The Funding-Productivity Nexus in Science: Family and Other Sources of Endogeneity

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Abstract

This paper contributes to the literature on the individual and institutional factors explaining academic scientific productivity. On the basis of very detailed information for a sample of 262 academics at the University of Turin over a ten year period, we test a series of econometric models that aim to solve omitted variable bias and endogeneity concerns. We show that after taking into account commonly omitted variables such as children and teaching, competitive funding has a slightly lower association with both publication and citation output. In a 2SLS model in which we control for endogeneity of career progress and instrument national competitive funding with a socio-political capital measure, funding is no longer associated to higher research productivity. In the impact-quality estimation models, we find a "fatherhood bonus" and a "motherhood penalty" for having small children; in robustness checks we provide evidence for a causal effect of the latter while we cannot rule out that men have children once they are on a high performance path. As in previous literature, we find that female researchers are less productive in terms of publications but not in terms of quality/impact of their research, after controlling for children.

Keywords: Competitive funding, research productivity, women in science, teaching-research nexus

1. Introduction

Universities are central in the production of new scientific and technological knowledge and understanding the factors explaining scientific productivity of university researchers has become a central concern. Scientific productivity of academics is said to be strongly influenced by the funding structure under which they operate. In many countries in Europe where universities had primarily been financed through block grants with little accountability to how they used their resources, governments have introduced or increased the amount of funding distributed through competitive schemes (Geuna, 1999; Bolli and Somogyi, 2011). While much attention has been given in the previous quantitative literature to the evaluation of the impact of competitive funding on scientific productivity, modelling issues surrounding endogeneity have remained.

The present study thus aims to improve the modelling of the interactions between different aspects of the scientific production function: competitive funding, career progress and scientific productivity, taking into account the omitted variable problem and the endogeneity of funding. In doing so, it fits in the larger stream of research that explores university knowledge production.

Specifically, this study takes into account the role of child care and teaching in investigating the funding-productivity nexus. The gender gap in scientific productivity, which showed that female researchers tend to publish less than their male peers, after controlling for observables, has been at the centre of science policy and research for many years. In the attempt to explain the 'productivity puzzle' (Cole and Zuckerman, 1984) scholars turned their attention to the time consuming activity that is early child rearing responsibility still with mixed results (Long and Fox, 1995, Hunter and Leahey, 2010). Due to lack of sufficient longitudinal data and more advanced econometric techniques, it has usually been poorly estimated.[1]

Further, while the time and effort devoted to teaching has been argued to impact scientific productivity there is still little empirical evidence, especially in Europe. In the US, where several studies exist, they generally find a very low positive significant correlation (Hattie and Marsh 1996; Marsh and Hattie 2002).

Child care and teaching not only impact scientific productivity directly, but, by significantly influencing the time allocation of researchers, could crowd out other activities. More specifically, we might expect that time devoted to drafting competitive research funding proposals could be affected, creating an omitted variable bias in previous model estimations of

[1] For a recent attempt to better estimate gender effect see Mairesse and Pezzoni, 2015

the effect of funding on scientific productivity. In this paper we deal with this modelling issue showing that after controlling for omitted variables competitive funding has a slightly lower association with publication quantity and quality/impact. We also model the endogeneity of funding using an instrument that captures the socio-political role of the academic in the national academic network. In a final three equations two-stage least square (2SLS) model, in which we also control for the endogeneity of promotion, funding is no longer associated with higher productivity. In equations measuring publication quality/impact, we also find evidence for a "fatherhood bonus" and a "motherhood penalty" with regard to the effect of child care. As in previous literature female researchers are less productive in terms of publications but not in terms of citation output. Finally, find that women receive less funding than their male peers. A series of robustness models using initial condition and alternative dependent variables confirm our main results.

The present work is organised as follows. Section 2 reviews the literature on productivity and competitive funding, as well as on the relations between productivity, gender and teaching and proposes a framework to model the various interactions. Section 3 introduces the econometric model chosen to address endogeneity and other modelling concerns. Section 4 briefly discusses the chosen case of chemistry and physics at the University of Turin. Section 5 presents the data and the main variables used in the empirical analysis, while section 6 reports the results. Finally, section 7 discusses the results and concludes.

2. Competitive funding, gender and teaching

2.1 Competitive funding and individual performance

Competitive funding has been seen as a mechanism to replace funding that was previously provided by the government based on student or staff numbers and as a mechanism to reward and thus provide incentives for the most able academics. It allows academics to secure funds for equipment and research assistance, leading to more autonomy and flexibility (Stephan 2012). Competitive funding is thus usually accompanied by an increase in productivity, regardless the sponsor (Jacob and Lefgren, 2011; Benavente et al., 2012; Hottenrott and Lawson, 2017).

Prior research has shown that this increase is often marginal. Arora et al. (1998), for example, assess the effect of national research grants in Italy on publications in biotechnology. Accounting for selectivity bias they find a positive but small effect that increases slightly for more prestigious researchers. Arora and Gambardella (2005) find similar weak positive results in the case of NSF funding. Jacob and Lefgren (2011), in turn, explain the small effect they find for NIH grants with other outside funding opportunities available to academics that can replace NIH funding. More recently, Hottenrott and Lawson (2017) look at public funding received by engineering academics in the UK and show that funding provides declining returns to scale. Chudnovsky et al. (2008) look at various scientific fields and grant support in Argentina and in difference-in-difference estimations show that the effect of funding is greater for younger researchers. Finally, Carayol and Lanoe (2017) look at the effect of public research funding for young researchers in France and find that it increases publication rates marginally.

Further, it is expected that public funding increases not just quantity but also quality of scientific research. Indeed sponsored academics have been shown to be more highly cited and publish in higher impact journals in a number of studies (Chudnovsky et al., 2008; Jacob and Lefgren, 2011; Carayol and Lanoe, 2017). The effect is consistently larger than that observed for publication quantity.

However, researchers source funding from a variety of sources and there is evidence that some public sponsors promote research more effectively than others. Azoulay et al. (2011) for instance find that scientists receiving funding from a sponsor that allows for more scientific freedom perform significantly better, i.e. publish more and receive more citations, than a group of similar researchers funded by a research agent that is more prescriptive. Grimpe (2012) further shows that grants given by the European Union are not strongly correlated with research publications unlike other types of public funding. These findings thus suggest that not all types of public grants may benefit academic performance.

2.2 Competitive funding and the lab

Carayol and Matt (2006) have argued in favour of analysing the funding-productivity nexus not only at the individual level but to also consider more aggregate levels as measurement errors will be smaller. In fact, many research inputs and outputs are the result of team work and are unevenly assigned if we only consider individual researchers. In the case of the funding and publication relationship, publications are assigned simultaneously to several researchers while research income is often measured at the level of the principal investigator without acknowledging the impact it may have on other lab members. Carayol and Matt (2006) therefore argues that while on the individual level we could expect positive effects of grants on productivity, this may be less so at the research group level.

Other research group characteristics may also impact the funding-productivity nexus at the individual level. Kyvik (1995) for instance, points out that larger labs may be better positioned to draw together research groups for competitive research grants. They may also have better access to equipment and technical staff and be more likely to attract top researchers (Kyvik, 1995). Large groups may thus be better placed to attract and make use of funding which could translate into more publications. Arora et al. (1998) assessing the effect of Italian National Research Council grants in biotechnology on lab publications indeed find a positive effect.

Kyvik (1995), however, also concedes that a negative effect on productivity may be expected due to internal rules required in larger labs that hinder innovation. Researchers in larger teams may also face stronger resource competition which could impact on productivity. Some previous studies have indeed found that large teams are less productive than small teams (Bonaccorsi and Daraio, 2003; Carayol and Matt, 2006), while other research showed increasing or constant returns to scale (Kyvik, 1995; Hottenrott and Thorwarth, 2011).

Considering the above, it becomes clear that it is of importance to consider lab structures when analysing the effect of funding on scientific productivity, as individual scientific productivity will be affected by individual competitive funding after controlling for laboratory supporting structures for research.

2.3 Scientific productivity and gender

Women have typically been found to publish less, commonly referred to as the 'productivity puzzle' in the literature (Cole and Zuckerman, 1984). The gender gap extends to other areas of research, such as grant receipt (Jagsi et al., 2009) and career progression (Xie and Shauman, 2003) and engagement with companies (Tartari and Salter, 2015). The reasons for this gap have been linked to women's family engagements which can create role conflicts (Mairesse and Pezzoni, 2015) or to higher teaching commitments (Xie and Shauman, 2003). It has also been linked to women's disadvantaged position with regard to career progression and network access, elements that may be important for grant success (Sonnert and Holten, 1995).

Caring and domestic roles have also disproportionately been borne by women, with women devoting more and better time to children (Craig, 2006; Rhoads and Rhoads, 2012; Mason et al., 2013). In Italy this is particularly relevant with surveys indicating a 70% time allocation of household tasks to women (Istat, 2008) and men having 80% more leisure time than women (OECD, 2009). Especially at a time when children are small and require more care, these domestic roles can have a negative impact on the scientific productivity and career progression of female academics (Mason et al., 2013). Men, on the other hand, incentivized by the arrival of small children, may find themselves in the role of the main "breadwinner" and thus feel encouraged to be more productive and creative in their daily activities (Stack, 2004). While these differences in caring roles exist, the arrival of a small child may also be accompanied by an increase in scientific productivity as a result of career planning, where academics only have children once they are on a strong publication track.

The existing evidence on child care and scientific productivity is mixed and largely limited to the case of the US (e.g. Long and Fox, 1995; Fox, 2005, Hunter and Leahey, 2010). The most comprehensive study based on the US Survey of Doctoral Recipients looks at the effects of different age-groups of children. It finds a positive effect of small children on the number of publications for fathers, but a negative effect for mothers (Stack, 2004). This evidence of a "fatherhood bonus" and a "motherhood penalty" may also be at work elsewhere and extend to research quality/impact.

2.4 Scientific productivity and teaching

Previous quantitative studies based on European data have rarely considered one of the core activities of academics: teaching. Teaching constitutes one of the main missions of the university and the majority of permanent academic staff caries teaching duties.[2] These commitments may not always be closely aligned to research goals and may limit the time devoted to raising funds for research. Moreover, with changes in the funding of academic research and especially in the context of research evaluation, academics may be induced to spend more time on sourcing research funding, an activity that in many countries does not come with a relief from teaching duties. Acquired funds may therefore not be able to raise publication profiles.

[2] In the case of Italy all tenured academics have a minimum number of teaching hours to deliver depending on the academic position, full professors should lecture about 90 to 120 house minimum a year.

Some early evidence from the US indicates trade-offs between teaching and research (Boyer, 1991; Clark, 1987; Kerr, 1963) while others point to complementarity or null effect (Braxton, 1996; Mitchell and Rebne, 1995). A more comprehensive review by Marsh and Hattie (2002) also found that teaching and research are not significantly linked. Recently, Bianchini et al. (2016) find that teaching quality is nonlinearly related to research experience in a technical university in Italy, while Landry et al. (2010), in the case of a Canadian university, find that teaching and publications are substitutes. These inconclusive results call for further evidence on the interaction between the two constitutive activities of academics.

2.5 The funding-productivity nexus in science

On the basis of the discussion above we would expect that new knowledge produced by the researcher (research output) K is a function of individual characteristics and laboratory resources. The higher the Cognitive Capabilities of the researcher (*CC*) and the amount of Individual Competitive Funding raised (*ICF*), the higher will be the research output produced. Competitive funding is not allocated exogenously but endogenously determined through prior scientific performance, with funding generally awarded to the most able researchers (Arora et al., 1998). Performance is also important in determining the decision to apply for funding (Seyed Rasoli, 2011). Competitive funding raised by the researcher, thus, depends on previous research performance (K_{t-1}) and Proposal Writing time (*PW*) requiring us to take this endogeneity into account in the econometric modeling. The output produced will be affected by the time devoted to research (T), that depends on Teaching duties (*Te*), Administration (*A*), Proposal Writing time (*PW*) and Family duties (*Fa*). Female researchers tend to devote more time to Family duties, tend to be more willing than male researchers to teach more than the minimum teaching charge set by university regulations/work contract and tend to do more Administration (Xie and Shauman, 2003). To preserve research time they might find themselves obliged to reduce Proposal Writing time, which will affect their probability of obtaining future funding which may have knock on effects on their future productivity. Other Individual Characteristics (*OIC*), such as academic rank or age, are correlated with individual productivity. As full professors head laboratories or research groups, they tend to be involved in the majority of publications produced by the lab, increasing their overall scientific productivity. Promotion to full professor in turn depends on previous research performance (K_{t-1}) generating an endogeneity that has to be taken into account in the empirical modeling. Age and cohort effects are important too, as increased accountability introduced in recent years as well as a decrease in available academic positions have introduced stronger incentives for publications in top journals for younger researchers. Finally, especially in hard sciences, Laboratory Resources (*LR*) crucially influence academics' performance (Carayol and Matt, 2006), as the availability of laboratory assistants (doctoral or postdoctoral level), equipment and materials are directly linked to individual productivity. In the case of Italy (and in most of the rest of Europe) research groups receive some basic funding directly from the university to run the lab and hire doctoral and postdoctoral students, still, increasingly competitive funding is used to support both the human and physical capital needed for the running of the lab. We can therefore write the model, which we will estimate empirically in the next section, as:

$$\begin{aligned} &K=f(CC, ICF, T, OIC, LR,) \qquad (1)\\ &ICF=h(K_{t-1}, PW)\\ &T = g(Te, A, PW, Fa)\\ &OIC=p(K_{t-1}) \end{aligned}$$

3. Estimation model

3.1 Base model

In line with the discussion above, we firstly estimate a simple model assessing the impact of Individual Competitive Funding (*ICF*) on new knowledge being produced, where funding is lagged. New knowledge *K* is proxied by research performance (*Y*) and measured as the number and quality/impact of articles. In the estimation we control for individual (*X*) and lab (*L*) characteristics:

$$Y_{it} = ICF_{it-1}\beta_1 + X_{it-1}\beta_2 + L_{it-1}\beta_3 + \epsilon_{it} \qquad (2)$$

An equation of this form suffers from omitted variable bias. If funding cannot be used to free time from teaching as is the case in most universities across continental Europe and academics experience competing demands in terms of how to allocate their time, then funding may not always lead to higher performance. Further, family commitments may also compete with research time and thus impact the funding-performance relationship, and effect that may be biased by gender. Omitting these variables from the regression may therefore skew results and overestimate the effect of funding on research performance. We therefore adapt equation (2) as follows:

$$Y_{it} = ICF_{it-1}\beta_1 + X_{it-1}\beta_2 + L_{it-1}\beta_3 + Te_{it-1}\beta_4 + G_i\beta_5 + C_{it-1}\beta_6 + G_iC_{it-1}\beta_7 + G_iTe_{it-1}\beta_8 + \epsilon_{it} \qquad (3)$$

where vector *Te* measures teaching, vector *G* whether the academic is a woman and vector *C* the existence of a small child.

3.2 Modelling endogeneity

There are other sources of bias that equation (3) does not address. As discussed in 2.5, endogeneity of competitive funding is the most important source of bias. While we control for lab-performance in equation (3) this will not sufficiently correct for this endogeneity and the OLS models will overestimate the effect of funding on research performance. We therefore need to find a way to isolate the variations in funding success.

To this end we firstly exploit the exogenous variation in time of Individual Competitive Funding as national and regional competitive funding budgets differ by year. Further, we develop an instrumental variable model. We define an instrument, namely the academic's national socio-political capital expecting that it will affect the probability of getting national competitive funding. In various countries there is evidence of some form of elite or alumni network effect - e.g. old boys network- (Feinberg and Price, 2004; Viner et al., 2004; Fisman et al, 2017; Jang et al., 2017) in the allocation of competitive funding. Viner et al. (2004: 447) call this "political hegemony over resources" which can be expected to be particularly dominant when resources are scarce. Here we measure academic national socio-political capital as holding a leading management role in the Italian Physics and Chemistry Societies. Whilst we acknowledge that some level of scientific excellence should be achieved to be appointed to such positions,[3] we claim that obtaining such influential roles is mainly the result of a socio-political process. More importantly, we expect the socio-political capital associated to these types of positions to be correlated with a higher probability of receiving funding from either national or regional funding agencies. In our sample 14 academics were elected for at least one year (maximum non-continuous 6 years) into one of these top management positions. The dummy variable measuring

[3] In our sample, four chemists received an important medal in Italy. Only two of them had a major administrative role in the Italian Chemical Society.

socio-political capital takes the value of 1 in the years of top management responsibility and the two years following it, to account for its expected longer term effects.

Although this instrument varies across the time window considered here, the variance is small. We therefore include a second instrument. Organisational studies show that human behaviour is affect by isomorphism; in other words, we tend to behave similarly to people in our organization. In science, academics within the same field will be affected by the fund raising behaviour of their peers in other research groups (Tartari et al., 2014). In other words, the more funding was raised by academics in other labs the more the academic of the focal lab's likelihood to apply for (put in proposal writing time, PW) and to receive funding should increase, without directly impacting their publication performance. We use the funding acquisition of other labs within the same discipline (in our sample we consider 82 research groups and two disciplines; see following data description) as additional instrument.

As pointed out in the previous section, there is a second important source of endogeneity we need to consider, namely promotion to higher academic ranks (P). Mairesse and Pezzoni (2015) observed that "career advancement and scientific productivity are strongly related" (p. 83) as high performing academics are more likely to advance to professorship and higher ranked academics have more access to resources and networks resulting in performance advantages. The authors therefore adopt a 2SLS model that includes the probability of being a professor in the performance regression instead of the actual rank dummy. We follow their approach and estimate a promotion equation using gender, age and its square term, year and department dummies and measures of the academic's lagged research performance. We then include the predicted promotion value into the instrumented variable regression and finally run the performance equations. The complete model will be:

$$
\begin{aligned}
Y_{it} &= IC\hat{F}_{it-1}\beta_1 + \hat{P}_{it-1}\beta_{21}X_{it-1}\beta_{22} + L_{it-1}\beta_3 + Te_{it-1}\beta_4 + G_i\beta_5 + C_{it-1}\beta_6 + G_iC_{it-1}\beta_7 + G_iTe_{it-1}\beta_8 + \epsilon_{it} \\
\widehat{ICF}_{it} &= Z_{it}\gamma_1 + \hat{P}_{it}\,\gamma_{21} + X_{it1}\gamma_{22} + L_{it1}\gamma_3 + Te_{it1}\gamma_4 + G_i\gamma_5 + C_{it1}\gamma_6 + G_iC_{it1}\beta_7 + G_iTe_{it-1}\beta_8 + \vartheta_{it} \\
\hat{P}_{it} &= X_{it}\delta_1 + \mu_{it} \qquad (4)
\end{aligned}
$$

where Z is the instrumental variable and the error term ϵ is uncorrelated with the fitted values of $\hat{F}$and $\hat{P}$.

Finally, to explore the possibility that the effect of child care is not determined by scientific productivity prior having children, we follow a suggestion by Wooldridge (2002, p. 594) to include the logarithm of an academic's "initial productivity" in the outcome equations in the

2SLS model. Initial productivity variables can capture path dependency and cumulative advantage effects in publication numbers and quality/impact. They also proxy for the otherwise unobserved permanent heterogeneity of individual academics, such as their cognitive capability, motivation and talent (Fernández-Zubieta et al., 2016). This measure has the advantage that it allows us to control for these biases while still allowing us to consider other invariant factors, such as gender, in our model. We consider research performance in the three years prior to the sample period, i.e. the 1998 to 2000 period, as initial value and include the logged average as well as a dummy to indicate the "zero" initial value into the model.

4. Chemistry and Physics at the University of Turin

Our empirical analysis relies on data of all academic staff at the chemistry and physics departments at the University of Turin, for the period 2000 to 2009. In this section we briefly review the funding situation for academics in Italy and in Turin.

The Italian university funding system is rather complex, and presents several enclaves of inefficient allocation of resources. Also before the beginning of the World Economic Crisis in 2008 Italian researchers mourned low levels of financing and budget cuts (Hellemans, 2002; Nature, 2008; Feresin and Abbott, 2008). National state funding for universities has been consolidated in a single grant, the FFO ("Fondo di Finanziamento Ordinario") since 1993.[4] FFO was allocated mainly on the basis of historical allocation and, in more recent years, on the basis of teaching and research performance (about 20% of FFO).

Apart from FFO income and students fees, a share of university financing derives from competitive funding. Together with international financing (e.g. competitive funding from the European Union) there are several national and regional programmes to support research but they are not well funded. The two main national competitive funding programmes are the PRIN ("Progretti di Ricerca di Interesse Nationale", National Relevance Research Projects) and the FIRB ("Fondo Italiano Ricerca di Base", Italian Basic Research Fund), established in 2001[5]. Between 2001 and 2009 FFO allocated between 54.3 and 61.5 percent of total financing; competitive funding instead allocated between 7.2 and 11.4 percent (Geuna and Rossi, 2013).

[4] See Rossi (2009) for an historical introduction to Italian University financing.
[5] PRIN financing has been described by Bellotti (2011) with specific attention to social networks in the field of particle physics.

The University of Turin is a large Italian university (Rolfo and Finardi, 2014). In the academic year 2016/2017 it counted almost 2,000 (1,916) academic staff (full, associate and assistant professors), as well as 1,858 technical staff. [6] It is the sixth largest university in Italy according to the number of professors.[7] There were about 20,000 first year students and about 70,000 in total in 2016 More than 12,000 students graduate from the University of Turin in 2016. The number of Ph.D. students was more than 1,200. The 2011 consolidated turnover was 751.3 Millions Euro (more than 1,000 Million US$ as of October 2013).

Chemistry and Physics have been historically two important research areas of the University of Turin.[8] In the 2004-2010 national research evaluation (VQR) the University of Turin was ranked in the area of physics 2nd out of 10 in the group of the large universities and in chemistry 4th out of the 7. The large university group in Italy includes among most research intensive universities in the country positioning physics and chemistry in Turin at the top of the Italian system.

The University of Turin performs well in international rankings, being in the 4th or 5th place amongst Italian Universities in the 2004-2009 issues of Academic Ranking of World Universities (ARWU[9]), and between 151 and 200's place at the international level in years 2004-2008. Chemistry is ranked particularly high, ranking 2nd in Italy, while Physics ranks 7th in 2017. Turin can thus be considered a leading university in the research fields of chemistry and physics in Italy and in Europe.

5. Data and variables

5.1 Data

Our data contains information on 276 full, associate and assistant professors in physics and chemistry and associated disciplines working at the University of Turin during the years 2000 to

[6] See: http://www.unito.it/ateneo/chi-siamo/unito-cifre (in Italian), link accessed February 2017

[7] Bigger Universities are Roma "La Sapienza", Bologna, Napoli "Federico II", Milano and Padova.

[8] Amedeo Avogadro (who discovered the homonymous law and number) taught physics in the first half of the 19th century. Since then several scientist of high reputation did operate in the university. Among them we can cite some names. Ascanio Sobrero, the first chemist to synthesize nitroglycerin and Sobrero, was a professor in the university; so was the chemist and patriot Raffaele Piria, who discovered the organic reaction who carries his name. The chemist and entrepreneur Luigi Casale, inventor of a process for the synthesis of ammonia, was educated and has been for a period assistant professor in the university. Also the chemist and writer Primo Levi, one of the most read scientific populariser, was a student of the University of Turin. In more recent years the most relevant name expressed by physics at the University of Turin is probably that of Tullio Regge, who was first a student and then professor of theoretical physics before joining Princeton University in the 1960s.

[9] See http://www.shanghairanking.com (link visited September 2017).

2009.[10] Name and years of service were retrieved via two sources: the central administration of the University of Turin and the website of the Italian University, Research and Education Department containing data on university personnel.[11] In the considered timespan academics were affiliated to 7 departments: General physics, Experimental physics, Theoretical physics, General and organic chemistry, inorganic, Physical and materials chemistry, Analytical chemistry, Pharmaceutical sciences.

We first retrieved full names, date of birth, scientific field, gender and academic role (full/associate/assistant professor) of 239 academics in service between 2007 and 2009. These data were provided by the central administration of the University of Turin, in particular by the office managing the central Catalogue of Scientific Production. The Catalogue was established in 2007, and records data from 2007 onwards. Then, from the government website we obtained the years of tenure of all 239 academics plus those of the 37 academics that had retired from the university between 2000 and 2009. Thus a total of 276 names of individual academics could be obtained. Tables 1 and 2 present data on entries and exits of university personnel and on the number of years academics are present in the sample. This was supplemented with information on postdoctoral researchers and doctoral students from the Doctorates and Research Grants Office of the Research and International Liaisons Division of the University.

Further, effort was undertaken to collect data on funding, teaching and children. The number and birth year of children was obtained by calling each academic in the data. Some retired staff could not be reached and the number of individuals was thus reduced to 264 academics. Teaching hours come from official university records but were not available for all academics or years. It could thus only be obtained for about 55% of the overall person-year observations (in the econometric model we use observations for 262 academics; for 220 we had original teaching information from 2003 onwards, while we had to estimate teaching time for 42 scientists and for all years prior to 2003).

Data on funding from competitive research was provided by the Research and International Liaisons Division of the university, and then integrated with public data posted on the university website. Academics received funding from four different funding sources: regional, national, EU

[10] Professors belong to Italian Scientific Sectors (as defined by the Italian Ministry of Research) indexed under CHIM (CHIM/1 to CHIM/12) and FIS (FIS/1 to FIS/8), and to Engineering (ING-IND/21). Definition of scientific sector and of their scientific research interests can be found on the website of the Italian Ministry at the address http://cercauniversita.cineca.it/php5/settori/index.php (in Italian) (accessed October 2012).

[11] http://cercauniversita.cineca.it, accessed march 2013

and industry. Full data on funding amounts was available for grants received through Italian national (PRIN, FIRB, etc.) and regional (Regione Piemonte) competitions. Data on national funding were retrieved from the website of the Italian University Ministry, while regional funding information was obtained by the university administration. Funding coming from EU Framework programmes were retrieved exploiting several sources. For most part funding data were retrieved from the database of EU framework programmes on the CORDIS website through extensive manual search, and checked against the EUPRO database (Roediger-Schluga and Barber 2008). When the share of funding allocated to the University of Turin was not available estimations based on number of partners and type of project were made.

In order to better describe the structure of the labs, a code indicating the research lab was assigned to each academic. Labs are generally grouped around a full professor, including associate and assistant professors, post-docs, and Ph.Ds. Overall we were able to identify 89 research groups of varying sizes from 1 to 16 permanent staff. For the three departments of chemistry composition of research groups was derived from the official websites of the departments. For the three departments of physics and the department of pharmaceutical sciences only some research groups were reported on the websites. In the other cases the lab composition was assumed using a method that involved the analysis of co-authorship among professors as well as the insights of one of the authors (see Appendix 1).

5.2 Dependent Variable

We collected data on scientific publications for all 276 academics from the Elsevier Scopus database[12] for all the years up to 2010. This includes publications prior to 2000 and prior to obtaining permanent positions at the University of Turin. The "author search" option on Scopus was used for most cases, carefully controlling for homonyms and spurious assignments of references. Some cases, due to homonyms or faults in the assignment of references, had to be collected by manually checking all papers. The downloaded records include the number of citations received as of 2013 (the year of data download) and the number of co-authors. In order

[12] Data were retrieved from Scopus database (https://www.scopus.com) in May-June 2013. Scopus was preferred over other similar web-based databases because: 1) It encompasses a wider set of data (it reports more than 20,500 titles, about 19,500 peer-reviewed journals plus other sources, from more than 5,000 international publishers); 2) it covers several non-English titles; 3) it encompasses a wider number of congress proceedings, which are particularly relevant in Physics.

to have an additional measure for publication impact/quality each publication was assigned its CiteScore citation impact measure from Elsevier. CiteScore uses the same methodology as the Thomson Reuters Journal Impact Factor, by taking a journal's citation average of the past three years.

We then build the following dependent variables: First, we create a co-author adjusted publication count by dividing each publication by the number of authors before summing by year. This is done to account for differences in the relative authorship contribution of different academics within the sample.[13] Second, we calculate the average number of citations received by these articles and their average CiteScore. Descriptive statistics for all three measures are reported in Table 3.

5.3 Independent Variable

The most common source of funding is from national and regional funders (from now onwards Italian funding). While this funding may be used by the full lab the PI is responsible for management and research decisions. We therefore consider funding at the individual level, splitting the amount received across the award period (typically three years).

In addition, in model 2, we consider factors that have been identified as core omitted variables in the analysis of academic productivity. Firstly, to capture family engagements we include a dummy that measures if the academic cares for a small child (0-3 yrs.). As we expect the effect of child care to differ between men and women, we interact the two variables. The share of women is 38%. The share of academics with small children during the observation period is 24%, accounting for 11.5% of observations (10% amongst men and 15% amongst women).

We further include the number of teaching hours in each year, a measure that is not often included in empirical analyses. Missing values in this measure were imputed using an individual's mean number of teaching hours in other years and the mean number of hours of teaching provided by other staff of the same rank and within the same department in the same year. In the final estimation about 45% of observations, taking into account missing values in

[13] Fractional count is important due to the presence in the sample of professors working in the field of particle physics. In this field scientists, working in huge experiments (such as those conducted at CERN) often sign each year tens of publications coauthored by hundreds of authors. In the robustness check we excluded those academics and use full count with consistent results

other measures, contain imputed teaching hours. The number of teaching varies between zero and 10.9 hours per week.

5.4 Controls

For each academic staff we were further able to obtain control variables based on the ministry records that are the basis for the data. These include the academic's age and whether they are full professor. We centre age on 40 and divide it by 10 for ease of reading the coefficients. We further included a field dummy for staff of *Chemistry* (the reference is *Physics*). All this data was available for the full population of academics. In the estimations of average citation numbers we also control for the number of coauthors as the literature shows a strong correlation between number of authors and citation received (Tahamtan et al. 2016; Wuchty et al. 2007).

Each academic is assigned to one of the 89 identified research groups/labs. Research group assignment enabled us to calculate the size of each group in terms of number of permanent academic staff. Some groups only consist of a single permanent member of staff, while others comprise 10 or more. The mean group/laboratory size is 5 and the median is 4.

We closely follow Carayol and Matt (2006) and compute research group characteristics based on all permanent members of the group, excluding the focal academic. We thus measure the average age of research group colleagues, and the share of full professors amongst colleagues in each research group. In addition, the group colleagues' average publication performance, after correcting for co-authorship, as well as their average citations (or CiteScore in the CiteScore equations) are included. All these measures are not available for research groups with just one permanent member of staff. We therefore include a dummy marking single person labs and set all group characteristics to zero. 17% of groups are single person labs accounting for 14% of observations.

As funding could be shared by researchers within a research group we also include a measure for the amount of national and regional Italian funding received by other members of the research group. Again, we split the research funding across the award period and calculate the average amount of funding received per research group member (not including the focal researcher) each year. In addition academics may receive funding from other sources, though to a lesser extent. During the 2004 to 2009 period 17 academics received EU funding. Given the larger size of these projects they cannot be considered individual projects and are therefore all split across the full lab. Given this, EU funding is incorporated into the lab funding measure for Italian funding.

In line with Carayol and Matt (2006) we also include data on Ph.D. students and post-doc fellows (Italian “Assegno di Ricerca”). We calculated the number of man months per year available to each lab and then divide it by the number of lab members. Data on Ph.D. students was available from year 2004 onwards and were therefore imputed for earlier years. Results for Ph.D. student hours are robust in reduced sample estimations. The mean number of postdoc months available to each academic per year is 2.6, and the mean Ph.D. student months are 4.6.

Table 3 shows descriptive statistics for all the measures used in the regressions. The final estimation including all variables is estimated for 262 academics and includes 2,097 person-year observations.

TABLE 3 ABOUT HERE

6. Empirical Analysis

6.1 OLS

We first estimate equation 1 taking logs plus the unit of the publication and funding measures to correct for their skewedness. All explanatory variables are lagged by one year, which means that publications in 2010 are estimated using individual and lab characteristics of 2009. Year fixed effects are included in all models and standard errors are clustered at the level of the individual. We estimate the model as OLS. Table 4, 5 and 6 report the results for the co-author adjusted publication count, the average number of citations and the average CiteScore, respectively.

In line with prior research we find a positive coefficient for individual competitive public funding. This effect is, however, small. Taking the antilog minus the unit, an increase from zero funding to the mean increases co-author adjusted publication by 8%, and an increase from the mean by one standard deviation increases co-author adjusted publication numbers by 17%. These results are similar for citations and CiteScore, where we find an increase in average citations and CiteScore of 17% and 9% respectively for an increase by one standard deviation from the mean

When we include gender and family characteristics (as well as teaching), in line with equation 2, the funding coefficients loose slightly in magnitude. This small loss in magnitude suggests that against our expectation, omitted variable bias is very small for family characteristics and non-existent for teaching commitments.

TABLES 4, AND 5 ABOUT HERE

Of the three variables, gender exerts the greatest influence. In the co-author adjusted publication count equation the female dummy enters negatively, in line with prior research, while the child coefficient is insignificant (Table 4). Calculating elasticities we find that women produce on average 15% fewer publications than men. The interaction between being female and having small children is also negative but insignificant.

In the citation models in Table 5, instead, the female dummy enters insignificantly but the interaction with children is significant and negative, while the children dummy for men is positive. This suggests that male academics with small children receive more citations than those without (an average of 29%), which may be explained by the family role separation, with young fathers taking on the role of the "breadwinner" and their partners the domestic role. Women do not commonly benefit from such a separation but tend to perform both work and domestic roles and their performance in terms of citation numbers reduces (difference significant at $p = 0.072$). A performance gap in terms of citations between men and women thus appears when they care for small children. The CiteScore model in Table 6, confirms the positive effect for small children, but the interaction term is insignificant, albeit negative, suggesting that women do not perform significantly worse than men. Teaching hours enter our model negatively, but the coefficient is small and non-significant.[14] The teaching of women enters positively but is also insignificant. This suggests that teaching does not correlate with scientific performance for men and women.

TABLE 6 ABOUT HERE

The control variables also provide some interesting insights. Publications, citations and CiteScore are highest for full professors but generally decrease with age. In the case of publications, their number drops off after the age of 40, while citations and CiteScore show a consistent negative trend. For the citation models we confirm the positive correlation with co-author numbers in line with prior research. Group/lab size correlates negatively with publication and citation numbers, but does not seem to be related to the article CiteScore. The average age of

[14] This is confirmed in models that do not include the imputed values (available from the authors upon request).

lab members has a negative effect in all outcome models, suggesting that academics working in groups with older members on average produce less and lower quality research than those working with younger colleagues. The share of full professors in the lab shows a positive sign in the citation and CiteScore models, but has no effect in the publication count model. The lab performance in terms of publication quantity has a positive effect in the publication equation and the lab performance in terms of its quality/impact correlates highly with citations and CiteScore, while lab funding is insignificant in all models. We further find that the number of Ph.D. hours is positively linked with all three outcome measures, while postdoc hours show a positive sign only in the citation and CiteScore models. This suggests that supervision of postgraduate research (also an aspect of teaching) is linked to performance advantages.

6.2 Instrumental Variables-Based Identification

The estimations reported above may suffer from endogeneity. We address this by instrumenting Individual Competitive Funding receipt and including a predicted promotion measure (*Pr(professor)*), reported in Table 7. The promotion equation shows that being a professor is closely linked to prior performance but unlike Mairesse and Pezzoni (2015) we do not find evidence of a significant promotion disadvantage for women (the female dummy is negative but not significant). The predicted professor effect is important and significant in both the 1st stage funding equation and in the main productivity equation. The 1st stage instrument equation further shows that our socio-political capital measure is a good predictor of funding, more than doubling the amount of funding received. Funding by other labs within the same field is also positive, predicting an increase in the focal academic's funding of more than 50%. Both instruments are jointly significant and satisfy the test for exogeneity. It is also interesting to note the strong significant negative correlation between female researchers and amount of competitive funding, suggesting serious gender differences in the access to resources.

After instrumenting, the 2SLS estimates no longer show a positive significant link between funding and publications, citations or CiteScore. They thus provide strong evidence that funding does not have a significant effect on performance, once we remove potential sources of endogeneity. Effects of family variables and teaching remain consistent with results in Tables 4, 5 and 6, and the interaction between female and child becomes slightly stronger negative in both the citation and CiteScore models, again suggesting a performance advantage for men and a disadvantage for women following the arrival of a young child.

The control variables largely confirm the findings from the OLS model, but the age effects are found to be stronger, possibly due to the stronger professor effect in the 2SLS model.

TABLE 7 ABOUT HERE

6.3 Controlling for unobserved heterogeneity

The results above showed that a performance gap in terms of publication quality/impact between men and women appears when they care for small children. While we may suspect that men are encouraged and able to put more focus into their work, we cannot completely rule out that the positive effect for men stems from them opting for fatherhood once a performance advantage is reached. In a descriptive analysis reported in Figure 1 we find that while men who opt for fatherhood outperform peers who do not have children already prior to becoming fathers, this performance advantage increases further once the child is born. The analysis is limited to academics under the age of 45 which represents the main period of childbirth for both men and women in the sample. Women opting for children also perform slightly above the average for women without any children, but, crucially, this performance advantage disappears once the child is born.

FIGURE 1 ABOUT HERE

To further investigate whether this gender effect is determined by performance prior to having children, we control for initial performance as described in section 3. This also has the advantage that we control for overall time-invariant unobserved heterogeneity and cumulative publication advantage. The results of the outcome equation of the 2SLS model reported in Table 8 show that the initial value enters positively and reduces the positive child effect for men, rendering it insignificant in the case of citations. Meanwhile the negative child effect for women remains almost unchanged. This suggests that that the female effect is causal while we cannot reject the hypothesis of reverse causality for male researchers, i.e. that they decide to have children once they are on a high performance path.

Most control variables also loose in magnitude once we control for initial performance, though signs remain largely unchanged, the one exception being lab size, which turns positive and significant in the CiteScore equation.

TABLE 8 ABOUT HERE

6.4 Robustness Checks

We have to concede that the reported results may be sensitive to changes in the dependent variables. In order to check for the sensitivity of our results we therefore test them in alternative regressions. Firstly, we report results for the normal publication count that is not adjusted for co-author numbers. Before estimating these models we exclude researchers in three applied physics labs as they work in large author teams of up to 300 authors and may skew the results, leaving us with a sample of 250 academics. The estimations are reported in columns 1 and 2 of Table 9. The results of the 2SLS are overall confirmed. Funding is found to be insignificant and the female dummy enters negatively, albeit insignificantly. Instead, the female-child dummy enters negatively and significant, suggesting that women produce overall fewer publications following the arrival of a child if we do not account for co-author numbers.

In a second robustness check we regress on the year normalised average citation count to address the potential year truncation problem in the citation measure. We follow the methodology suggested in Hall et al. (2001) and Crespi and Geuna (2008) and scale citation counts by dividing them by the within sample average citation count of the same year. This effectively gives a higher weight to more recent years. The results again confirm results for the non-normalised citation measure: Funding enters insignificantly, and the positive child effect disappears once we control for initial performance while the negative child effect for women remains strong and significant.

TABLE 9 ABOUT HERE

We estimate additional robustness checks using alternative quality/impact measures provided by Elsevier, the Source-Normalized Impact per Paper (SNIP) and the SCImago Journal Rank (SJR) (descriptive statistics in Appendix Table A1). These results are reported in the Appendix Table A2, confirming the effects reported in the CiteScore estimations. Further, for a subset of publications we were able to record the Thomson Reuters Journal Impact Factor (JIF) and Article Influence Score (AIS). Unreported results again confirmed the overall findings of the Elsevier measures.

7. Conclusions

In this study we revisited the funding-productivity nexus. We expanded on existing studies by using information on family commitments and teaching which may compete with academics' efforts to raise funding or to publish their research. We propose a productivity model and implement a possible estimation employing a 2SLS model with a promotion equation and an instrumental variable equation for individual competitive funding to address potential endogeneity concerns. We also controlled for unobserved heterogeneity trying to capture the differences in ex-ante cognitive capabilities allowing us to validate the direction of causality of the gender related results. Given the problem associated to the correct measurement of the production of new knowledge, in this paper we proxied research output with a large set of measurements trying to capture both output quantity and quality/impact. All robustness checks confirmed our main results.

Our findings show that once we control for commonly omitted variables, funding has a slightly lower association with scientific output both in term of publication and citation count. This suggests that the omitted variable problem is less important than expected. To address endogeneity concerns we developed a 2SLS instrumental variable based model in which we showed that funding is inherently linked to career stage, socio-political capital and time availability. Taking these differences in access to research funding into account we showed that research funding does not translate into higher publication or citation numbers.

In addition, we were also able to shed new light on the relationship between family commitments and research as well as teaching and research. We showed that women produce fewer research papers but not of lower quality, consistent with previous literature. Female researchers are also less likely to raise competitive funding, which may contribute to the observed difference in publication output. Looking at the impact of caring for a small child, we found that women produce research of lower impact ("motherhood penalty") while men produce research of higher impact ("fatherhood bonus"). This suggests that women are not able to devote the necessary time for developing or promoting research with high impact when they care for small children. For instance, women may not be able to denote the time required for extensive revisions or may not be able to present the paper at international meetings, lessening their visibility. The only group producing research that is higher cited are men with young children which points towards their embracing of the role of the breadwinner. Still, this effect does not hold up to scrutiny and becomes insignificant when we control for past performance levels. This indicates that for men having children may be a strategic decision. Teaching, finally, is not associated with publication performance, suggesting that teaching and research do not act as supplements.

In terms of policy implications we can conclude that unless support systems are in place for women with childcare responsibilities, funding will not translate into more or more highly cited publications. Further, holding a leading management role in the Italian Physics and Chemistry Societies is shown to more than double the amount of funding received, which is highly concerning from a policy perspective. This situation is not unique to Italy, but has previously been shown for China and the US (Feinberg and Price, 2004; Fisman et al., 2017). Appointment to the apical positions of these membership bodies is not always linked to merit and even in cases where merit plays an important role, other networks should be given the same opportunity for funding. Especially in Italy, were funding resources are scarce this dominance of such elite networks may seriously thwart research progress.

Appendix

Appendix 1: Methodology used to assign professors in Physics to research groups based on coauthorship.

All professors in a department were arranged in an $n \times n$ matrix, where n is the number of professors. All publications of professors were scanned in order to check for coauthorship, and a coauthorship matrix was built. Stronger links (a steady coauthorship in the 2000-2009 timespan) and weaker links (some publications in previous years or only sporadic coauthorship) were inserted in the matrix. Finally from stronger coauthorship research groups were built around one or, in few cases, two full professors. The assumption made is that professors in the same group tend to have a steady pattern of recent coauthorship (when research groups are steady) but may from time to time collaborate with colleagues external to the group or may have done in the past, either due to a different organization or to old connections such as a former professor-student relationship.

Appendix 2: Results of robustness tests

[Insert Tables A1 and A2 here]

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Figures

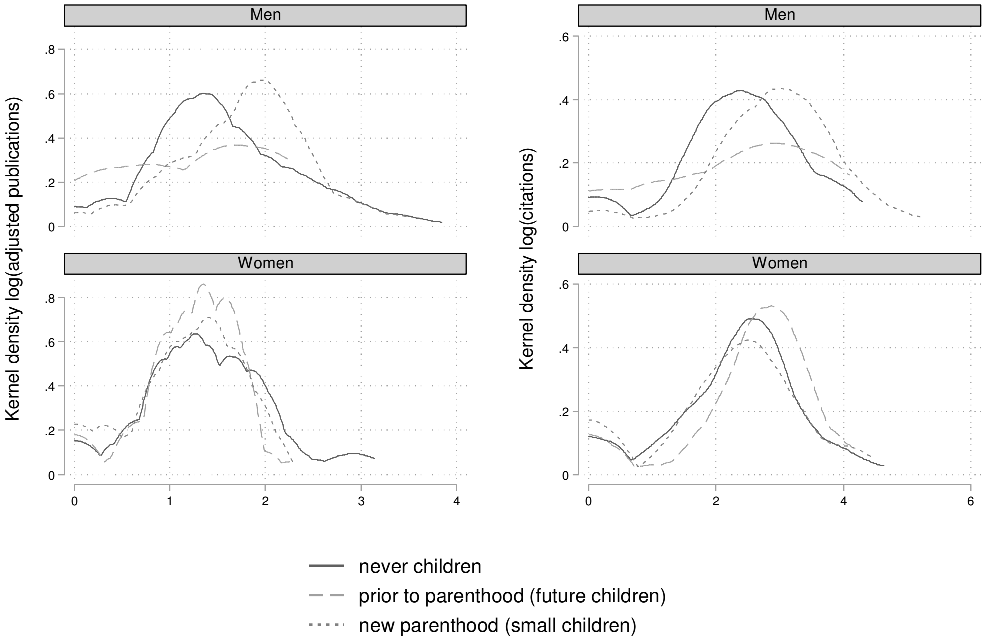

Figure 1: Kernel density of publications and citations for men and women and by parenthood status

Tables

Table 1: Entry and exit into the sample by year

Year	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
Total presences	211	212	213	213	221	229	230	230	228	224
Out (first year of absence)	-	7	2	6	5	3	9	8	10	4
In (first year of presence)	-	8	8	0	10	11	10	9	8	0

Note: Employment is only observed until 2009. Dependent variables were collected up to 2010.

Table 2: Years of tenure of each academic

# of years	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Academics present	7	9	12	11	12	14	16	16	19	160

Table 3: Descriptive statistics

	mean	sd	p50	min	max
Publications (co-author adjusted)	0.75	1.26	0.50	0.00	45.13
Citations (average)	16.54	21.31	10.67	0.00	262.00
CiteScore (average)	2.65	1.88	2.71	0.00	17.03
Publications (normal count)	4.58	6.58	3.00	0.00	73.00
Citations (year normalized average)	0.81	1.00	0.56	0.00	11.41
Independent variables					
Italian funding	1.07	6.14	0.00	0.00	131.57
Ln(Italian funding+1)	1.72	3.89	0.00	0.00	14.09
Female	0.38	0.48	0.00	0.00	1.00
Small child (0-3)	0.12	0.32	0.00	0.00	1.00
Teaching hours	3.77	1.62	3.66	0.00	10.93
Controls					
(Age-40)/10	1.01	1.13	1.00	-1.20	3.50
Professor	0.35	0.48	0.00	0.00	1.00
Chemistry	0.61	0.49	1.00	0.00	1.00
Average number of coauthors	9.62	25.13	5.25	0.00	310.36
Lab measures					
Single person lab	0.14	0.35	0.00	0.00	1.00
Lab size	4.75	3.17	4.00	1.00	16.00
(Mean age lab-40)/10	0.81	0.70	0.73	-0.85	3.10
Professors lab	0.31	0.28	0.33	0.00	1.00
Publications lab	0.65	0.56	0.52	0.00	4.64
Citations lab	16.29	18.26	11.30	0.00	201.00
CiteScore lab	2.41	1.54	2.49	0.00	10.04
Ln(funding lab+1)	4.74	5.35	0.00	0.00	14.15
Postdoc hours	2.59	3.98	1.13	0.00	48.00
Student hours	4.56	4.73	3.33	0.00	24.50
Instruments					
Social capital	0.02	0.14	0.00	0.00	1.00
Ln(Italian funding other labs+1)	13.72	0.92	13.89	11.26	15.03
Initial and lagged performance					
Zero initial publications	0.09	0.29	0.00	0.00	1.00
Ln(initial adj. publications)	0.42	0.86	0.46	-2.48	2.30
Ln(initial publications)	1.98	1.05	2.08	0.00	4.33
Zero initial citations	0.09	0.29	0.00	0.00	1.00
Ln(initial citations)	3.55	1.46	3.95	-0.29	5.81
Ln(initial year norm. citations)	0.57	0.94	0.71	-3.70	2.52
Zero initial CiteScore	0.09	0.29	0.00	0.00	1.00
Ln(initial CiteScore)	1.81	0.83	2.08	-2.02	3.36
Ln(l.adj.publications+1)	0.46	0.37	0.41	0.00	1.95
Ln(l.citations+1)	2.29	1.29	2.54	0.00	5.57

Note: Number of observations = 2097, number of academics is 262, and observation period is 2001 to 2010. The citation variables refer to the citations received until autumn 2013 by publications published in each year. The average CiteScore of the 2011 to 2014 period is applied. The initial performance variables refer to the pre-sample period 1998 to 2000. All independent variables are lagged by one year. Funding variables are in 10.000€.

Table 4: Stepwise results of OLS regression on co-author adjusted publications

Dep: Ln(Co-author adjusted publications+1)	(1) b	se	(2) b	se	(3) b	se
Ln(Italian funding+1)	0.018***	0.004	0.016***	0.004	0.016***	0.004
Female			-0.145***	0.031	-0.228***	0.062
Small child (0-3)			0.001	0.056	0.002	0.057
Female#small child			-0.069	0.070	-0.069	0.070
Teaching hours					-0.012	0.010
Female#Teaching hours					0.022	0.016
Controls						
(Age-40)/10	0.017	0.031	-0.002	0.028	0.001	0.030
$(Age-40)/10^2$	-0.032**	0.013	-0.030**	0.013	-0.031**	0.013
Professor	0.115***	0.043	0.105**	0.042	0.109**	0.042
Lab measures						
Single person lab	-0.187***	0.056	-0.180***	0.055	-0.182***	0.055
Lab size	-0.016***	0.004	-0.014***	0.004	-0.014***	0.004
Mean age lab	-0.063**	0.027	-0.057**	0.025	-0.056**	0.025
Professors lab	0.058	0.078	0.046	0.073	0.047	0.072
Publications lab	0.057**	0.028	0.057**	0.026	0.055**	0.027
Citations lab	0.000	0.001	0.000	0.001	0.000	0.001
Ln(funding lab+1)	-0.002	0.002	-0.002	0.002	-0.002	0.002
Postdoc hours	-0.002	0.003	-0.003	0.003	-0.003	0.003
Student hours	0.017***	0.004	0.016***	0.004	0.016***	0.004
Chemistry	-0.029	0.032	-0.004	0.032	0.000	0.032
Constant	0.553***	0.064	0.618***	0.067	0.662***	0.073
Adjusted R^2	0.177		0.209		0.211	
Joint sig. Female#small child (3)			10.93***		5.82***	

Note: N = 2097; clusters = 262. *** (**,*) indicate a significance level of 1% (5%, 10%). Year dummies included; robust clustered standard errors. Publication counts are co-author adjusted.

Table 5: Stepwise results of OLS regression on average citations

Dep: Ln(average citations +1)	(1)		(2)		(3)	
	b	se	b	se	b	se
Ln(Italian funding+1)	0.028***	0.008	0.026***	0.008	0.026***	0.007
Female			-0.074	0.082	-0.300*	0.179
Small child (0-3)			0.289**	0.131	0.294**	0.133
Female#small child			-0.326*	0.181	-0.325*	0.182
Teaching hours					-0.029	0.027
Female#Teaching hours					0.061	0.042
Controls						
(Age-40)/10	-0.218***	0.074	-0.208***	0.074	-0.204***	0.075
$(\text{Age-40})/10^2$	-0.033	0.027	-0.035	0.027	-0.035	0.028
Professor	0.379***	0.118	0.375***	0.119	0.384***	0.119
Ln(coauthors+1)	0.427***	0.039	0.426***	0.039	0.426***	0.040
Lab measures						
Single person lab	-0.370**	0.164	-0.369**	0.162	-0.376**	0.162
Lab size	-0.030***	0.011	-0.027**	0.011	-0.028**	0.011
Mean age lab	-0.200***	0.073	-0.198***	0.071	-0.195***	0.071
Professors lab	0.352*	0.183	0.355**	0.179	0.358**	0.176
Publications lab	0.068	0.063	0.066	0.063	0.061	0.063
Citations lab	0.009***	0.002	0.009***	0.002	0.009***	0.002
Ln(funding lab+1)	0.001	0.006	0.001	0.006	0.001	0.006
Postdoc hours	0.018**	0.008	0.017**	0.008	0.017**	0.008
Student hours	0.023***	0.008	0.021***	0.008	0.022***	0.008
Chemistry	-0.007	0.091	0.022	0.091	0.031	0.091
Constant	1.031***	0.193	1.027***	0.197	1.132***	0.221
Adjusted R^2	0.306		0.309		0.310	
Joint sig. Female#small child (3)			2.50*		2.80*	

Note: N = 2097; clusters = 262. *** (**,*) indicate a significance level of 1% (5%, 10%). Year dummies included; robust clustered standard errors.

Table 6: Stepwise results of OLS regression on average CiteScore

Dep: Ln(CiteScore+1)	(1)		(2)		(3)	
	b	se	b	se	b	se
Ln(Italian funding+1)	0.015***	0.004	0.013***	0.004	0.013***	0.004
Female			-0.052	0.051	-0.126	0.123
Small child (0-3)			0.106*	0.057	0.107*	0.057
Female#small child			-0.159	0.103	-0.159	0.103
Teaching hours					-0.011	0.014
Female#Teaching hours					0.020	0.030
Controls						
(Age-40)/10	-0.188***	0.048	-0.190***	0.047	-0.188***	0.048
$(Age-40)/10^2$	-0.001	0.018	-0.001	0.018	-0.001	0.018
Professor	0.313***	0.068	0.310***	0.069	0.313***	0.068
Lab measures						
Single person lab	-0.275***	0.090	-0.276***	0.088	-0.280***	0.088
Lab size	-0.009	0.010	-0.007	0.010	-0.007	0.010
Mean age lab	-0.143***	0.038	-0.141***	0.037	-0.140***	0.038
Professors lab	0.291***	0.103	0.289***	0.102	0.290***	0.102
Publications lab	-0.049	0.034	-0.049	0.034	-0.050	0.035
CiteScore lab	0.056***	0.015	0.056***	0.015	0.055***	0.015
Ln(funding lab+1)	-0.003	0.003	-0.003	0.003	-0.003	0.003
Postdoc hours	0.011***	0.004	0.011**	0.004	0.011**	0.004
Student hours	0.017***	0.004	0.016***	0.004	0.016***	0.005
Chemistry	-0.036	0.046	-0.021	0.047	-0.017	0.047
Constant	1.175***	0.093	1.189***	0.097	1.229***	0.108
Adjusted R^2	0.213		0.216		0.216	
Joint sig. Female#small child (3)			2.67**		1.98	

Note: N = 2097; clusters = 262. *** (**,*) indicate a significance level of 1% (5%, 10%). Year dummies included; robust clustered standard errors.

Table 7: Results of two-stage least square regression on research outcomes

	Probit		1st Stage		2SLS		2SLS		2SLS	
	Professor		Ln(Italian funding+1)		Ln(adj.publications+1)		Ln(citations+1)		Ln(CiteScore+1)	
	b	se	b	se	b	se	b	se	b	se
Ln(Italian funding+1)					0.003	0.026	0.031	0.053	0.015	0.036
Female	-0.141	0.246	-0.982*	0.575	-0.183***	0.062	-0.137	0.176	-0.023	0.116
Small child (0-3)			0.244	0.552	0.034	0.060	0.375***	0.126	0.152***	0.057
Female#small child			0.040	0.639	-0.113	0.071	-0.471***	0.175	-0.229**	0.100
Teaching hours			0.075	0.120	-0.005	0.009	-0.017	0.026	0.000	0.015
Female#Teaching hours			0.027	0.142	0.016	0.014	0.035	0.040	0.004	0.028
Controls										
(Age-40)/10	2.314***	0.301	0.132	0.222	-0.105***	0.029	-0.498***	0.087	-0.333***	0.054
(Age-40)/10^2	-0.340***	0.096	-0.277**	0.122	-0.046***	0.015	-0.066**	0.032	-0.018	0.021
Pr(professor)			3.747***	1.060	0.635***	0.144	1.637***	0.339	0.962***	0.192
Ln(coauthors+1)							0.343***	0.042		
Lab measures										
Single person lab			-1.251**	0.549	-0.183***	0.064	-0.378**	0.165	-0.282***	0.089
Lab size			-0.058	0.045	-0.011**	0.005	-0.023*	0.012	0.001	0.009
Mean age lab			0.334	0.317	-0.019	0.025	-0.207***	0.066	-0.096**	0.039
Professors lab			-1.991**	0.770	-0.044	0.079	0.450**	0.184	0.191*	0.115
Publications lab			-0.332	0.235	0.053*	0.027	-0.004	0.064	-0.048	0.034
Citations lab			-0.001	0.007	-0.001	0.001	0.008***	0.002		
CiteScore lab									0.046***	0.014
Ln(funding lab+1)			0.011	0.025	-0.002	0.002	0.005	0.005	-0.004	0.003
Postdoc hours			0.053	0.033	-0.001	0.003	0.012	0.008	0.014***	0.004
Student hours			0.093***	0.033	0.016***	0.005	0.023**	0.009	0.013**	0.005
Chemistry			-0.436	0.427	-0.018	0.033	-0.091	0.092	-0.046	0.047
Instruments										
Social capital			2.505*	1.385						
Ln(Italian funding other labs+1)			0.530***	0.174						
Ln(l.adj.pub+1)	0.521**	0.230								
Ln(l.citations+1)	0.219***	0.065								
Joint sign. of department dummies (6)	7.29									
Constant	-3.520***	0.415	-5.801**	2.265	0.530***	0.064	1.624***	0.216	1.060***	0.096
Pseudo/Adjusted R^2	0.496		0.152		0.234		0.312		0.236	
Hansen J-test (p-value)					0.251		0.320		0.854	
Underidentification test (p-value)					0.00212		0.00217		0.00193	
Joint sig. Female#small child (3)					15.41***		10.54**		8.17**	

Note: N = 2097; clusters = 262. *** (**,*) indicate a significance level of 1% (5%, 10%). Year dummies included; robust clustered standard errors. Publication counts are co-author adjusted. First stage regression for adjusted publication count is reported. First stage estimations for citations and CiteScore are available upon request.

Table 8: Results of two-stage least square regression on research outcomes controlling for initial condition

	(1) Ln(adj.publications+1)		(2) Ln(citations+1)		(3) Ln(CiteScore+1)	
	b	se	b	se	b	se
Ln(Italian funding+1)	-0.008	0.025	0.018	0.045	0.011	0.027
Female	-0.116**	0.059	0.091	0.154	0.082	0.093
Small child (0-3)	0.030	0.057	0.172	0.120	0.084*	0.048
Female#small child	-0.108	0.072	-0.442**	0.179	-0.223**	0.097
Teaching hours	-0.003	0.008	0.013	0.023	0.009	0.010
Female#Teaching hours	0.003	0.014	-0.014	0.035	-0.011	0.021
Controls						
(Age-40)/10	-0.119***	0.029	-0.581***	0.080	-0.375***	0.045
(Age-40)/10^2	-0.023*	0.013	-0.022	0.029	0.017	0.016
Professor	0.480***	0.126	1.516***	0.275	0.785***	0.139
Ln(coauthors+1)			0.189***	0.042		
Lab measures						
Single person lab	-0.121**	0.062	-0.225	0.156	-0.157**	0.072
Lab size	-0.003	0.004	0.003	0.011	0.014**	0.006
Mean age lab	-0.032	0.025	-0.142**	0.059	-0.093***	0.034
Professors lab	-0.018	0.074	0.231	0.165	0.132	0.102
Publications lab	0.026	0.029	-0.013	0.055	-0.024	0.030
Citations lab	-0.001	0.001	0.006***	0.002		
CiteScore lab					0.022*	0.012
Ln(funding lab+1)	-0.002	0.002	0.006	0.005	-0.003	0.003
Postdoc hours	-0.002	0.003	0.007	0.007	0.013***	0.004
Student hours	0.013***	0.004	0.012	0.007	0.009**	0.004
Chemistry	-0.013	0.031	-0.166**	0.080	-0.022	0.037
Zero initial adj.pub | cit | CiteScore	-0.142***	0.036	0.521***	0.179	-0.019	0.083
Ln(initial adj.pub | cit | CiteScore)	0.140***	0.027	0.356***	0.041	0.263***	0.029
Constant	0.494***	0.059	0.541**	0.217	0.551***	0.088
Adjusted R^2	0.283		0.380		0.340	
Hansen J-test (p-value)	0.582		0.267		0.733	
Underidentification test (p-value)	0.00159		0.00233		0.00192	
Joint sig. Female#small child (3)	9.24**		6.39*		6.34*	

Note: N = 2097; clusters = 262. *** (**,*) indicate a significance level of 1% (5%, 10%). Year dummies included; robust clustered standard errors. Publication counts are co-author adjusted. First stage regressions are available upon request.

Table 9: Results of two-stage least square regression on research outcomes, robustness test

	(1)		(2)		(3)		(4)	
	Ln(publications+1)		Ln(publications+1)		Ln(norm.citations+1)		Ln(norm.citations+1)	
			b	se	b	se	b	se
Ln(Italian funding+1)	0.026	0.039	-0.001	0.030	0.004	0.015	0.002	0.013
Female	-0.138	0.145	-0.052	0.141	-0.036	0.059	0.030	0.052
Small child (0-3)	0.139	0.102	0.104	0.101	0.136**	0.055	0.068	0.053
Female#small child	-0.314**	0.137	-0.303**	0.143	-0.152**	0.067	-0.138**	0.068
Teaching hours	0.021	0.021	0.015	0.016	-0.008	0.009	0.000	0.008
Female#Teaching hours	0.010	0.036	-0.004	0.034	0.010	0.013	-0.004	0.011
Controls								
(Age-40)/10	-0.376***	0.069	-0.404***	0.062	-0.100***	0.029	-0.117***	0.028
(Age-40)/10^2	-0.069**	0.029	-0.014	0.023	-0.017*	0.010	-0.006	0.010
Professor	1.590***	0.278	1.182***	0.205	0.323***	0.111	0.274***	0.096
Ln(coauthors+1)					0.093***	0.014	0.048***	0.014
Lab measures								
Single person lab	-0.417***	0.121	-0.173	0.106	-0.037	0.053	-0.002	0.051
Lab size	0.005	0.012	0.014	0.009	-0.006*	0.003	-0.000	0.004
Mean age lab	-0.044	0.052	-0.054	0.047	-0.037	0.025	-0.010	0.023
Professors lab	0.097	0.144	0.063	0.127	0.071	0.068	-0.011	0.064
Publications lab	-0.053	0.047	0.003	0.043	0.027	0.025	0.023	0.021
Citations lab	-0.001	0.001	-0.001	0.001	0.004***	0.001	0.003***	0.001
Ln(funding lab+1)	-0.007**	0.003	-0.005	0.003	0.001	0.002	0.001	0.002
Postdoc hours	0.011*	0.006	0.005	0.005	0.008**	0.003	0.006**	0.003
Student hours	0.043***	0.009	0.022***	0.007	0.005*	0.003	0.002	0.003
Chemistry	-0.251***	0.067	-0.103*	0.054	-0.040	0.033	-0.065**	0.029
Zero initial pub | norm.cit			0.133	0.118			-0.115***	0.032
Ln(initial pub | norm.cit)			0.373***	0.048			0.124***	0.017
Constant	1.201***	0.151	0.488***	0.143	0.305***	0.078	0.331***	0.071
Adjusted R^2	0.304		0.417		0.223		0.284	
Hansen J-test (p-value)	0.297		0.516		0.0778		0.0704	
Underidentification test (p-value)	0.00174		0.00180		0.00217		0.00234	
Joint sig. Female#small child (3)	6.78*		5.46		7.16*		4.59	

Note: N = 2001; clusters = 250 in the publication model. N = 2097; clusters = 262 in the citation model. *** (**,*) indicate a significance level of 1% (5%, 10%). Year dummies included; robust clustered standard errors. High energy physics and other areas of physics relying on large coauthor teams are excluded in the publication model. Citations are year normalized. First stage regressions are available upon request.

Table A1: Additional descriptive statistics

	mean	sd	p50	min	max
SNIP (average)	1.08	0.69	1.20	0.00	8.85
SJR (average)	1.43	1.16	1.37	0.00	17.35
SNIP lab	0.98	0.59	1.06	0.00	5.29
SJR lab	1.30	0.93	1.27	0.00	9.29
Zero initial SNIP	0.09	0.29	0.00	0.00	1.00
Ln(initial SNIP)	1.04	0.58	1.18	-2.14	2.18
Zero initial SJR	0.10	0.30	0.00	0.00	1.00
Ln(initial SJR)	1.23	0.78	1.41	-1.91	2.85

Note: Number of observations = 2097 and observation period is 2001 to 2010. The average SNIP and SJR of the 2011 to 2014 period is applied.

Table A2: Results of two-stage least square regression on research outcomes, robustness test

	(1) Ln(SNIP+1)		(2) Ln(SNIP+1)		(3) Ln(SJR+1)		(4) Ln(SJR+1)	
			b	se	b	se	b	se
Ln(Italian funding+1)	0.014	0.019	0.008	0.017	0.007	0.026	0.008	0.019
Female	-0.017	0.062	0.033	0.053	0.005	0.086	0.076	0.072
Small child (0-3)	0.089**	0.036	0.057*	0.032	0.166***	0.051	0.093**	0.041
Female#small child	-0.127**	0.054	-0.128**	0.053	-0.231***	0.073	-0.194***	0.067
Teaching hours	0.005	0.009	0.009	0.007	0.004	0.012	0.011	0.008
Female#Teaching hours	0.005	0.015	-0.001	0.012	-0.003	0.020	-0.013	0.016
Controls								
(Age-40)/10	-0.200***	0.029	-0.226***	0.026	-0.235***	0.039	-0.250***	0.031
(Age-40)/10^2	-0.008	0.011	0.011	0.010	-0.013	0.015	0.013	0.012
Professor	0.581***	0.110	0.494***	0.092	0.700***	0.150	0.504***	0.108
Lab measures								
Single person lab	-0.160***	0.051	-0.087**	0.044	-0.168**	0.075	-0.081	0.062
Lab size	0.001	0.005	0.007**	0.003	0.002	0.006	0.010**	0.004
Mean age lab	-0.044**	0.021	-0.041**	0.019	-0.052*	0.031	-0.044	0.027
Professors lab	0.122**	0.059	0.087	0.054	0.118	0.087	0.078	0.077
Publications lab	-0.019	0.018	-0.007	0.018	-0.054**	0.026	-0.033	0.024
SNIP/SJR lab	0.051***	0.018	0.023	0.017	0.074***	0.023	0.035*	0.019
Ln(funding lab+1)	-0.002	0.002	-0.002	0.002	-0.004**	0.002	-0.002	0.002
Postdoc hours	0.005**	0.002	0.005***	0.002	0.011***	0.004	0.010***	0.003
Student hours	0.009***	0.003	0.006**	0.002	0.013***	0.004	0.009***	0.003
Chemistry	-0.129***	0.027	-0.078***	0.022	-0.169***	0.037	-0.095***	0.028
Zero initial SNIP ǀ SJR			-0.093**	0.045			-0.088*	0.048
Ln(initial SNIP ǀ SJR)			0.181***	0.024			0.213***	0.022
Constant	0.655***	0.057	0.445***	0.052	0.769***	0.080	0.468***	0.075
Adjusted R^2	0.227		0.318		0.225		0.333	
Hansen J-test (p-value)	0.344		0.174		0.821		0.859	
Underidentification test (p-value)	0.00195		0.00196		0.00170		0.00169	
Joint sig. Female#small child (3)	7.35*		6.19		12.50***		9.51**	

Note: N = 2097; clusters = 262. *** (**,*) indicate a significance level of 1% (5%, 10%). Year dummies included; robust clustered standard errors. First stage regressions are available upon request.