funding source. For example, the articles' or authors' characteristics, such as collaborative behaviors, team composition, and stock of knowledge, might relate both to the likelihood of observing grant-funded research and to the articles' impact (Wuchty et al., 2007; Ebadi and Schiffauerova, 2015; Mukherjee et al. 2017; Bol et al., 2018; Bianchini et al., 2022). Therefore, we adopt a Propensity Score Matching (PSM) procedure that relies on the "nearest neighbor" approach to mitigate the potential selection bias. This approach compares each of the 6,441 articles funded by an ANR grant with a similar article without grant funding. The similarity between articles is assessed by a probabilistic score based on the articles' and authors' observable characteristics. Specifically, we run a logistic regression where the left-hand-side variable is represented by the dummy variable *Grant-funded* which equals one if the article acknowledges an ANR grant as the unique funding source, and zero if it does not report any acknowledgment. As right-hand-side variables, we consider variables measuring the article's and authors' characteristics. We include three dummy variables characterizing the co-authorship behavior. Specifically, the dummy variable *Single-author article* equals one if the article has only one author, zero otherwise. The dummy variable *Multi-author article 2-4* equals one if the article has between two and four authors, and the dummy variable *Multi-author article > 4* equals one if the article has more than four authors. To account for international collaborations, we include the dummy variable *At least one international author* that equals one if there is at least one international author among the article's authors, zero otherwise. We define international authors as those reporting only non-French affiliations in the focal article. To account for the team gender composition, we add the dummy variable *At least one female author* which equals one if there is at least one female

among the article’s authors, zero otherwise. Moreover, we identify the article’s authors affiliated with top-ranked universities with the dummy variable *At least one top-affiliate author* which equals one if there is at least one author affiliated with a top-ranked university among the article’s authors, zero otherwise. To identify the top-ranked universities, we rely on the *QS ranking*<sup>9</sup>. Specifically, we identify the top-ten-ranked universities in France and the top-fifty-ranked universities worldwide. We include the dummy variable *Multiple affiliations* to account for the geographical dispersion of the authors. The dummy variable *Multiple affiliations* equals one if the number of distinct affiliations reported in the focal article is greater than one, zero otherwise. We also include four dummy variables representing the quartiles of the articles’ backward citation distribution. Specifically, we created the dummy variable *Backward citations Q1* in three steps. First, we select all the articles in our sample published in the same year as the focal article. Then, we calculate the quartiles of the distribution of the number of backward citations. Finally, we define the dummy variable *Backward citations Q1* as equal to one if the focal article’s backward citation number belongs to the first quartile, zero otherwise. With the same logic, we created the dummy variables *Backward citations Q2*, *Backward citations Q3*, and *Backward citations Q4*, for the second, third, and fourth quartiles, respectively. To account for the heterogeneity in the publication behavior across fields of study, we add a set of dummy variables that classify the articles in four fields of study, according to the journals where they have been published<sup>10</sup>. The dummy variable *Mathematics* equals one if the article is published in a Mathematical journal, zero otherwise. Similarly, we calculate the dummy variables *Engineering*, *Physical sciences*, and *Life sciences and Medicine*. Finally, to control for the cohort publication effect, we include a set of five dummy variables defined according to the year of publication of the focal article (*Year of publication*).

Table 1 reports the variables’ names and briefly describes how variables are calculated.

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<sup>9</sup> <https://www.topuniversities.com/university-rankings>. We gather the ranking information in 2020, however university ranking has minor variation over the years when considering top-universities.

<sup>10</sup> See Appendix H for a detailed explanation of the methodology used to classify articles in research fields.

**Table 1. List of variables used to predict the probability of observing an ANR grant-funded article.**

Articles' and authors' characteristics	Variable description
<i>Explained variable</i>	
Grant-funded	Dummy variable that equals one if the article reports ANR grants as the unique funding source in the acknowledgments.
<i>Explanatory variables</i>	
Single-author article	Dummy variable that equals one if the article has only one author.
Multi-author article 2-4	Dummy variable that equals one if the article has two to four authors.
Multi-author article > 4	Dummy variable that equals one if the article has more than four authors.
At least one international author	Dummy variable that equals one if the article has at least one international author.
At least one female author	Dummy variable that equals one if the article has at least one female author.
At least one top-affiliate author	Dummy variable that equals one if at least one article's author is affiliated with a university ranked in the top ten in France or the top 50 worldwide according to the QS ranking.
Multiple affiliations	Dummy variable that equals one if the affiliations of the article's authors are more than one at the publication date.
Backward citations Q1	Dummy variable that equals one if the number of article's backward citations belongs to the first quartile of the backward citation distribution of our sample of articles in the same publication year.
Backward citations Q2	Dummy variable that equals one if the number of article's backward citations belongs to the second quartile of the backward citation distribution of our sample of articles in the same publication year.
Backward citations Q3	Dummy variable that equals one if the number of article's backward citations belongs to the third quartile of the backward citation distribution of our sample of articles in the same publication year.
Backward citations Q4	Dummy variable that equals one if the number of article's backward citations belongs to the fourth quartile of the backward citation distribution of our sample of articles in the same publication year.
Life sciences and Medicine	Dummy variable that equals one if the article is published in a journal classified in Life sciences or Medicine.
Mathematics	Dummy variable that equals one if the article is published in a journal classified in Mathematics.
Engineering	Dummy variable that equals one if the article is published in a journal classified in Engineering.
Physical sciences	Dummy variable that equals one if the article is published in a journal classified in Physical sciences.
Year of publication	The publication year of the article.

Table 2 shows the average marginal effects calculated from the coefficients estimated with a logistic regression. We find that articles with 2 to 4 authors have a 4.4 percentage point higher probability of acknowledging an ANR grant than single-author articles. Articles with more than four authors have a 5.8 percentage point higher probability of acknowledging an ANR grant than single-author articles. Interestingly, we find that the presence of an international author among the article's authors is associated with a 7.3 percentage point lower probability of acknowledging an ANR grant than articles without international authors. Moreover, the presence of a female author is associated with a lower probability that an ANR grant is acknowledged by the article (-0.71

percentage points), while the presence of an author affiliated with a top-ranked university is associated with a 2 percentage point higher probability to acknowledge ANR. Moreover, articles reporting multiple affiliations are associated with a 1.1 percentage point higher probability of acknowledging ANR. Concerning the article's characteristics, articles belonging to the fourth quartile of the backward citations distribution are 6 percentage points more likely to acknowledge ANR grants than articles belonging to the first quartile. Finally, articles published in Mathematical and Physical journals are more likely to acknowledge an ANR grant than those published in Life sciences, Medicine, and Engineering.

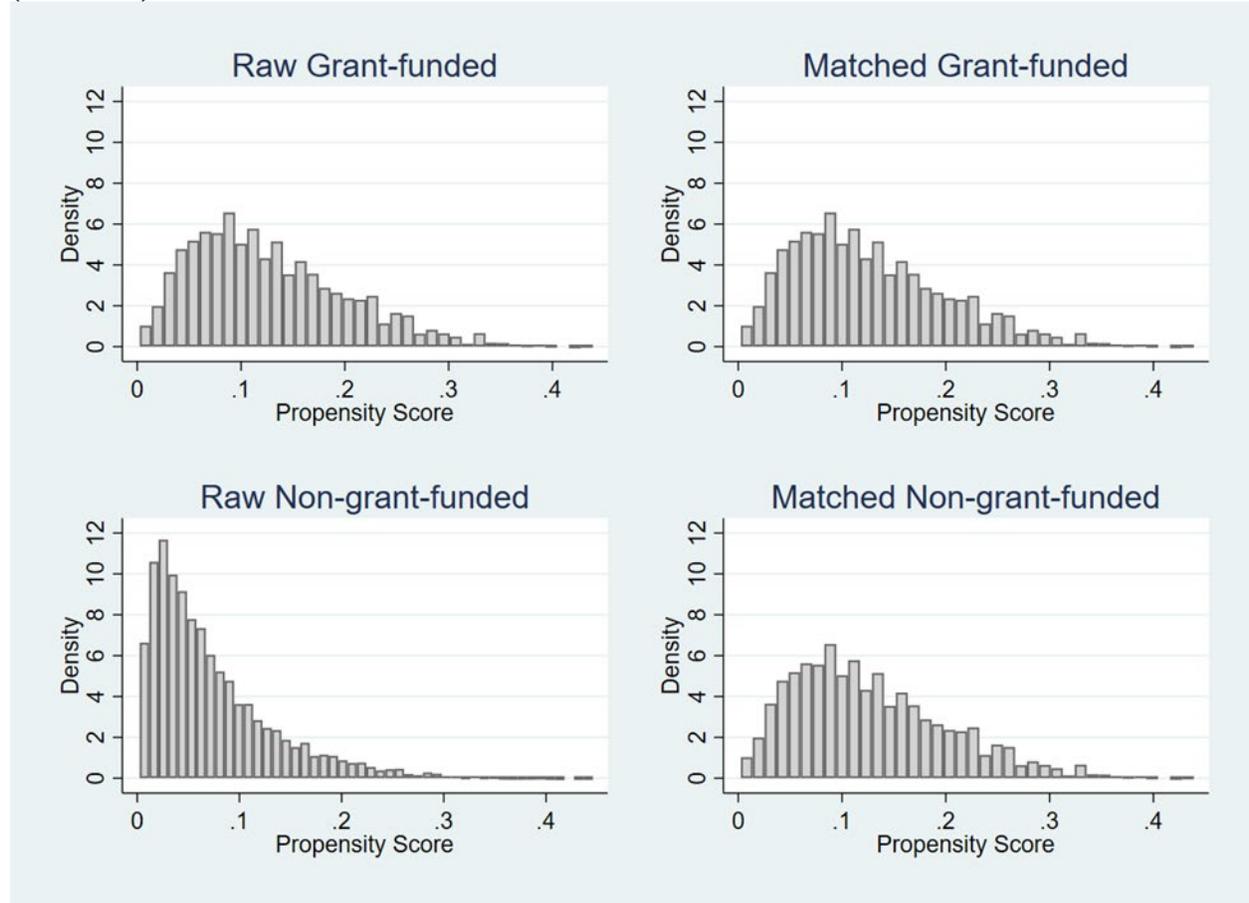
Using the estimates reported in Table 2, we predict the probability of an article to acknowledge an ANR grant. According to these predictions, for each of the 6,441 articles funded by ANR, we match an article drawn from the sample of 76,615 articles without grant acknowledgments and with the most similar probability of acknowledging ANR. In other words, we select the “nearest neighbor” to the grant-funded article according to the propensity score value. Figure 1 reports the histograms of the density of propensity scores for the articles before (raw grant-funded versus raw non-grant-funded) and after matching (matched grant-funded versus matched non-grant-funded). We observe that after the matching, the propensity score distribution of the grant-funded articles is almost identical to the propensity score distribution of the non-grant-funded articles. The similarity between the two distributions after the matching ensures the quality of the matching exercise. To further assess the quality of the matching exercise, Table 3 compares the characteristics of the grant-funded articles with those of the non-grant-funded articles for the raw sample before the Propensity Score Matching (columns 1 and 2) and the sample of similar articles obtained after the matching resulting by applying the Propensity Score Matching procedure (columns 3 and 4). Columns 3 and 4 show that the matched samples of grant-funded and non-grant-funded articles have statistically equivalent articles' and authors' characteristics. Indeed, the P-values of all the tests of the difference between the means reported in Column 3 and Column 4 cannot reject the null hypothesis that the two means are statistically equivalent.

**Table 2. Average marginal effects of the article's probability of acknowledging an ANR grant.**

	(1) Grant-funded
Single-author article	Ref.
Multi-author article 2-4	0.044*** (0.0037)
Multi-author article > 4	0.058*** (0.0042)
At least one international author	-0.073*** (0.0026)
At least one female author	-0.0071*** (0.0021)
At least one top-affiliate author	0.020*** (0.0019)
Multiple affiliations	0.011*** (0.0022)
Backward citations Q1	Ref.
Backward citations Q2	0.026*** (0.0030)
Backward citations Q3	0.042*** (0.0029)
Backward citations Q4	0.060*** (0.0028)
Life sciences and Medicine	Ref.
Mathematics	0.070*** (0.0024)
Engineering	-0.0052** (0.0022)
Physical sciences	0.068*** (0.0020)
Year of publication	0.014*** (0.00064)
Pseudo R2	0.0858
Number of articles	83,056

NOTE: Average marginal effects are calculated from estimated logit coefficients. Standard errors in parentheses. Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

**Figure 1. Histograms of the density of propensity scores before (Raw) and after matching (Matched).**



NOTE: Distribution of the propensity scores for grant-funded articles (upper part of the figure) and non-grant-funded articles (bottom part), before (left part) and after (right part) the *nearest neighbor* Propensity Score Matching.

**Table 3. Means of the articles' and authors' observable characteristics for grant- and non-grant-funded articles, before (Columns 1 and 2) and after matching (Columns 3 and 4).**

	Raw sample before PSM			PSM sample		
	(1) Grant-funded	(2) Non-grant-funded	p-value	(3) Grant-funded	(4) Non-grant-funded	p-value
Single-author article	0.075***	0.109	0.000	0.075	0.075	0.973
Multi-author article 2-4	0.539***	0.483	0.000	0.539	0.549	0.265
Multi-author article > 4	0.386***	0.408	0.001	0.386	0.376	0.246
At least one international author	0.153***	0.279	0.000	0.153	0.155	0.714
At least one female author	0.596***	0.628	0.000	0.596	0.599	0.788
At least one top-affiliate author	0.399***	0.315	0.000	0.399	0.400	0.928
Multiple affiliations	0.693*	0.682	0.058	0.693	0.692	0.924
Backward citations Q1	0.145***	0.269	0.000	0.145	0.143	0.861
Backward citations Q2	0.225***	0.249	0.000	0.225	0.225	0.950
Backward citations Q3	0.278***	0.241	0.000	0.278	0.280	0.829
Backward citations Q4	0.352***	0.240	0.000	0.352	0.352	0.985
Life sciences and Medicine	0.265***	0.492	0.000	0.265	0.257	0.316
Mathematics	0.280***	0.189	0.000	0.280	0.282	0.829
Engineering	0.231***	0.199	0.000	0.231	0.228	0.691
Physical sciences	0.577***	0.380	0.000	0.577	0.577	0.957
Year of publication	2011.31***	2010.90	0.000	2011.31	2011.30	0.661
<i>N. of publications</i>	<i>6,441</i>	<i>76,615</i>		<i>6,441</i>	<i>6,441</i>	

NOTE: Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

#### 4. Results

We estimate the impact of grant-funded articles by calculating the difference between the number of citations received by grant-funded articles and non-grant-funded articles. As explained in section 3.3., we measure the articles' impact in the short and long run by counting the citations received by the article from  $t$  to  $t+2$  and from  $t+3$  to  $t+5$ , respectively. We rely on t-tests to estimate the impact differences. T-tests are valid for any distribution in large samples, including highly non-normal distributions (Lumley et al. 2002; Tonta and Akbulut, 2020).

Table 4, Column 1, shows that in the short run there is no statistically significant difference between the impact of articles acknowledging ANR grants and those not supported by any grant. On the contrary, Table 4, Column 2, shows that articles acknowledging ANR grants receive, on average, 0.580 more citations than articles not supported by any grant in the long run (*Grant-funded effect*). The value of 0.580 corresponds to 6.93% more citations received by grant-funded articles than by non-grant-funded articles (*Grant-funded relative effect*).

**Table 4. Grant funding effect on publications' number of citations received.**

	(1) Short run Citations from t to t+2	(2) Long run Citations from t+3 to t+5
6,441 Grant-funded + 6,441 Non-grant-funded		
Average citations Grant-funded articles (A)	6.403	8.943
Average citations Non-grant-funded articles (B)	6.628	8.363
Grant-funded effect (A-B)	-0.225	0.580 **
Grant-funded relative effect (A-B)/B	-3.4%	+6.93% **
<i>t</i> -statistic	-1.438	2.450
<i>p</i> -value	0.15	0.014

NOTE: Significance levels at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

## 5. Heterogeneity across research fields

To dig into a possible cross-field heterogeneity of the grant funding effect on articles' impact, we run four separated Propensity Score Matching exercises, one for each of the research fields in which we classify the articles. Specifically, we analyze articles in Life sciences and Medicine, Mathematics, Engineering, and Physical sciences. We use the journal field classification provided by SCOPUS<sup>11</sup> to classify the articles according to their research field. To avoid ambiguities in the classification, we excluded articles published in multidisciplinary journals, such as *Nature* or *Science*, given the impossibility of assigning a research field to those journals. If an article is published in a journal that SCOPUS classifies in more than one field, we attribute the article to each of the fields in which the journal is classified. In doing so, we obtain a sample of 3,416 articles in Life sciences and Medicine (1,708 grant-funded and 1,708 non-grant-funded articles, respectively), 3,612 articles (1,806\*2) in Mathematics, 2,978 articles (1,489\*2) in Engineering, and 7,438 articles (3,719\*2) in Physical sciences, for a total of 17,444 articles. This latter number is higher than the one reported in Table 4 (12,882=6,441\*2) due to the double counting of articles published in journals classified in more than one field.

Table 5, Column 1, shows that in the short run, articles in Mathematics acknowledging ANR grants receive, on average, 13.08% fewer citations than articles not supported by grants. On the contrary, grant-funded articles in Engineering receive 8.15% more citations than non-grant-funded articles. Looking at the other research fields in the short run, we do not find any statistically significant difference in the number of citations received by grant-funded and non-grant-funded articles.

<sup>11</sup> See Appendix H for a detailed explanation of the methodology used to classify articles in research fields.

Table 5, Column 2, shows that in the long run, articles acknowledging ANR grants benefit from a higher impact than articles without grant support in three research fields: Life sciences and Medicine, Engineering, and Physical sciences. Life sciences and Medicine and Engineering, show the largest citation gap between grant-funded and non-grant-funded articles, +15.06% and +13.87%, respectively. In Physical sciences, the citation gap in favor of grant-funded articles equals +7.67%. Interestingly, in Mathematics, grant-funded and non-grant-funded articles do not show any citation gap in the long run.

In Appendix A, we report the tables showing the logit estimates of the articles' probability of acknowledging an ANR grant and the covariate balance tables pre- and post-matching for each of the four research fields analyzed.

**Table 5. Grant funding effect on publications' number of citations received by field of research.**

	(1) Short run Citations from t to t+2	(2) Long run Citations from t+3 to t+5
<b>Life sciences and Medicine</b>		
1,708 Grant-funded + 1,708 Non-grant-funded		
Average citations Grant-funded articles (A)	8.228	11.888
Average citations Non-grant-funded articles (B)	8.338	10.332
Grant-funded effect (A-B)	-0.11	1.556 ***
Grant-funded relative effect (A-B)/B	-1.32%	+15.06% ***
<i>t-statistic</i>	-0.333	2.931
<i>p-value</i>	0.74	0.003
<b>Mathematics</b>		
1,806 Grant-funded + 1,806 Non-grant-funded		
Average citations Grant-funded articles (A)	3.950	5.679
Average citations Non-grant-funded articles (B)	4.545	5.946
Grant-funded effect (A-B)	-0.595 **	-0.267
Grant-funded relative effect (A-B)/B	-13.08% **	-4.5%
<i>t-statistic</i>	-2.163	-0.639
<i>p-value</i>	0.031	0.52
<b>Engineering</b>		
1,489 Grant-funded + 1,489 Non-grant-funded		
Average citations Grant-funded articles (A)	7.126	10.462
Average citations Non-grant-funded articles (B)	6.589	9.188
Grant-funded effect (A-B)	0.537 *	1.274 **
Grant-funded relative effect (A-B)/B	+8.15% *	+13.87% **
<i>t-statistic</i>	1.959	2.521
<i>p-value</i>	0.0502	0.012
<b>Physical sciences</b>		
3,719 Grant-funded + 3,719 Non-grant-funded		
Average citations Grant-funded articles (A)	6.805	9.292
Average citations Non-grant-funded articles (B)	6.770	8.630
Grant-funded effect (A-B)	0.035	0.662 **
Grant-funded relative effect (A-B)/B	+0.51%	+7.67% **
<i>t-statistic</i>	0.169	2.227
<i>p-value</i>	0.87	0.026

NOTE: Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

## 6. Robustness checks

This section presents six robustness checks of the analyses conducted in Table 4 to estimate the impact of articles published with the support of ANR grants.

### 6.1 *Measuring the impact as a yearly citation number*

In Appendix B, we estimate the effect of grant funding on the articles' number of citations received in each of the six years after publication, instead of defining two periods of three years as in the main analysis reported in Table 4. Table B1 shows that grant-funded articles receive fewer citations than non-grant-funded articles in the first year after publication (-30.85%). On the contrary, grant-funded articles receive more citations than non-grant-funded articles starting from the third year after publication. This robustness check is in line with the results reported in Table 4, showing that grant-funded articles receive fewer citations in the short run and more citations in the long run than non-grant-funded articles.

### 6.2 *Using SCOPUS citation data*

In Appendix C, we calculate the articles' impact using the SCOPUS bibliometric dataset instead of *Microsoft Academic Graph* as the citation data source. SCOPUS does not provide punctual information on the citations received by an article each year, but only the aggregate number of citations at the moment of the data query (in our case, 2019). Therefore, we calculate the SCOPUS average yearly citations retrieving the cumulated number of each article's citations in 2019, and dividing it by the years elapsed between the article's publication date and 2019. In doing so, we can not distinguish between the short and long run. Using SCOPUS as an alternative source of citation data, we find that grant-funded articles receive, on average, 4.40% more yearly citations than articles without grant support (Table C1). This result is consistent with the positive effect of grant funding on the articles' citations received in the long run reported in Table 4.

### 6.3 *Including French authors' characteristics*

In Appendix D, we add three variables describing the French authors' academic status to the propensity score matching equation. We include the dummy variable *At least a French star author* that equals one if there is at least one French star scientist among the article's authors. We define a French star scientist as a researcher with a French affiliation who belongs to the highest quartile of the distribution of French researchers according to their cumulative stock of citation-weighted

publications from 1990 to the focal article's publication year. Then, we add the dummy variable *At least a French senior author* which equals one if there is at least one French senior scientist among the article's authors. We define a French senior scientist as a researcher with a French affiliation whose first publication is more than 10 years before the publication year of the focal article. Finally, we include the dummy variable *At least a French Ph.D. student author* that equals one if there is at least one French Ph.D. student among the article's authors. To identify French Ph.D. students we rely on the French repository of *Electronic Doctoral Theses* (EDT) from which we retrieve the list of all French Ph.D. students and their graduation year.

This robustness check allows us to account for the French authors' characteristics when constructing the control sample of non-grant-funded articles using the Propensity Score Matching procedure. French authors' characteristics are likely to influence the ANR selection process for attributing grants the most. Indeed, ANR's goal is to fund researchers affiliated with French universities, and existing literature has shown that highly recognized scientists are more likely to have access to grants (Allison et al., 1982; Ebadi and Schiffauerova, 2015; Wang et al., 2018).

Table 6 reports the results of the Propensity Score Matching. The number of article pairs in Table 6 reduces to 5,537 from the 6,441 article pairs analyzed in Table 4. This reduction is due to applying a restriction on the maximum difference in propensity score between the grant-funded articles and the corresponding non-grant-funded articles. The 904 (6,441-5,537) article pairs which overcome this maximum value are not considered in the study sample (see Appendix D for a detailed explanation). This restriction is necessary to keep our sample balanced in the covariates after the matching, i.e., to have the characteristics of the grant-funded and non-grant-funded articles statistically equivalent. Results reported in Table 6 are largely consistent with our main results: grant-funded articles receive 7.33% more citations than articles not supported by grant funding in the long run. Given the similarity of the results with our main analysis and the loss of 904 observations, we refrain from reporting this analysis as our main analysis and consider it a robustness check.

Appendix D reports the table of the average marginal effects of the articles' probability of acknowledging an ANR grant (Table D1) and the covariate balance table pre- and post-matching (Table D2), including the three new covariates.

**Table 6. Grant funding effect on publications' number of citations received.**

	(1) Short run Citations from t to t+2	(2) Long run Citations from t+3 to t+5
5,537 Grant-funded + 5,537 Non-grant-funded		
Average citations Grant-funded articles (A)	6.338	8.758
Average citations Non-grant-funded articles (B)	6.392	8.160
Grant-funded effect (A-B)	-0.054	0.598 **
Grant-funded relative effect (A-B)/B	-0.84%	+7.33% **
<i>t</i> -statistic	-0.318	2.196
<i>p</i> -value	0.75	0.028

NOTE: Significance levels at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

#### 6.4 Exact matching of publication year and journal

In our main matching exercise, we include the variable *Year of publication* and four dummy variables identifying the fields in which the articles are published. Although the Propensity Score Matching selects the most similar articles, we allow grant-funded articles to be paired with non-grant-funded articles published in different years and journals. Among the 6,441 pairs included in the analysis conducted in Table 4, only 120 pairs (1.8%) show different publication years, while 6,332 (98.3%) pairs are published in different journals. In this robustness check, we propose two exercises in which we run the Propensity Score Matching conditional on pairing only articles published in the same year (Table 7), and in the same year and journal (Table 8).

Table 7 reports the results of the Propensity Score Matching using the exact matching of the *Year of publication*. The results reported in Table 7 are largely consistent with our main analysis (Table 4), estimating an impact of grant-funded articles 7.05% higher than non-grant-funded articles in the long run. Table E1 in Appendix E reports the covariate balance table pre- and post-matching.

Table 8 reports the results of the Propensity Score Matching using the exact matching of the *Year of publication* and the *Journal of publication*. The number of article pairs in Table 8 reduces to 1,643 from the 6,441 analyzed in Table 4. This reduction is due to the impossibility of pairing 4,798 grant-funded articles with non-grant-funded articles published in the same year and journal. The results reported in Table 8 show no statistically significant difference in the impact of grant-funded and non-grant-funded articles, both in the short and long run. Nonetheless, the difference between the average citations received by grant-funded and non-grant-funded articles, in the long run, is similar to that found in the main analysis of Table 4. We explain this lack of statistically

significant results by the reduced sample size that affects the precision of the t-test. Table E2 in Appendix E shows the covariate balance table pre- and post-matching.

**Table 7. Grant funding effect on publications' number of citations received.**

	(1) Short run Citations from t to t+2	(2) Long run Citations from t+3 to t+5
6,441 Grant-funded + 6,441 Non-grant-funded		
Average citations Grant-funded articles (A)	6.404	8.943
Average citations Non-grant-funded articles (B)	6.624	8.354
Grant-funded effect (A-B)	-0.22	0.589 **
Grant-funded relative effect (A-B)/B	-3.32%	+7.05% **
<i>t</i> -statistic	-1.403	2.494
<i>p</i> -value	0.16	0.013

NOTE: Significance levels at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

**Table 8. Grant funding effect on publications' number of citations received.**

	(1) Short run Citations from t to t+2	(2) Long run Citations from t+3 to t+5
1,643 Grant-funded + 1,643 Non-grant-funded		
Average citations Grant-funded articles (A)	6.839	9.447
Average citations Non-grant-funded articles (B)	6.471	8.986
Grant-funded effect (A-B)	0.368	0.461
Grant-funded relative effect (A-B)/B	+5.68%	+5.13%
<i>t</i> -statistic	1.241	1.005
<i>p</i> -value	0.21	0.31

NOTE: Significance levels at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

### 6.5 Including articles supported by other competitive grants in addition to ANR grants

In our main analysis, we compare the impact of articles supported by ANR grants with those not supported by grants. To select articles supported by ANR grants, we look at those that acknowledge only ANR as the unique source of grant funding. In doing so, we exclude all the publications resulting from ANR grants bundled with other competitive grants. In this robustness check, we consider as ANR grant-funded articles all the articles acknowledging at least one ANR grant, allowing for the presence of other non-ANR grant funding sources. We expect that considering multiple funding sources in our study sample will boost the positive impact of grant funding on the articles' number of citations received. Indeed, if the increase of citations observed for ANR grant-funded articles is due to the grant's additional financial resources, having grants other than ANR should further increase the articles' impact. In the same vein, if the increase of citations observed for ANR grant-funded articles is due to the funding agencies' ability to select breakthrough research, having multiple agencies that fund the same research proposal signals the high quality of the research idea and its potential impact.

We identify 21,381 articles funded by at least one ANR grant and match them with 21,381 similar non-grant-funded articles. On average, the 21,381 grant-funded articles are supported by 3.46 competitive grants. As in our main analysis, we apply the Propensity Score Matching procedure. For the equation predicting the probability of being grant-funded (Table F1 in Appendix F), we use the set of covariates reported in Table 1 and pair grant-funded and non-grant-funded articles by selecting the “nearest neighbor.” Table F2 shows the covariate balance tables pre- and post-matching.

Table 9 reports the grant funding effect on the number of citations received in the short and long run. We find that articles supported by at least an ANR grant are significantly more impactful than non-grant-funded articles in the short and long run. Specifically, in the short run, the articles acknowledging grants receive 27.23% more citations than those without grant funding, while in the long run, they receive 25.56% more citations. These findings suggest that the presence of multiple competitive grants enhances the impact of grant-funded publications.

**Table 9. Grant funding effect on publications’ number of citations received.**

	(1) Short run Citations from t to t+2	(2) Long run Citations from t+3 to t+5
21,381 Grant-funded + 21,381 Non-grant-funded		
Average citations Grant-funded articles (A)	9.129	12.268
Average citations Non-grant-funded (B)	7.175	9.771
Grant-funded effect (A-B)	1.954 ***	2.497 ***
Grant-funded relative effect (A-B)/B	+27.23% ***	+25.56% ***
<i>t</i> -statistic	13.21	6.030
<i>p</i> -value	0.000	0.000

NOTE: Significance levels at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

### 6.6 Coarsened Exact Matching

The Propensity Score Matching procedure estimates the probability that an article is supported by an ANR grant given the set of articles’ and authors’ characteristics reported in Table 1. In this robustness check, we implement the *Coarsened Exact Matching* (CEM) non-parametric procedure (Azoulay, 2010; Iacus et al., 2012) to pair grant-funded publications with non-grant-funded publications. The difference between the Propensity Score Matching procedure applied in our main analysis and CEM is that CEM stratifies articles ex-ante using a non-parametric approach. CEM guarantees the covariate balance ex-ante at the cost of having grant-funded articles that remain unmatched due to the impossibility of finding a non-grant-funded article to pair within the same stratum.

We consider the covariates in Table 1 as the characteristics that allow us to match non-grant-funded articles with grant-funded articles. With the CEM procedure, we coarsen the support of the joint distribution of the covariates into a set of strata. Each article is then allocated into a unique stratum. We drop 212 strata that do not contain at least one grant-funded article and one non-grant-funded article. We end up with 6,229 strata (6,441-212). Finally, we match each grant-funded article with a non-grant-funded article allocated in the same stratum. If a stratum contains multiple articles, we match a grant-funded article with the most similar non-grant-funded article using the Propensity Score Matching procedure. We end up with a matched sample of 6,229 articles acknowledging ANR grants paired with 6,229 articles not supported by grants.

Appendix G reports the covariate balance table pre- and post-matching (Table G1). All the articles' and authors' characteristics do not show any statistically significant difference between the sample of grant-funded and non-grant-funded articles. Table 10 reports the results of our analysis applying CEM. In the long run, articles acknowledging grants are 5.95% more impactful than those not supported by grant funding. The magnitude of the effect is slightly smaller than the one found in Table 4 (+6.93%). In the short run, grant-funded articles are 4.39% less impactful than non-grant-funded articles, while in our main analysis, we did not find a statistically significant difference between the impact of grant-funded articles and non-grant-funded articles in the short run.

**Table 10. Grant funding effect on publications' number of citations received.**

	(1) Short run Citations from t to t+2	(2) Long run Citations from t+3 to t+5
6,229 Grant-funded + 6,229 Non-grant-funded		
Average citations Grant-funded articles (A)	6.365	8.887
Average citations Non-grant-funded articles (B)	6.658	8.387
Grant-funded effect (A-B)	-0.292 *	0.499 **
Grant-funded relative effect (A-B)/B	-4.39% *	+5.95% **
<i>t</i> -statistic	-1.826	2.072
<i>p</i> -value	0.068	0.038

NOTE: Significance levels at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

## 7. Conclusion

Over the last fifteen years in Europe, the block funding model has been increasingly replaced by the grant funding model. This trend relies on the policymakers' assumption that funding science through a competitive grant model is more effective than a block funding model. National funding agencies distributing competitive grants to researchers have recently sprung up in several European countries. In France, *l'Agence Nationale de la recherche* (ANR) was founded in 2005 to support French researchers through a competitive allocation of funds.

In this study, we compare the impact of scientific articles resulting from the support of competitive grants with the impact of articles published without grant support, both in the short and long run. We rely on publications' acknowledgment data to identify articles supported by grants. We include in our sample all the articles supported by grants distributed by the ANR agency between 2009 and 2013. Using a comprehensive set of articles' and authors' characteristics, we propose a Propensity Score Matching approach to assess the effect of grant funding.

We find that articles supported by ANR grants receive +6.93% more citations than articles not supported by grant funding in the long run, while the difference in the citations received is not statistically significant in the short run. This result can be interpreted in light of the work of Wang et al. (2017), showing that breakthrough novel articles outpace non-novel articles in the number of citations received starting from three years after publication. Like Wang et al. (2017), we find that ANR grant-funded articles are more impactful than non-grant-funded articles from three to five years after publication. Interpreting our and Wang et al. (2017) results jointly, we can speculate that the ANR funding agency successfully identifies and supports breakthrough research that leads to publishing articles highly cited in the long run.

We also find that the grant funding effect differs across research fields. Publications in Life sciences and Medicine, and Engineering, are those showing the highest increase of citations in the long run when resulting from the support of grants (+15.06% and +13.87%, respectively). Engineering is the only field of research where articles are more impactful when supported by grants also in the short run (+8.15%). This result is in line with previous studies showing the beneficial effect of grant funding on research outcomes in Engineering and Nanotechnology (Hottenrott and Thorwarth, 2011; Beaudry and Allaoui, 2012; Wang and Shapira, 2015; Tahmooresnejad and Beaudry, 2019). Interestingly, Mathematics is the only field in which articles

resulting from grant funding are less impactful than non-grant-funded articles in the short run (-13.08%).

Moreover, in a robustness check, we show that articles supported by ANR grants bundled with other grants from different funding agencies have a higher impact than non-grant-funded articles. This finding supports the idea of a beneficial effect of competitive grants in science and goes opposite to Mali et al. (2017) findings showing that public grants produce impactful research only if researchers' funds come from a unique source.

Our study is not exempt from limitations. First, we are forced to use articles published from 2009 to 2013 due to Web of Science and Microsoft Academic Graph data coverage. According to the selected time window, we can trace citations to articles only up to six years after publication. This time limitation does not allow us to know the articles' citation patterns after six years from the publication date. Second, when pairing grant-funded and non-grant-funded articles, we do not control for the manuscripts' content and other unobserved factors influencing the probability of acknowledging an ANR grant.

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## Appendix A

For each field, we run a separate Propensity Score Matching procedure to pair each grant-funded article with a non-grant-funded article having the highest propensity score similarity (i.e., the “nearest neighbors”). We assign an article to a research field according to its SCOPUS journal classification. Some journals, and consequently articles, might be classified in multiple research fields. In case of multiple classifications of an article, we assign it to each research field<sup>12</sup>.

Tables A1 and A2 refer to articles in Life sciences and Medicine. We identify 1,708 grant-funded articles in Life sciences and Medicine matched with 1,708 similar non-grant-funded articles drawn from a pool of 37,657 articles in the same field. Table A1 reports the marginal effects of the equation predicting the probability that an ANR grant is acknowledged by an article in Life sciences and Medicine. Table A2 shows that after the Propensity Score Matching, all the average articles’ and authors’ characteristics are statistically equivalent for grant-funded and non-grant-funded articles at standard significance levels.

Tables A3 and A4 refer to articles in Mathematics. We match 1,806 grant-funded articles in Mathematics with 1,806 similar non-grant-funded articles drawn from a pool of 14,453 articles in the same field. Table A3 shows the marginal effects of the equation predicting the probability that an ANR grant is acknowledged by an article in Mathematics. Table A4 shows that after the Propensity Score Matching, all the average articles’ and authors’ characteristics are statistically equivalent for grant-funded and non-grant-funded articles at standard significance levels.

Tables A5 and A6 refer to articles in Engineering. We identify 1,489 grant-funded articles in Engineering that we match with 1,489 similar non-grant-funded articles drawn from a pool of 15,261 articles in the same field. Table A5 shows the marginal effects of the equation predicting the probability that an ANR grant is acknowledged by an article in Engineering. Table A6 shows that after the Propensity Score Matching, all the average articles’ and authors’ characteristics are statistically equivalent for grant-funded and non-grant-funded articles at standard significance levels.

Finally, tables A7 and A8 refer to articles in Physical sciences. We match 3,719 grant-funded articles in Physical sciences with 3,719 similar non-grant-funded articles drawn from a pool of 29,081 articles in the same field. Table A7 shows the marginal effects of the equation predicting

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<sup>12</sup> For articles classified in multiple research fields, we estimate the equation predicting the propensity score including dummy variables for each research field in which the article is classified.

the probability that an ANR grant is acknowledged by an article in Physical sciences. Table A8 shows that after the Propensity Score Matching, all the average articles' and authors' characteristics are statistically equivalent for grant-funded and non-grant-funded articles at standard significance levels.

Life sciences and Medicine

**Table A1. Average marginal effects of the article's probability of acknowledging an ANR grant for articles in Life sciences and Medicine.**

	(1) Grant-funded
Single-author article	Ref.
Multi-author article 2-4	0.042*** (0.0068)
Multi-author article > 4	0.039*** (0.0070)
At least one international author	-0.037*** (0.0029)
At least one female author	0.0067** (0.0028)
At least one top-affiliate author	0.012*** (0.0021)
Multiple affiliations	0.011*** (0.0026)
Backward citations Q1	Ref.
Backward citations Q2	0.033*** (0.0048)
Backward citations Q3	0.059*** (0.0045)
Backward citations Q4	0.085*** (0.0044)
Life sciences and Medicine	Ref.
Mathematics	0.051*** (0.0045)
Engineering	0.029*** (0.0036)
Physical sciences	0.034*** (0.0025)
Year of publication	0.0073*** (0.00071)
Pseudo R2	0.1255
Number of articles	39,365

NOTE: Average marginal effects are calculated from estimated logit coefficients. Standard errors in parentheses. Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

**Table A2. Means of the articles' and authors' observable characteristics for grant- and non-grant-funded articles in Life sciences and Medicine, before (Columns 1 and 2) and after (Columns 3 and 4) the Propensity Score Matching.**

	Sample before PSM			PSM sample		
	(1) Grant-funded	(2) Non-grant-funded	p-value	(3) Grant-funded	(4) Non-grant-funded	p-value
N. of publications	1,708	37,657		1,708	1,708	
<i>Covariates</i>						
Single-author article	0.023***	0.076	0.000	0.023	0.022	0.817
Multi-author article 2-4	0.403***	0.343	0.000	0.403	0.407	0.780
Multi-author article > 4	0.574	0.581	0.565	0.574	0.571	0.836
At least one international author	0.153***	0.239	0.000	0.153	0.159	0.637
At least one female author	0.828***	0.776	0.000	0.828	0.827	0.964
At least one top-affiliate author	0.391***	0.303	0.000	0.391	0.391	0.972
Multiple affiliations	0.783***	0.711	0.000	0.783	0.790	0.616
Backward citations Q1	0.059***	0.280	0.000	0.059	0.054	0.505
Backward citations Q2	0.134***	0.233	0.000	0.134	0.131	0.762
Backward citations Q3	0.271***	0.240	0.004	0.271	0.270	0.969
Backward citations Q4	0.536***	0.247	0.000	0.536	0.545	0.583
Life sciences and Medicine	1.000	1.000	1.000	1.000	1.000	1.000
Mathematics	0.066***	0.017	0.000	0.066	0.055	0.196
Engineering	0.111***	0.033	0.000	0.111	0.110	0.956
Physical sciences	0.287***	0.110	0.000	0.287	0.292	0.734
Year of publication	2011.34***	2010.94	0.000	2011.34	2011.31	0.604

NOTE: Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Mathematics

**Table A3. Average marginal effects of the article’s probability of acknowledging an ANR grant for articles in Mathematics.**

	(1) Grant-funded
Single-author article	Ref.
Multi-author article 2-4	0.049*** (0.0073)
Multi-author article > 4	0.068*** (0.012)
At least one international author	-0.11*** (0.0070)
At least one female author	-0.014*** (0.0053)
At least one top-affiliate author	0.018*** (0.0050)
Multiple affiliations	0.021*** (0.0061)
Backward citations Q1	Ref.
Backward citations Q2	0.028*** (0.0067)
Backward citations Q3	0.040*** (0.0068)
Backward citations Q4	0.038*** (0.0076)
Mathematics	Ref.
Life sciences and Medicine	0.011 (0.011)
Engineering	-0.060*** (0.0065)
Physical sciences	-0.0018 (0.0063)
Year of publication	0.023*** (0.0017)
Pseudo R2	0.056
Number of articles	16,259

NOTE: Average marginal effects are calculated from estimated logit coefficients. Standard errors in parentheses. Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

**Table A4. Means of the articles' and authors' observable characteristics for grant- and non-grant-funded articles in Mathematics, before (Columns 1 and 2) and after (Columns 3 and 4) the Propensity Score Matching.**

	Sample before PSM			PSM sample		
	(1) Grant-funded	(2) Non-grant-funded	p-value	(3) Grant-funded	(4) Non-grant-funded	p-value
N. of publications	1,806	14,453		1,806	1,806	
<i>Covariates</i>						
Single-author article	0.185***	0.232	0.000	0.185	0.190	0.702
Multi-author article 2-4	0.729***	0.691	0.001	0.729	0.736	0.625
Multi-author article > 4	0.085	0.078	0.267	0.085	0.073	0.175
At least one international author	0.159***	0.305	0.000	0.159	0.162	0.821
At least one female author	0.358	0.362	0.785	0.358	0.350	0.602
At least one top-affiliate author	0.417***	0.356	0.000	0.417	0.421	0.840
Multiple affiliations	0.625	0.609	0.182	0.625	0.628	0.863
Backward citations Q1	0.223***	0.306	0.000	0.223	0.215	0.546
Backward citations Q2	0.297	0.295	0.820	0.297	0.306	0.587
Backward citations Q3	0.285***	0.238	0.000	0.285	0.291	0.659
Backward citations Q4	0.195***	0.161	0.001	0.195	0.188	0.612
Life sciences and Medicine	0.062***	0.044	0.002	0.062	0.052	0.197
Mathematics	1.000	1.000	1.000	1.000	1.000	1.000
Engineering	0.169***	0.249	0.000	0.169	0.159	0.419
Physical sciences	0.189	0.179	0.288	0.189	0.188	0.898
Year of publication	2011.41***	2010.93	0.000	2011.41	2011.40	0.831

NOTE: Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Engineering

**Table A5. Average marginal effects of the article’s probability of acknowledging an ANR grant for articles in Engineering.**

	(1) Grant-funded
Single-author article	Ref.
Multi-author article 2-4	0.043*** (0.011)
Multi-author article > 4	0.092*** (0.012)
At least one international author	-0.10*** (0.0068)
At least one female author	-0.0056 (0.0047)
At least one top-affiliate author	0.026*** (0.0048)
Multiple affiliations	0.0085* (0.0051)
Backward citations Q1	Ref.
Backward citations Q2	0.033*** (0.0066)
Backward citations Q3	0.042*** (0.0066)
Backward citations Q4	0.058*** (0.0067)
Engineering	Ref.
Life sciences and Medicine	0.025*** (0.0068)
Mathematics	0.018*** (0.0060)
Physical sciences	0.038*** (0.0054)
Year of publication	0.018*** (0.0015)
Pseudo R2	0.0817
Number of articles	16,750

NOTE: Average marginal effects are calculated from estimated logit coefficients. Standard errors in parentheses. Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

**Table A6. Means of the articles' and authors' observable characteristics for grant- and non-grant-funded articles in Engineering, before (Columns 1 and 2) and after (Columns 3 and 4) the Propensity Score Matching.**

	Sample before PSM			PSM sample		
	(1) Grant-funded	(2) Non-grant-funded	p-value	(3) Grant-funded	(4) Non-grant-funded	p-value
N. of publications	1,489	15,261		1,489	1,489	
<i>Covariates</i>						
Single-author article	0.038***	0.070	0.000	0.038	0.036	0.770
Multi-author article 2-4	0.510***	0.632	0.000	0.510	0.516	0.742
Multi-author article > 4	0.453***	0.298	0.000	0.453	0.449	0.825
At least one international author	0.118***	0.292	0.000	0.118	0.118	0.955
At least one female author	0.596***	0.527	0.000	0.596	0.602	0.737
At least one top-affiliate author	0.298***	0.234	0.000	0.298	0.302	0.810
Multiple affiliations	0.680	0.666	0.273	0.680	0.685	0.753
Backward citations Q1	0.159***	0.271	0.000	0.159	0.163	0.765
Backward citations Q2	0.269	0.285	0.183	0.269	0.271	0.934
Backward citations Q3	0.291***	0.252	0.001	0.291	0.295	0.809
Backward citations Q4	0.281***	0.192	0.000	0.281	0.271	0.566
Life sciences and Medicine	0.127***	0.081	0.000	0.127	0.116	0.370
Mathematics	0.205***	0.236	0.005	0.205	0.197	0.615
Engineering	1.000	1.000	1.000	1.000	1.000	1.000
Physical sciences	0.727***	0.609	0.000	0.727	0.733	0.710
Year of publication	2011.42***	2010.91	0.000	2011.42	2011.45	0.550

NOTE: Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Physical sciences

**Table A7. Average marginal effects of the article’s probability of acknowledging an ANR grant for articles in Physical sciences.**

	(1) Grant-funded
Single-author article	Ref.
Multi-author article 2-4	0.086*** (0.0083)
Multi-author article > 4	0.14*** (0.0090)
At least one international author	-0.12*** (0.0050)
At least one female author	-0.0095** (0.0039)
At least one top-affiliate author	0.035*** (0.0036)
Multiple affiliations	0.0065 (0.0041)
Backward citations Q1	Ref.
Backward citations Q2	0.032*** (0.0058)
Backward citations Q3	0.047*** (0.0056)
Backward citations Q4	0.058*** (0.0055)
Physical sciences	Ref.
Life sciences and Medicine	-0.024*** (0.0052)
Mathematics	0.012* (0.0061)
Engineering	-0.016*** (0.0038)
Year of publication	0.019*** (0.0012)
Pseudo R2	0.0665
Number of articles	32,800

NOTE: Average marginal effects are calculated from estimated logit coefficients. Standard errors in parentheses. Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

**Table A8. Means of the articles' and authors' observable characteristics for grant- and non-grant-funded articles in Physical sciences, before (Columns 1 and 2) and after (Columns 3 and 4) the Propensity Score Matching.**

	Sample before PSM			PSM sample		
	(1) Grant-funded	(2) Non-grant-funded	p-value	(3) Grant-funded	(4) Non-grant-funded	p-value
N. of publications	3,719	29,081		3,719	3,719	
<i>Covariates</i>						
Single-author article	0.045***	0.093	0.000	0.045	0.045	0.956
Multi-author article 2-4	0.506***	0.559	0.000	0.506	0.508	0.799
Multi-author article > 4	0.449***	0.348	0.000	0.449	0.446	0.816
At least one international author	0.144***	0.321	0.000	0.144	0.144	0.947
At least one female author	0.619***	0.580	0.000	0.619	0.621	0.848
At least one top-affiliate author	0.405***	0.320	0.000	0.405	0.405	0.981
Multiple affiliations	0.685	0.681	0.571	0.685	0.689	0.708
Backward citations Q1	0.130***	0.206	0.000	0.130	0.131	0.863
Backward citations Q2	0.222***	0.241	0.009	0.222	0.220	0.867
Backward citations Q3	0.283***	0.253	0.000	0.283	0.286	0.777
Backward citations Q4	0.366***	0.301	0.000	0.366	0.363	0.810
Life sciences and Medicine	0.132*	0.143	0.062	0.132	0.124	0.297
Mathematics	0.092	0.089	0.550	0.092	0.088	0.543
Engineering	0.291***	0.320	0.000	0.291	0.286	0.645
Physical sciences	1.000	1.000	1.000	1.000	1.000	1.000
Year of publication	2011.26***	2010.82	0.000	2011.26	2011.25	0.831

NOTE: Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

## Appendix B

This appendix estimates the effect of grant funding on the articles' citations in each of the 6 years after publication. Table B1 reports the results. In the first year after publication, articles resulting from ANR grants receive 30.85% fewer citations than articles not supported by grant funding. In the second year after publication, there is no statistically significant difference between grant-funded and non-grant-funded articles' impact. From the third year after publication until the sixth year, grant-funded articles receive more citations than non-grant-funded articles. The largest impact is in the fifth year when grant-funded articles receive 8.57% more citations than articles not supported by grant funding.

**Table B1. Grant funding effect on publications' number of citations received each year.**

	(1)	(2)	(3)	(4)	(5)	(6)
6,441 Grant-funded + 6,441 Non-grant-funded	First year citations	Second year citations	Third year citations	Fourth year citations	Fifth year citations	Sixth year citations
Avg. citations Grant-funded articles (A)	0.778	2.473	3.151	3.231	2.992	2.720
Avg. citations Non-grant-funded articles (B)	1.126	2.544	2.958	3.039	2.756	2.568
Grant-funded effect (A-B)	-0.347 ***	-0.071	0.193 **	0.192 **	0.236 ***	0.152 *
Grant-funded relative effect (A-B)/B	-30.85% ***	-2.79%	+6.52% **	+6.32% **	+8.57% ***	+5.90% *
<i>t</i> -statistic	-10.973	-1.082	2.514	2.289	2.832	1.816
<i>p</i> -value	0.000	0.279	0.012	0.022	0.005	0.069

NOTE: Significance levels at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

## Appendix C

This appendix relies on SCOPUS citation data to assess the effect of grant funding on articles' impact. Different from the main analysis reported in Table 4, we use SCOPUS average yearly citations instead of Microsoft Academic Graph annual citations to assess the articles' impact. Specifically, we retrieved the cumulated number of each article's citations in 2019 from SCOPUS. Then, we calculate the average yearly citations received by each article by dividing the cumulated number of citations by the years elapsed between the article's publication date and 2019. The main disadvantage of using SCOPUS cumulated number of citations is that we do not have punctual information on the number of citations received by the articles each year. This lack of information does not allow us to distinguish between short and long run periods. Table C1 reports the results. Articles resulting from ANR grants receive, on average, 4.40% more yearly citations than articles not supported by grant funding. This result is in line with that reported in Table 4 for the long run impact of grant-funded articles.

**Table C1. Funding effects on publications' average number of yearly citations received.**

(1)	
6,441 Grant-funded + 6,441 Non-grant-funded	Avg. yearly citations from the publication date to 2019
Average yearly citations Grant-funded articles (A)	2.983
Average yearly citations Block-funded articles (B)	2.857
Grant-funded effect (A-B)	0.126 *
Grant-funded relative effect (A-B)/B	+4.40% *
<i>t-statistic</i>	1.718
<i>p-value</i>	0.086

NOTE: Significance levels at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . Citations are calculated using SCOPUS data.

## Appendix D

In this appendix, we add three variables describing the French authors' academic status in the matching exercise. We include the dummy variables *At least a French star author*, *At least a French senior author*, and *At least a French Ph.D. student author* as defined in Section 6.3. Table D1 reports the marginal effects of the equation predicting the probability that an ANR grant is acknowledged by an article. The presence of a French star scientist among the article's authors is associated with an increased probability that an article acknowledges an ANR grant of 2 percentage points; the presence of a Ph.D. student is associated with an increased probability of 1.3 percentage points; while the presence of a French senior scientist is not related to the likelihood that an article acknowledges an ANR grant.

Table D2 shows that after the Propensity Score Matching, all the average articles' and authors' characteristics are statistically equivalent for grant-funded and non-grant-funded articles at standard significance levels. To ensure the equivalence between the articles' and authors' characteristics, we set the Caliper option in the Propensity Score Matching procedure at 0.000001 standard deviations. Doing so, we discard the matches where the propensity score difference between the grant-funded and non-grant-funded articles is larger than 0.000001 standard deviations. Applying the Caliper leads us to lose 904 article pairs that overcome the Caliper threshold. We end up with 5,537 grant-funded articles matched with 5,537 similar non-grant-funded articles. In the matched sample, 53.5% of the article pairs have *At least a French star author*, 91.8% have *At least a French senior author*, and 38% have *At least a French Ph.D. student author*.

**Table D1. Average marginal effects of the article's probability of acknowledging an ANR grant.**

	(1) Grant-funded
Single-author article	Ref.
Multi-author article (from 2 to 4 authors)	0.037*** (0.0039)
Multi-author article (more than 4 authors)	0.043*** (0.0045)
At least one international author	-0.068*** (0.0027)
At least one female author	-0.0078*** (0.0021)
At least one top-affiliate author	0.018*** (0.0019)
Multiple affiliations	0.011*** (0.0022)
Backward citations Q1	Ref.
Backward citations Q2	0.025*** (0.0030)
Backward citations Q3	0.040*** (0.0029)
Backward citations Q4	0.057*** (0.0028)
Life sciences and Medicine	Ref.
Mathematics	0.075*** (0.0025)
Engineering	-0.0045** (0.0022)
Physical sciences	0.069*** (0.0020)
Year of publication	0.014*** (0.00064)
<b>At least a French star author</b>	<b>0.020***</b> <b>(0.0021)</b>
<b>At least a French senior author</b>	<b>-0.0014</b> <b>(0.0032)</b>
<b>At least a French Ph.D. student author</b>	<b>0.013***</b> <b>(0.0020)</b>
Pseudo R2	0.0892
Number of articles	83,056

NOTE: Average marginal effects are calculated from estimated logit coefficients. Standard errors in parentheses. Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

**Table D2. Means of the articles' and authors' observable characteristics for grant- and non-grant-funded articles, before (Columns 1 and 2) and after (Columns 3 and 4) the Propensity Score Matching.**

	Sample before PSM			PSM sample		
	(1) Grant-funded	(2) Non-grant-funded	p-value	(3) Grant-funded	(4) Non-grant-funded	p-value
N. of publications	6,441	76,615		5,537	5,537	
<i>Covariates</i>						
Single-author article	0.075***	0.109	0.000	0.075	0.075	1.000
Multi-author article (from 2 to 4 authors)	0.539***	0.483	0.000	0.537	0.537	0.985
Multi-author article (more than 4 authors)	0.386***	0.408	0.001	0.387	0.387	0.984
At least one international author	0.153***	0.279	0.000	0.153	0.153	1.000
At least one female author	0.596***	0.628	0.000	0.613	0.613	1.000
At least one top-affiliate author	0.399***	0.315	0.000	0.384	0.384	0.984
Multiple affiliations	0.693*	0.682	0.058	0.706	0.706	0.983
Backward citations Q1	0.145***	0.269	0.000	0.142	0.142	1.000
Backward citations Q2	0.225***	0.249	0.000	0.223	0.223	0.982
Backward citations Q3	0.278***	0.241	0.000	0.281	0.281	0.983
Backward citations Q4	0.352***	0.240	0.000	0.354	0.354	1.000
Life sciences and Medicine	0.265***	0.492	0.000	0.259	0.259	1.000
Mathematics	0.280***	0.189	0.000	0.250	0.250	0.982
Engineering	0.231***	0.199	0.000	0.199	0.199	1.000
Physical sciences	0.577***	0.380	0.000	0.580	0.580	0.985
Year of publication	2011.31***	2010.90	0.000	2011.29	2011.29	0.989
<b>At least a French star author</b>	<b>0.534***</b>	<b>0.470</b>	<b>0.000</b>	<b>0.535</b>	<b>0.535</b>	<b>0.985</b>
<b>At least a French senior author</b>	<b>0.899***</b>	<b>0.867</b>	<b>0.000</b>	<b>0.918</b>	<b>0.918</b>	<b>1.000</b>
<b>At least a French Ph.D. student author</b>	<b>0.400***</b>	<b>0.326</b>	<b>0.000</b>	<b>0.380</b>	<b>0.381</b>	<b>0.984</b>

NOTE: Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

## Appendix E

This appendix reports the Propensity Score Matching conditional on the exact matching of the articles' *Year of publication* (Table E1) and the articles' *Year of publication* and *Journal of publication* (Table E2).

Table E1 shows that, after matching conditioning on publication year, the average articles' and authors' characteristics are statistically equivalent between the group of grant-funded articles and that of non-grant-funded articles, at standard significance levels. As expected, the *Year of publication* is perfectly balanced between grant-funded and non-grant-funded articles due to the exact matching condition imposed.

Table E2 reports the analysis for the matching conditioning on the *Year of publication* and *Journal of publication*. In this case, our sample reduces to 1,643 grant-funded articles matched with 1,643 similar non-grant-funded articles. This reduction is due to two reasons. First, for several grant-funded articles, we do not find non-grant-funded articles published in the same year and in the same journal. Second, intending to keep the balance between covariates, we match a grant-funded article with a non-grant-funded article only when the propensity score difference between the two is less than 0.02 standard deviations (i.e., Caliper is set at 0.02). Table E2 shows that, after matching, the average articles' and authors' characteristics are statistically equivalent between the group of grant-funded and non-grant-funded articles, at standard significance levels.

**Table E1. Means of the articles' and authors' observable characteristics for grant- and non-grant-funded publications, before (Columns 1 and 2) and after (Columns 4 and 5) the Propensity Score Matching conditional on an exact matching on the year of publication.**

	Sample before PSM			PSM sample		
	(1) Grant-funded	(2) Non-grant-funded	p-value	(3) Grant-funded	(4) Non-grant-funded	p-value
N. of publications	6,441	76,615		6,441	6,441	
<i>Covariates</i>						
Single-author article	0.075***	0.109	0.000	0.075	0.076	0.815
Multi-author article 2-4	0.539***	0.483	0.000	0.539	0.546	0.437
Multi-author article > 4	0.386***	0.408	0.001	0.386	0.378	0.355
At least one international author	0.153***	0.279	0.000	0.153	0.156	0.643
At least one female author	0.596***	0.628	0.000	0.596	0.595	0.872
At least one top-affiliate author	0.399***	0.315	0.000	0.399	0.398	0.900
Multiple affiliations	0.693*	0.682	0.058	0.693	0.693	1.000
Backward citations Q1	0.145***	0.269	0.000	0.145	0.143	0.802
Backward citations Q2	0.225***	0.249	0.000	0.225	0.225	0.950
Backward citations Q3	0.278***	0.241	0.000	0.278	0.282	0.624
Backward citations Q4	0.352***	0.240	0.000	0.352	0.350	0.825
Life sciences and Medicine	0.265***	0.492	0.000	0.265	0.255	0.178
Mathematics	0.280***	0.189	0.000	0.280	0.277	0.709
Engineering	0.231***	0.199	0.000	0.231	0.228	0.660
Physical sciences	0.577***	0.380	0.000	0.577	0.578	0.957
Year of publication	2011.31***	2010.90	0.000	2011.314	2011.314	1.000

NOTE: Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

**Table E2. Means of the articles' and authors' observable characteristics for grant- and non-grant-funded publications, before (Columns 1 and 2) and after (Columns 3 and 4) the Propensity Score Matching conditional on an exact matching on the year and journal of publication.**

	Sample before PSM			PSM sample		
	(1) Grant-funded	(2) Non-grant-funded	p-value	(3) Grant-funded	(4) Non-grant-funded	p-value
N. of publications	6,441	76,615		1,643	1,643	
<i>Covariates</i>						
Single-author article	0.075***	0.109	0.000	0.077	0.091	0.147
Multi-author article 2-4	0.539***	0.483	0.000	0.492	0.500	0.650
Multi-author article > 4	0.386***	0.408	0.001	0.432	0.410	0.203
At least one international author	0.153***	0.279	0.000	0.160	0.167	0.572
At least one female author	0.596***	0.628	0.000	0.629	0.605	0.151
At least one top-affiliate author	0.399***	0.315	0.000	0.413	0.406	0.696
Multiple affiliations	0.693*	0.682	0.058	0.704	0.696	0.621
Backward citations Q1	0.145***	0.269	0.000	0.168	0.165	0.815
Backward citations Q2	0.225***	0.249	0.000	0.214	0.205	0.548
Backward citations Q3	0.278***	0.241	0.000	0.276	0.264	0.432
Backward citations Q4	0.352***	0.240	0.000	0.342	0.366	0.155
Life sciences and Medicine	0.265***	0.492	0.000	0.181	0.180	0.928
Mathematics	0.280***	0.189	0.000	0.211	0.211	1.000
Engineering	0.231***	0.199	0.000	0.187	0.186	0.893
Physical sciences	0.577***	0.380	0.000	0.708	0.707	0.939
Year of publication	2011.31***	2010.90	0.000	2011.133	2011.133	1.000

NOTE: Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

## Appendix F

In this robustness check, we extend the group of grant-funded articles by considering those acknowledging at least one ANR grant. In other words, we include in our study sample articles resulting from multiple competitive grants.

Table F1 reports the marginal effects of the equation estimating the probability of observing an article acknowledging at least an ANR grant. The sample includes 100,565 articles, 23,950 grant-funded articles and 76,615 non-grant-funded articles.

Table F2 reports the covariate balance table before and after applying the Propensity Score Matching procedure. To ensure that grant-funded articles and non-grant-funded articles have a similar propensity score distribution after matching, we set Caliper at 0.0001 standard deviations. In doing so, we discard the matches where the propensity score difference between the grant-funded and non-grant-funded articles is larger than 0.0001 standard deviations. The Caliper restriction leads us to lose 2,569 article pairs. We end up with 21,381 grant-funded articles matched with 21,381 similar non-grant-funded articles. Table F2 shows that, after the matching, the average articles' and authors' characteristics are statistically equivalent between the group of grant-funded and non-grant-funded articles, at standard significance levels.

**Table F1. Average marginal effects of the article's probability of acknowledging at least an ANR grant.**

	(1) Grant-funded
Single-author article	Ref.
Multi-author article 2-4	0.14*** (0.0067)
Multi-author article > 4	0.21*** (0.0071)
At least one international author	0.010*** (0.0029)
At least one female author	0.011*** (0.0031)
At least one top-affiliate author	0.076*** (0.0026)
Multiple affiliations	0.026*** (0.0036)
Backward citations Q1	Ref.
Backward citations Q2	0.091*** (0.0046)
Backward citations Q3	0.16*** (0.0043)
Backward citations Q4	0.25*** (0.0040)
Life sciences and Medicine	Ref.
Mathematics	0.10*** (0.0037)
Engineering	-0.052*** (0.0035)
Physical sciences	0.099*** (0.0027)
Year of publication	0.033*** (0.00088)
Pseudo R2	0.1144
Number of articles	100,565

NOTE: Average marginal effects are calculated from estimated logit coefficients. Standard errors in parentheses. Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

**Table F2. Means of the articles' and authors' observable characteristics for grant- and non-grant-funded articles, before (Columns 1 and 2) and after (Columns 3 and 4) the Propensity Score Matching.**

	Sample before PSM			PSM sample		
	(1) Grant-funded	(2) Non-grant-funded	p-value	(3) Grant-funded	(4) Non-grant-funded	p-value
N. of publications	23,950	76,615		21,381	21,381	
<i>Covariates</i>						
Single-author article	0.034***	0.109	0.000	0.036	0.037	0.625
Multi-author article 2-4	0.424***	0.483	0.000	0.460	0.461	0.869
Multi-author article > 4	0.542***	0.408	0.000	0.504	0.502	0.728
At least one international author	0.373***	0.279	0.000	0.356	0.356	0.864
At least one female author	0.709***	0.628	0.000	0.695	0.695	0.975
At least one top-affiliate author	0.460***	0.315	0.000	0.427	0.427	0.907
Multiple affiliations	0.811***	0.682	0.000	0.797	0.796	0.737
Backward citations Q1	0.090***	0.269	0.000	0.098	0.098	0.935
Backward citations Q2	0.171***	0.249	0.000	0.183	0.182	0.930
Backward citations Q3	0.264***	0.241	0.000	0.280	0.278	0.682
Backward citations Q4	0.475***	0.240	0.000	0.440	0.442	0.626
Life sciences and Medicine	0.439***	0.492	0.000	0.426	0.423	0.564
Mathematics	0.180***	0.189	0.002	0.181	0.182	0.880
Engineering	0.157***	0.199	0.000	0.155	0.155	0.936
Physical sciences	0.506***	0.380	0.000	0.498	0.498	0.915
Year of publication	2011.35***	2010.90	0.000	2011.28	2011.28	0.900

NOTE: Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

## Appendix G

In this robustness check, we use the Coarsened Exact Matching (CEM) as a matching procedure instead of the Propensity Score Matching used in our main analysis. The CEM procedure coarsens the support of the joint distribution of the covariates into a circumscribed number of strata. Then, each article is assigned to a unique stratum. Grant-funded articles and non-grant-funded articles that are matched together are selected from the same stratum. We use as a set of covariates to be coarsened the variables listed in Table 1. CEM creates a number of strata by coarsening the joint distributions of these covariates. Strata that do not contain at least one grant-funded article and one non-grant-funded article are discarded. We end up with 6,229 strata (96.7% of the 6,441 grant-funded publications of the main analysis). Each grant-funded article is matched with a non-grant-funded article in the same stratum. If a stratum contains multiple articles, a grant-funded article is matched with the most similar non-grant-funded article within the same stratum by relying on the Propensity Score Matching and applying the nearest-neighbor approach.

Table G1 shows the covariate balance table pre- and post-matching.

**Table G1. Means of the articles' and authors' observable characteristics for grant- and non-grant-funded articles, before (Columns 1 and 2) and after (Columns 3 and 4) the Coarsened Exact Matching.**

	Sample before CEM			CEM sample		
	(1) Grant-funded	(2) Non-grant-funded	p-value	(3) Grant-funded	(4) Non-grant-funded	p-value
N. of publications	6,441	76,615		6,229	6,229	
<i>Covariates</i>						
Single-author article	0.075***	0.109	0.000	0.074	0.074	1.000
Multi-author article 2-4	0.539***	0.483	0.000	0.547	0.547	1.000
Multi-author article > 4	0.386***	0.408	0.001	0.379	0.379	1.000
At least one international author	0.153***	0.279	0.000	0.154	0.154	1.000
At least one female author	0.596***	0.628	0.000	0.599	0.599	1.000
At least one top-affiliate author	0.399***	0.315	0.000	0.398	0.398	1.000
Multiple affiliations	0.693*	0.682	0.058	0.696	0.696	1.000
Backward citations Q1	0.145***	0.269	0.000	0.143	0.143	1.000
Backward citations Q2	0.225***	0.249	0.000	0.226	0.226	1.000
Backward citations Q3	0.278***	0.241	0.000	0.281	0.281	1.000
Backward citations Q4	0.352***	0.240	0.000	0.350	0.350	1.000
Life sciences and Medicine	0.265***	0.492	0.000	0.257	0.257	1.000
Mathematics	0.280***	0.189	0.000	0.270	0.270	1.000
Engineering	0.231***	0.199	0.000	0.222	0.222	1.000
Physical sciences	0.577***	0.380	0.000	0.577	0.577	1.000
Year of publication	2011.31***	2010.90	0.000	2011.30	2011.30	1.000

NOTE: Significance levels at \*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

## Appendix H

This appendix describes how we classify the articles in our sample according to their research fields. To assign an article to a field of research, we refer to the *All Science Journal Classification* (ASJC) scheme that SCOPUS uses to classify journals. As stated by SCOPUS, “the classification is based on the aims and scope of the title, and on the content [the journal] published”<sup>13</sup>. To obtain the four research fields used in our analysis, i.e., Life sciences and Medicine, Mathematics, Engineering, and Physical sciences, we group the 30 subject areas reported by SCOPUS according to their affinity, as shown in Table H1. We do not consider articles published in multidisciplinary journals due to the impossibility of identifying a specific research field for them.

**Table H1. Reaggregation scheme of the articles’ fields of research.**

Field of research	SCOPUS ASJC Subject Area Classifications
Life sciences and Medicine	Agricultural and Biological Sciences Biochemistry, Genetics and Molecular Biology Immunology and Microbiology Neuroscience Pharmacology, Toxicology and Pharmaceutics Medicine Nursing Veterinary Dentistry Health Professions
Mathematics	Mathematics Computer Science
Engineering	Engineering Chemical Engineering Energy
Physical sciences	Physics and Astronomy Earth and Planetary Sciences Environmental Science Material Science Chemistry

<sup>13</sup> Website: [https://service.elsevier.com/app/answers/detail/a\\_id/14882/supporthub/scopus/~/what-are-the-most-frequent-subject-area-categories-and-classifications-used-in/](https://service.elsevier.com/app/answers/detail/a_id/14882/supporthub/scopus/~/what-are-the-most-frequent-subject-area-categories-and-classifications-used-in/)

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