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The impact of funding on research collaboration: Evidence from a developing country[☆]

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ABSTRACT

In this paper we evaluate the impact of research grants on the amount of collaboration among scientific researchers in Argentina. We find a positive and significant impact of funding on collaboration which is measured in terms of the number of co-authors for publications in peer-reviewed journals. Our identification strategy is based on comparing collaboration indicators for researchers with financially supported projects with those of a control group of researchers who submitted projects that were accepted in terms of quality, but not supported because of shortage of funds. We obtain consistent results by using different non-experimental techniques including difference-in-differences models combined with propensity score matching algorithms.

1. Introduction

Government agencies throughout the developed world have a long history of funding the production and diffusion of scientific knowledge. In the last decades this support has also focused on fostering research collaboration and the formation of research networks (Katz and Martin, 1997; Lee and Bozeman, 2005). In Latin America, recent reforms have involved the introduction of competitive grants as a new way to fund research. One of the goals of these grants is to create an incentive for the diffusion of knowledge and the consolidation of scientific networks (ECLAC, 2004; Maffioli, 2007).

Nevertheless, there is no clear empirical evidence showing that public funding has indeed fostered collaboration. Few empirical studies have analyzed the impact of public funding on collaboration among scientists, and all of them have focused on developed countries. Bozeman and Corley (2004) and Lee and Bozeman (2005) find that research grants have a significant positive impact on collaboration among a group of scientists affiliated with university research centers in the United States. Adams et al. (2005) show, also for the U.S., that top universities academic departments receiving larger amounts of federal funding tend to participate in larger teams. Defazio et al. (2009) study a panel of scientists in European Union research networks and argue that funding might have a role in fostering new collaborations, but it does not create effective collaborations measured by co-authorships. This last contribution concludes that future research would be benefited from including a control group of researchers applying for the same source of funding, but not being granted the funds.

Our paper contributes to the literature by evaluating the impact of scientific research grants on research collaboration in a developing country. In particular, we study the impact that the subsidies granted by the Fund for the Scientific and Technological Research (FONCYT) have on the collaboration outcomes of a panel of researchers in Argentina. In a previous evaluation of this program, Chudnovsky et al. (2008) show that the grants have a positive effect on the quantity and quality of the publications when comparing a group of researchers who received the grants with another group that applied for them, but was not funded due to scarcity of resources. Our paper complements this finding with the effect

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of the program on the collaboration among scientists measured by social-network indicators based on co-authorships in scientific articles.

The study of the effect of funding on collaboration for developing countries is particularly relevant. Constraints faced by researchers in developing countries are usually more stringent, for example, private mechanisms of funding are not as widespread as in developed countries and public funding may be the only option for a scientist. Furthermore, the production and diffusion of knowledge are usually affected by poor infrastructure conditions for scientific research, short planning horizon brought on by persistent macro volatility, financial constraints, weak intellectual property rights, and low quality research institutions (Lederman and Maloney, 2003). In particular, it is usually mentioned that the lack of coordination among researchers operating in different public and private organizations is one of the major weaknesses of the National Innovation Systems (NIS) of developing countries, as it is the case in Argentina. Therefore, public funding fostering research collaboration and the consolidation of networks can have significant effects in these contexts in addition to those observed in developed countries.

Our paper focuses on studying the effects of research grants on the number of direct and indirect research links for granted researchers. Firstly, we study the effect on direct links (total number of different co-authors) for researchers in our sample including all their co-authors. Secondly, we study both direct and indirect links (2-step relationships) within a sub-sample of domestic co-authors. A series of econometric techniques provide consistent evidence pointing towards a positive and significant impact of the grants on the number of both direct and indirect research links.

The rest of the paper is organized as follows. Section 2 presents a conceptual discussion of the potential effects of funding on collaboration. Section 3 provides some information on Argentina's NIS and explains the main characteristics of FONCYT grants' program. Section 4 describes the database and Section 5 presents the methodology and results. Finally, Section 6 reports some concluding remarks.

2. Conceptual background

2.1. Rationale for public research funding fostering collaboration

The highly cited article by Katz and Martin (1997) defines collaboration as the process through which researchers work together to achieve the common goal of producing new scientific knowledge. On the basis of this definition, the literature has pointed out several sources of both private and social returns to collaboration.

Collaboration benefits scientists by means of an increase in quality and quantity of their research output. Adams et al. (2005) find that scientific production is higher for larger research teams, which implies that a scientist can personally benefit from collaborating in a team. In addition, other scholars pointed out that co-authorship may provide internal refereeing and thus increase the likelihood of a good-quality article being accepted for publication (Salter and Martin, 2001; Lee and Bozeman, 2005; Adams et al., 2005). Other channels through which collaboration may positively affect the research outputs of a given scientist include access to expertise (Katz and Martin, 1997), to resources (Katz and Martin, 1997; Melin, 2000; Beaver, 2001; Heinze and Kuhlmann, 2008) and to funding (Beaver, 2001; Heinze and Kuhlmann, 2008).

A few studies using econometric techniques provide empirical evidence on these effects. For instance, Lee and Bozeman (2005) find a positive correlation between collaboration and productivity. Medoff (2003) finds no impact of collaboration measured by the number of authors in a paper on the quality of economic papers in eight top journals. However, Wuchty et al. (2007) analyze a broader set of data and show that co-authored articles receive more citations than sole-authored papers. In a panel analysis of scientists from New Zealand, He et al. (2009) find that collaboration is positively related to article's quality.

From a social point of view, returns to collaboration are potentially large as well. The creation and diffusion of knowledge is often enhanced by the combination of different skills, cross-pollination of ideas and pooling of resources possible through collaboration, which generates economies of scale in research activities and may help avoid duplication of research effort.

Research collaboration is also considered key for the development of the national stock of human capital since the transmission of tacit knowledge and the learning experience generated by collaboration are key factors in the formation of scientists. For example, Lee and Bozeman (2005) highlight how collaboration fosters the replication of skills and the development of new capabilities.

Although collaboration seems to be beneficial from both individual and social points of view, some of its social benefits are not incorporated into the individual choice for the optimal level of collaboration. Several constraints may affect private decisions making the optimal level of collaboration chosen by scientists fall short of the socially optimal level of collaboration. Collaboration implies several costs, such as the one of finding and assessing partners, establishing agreements and coordinating research (He et al., 2009). Landry and Amara (1998) use the framework of transaction costs to remark the need for monitoring, enforcing and renegotiating joint projects due to the impossibility of designing complete cooperative contracts, and the risk of facing opportunistic behavior. This implies that coordination failures can be an obstacle for collaboration as Cummings and Kiesler (2007) remark by bringing evidence of a negative effect of coordination costs on collaboration among U.S. universities. Moreover, as Duque et al. (2005) highlight, collaboration in developing countries can be particularly affected by transaction and coordination costs, which may be intensified by a higher uncertainty about scientific recognition (Wray, 2006; Heinze and Kuhlmann, 2008).

Externalities may also play a role in this context contributing to the differential between social and private returns to research collaboration. The effort put in place to create and manage research links by one individual could be highly beneficial to other researchers who may join the network later on or may participate in the network without paying part of the coordination costs. As Jackson and Wolinsky (1996) and Jackson (2003) point out, the sole interaction of utility-maximizing agents might not lead to the formation of an efficient network. For example,[1] they show that the efficient network, which is a star network with all other actors connected to one central actor, is not stable. The central actor will not be willing to bear the cost of direct connections with all other actors even though this would provide the crucial links for other actors to access each other's resources. This shows that the central actor in a star network might accomplish a socially desirable goal, but it is not his private interest to offer such public good.

As a result, individual incentives might not lead to the level of collaboration that is socially optimal. The relationship between individual incentives and social benefits must be carefully considered when evaluating policies aimed at fostering collaboration. In fact, the previously mentioned case of the star network might indicate that the existence of more collaboration links is not always socially desirable. In these cases, research funding may even distort the science system because public funding for collaboration may end up inducing more collaboration than the social optimum.

[1] We thank a referee for pointing out this case.

However, it is very unlikely that this is the case for emerging countries such as Argentina. Many recent studies (see García de Fanelli and Estébanez, 2007) have pointed out that the lack of links among researchers operating in different public and private organizations is one of the major weaknesses of the Argentinean NIS. In particular, lack of coordination in the use of infrastructure and equipment, with the consequent inefficient use of these assets, and duplication of research effort, are often mentioned among the most important challenges for the Argentinean research community.

For these reasons, public programs funding scientific research and including specific incentives to foster research collaboration can be particularly effective in developing countries. In these contexts with large coordination problems, the theory of missing markets for the creation of social links with economic returns is specifically relevant. Therefore, for researchers in developing countries who decide to either collaborate or not with other partners by comparing individual benefits with individual costs, public funding can reduce the cost of coordination and provide additional incentives for the formation and consolidation of research networks.

Public programs provide funding for research projects to cope with administration and coordination costs and to cover networking and searching costs. Public funding usually covers most of the expenses related to the coordination of research teams, directly affecting transaction costs of individual researchers. This mechanism allows the researcher who takes leadership of the network to internalize part of the externalities generated by her coordination efforts. In addition, when public funding is linked to subsidizing trips to conferences, it may reduce communication and search costs and, correspondingly, increase co-authorships keeping other factors fixed.

As we mentioned in Section 1, few studies analyze the impact of funding on collaboration. All of them focus on developed countries and they do not usually count with a control group of non-funded researchers to measure the impact of a particular source of funding on collaboration. For instance, Defazio et al. (2009) argue that public funding may be a key input to help build more effective collaborations for research networks in the European Union. In the same direction, Porac et al. (2004) explain that the availability of funding can be essential to balance the generation of new knowledge with the management of existing relationships as a condition for collaboration. Our paper provides evidence that public funding can be an effective way of fostering collaborations in a developing country.

2.2. Measuring collaboration

The problem of measuring a complex phenomenon such as scientific collaboration immediately emerges when one wants to understand the factors that may lead to different levels of collaboration. A widely diffused measure is co-authorship in published articles, the main advantage being its objectivity and specificity to research activities.

As a note of caution, we should mention that co-authorship can only be a partial indicator for collaboration since it cannot reflect the cases when two researchers work together and decide to publish separately or the many circumstances where collaboration does not lead to a joint article (Katz and Martin, 1997). In fact, the existence of a collaborative relationship could be attributed to researchers who never co-author a publication but who work together on a research project that leads to separate publications, whose names are only in the initial project's proposal, who make substantial contributions to the project or even who are just fund raisers. Furthermore, collaboration may just imply the sharing of knowledge through seminars or workshops without a joint involvement in a research project. These limitations notwithstanding, co-authorship has become the most used measure for scientific research by studies that adopted a quantitative approach to the topic, such as in co-authorship models.

Furthermore, indicators to measure the collaboration of actors in networks have been developed by the so-called Social Network Analysis (Freeman, 1979; Freeman et al., 1991; Wasserman and Faust, 1994). According to this approach, actors are identified through the relations they have among themselves and are distinguished by their position in a structured network. This is basically a theory of graphs in which researchers are represented as connected nodes or in columns of an adjacency matrix with coefficients reflecting the extent of collaboration.

In this paper, we focus on the total number of different co-authors as our main measure for collaboration and we provide a more detailed analysis on indirect links through co-authorships for a sub-sample of domestic co-authors. These two measures can be expressed in the terminology of the Social Network Analysis: the total number of different co-authors is the "size of the ego network" for each individual, and the 2-step-co-authorships measure capture both direct and 1-step indirect links for each individual. The former was used as well by Defazio et al. (2009).

In conclusion, while empirical evidence and theoretical arguments support the importance of collaboration and the relevance of public funding, as Defazio et al. (2009) remark, the process linking funding, collaboration and research productivity is complex and has not been conceptualized in an accepted framework. Our paper aims to further explore part of these channels by estimating the effect of funding on collaboration through a reduced form equation for a developing country such as Argentina. In the next section, we describe some of the specific characteristics of the Argentinean case, as well as it is similarities with other developing countries.

3. Argentina S&T sector and FONCYT program

Argentina's level of expenditure in research and development (R&D) activities has been low, representing only 0.43% of its GDP in 2004.[2] This is a low level when compared not only to developed countries (where often more than 2% of GDP is devoted to R&D) but also to some neighbor developing countries such as Brazil (0.82%) or Chile (0.67%). The same conclusion is derived if we look at expenditures in R&D activities per researcher, an indicator of available resources for research teams. In 2004, Argentina counted with 22.5 thousand dollars on expenditures in R&D per researcher, while the Latin American average was 54.8 thousand dollars.[3]

The scarce availability of resources is made even a more relevant constraint when combined with a lack of coordination among the institutions in the NIS. The Argentinean NIS is characterized by high quality isolated clusters with strong geographic concentration and a marked lack of articulation (Lugones et al., 2005). Therefore, researchers find it difficult to face the lack of resources by sharing inputs through cooperation agreements with other peers or institutions.

Furthermore, a large majority of researchers are professors at public universities, without full time positions, with negligible salaries and with no appropriate instruments at the university level to provide incentives for scientific research or collaboration. This makes the Argentinean case even more relevant for studying the effect of new funding for collaboration.

In the last two decades, Argentina and many Latin American countries have adopted a new demand-driven model for funding science and technology. At the end of the 1980s, the supply side approach gave place to a new approach based on horizontal policies

[2] Source: World Development Indicators Database, World Bank, World Development Indicators 2009.

[3] Source: Network on Science and Technology Indicators, RYCYT, 2007.

aimed at responding to the actual demand for research from the production system (ECLAC, 2004). In this context, research councils and national research institutes that were responsible for planning and implementing S&T policies lost part of their roles in favor of new government agencies or S&T ministries. A new structure was put into place in which the planning function was separated from the execution and implementation functions.

Before this reform, the main source of public funding for scientific research in Argentina was the National Council of Technical and Scientific Research (CONICET), an institution founded in 1958 and based on the concept of a "career researcher" by which scientists are permanent staff of the Federal Government (the so-called French Model). The CONICET was not only responsible for the definition of political guidelines and the allocation of resources, but it also carried out research activities.

Nowadays, an increasing part of the funds available for R&D activities in Argentina comes from the National Agency of Scientific and Technological Promotion (ANPCYT), created in 1996.[4] The ANPCYT administers three funds, the Argentine Technological Fund (FONTAR) which gives credits and subsidies to technological projects, FONCYT, which is dedicated to grant funds in the form of non-reimbursable subsidies to scientific research projects, and FONSOFT, which finances research projects related to the software industry.

The activities of FONCYT began in 1997. One of the objectives of its creation was the public funding of science based on competitive mechanisms and on quality evaluation through peer review and pertinence criteria. In this paper, as in Chudnovsky et al. (2008), we focus our analysis on the impact of the Scientific and Technological Research Projects (PICT) funded by FONCYT in 1998 and 1999.[5]

During the period under analysis the maximum amount of the grant was $50,000 per year, for a maximum of three years.[6] With FONCYT's grant researchers can fund inputs, the purchase of bibliography, publication edition, scholarships, trips to scientific conferences, specialized technical services, and equipment; but not the salaries of researchers. A requirement for receiving the grant is having a permanent source of income from the institution at which the researcher works.

The selection process of the projects to be funded consists of three steps. The first one involves admissibility of the projects which implies some minimum requirements.[7] The second step is the peer evaluation of quality. Only those projects given a category of good, very good, or excellent quality are considered for funding. We have information on this peer-evaluation, but not on the score given in the last step in which the pertinence of the project is evaluated. Pertinence is understood as the possible impact of the proposal on the socioeconomic development of the country or region, and on the training of human resources. The order of merit for the projects in condition of being funded is the following one: excellent, very good, and good quality projects of high pertinence, excellent and very good projects of medium pertinence, and excellent projects of low pertinence.

4. Data

We use a unique dataset for 768 Argentinean researchers,[8] who represent a random sample of the population stratified approximately evenly in three groups: a group applying for FONCYT grants in 1998, 1999 or 2000 and being granted the funds (our *treatment group*), a second group applying in the same years and not being granted the funds (our *control group*), and a third group of researchers who never applied. From this sample, hereafter referred to as *the overall sample*, we focus the main part of our analysis on the first two groups, 496 researchers who applied for FONCYT support. We restrict our analysis to these two groups since by considering only those researchers who applied to the program we can control for selection into the application for the grants. After dropping 139 researchers applying to FONCYT in the year 2000 (for whom we would not have two five-year publication windows after the subsidy) and 34 researchers from the social sciences (for whom our database of publications does not reflect appropriately their scientific outcomes), we end up focusing on a sub-sample of 323 researchers who applied for FONCYT grants in the years 1998 and 1999.[9] This subsample, hereafter referred to as *the core sample*, includes 218 funded researchers and 105 non-funded researchers. The proposals of the two groups of researchers were approved for funding (they were evaluated as good, very good, or excellent quality), though some of them were not supported due to scarcity of resources.

Data available for each researcher in the core sample includes the average peer review score received by the proposals (Peer-Review Evaluation), researchers' age (Age), a set of binary variables that take the value of one for researchers with doctoral degree (Doctorate), for male researchers (Gender), for researchers being part of a team that was constituted after 1994 (New Team), for researchers working at a private institution (Private Institution), and a set of binary variables for the region, year in which the subsidy was granted, and project field.[10] Summary statistics are presented in Table 1.

We can see that several of the variables are similar on average for funded and non-funded researchers, even when the funding decision was not random. The exceptions are age and location of the scientists, variables for which we control in our regressions.

As a second source of data, the number of publications for each researcher in our database and the impact factor[11] of the journal in which the papers were published were collected from the Science Citation Index.[12] Table 1 also presents summary statistics for these variables before FONCYT. The Impact Factor variable is the average of the impact factors of each journal where researchers have published articles between 1994 and 1998. For publications, we present the total number of publications including all registered

[4] The ANPCYT depended originally on the Secretary of Science and Technology, which in turn depended administratively on the Ministry of Education, Science and Technology. Since 2008, ANPCYT depends on the newly created Ministry of Science, Technology and Productive Innovation.

[5] PICTs are research projects on different disciplines carried out by private or public institutions, which are presented in public calls.

[6] The mean subsidy in the sample was $39,000 per year. The exchange rate between the Argentine peso and the U.S. dollar was one to one until 2002. The annual wage for the highest category of a scientist in the CONICET was around 27,000 pesos in 2002.

[7] The minimum requirements are that the researchers of the group (i) have a labor relationship with an S&T institution, (ii) dedicate a minimum of 50% of their time to the execution of the project, and (iii) have previous experience in academic research.

[8] This number represents about 2.5% of all active researchers in Argentina in 1998, based on data provided by RICYT.

[9] The sample has been chosen with the condition that a funded researcher did not submit a proposal in an ex-post not funded project. Members of the non-funded projects were not funded by the program in any of the years under study.

[10] There are twelve fields grouped in three broadly defined areas: Biomedical Sciences (Biological Sciences and Medical Sciences), Exact Sciences (Physical and Mathematical Sciences, Chemical Sciences, and Earth and Hydro-atmospheric Sciences), and Technologies (Food Technology, Agricultural, Forestry, and Fishing Technology, Information Technology, Electronic and Communication Technology, Mechanic and Material Technology, Environmental Technology, and Chemical Technology).

[11] The impact factor is a measure of the frequency with which the "average" article of a journal was mentioned in a certain year. Available data do not include values for around 10% of the journals in our sample. Impact factors before 1998 were also missing; therefore the values of the nearest year were attributed in this last case, whereas a null value of impact has been assigned to the other cases.

[12] The Science Citation Index is developed by the Institute for Scientific Information (ISI) and it covers approximately 3200 high quality journals.

Table 1
Summary statistics.

	(1) FONCYT = 0	(2) FONCYT = 1	(3) Difference $F=1-F=0$	(4) P-value[+]
Peer-reviewed Evaluation	6.828	8.277	1.449	0.000
	(0.79)	(0.97)		
Field Biomedical Sciences	0.371	0.376	0.005	0.935
	(0.49)	(0.49)		
Field Exact Sciences	0.162	0.174	0.012	0.780
	(0.37)	(0.38)		
Field Technologies	0.467	0.450	−0.017	0.773
	(0.50)	(0.50)		
New Team	0.505	0.408	−0.097	0.104
	(0.50)	(0.49)		
Gender	0.629	0.661	0.032	0.577
	(0.49)	(0.48)		
Age (as of 2005)	56.7	55.0	−1.724	0.088
	(8.65)	(8.18)		
Doctorate	0.771	0.844	0.073	0.131
	(0.42)	(0.36)		
Private Institution	0.029	0.023	−0.006	0.770
	(0.17)	(0.15)		
Region Buenos Aires	0.600	0.592	−0.008	0.888
	(0.49)	(0.49)		
Region Centre	0.152	0.239	0.086	0.060
	(0.36)	(0.43)		
Region Patagonia	0.038	0.087	0.049	0.068
	(0.19)	(0.28)		
Region Cuyo	0.076	0.023	−0.053	0.057
	(0.27)	(0.15)		
Region Northeast	0.057	0.009	−0.048	0.043
	(0.23)	(0.10)		
Region Northwest	0.076	0.050	−0.026	0.391
	(0.27)	(0.22)		
Impact Factor before FONCYT[a]	1.304	2.582	1.278	0.001
	(2.89)	(3.60)		
Publications 1989–1993[b]	3.486	6.261	2.776	0.000
	(5.26)	(8.43)		
Publications 1994–1998[b]	5.457	9.156	3.699	0.001
	(8.18)	(11.22)		
Publications 94–98 (articles)[c]	4.543	7.807	3.264	0.001
	(7.60)	(9.23)		

Notes: (+) For a p-value larger than 0.10 we cannot reject that the difference in means is 0 at the 10% significance level.
[a] Average of impact factors for 1994–1998.
[b] Include all registered items in the SCI, such as articles, reviews, letters, editorial material, research notes and abstracts.
[c] Includes only articles.

items in the SCI, such as articles, reviews, letters, editorial material, research notes and abstracts from 1989 to 1993 and 1994 to 1998. For the later period, we also present the total number of publications including only articles. Since the correlation between the measure including all registered items and the one including only articles is very high (0.93), and because we only count with information for total registered items for 1989–1993, we carry out our analysis using the two total items measures as control variables.[13] None of the pre-program output variables were balanced between funded and non-funded researchers, thus we will include them in the regressions as way to control for differential researchers' capabilities.

4.1. Empirical strategy

We divide our analysis in two parts. In the first part we study the effect of the funding on the total number of different co-authors for the 323 researchers in our core sample. Secondly, to complement these results, we study the effect of the program on both the number of different co-authors and the number of 2-step indirect links, including direct and indirect co-authorships, within the 768 researchers in our overall sample.

We follow these two strategies because for the 323 researchers in our core sample we were able to obtain data on all co-authors from 1989 to 2004, though we do not have data on the co-authors of the co-authors. On the other hand, when we consider the 768 researchers in the overall sample, which includes the 323 of the core sample, we can observe all possible co-authorship links within the sample from 1994 to 2004, though we cannot observe links with foreign researchers or with domestic researchers not in the sample. This gives us the possibility to treat this group of 768 Argentinean researchers as a domestic network and to calculate 2-step research links within the overall sample.

In Table 2, we present averages for the outcome variables for the two empirical strategies. In the first panel we can see that when we take into account all co-authors for the 323 scientists in our core sample, the mean number of different co-authors in a five-year window is always higher for funded researchers. We can also see that the means increase significantly for the two groups when we look at the two five-year windows before the program. In the next section, we will show that these pre-treatment trends are not statistically different for funded and non-funded researchers once we restrict the sample to comparable researchers, while post-treatment trends remain statistically different even after restricting the sample. Furthermore, the fact that the means for 2005–2009,

[13] Results using the number of articles for 1994–1998 as a control variable with and without including the total items variable for 1989–1993 are similar, and available upon request.

Table 2
Collaboration variables.

Variable	FONCYT = 0 105 observations		FONCYT = 1 218 observations	
	Mean	Standard deviation	Mean	Standard deviation
A. All co-authors[a]				
Co-authors 89–93	5.04	8.12	8.72	11.66
Co-authors 94–98	7.36	11.19	13.66	15.16
Co-authors 00–04	9.94	13.38	19.40	19.12
Co-authors 05–09	9.62	17.08	19.64	21.22
B. Within overall sample				
Co-authors 94–98	0.30	0.62	0.49	0.83
Co-authors 00–04	0.20	0.49	0.53	0.88
2-Step Links 94–98	0.37	0.81	0.69	1.25
2-Step Links 00–04	0.30	0.84	0.90	1.58

[a] Publications used to construct co-authorships measures include all registered items in the SCI, such as articles, reviews, letters, editorial material, research notes and abstracts.

the second five-year window after the program, do not decrease indicates that the effect of the program is sustainable over time, as we will show formally in next section.

In the second panel of Table 2, we can see that both the mean number of direct co-authors and direct and indirect co-authors within the overall sample increased for funded researchers, while they decreased for researchers who applied but were not funded when considering the years 1994–1998 as pre-program and 2000–2004 as post-program. The mean values are low in both cases because of the little co-authorship within this sample, but we can still capture the effect of the funding as we will see in next section.

5. Methodology and results

The objective of this paper is to estimate the impact of research grants on research collaboration. In an experimental setting, in which research grants are randomly allocated to researchers, unobserved characteristics would be balanced across successful and unsuccessful applicants and we could identify the causal effect of receiving a grant by simply comparing the collaboration outcomes of those researchers who received and did not receive the grant. In the case of FONCYT, allocation of grants was not random, implying that funding is likely to be positively correlated with some unobserved characteristics, such as motivation, skills, ability, that could also affect collaboration outcomes. If this were to be the case, the simple comparison of the collaboration outcomes of successful and unsuccessful applicants would give an impact that is biased upwards.

A usual approach to deal with non-experimental data is to use difference-in-differences (DID) methods. The data of this paper fit into the basic setup where outcomes are observed for two groups and two periods, and one group is exposed to the treatment only in the second period.

The theoretical argument for dividing the periods into two five-year windows rests on the fact that it takes time to publish and to see a collaboration reflected in co-authorship. In particular, Crespi and Geuna (2005) provide evidence of the lag between the reception of funding and the actual publication. They estimate that the maximum level of publications is obtained only after five years of the reception of the funding. Furthermore, the grouping of the data into two periods alleviates the problems of serial correlation, which may result in biased standard errors and may generate over-rejection (Bertrand et al., 2004).

The standard DID estimator basically subtracts the average difference over time for non-funded researchers from the average difference over time for funded researchers, as in Eq. (2). This procedure removes biases associated to permanent differences between the two groups, as well as biases from possible before and after comparisons in the funded group that could be the result of trends unrelated to the grants.

Taking the difference between the equation for the post- and pre-treatment outcomes, we can express the change in collaboration outcomes for any researcher in the sample as:

$$\Delta Y_i = \beta_0 + \beta_1 F_i + \beta X_i + \varepsilon_i \tag{1}$$

Here ΔY_i s the difference in the value of the collaboration outcome between the post-program period 2000–2004 and the pre-program period 1994–1998 for researcher i; F is a dummy for funded researchers, and X_i is a vector containing variables that might affect the change in collaboration outcomes and are not affected by the reception of the grants (for example: gender, the possession of a doctorate before the program, age, previous level of publications); and ε_i is the error term. The coefficient of interest is β_1, the DID estimate, which is equal to the double difference in means presented in Eq. (2) in the basic case without controls, where *NF* represents the non-funded group, *F* the funded group, and 0 and 1 the five-year windows before and after the grant respectively:

$$\hat{\beta}_1 = (\bar{y}_{F,1} - \bar{y}_{F,0}) - (\bar{y}_{NF,1} - \bar{y}_{NF,0}) \tag{2}$$

Because this approach may not completely eliminate time-varying unobserved heterogeneity, resulting estimates should be considered only upper bounds for the causal effect. The assumption is that the change in collaboration outcomes for control researchers is an unbiased estimate for the counterfactual—i.e. the change in outcomes for funded researchers had they not been funded.

5.1. *Results for the core sample*

Column (1) of Table 3 presents the basic DID estimates for the effect of the funding on the number of different co-authors. The coefficient of FONCYT is positive and significantly different from zero. Comparing the pre- and post-grants periods (1994–1998 vs. 2000–2004), the change in the number of different co-authors for funded researchers was greater than the change for the non-funded researchers in about three co-authors.

Column (3) incorporates control variables that might affect the change in the number of co-authors, but are not influenced by the grants, since we use their pre-program value. The impact of the grants is still significant. The coefficient on FONCYT is smaller, but it is not statistically different from the one obtained without control variables.

It is interesting that the age of a researcher has a non-linear effect on the change in the number of co-authors. The change in the number of co-authors increases with age up to a value of 49.5 years, and then it decreases with age. This reflects scientists'

Table 3
Difference-in-differences estimates.

	Dependent variable: Change in number of different co-authors (2000–2004 vs. 1994–1998)			
	(1)	(2)	(3)	(4)
FONCYT	3.162	2.735	2.891	3.690
	(1.15)***	(1.28)**	(1.33)**	(1.41)***
Age			1.98	1.61
			(0.72)***	(0.88)*
Age squared			−0.02	−0.02
			(0.01)***	(0.01)**
Doctorate			1.19	0.28
			(1.35)	(1.86)
Gender			0.69	0.46
			(1.30)	(1.33)
Peer-Review Score			0.72	−0.34
			(0.65)	(0.83)
Pub 89–93			0.08	0.06
			(0.16)	(0.18)
Pub 94–98			−0.18	−0.03
			(0.13)	(0.14)
Impact Factor			−0.28	−0.58
			(0.49)	(0.51)
Observations	323	210	323	210
Type of estimation	OLS	OLS	OLS	OLS

Notes: Heteroskedasticity robust standard errors are shown in parentheses. Regressions in columns (2) and (4) use the sample restricted to common support. Regressions in columns (3) and (4) include region and field dummies, a dummy for applying in 1998, and a dummy for working in a private institution.
** Significant at the 5% level.
*** Significant at the 1% level.

natural career trajectories. In our sample, we study researchers who are responsible for the projects with age ranging from 41 to 83 in 2005 (they applied for the grants in 1998 or 1999). Since the effect of FONCYT is still significant even after controlling for the non-linear effect of age, we can discard the alternative explanation pointing that it is the difference in age between funded and non-funded researchers the one generating a difference in outcomes.[14]

One important source of bias in the estimation could arise from the lack of comparable control researchers for some funded researchers and vice versa. To deal with this potential source of bias, we re-estimate the DID model in the common support of the probability of receiving the grants. For this purpose, we estimate the propensity score by means of a probit regression of the probability of being funded on a number of pre-treatment characteristics such as Peer Review Evaluation, Age, Gender, Doctorate, New Team, Publications, Impact Factor and a set of indicator variables for region and scientific area.[15] We obtain the common support by excluding observations from control researchers with an estimated propensity score smaller than the minimum estimated for the treated group, and observations from treated researchers with an estimated propensity score larger than the maximum estimated for the control group.

Results presented in columns (2) and (4) of Table 3 are consistent with the previous findings. FONCYT is still significant and the magnitude of the coefficient is statistically similar when we restrict the estimation to the common support.

Another source of bias could arise in DID estimations when the distribution of the variables on which we condition differs between funded and non-funded researchers, even within the common support. To control for this source of bias, control group observations must be re-weighted. The DID matching estimator accomplishes this task by combining both matching and DID estimators (Heckman et al., 1998; Blundell and Costa-Dias, 2002; Todd, 2006). The estimator can be expressed as:

$$\hat{\beta} = \frac{1}{N_F}\sum_{i \in F}[Y_{i1} - Y_{i0}] - \sum_{j \in NF} w_{ij}[Y_{j1} - Y_{j0}]$$

where 1 is the time period after applying to FONCYT and 0 is the time period before applying, N_F is the number of funded researchers, F and NF indicate respectively the funded and the matched group of non-funded researchers in the common support, and w_{ij} represent the weights corresponding to researcher j matched to a funded researcher i.

DID matching estimates are presented in Table 4 for two different schemes of weighting, kernel matching and radius

Table 4
DID matching estimates.

	Change in number of different co-authors (2000–2004 vs. 1994–1998)	
	(1) 136 treated and 74 controls	(2) 215 treated and 87 controls
Kernel matching[a]	2.737	3.163
	(1.310)**	(1.285)**
Radius matching[b]	2.735	3.160
	(1.319)**	(1.227)**

Notes: Bootstrapped standard errors (1000 replications) are shown in parentheses.
[a] Gaussian kernel function with bandwidth parameter using Silverman's (1986) rule of thumb method (3.26 and 3.78 for columns (1) and (2) respectively).
[b] Radius equal to 3.26 and 3.78 for columns (1) and (2) respectively.
** Coefficient significant at the at the 5% level.

[14] Furthermore, when we restrict the sample to the common support, we cannot reject the hypothesis that there is no difference in average age between funded and non-funded researchers at the 10% level.

[15] The specification of this probit model satisfies a series of balancing tests—balancing the distribution of pre-treatment covariates for matched researchers after conditioning on the propensity score (Rosenbaum and Rubin, 1985; Lechner, 2000).

matching.[16,17] In the two cases standard errors were obtained by bootstrapping with 1000 replications. The propensity score was re-estimated at each replication of the bootstrap to account for the error that comes from both probit estimation and the determination of the common support. Column (1) of Table 4 presents results for the common support defined above, while column (2) presents results for a less restrictive common support that keeps 302 researchers (in comparison to the 210 remaining for the first definition of the common support). The second common support was obtained by excluding the observations from non-funded researchers whose propensity scores are smaller than the propensity score of the researcher at the first percentile of the funded propensity score distribution, and excluding funded researchers' observations whose propensity scores are greater than the propensity score of the non-funded researcher at the ninety-ninth percentile.

In the two cases, when we add matching to the difference-in-differences procedure, our estimates are still significant, and with similar magnitudes to those presented in Table 3.

5.2. Placebo test

Another plausible source of bias in our DID research strategy would arise if funded researchers followed a different trend in the number of co-authors over time even in the absence of funding. In Fig. 1a we graph the trend in the number of co-authors for funded and non-funded researchers using observations for the four five-year windows for which we have data. The change in number of different co-authors between the two five-year windows that precede the granting of FONCYT funds seems to be more pronounced for funded researchers. However, when we restrict the sample of researchers to the common support, we can see in Fig. 1b that changes before the program appear to be more similar for funded and non-funded researchers. That is, by restricting the sample to make the two groups more comparable, we also make the assumption of the DID strategy more plausible.

Given that pre-treatment trends still appear somehow divergent even in the common support sample (see Fig. 1b), we run a placebo test to provide additional evidence for the validity of our results. This test consists of estimating the effect of the grants on the change in the number of co-authors by comparing two five-year windows before the program: 1994–1998 vs. 1989–1993. Since the application for the grants for researchers in our sample began in 1998, there is no reason to expect that FONCYT should affect collaboration outcomes when comparing these pre-program windows. Table 5 presents results replicating the DID methods used above, but now with the new dependent variable reflecting the change between 1989–1993 and 1994–1998. We can see that if we do not restrict the sample to the common support, there appears to be a spurious impact of FONCYT in this regression. However, when we restrict the sample to the common support in columns (2) and (4) the effect disappears. Since all our findings for a positive effect of the program hold both for the full and the common support sample,[18] this

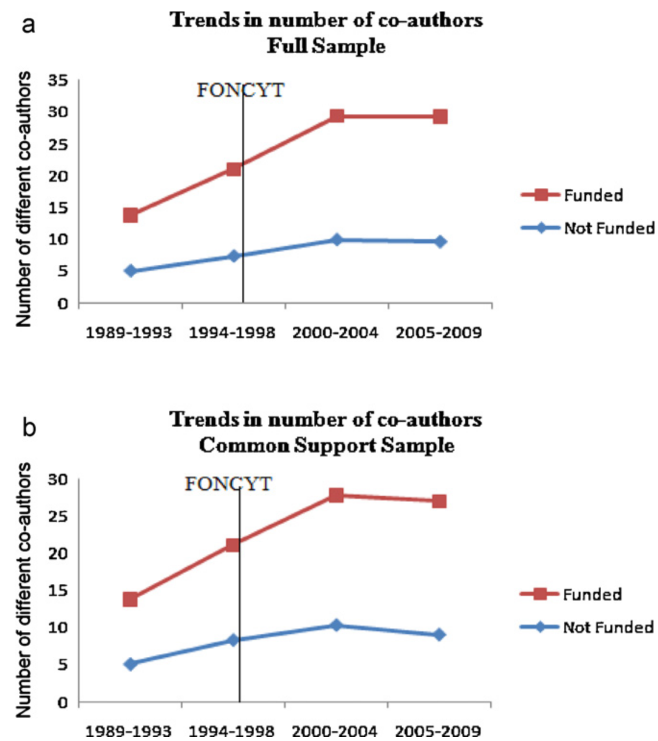

Fig. 1. Trends in number of co-authors: (a) full sample and (b) common support sample.

placebo test provides additional evidence for the internal validity of our estimation.

In conclusion, even though we cannot control for unobserved time-varying heterogeneity, the results of our placebo test minimize the potential concern that time-varying omitted variables correlated with both funding and collaboration opportunities may be biasing our estimates. Furthermore, by including number and quality of publications before FONCYT in our regressions, we are able to control for researchers' capabilities, which is one of the most important potential sources of time-varying heterogeneity when measuring the effect of funding on collaboration.

5.3. Persistence of the effects after funding

It might be argued that as collaboration is required by funding agencies as a condition to apply for funding, it is not surprising to see an increase in collaboration measured by the number of co-authors immediately after project funding (after taking into account publication lags). One can argue[19] that the program's *additionality* should be assessed by studying the effect of the funding after researchers have finished their funded project and have published the research outcomes related to that project. Finding that funded researchers have maintained relatively high levels of collaboration in the long run would prove that the program has effectively contributed to expanding their research networks.

In order to explore this idea, we collected additional information on co-authors for researchers in our core sample between 2005 and 2009. In Table 6 we replicate the DID analysis presented above, we study whether the effect of FONCYT persists when we use as dependent variable the change in co-authorship between the window before the funding (1994–1998) and the window that follows the one after funding (2005–2009). We can see that both for the full and the common support sample the effect is significant and

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[16] In kernel matching each funded researcher is matched with a weighted average of all non-funded researchers, and the weights are constructed on an inversely proportional factor to the distance between their estimated propensity scores. In radius matching each funded researcher is matched with the non-funded researchers who have an estimated propensity score differing less than an established distance from the score of the corresponding treated unit.

[17] Results are robust to the use of different types of kernel (at least with Gaussian and Epanechnikov kernels), bandwidths and radius. Bandwidths were selected by applying Silverman's (1986) rule of thumb method, but results were very similar when other criteria were utilized. Results are available upon request.

[18] Our results are also robust to including the change in the number of co-authors for the two pre-program five-year windows as control variables in our regressions. Results are available upon request.

[19] We thank a referee for pointing out this idea.

Table 5
DID estimates for placebo test.

	Change in number of different co-authors (1994–1998 vs. 1989–1993)			
	(1)	(2)	(3)	(4)
FONCYT	2.612	0.816	2.336	0.423
	(1.01)***	(1.27)	(1.13)**	(1.32)
Age			−0.16	0.03
			(0.91)	(0.98)
Age squared			0.01	−0.01
			(0.01)	(0.01)
Doctorate			1.26	0.52
			(1.18)	(1.39)
Gender			0.15	−0.72
			(1.06)	(1.41)
Pub 89–93			0.05	0.12
			(0.09)	(0.09)
Observations	323	210	323	210
Type of estimation	OLS	OLS	OLS	OLS

Notes: Heteroskedasticity robust standard errors are shown in parentheses. Regressions in columns (2) and (4) use the sample restricted to common support. Regressions in columns (3) and (4) include region and field dummies, a dummy for applying in 1998, and a dummy for working in a private institution.
** Significant at the 5% level.
*** Significant at the 1% level.

with a higher magnitude than the one found for the period immediately after funding. This evidence confirms that funding allows funded researchers to maintain their high levels of collaboration even in the long-run, which may be related to an expansion of their research networks.

5.4. Indirect links for collaborations within the overall sample

To further explore how funding affect the size of research networks, we used our overall sample of 768 Argentinean researchers to analyze collaboration patterns for the 323 researchers in our core sample with the other researchers in the overall sample. In this way, we can complement the measure of total direct links (number of co-authors) with a 2-step-indirect links measure. However, we also incur into two limitations: first, we have complete data for these co-authorships only between 1994 and 2004; second, we do not have complete information on co-authorship with foreign researchers or with domestic researchers outside the sample. The new outcome variable consists of the total number of researchers having a direct or indirect co-authorship with each researcher, and captures the level of integration of a researcher into the scientific community.

Columns (1) and (5) of Table 7 present the basic DID estimates for the direct links and the 2-step indirect links measures. In both cases the coefficient of FONCYT is positive and significantly different from zero; its value indicates that, comparing the pre- and post-grants periods, the change in the collaboration measure for funded researchers was greater than the change for non-funded researchers by about 0.14 direct links and 0.28 direct and indirect links. This might seem to be a low impact, but one must consider that the mean of the two measures for all researchers in our sample was 0.42 and 0.59 respectively, and the standard deviation 0.77 and 1.13.

After incorporating control variables in columns (3) and (7), we still find a positive and significant impact of the grants. Qualitatively

Table 6
Additionality. DID estimates.

	Dependent variable: Change in number of different co-authors (2004–2009 vs. 1994–1998)			
	(1)	(2)	(3)	(4)
FONCYT	3.724	4.469	5.171	5.282
	(1.82)**	(2.17)**	(2.43)**	(2.70)*
Age			3.06	4.08
			(1.29)**	(1.66)**
Age squared			−0.03	−0.03
			(0.01)***	(0.01)**
Doctorate			0.48	0.17
			(2.46)	(3.32)
Gender			0.34	2.78
			(1.95)	(2.41)
Peer-Review Score			−0.25	−0.87
			(1.00)	(1.43)
Pub 89–93			0.56	0.75
			(0.25)**	(0.38)**
Pub 94–98			−0.63	−0.57
			(0.23)***	(0.31)*
Impact Factor			−0.16	−0.75
			(0.63)	(0.85)
Observations	323	210	323	210
Type of estimation	OLS	OLS	OLS	OLS

Notes: Heteroskedasticity robust standard errors are shown in parentheses. Regressions in columns (2) and (4) use the sample restricted to common support. Regressions in columns (3) and (4) include region and field dummies, a dummy for applying in 1998, and a dummy for working in a private institution.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 7
DID estimates within overall sample.

	Dependent variable: Change in number of direct links (2000–2004 vs. 1994–1998)				Dependent variable: Change in total direct and indirect links (2000–2004 vs. 1994–1998)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FONCYT	0.141	0.215	0.218	0.271	0.282	0.460	0.366	0.446
	(0.08)[*]	(0.10)[**]	(0.11)[**]	(0.12)[**]	(0.14)[**]	(0.15)[***]	(0.18)[**]	(0.20)[**]
Age			0.05	0.09			0.03	0.22
			(0.05)	(0.07)			(0.10)	(0.13)[*]
Age squared			−0.00	−0.00			−0.00	−0.00
			(0.00)	(0.00)			(0.00)	(0.00)[*]
Doctorate			−0.06	0.17			−0.12	0.37
			(0.09)	(0.11)			(0.16)	(0.21)
Gender			0.00	−0.05			0.17	0.18
			(0.08)	(0.11)			(0.15)	(0.18)
Peer-Review Score			−0.02	−0.01			−0.08	0.05
			(0.04)	(0.08)			(0.08)	(0.12)
Pub 94–98			−0.09	−0.07			−0.18	−0.16
			(0.05)[*]	(0.06)			(0.07)[**]	(0.09)[*]
Impact Factor			0.02	0.02			0.07	0.07
			(0.03)	(0.03)			(0.04)	(0.06)
Observations	323	210	323	210	323	210	323	210
Type of estimation	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS

Notes: Heteroskedasticity robust standard errors are shown in parentheses. Results in columns (2), (4), (6), and (8) use the sample restricted to the common support. Results in columns (3), (4), (7) and (8) include region and field dummies, a dummy for applying in 1998, and a dummy for working in a private institution.
[*] Significant at the 10% level.
[**] Significant at the 5% level.
[***] Significant at the 1% level.

Table 8
DID matching estimates within overall sample.

	Change in number of different co-authors (2000–2004 vs. 1994–1998)		Change in total direct and indirect links (2000–2004 vs. 1994–1998)	
	(1) 136 treated and74 controls	(2) 215 treated and 87 controls	(3) 136 treated and 74 controls	(4) 215 treated and 87 controls
Kernel matching[a]	0.237[**]	0.215[**]	0.473[***]	0.370[***]
	(0.103)	(0.093)	(0.148)	(0.136)
Radius matching[b]	0.259[**]	0.241[**]	0.460[***]	0.383[**]
	(0.106)	(0.095)	(0.158)	(0.149)

Notes: Bootstrapped standard errors (1000 replications) are shown in parentheses.
[a] Gaussian kernel function with bandwidth parameter using Silverman (1986) rule of thumb method (0.27, 0.25, 0.43 and 0.43 for columns (1), (2), (3) and (4) respectively).
[b] Radius equal to 0.27, 0.25, 0.43, and 0.43 for columns (1), (2), (3) and (4) respectively.
[**] Coefficient significant at the at the 5% level.
[***] Significant at the 1% level.

similar results are obtained when we estimate the DID model in the common support. Results are presented in columns (2), (4), (6) and (8) of Table 7.

Finally, DID matching estimates for the two outcome variables are presented in Table 8. When we add matching to the DID procedure, our estimates are all significant, and their values are higher than the ones reported in Table 7.

6. Concluding comments

In this paper we evaluate the impact of research grants on collaboration outcomes for a group of Argentinean researchers. We compare the performance of researchers with funded projects with the outcomes of a control group of researchers that submitted projects accepted in terms of quality, but not financed because of lack of funds. We find a positive and statistically significant effect of the grants on the total number of different co-authors, and we also find evidence of positive effects of the funding on a measure of integration of researchers into the scientific community (direct and indirect links) within a sample of domestic scientists. We obtain these results and check their robustness using a series of non-experimental econometric techniques, including DID and matching DID, together with a placebo test. Furthermore, we estimate that the effect of the funding persists over time, which indicates that funded researchers might be able to expand their research networks and maintain high levels of collaboration in the long run.

Some caveats should be considered. Firstly, our estimates only capture the impact of receiving FONCYT grant relative to the next best funding option. While in Argentina there are not many alternative sources of funding, some funding may still come through co-authors, as Jacob and Lefgren (2007) suggest. Additionally, the fact that we only study those researchers who applied to the grants contributes to the robustness of our analysis by increasing the homogeneity across the funded and non-funded group, but it also restricts the external validity of our results. Our results could not be used to infer the impact of funding on those researchers who do not have access to the funds because of lack of information or low approval expectations.

Secondly, our results are non-experimental and should be interpreted with caution. The methods used in this paper will give biased estimates if there are differences in collaboration outcomes across matched funded and non-funded researchers due to unobserved factors that are not fixed over time. Nevertheless, the facts that our results are robust to using different methodologies and that our placebo test gives the correct conclusion for the common support sample provide evidence in favor of the internal validity of our findings.

Some potential extensions could complement the results from this paper. Future research can focus on assessing the differential effects of public funding for researchers with different characteristics. In the working paper version of this paper we present some evidence that impacts of funding are larger for researchers with higher levels of publications before the program.[20] This is consistent with a need to study the behavior of "star scientists" as in Zucker and Darby (2006). In the same direction, a larger dataset would allow identifying heterogeneous effects by other ex-ante researcher characteristics and by scientific sectors. Furthermore, if more data were available on the channels by which funding may affect collaboration (for example: use of funding for traveling to seminars or time spent in joint projects), we could explain with more detail the observed patterns of co-authorships in terms of individual incentives.

Taking these caveats into account, the findings of this paper can be considered as the first empirical evidence indicating that public research grants can foster collaboration among researchers in developing countries. On this basis, some useful insights for policy makers can be drawn.

First, given potentially large social returns to scientific collaboration, policy makers should attribute more emphasis to the role that funding can play in creating the incentives needed to reach an optimal level of collaboration. This is particularly relevant in emerging economies, where the NISs are usually affected by high levels of disarticulation, making the social returns to increased collaboration even higher. These gains should be more explicitly considered in the design of policy instruments and in the estimation of their rate of return.

Second, policy makers should carefully adjust the instruments aimed at promoting collaboration over time. As discussed in the paper, more collaboration is not a benefit per se. Therefore, the incentives generated through public funding should not be static over time, but evolve with the needs of a specific NIS. In theory, during a preliminary stage of development of a NIS, policy makers may want to support collaboration in a generalized manner in order to reach a certain level of economies of scale and avoid duplication of efforts. In subsequent stages, however, policy instruments may need to be revised and targeted towards either specific categories of researchers or specific types of collaboration that face higher transaction costs, but can also generate higher social returns.

Finally, policy makers should include in the design of instruments aimed at fostering scientific collaboration stronger ex-ante arrangements on how to evaluate their impact. Most of the limitations of studies in the field are due to the lack of an ex-ante evaluation design. The definition of a clear evaluation plan during the design stage would facilitate the estimation of the appropriate counterfactual, the generation of data and the estimation of results with both internal and external validity; a relevant point for both future non-experimental and potential experimental studies. This concern is even more important in an area where there have been few rigorous impact evaluations and where the dynamic nature of the policy-making process requires continuous learning from experience.

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[20] See Ubfal and Maffioli (2010) where we use a non-parametric DID estimator to obtain these results.