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The Impact of Funding on Research Collaboration: Evidence from Argentina

Abstract

Diego Ubfal[*] Alessandro Maffioli[**]

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. In particular, we find a significant impact of the grants for funded researchers both on the size of their ego network, and on their 2-step indirect links, measured by the number of direct and 1-step indirect co-authors. We also find evidence that this impact was driven by the results of funded researchers at the upper tail of the distribution of collaboration outcomes. 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 such as difference-in-differences models combined with propensity score matching methods and a non-parametric difference-in-differences estimator.

JEL Classification: O31, D85

Keywords: Scientific Collaboration, Social Networks, Program Evaluation, Nonparametric Difference-in-Differences Estimator, Latin America, Argentina

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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, 2001; Lee and Bozeman, 2005). A parallel reform in developing countries, in particular in Latin America, involves the introduction of competitive grants, which have shifted the way in which research is funded. 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).

In a similar direction, scholars providing a rationale for the public funding of scientific research have noted the importance of complementing the traditional argument based on the public good nature of scientific knowledge (Nelson, 1959; Arrow, 1962) with ideas coming from the study of the dynamic nature of the knowledge creation process. The relevance of this kind of analysis can be linked to the more recent approaches focusing on the costs of knowledge diffusion, which argue that the success of scientific research requires the formation of scientific networks (Lundvall, 1992; Callon 1994, Salter and Martin, 2001; Pavitt, 2005). Furthermore, the authors in the so-called "New Economics of Science" (Dasgupta and David, 1994) highlight the importance of analyzing the incentives that affect scientists' decisions. Some recent papers are beginning to follow this direction[1] by studying scientists' decisions on whether to publish alone or to co-author a paper, on the choice of the number of co-authors and on the amount of effort in each collaboration relationship (see Jackson, 2003 for a survey). The existence of public funding to promote research collaboration can be seen as an additional incentive that influences these decisions.

Our paper contributes to the literature by evaluating econometrically the impact of scientific research grants on research collaboration in Argentina. 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

[1] The importance of collaboration and co-authorship relationships has been widely remarked in the Social Networks literature. Jackson (2003) points out the need to bridge that literature with the economics one by introducing the study of player's incentives.

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

The theoretical support on the potential role of funding on collaboration and network formation comes from a branch of game theory showing that the simple interaction among agents does not always lead by itself to the optimal structure of a research network. It is only under some particular allocation rules that efficiency can be reached (Jackson and Wolinsky, 1996; Bala and Goyal, 2000; Jackson, 2003). Therefore, funding could provide an incentive to achieve desired levels of collaboration by re-allocating the value of collaborations. As Bloch and Jackson (2007) show, subsidization can lead to efficiency.

Nevertheless, few empirical studies have analyzed the impact of public funding on the 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 US. Adams et al. (2005) show that top universities academic departments receiving larger amounts of federal funding in the US tend to participate in larger teams. Defazio et al. (2009) study a panel of scientists in European Union research networks and argue that the 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 that applied for the same source of funding but who were not granted it.

The constraints faced by researchers in developing countries are usually more stringent. 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). Therefore, public funding fostering research collaboration and the consolidation of networks could be even more relevant for these countries.

Our paper focuses on studying the effects of research grants on the number of direct and indirect research links of granted researchers. A series of econometric techniques provide consistent evidence pointing towards a positive and significant impact of the grants. In addition, we present evidence indicating that this impact was concentrated in the upper tail of the collaboration outcomes distribution.

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 Science and Technology System 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 Why funding 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 developed two fundamental arguments on the potentially beneficial nature of scientific collaboration.

Firstly, collaboration improves scientific knowledge. The creation and diffusion of knowledge is often enhanced by the combination of different skills, cross-pollination of ideas, division of labor, and pooling of resources. Collaboration generates economies of scale in research activity, increases the quantity and improves the quality of publications[2]. In addition, co-authorship may also provide internal refereeing and thus increase the likelihood of a good-quality article being accepted for publication (Salter and Martin, 1997; Lee and Bozeman, 2005; Adams et al., 2005), and avoid duplication of research effort[3].

Secondly, collaboration fosters the development of human capital. The transmission of tacit knowledge and the learning experience generated by research collaboration are usually mentioned as key factors in the professional development of scientists. For example, Lee and Bozeman (2005) highlight how collaboration fosters the replication of skills and the formation of new capabilities. Following a similar way of reasoning, evolutionist scholars emphasize the role of collaboration in strengthening the learning capabilities of the entire innovation system through the creation of knowledge networks (Lundvall, 1992; Salter and Martin, 2001), and the increased systemic capacity to solve problems (Patel and Pavitt, 2000). According to the "network of learning" (Powell et al. 1996) and to the "interactive learning" approaches (Lundvall, 1992), collaboration in research networks facilitates interactive learning processes. In fact, the external knowledge that can be reached through the participation in networks complements internal capabilities and allows researchers to better exploit and build up their own knowledge (Dosi et

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[2] Although Medoff (2003) finds no impact of collaboration (measured by the number of authors in a paper) on the quality (measured by number of citations) of economic papers in eight top journals, 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 measured by the impact factor of the journal or the number of citations in a two-year window after publication.

[3] On the other hand, one could argue that collaboration may inhibit individual creativity, jeopardize the peer-monitoring system and obstruct the individual verification of findings.

al. 2000). Finally, Salter and Martin (2001) also point out that the creation of research networks plays a vital role in providing an entry point into networks of expertise, especially for young researchers.

Given these benefits, why do scientists need additional incentives to collaborate? In a parallel reasoning to the arguments by Nelson (1959) and Arrow (1962), additional incentives could be needed because the impossibility to completely appropriate collaboration's benefits may generate a difference between the private and the social marginal returns to collaboration, making private investment fall short of optimal levels. In addition, the uncertainty of the outcomes of collaboration efforts might contribute to this inefficient allocation of resources.

Collaboration also 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) utilize the framework of transaction costs and highlight the impossibility of designing complete cooperative contracts, which leaves room for opportunistic behavior, and the consequent need for monitoring, enforcing and renegotiating joint projects. Cummings and Kiesler (2007) bring evidence that collaboration among US universities might be affected by coordination costs. Moreover, Duque et al. (2005) claim that for developing countries, in particular, transaction and coordination costs can set obstacles to collaboration and affect its potential impact.

The promotion of collaboration through public funding is many times justified on the basis of the above-mentioned benefits and the existence of costs that can prevent it from expanding. However, it is not clear in those arguments whether public funding can actually change individual decisions on collaboration and how its existence could lead to a most efficient social outcome. The study of individual incentives is a key step in the search to answer those questions.

2.2 Co-authorship models and the impact of funding

"The New Economics of Science", term coined by Dasgupta and David (1994), introduces the importance of analyzing the role of public funding in generating the right incentives for the creation of scientific knowledge. In this context, a branch of game theory dealing with the formation of knowledge-sharing networks has contributed significantly to the analysis of the incentives that lead scientists to create research linkages. Even when its focus is not directly placed on the impact of public funding, this literature provides useful insights on the mechanisms through which public funding plays its role.

Examples of these models are the ones developed by Jackson and Wolinsky (1996) and Goyal et al. (2004). The latter categorize researchers as low or high types according to their academic status and study individual decisions on whether to write alone or with others, on the choice of the number of co-authorships, of the type of links (with low- or high-type researchers), of the number of papers to write and of the effort to put into each project. Basically, a strategy for each player consists of her decision on whether to participate in a project with other researchers and the effort (time spent) in each project. This decision is determined by comparing costs (opportunity cost of time spent in writing more papers with different co-authors due to communication and coordination costs) and rewards (they assume they are based on the quality-weighted index of published papers, which is discounted for joint work).

Goyal et al. (2004) study a cooperative equilibrium of the model. Contemplating the fact that the formation of links requires agreement at least between two researchers, they use the notion of "pair-wise" stability, which implies that no player may gain by cutting an existing link and no two players not yet connected can profit from creating a direct link with each other.

One interesting finding of these models is that the interaction among agents may not lead to the formation of an efficient network (Jackson and Wolinsky, 1996, Jackson, 2003). Under some configuration of parameters, a pair-wise stable equilibrium might involve fewer links than the ones formed under efficient networks.

Thus, we could think at the problem as one of missing markets for the creation of social links with economic returns. In a context in which agents decide to either collaborate or not with other partners by comparing individual benefits with individual costs, public funding can contribute to the formation of larger and more efficient networks. As Bloch and Jackson (2007), show the possibility of subsidies among players can lead to efficient outcomes.

In the model by Goyal et al. (2004), a decline in communication costs can lead to an increase in the optimal number of co-authors. If public funding is linked to subsidizing trips to conferences as in the program that we study, we could understand its impact as a reduction on communication costs and expect a corresponding increase in co-authorships keeping other factors fixed. Alternatively, we could see the reception of the grants as a change in resources among researchers of different types, which could foster efficient interactions between low- and high-type researchers that might not be observed without the availability of public funding.

In an empirical paper, 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.

As we mentioned in the introduction, 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 net impact of a particular source of funding on collaboration.

2.3 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, it is worth noting that co-authorship can only be a partial indicator of 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 produce 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.[4] These limitations notwithstanding, co-authorship has become the most used measure of scientific research by studies that adopted a quantitative approach to the topic, such as in co-authorship models.

[4] For this reason some studies use alternative indicators that combine sociometric measures of collaboration with self-reported measures captured by ad-hoc surveys.

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 use two of the measures that have been developed by the Social Network Analysis:[5] the size of the ego network for each individual, which measures the total number of nodes having direct contact with the specific node; and the "2-step links" which captures both the direct and 1-step indirect links of each individual. In the context of research collaboration, we could interpret the measure of 2-step links as the total number of scientists having a direct or indirect co-authorship with the specific scientist, which captures the level of integration of a researcher into the scientific community. On the other hand, the size of the ego network (sometimes called degree of centrality) would measure the actual direct co-authorships and captures the prestige or central position of the researcher within the academic community. This last measure 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 yet conceptualized in an accepted framework.

This paper aims to further explore these channels by estimating the effect of funding on collaboration through a reduced form equation inspired by the previously mentioned models such as in Goyal et al. (2004).

[5] To complement these co-authorship measures, we also present some descriptive evidence of self-reported measures of collaboration in the appendix.

3. Argentina S&T Sector and FONCYT Program

The trend towards a demand-driven model for funding science and technology impacted the policies of Latin American countries in the 1980s. The supply-side approach that was predominant at the time gave place to a new approach based on horizontal policies guided by the actual demand of the production system (ECLAC, 2004).

In this context, research councils and national research institutes that were responsible for the political planning and the implementation of the science and technology (S&T) policy lost part of their roles with the creation of S&T agencies or ministries. A new structure was put into place in which the planning function was separated from the execution and implementation functions.

In general terms, Argentina's level of expenditure in research and development (R&D) activities is low, representing only 0.43 percent of its GDP in 2004.[6] This is a low level when compared not only to developed countries (where often more than 2 percent of GDP is devoted to R&D) but also to some neighbor developing countries such as Brazil (0.82 percent) or Chile (0.67 percent).

Traditionally, the main source of public funding for scientific research was the Argentinean 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 research and development activities in Argentina comes from the National Agency of Scientific and Technological Promotion (ANPCYT), created in the mid 1990s.[7] The ANPCYT administers three funds, the Argentine Technological Fund (FONTAR) which gives credits and subsidies to technological projects, the Scientific, and Technological Research Fund (FONCYT), which is dedicated to grant funds in the form of non-reimbursable subsidies to scientific research projects, and the

[6] The source of the values in this paragraph is the World Development Indicators Database, World Bank, World Development Indicators 2009.

[7] The ANPCYT, created in 1996, 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.

Software Industry Development Fund (FONSOFT), which finances research projects related to the software industry.[8] These projects must be developed by researchers working at public or private, non-profit organizations located in Argentina.

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.[9]

During the period under analysis, the maximum amount of the grant is US$50,000 per year, for a maximum of three years.[10] 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. In this stage, it is verified that the projects fulfill some minimum requirements.[11] Once the project is admitted, the following step is the peer evaluation of its quality. Only those projects evaluated as good, very good, or excellent quality are considered for funding. Finally, the pertinence of the project is evaluated (intrinsic relevance of the proposal, its possible impact 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 projects of high pertinence, excellent and very good projects of medium pertinence, and excellent projects of low pertinence.

[8] The FONSOFT is the latest of the funds and began in 2004.

[9] PICTs are research projects on different topics (Biology, Medicine, Physics, Technology, etc.) carried out by private or public institutions, which are presented in public calls.

[10] The mean subsidy in the sample was US$39,000 per year. The exchange rate between the Argentine peso and the US 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.

[11] The minimum requirements are that the researchers of the group (i) have a labor relationship with an Argentine institution of science and technology, (ii) dedicate a minimum of 50 percent of their time to the execution of the project, and (iii) have previous experience in academic research.

4. Data

We use a unique dataset based on a sample of 768 Argentinean researchers.[12] Out of this sample, hereafter referred to as *the overall sample*, 496 researchers applied for FONCYT support. Because some administrative information is available only for FONCYT applicants, we restrict our analysis to this group. After cleaning the data, we end up focusing on a subsample of 323 researchers who applied for FONCYT grants in the years 1998 and 1999.[13] This subsample, hereafter referred to as *the core sample*, includes 218 funded projects and 105 non-funded researchers. All projects were approved for funding (they were evaluated as good, very good, or excellent) though some of them were not supported due to scarcity of resources.[14]

Data available for each researcher in the core sample includes the average peer-review score received by the proposals (Peer-Review Evaluation)[15], researchers' age (Age), a binary variable that takes the value of one if the researcher has a doctorate (Doctorate), a binary variable that takes the value of one for male researchers (Gender), a binary variable that takes the value of one if the researcher is part of a group that was constituted after 1994 (New group), a binary variable that takes the value of one if the researcher works 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[16]. Summary statistics are presented in Table 1.

[12] This number represents about 2.5 percent of all active researchers in Argentina in 1998, based on data provided by the Network on Science and Technology Indicators (RICYT).
[13] The core sample has been chosen with the condition of avoiding the repetition of members among funded and not funded projects. Among funded projects, only those projects that were completed were considered.
[14] It was checked that participants of these non-funded project were not funded by the program in later years.
[15] There are no data on the score attributed to the pertinence of each project.
[16] 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).

Table 1. Summary statistics

	FONCYT = 0 *105 observations*		*FONCYT = 1* *218 observations*	
Variable	Mean	Standard Deviation	Mean	Standard Deviation
Publications Pre-Treatment	1.07	1.76	1.74	2.01
Publications Post-Treatment	1.02	1.09	1.94	2.02
Impact Factor Pre-Treatment	1.49	2.96	3.13	4.49
Impact Factor Post-Treatment	1.79	2.51	4.05	5.03
Peer-Review Evaluation	6.83	0.79	8.28	0.97
Field-Biomedical Sciences	0.37	0.49	0.38	0.49
Field- Exact Sciences	0.16	0.37	0.17	0.37
Field-Technologies	0.47	0.50	0.45	0.50
New Group	0.50	0.50	0.41	0.49
Gender	0.63	0.49	0.66	0.48
Age (as of 2005)	56.72	8.65	55.00	8.18
Doctorate	0.77	0.42	0.84	0.36
Private Institution	0.03	0.17	0.02	0.14
Region Buenos Aires	0.60	0.49	0.59	0.49
Region Centre	0.15	0.36	0.24	0.43
Region Patagonia	0.04	0.19	0.09	0.28
Region Cuyo	0.08	0.27	0.02	0.15
Region Northeast	0.06	0.23	0.01	0.10
Region Northwest	0.08	0.27	0.05	0.22

Source: authors' calculations

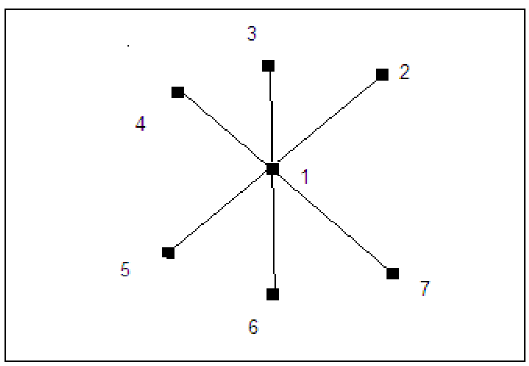
As a second source of data, the number of publications for each researcher in our database (Publications) and the impact factor[17] of the journal in which the papers were published (Impact) from 1994 to 2004 were collected from the Science Citation Index.[18] Table 1 presents summary statistics for these variables before and after the grants.

[17] The impact factor is a measure of the frequency with which the "average" article of a journal was mentioned in a certain year. It is calculated by dividing the number of citations to articles published in the two previous years by the number of publications in those years for each journal.
[18] The Science Citation Index is developed by the Institute for Scientific Information (ISI) and covers approximately 3200 journals.

Finally, we also obtained data on publications and impact factors for the remaining 445 researchers in the overall sample.[19]

The two outcome variables used in this study to capture collaboration among scientists are the size of the ego network and the 2-step links measure, as described in section 2.3. To get an intuition of these measures, we can think of a network formed by seven researchers with the shape of a star as in Figure 1, where each line measures a co-authorship between two of them. The size of the ego network measures the number of direct links in the network for each researcher. It is equal to six for researcher one and it takes the value of one for the other researchers, indicating the central position of researcher number one. The 2-step links measure counts both the direct and 1-step indirect links; it is equal to six for all researchers in the star network.

Figure 1. Star Network



Source: authors' elaboration

In order to construct collaboration indicators for the 323 researchers in the core sample, we consider the publications of the overall sample of 768 researchers. This gives a total of 8,337 publications[20] in the 11 years from 1994 to 2004, 89 percent of which are articles[21], with a mean number of 4.39 authors per publication and a median of four authors; only 396 publications have

[19] As previously pointed out, these researchers either never applied to the FONCYT program or applied in later proposals and were taken as a random sample within regions and fields.
[20] The average is 758 publications per year. The same number was the one for the year 2000 when the total number of publications of Argentinean researchers was 4184. Therefore, the sample captures 20% of the population values.
[21] To construct collaboration indicators we consider articles, reviews, letters, editorial material, research notes, abstracts, etc. We included only the first four to calculate the number of publications in table 1. As He et al. (2009) note, this difference is also helpful because collaboration indicators will not be perfectly correlated with the measure of publications.

a single author. Moreover, the mean impact factor of the publications that are co-authored is 2.1 with a standard deviation of 2.4 while the mean for single-authors is 1.93, with a standard deviation of 3.7. The difference between the two means is not statistically different from zero and the correlation between the impact factor and the number of authors is 0.07, giving some preliminary evidence that the number of authors in a paper might not be an important factor in explaining the quality of the papers in our sample.

To measure the collaboration among the 768 researchers, we consider co-authorships between two or more of these researchers. This is a limitation in the study, because we are not able to capture co-authorships with foreign researchers or with national researchers that are not in the sample[22, 23].

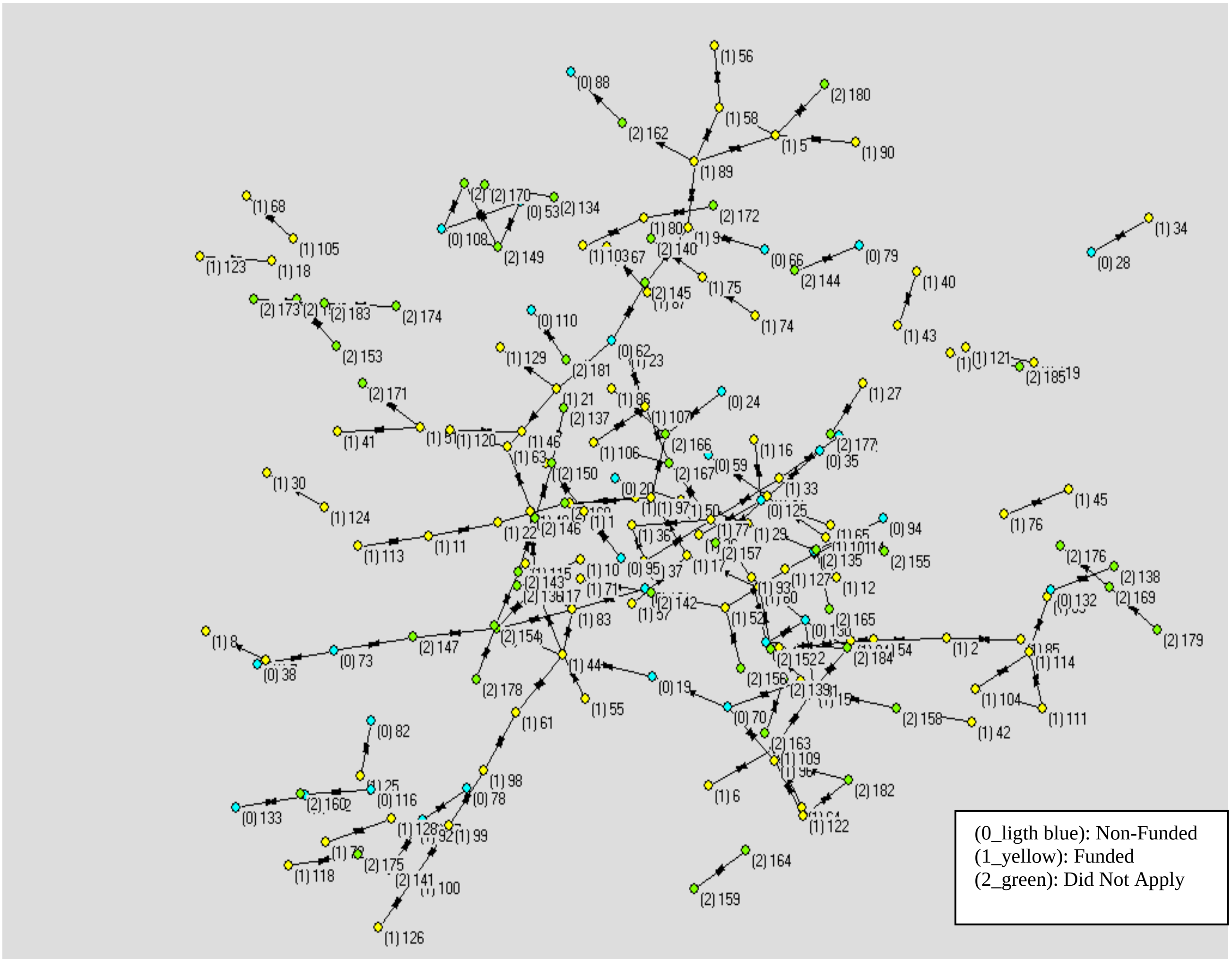
In the appendix of the paper, some evidence on self-reported collaboration agreements is presented, but the number of observations is too small to estimate any significant impact of the grants.

On the basis of the co-authorships among the 768 researchers in the database, we construct an adjacency matrix, we calculate the values of the size of the ego network, and 2-step links for each researcher.

Figure 2 shows the collaboration network among these 768 researchers from 1994 to 2004. There is an important number of links between researchers of the three groups: those who applied and were funded by FONCYT, those who applied and were not funded, and those who never applied to the grants. However, when we divide the analysis by year, collaborations are sparser, thus we focus on the pre- and post-funding collaboration indexes.

[22] We adopt this approach because we are not able to identify the name of co-authors in the database and thus it is not possible for us to distinguish whether a researcher is publishing with different co-authors or many times with the same co-author. We checked that the code of the publication for one researcher in our database matches the one for another researcher in our database.
[23] A similar logic is followed by Mairesse and Turner (2005) who only consider publications with two or more researchers from the same institution when they face the problem of not being available to distinguish the institution of co-authors in the SCI database.

Figure 2. Research Collaboration. Sample of Argentinean Researchers 1994-2004



Source: authors' elaboration

As it can be seen in table 2, both the mean number of direct links (size) and direct and indirect links increased for the funded researchers in our original sample, while they decreased for the ones who applied but were not funded, when considering the years 1994 to 1998 as pre-program and 2000 to 2004 as post-program. The mean values are low in both cases because many researchers in our sample do not have co-authorships with other researchers in our database, but it is still possible to capture the effect of the funding.

Table 2. Collaboration Variables

	FONCYT = 0 *105 observations*			*FONCYT = 1* *218 observations*		
Variable	Mean	Standard Deviation	Max	Mean	Standard Deviation	Max
Size Network Pre-Program	0.30	0.62	3	0.49	0.83	4
Size Network Post-Program	0.20	0.49	2	0.53	0.88	5
2-step Links Pre-Program	0.37	0.81	4	0.69	1.25	6
2-step Links Post-Program	0.30	0.84	5	0.90	1.58	9

Source: authors' calculations

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 that received and did not receive the grant. In the case of FONCYT, the allocation of grants was not random, implying that funding is likely to be positively correlated with unobserved characteristics, such as motivation, skills, ability, which 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 5 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 as Bertrand, Duflo, and Mullainathan (2004) remark.

The standard DID estimator basically subtracts the average difference over time in the non-funded group of researchers from the average difference over time for the funded researchers, see equation (2). This procedure removes biases that can be 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:

$$\Delta Y_i = \beta_0 + \beta_1 F_i + \beta X_i + \varepsilon_i \quad (1)$$

Here ΔY_i is 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 degree before the program, age at the year of application, 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 equation (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 window before and after the grant respectively.

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

Because this approach may not completely eliminate time-varying unobserved heterogeneity, the 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 of the counterfactual—i.e., the change in outcomes for funded researchers had they not been funded[24].

Columns (1) and (5) of table 3 present the basic DID estimates for the size of the ego network and the 2-step links measure. 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 variation in the collaboration outcome for funded researchers was greater than the variation for the non-funded researchers in about 0.14 direct links and 0.28 direct and 1-step 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.

[24] This assumption cannot be tested directly. If the outcomes variables were constructed by year we could test whether the trends in the mean level of collaboration outcomes were the same for treated and controls before the treatment. We have checked that indeed this appears to be the case. However, we believe that the five-year windows of data are a better characterization for our indicators.

Table 3. Difference-in-differences estimates

	Dependent variable: Change in Size of ego network				Dependent variable: Change in number of 2-step links			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FONCYT	0.14	0.21	0.22	0.27	0.28	0.47	0.36	0.44
	(0.08)*	(0.10)**	(0.11)**	(0.12)**	(0.14)**	(0.15)***	(0.18)**	(0.20)**
Age			-0.01	-0.00			-0.01	0.00
			(0.00)	(0.01)			(0.00)	(0.01)
Doctorate			-0.07	0.16			-0.13	0.35
			(0.09)	(0.11)			(0.16)	(0.21)
Gender			-0.00	-0.07			0.17	0.13
			(0.08)	(0.11)			(0.15)	(0.18)
Peer-Review Score			-0.02	-0.02			-0.08	0.04
			(0.04)	(0.08)			(0.08)	(0.12)
N° of Publications			-0.09	-0.06			-0.17	-0.15
			(0.05)*	(0.05)			(0.07)**	(0.09)*
Impact Factor			0.02	0.02			0.07	0.06
			(0.03)	(0.03)			(0.04)	(0.06)
Number of 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 common support. Results in columns (3), (4), (7) and (8) also include 5 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.

Columns (3) and (7) incorporate control variables that might affect the change in collaboration outcomes, but are not influenced by the grants (we use the pre-program value of the variables). We still find a positive and significant impact of the grants, the fact that the coefficient on FONCYT increases significantly is a cause of concern, and indicates that we should use additional techniques to guarantee that we are comparing two comparable groups.

Note that the number of publications in the five-year window before the program affects negatively the change in collaboration outcomes. This might lead us to suspect that the increase in publications is the factor leading to an increase in the collaboration variable because of the way it is measured. We cannot give a definitive answer to this question because the funding also affected the number of publications, and we are considering co-authorships only among researchers in our database, but all the publications for each researcher[25]. However, for 31 percent of the researchers that show an increase in the number of direct co-authors, this increase was higher than the rise in the number of publications (even when only co-authorships among researchers in the database are considered), which indicates that the increase in publications cannot be the whole explanation for the increase in collaboration outcomes.

One important source of bias in the estimation could arise when there are no comparable control researchers for some funded researchers and vice versa. To deal with this potential source of bias it is possible to 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 group, Publications, Impact, Collaboration and a set of indicator variables for region and scientific area.[26] Then, 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 are presented in columns (2), (4), (6) and (8) of table 3. Now the coefficient on FONCYT is much closer between the regression with and without controls, indicating that the funded and non-funded groups are more comparable once we restrict the estimation to the common support. We still find a positive and significant impact of the program.

Another source of bias could arise in difference-in-differences estimations when the distribution of the variables on which we condition differs between funded and non-funded researchers, even within the common support. To avoid this source of bias, control group observations must be re-weighted. The difference-in-differences 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:

[25] This is why using as a dependent variable the ratio between collaboration outcomes and the number of publications is not helpful here.

[26] The specification of this probit model is chosen to satisfy 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).

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

where 1 is the time period after applying for 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 matching[27, 28]. 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 in order to account for the error that comes from both probit estimation and determination of the common support. Columns (1) and (3) of table 5 present results for the common support defined above, in column (2) and (4) the differences are taken on a common support obtained 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.

As shown in Table 4 when we add matching to the difference-in-differences procedure, our estimates are all significant, and their values are higher than the ones reported in Table 3.

[27] 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 way 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.

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

Table 4. Difference-in-differences matching estimates

	Size of ego network		2-step links	
	(1)	(2)	(3)	(4)
	136 treated and 74 controls	215 treated and 87 controls	136 treated and 74 controls	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's (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.

As a final piece of evidence we use the nonparametric DID estimator described in Athey and Imbens (2006) to estimate the entire counterfactual distribution of the effects of the grants on the funded group. This approach relaxes some of the restrictive assumptions of the standard DID model such as additivity and linearity.

Since collaboration outcomes are discrete, we use the "changes in changes" (CIC) model proposed by Athey and Imbens. This model is based on recovering bounds *à la* Manski[29], which yields CICdisclow and CICdiscup in table 5, or regaining point identification by imposing stricter conditional independence assumptions which yields CICdiscci in table 5. We can then present the results for four estimators: the standard DID model, the discrete CIC model assuming conditional independence (for which point identification is recovered) and the lower and upper bounds for the discrete CIC. We present five statistics in each case: the average effect on the number of publications and four differences in quantiles (at 0.25, 0.5, 0.75 and 0.90) of the distribution of collaboration outcomes between the five-year period after the grant for funded researchers and the counterfactual distribution.

The method developed by Athey and Imbens (2006) assumes that all relevant unobservables can be captured in a single index and that the potential outcome of a researcher with a given value for this index, in the absence of the grant, will be the same in a particular time period irrespective of her being one of the funded researchers or one of the non-funded

[29] For a recent description of Manski's work see Manski (2007).

researchers. In our case, their assumptions also imply that within the groups of funded and non-funded researchers, the population distribution of the index of unobservables is the same before and after the application to the grant. This is still a strong assumption, and it would be interesting in future research to derive non-parametric DID estimators based on a combination of monotonicity assumptions with some exchangeability assumption for example, as in Altonji and Matzkin (2005).

Results for Athey and Imbens (2006) estimators are presented in table 5. Only for the upper bound of the discrete non-parametric estimator, we can see significant effects of FONCYT at the mean. Thus, our results are guided by what it is happening at the upper tail of the distribution. Most of the significant coefficients are observed at the 90th percentile of the collaboration outcomes. In particular, according to the bounds provided by the CIC estimator we can conclude that the funding increases the size of the ego network for those researchers in the upper tail of the distribution. Following Imbens and Manski (2004)[30], we construct a 95% confidence interval for the effect of the funding on the size of the ego network at the 90th percentile and we find that the confidence interval is [0.16, 3.27], which brings evidence of a positive impact at this percentile.

[30] It is basically calculated as the lower bound minus 1.645 times its standard error and the upper bound plus 1.645 its standard error.

Table 5. Non parametric DID estimates

Size of ego network	*Mean*	*25th perc*	*50th perc*	*75th perc*	*90th perc*
DID	0.14	0.10	0.10	0.10	1.10**
	(0.11)	(0.08)	(0.08)	(0.08)	(0.54)
CIC disc ci	0.21*	0.00	0.00	1.00***	1.00**
	(0.11)	(0.00)	(0.00)	(0.26)	(0.51)
CIC disc low	0.10	0.00	0.00	0.00	1.00**
	(0.28)	(0.26)	(0.26)	(0.26)	(0.51)
CIC disc up	0.40***	0.00	0.00	1.00***	2.00***
	(0.12)	(0.00)	(0.00)	(0.26)	(0.77)
2-step links					
DID	0.28	0.07	0.07	1.07***	1.07*
	(0.18)	(0.12)	(0.12)	(0.36)	(0.58)
CIC disc ci	0.30	0.00	0.00	1.00	1.00
	(0.22)	(0.00)	(0.00)	(0.77)	(1.28)
CIC disc low	0.08	0.00	0.00	1.00	0.00
	(0.39)	(0.26)	(0.26)	(0.77)	(1.02)
CIC disc up	0.49**	0.00	0.00	2.00***	2.00**
	(0.20)	(0.00)	(0.00)	(0.51)	(1.02)

Notes: standard errors are based on 1000 bootstrap replications. All calculations follow the details provided in the supplementary materials for Athey and Imbens (2006). For example, we use 1000 bootstrap draws and calculate the difference between the 0.975 and 0.025 quantiles, dividing it by 2 times 1.96 to get standard error estimates.
*Coefficient significant at the 10% level, **significant at the 5% level, *** significant at the 1% level.

5.1 Control Experiment

As a robustness test for the previous results, this section carries out a check on whether there is any effect of the grants on the size of the network of funded researchers by comparing the number of direct co-authors for 1994-95 to the one for 1996-97. 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 years.

Table 6 presents results replicating the matching DID methods used above, but now with the new dependent variable reflecting the change between 1994-95 and 1996-97. As expected, no significant impact of the grants is found, which satisfies this robustness check for our results.

Table 6. Difference-in-differences matching estimates for control experiment

	Size of ego network	
	(1) 136 treated and 74 controls	(2) 215 treated and 87 controls
Kernel matching[a]	-0.028	-0.071
	(0.174)	(0.171)
Radius matching[b]	-0.043	-0.078
	(0.181)	(0.163)

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 (0.29 and 0.28 for columns 1, and 2 respectively).
[b] Radius equal to 0.29 and 0.28 for columns 1 and 2 respectively

6. Concluding Comments

In this paper we evaluate the impact of research grants on the collaboration outcomes of 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 that were accepted in terms of quality, but not supported because of unavailability of funds. We find a positive and statistically significant effect of the grants on the number of direct co-authorships and the sum of direct and indirect links. We obtain these results and check their robustness using a series of non-experimental econometric techniques, including DID, matching DID and non-parametric DID techniques.

Although our overall results confirm that public funding can play an important role in fostering scientific collaboration in emerging countries, we also find that in FONCYT case the public funding affects only those researchers at the upper tail of the distribution of collaboration, suggesting that the program is indeed beneficial, but mainly for those scientists that had a high level of collaboration ex-ante.

This result suggests that future research should focus on assessing the differential effects of public funding on the behavior of “star scientists” (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 on the channels by which funding can affect collaboration were available (for example: use of funding for traveling to seminars or time spent in joint projects), we could compare our findings with the predictions of a theoretical model such as the one developed by Goyal et al. (2004) and explain with more detail the observed patterns of co-authorships in terms of individual incentives.

As a note of caution, it is worth remarking that 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, it is possible to think that alternative sources of funding may come through co-authors, as Jacob and Legfren (2007) suggest. In particular, if non-funded researchers tend to co-author relatively more with foreign researchers, it is likely that they can get their projects financed even when they are not granted FONCYT subsidy. This could explain the absence of positive effects at the mean level of FONCYT grants and it is a topic that should also be studied in future research. Additionally, the fact that we only study those researchers who applied to the grants is useful to get homogeneity across the funded and non-funded group, but does not give us the possibility of looking at the effect for those researchers who do not even have access to the funds because of lack of information or of low expectations of approval chances.

Finally, 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 fact that our results are robust to using different methodologies provides evidence in favor of their validity.

Taking these caveats into account, the findings of this paper can be considered as the first empirical evidence indicating that research grants can foster collaboration relationships among researchers in developing countries.

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Appendix: *Self Reported Collaboration Outcomes*

In this appendix, we use a third set of data. It consists of a survey carried out in 2007 to a subsample of 429 researchers from the three groups of researchers (250 funded, 143 non-funded and 95 who never applied). 177 funded researchers and 51 non-funded researchers can be matched to our core sample. In the survey researchers were asked to declare the number of signed agreements in the four years before applying to FONCYT and in the years during the development of the project for which they applied to the grants[31]. Agreements with national and foreign Universities, national and foreign S&T Institutions and with private enterprises were reported. Although only 32 of the non-funded researchers in our core sample answered this question, these data bring an opportunity to analyze, at least informally, other types of collaboration which may not result in a published paper.

The first two columns of table A1 present basic statistics for these variables for researchers in our core sample, and the second two columns present statistics for the full sample in the survey; results are similar in general. As it can be appreciated in the table, it appears that non-funded researchers had more agreements with national institutions, but fewer agreements with foreign institutions than funded researchers before applying to the grants. On the other hand, the non-funded group is seeing the largest relative increases in agreements with foreign institutions, while the funded group appears to have particularly intensified on average the collaboration with domestic institutions.

However, as it can be appreciated in table A2, no significant effect of the grants is found for any of the self-reported collaboration measures when we use the kernel DID matching technique. Due to the low number of non-funded researchers with answers for the agreements question in the survey, the small size of the sample can be an obstacle for finding any significant effect. It is possible that the way the question was framed (agreements in the four years before the application and agreements during the development of the project for which the researcher applied to the funds) generates the null result. Although we cannot draw any conclusion from these estimations, we report the results to provide additional information.

[31] For non-funded researchers the question was only asked of those that declared having carried out their project even when they had not received FONCYT's grants.

Table A1. Self-reported measures of Collaboration.

Agreements with:	*FONCYT = 0* *32 observations*		*FONCYT = 1* *177 observations*		*FONCYT = 0* *88 observations*		*FONCYT = 1* *250 observations*	
	Mean	Std Dev.	Mean	Std Dev.	Mean	Std Dev.	Mean	Std Dev.
Argentinean Universities, pre	0.56	1.01	0.29	0.65	0.56	1.50	0.32	0.70
Argentinean Universities, post	0.72	1.02	0.46	0.83	0.55	0.93	0.54	0.93
Foreign Universities, pre	0.16	0.37	0.42	0.89	0.26	0.58	0.44	0.91
Foreign Universities, post	0.34	0.65	0.68	1.51	0.49	0.74	0.70	1.52
Argentinean S&T inst, pre	0.22	0.61	0.19	0.54	0.30	0.90	0.17	0.52
Argentinean S&T inst, post	0.25	0.62	0.27	0.7	0.25	0.63	0.24	0.65
Foreign S&T inst, pre	0.19	0.40	0.24	0.7	0.10	0.34	0.20	0.61
Foreign S&T inst, post	0.40	0.80	0.34	0.79	0.23	0.60	0.31	0.76
Private firms, pre	0.53	1.57	0.56	1.99	0.51	1.92	0.69	3.68
Private firms, post	1.13	3.63	0.51	1.53	0.97	2.84	0.78	4.36

Table A2. Difference-in-differences matching estimates for self-reported collaboration measures.

	Kernel Matching	
	(1)	(2)
	113 treated and 23controls	176 treated and 29 controls
Argentinean Universities	-0.027 (0.206)	0.103 (0.118)
Foreign Universities	-0.121 (0.279)	0.094 (0.246)
Argentinean S&T Institutions	0.046 (0.081)	0.066 (0.061)
Foreign S&T Institutions	-0.118 (0.280)	0.012 (0.229)
Private Enterprises	-0.248 (0.317)	-0.086 (0.228)

Notes: bootstrapped standard errors (500 replications) are shown in parentheses.
[a] Gaussian kernel function with a bandwidth parameter of 0.14. [b] Radius equal to 0.14.