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Production of knowledge relies on peer effects and interactions between researchers. However, little is known on how much policies may stimulate these peer effects. In this paper we shed light on this question, and show how a public "research cluster" policy, which funds local networks of researchers working on a common theme, affects the organization of research within these clusters and the productivity of its members. Using data from a large scale financing program in France, and relying on an identification strategy based on grades awarded by reviewers, we show that members of financed clusters increase by up to 30% the research collaborations they have with other members of the cluster, compared to researchers of non selected proposals. This very large reorganization of the research network translates into a more modest positive effect on research productivity. Paradoxically, those who benefit the most from the financing, are those who were not at the core of the research topic, i.e. were not cited in the bibliography of the research proposal, who significantly increase their links with core members and their total publication counts. Consistently, the policy reduces inequality in publication outcomes within the cluster. It stimulates peer effects to the benefit of periphery members.

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Stimulating Peer Effects?
Evidence from a Research Cluster Policy

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April 7, 2020

Abstract

Production of knowledge relies on peer effects and interactions between researchers. However, little is known on how much policies may stimulate these peer effects. In this paper we shed light on this question, and show how a public "research cluster" policy, which funds local networks of researchers working on a common theme, affects the organization of research within these clusters and the productivity of its members. Using data from a large scale financing program in France, and relying on an identification strategy based on grades awarded by reviewers, we show that members of financed clusters increase by up to 30% the research collaborations they have with other members of the cluster, compared to researchers of non selected proposals. This very large reorganization of the research network translates into a more modest positive effect on research productivity. Paradoxically, those who benefit the most from the financing, are those who were not at the core of the research topic, i.e. were not cited in the bibliography of the research proposal, who significantly increase their links with core members and their total publication counts. Consistently, the policy reduces inequality in publication outcomes within the cluster. It stimulates peer effects to the benefit of periphery members.

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1 Introduction

The production of knowledge, a key fuel for economic growth (Romer, 1990; Aghion and Howitt, 1992), critically depends on peer effects.[1] According to Borjas and Doran (2015), peer effects can exist along three dimensions of proximity: in the collaboration space (as co-authors), in the geographical space (as researchers working in the same location) or in the idea space (as researchers working on the same topic). Though it remains essentially unknown whether policies can be designed to stimulate such peer effects, we have recently witnessed policy initiatives explicitly aiming to do so by financing academic "research clusters", i.e. networks of researchers working in the same location (geographical space), on a common theme (ideas space) with the goal of encouraging new interactions (collaboration space).[2] In this paper, using a public policy experiment in France where a national contest was run to select research clusters, we study its impact, how it materializes into collaborations, how it affects overall productivity of clusters and how members are differentially affected.

Exploiting an identification strategy based on grades given by reviewers, we show that the program led to a significant restructuring of the collaboration network of researchers. Members of selected academic clusters compared to those working in clusters that were not chosen but received similar grades, increased their collaborations with other cluster members by up to 30% after the financing was obtained. They both strengthened existing teams, but also initiated new ones. This very large reorganization of the collaboration network is accompanied by a more modest increase in productivity. Paradoxically, the researchers who benefited the most from the financing were those not included in the bibliography of the proposal (that we call "periphery members"), in other words not at the core of the topic. They saw an increase of up to 20% in their number of publications, driven mostly by collaborations with "core members" (those cited in the bibliography), with no drop in the publications with only co-authors outside the cluster. We show that overall the policy reduced the inequality of publication in the group. In short, the policy did stimulate peer effects, in particular via new collaborations, but those benefits were very asymmetrically distributed in favor of periphery members.

The policy experiment we study is a large scale research funding initiative in France, called LabEx program, that was launched in 2010. In 2010 and 2011, 395 research cluster proposals were submitted, out of which 170 were funded. The average allocation was 8.8 million euros (approximately 10 millions USD) over 10 years. These clusters bring together researchers from different research units, not necessarily part of the same institution. Our research design exploits

[1] This literature includes numerous papers such as Azoulay, Graff Zivin and Wang (2010); Waldinger (2012); Borjas and Doran (2012); Oettl (2012); Borjas and Doran (2015); Jaravel, Petkova and Bell (2018).

[2] The Exzellenzinitiative in Germany, the "Severo Ochoa" Centers of Excellence in Spain, the Centers of Excellence in the Nordic countries (descriptive evidence in Möller, Schmidt and Hornbostel (2016) and Langfeldt et al. (2015)) or the Initiative d'Excellence in France. Universities also increasingly divert funds from traditional discipline based funding to invest in specific themes. There are numerous instances of clusters (or centers) of excellence created recently within (or sometimes across) universities such as the University of British Columbia, Stanford University, MIT, or the University of Cambridge. Other policies trying to encourage peer effects include the creation of departments and labs, or the financing of collaborative projects.

different key pieces of information. First, we obtained from the agency running the program the grades given by reviewers for all projects, both those accepted and those rejected. Second, we had access to all detailed proposals from which we extracted the list of associated research units and the names of authors cited in the project reference list. Third, we combined these data with a unique country-wide roster of tenured professors and researchers employed by all universities and research institutes to identify the members of each cluster. Matching author names of each cluster reference list with the names of its members, allowed us to determine in a very precise way the core and periphery members of each proposal. Lastly, we extracted from the Web of Science bibliographic information of each cluster member. Our final dataset tracks from 2005 to 2017 nearly thirty thousand professors or researchers attached to at least one cluster proposal.

Most of our analysis is conducted at the individual researcher level and includes time and researcher fixed effects. These fixed effects correct for differences in levels between members of financed and non-financed clusters, but cannot capture differential trends. We thus, in our preferred specification, restrict our analysis to researchers who were part of only one cluster proposal and that received similar grades on that unique proposal. Specifically, we restrict to a range of grades where the probability of selection sharply moves from 20% to 80%. The fact their unique proposal is ultimately selected or rejected can be considered essentially random, an assumption we will verify by examining pre-trends. We further check the robustness to several alternative identification strategies, including one where we restrict the analysis to clusters receiving the same grade for the research potential criterion, one of the components of the overall grade, the final decision being then driven by factors less likely to directly influence research productivity, such as teaching potential.

Using our main identification strategy, we first show a very large effect on the organization of research. On average, the number of publications with at least one co-author from the same cluster, increases by 14% for members of funded clusters compared to researchers who belong to a rejected cluster. This is due to both a strengthening of the existing collaborations, but also a large difference in the number of new collaborations initiated, in the order of 27% when comparing the two groups. Importantly we show that given our restriction on overall grades, we do not observe any significant pre-trends for any of these variables, thus supporting our identification strategy. These results are confirmed when we perform dyadic regressions with fixed effects for each dyad, still restricting to researchers receiving similar grades on their unique proposal. This alternative approach better captures differences in the type of interactions within a cluster. The probability of having a link increases by 27% on average for the members of funded clusters compared to those that were not selected.

Such large restructuring of collaborations translates into an increase in productivity, but of a smaller magnitude. To analyze the effect on productivity, we both do an analysis at the cluster level, comparing aggregate productivity of financed and non-financed clusters, restricting to those with similar grades, and one at the individual researcher level. The analysis at the cluster level has the advantage of avoiding double counting, when there are several co-authors from the same cluster, but suffers from the fact that researchers might be part of several clusters. It shows no significant effect on productivity. However the results might be biased downwards since many researchers are part of several proposals and thus members in the control group could be potentially treated in other clusters. At the individual level, using our identification strategy based on grades, we do find significant effects on productivity, in the order of 3 to 5 % depending on whether measures are weighted by the number of authors. These effects on productivity have to be interpreted in light of the relatively small amounts per capita that were at stake. If the funding was equally shared among all the researchers that we identify as cluster members, this would represent 50K euros per researcher over a 10 year period, a much smaller amount than the typical individual grant.

These average effects in fact hide significant heterogeneity, in particular function of the proximity to the topic (core vs. periphery members). It is natural to expect that those who would benefit the most from the funding, would be the core members. In fact, the policy maker could even worry that the funds might be appropriated by a small group of core members. Paradoxically we show that the effect of the funding is much larger for periphery members, both in terms of quantity and quality. We interpret this as indirect evidence that the funding induces activities, such as seminars on the cluster topic, where core members provide local public goods that benefit periphery members. In the absence of the financing, these peer effects might not have been stimulated. Consistently, when we examine heterogeneity of the treatment effect in the dyadic regressions, we find that the probability of a link between a core and a periphery member increases by twice as much as that of a link between two core members.

Finally, since a significant number of the researchers are involved in several clusters, we evaluate the effect of being part of several funded clusters relative to being part of only one. In the same spirit as before, we restrict ourselves to researchers who were part of exactly two cluster proposals, who got at least one funded, and received similar grades for their worst graded proposal. We then compare the researcher having only one cluster selected, versus the one having two selected, the second selection being considered as good as random. We show that the effect on productivity of having two rather than one cluster is negative. This seems mostly driven by a smaller investment of the involved researchers.

Overall, this draws a general picture where research cluster funding encourages a large restructuring of the network of collaborations, that benefits mostly those who are not initially part of the core of the project. The policy worked more as an instrument encouraging periphery members to catch up and to connect to the core. We show that in fact the policy decreased the inequality within the group in terms of publication (measured by a Gini coefficient). This suggests the policy stimulated peer effects that often materialize via collaborations. However policy induced peer effects are asymmetrically distributed, essentially to the benefit of periphery members. Besides, the policy did not promote scientific excellence, which was a stated objective of this policy and of many other similar policies. We discuss this in depth in Section 7.

Our results could be on interest for several other strands of the literature.

The first one studies the design and impacts of research funding programs. A number of papers have investigated the effectiveness of competitive grant allocation *ex-ante* and *ex-post*. Studies that focus on the *ex-ante* stage typically either examine how accurate reviewers are in predicting projects outcomes (Li and Agha, 2015; Park, Lee and Kim, 2015; Fang, Bowen and Casadevall, 2016), or how biased evaluations are with respect to PI's, proposal's or reviewer's characteristics (Ginther et al., 2011; Boudreau et al., 2016; Li, 2017; Banal-Estañol, Macho-Stadler and Pérez-Castrillo, 2019). *Ex-post* studies examine the impact of fund allocation on the treated, typically considering productivity as the variable of interest.Most studies find a positive but limited impact on the quantity and quality of scientific outputs. Assessing the impact of R01 NIH grants, Jacob and Lefgren (2011) find an a 7% increase in cites. In the French context, Carayol and Lanoe (2019) find that a grant from the French research funding agency increases publications by 3.5%, journal Impact Factor weighted papers by 8.2%, and total cites by 15%. Besides identifying the impact of funding programs, few studies compare how the very design of fund allocation affects outcomes. Azoulay, Graff Zivin and Manso (2011) show that funding schemes that do not excessively punish early failures are more susceptible of generating high impact research. Carayol and Lanoe (2019) compare directed programs which target a given research theme with non-directed funding programs. They show the latter have significantly larger scientific impact though the former likely pick principal investigators whose research is more original. A few studies examine more large scale financing programs. Defazio, Lockett and Wright (2009) looks at EU level schemes that fund team with members from multiple EU countries and show some long term effects on collaborations. To the best of our knowledge, this paper is the first to empirically assess the impact of a very different science funding design, funding research groups rather than individuals or small teams.

As described above, cluster policies are specifically designed to stimulate peer effects. There is a large literature on peer effects in research. Using the distinction made in Borjas and Doran (2015), peer effects can occur along the collaboration, the idea and/or the geographical space. There is now strong evidence of peer effects in the collaboration space. In particular, several papers (Azoulay, Graff Zivin and Wang, 2010; Oettl, 2012; Jaravel, Petkova and Bell, 2018) exploit the unexpected deaths of scientists to estimate the causal effect on the productivity of their co-authors or collaborators. Azoulay, Graff Zivin and Wang (2010) find a strong effect following the death of star scientists, while Oettl (2012) qualifies this result by showing that the effect is restricted to helpful scientists (i.e. those acknowledged in several papers per year). Jaravel, Petkova and Bell (2018), using patent data, show that the effect is not restricted to the stars. The evidence on the importance of joint location of these peers is weaker. Waldinger (2012) shows that the scientists whose departments suffered losses during the period from 1925 to 1938 did not publish less or worse compared to other scientists. Similarly, Borjas and Doran (2012) show a negative effect of the influx of Soviet Union mathematicians on the productivity of American mathematicians, due to competition for scarce resources, but no effect on overall productivity. Finally there is some evidence of peer effects in the ideas space (Iaria, Schwarz and Waldinger, 2018; Bosquet et al., 2020). Our paper shows that policies can affect these peer effects, in particular stimulate new collaborations, but that peer effects appear to be very asymmetric.[3]

[3] As we consider specifically the effects of the creation of these academic clusters on team formation and collabo-

Our paper also speaks to the active literature more generically interested in the formation of social relations (see Jackson (2008) for an overview of that literature). Only a few papers in this literature study the impact of policy interventions on the structure of the network. Banerjee et al. (2019) analyze the reorganization of social networks within rural villages in India due to an exposure to micro-credit and Hess, Jaimovich and Schndeln (2019) examine the consequences of community-driven development programs in west African villages. Both papers find that the treatment induces a significant decline in the probability of connections in villages. Interestingly, Banerjee et al. (2019) show that those who are less likely to be personally targeted by microfinance are the ones who experience the stronger decline in connection probability (even between them).

The problem of reorganizing funding and priorities inside a group is ubiquitous, faced widely in many social groups, be it units within a firm or members of a village community. The advantage of observing this process within academia, is that the patterns of collaboration can be directly observed and that common productivity measures are available. In this respect, our paper demonstrates that even relatively modest shocks in terms of financial capacities may have large implications in terms of the network of collaborations.

The rest of the paper is organized as follows. In Section 2, we present institutional details on the French academic research system and on the research cluster policy whose impact we investigate. Section 3 describes data collection and the data set. Section 4 provides some descriptive statistics, gives evidence on the selection procedure and exposes the identification strategy. Section 5 is dedicated to presenting the results on the collaboration network and Section 6 the results on research productivity. Section 7 interprets the results and discusses policy implications.

2 Institutional Details

In this section we provide some details on the institutional organization of research in France and on the recent policy reforms whose impact we study.

2.1 The Organization of Academic Research in France

The French academic research system is quasi exclusively within the public sector. It is based on both universities and large research institutes. The main research institute is the Centre National de la Recherche Scientifique (CNRS) created in 1939, that recruits researchers across all disciplines, granting tenured positions with no teaching obligations. Other research institutions such as INRA or INSERM have more specific lines of investigation (agriculture and health respectively).

At the micro level, as in several continental European countries, research is mostly performed in research units (see Carayol and Matt, 2004) which may be considered the fundamental elementary

rations, our study therefore relate to the literature on teams in science. Wuchty, Jones and Uzzi (2007), using several decades of data on publications, show that research is increasingly reliant on teamwork across fields and furthermore that the knowledge produced by teams are more likely to create very high impact research. Adams (2013) shows that international teams are particularly productive.

block for the organization of academic research. Some research units are attached to only one institution, but many are mixed in the sense that they are supported on a contractual basis by several institutions, most of the time one research institution (CNRS for example) and one university. Research units are evaluated every five years by a dedicated national agency. On the basis of those evaluations, units are maintained, closed or may be reorganized or merged. Each research unit is governed by its own statutes but typically has a director and an elected council which define and implement its strategy. Research units receive block funding from their supporting research institutes and universities used partly to finance researchers, professors, support staff, PhD students, and post docs whom they employ.[4]

2.2 The Research Cluster Policy Initiative

On the basis of a bi-partisan report written by two former prime ministers, the French president, Nicolas Sarkozy, announced in 2009 a large scale investment plan for research and productivity. The 35 billion euros (about 39 billion USDs) initial budget was divided in the following way: 21.9 billion euros were allocated to research in the public sector and higher education. This included pure research financing, renovation of university campuses as well as the creation of technology transfer offices. 7 billions were dedicated to the financing of small and medium firms and the rest to a program targeting renewable resources and development of digital technologies. The budget allocated to higher education and research was administered by the Agence Nationale de la Recherche (ANR) whereas the segment relative to the financing of firms was administered by the Banque Publique d'Investissement (BPI).[5]

We focus on the program called "Laboratoires d'Excellence" (LabEx). It aims at financing consortia of research units planning to work on a common theme (what we refer to as research clusters).[6] It was an explicit objective of the policy to provide incentives to local research communities and local stakeholders to bypass institutional or even disciplinary boundaries and to create synergies between teams and research units located in the same city.

The program was run on a bottom up and fully competitive basis at the national level by the ANR. A fist call for research clusters proposals was issued in 2010. Each application was carried by several research units (described in the previous section) with one coordinator in charge. The 200 applications received were sent to external reviewers and the independent international committee selected 99 winners that were announced on March 25th 2011. A second call was made in October 2011, 195 proposals were submitted (including 55 re-submissions from the first stage) out of which 71 were funded. The large part of the pre financing of the first wave was paid between July and

[4]There is a large degree of heterogeneity in research units. Some may host several hundred of members whereas others barely gather more that a dozen of researchers. This means some research units may actually be considered as full-fledged local research departments, as others are more like teams around a handful of principal investigators.

[5]The ANR has been created in 2005 to perform grant based research funding. Its organization has been redesigned to also administer this program. BPI is a public administration targeted towards the financing of small and medium firms in particular innovative firms (see http://investissementsdavenir.bpifrance.fr/ for details).

[6]Similar policies have been developed in other countries such as Germany, or the Nordic countries with the similar goal to support and develop a limited number of world class research clusters.

November 2011 whereas the second wave was paid between May and August 2012.

The funding for these research clusters was for a ten year period, with an average allocation of 10 million euros, ranging from 2 to 30 millions. In many cases, this amount allowed them to raise further funds. Each cluster is organized in a specific way, but most of them have a director, an executive and a scientific committee. Some also have a steering committee. Most of the time, leading scholars were involved in the top management.[7]

3 Data and Variables

3.1 Data

3.1.1 Research Clusters

The ANR shared with us all the application files they received for the LabEx program, including those that were not ultimately selected. All those files include the name of the coordinator, the name and identifying codes of the partner research units, the amounts requested and the funding decision. It also includes a summary of the project.[8] In addition each file contains a bibliography from which we extract the names of all authors.

The ANR also provided us with an additional piece of information, essential for our identification strategy, namely the grades awarded by referees to each proposal. External referees graded proposals on seven criteria: the quality of the teams and facilities, the relevance of the research project goals, the potential in terms of innovation and impact, involvement in training (especially masters degrees and PhD), organization and management, strategy of institutions (universities and research institutes), project/means adequacy and ability to generate resources.

3.1.2 Cluster Memberships

We define, for both the selected and non selected proposals, research cluster membership as being a tenured professor or researcher and being member of a research unit listed as a founding partner in the proposal file described above. Note that this is a liberal definition since not all members of the associated units necessarily effectively participate in the activities of the research cluster. It is however the natural definition as effective memberships to those research clusters was not recorded.

Given this definition, to identify the members of the clusters we thus had to recover the list of all members of the involved research units. To obtain such a list, we used a country-wide roster of academic researchers and professors that contains approximately 85% of all tenured professors and researchers who have been employed in academia in France since year 2005. This unique dataset (described in more details in the Appendix) has been built using a variety of official sources thanks to the centralization of that information at the national level in France. As it offers information on

[7]For instance, Jean Tirole is the President and Chairman of the Executive Committee of the research cluster IAST (Institute of Advanced Studies in Toulouse) dedicated to the interactions between economics and other disciplines.

[8]For confidentiality concerns, we were not given access to the full text of the proposal.

the employing university or research institute and on the research unit, it was possible to attach each person to cluster proposals.

Besides, we use data extracted from the project bibliography to further refine the membership definition. For each research cluster (financed or non financed), we identify two subgroups:

- The **Core members** are members of the research cluster (i.e members of one of the research units listed as partners) who also appear as author of articles listed in the bibliography of the proposal.
- The **Periphery members** who are members of the research cluster but whose work is not referenced in the bibliography.

This should be a relatively precise measure of core and periphery members, since it was in the interest of those writing the cluster proposal to include all the relevant papers in the field. There are two potential sources of inaccuracy. On the one hand, researchers cited in the bibliography who are no longer working in the field or even active in research. On the other hand, researchers not cited because they just started their career. However, this seems unlikely since descriptive statistics in Table 15 show that core and periphery members are very similar in age.

3.1.3 Scientific Publications

We then build bibliometric information on all cluster members. For that purpose, we first match all cluster members names to the authors of scientific articles (on the basis of surname and first name initials) in the Clarivate Web of Science (in house XML datafiles and online access), which gathers all the documents published in the main scientific journals. We retrieve more than ten million documents published until 2017 that need to be filtered out to keep only those that have been authored by professors and researchers in the research clusters we study and not by homonyms across the world. We do so using all available information we have on individual profiles through a "seed and expand" methodology (Reijnhoudt et al., 2014).[9] As all regressions below use individual fixed effects, we consistently restrict the data to those professors and researchers for whom we have retrieved at least one article over the period. This drops out a significant number of researchers in particular in the social sciences and humanities. Though it is one of the largest available source of scientific outcomes, the Web of Science only partially covers fields such as arts, humanities and some social sciences in particular in non English speaking countries.

[9] In a first step (seed), the algorithm validates articles by imposing strong and reliable conditions, particularly on the scientific field and on the hosting institution that need to be fully consistent with what we know for each person. The "expand" stage is in fact composed of a series of loops in which information on validated articles is used to make decisions on articles which pass only some of the conditions imposed at the "seed" stage. For instance, if it turns out that a candidate paper has the same co-authors, cite the same references, or use the same keywords than validated articles, this increases the conditional probability of a correct match. We use machine learning algorithms that are trained on a subset of French professors and researchers who have created an ORCID identifier and are thus likely to have carefully selected their own publications. From end to end, this filtering process is controlled for and fine tuned to improve efficiency in terms of precision and recall.

Our final data cover 382 cluster proposals, 2,130 distinct research units and 29,886 researchers or professors. Out of this sample, 10,806 are core members of at least one proposal whereas 19,080 are only periphery members. 21,383 scientists are members of at least one funded cluster whereas 8,503 were never funded.

3.2 Variables

A series of personal variables were obtained from the administrative data, in particular age, gender and professional status of the researchers. We rely on several scientometric indicators to appreciate different dimensions of research outcomes. The number of publications (*Pubs*) published in a given year proxies the intensity of research activity whereas weighting each paper by 3-year forward citations or by the journal impact factor better takes into account the quality of each paper (*Cites* and *JIF*).[10] There is a longstanding and still ongoing debate in the scientometric literature over using full counting methods or fractional counts for different purposes.[11] We thus also calculate adjusted for co-authorship versions of productivity indicators (*PubsAdj*, *CitesAdj*, *JIFAdj*).

As the cluster policy aims at fostering scientific excellence, we also build indicators focusing on top "quality" scientific outcomes. For each researcher, we count the number of papers that are among the top 5% and top 10% most cited papers as well as the share of such papers in their yearly publication outcomes.[12] Scientometric data may also be used to build indicators over the entire career. Though it has some well known flaws, the h-index (Hirsch, 2005) captures sustained research activity over the career path (*Hindex*).

Scientometric data are also helpful to appreciate collaboration patterns, which is a key focus of our study. We measure the average team size (*TeamSize*) on each paper by the average number of authors (cf. Wuchty, Jones and Uzzi, 2007). We are particularly interested in the specific composition of teams within the targeted research clusters. Though the complete disambiguation of authors in the Web of Science is way beyond the scope of this study (there is not an available author identifier in these data), we can however take advantage of the complete retrieval and disambiguation of the publications authored by the members of cluster proposals exposed above. How intensively professors and researchers collaborate with other people within their research cluster is captured via five different variables, all measured for each year. First, the number of papers with at least one other author from the cluster (*CollaPubs*), and the corresponding measure of the number of papers without co-authors from the cluster (*ExternalPubs*). Second, the number of links, i.e co-authors, the individual has within the cluster (*Links*), and the corresponding variable restricting to links never formed in the past (*NewLinks*). Finally the number of collaborations

[10] The Journal Impact Factor is one of the most famous and frequently used measures to assess a journals' audience or prestige. We calculate our own version as the average number of citations that a paper published in year t receives from papers published in $[t; t+2]$.

[11] Fractional counting divides each paper contribution to a given indicator by the number of authors (or the number of institutions if the assessment is made at the institutional level).

[12] Formally, top cited over a three-year period and among papers in the same scientific discipline (WoS "subject category"), year and document type (research article, letter, review).

within the cluster, which measures the intensity of the links (*Collaborations*).[13]

We also build variables at the cluster level, to avoid double counting when multiple co-authors from the same cluster are involved in a publication. Specifically we construct the total number of articles in the cluster (*PubsRC*), the papers weighted by citations (*CitesRC*), the articles weighted by the Journal Impact Factor (*JIFRC*), and the average team size (*TeamSizeRC*). To appreciate within cluster inequality, we calculate the Gini coefficient of the publications distributions.

4 Identification Strategy and the Selection Process

In this section we set the stage by first examining empirically how proposals were selected based on grades, and present average characteristics of the research clusters and researchers involved in them. This selection process will be the basis of our identification strategy described in Section 4.3.

4.1 Research clusters and selection process

We present in Table 1 the average characteristics of the research clusters (Column (1)) and compare those that were selected in Column (2) to those that were rejected in Column (3) (Column (4) presents the comparison of means test). On average we observe 171 researchers in each research cluster with a relatively large variance. Among those, 32% are core members. These clusters group on average 17 different research units. The striking feature is that, even though the selected clusters tend to be larger and more productive than the rejected ones, the differences are not significant, except for an over-representation of clusters in computer science. Particularly striking, and a feature important for us in the rest of the analysis, is that the proportion of core members is exactly the same across selected and non selected clusters.

As described in Section 3.1, we obtained the grades awarded to each proposal and therefore provide some evidence on the selection process. In Table 2, we compare grades for selected projects to grades of those rejected, distinguishing the different components of the grade. Reassuringly grades are significantly higher for those selected, and this for all the components of the overall grade. The difference between grades of those selected and rejected is highest for the grade on the quality of the team (criterion 1), goal of the project (criterion 2) and on the potential for research output (criterion 3), and this is confirmed by a regression analysis of the drivers of selection (see Table 14 in the Supplementary Appendix).

As described in Section 2, the final decision of which academic clusters to select did not follow a cutoff rule. We plot in Figures 1 and 2, the probability of being accepted as a function of the total grade, distinguishing between the 2010 and 2011 contests. Consistently, the probability of acceptance is increasing in grades. However there is a range of grades where the probability of

[13] We define a collaboration as active dyads on given papers, so that if a scientist has, in a given year, two papers with two co-authors each, this always counts as four collaborations whether the co-authors on the two articles are the same researchers or different ones. This distinction matters however for the calculation of the number of links.

acceptance hovers between 20% and 80%. Later in the paper, we restrict the analysis to this intermediate range of grades, in order to compare projects with similar characteristics. We then plot in Figures 3 and 4, the probability of being accepted as a function of the grade on criterion 3, that corresponds to the research potential of the project. We see that receiving a grade of 4 out of 5 on this dimension, gives a roughly 50% chance of being selected. This will also be used to construct an alternative identification strategy.

4.2 Researchers

After having described the characteristics of the research clusters and the selection process, we now examine the characteristics of researchers. In Table 3 we present bibliometric information on the years before 2010, i.e. before the financing. Column (1) shows that we have in our data a pool of relatively active researchers. The average researcher in our sample publishes 1.62 papers per year, which divided by the number of authors corresponds to .39 publications per year. The average h-index in the sample is 4.79. Comparing the selected and rejected projects, we see that the characteristics of the group members are quite different. Members of selected projects are significantly more productive. For instance they publish 1.65 papers a year in the financed groups as opposed to 1.5 in the clusters that were not approved. The h-index is also significantly different across groups. We show below that when we impose restrictions on grades, restrictions explained in more detail below, the average characteristics of the researchers involved are much more similar.

4.3 Identification

The main specification that we will use is the following:

$$y_{it} = \mu \text{ Treatment}_i \text{ Post}_t + \gamma_i + \eta_t + \epsilon_{it}, \tag{1}$$

where Treatment_i identifies whether individual i is a member of a research cluster that was funded and Post_t identifies the post policy period, i.e. the year 2012 onwards.[14] This specification includes individual and year fixed effects, that for instance take into account the fact that researchers in clusters that were selected to receive funding tend to be of higher average quality. The time period ranges from year 2005 up to year 2017 included.

As shown in the descriptive statistics of Table 3, researchers in funded projects are different from those in non funded ones, in all the measures of productivity (publications, citations, co-authorships). The differences in levels are captured by the individual fixed effect in Equation (1). As is always the case with difference in difference specifications, the key identifying assumption is that trends leading to the policy change are not different. However there are some reasons for these trends to potentially differ. For instance, if the committee is good at selecting more promising projects with better potential, the results would be biased upwards. On the contrary,

[14] Even for the 2010 competition, the first funds were obtained only in 2011, so we position the actual start of the policy in 2012.

if the committee over-weights past achievements that might be negatively correlated with future trends, in other words selects research clusters that just reached their peak, the bias would go in the opposite direction.

To overcome this challenge to identification, our main strategy exploits the grades attributed by reviewers to the different projects. Specifically, we restrict our sample to researchers who (i) are members of a single research cluster application and (ii) this cluster received a grade in a specific range. We chose this range as a the set of grades that gave a probability of approval between 20% and 80%.[15] We thus restrict to projects having a priori a similar potential, interpreting the final selection as reflecting orthogonal factors such as for instance geographical coverage of the territory. We show in Table 4 that when we impose the restrictions, researchers in financed vs rejected clusters become non distinguishable on yearly publication data, even though they remain significantly different in terms of international collaborations.[16] Moreover we will verify for our main variables that when we impose this restriction, there are no significant pre-trends between the control and treatment groups.

Throughout the paper, we will refer to this first set of restrictions as "restriction on overall grade". This will be our main identification strategy. We will also use a second strategy that exploits a particular component of the grade measuring research potential. We restrict to researchers who (i) applied in a single research cluster and (ii) this cluster received a grade of 4 out of 5 for the potential of the project (criterion 3). These projects were judged by the reviewers to have the same potential future trends, but some got financed for reasons possibly orthogonal to research output, like the potential to generate training (criterion 4) or the strategy of the supervising institutions (criterion 6).[17] We refer to the second set of restrictions as "restriction on criterion 3", and this will be used to verify robustness of our main results. We will conduct two additional robustness exercises. First, for our main tables we present the results when the sample is not restricted (relax the main restriction). Second, we do the opposite and apply a stronger restriction on the data.[18]

[15]The specific condition is that the cluster received an overall grade between 26 and 32 for the 2010 contest and between 30 and 32 for the 2011 contest.

[16]In Table 15 in the Supplementary Appendix, we do the same comparison of core vs non core members. Core members are much more productive than non core members, a fact that will turn out to be important in the rest of the analysis.

[17]Note that the projects receiving a grade of 4 on this criterion had roughly a 50% chance of being selected. Table 25 in the Supplementary Appendix, shows that this restriction does make the involved researchers very similar, independently of whether their cluster was financed or not.

[18]Specifically, for this stronger restriction, we require the grade of the unique proposal to be between 28 and 31 for 2010 and equal to 31 in 2011, which guarantees a probability of selection between 40 and 60 %. We perform in the Supplementary Appendix the equivalent exercise for these restrictions as in Table 4. In Table 15 in the Supplementary Appendix, we do the same comparison of core vs non core members. Core members are much more productive than non core members, a fact that will turn out to be important in the rest of the analysis.

5 The Impact of Research Clusters Funding on the Internal Network of Collaborations

The research cluster funding policy we study was an intervention targeting relatively large groups of individuals with the ambition of affecting the interactions between them. This is what makes this funding instrument potentially different from an aggregation of individual grants. We therefore start by investigating whether the program reshaped research links.

To illustrate the potential effects on the network of collaborations and to preview our empirical results, we start by presenting in Figures 5 and 6 an illustration of two research clusters, one funded and the other rejected. We present the graph of the collaboration networks of these two cluster proposals (where a link is a co-publication over the period) separately before and after 2012, i.e the first treatment year for the funded cluster. We also restrict for representation purposes to nodes corresponding to individuals involved in a unique cluster proposal. The two research clusters we selected received similar grades, have similar number of nodes (58 and 60 for the treated and the non treated respectively) and similar number of links before treatment (69 and 74). This gives nearly the same network density before treatment (≈ 0.0209). We represent the periphery members in blue and the core members in green.

The first striking feature visible in Figure 5 is that for the funded cluster, the network becomes much denser in the after treatment period, while changes are more limited for the rejected cluster in Figure 6. The second salient feature is that the periphery members represented in blue increase very significantly their connectivity in the funded cluster compared to the core members. We show below that these features are not specific to these two networks, but apply much more generally.

5.1 Organization of the Research Network

Table 5 reports the results of the estimation of specification (1), using the first identification strategy mentioned above, i.e restricting to researchers involved in a unique proposal that obtained similar overall grades. Column (1) shows that the researchers in a funded cluster, after being financed, increase their number of publications involving at least another co-author from the same cluster, while Column (2) proves that there is no effect on publications involving only co-authors outside the cluster.

In Figure 7 and 8 we present graphically the results. Specifically we estimate the following equation:

$$y_{it} = \gamma_i + \eta_t + \epsilon_{it}, \tag{2}$$

and plot year by year the difference between the fixed effect η_t in the treatment group (members of a funded cluster) and in the control group (members of a rejected cluster), imposing the restriction on overall grades. These figures illustrate the fact that, for the publications inside the cluster, there are no pre-trends before the treatment, thus validating our identification strategy. Moreover there is then a gradual increase from year to year. On the contrary, for the publications outside the cluster there are no differential trends after treatment. The effect is large since the average difference of 0.118 publications between the treatment and control groups represents an increase of 14%, while the effect at the end of the period visible in Figure 7 represents an increase of 24%. Figure 8 shows no significant effect on publications outside the cluster.

In columns (3) to (5) of Table 5, we examine whether these extra publications correspond to the creation of new collaborations or rather strengthening of existing ones. The results appear to show that both mechanisms are at play. Column (3) shows that the number of links with other members of the cluster increases when the cluster is financed. Column (4) shows that this parallels an increase in the creation of links that had never been formed before. Finally Column (5) shows that the intensity of use of each link also increased. Once again the magnitude is large and the increase gradual across the years as shown in Figure 9 (that also shows the absence of pre-trends). In fact these links take some time to be formed, as visible Figure 9 where the increase only starts in 2014. By the end of our observation period, the increase is in the order of 30% compared to the control group. We do the same exercise in Figure 10 and obtain the same results for the number of collaborations.

We present in the Supplementary Appendix robustness exercises where we either apply no restrictions on the clusters included (Table 18) or restrict only on the grade specific to the goal of the project, i.e apply the second identification strategy (Table 22) or apply more stringent restrictions on the overall grade (Table 26). The results are very similar when we apply the alternative restrictions. They tend to be somewhat weaker in the specification without restrictions. This suggests that there is a downwards bias. One plausible interpretation is that reviewers, by selecting projects of higher baseline quality, might also be selecting clusters with a more established international network and less inclined to revisit their structure of collaborations.

5.2 Dyadic Regressions

In this section, we study directly the process of link formation within the cluster via dyadic regressions. One of the main advantages of this approach is that dyadic regressions allow us to precisely quantify the impact of the cluster policy on the probability that two treated researchers work together. Moreover, as explained below, it offers the possibility to impose the restriction on overall grades on both members of the dyad.

We use the following variant of specification 1:

$$g_{ijt} = \mu \text{ Treatment}_{ij} \text{ Post}_t + \gamma_{ij} + \eta_t + \epsilon_{it}, \tag{3}$$

where g_{ijt} is a dummy equal to one if there is at least one paper published in year t that is coauthored by i and j who are both members of the same research cluster proposal (and zero otherwise). The dummy Treatment_{ij} identifies whether the cluster in which individuals i and j participate was funded, and Post_t identifies the post policy period (when $t \geq 2012$). Furthermore we include time and dyad fixed effects. The dyad fixed effect controls for time-invariant characteristics of the nodes involved, what was not possible when in Table 5 we looked at the impact of funding on the number of links at the individual level. Note that all observations of dyads for which there is no variation on the dependent variable over time (links are never formed, or are formed every year) are differentiated out. As the dependent variable is a dummy, we use a linear probability model with fixed effects (conditional logit model) to estimate Equation 3. Importantly, we adopt the same restriction on overall grades used in the previous results, considering only dyads ij, for which both i and j satisfy the restriction. The dyadic regressions thus have two advantages compared to our previous analysis. First, we can include dyadic fixed effects, controlling for specific interactions. Second, it makes it possible to apply restrictions on grades to both members of all considered pairs.

We show in Column (1) of Table 6 that being in a selected cluster increases the probability that a link is formed by 26.6%.[19] The effect is thus even larger than when we examined in Table 5 Column (3) the impact on the number of links at the individual level, where we found an effect in the order of 15%.[20]

5.3 Collaborations within and across the Core and the Periphery

We have shown a large effect of the financing on the network structure. It is thus natural to ask who is most affected by this restructuring? It could be expected that those at the core of the cluster's theme might be more affected by the financing, if for instance they obtain more research money via internal fund allocation. There could even have been an initial worry that the funds would be to some extent captured by the leading members of the cluster. Our results suggest otherwise. We estimate the dyadic specification (3) on sub-samples of dyads: the ones between periphery members, the ones between core members, and the ones between periphery and core members of the cluster. The treatment has a greater impact on the probability that core-periphery dyads form a link. Column (3) of Table 6 indicates that the treatment increases the probability of a link in a core-periphery dyad by nearly 33%, whereas it increases the probability of a link in a core-core dyad by 23% and by 29% for a periphery-periphery dyad.

In Column (5) we estimate an extended specification:

$$g_{ijt} = \mu \text{Treatment}_{ij}\text{Post}_t + \phi \text{Treatment}_{ij}\text{Post}_t\text{PP}_{ij} + \psi \text{Treatment}_{ij}\text{Post}_t\text{CP}_{ij} + \gamma_{ij} + \eta_t + \epsilon_{it}, \quad (4)$$

where PP_{ij} is a dummy equal to one when the dyad (i and j) is composed of two periphery members. The dummy CP_{ij} equals one when the dyad is made of a member of the core and a member of the periphery. We are interested here in estimating ϕ (resp. ψ) which captures the magnitude of the average treatment impact on the probability of a link between a periphery and a core member (resp. two periphery members) relative to its impact on the formation of a link between any two

[19] Table 6 reports the odds ratio, the coefficients are presented in Table 16 in the Supplementary Appendix.

[20] The positive impact of cluster financing on the probability to connect is essentially supported by most robustness checks. When we remove all restrictions, the estimated effect remains, though it is much smaller in magnitude (5.4% effect in Column (1) of Table 19 in the Supplementary Appendix). It is non significant when restricting on grades obtained on the third criterion (Table 23) but it is significantly larger when imposing a more stringent restriction on the overall grade (a 68% increase reported in Column (1) of Table 27).

core members. Column (5) of Table 6 reports an $exp(\hat{\phi}) \approx 1.9$, which indicates that the treatment is 90% more effective on the probability that core-periphery dyads connect than on the probability that core members create a link. In turn dyads among periphery members are in average 51% more impacted than dyads among core members ($exp(\hat{\psi}) \approx 1.508$).[21]

6 The Impact on Scientific Productivity

There is clear evidence of a large reorganization of the collaboration networks induced by the policy. Does this in turn have an effect on the productivity of these research clusters? Is the effect different for core and periphery members? In this section we present evidence on this issue, using two distinct methodologies.

1. The first methodology is to aggregate the variable of interest (publications, citations) at the research cluster level and compare financed and non financed clusters, restricting on the grades awarded by the referee. The advantage of this approach is to avoid double counting of publications with multiple authors of the same cluster that can occur when doing the analysis at the individual level. It is also easier with this method to compute measures of excellence such as number of top publications in the field and measures of inequality of the distribution of publications. The disadvantage is that some researchers might be part of multiple clusters and the treatment is not in that sense at the cluster level.

2. The second approach is to use specification (1) above and perform the analysis at the individual level. Here the potential issue is the double counting of publications with multiple coauthors in the cluster. This concern can be mitigated by focusing on variables adjusted for the number of co-authors (fractional counting).

6.1 Analysis at the cluster level

We start by presenting the results using the first methodology. Starting from the sample of 382 clusters for which we have productivity data, we restrict to clusters with similar grades. The results are presented in Table 7. Overall the results indicate no significant effect of the financing on measures of productivity, number of publications in column (1), weighted by cites in column (2) or weighted by IF in column (3). Note that, as reported in Table 17, if we do not impose restrictions, we do find a positive effect of the policy on productivity. One of the stated objectives of the policy was to encourage excellence. We show in Table 8 that this goal was not attained. On the contrary, financing tended to have a negative (although non significant) effect on the number of publications at the cluster level in the top 10% (Column (1)) or top 5% (Column (2)) in their field. In terms

[21] All robustness checks (see Column (4) of Tables 19, 23 and 27) support the statement that the formation of links in core-periphery dyads is significantly more impacted by cluster policy than in core-core dyads, with incidence ratio rates ranging from 57% to 97%, as well as the formation periphery-periphery dyads in a smaller extent with incidence ratio rates ranging from 33% to 69%.

of proportion of publications in the top 10 (Column (2)) or top 5 (Column (4)), there is no effect either.

However we find a significant effect of the policy on the measure of inequality of the distribution of publications at the cluster level. For each cluster - year combination, we calculate the Gini coefficient of the inequality of distribution of publications. The policy decreases the Gini index by 4%. Overall, this suggests that the main effect of the policy was to reduce the disparity in publication levels, without affecting much the average productivity.

6.2 Analysis at the individual level

The cluster level analysis has the drawback that many researchers are in fact part of several proposals and might thus be both in a treated and in a non treated cluster. In Table 9 we therefore perform the analysis at the individual level, using the identification strategy restring on overall grades. When doing so, we find a positive effect of financing. There is a 5% increase in publications (Column (1)) and 7% increase in publications weighted by the Journal Impact Factor (Column (3)). However, as highlighted above, the full counting approach at the individual level may lead to estimates partly reflecting induced differential variations in the size of author teams. Indeed Column (5) shows that one of the effects of financing is to increase the number of coauthors per paper. In turn, when the variables are normalized by the number of authors, publications in Column (2) and publications weighted by Journal Impact Factor in Column (4), the effect is smaller, in the order of 3%.

Are these large or small effects? The financing is rather small when brought back to a figure per researcher: 8.8 million Euros on average to be shared among 165 researchers in our data, which underestimates the pool of people that could have access to the financing. If the amounts were equally shared among all these 165 researchers, this would represent 50K Euros per individual over the length of the project. In any case this is significantly less than the typical individual grant considered in the literature. The average new NIH grant in 2011 was about 407k USDs[22] and the average ANR grant (per PI) is about 150k Euros.

Overall this suggests that the group financing, although it had a very large effect on the structure of the network, has a more modest impact on productivity: a small increase in number and quality of papers produced. The combination of Tables 7 and 9 also suggests that a change in the norms of co-authorship might have occurred. After the financing of the cluster and the creation of rules and procedures, researchers might have included co-authors from the cluster for more minor contributions than what they would have required without the financing. Moreover the policy had not effect on excellence, a discussion we return to in the conclusion.

[22]Statistics available online on the NIH website: https://report.nih.gov.

6.3 Heterogeneity of the effects

6.3.1 Core versus periphery members

As shown in Section 5.1, the intense restructuring of the research network following financing, affected in particular the formation of links between core and periphery members. We now examine whether this translated in a differential impact in terms of productivity across these two groups.

In Table 10 we report results for the core members while Table 11 presents results for periphery members. In Column (1) of the two tables we see that the increase in the number of publications is non significant for core members, while it is significantly different from zero and large for periphery members. The increase of 0.105 publications per year represents an 7% increase for the members of this group. These results are presented graphically in Figure 11 for core members and Figure 12 for periphery members. In both cases there is no clear pre trend in the number of publications per year. However, after the policy there is a clear and very gradual increase in the number of publications for periphery members, while the pattern is much less clear for core members.

The same pattern is present for the other variables. In Column (2), while the increase in publications weighted by number of authors is not significantly different from zero for either group, the increase of 0,016 in the case of periphery members does represent a 4.5% increase. In Column (3) we present the effect on number of publications weighted by IF. For this variable, the increase appears at first sight to be much more sizeable for the core members. However this hides significant pre trends for that group, visible in Figure 13. It appears that after restricting on grades, financed groups have significantly fewer publications weighted by Journal Impact Factor before the policy was put in place. On the contrary, we see in Figure 14 that for the periphery researchers, if anything the pre trends are slightly negative. Importantly, after the financing the increase is gradual, reaching 20% at the end of our observation period.

Overall the evidence strongly suggests that the financing benefits more the periphery members than those at the core of the research topic. They increase their collaborations with members of the cluster, in particular with core members, without decreasing their collaborations with outside researchers, as shown in column (7). The funding can thus have large spillover effects, even on those that were not initially targeted. One interpretation of these results is that the distinction core vs periphery members is in fact capturing a different dimension of heterogeneity. For instance, younger researchers might both be less likely to be part of the bibliography (too early in their career) and also be more susceptible of reacting to funding. This does not appear to be the case as shown in Table 15, since members of the periphery are not significantly different in age compared to core members.

We view these results as reflecting the restructuring of research activity induced by the financing. The first effect is that core and periphery members start working together, as shown in Section 5.1. This might benefit more periphery members who on average have lower initial productivity. There is however a second potential channel. A funded cluster creates a novel research environment. For instance several of these clusters created seminar series on the research topic at stake. These are venues where core members, because of their expertise and reputation in the domain, create public goods that benefit all the researchers in the cluster even absent formal co-authorship links. These peer effects in the ideas space are provided by the core members and periphery members disproportionately benefit from them.

6.3.2 Participation in several funded clusters

There is a second dimension of heterogeneity that might matter, which is the exposure to multiple treatments. In our sample, a significant number of researchers are involved in multiple funded clusters. Specifically, 17% of our sample participates in two funded clusters, while 7% are in three or more clusters that were selected. Our identification strategy up till now was based on the idea of restricting ourselves to researchers involved in a single cluster, having received similar grades, and comparing a researcher whose unique cluster was financed with a researcher who saw her unique cluster rejected. In this section, we now examine the impact of being treated multiple times.

We in fact adopt an identification strategy similar to the restriction on grades used above. We restrict ourselves to researchers being part of exactly two submitted proposals and compare those who had two clusters selected to those who had only one financed, but whose rejected proposal was barely rejected. Specifically, we restrict ourselves to researchers who (i) are part of exactly two cluster proposals, (ii) who got at least one accepted and (iii) who received a similar grade on their lower ranked cluster proposal.[23]

Using this identification strategy we first compare the impact of being funded twice rather than once on measures of productivity. Surprisingly, results in Table 12 indicate that being financed twice rather than once has a negative effect on productivity. Compared to researchers in the control group who take part in only one financed cluster, researchers involved in two financed clusters publish less, whether the measure is number of publications (Column (1)) or whether we put a weight for the Impact Factor of the journal (Column (3)). There is also a negative effect when the measures are weighted by the number of coauthors (columns (2) and (4)). The effect is large, in the order of 10% decrease in publications, implying that for those funded twice there is no difference than being not funded.

We argue that this surprising result could be driven by the fact researchers involved in more clusters inefficiently spread their efforts over too many projects. Consistent with this interpretation, we present results in Table 13 on how being treated multiple times affects the structure of links. All the dependent variables are computed aggregating the variables over the two cluster proposals, regardless of eventual funding. Columns (1) and (2) shows that those participating in two funded clusters have significantly fewer publications with co-authors from these clusters (Column (1)), while the publications outside the cluster are not affected (Column (2)). The variable number of publication with cluster co-authors requires that the publications has at least one co-author from either of the two clusters submitted. Furthermore, Column (3) shows that there are significantly

[23]We calculate the minimum grade among the grades received by the two proposals and restrict it to be between 26 and 32.

fewer links with cluster coauthors for those involved in several clusters. The effect reported in Column (3) corresponds to 17% fewer links for those in two financed clusters.

This result is visible in Figure 15, where we plot the effect on number of collaborations year by year. The difference between the two groups is most striking two years after the financing was received and then stays stable. This Figure also provides a validation of our identification strategy since it shows the absence of significant pre-trends.[24]

7 Discussion and conclusion

The funding of academic cluster is an example of an ambitious public policy trying to stimulate peer effects. This paper shows that this policy generated collaborations. Even though the funding was relatively modest, the probability of forming a within-cluster collaboration increases by 27% thanks to this funding. However, this translates into a more modest increase in average productivity, an effect which interestingly is unevenly distributed across members. We find evidence that the program mostly benefits periphery members, who we show increasingly connect with core members and might also have benefited from the public goods provided by the core members. As the funding of these clusters reportedly led to the creation of activities around the cluster's themes (seminars, training, visitors), it is natural to think that these activities were mostly run by the core members who had the expertise in the topic, an organization possibly taxing in time, and helped others to connect and catch up. We interpret these findings as the policy asymmetrically leveraging peer effects to the benefit of periphery members.

Therefore, in terms of policy, our results suggest that this recent evolution towards these types of financial instruments is warranted if the objective is to increase the connections among local researchers and to raise average quality. However, one of the additional objectives put forward when the policy was put in place was to promote excellence. In that respect, the policy did not achieve its goal, since it had no effect on the top quantiles of the distribution of quality at the cluster level. In fact, the main impact was to equalize the productivity across members of the cluster.

A natural question that emerges is why core members chose to engage in these activities, even though they did not seem to benefit so much from them? One interpretation is that they gain in terms of reputation, both internally and externally or potentially foresee more long term benefits. Another is that they get a warm glow from conducting these activities, but do not engage in them if the cluster is not funded for lack of coordination with other core members. These questions should be the object of future work. The current paper has in any case demonstrated that cluster funding leads to the creation of a more close knit community of researchers, decreasing the inequality in production inside these groups.

[24] The results are not driven by our particular identification strategy. When we do the same exercise, and compare those part of exactly one financed cluster versus those in more than one, without restriction on grades or number of clusters, we find that the same results apply: those in multiple clusters are less productive and create fewer links, although the results are of smaller magnitude.

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Tables and Figures

Figure 1: Cluster selection in 2010 as a function of overall grade.

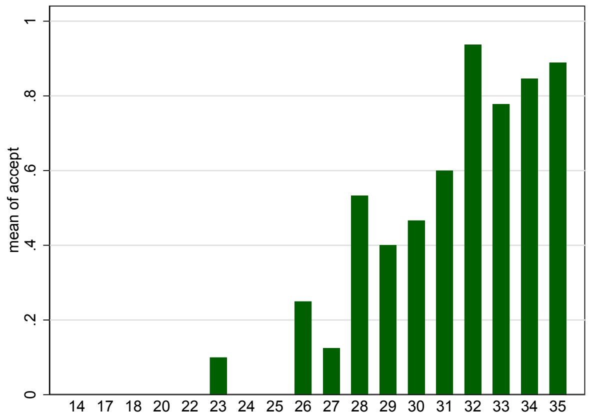
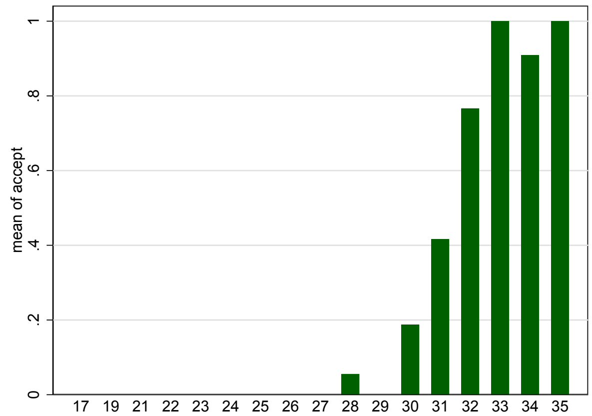


Figure 2: Cluster selection in 2011 as a function of overall grade.



Note: The graphs plot separately for 2010 and 2011 the distribution of the overall grade of the project, calculated as the sum of grades (out of 5) for each of the 7 criteria.

Figure 3: Labex selection in 2010 as a function of grade on research potential (criterion 3).

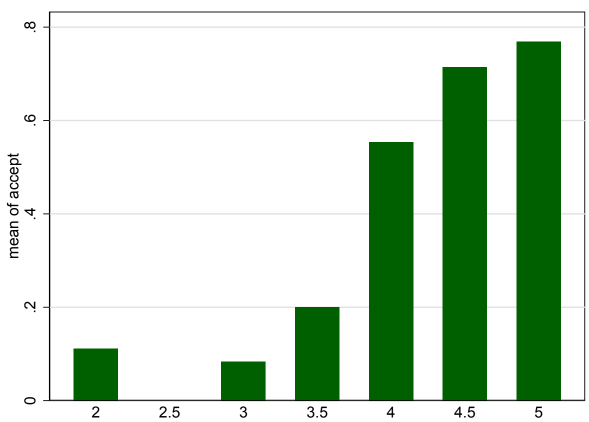


Figure 4: Labex selection in 2011 as a function of grade on research potential.

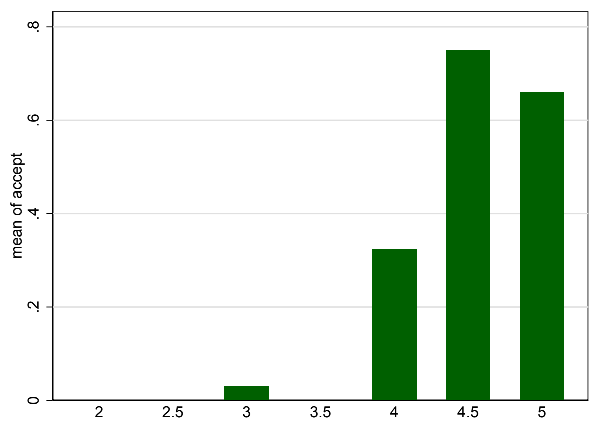
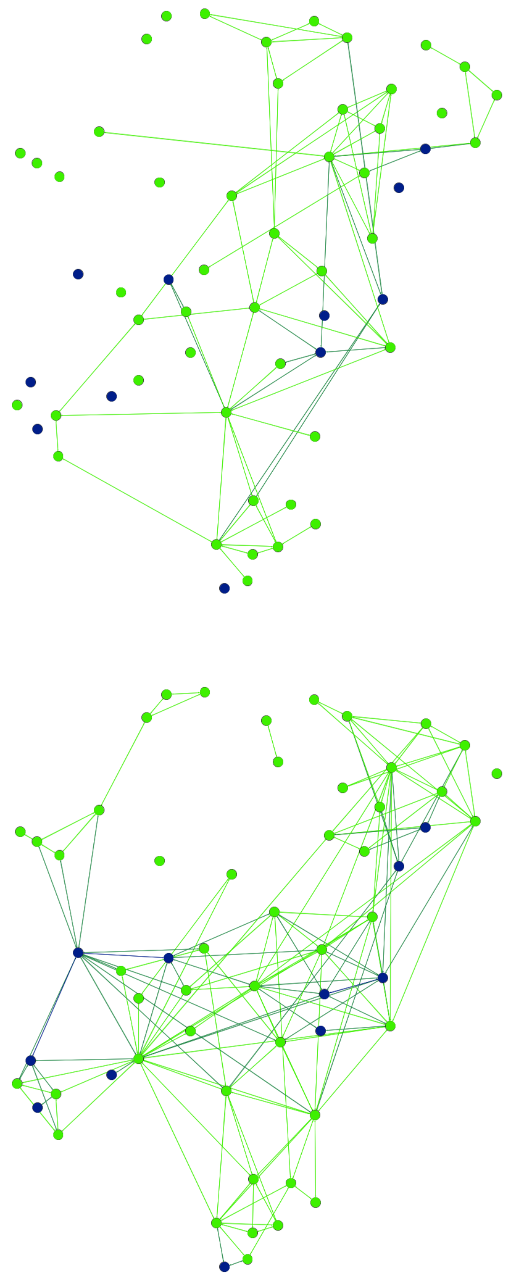
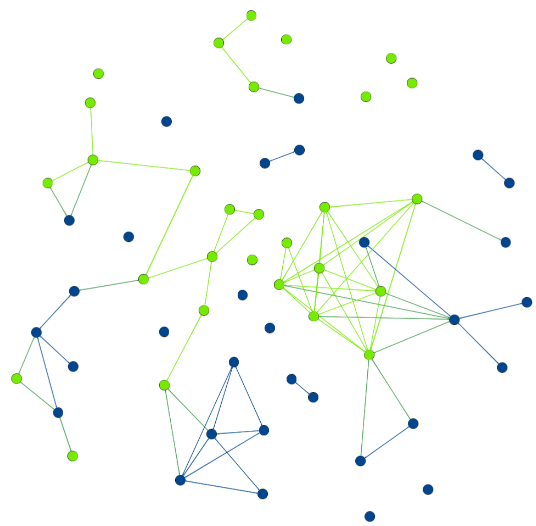


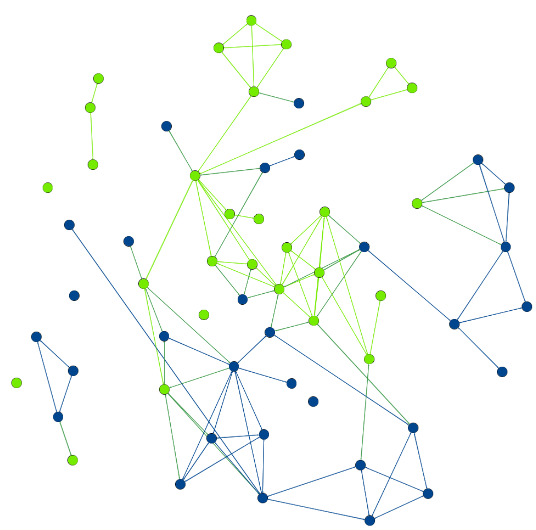
Figure 5: Network of collaborations for a treated cluster, before (top) and after treatment year (bottom).



Notes: we represent the network of collaborations for a particular cluster. Before treatment graph on the top (all years <2012); after treatment graph at the bottom (all years ≥ 2012). Nodes represent researchers (we restrict to those who were part of a single proposal). Light green nodes represent core members and dark blue nodes are periphery members. An edge stands for at least one joint paper in each considered period. The color of each edge is a mixture of nodes' color at both ends.

Figure 6: Collaborations in a non treated research cluster proposals, before (top) and after treatment year (bottom).





Notes: Same as Figure 5 but for a particular cluster that was not funded.

Figure 7: Number of publications with a co-author in cluster: financed vs non financed.

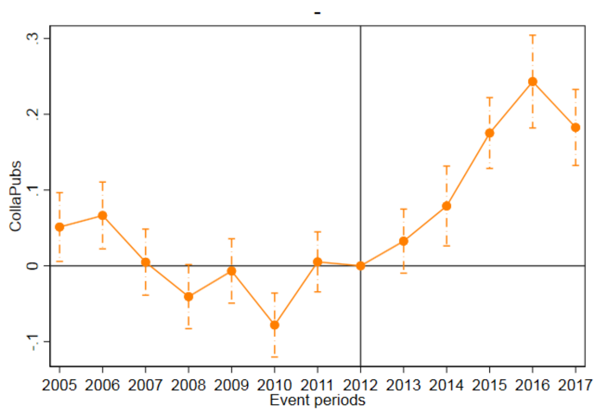


Figure 8: Number of publications with no co-author in cluster: financed vs non financed.

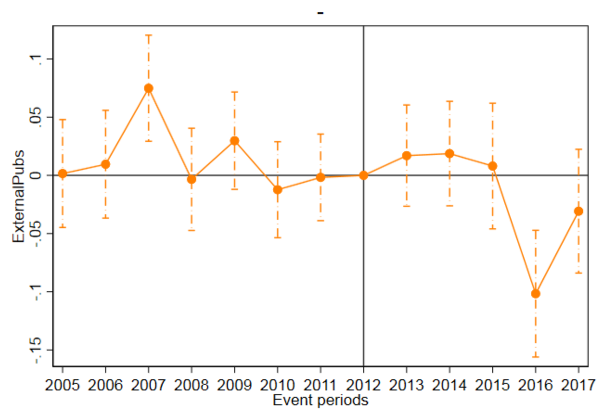
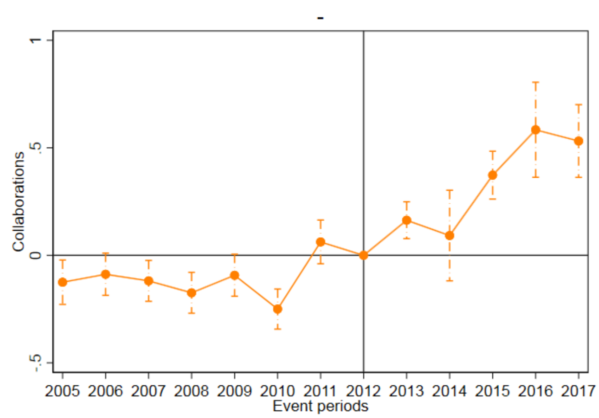


Figure 9: Number of links same cluster: financed vs non financed.

Figure 10: Number of collaborations same cluster: financed vs non financed.



Note: The four graphs plot the estimates of "event" dummies. Specifically, we estimate Equation 1, separately for individuals in the control (members of a non funded cluster) and treatment (members of a funded clusters), applying to the data the restriction on overall grades (which implies that they only have one cluster submitted). We plot the difference year by year between the year fixed effect η_t *of the treatment and control groups. The dashed vertical lines are 95 percent confidence intervals of robust standard errors clustered at the individual level.*

Figure 11: Number of publications core members: financed vs non financed.

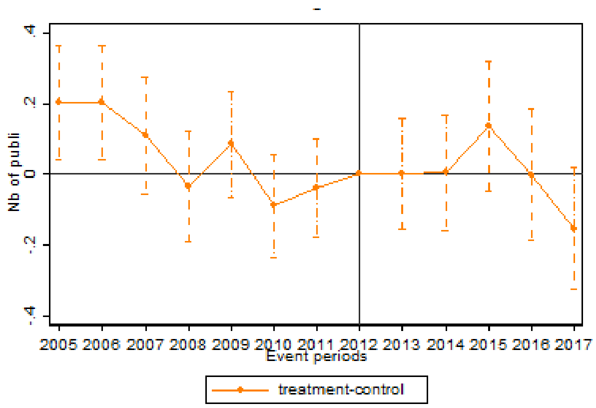


Figure 12: Number of publications periphery members: financed vs non financed.

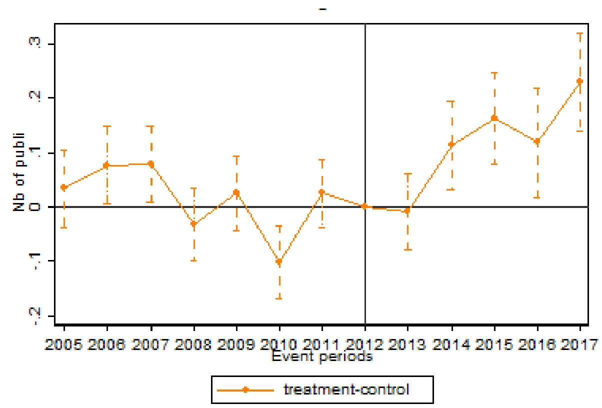


Figure 13: Number of publications weighted by IF core members: financed vs non financed.

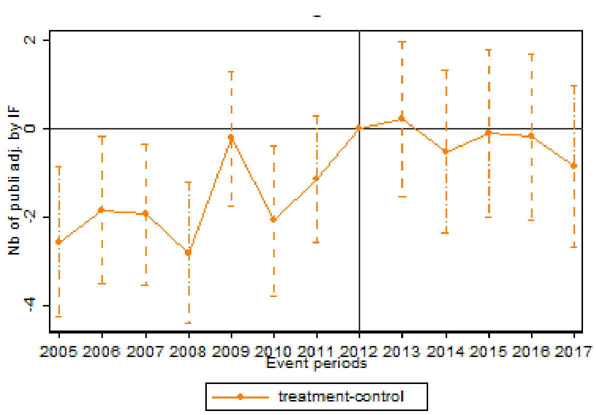
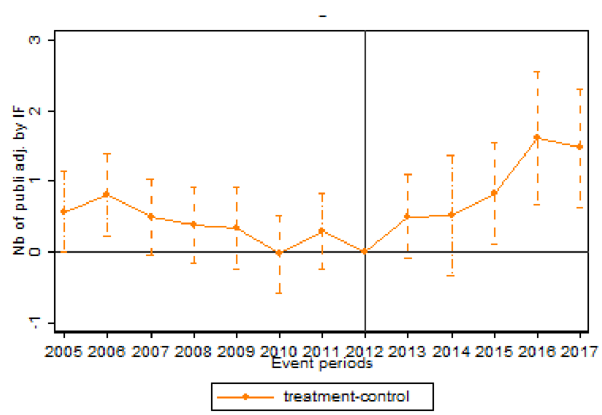


Figure 14: Number of publications weighted by IF periphery members: financed vs non financed.



Note: Same exercise as in Figures 7 to 10 but applying supplementary restrictions to the data. In Figures 11 and 13 we restrict to the core members of the cluster, while in Figures 12 and 14 we restrict to members of the periphery. The dependent variable is either the number of publications in Figures 11 and Figures 12 and number of publications weighted by IF in Figures 13 and 14.

Figure 15: Number of links in cluster: 2 versus 1 cluster financed.

Note: We estimate Equation 1, separately for individuals in the control (members of exactly one funded cluster) and treatment (members of exactly two funded clusters). We apply the restrictions that researchers (i) are part of exactly two cluster proposals, (ii) got at least one accepted and (iii) received a grade between 26 and 32 on their lower ranked cluster proposal. The dependent variable y_{it} *tracks the number of links per year that involve another member of either of the two cluster proposals initially submitted. We plot the difference year by year between the year fixed effect* η_t *of the treatment and control groups. The dashed vertical lines are 95 percent confidence intervals of robust standard errors clustered at the individual level.*

Table 1: Descriptive statistics on research clusters.

	(1) All		(2) Treated		(3) Non Treated		(4) Difference t-test	
	mean	sd	mean	sd	mean	sd	b	p
Number of scientists	171.63	172.25	188.74	178.34	159.49	166.81	-29.24	(0.10)
Number of research units	16.90	15.04	18.60	15.53	15.69	14.57	-2.91	(0.06)
Share of scientists in the core	0.32	0.27	0.32	0.28	0.31	0.26	-0.00	(0.87)
Number of articles (*PubsRC*)	173.76	214.58	196.15	217.26	157.65	211.70	-38.51	(0.08)
Number of articles weighted by cites (*CitesRC*)	1134.74	1507.79	1311.67	1492.31	1007.30	1511.12	-304.37	(0.05)
Nbr of articles w. by Impact Factor (*JIFRC*)	894.48	1160.89	1000.88	1138.96	818.18	1174.76	-182.70	(0.13)
Mean number of authors (*TeamSizeRC*)	6.65	7.34	6.99	7.26	6.39	7.41	-0.60	(0.43)
Field: health	0.40	0.49	0.39	0.49	0.41	0.49	0.02	(0.79)
Field: environment	0.31	0.46	0.33	0.47	0.29	0.46	-0.04	(0.54)
Field: computer science	0.23	0.42	0.30	0.46	0.15	0.36	-0.14	(0.02)
Field: social sciences	0.29	0.46	0.32	0.47	0.27	0.45	-0.05	(0.44)
Field: other	0.27	0.45	0.28	0.45	0.27	0.45	-0.01	(0.90)
Observations	381		164		217		381	

Note: Column (1) presents the mean and sd of our main variables for the overall sample. Column (2) restricts the sample to research clusters that were financed and column (3) restricts to those that did not receive financing. Column (4) presents the difference between the means of columns (3) and (2) and the p value of a test of differences of means.

Table 2: Descriptive statistics on grades.

	(1) Treated		(2) Non Treated		(3) Difference t-test	
	mean	sd	mean	sd	b	p
Overall grade	31.62	4.12	26.61	4.68	-5.01	(0.00)
Grade criterion 1: team quality	4.76	0.63	4.09	0.84	-0.68	(0.00)
Grade criterion 2: goal	4.53	0.74	3.72	0.91	-0.81	(0.00)
Grade criterion 3: potential research	4.42	0.74	3.62	0.91	-0.81	(0.00)
Grade criterion 4: potential training	4.55	0.75	3.94	0.84	-0.61	(0.00)
Grade criterion 5: organization	4.34	0.78	3.71	0.84	-0.63	(0.00)
Grade criterion 6: structure	4.59	0.72	3.91	0.87	-0.67	(0.00)
Grade criterion 7: resource generation	4.43	0.77	3.63	0.89	-0.80	(0.00)
Observations	164		217		381	

Note: Column (1) presents the mean and sd of different grades for the sample restricted to research clusters that were financed and column (2) restricts to those that did not receive financing. Column (3) presents the difference between the means of columns (2) and (1) and the p value of a test of differences of means.

Table 3: Descriptive statistics full sample.

	(1) All		(2) Treated		(3) Non Treated		(4) Difference t-test	
	mean	sd	mean	sd	mean	sd	b	p
Age (*Age*)	41.79	9.80	41.82	9.83	41.67	9.68	-0.15	(0.35)
Number of articles (*Pubs*)	1.62	2.03	1.65	2.08	1.52	1.85	-0.13	(0.00)
Adjusted number of articles (*PubsAdj*)	0.39	0.48	0.40	0.49	0.35	0.41	-0.05	(0.00)
Number of articles weighted by cites (*Cites*)	14.76	33.81	15.38	35.66	12.64	26.40	-2.74	(0.00)
Adjusted number of articles weighted by cites (*CitesAdj*)	2.55	4.49	2.65	4.79	2.21	3.22	-0.43	(0.00)
Number of articles weighted by Impact Factor (*JIF*)	9.22	15.68	9.30	16.04	8.96	14.37	-0.35	(0.02)
Adjusted number of articles weighted by IF (*JIFAdj*)	1.80	2.87	1.83	2.95	1.68	2.57	-0.15	(0.00)
Mean number of authors (*TeamSize*)	8.89	53.89	9.77	60.68	5.91	15.20	-3.86	(0.00)
Hirsch index (*Hindex*)	4.79	4.28	4.85	4.33	4.60	4.12	-0.26	(0.00)
Number of collaborative articles within the cluster (*CollaPubs*)	0.75	1.27	0.75	1.31	0.73	1.16	-0.02	(0.09)
Number of links within the cluster (*Links*)	0.74	1.14	0.73	1.15	0.74	1.11	0.01	(0.36)
Number of collaborations within the cluster (*Collaborations*)	1.27	2.71	1.30	2.88	1.17	2.01	-0.14	(0.00)
Number of new links within the cluster (*NewLinks*)	0.64	0.72	0.63	0.73	0.67	0.69	0.04	(0.00)
Number of external articles (*ExternalPubs*)	0.87	1.38	0.90	1.42	0.79	1.23	-0.11	(0.00)
Observations	58308		45151		13157		58308	

Note: Column (1) presents the mean and sd of our main variables for the overall sample of researchers. We restrict our data to values before 2010 to compare the pre-treatment samples. Column (2) restricts the sample to researchers in research clusters that were financed and Column (3) restricts to those that were in research clusters proposals that did not receive financing. Column (4) presents the difference between the means of columns (2) and (3) and the p value of a test of differences of means.

Table 4: Descriptive statistics restricted on overall grades.

	(1) All		(2) Treated		(3) Non Treated		(4) Difference t-test	
	mean	sd	mean	sd	mean	sd	b	p
Age (*Age*)	42.07	9.70	42.25	9.70	41.19	9.66	-1.07	(0.09)
Number of articles (*Pubs*)	1.49	1.91	1.49	1.93	1.48	1.86	-0.01	(0.91)
Adjusted number of articles (*PubsAdj*)	0.36	0.45	0.37	0.46	0.36	0.42	-0.01	(0.42)
Number of articles weighted by cites (*Cites*)	12.91	29.32	13.47	30.64	11.20	24.77	-2.27	(0.01)
Adjusted number of articles weighted by cites (*CitesAdj*)	2.31	3.85	2.43	4.03	1.95	3.24	-0.49	(0.00)
Number of articles weighted by Impact Factor (*JIF*)	8.05	14.47	8.19	14.42	7.56	14.63	-0.63	(0.13)
Adjusted number of articles weighted by IF (*JIFAdj*)	1.60	2.60	1.65	2.66	1.43	2.37	-0.22	(0.00)
Mean number of authors (*TeamSize*)	6.25	15.63	6.58	17.88	5.24	3.59	-1.34	(0.00)
Hirsch index (*Hindex*)	4.46	4.12	4.59	4.17	4.07	3.94	-0.52	(0.00)
Number of collaborative articles within the cluster (*CollaPubs*)	0.68	1.18	0.66	1.20	0.72	1.12	0.05	(0.10)
Number of links within the cluster (*Links*)	0.67	1.08	0.66	1.08	0.71	1.05	0.06	(0.05)
Number of collaborations within the cluster (*Collaborations*)	1.13	2.93	1.13	3.17	1.13	1.95	0.01	(0.92)
Number of new links within the cluster (*NewLinks*)	0.69	0.72	0.68	0.72	0.70	0.70	0.02	(0.51)
Number of external articles (*ExternalPubs*)	0.81	1.26	0.82	1.27	0.76	1.23	-0.06	(0.09)
Observations	6714		5134		1580		6714	

Note: This is the same table as Table 3 except that we apply our restriction on grades (the sample is restricted to researchers who were part of a single cluster proposal that received an overall grade between 26 and 32 for the 2010 contest and between 30 and 32 for the 2011 contest.

Table 5: Effect of group financing on structure of network, restricting on grades.

	(1) *CollaPubs*	(2) *ExternalPubs*	(3) *Links*	(4) *NewLinks*	(5) *Collaborations*
Treatment × Post	0.118***	-0.029	0.133***	0.112***	0.403***
	(0.031)	(0.034)	(0.029)	(0.026)	(0.067)
Observations	87282	87282	87282	36092	87282
Mean dep variable	.83	.88	.85	.66	1.5
Adj. R-Square	.46	.49	.44	.086	.42

Standard errors in parentheses

*Note: we present the results of the estimation of Equation 1, for outcome variables measuring connections, applying to the data the restriction on grades. We include individual and time fixed effects. The standard errors are clustered at the individual level. Significance level are given by: p<0.1, ** p<0.05, *** p<0.01.*

Table 6: Conditional logit dyadic regressions (incidence ratio rates).

	(1) All	(2) CC	(3) CP	(4) PP	(5) All
Treatment × Post	1.266***	1.232**	1.329***	1.289***	0.870***
	(0.041)	(0.110)	(0.107)	(0.052)	(0.039)
Core-Periphery × Treatment × Post					1.906***
					(0.089)
Periphery-Periphery × Treatment × Post					1.508***
					(0.061)
Observations	305344	57616	73554	174174	305344
ll	-9.7e+04	-2.0e+04	-2.2e+04	-5.6e+04	-9.7e+04
bic	2.0e+05	4.0e+04	4.4e+04	1.1e+05	1.9e+05

Exponentiated coefficients; Standard errors in parentheses

*Note: Columns (1)-(4) present the results from estimating Equation 3 on respectively: all dyads, Core-Core dyads, Core-Periphery dyads, and Periphery-Periphery dyads. Column (5) reports regressions results from estimating Equation 4. Observations are restricted to scientists member of only one cluster proposal, which obtained similar total grades. Standard errors are clustered at the dyad level and significance level are given by: p<0.1, ** p<0.05, *** p<0.01.*

Table 7: Analysis at the cluster level; effect of financing on productivity.

	(1) *PubsRC*	(2) *CitesRC*	(3) *JIFRC*	(4) *TeamSizeRC*
Treatment × Post	-3.846	14.289	1.907	0.208
	(10.563)	(121.379)	(151.109)	(7.039)
Observations	1599	1593	1599	1585
Mean dep variable	255	1694	1561	15
Adj. R-Square	.97	.81	.93	.45

Standard errors in parentheses

*Note: observations are at the cluster×year level. We restrict our analysis to clusters that received an overall grade between 26 and 32 for the 2010 contest and between 30 and 32 for the 2011 contest. The variable Treatment takes value of 1 if the cluster was selected and the variable is interacted with post, a dummy for years after 2012. The specification includes year and cluster fixed effects. The standard errors are clustered at the research cluster level. Significance level are given by: p<0.1, ** p<0.05, *** p<0.01.*

Table 8: Analysis at the cluster level; effect of financing on excellence.

	(1) *NbTop10*	(2) *PropTop10*	(3) *NbTop5*	(4) *PropTop5*	(5) *GiniPubsRC*
Treatment × post	-3.606	0.002	-2.300	0.002	-0.014**
	(3.289)	(0.018)	(1.982)	(0.009)	(0.007)
Observations	1593	1585	1593	1585	1599
Mean dep variable	43	.18	23	.095	.36
Adj. R-Square	.92	.35	.88	.31	.88

Standard errors in parentheses

*Note: observations are at the cluster×year level. We restrict our analysis to clusters that received an overall grade between 26 and 32 for the 2010 contest and between 30 and 32 for the 2011 contest. The variable Treatment takes value of 1 if the cluster was selected and the variable is interacted with post, a dummy for years after 2012. The specification includes year and cluster fixed effects. The standard errors are clustered at the research cluster level. Significance level are given by: p<0.1, ** p<0.05, *** p<0.01.*

Table 9: Analysis at the individual level; effect of financing on productivity.

	(1) *Pubs*	(2) *PubsAdj*	(3) *JIF*	(4) *JIFAdj*	(5) *TeamSize*
Treatment × Post	0.090*	0.010	0.768*	-0.000	2.641***
	(0.048)	(0.010)	(0.423)	(0.072)	(0.627)
Observations	87282	87282	87282	87282	47676
Mean dep variable	1.7	.38	11	2	9.2
Adj. R-Square	.53	.46	.51	.49	.41

Standard errors in parentheses

*Note: we present the results of the estimation of Equation 1 applying the restriction on grades to the data. The specification includes individual and time fixed effects. The standard errors are clustered at the individual level. Significance level are given by: p<0.1, ** p<0.05, *** p<0.01.*

Table 10: Effect of group financing on productivity for core members.

	(1) *Pubs*	(2) *PubsAdj*	(3) *JIF*	(4) *JIFAdj*	(5) *CollaPubs*	(6) *ExternalPubs*
Treatment × Post	0.031	-0.009	1.348	0.089	0.097	-0.065
	(0.131)	(0.027)	(1.287)	(0.202)	(0.083)	(0.087)
Observations	20033	20033	13869	13869	20033	20033
Mean dep variable	2.4	.52	19	3.4	1.2	1.2
Adj. R-Square	.54	.5	.57	.53	.49	.5

Standard errors in parentheses

Note: this table is identical to Table 9, restricting the sample to members of the core of the unique cluster (i.e. appearing in the bibliography).

Table 11: Effect of group financing on productivity for periphery members.

	(1) *Pubs*	(2) *PubsAdj*	(3) *JIF*	(4) *JIFAdj*	(5) *TeamSize*	(6) *CollaPubs*	(7) *ExternalPubs*
Treatment × Post	0.105**	0.016	0.551	0.020	2.549***	0.125***	-0.020
	(0.051)	(0.011)	(0.414)	(0.076)	(0.816)	(0.033)	(0.037)
Observations	67249	67249	46557	46557	34341	67249	67249
Mean dep variable	1.5	.34	10	1.8	9.6	.71	.78
Adj. R-Square	.5	.42	.53	.5	.45	.43	.47

Standard errors in parentheses

Note: this table is identical to Table 9, restricting the sample to members of the periphery of the unique cluster (i.e. not appearing in the bibliography)

Table 12: More than 2 labs funded with restrictions: productivity.

	(1) *Pubs*	(2) *PubsAdj*	(3) *JIF*	(4) *JIFAdj*
Treated twice × post	-0.192***	-0.018	-2.062***	-0.200**
	(0.066)	(0.012)	(0.640)	(0.079)
Observations	48568	48568	48568	48568
Mean dep variable	1.6	.37	10	1.8
Adj. R-Square	.46	.43	.4	.47

Standard errors in parentheses

*Note: we present the results of the estimation of Equation 1, restricting the sample to researchers who are members of exactly two proposals, got at least one funded and the minimum of the two grades they received was between 26 and 32. We report the coefficient of the interaction between being financed exactly twice and be in a year post 2012. The data is at the researcher×year level. The regression includes individual and time fixed effects. Standard errors are clustered at the individual level. Significance level are given by: p<0.1, ** p<0.05, *** p<0.01.*

Table 13: More than 2 labs funded with restrictions: organization.

	(1) *CollaPubs*	(2) *ExternalPubs*	(3) *Links*	(4) *NewLinks*
Treated twice × post	-0.268***	-0.119	-0.282***	-0.061**
	(0.084)	(0.094)	(0.066)	(0.027)
Observations	48568	48568	48568	48568
Mean dep variable	1.5	1.8	1.6	.49
Adj. R-Square	.46	.39	.48	.054

Standard errors in parentheses

Note: the analysis is the same as in Table 12. The dependent variable Collapubs counts all the publications with at least one co-author from either of the two clusters submitted (regardless of funding status). The dependent variable ExternalPubs, counts all publications with no coauthor from either of the two clusters. Similarly, Links (or NewLinks) counts all links (or new links) with members of either cluster.

Data Construction: Tenured Professors and Researchers

Data come from different sources through bilateral contracting with the government and research institutes. This collection is eased in France thanks to the centralization of information at the national level. For instance, research units report every four-to-five years the list of their tenured research staff to the MHER. The ministry also maintains a list of all professors and assistant professors since 2000 as, though they are in practice employed by universities, those persons are formally civil servants and thus paid by the government. National research institutes like the CNRS, also maintain the information of all their employees (this information is also often available online). As information on specific personal profiles come from observations at different points in time and sometimes from different sources, a huge manual and automatic disambiguation work has been performed. The disambiguation of individual profiles is easy when they scientists are associated to the same location, research unit and institution across tables. As research units evolve over time (either birth, extinct, merge or split), we used a very convenient national roster of research units in which research units have specific identifiers that are consolidated over time by all research institutes, the ministry and universities.

Researchers and professors may however move over their career or be simultaneously associated to different units. Then, partial information, such a birth dates, or even web search procedures were designed to obtain the best possible list of professors and researchers. At the end of this task, we end out with a consistent roster of 84,066 tenured researchers and professors affiliated to 234 universities and research institutes and twenty seven hundreds distinct research units.

We estimate this dataset gathers nearly 85% of the reference population at the national level over the considered period. Indeed, The MHER documents there are about 56,000 professors and assistant professors in France in 2015 and 17,000 tenured researchers in the national research institutes. From yearly counts of final exits (retirements and death) in those data, we estimate that about 26,000 more distinct persons (22,000 professors and 4,000 researchers) have been part of this population over the period 2005-2017. This leads to a raw estimate of the total population of tenured professors and researchers over the period of about 99,000 persons. A few research units may not certified by the Ministry of Higher Education and Research (MHER). This happens when the research units are funded only by other ministries (Industry, Agriculture, Defense) via specific higher education schools or research institutes.

Supplementary Tables

Additional results

Table 14: Explaining selection of a project.

	(1) OLS	(2) Logit
main		
Grade: team quality	0.056	0.917***
	(0.042)	(0.277)
Grade: goal	0.076*	0.528**
	(0.039)	(0.240)
Grade: potential research	0.069*	0.411*
	(0.038)	(0.219)
Grade: potential training	0.000	0.274
	(0.039)	(0.241)
Grade: organization	0.009	0.184
	(0.040)	(0.230)
Grade: structure	0.022	0.412*
	(0.040)	(0.245)
Grade: resource generation	0.091**	0.562**
	(0.037)	(0.226)
Observations	381	381
Adjusted R^2	0.235	

Standard errors in parentheses

Note: Column (1) presents the results of an OLS regression of a dummy variable indicating whether the cluster proposal was selected, explained by grades given by reviewers. Column (2) presents the same results with a logit specification.

Table 15: Comparing core vs periphery members.

	(1) All		(2) Core		(3) Periphery		(4) Difference t-test	
	mean	sd	mean	sd	mean	sd	b	p
Age (*Age*)	42.25	9.70	42.31	9.72	41.29	9.50	-1.02	(0.38)
Number of articles (*Pubs*)	1.49	1.93	2.23	2.43	1.24	1.66	-0.99	(0.00)
Adjusted number of articles (*PubsAdj*)	0.37	0.46	0.52	0.56	0.32	0.41	-0.20	(0.00)
Number of articles weighted by cites (*Cites*)	13.47	30.64	20.39	40.58	10.90	25.53	-9.49	(0.00)
Adjusted number of articles weighted by cites (*CitesAdj*)	2.43	4.03	3.72	5.66	1.95	3.08	-1.77	(0.00)
Number of articles weighted by Impact Factor (*JIF*)	8.19	14.42	13.74	19.84	6.35	11.53	-7.39	(0.00)
Adjusted number of articles weighted by IF (*JIFAdj*)	1.65	2.66	2.74	3.78	1.29	2.05	-1.45	(0.00)
Mean number of authors (*TeamSize*)	6.58	17.88	6.37	10.88	6.66	19.93	0.29	(0.56)
Hirsch index (*Hindex*)	4.59	4.17	6.14	4.94	4.01	3.68	-2.13	(0.00)
Number of collaborative articles within the cluster (*CollaPubs*)	0.66	1.20	1.08	1.56	0.53	1.02	-0.55	(0.00)
Number of links within the cluster (*Links*)	0.66	1.08	1.04	1.35	0.53	0.94	-0.51	(0.00)
Number of collaborations within the cluster (*Collaborations*)	1.13	3.17	1.75	3.38	0.92	3.07	-0.82	(0.00)
Number of new links within the cluster (*NewLinks*)	0.68	0.72	0.72	0.68	0.67	0.74	-0.06	(0.03)
Number of external articles (*ExternalPubs*)	0.82	1.27	1.15	1.56	0.72	1.14	-0.44	(0.00)
Observations	5134		1279		3855		5134	

Note: Column (1) presents the mean and sd of our main variables for the overall sample of researchers. Column (2) restricts the sample to researchers who are core members and column (3) restricts to those that were members of the periphery. Column (4) presents the difference between the means of column (2) and (3) and the p value of a test of differences of means.

Table 16: Conditional logit dyadic regressions (coefficients).

	(1) All	(2) CC	(3) CP	(4) PP	(5) All
Treatment × Post	0.236***	0.209**	0.284***	0.254***	-0.139***
	(0.033)	(0.090)	(0.081)	(0.040)	(0.044)
Core-Periphery × Treatment × Post					0.645***
					(0.047)
Periphery-Periphery × Treatment × Post					0.411***
					(0.041)
Observations	305344	57616	73554	174174	305344
ll	-9.7e+04	-2.0e+04	-2.2e+04	-5.6e+04	-9.7e+04
bic	2.0e+05	4.0e+04	4.4e+04	1.1e+05	1.9e+05

Standard errors in parentheses

*Note: Columns (1)-(4) present the results from estimating Equation 3 on respectively: all dyads, Core-Core members dyads, Core-Periphery members dyads, and Periphery-Periphery members dyads. Column (5) reports regressions results from estimating Equation 4. Observations are restricted to scientists member of only one cluster proposal, which obtained similar total grades. Standard errors are clustered at the dyad level and significance level are given by: p<0.1, ** p<0.05, *** p<0.01.*

Table 17: Analysis at the cluster level, no restriction; effect of financing on productivity.

	(1) *PubsRC*	(2) *CitesRC*	(3) *JIFRC*	(4) *TeamSizeRC*	(5) *GiniPubsRC*
Treatment × Post	4.734	50.792	92.653	6.882	-0.001
	(5.532)	(71.302)	(89.722)	(4.398)	(0.005)
Observations	4264	4249	4264	4203	4264
Mean dep variable	230	1626	1462	14	.34
Adj. R-Square	.98	.83	.93	.38	.86

Standard errors in parentheses

Note: this is the equivalent of Table 7 except that we do not impose any restrictions on the clusters we include.

Robustness

We examine how our main results change when varying the identification strategy. We start by showing the results when we do not impose any restrictions, before presenting the results using two alternative identification strategies.

Full sample

We study the results when no restriction is imposed on the data.

Table 18: Effect of group financing on structure of network, no restrictions.

	(1) *CollaPubs*	(2) *ExternalPubs*	(3) *Links*	(4) *NewLinks*	(5) *Collaborations*
Treatment × Post	0.022*	-0.005	0.013	0.034***	0.105***
	(0.011)	(0.015)	(0.010)	(0.009)	(0.028)
Observations	758004	758004	758004	337430	758004
Mean dep variable	.88	.94	.9	.62	1.6
Adj. R-Square	.46	.48	.46	.15	.38

Standard errors in parentheses

Note: this is exactly the same analysis as in Table 5, except we do not impose the restriction on grades and use the full sample.

Table 19: Conditional logit dyadic regressions (incidence ratio rates). No restriction on grades and multiple applications.

	(1) All	(2) CC	(3) CP	(4) PP	(5) All
Treatment × Post	1.054***	1.048**	1.042*	1.069***	0.809***
	(0.010)	(0.023)	(0.023)	(0.014)	(0.012)
Core-Periphery × Treatment × Post					1.579***
					(0.029)
Periphery-Periphery × Treatment × Post					1.333***
					(0.021)
Observations	1778530	364027	405546	888563	1778530
ll	-5.6e+05	-1.2e+05	-1.2e+05	-2.8e+05	-5.6e+05
bic	1.1e+06	2.4e+05	2.4e+05	5.7e+05	1.1e+06

Exponentiated coefficients; Standard errors in parentheses

*Note: Columns (1)-(4) present the results from estimating Equation 3 on respectively: all dyads, Core-Core members dyads, Core-Periphery members dyads, and Periphery-Periphery members dyads. Column (5) reports regressions results from estimating Equation 4. Observations are restricted to scientists member of only one cluster proposal, which obtained similar total grades. Standard errors are clustered at the dyad level and significance level are given by: p<0.1, ** p<0.05, *** p<0.01.*

Table 20: Effect of group financing on productivity.

	(1) Pubs	(2) PubsAdj	(3) JIF	(4) JIFAdj	(5) TeamSize
financed more than one × post 2012	0.006	-0.004	0.916***	0.073**	0.313
	(0.023)	(0.005)	(0.208)	(0.034)	(0.610)
Observations	380887	380887	380887	380887	210431
Mean dep variable	1.7	.38	11	2	11
Adj. R-Square	.51	.45	.47	.47	.48

Standard errors in parentheses

Note: this is exactly the same analysis as in Table 9, except we do not impose the restriction on grades and use the full sample.

Identification strategy 2

We examine the results when using the second identification strategy where we restrict to researchers in a single cluster that received a grade of 4 on criterion 3 that measures the goal of the project.

Table 21: Descriptive statistics restricted on grades for research potential.

	(1) All		(2) Treated		(3) Non Treated		(4) Difference t-test	
	mean	sd	mean	sd	mean	sd	b	p
Age (*Age*)	42.76	9.87	42.82	9.99	42.61	9.58	-0.21	(0.70)
Number of articles (*Pubs*)	1.52	2.07	1.58	2.13	1.38	1.92	-0.19	(0.00)
Adjusted number of articles (*PubsAdj*)	0.35	0.46	0.37	0.48	0.31	0.39	-0.06	(0.00)
Number of articles weighted by cites (*Cites*)	16.27	49.90	17.06	48.94	14.51	51.97	-2.54	(0.13)
Adjusted number of articles weighted by cites (*CitesAdj*)	2.37	3.86	2.49	4.09	2.10	3.24	-0.39	(0.00)
Number of articles weighted by Impact Factor (*JIF*)	8.84	17.54	8.90	17.71	8.71	17.14	-0.18	(0.72)
Adjusted number of articles weighted by IF (*JIFAdj*)	1.61	2.64	1.64	2.73	1.53	2.42	-0.11	(0.14)
Mean number of authors (*TeamSize*)	10.17	42.19	11.99	50.14	6.02	9.13	-5.96	(0.00)
Hirsch index (*Hindex*)	4.82	4.38	4.90	4.44	4.66	4.24	-0.23	(0.10)
Number of collaborative articles within the cluster (*CollaPubs*)	0.67	1.33	0.72	1.41	0.55	1.14	-0.18	(0.00)
Number of links within the cluster (*Links*)	0.65	1.11	0.71	1.21	0.51	0.86	-0.19	(0.00)
Number of collaborations within the cluster (*Collaborations*)	1.19	3.43	1.34	3.87	0.85	2.07	-0.49	(0.00)
Number of new links within the cluster (*NewLinks*)	0.65	0.74	0.69	0.78	0.57	0.62	-0.11	(0.00)
Number of external articles (*ExternalPubs*)	0.85	1.34	0.85	1.35	0.84	1.31	-0.02	(0.69)
Observations	5393		3728		1665		5393	

Note: This is the same table as Table 3 except that the sample is restricted to researchers who applied in a single cluster that received a grade of 4 for research potential.

Table 22: Effect of group financing on structure of network, restriction on criterion 3.

	(1) CollaPubs	(2) ExternalPubs	(3) Links	(4) NewLinks	(5) Collaborations
Treatment × Post	0.094***	-0.019	0.116***	0.029	0.473***
	(0.032)	(0.037)	(0.029)	(0.029)	(0.098)
Observations	70109	70109	70109	27911	70109
Mean dep variable	.82	.93	.83	.65	1.6
Adj. R-Square	.46	.46	.45	.11	.38

Standard errors in parentheses

Note: this is exactly the same analysis as in Table 5, except we do not impose the restriction on grades but we restrict the sample to researchers who applied in a single cluster that received a grade of 4 for research potential (criterion 3).

Table 23: Conditional logit dyadic regressions (incidence ratio rates), restriction on criterion 3.

	(1) All	(2) CC	(3) CP	(4) PP	(5) All
Treatment × Post	0.941	0.824*	1.008	1.004	0.691***
	(0.038)	(0.082)	(0.094)	(0.052)	(0.034)
Core-Periphery × Treatment × Post					1.647***
					(0.079)
Periphery-Periphery × Treatment × Post					1.473***
					(0.063)
Observations	230854	54340	60424	116090	230854
ll	-7.3e+04	-1.8e+04	-1.8e+04	-3.7e+04	-7.3e+04
bic	1.5e+05	3.7e+04	3.6e+04	7.3e+04	1.5e+05

Exponentiated coefficients; Standard errors in parentheses

*Note: Columns (1)-(4) present the results from estimating Equation 3 on respectively: all dyads, Core-Core members dyads, Core-Periphery members dyads, and Periphery-Periphery members dyads. Column (5) reports regressions results from estimating Equation 4. Observations are restricted to scientists member of only one cluster proposal, which obtained similar total grades. Standard errors are clustered at the dyad level and significance level are given by: p<0.1, ** p<0.05, *** p<0.01.*

Table 24: Effect of group financing on productivity, restriction on criterion 3.

	(1) *Pubs*	(2) *PubsAdj*	(3) *JIF*	(4) *JIFAdj*	(5) *TeamSize*
Treatment × Post	0.076	-0.003	2.241***	0.208***	2.869**
	(0.050)	(0.010)	(0.454)	(0.070)	(1.219)
Observations	70109	70109	70109	70109	37770
Mean dep variable	1.8	.37	11	1.9	15
Adj. R-Square	.5	.45	.45	.47	.61

Standard errors in parentheses

Note: this is exactly the same analysis as in Table 9, except we do not impose the restriction on grades but we restrict the sample to researchers who applied in a single cluster that received a grade of 4 for research potential (criterion 3).

Strategy 1 using different range of grades

We examine the robustness of our main results when we are more restrictive in the range of grades we use to describe labs as similar. Specifically, we restrict the approval probability to be between 40% and 60% which implies keeping grades between 28 and 31 in 2010 and equal to 31 in 2011.

Table 25: Descriptive statistics restricted on grades for research potential.

	(1)		(2)		(3)		(4)	
	All		Treated		Non Treated		Difference t-test	
	mean	sd	mean	sd	mean	sd	b	p
Age (*Age*)	42.81	9.83	43.11	9.77	41.28	10.03	-1.83	(0.06)
Number of articles (*Pubs*)	1.60	2.11	1.58	2.10	1.80	2.22	0.22	(0.07)
Adjusted number of articles (*PubsAdj*)	0.41	0.50	0.41	0.50	0.43	0.49	0.02	(0.37)
Number of articles weighted by cites (*Cites*)	13.77	36.23	13.95	37.88	12.47	20.69	-1.48	(0.30)
Adjusted number of articles weighted by cites (*CitesAdj*)	2.36	3.82	2.33	3.83	2.57	3.77	0.23	(0.31)
Number of articles weighted by Impact Factor (*JIF*)	7.99	15.54	7.97	15.78	8.09	13.71	0.12	(0.88)
Adjusted number of articles weighted by IF (*JIFAdj*)	1.62	2.65	1.61	2.66	1.71	2.55	0.10	(0.49)
Mean number of authors (*TeamSize*)	6.94	21.44	7.26	22.88	4.74	1.90	-2.52	(0.00)
Hirsch index (*Hindex*)	4.38	4.08	4.36	4.08	4.54	4.03	0.18	(0.47)
Number of collaborative articles within the cluster (*CollaPubs*)	0.75	1.39	0.72	1.38	0.98	1.51	0.26	(0.00)
Number of links within the cluster (*Links*)	0.73	1.21	0.70	1.20	0.88	1.26	0.18	(0.01)
Number of collaborations within the cluster (*Collaborations*)	1.35	3.95	1.33	4.11	1.52	2.56	0.19	(0.21)
Number of new links within the cluster (*NewLinks*)	0.70	0.74	0.70	0.74	0.71	0.77	0.00	(0.95)
Number of external articles (*ExternalPubs*)	0.85	1.31	0.85	1.32	0.82	1.23	-0.03	(0.62)
Observations	3030		2657		373		3030	

Note: This is the same table as Table 3 except that we impose a more restrictive condition on the overall grade.

Table 26: Effect of group financing on structure of network, stricter restrictions on overall grade.

	(1)	(2)	(3)	(4)	(5)
	CollaPubs	*ExternalPubs*	*Links*	*NewLinks*	*Collaborations*
Treatment × Post	0.174**	-0.149**	0.141**	0.063	0.516***
	(0.069)	(0.068)	(0.058)	(0.051)	(0.142)
Observations	39390	39390	39390	16097	39390
Mean dep variable	.88	.88	.89	.69	1.7
Adj. R-Square	.46	.47	.46	.091	.43

Standard errors in parentheses

Note: this is exactly the same analysis as in Table 5, except that we impose a more stringent restriction on the overall grade.

Table 27: Conditional logit dyadic regressions (incidence ratio rates), with stricter restrictions on overall grade.

	(1) All	(2) CC	(3) CP	(4) PP	(5) All
Treatment × Post	1.681***	1.041	0.799	2.185***	1.074
	(0.128)	(0.190)	(0.140)	(0.207)	(0.092)
Core-Periphery × Treatment × Post					1.973***
					(0.118)
Periphery-Periphery × Treatment × Post					1.696***
					(0.093)
Observations	138710	29146	39884	69680	138710
ll	-4.5e+04	-9.9e+03	-1.2e+04	-2.2e+04	-4.4e+04
bic	8.9e+04	2.0e+04	2.4e+04	4.5e+04	8.9e+04

Exponentiated coefficients; Standard errors in parentheses

*Note: Columns (1)-(4) present the results from estimating Equation 3 on respectively: all dyads, Core-Core members dyads, Core-Periphery members dyads, and Periphery-Periphery members dyads. Column (5) reports regressions results from estimating Equation 4. Observations are restricted to scientists member of only one cluster proposal, which obtained similar total grades. Standard errors are clustered at the dyad level and significance level are given by: p<0.1, ** p<0.05, *** p<0.01.*

Table 28: Effect of group financing on productivity, stricter restrictions on overall grade.

	(1) *Pubs*	(2) *PubsAdj*	(3) *JIF*	(4) *JIFAdj*	(5) *TeamSize*
Treatment × Post	0.025	-0.031	-0.457	-0.280*	3.511***
	(0.097)	(0.022)	(0.854)	(0.150)	(1.022)
Observations	39390	39390	39390	39390	21512
Mean dep variable	1.8	.41	11	2	11
Adj. R-Square	.52	.44	.49	.48	.43

Standard errors in parentheses

Note: this is exactly the same analysis as in Table 9, except that we impose a more stringent restriction on the overall grade.