Department of Economics and Statistics "Cognetti de Martiis"
Campus Luigi Einaudi, Lungo Dora Siena 100/A, 10153 Torino (Italy)
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# NURTURING KNOWLEDGE? THE IMPACT OF FUNDING AND FAMILY ON SCIENTIFIC PERFORMANCE

CORNELIA LAWSON, ALDO GEUNA
and UGO FINARDI

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# The funding-productivity-gender nexus in science, a multistage analysis*

Cornelia Lawson
*University of Manchester, Alliance Manchester Business School*

Aldo Geuna
*University of Torino, Department Culture, Politics and Society*
*&*
*Collegio Carlo Alberto*

Ugo Finardi
*CNR-IRCrES*

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**Abstract**

This paper contributes to the literature on the observed research funding and scientific productivity gender gap in science. On the basis of very detailed information for a sample of 276 academics at the University of Turin over a ten year period, we develop a robust new model that takes into account the three main stages of the funding-productivity nexus: applying for a grant, successful fund raising and conducting the research, to investigate at which stage the gender gap emerges. In the model, we control for differences – not previously examined together - in the time allocated to teaching, administration and child care, which might moderate the gender effect. Using a Two-Stage Least Square (2SLS) model we control, for selection into funding, endogeneity of career progress and endogeneity of funding success, and find, first, that researchers who apply for grants are active in teaching and administration and show persistent funding application behaviour, but find no evidence of a significant gender bias; second, when we control for application selection, the negative gender correlation with funding acquisition becomes stronger, while teaching is negatively correlated to the amount of funding raised; and, third, controlling for selection and reverse causality, we find that funding is not associated to higher research productivity. At all stages of the funding-productivity nexus we find negative, albeit insignificant, secondary gender effects associated with administrative tasks, but less so with teaching. In the research impact-quality estimations we provide evidence of a 'motherhood penalty' for female academics with young children who did not apply for funding (including evidence of a causal effect). In line with the literature, we find that, after controlling for children, female researchers are less productive in terms of publications, but not in terms of research quality or impact.

***Keywords***: competitive funding, research productivity, women in science

***JEL Codes***: I23, J16, O31

## 1. Introduction

Universities are central to the production of new scientific and technological knowledge, and the process that explains the scientific productivity of university researchers remains to be better understood. The gender gap in scientific productivity, that is, the finding that female researchers tend to publish less than their male peers after controlling for observables, has, for many years, been central to this discussion and explaining this 'productivity puzzle' (Cole and Zuckerman, 1984) remains a priority.

Recent contributions show that the gender gap extends to competitive funding (Lerchenmueller & Sorenson, 2018; Steinþórsdóttir et al., 2020). Since academics' scientific productivity is said to be strongly influenced by the funding and governance structure under which they operate (Aghion et al., 2010), this could provide an explanation for the 'productivity puzzle'. In many countries in Europe, where universities were financed, primarily, by block grants, with little accountability for how these resources are used, governments have increased the amounts of funding distributed through competitive schemes (Geuna, 1999; Bolli and Somogyi, 2011). While individual competitive funding has received attention, with a large number of studies analysing different aspects relevant to our understanding of scientific productivity many of these works (due, mostly, to data accessibility issues) tend to focus on a subset of factors, but fail to capture the complexity of knowledge production including the productivity puzzle. These complexities include questions about whether any final productivity gap is due to mechanisms at work during the production of the research, reduced funding or female researchers selecting themselves out of the competition for resources and what are the relevant mechanisms at each stage of knowledge production that contribute to the gender gap.

The present study addresses these questions and offers a more encompassing view of the funding-productivity-gender nexus in science. We model the interactions among different aspects of the science production function by considering it a three-stage process starting with selection into applying for competitive funding, receipt of funding and scientific productivity (see Figure 1), for men and for women. We consider differences between men and women in the time available for research, specifically, differences in time devoted to other academic activities such as teaching and administration, and non-academic activities such as caring for a small child. All three activities not only affect scientific productivity directly but also, by significantly influencing researchers' time allocation, might crowd out other research related activities resulting in fewer applications and less funding and productivity. This effect should be stronger for women, who have been shown to devote more time to non-research activities (Xie and Shauman, 2003; Babcock et al., 2017; Blake and La Valle, 2001), which could create secondary gender effects. Of particular relevance is the possible differential impact on men and women of having a small child; caring for a new-born could result in gender-biased time allocation decisions, but we do not know whether and at which stage in the funding-productivity relationship, this happens.

In summary, for each of the three stages of research productivity, we assess the existence of primary gender effects and secondary gender effects mediated by (self-)selection of female researchers in teaching, administration and parental activities. This allows us to identify at what stage differences between men and women emerge. The aim is not to explain the reasons for the phenomenon, but rather to highlight its relevance, if any, to research performance.

Empirically, we rely on detailed information for a sample of 276 academics working in the physics and chemistry field at the University of Turin, over a ten-year period. We model fund-raising success using a novel instrument that captures the academic's socio-political role in the national academic network. In a final, four equation Two-Stage Least Square (2SLS) estimation, we account for selection into grant application, endogeneity of funding and endogeneity of career progression, to estimate a productivity equation for a series of output measures including number of publications, citations and journal impact adjusted publications, to investigate gender differences at each stage.

Although the amount of competitive research funding in Italy is small (Geuna and Rossi, 2015), we find that researchers who apply for grants show persistent funding application activity. We find no evidence of a significant gender bias at the application stage. However, also when we control for this selection into application, we find that women receive significantly less funding than men. When we account for selection and causality, we find that, although funding is not associated to higher research productivity, a productivity gap for women persists. At all stages of the funding-productivity nexus we find negative albeit insignificant secondary gender effects associated with administrative tasks, but less so with teaching. In the estimations that include citations to research publications, we find evidence of a 'motherhood penalty' for having young children, mainly for female academics who do not apply for funding. Our main results are confirmed in a series of robustness models using alternative dependent variables.


Figure 1: Three stages of research productivity

## 2. Competitive funding, scientific performance and the gender gap

### *2.1 The funding-productivity-gender nexus*

In the literature, funding and research output are linked closely, since competitive funding can help researchers to secure funds for equipment and research assistance, which leads to more autonomy and flexibility (Stephan 2012). However, funding is not allocated exogenously; it depends on a decision by the academic to apply for funding, as part of a three stage funding-research productivity process starting with the scientist's decision to apply, followed by the award of funding, which lead to scientific research output (see Figure 1).

Women have been found to lag behind at all three stages. For instance, there is a persistent gap in publication count, a phenomenon that has been described as the 'productivity puzzle' (Cole and Zuckerman, 1984). Some papers have also shown that women receive fewer citations to their work than men (Aksnes et al., 2011; Beaudry and Lariviere, 2016), though this is not confirmed in the majority of studies (van den Besselaar and Sandstrom, 2017; Lynn et al. 2019).

A gap has been observed, also, in research funding where women are less likely to succeed and attract lower amounts of funding (Wenneras and Wold, 1997; Jagsi et al., 2009; Pohlhaus et al., 2011; van der Lee and Ellemers, 2015; Witteman et al., 2019).[1] Blake and La Valle (2001), who investigated application behaviour based on surveys of potential funding applicants in the UK, further suggest that, even when eligible, women are less likely to apply for funding.

However, these findings do not apply to all fields or all countries; and several studies do not find strong evidence of a gender gap in competitive fund raising (Marsh et al., 2011, Mutz et al., 2012). Also, Waisbren et al. (2008) found that the difference in funding success disappeared when controlling for seniority, since female researchers are underrepresented in senior positions (Ginther and Hayes, 1999). This is in line with the Matthew effect of accumulated advantage in the award of funding, which recognizes past success, experience and visibility as critical for funding success (Merton, 1988; Laudel, 2006; Perc, 2014). In addition, while several studies suggest that women are less likely to apply for funding, this tends to be explained by career stage differences or lower levels of ambition (see Steinþórsdóttir et al., 2020 for a review). However, empirical evidence on a possible gender gap in the decision to apply for a grant is scarce due to lack of appropriate data.

To summarize, the gender literature focuses on productivity and funding separately and there are no studies that consider their interaction. Therefore, whether the final productivity gap is due to mechanisms at work during the production of the research, to reduced funding or to female researchers selecting themselves out of the competition for resources is unclear.

### *2.2 Competitive funding and research performance*

To understand why women receive less funding and publish less, we need, first, to understand the relationship between the three stages of scientific productivity depicted in Figure 1. Since competitive research funding is considered a mechanism to reward and, thus, incentivize the most able academics, the prior research generally assumes that funding is awarded to the best researchers. As a result, competitive funding tends to be associated to increased productivity, regardless of the sponsor (Jacob and Lefgren, 2011; Benavente et al., 2012; Hottenrott and Lawson, 2017).

However, the literature suggests that not all types of public grants benefit academic performance and that, depending on the national scientific system and the way in which output is measured (publications vs citations), the effect might be more or less sizeable. For example, Arora et al. (1998), who assess national research grants for biotechnology in Italy and Arora and Gambardella (2005) who study National Science Foundation (NSF) funding in the US, find positive, but very weak effects on publications. Jacob and Lefgren (2011) explain the small effect

[1] This difference in funding has been linked, in part, to the discounting of women's research efforts, leading to undervaluation of proposals (Lerchenmueller and Sorensen, 2018; van der Lee and Ellemers, 2015; Witteman et al., 2019).

they find for US National Institutes of Health (NIH) grants as due to other outside funding opportunities available to academics which can replace lost NIH funding. More controversially, Stephan (2012) suggests that the funding application and management process reduces the time available for research, which might explain the small performance effects. However, in the case of Russia, Ganguli (2017) finds that grants more than double publication numbers and explains this strong effect as due to low relative levels of funding in Russian universities. There are also several studies showing that public funding has a positive impact on the quality of scientific research and that sponsored academics are more highly cited and publish in higher impact journals (Chudnovsky et al., 2008; Jacob and Lefgren, 2011; Carayol and Lanoe, 2017). These effects are consistently larger than those observed for publication numbers.

Nevertheless, some studies concede that selection biases may be driving the results for the effect of funding since more able researchers are not only more likely to be successful but also are more likely to actively select into funding competitions. In one of the very few papers investigating selection into applying for funding, Seyed Rasoli (2011) finds that, in the French context, publication performance is crucial for the researcher's decision to apply. Accounting for this selection, she finds that funding success is not driven by individual performance, but rather by department prestige. However, she does not look at subsequent research outcomes and, to our knowledge, only Ayoubi et al. (2019) study how the decision to apply for competitive funding might influence future performance. Correcting for the selection bias present in all other studies, these authors find that, in the case of a Swiss collaborative funding programme, those competing for funding increase the number and quality of their publications, regardless of whether the application was successful, which, again, highlights the importance of self-selection.

On the basis of the above discussion, we would expect the new knowledge produced to be a function of the academic's cognitive capabilities and the amount of individual competitive funding raised. Funding might not be a direct causal factor of increased productivity since selection into applying for funding may indicate the start of a research path leading to higher research output, regardless of funding success. This situation is likely to be more frequent in scientific systems where researchers also receive non-competitive funding to run laboratories. In the hard sciences, in particular, laboratory resources have a major influence on academics' performance (Carayol and Matt, 2006), since availability of laboratory assistants (doctoral or postdoctoral), equipment and materials is linked directly to individual productivity. In the case of Italy (and in most of the rest of Europe), research groups receive some level of basic funding from the university, to run the lab and hire doctoral and postdoctoral staff, but competitive funding is used increasingly to support the human and physical capital required.

The above discussion indicates, also, that women, who may be more likely to remove themselves from the funding competition (Waisbren et al., 2008) and who may be disadvantaged in promotion and, thus, access to lab resources (Sonnert and Holten, 1995; Ginther and Hayes, 1999; Mairesse and Pezzoni, 2015), are less able to pursue research paths leading to higher research output compared to men, which might explain the productivity puzzle.

*2.3 Mechanisms: Teaching, administration and child care*

The three stages of research productivity are affected, also, by the time allocated to other time-intensive activities, which reduce the time available for research and for drafting research proposals and research papers. Of particular interest are teaching, administration and parental responsibilities, which, to date, have received little attention in the economics of science literature. Each of these activities may be gender-biased, introducing more time constraints on women, which result in lower funding application activity, less funding and lower productivity (secondary gender effects) compared to men.

Indeed, prior studies have linked the gender gap in science to women's higher teaching commitments (Xie and Shauman, 2003) and higher administrative responsibilities (Babcock et al., 2017). Specifically, while teaching commitments are measured on the basis of class teaching hours, there are large differences in the time devoted to preparing for classes, marking exams and interacting with students. These differences apply, also, to administrative tasks, where the actual number of hours spent can vary significantly. Women tend to attach more importance to these 'thankless', 'low-promotability' tasks and, thus, devote more (quality) time and effort to them, not all of which is measured (e.g., even if there is a time allocation attached, these tasks may receive different attention and care) (Babcock et al., 2017).

The productivity gap has been linked, also, to women's childcare responsibilities (Carr et al., 1998; Fox, 2005, Hunter and Leahey, 2010, Ceci and Williams, 2011), since they continue to shoulder a larger share of parental responsibilities compared to men. Indeed, several studies show that women in academia are less able to manage the time devoted to work and family life and can find themselves 'stuck' in caring responsibilities, with consequences for the time allocated to research (Acker and Armenti, 2004; Rafnsdóttir and Heijstra, 2013; Myers et al. 2020).

*2.3.1 Scientific productivity, teaching and administration*

Teaching is one of the university's main missions and the majority of permanent academic staff have teaching duties.[2] These commitments may not be closely aligned to their current research and may reduce the time available for raising research funding. However, due to the difficulty related to measuring teaching, the evidence is scarce and inconclusive. For instance, early evidence for the US suggests a trade-off between teaching and research (Boyer, 1991; Clark, 1987) or a complementarity or null effect (Braxton, 1996; Mitchell and Rebne, 1995; Marsh and Hattie, 2002). More rrecently, Landry et al. (2010), for the case of a Canadian university, and Rahmandad and Vakili (2019) for the US case, find that teaching time and publications are substitutes. Finally, Bianchini et al. (2016) for the case of a technical university in Italy and García-Gallego et al. (2015) for a university in Spain, observe a nonlinear relationship between research

[2] Surveys in Germany and the UK find that academics spend between 20% and 30% of their time teaching and 20% of their time on administrative tasks (Hughes et al., 2016; Fudickar et al., 2018). In the case of Italy, all tenured academics have to provide a minimum number of teaching hours depending on their academic position; full professors are required to deliver 90 to 120 hours of lectures a year.

publications and teaching quality, that is, an initial positive link with diminishing returns for high numbers of publication.

Thus, a higher teaching commitment may crowd-out time from research and applying for funding. Recent changes to the funding of academic research in Europe and, especially, in the context of research evaluations, are incentivizing academics to spend more time on sourcing research grants. In many countries, this does not imply some relief from teaching duties and, therefore, any funding acquired may not result in increased productivity.

In addition to teaching, administrative duties can also affect the research activity of academics. The findings from investigations of the publication performance of academics in top managerial posts, show a decline in the numbers of both publications and citations during the appointment (Lou et al., 2018; Zhao et al, 2019). Lou et al (2018) studied more than a hundred department deans and university presidents in 29 universities worldwide and found this effect to be more pronounced for those serving in higher ranked universities. The drop in performance can be severe. For instance, Zhao et al. (2019) observed a drop of 20% in publication numbers and 60% in citations, in the case of US university presidents. Thus, there is evidence of a relation between appointment to an administrative role and scientific productivity; research productivity and the time available for research are both reduced.

The potential crowding out of research by teaching and administration may be higher for women since they tend to dedicate more time (accounted for and not accounted for) to these activities, which further amplifies any substitution effect at each stage of the research process.

*2.3.2 Scientific productivity and childcare*

In all countries, caring and domestic responsibilities are borne disproportionately by women, with women devoting more and better time to children (Craig, 2006; Rhoads and Rhoads, 2012; Mason et al., 2013). Parental responsibility is of specific interest for policy and relevant to the case of Italy where surveys indicate that 70% of women's time is allocated to family responsibilities (ISTAT, 2017),[3] and that men have 80% more leisure time than women (OECD, 2009). When the children are young and require more care, these domestic roles can have an especially negative impact on the time devoted to research with potentially long-term consequences for the careers of female academics (Mason et al., 2013; Myers et al., 2020).

The evidence on childcare and scientific productivity is mixed and mostly limited to the US case. The most comprehensive study, based on the US Survey of Doctoral Recipients, looks at the effects of different child age groups. In the case of pre-school age children, it finds a positive effect on the number of publications for fathers and a negative effect for mothers (Stack, 2004). However, evidence of a fatherhood bonus, where men become the main breadwinners and are incentivized to be more productive and creative, and a motherhood penalty related to extra time caring for a new-born, might not be causal. For example, for male researchers, career planning might mean that they have children only after becoming established on a strong publications track.

[3] The recorded asymmetry index in 2013-14, was below the 70% threshold (at 65.2%) for the first time (ISTAT, 2017).

Also, Stack (2004) does not consider research funding and the funding application decision and, therefore, leaves the stage in the research process when childcare has an impact an open question.

To conclude, the above-discussed literature highlights a correlation between the academic's gender and scientific productivity, but proposes only partial explanations for this relationship. It might be related directly to the academic's gender (first level gender effect) or to a time allocation decision process that induces women to allocate less time to research relevant activities and more to teaching, administration and parental tasks (second level gender effect). These two effects may emerge at different stages in the funding-productivity chain: 1) at decision to apply for funding; 2) at funding success; or 3) in relation to research outcomes. These actions are not independent; female researchers might reduce proposal writing time to allow time for other commitments (e.g., may submit a small number of proposals to specific funding agencies) or refrain from applying for funding (selecting out of funding) to preserve the time for current research although this is likely to affect future research. In either case, the decision will affect both the probability of the woman obtaining future funding and the time available to carry out research, with knock-on effects for her future productivity, in line with the Matthew effect related to accumulated advantage (Merton, 1988; Perc, 2014; Azoulay et al., 2014). In the econometric analysis, we test these alternative explanations for the funding and productivity gender gaps.

## 3. Chemistry and physics at the University of Turin

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

The Italian university funding system is quite complex and there are areas of inefficient resource allocation. Prior to the onset of the 2008 global economic crisis, Italian researchers bemoaned the low levels of financing and budget cuts (Hellemans, 2002; Nature, 2008; Feresin and Abbott, 2008). Since 1993, national state funding for universities consisted of a single grant, the Fondo di Finanziamento Ordinario or FFO,[4] which was allocated mainly on a historical basis, although, more recently, has been based more on teaching and research performance (about 20% of the FFO). In addition to FFO income and student fees, a share of university financing is derived from project-based competitive sources. These include international financing (e.g., European Union competitive funding) and several national and regional research programmes, which, however, are not well funded. The two main national project-based competitive funding programmes are PRIN (Progretti di Ricerca di Interesse Nationale, National Relevance Research Projects) and FIRB (Fondo Italiano Ricerca di Base, Italian Basic Research Fund) which was established in 2001.[5] Between 2001 and 2009, FFO allocated between 54.3% and 61.5% of total financing, while project-based competitive funding accounted for between 7.2% and 11.4% (Geuna and Rossi, 2015).

[4] See Rossi (2009) for a historical introduction to Italian university financing.
[5] PRIN financing is described in Bellotti (2011), which focuses, in particular, on social networks in the field of particle physics.

The University of Turin is a large Italian university (Rolfo and Finardi, 2014), which, in the academic year 2019-20, included 2,012 academic staff (full, associate and assistant professors) and 1,846 technical staff. It is the sixth largest university in Italy based on professor numbers.[6] It has some 23,600 first year students and total student enrolment of around 79,000 including over 1,100 doctoral students. In 2019, approximately 13,800 students graduated from the University of Turin. Its consolidated income in 2018 was €461.9 million.[7] Historically, chemistry and physics are among the University of Turin's most important research areas. In the 2011-2014 national research evaluation (VQR), out of the group of the nine largest universities, the University of Turin was ranked second for physics, and combined first (with Florence University) for chemistry. The group of large universities in Italy includes the most research intensive universities, positioning physics and chemistry in Turin at the top of the Italian system. The University of Turin also performs well in international rankings. In the 2005 to 2018 Academic Ranking of World Universities (ARWU),[8] Turin was in the top nine Italian universities; it was ranked fifth and sixth in 2014 and 2015 respectively and was ranked between fourth and sixth during the period 2004-2008. Internationally, Turin was ranked between 151st and 200th in the period 2004-2008, and between 201st and 300th in 2009-2018 (151st-200th in 2014 and 2015). Therefore, the University of Turin can be considered a leader in the fields of chemistry and physics, in Italy and in Europe.

## 4. Data and variables

### *4.1 Data*

Our data contain detailed information on all 276 full, associate and assistant professors in physics and chemistry and associated disciplines, working at the University of Turin during the years 2000 to 2009.[9] In the timespan considered, academics were affiliated to seven departments: General physics, Experimental physics, Theoretical physics, General and organic chemistry, Inorganic physical and materials chemistry, Analytical chemistry and Pharmaceutical sciences.

We retrieved full names, dates of birth, scientific field, gender and academic role (full/associate/assistant professor) for 239 academics in service between 2007 and 2009, from the University of Turin's central administration, provided by the office responsible for managing the central Catalogue of Scientific Production. This catalogue was established in 2007 and records data from 2007 onwards. Information on years of tenure for 239 academics plus 37 who retired from the university between 2000 and 2009 were retrieved from the Italian University Research and Education Departments website which provides information on university staff in Italy. This resulted in a total of 276 names of individual academics. Appendix Tables A1 and A2 present data

[6] After Roma "La Sapienza", Bologna, Napoli "Federico II", Milano and Padova universities.
[7] See: https://www.unito.it/ateneo/chi-siamo/unito-cifre and https://www.unito.it/sites/default/files/bilancio_esercizio_2018.pdf (both in Italian, last accessed February 2020).
[8] See http://www.shanghairanking.com (last accessed February 2020).
[9] Professors in Science Sectors in Italy (as defined by the Italian Ministry of Research) are indexed as CHIM (CHIM/1 to CHIM/12) and FIS (FIS/1 to FIS/8), and Engineering (ING-IND/21). Science sector definitions and associated scientific research interests are available at the Italian ministry website http://cercauniversita.cineca.it/php5/settori/index.php (in Italian, last accessed February 2020)

on university academics' entries and exits and number of years present in the sample. These data are supplemented by information on postdoctoral researchers and doctoral students obtained from the Doctorate and Research Grants Office of the university's Research and International Liaisons Division.

Data on competitive research funding applications and awards were obtained from the university's Research and International Liaisons Division and integrated with public data posted on the university's website. Academics receive funding from four different sources: regional, national, EU and industry. Full data on funding applications and award amounts are available for Italian national (PRIN, FIRB, etc.) and regional (Regione Piemonte) competitions. Data on national funding were complemented by data from the Italian University Ministry website; regional funding information was obtained from the university's administration.

Funding from EU Framework Programmes (EU FP) were retrieved from several sources. For the most part, funding data were retrieved by manually searching the EU FP database on the CORDIS website, and checking against the EUPRO database (Roediger-Schluga and Barber 2008). Where the share of funding allocated to the University of Turin was not available, we estimated it based on the number of partners and type of project. Information on industry funding was collected, but, since it was neither complete nor reliable at the individual level, we excluded it from the analysis.[10]

We also collected data on teaching, administrative posts and children. Information on teaching hours are from official university records, but are not available for all academics or all years. The econometric model is based on observations for 262 academics, for 220 of whom we have original teaching information from 2003 onwards. For all years prior to 2003 and for the 42 missing cases we imputed teaching time. Teaching in Italy is a fixed part of academic work and, in theory, all professors must contribute a minimum number of teaching hours since teaching buyouts were not allowed in the period considered. However, there are several exceptions to this rule, in terms of both a smaller number of teaching hours (e.g., due to administrative appointments such as Vice-rector, School Dean or Department Director, sabbatical leave, etc.) or a higher number of hours (e.g., due to understaffing with respect to teaching needs, resulting in either voluntary higher teaching loads or, in the case of junior staff, contracted hours of teaching attracting minimal extra pay). Administrative positions were collected from official university documents and archived university websites; they include the most senior positions of School Dean and Department Director, as well as the position of Degree Programme Director and of Degree Coordinator. . Finally, number and year of birth of the children of each academic in the dataset were obtained through telephone contact. Since we were unable to reach some retired staff, the number of academics was reduced to 264.

For all 276 academics, we collected data on scientific publications for the years 1998 to 2010 from the Elsevier Scopus database.[11] This included publications prior to obtaining a

[10] Department aggregate data underscore the small relevance of industry funding, with a relatively more important role in chemistry, captured in the model by a science field dummy.

[11] Data were retrieved from the Scopus database (https://www.scopus.com) in May-June 2013. Scopus was preferred to other similar web-based databases because: 1) it includes a wider set of data (it reports more than 20,500 titles,

permanent position at the University of Turin. In most cases, we used the 'author search' option on Scopus, controlling for homonyms and spurious reference assignments. In some cases, homonyms or faulty assignment of references forced us to collect or check the information manually. The downloaded records included number of citations received at 2013 (year of data collection) and number of co-authors. To obtain an additional measure for publication impact/quality, each publication was ascribed a citation impact measure derived from Elsevier CiteScore.[12]

We assigned each academic to a research laboratory. Most labs are grouped around a full professor and include associate and assistant professors, post-docs and doctoral students. We were able to identify 89 such research labs among our 7 departments, varying in size from 1 to 16 permanent staff. For the three chemistry departments, research lab composition was derived from the respective department's official website. For the three physics departments and the pharmaceutical sciences department, the websites reported the composition of only some of the labs. For the missing labs, we made assumptions, based on a method involving analysis of co-authorship among professors and the personal knowledge of one of the authors of this paper (see Appendix 1).

Complete information on all the variables was available for 262 academics in the database. The 14 academics for whom we have only incomplete information are still included in the calculation of relevant laboratory measures. Table 1 presents the descriptive statistics and correlations for the measures used in the regressions. The final empirical model, including all the variables, is estimated for 262 academics and includes 2,097 person-year observations

### *4.2 Dependent Variable*

Our dependent variable is academic research performance. We construct three alternative variables of research performance based on publications information, as follows. We created a co-author adjusted publications count (*adj. publications*) by dividing each publication by the number of authors and summing by year. This accounts for differences in the relative authorship contribution of different academics in the sample.[13] Next, we calculated the year normalized average number of citations received by these articles (*norm. citations*). Normalization addresses the potential year truncation problem in the citations 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 for the same year. This gives a higher weight to

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some 19,500 peer-reviewed journals plus other sources, from more than 5,000 international publishers); 2) it covers several non-English language titles; 3) it includes a larger number of proceedings which, for physics, are particularly relevant.

[12] CiteScore is based on the journal's citation average over the previous 3 years which is the methodology used for Thomson Reuters Journal Impact Factor.

[13] Fractional counts are considered due to the presence in the sample of professors working in the field of particle physics, which involves huge experiments (such as those conducted at CERN) and can involve multiple publications per year coauthored by hundreds of authors. In the robustness check in Appendix 2, we exclude those academics and use full counts with consistent results.

## Table 1: Descriptive statistics and Correlation Table

| | mean | sd | min | max | Correlations (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Dependent variables* | | | | | | | | | | | | | | | | | | | | |
| (1) Adj. publications | 0.73 | 0.80 | 0.00 | 7.00 | 1.000 | | | | | | | | | | | | | | | |
| (2) Norm. citations | 0.81 | 1.00 | 0.00 | 11.41 | 0.141 | 1.000 | | | | | | | | | | | | | | |
| (3) CiteScore (average) | 2.65 | 1.88 | 0.00 | 17.03 | 0.314 | 0.454 | 1.000 | | | | | | | | | | | | | |
| *Independent variables* | | | | | | | | | | | | | | | | | | | | |
| (4) Italian funding (in €10k) | 1.07 | 6.14 | 0.00 | 131.57 | 0.270 | 0.043 | 0.116 | 1.000 | | | | | | | | | | | | |
| (5) Ln(Italian funding+1) | 1.72 | 3.89 | 0.00 | 14.09 | 0.238 | 0.053 | 0.102 | 0.459 | 1.000 | | | | | | | | | | | |
| (6) Female | 0.38 | 0.48 | 0.00 | 1.00 | -0.236 | -0.044 | -0.034 | -0.102 | -0.195 | 1.000 | | | | | | | | | | |
| (7) Teaching hours | 3.77 | 1.62 | 0.00 | 10.93 | 0.026 | -0.052 | -0.000 | -0.011 | 0.064 | -0.104 | 1.000 | | | | | | | | | |
| (8) Administrative role | 0.12 | 0.32 | 0.00 | 1.00 | 0.113 | 0.013 | 0.029 | 0.012 | 0.129 | -0.094 | 0.137 | 1.000 | | | | | | | | |
| (9) Small child (0-3yrs) | 0.12 | 0.32 | 0.00 | 1.00 | -0.021 | 0.081 | 0.090 | -0.045 | -0.053 | 0.080 | -0.025 | -0.050 | 1.000 | | | | | | | |
| *Controls* | | | | | | | | | | | | | | | | | | | | |
| (10) (Age-50)/10 | 0.01 | 1.13 | -2.20 | 2.50 | -0.003 | -0.121 | -0.184 | 0.115 | 0.205 | -0.264 | 0.048 | 0.193 | -0.361 | 1.000 | | | | | | |
| (11) Professor | 0.35 | 0.48 | 0.00 | 1.00 | 0.115 | 0.009 | 0.055 | 0.166 | 0.291 | -0.224 | 0.039 | 0.317 | -0.239 | 0.653 | 1.000 | | | | | |
| (12) Chemistry | 0.61 | 0.49 | 0.00 | 1.00 | 0.040 | -0.097 | 0.106 | 0.085 | 0.061 | 0.178 | 0.103 | -0.084 | 0.028 | -0.186 | -0.059 | 1.000 | | | | |
| (13) Ln(avg. # coauthors+1) | 1.77 | 0.98 | 0.00 | 5.74 | 0.120 | 0.251 | 0.281 | 0.017 | 0.017 | -0.053 | -0.053 | 0.061 | 0.019 | -0.070 | 0.114 | -0.264 | 1.000 | | | |
| *Instruments* | | | | | | | | | | | | | | | | | | | | |
| (14) Social capital | 0.02 | 0.14 | 0.00 | 1.00 | 0.046 | -0.023 | 0.024 | 0.056 | 0.141 | -0.024 | -0.022 | 0.065 | -0.019 | 0.086 | 0.136 | 0.114 | -0.020 | 1.000 | | |
| (15) Ln(other lab fund+1) | 13.72 | 0.92 | 11.26 | 15.03 | 0.034 | -0.069 | 0.085 | 0.101 | 0.103 | 0.160 | 0.060 | -0.032 | 0.053 | -0.140 | -0.041 | 0.834 | -0.226 | 0.119 | 1.000 | |
| *Selection variable* | | | | | | | | | | | | | | | | | | | | |
| (16) Application | 0.23 | 0.42 | 0.00 | 1.00 | 0.196 | 0.051 | 0.096 | 0.231 | 0.457 | -0.149 | 0.103 | 0.125 | -0.042 | 0.169 | 0.229 | 0.014 | 0.078 | 0.111 | 0.035 | 1.000 |
| *Lab measures* | | | | | | | | | | | | | | | | | | | | |
| Single person lab | 0.14 | 0.35 | 0.00 | 1.00 | -0.107 | -0.121 | -0.237 | -0.036 | -0.046 | -0.042 | 0.001 | -0.070 | -0.062 | 0.142 | -0.107 | -0.122 | -0.229 | -0.018 | -0.112 | -0.055 |
| Lab size | 4.75 | 3.17 | 1.00 | 16.00 | -0.059 | -0.038 | 0.089 | 0.003 | -0.040 | 0.120 | 0.055 | -0.011 | 0.048 | -0.114 | 0.014 | 0.181 | 0.077 | 0.011 | 0.169 | -0.031 |
| (Mean age lab-50)/10 | -0.05 | 0.62 | -1.85 | 2.10 | -0.065 | 0.002 | -0.091 | -0.077 | -0.080 | 0.017 | -0.025 | 0.020 | -0.004 | -0.066 | -0.136 | -0.280 | 0.069 | -0.122 | -0.205 | -0.074 |
| Professors lab | 0.31 | 0.28 | 0.00 | 1.00 | 0.016 | 0.128 | 0.121 | -0.035 | -0.094 | 0.028 | -0.039 | -0.003 | 0.03 | -0.199 | -0.092 | -0.149 | 0.236 | -0.085 | -0.114 | -0.073 |
| Publications lab | 0.65 | 0.56 | 0.00 | 4.64 | 0.193 | 0.141 | 0.208 | 0.050 | 0.041 | -0.016 | -0.053 | 0.049 | 0.064 | -0.113 | 0.022 | 0.099 | 0.075 | 0.029 | 0.091 | 0.056 |
| Citations lab | 16.29 | 18.26 | 0.00 | 201.00 | 0.096 | 0.262 | 0.200 | 0.049 | 0.045 | 0.005 | -0.020 | 0.011 | 0.008 | -0.060 | 0.092 | -0.015 | 0.186 | -0.017 | -0.035 | 0.007 |
| CiteScore lab | 2.41 | 1.54 | 0.00 | 10.04 | 0.143 | 0.186 | 0.305 | 0.083 | 0.043 | 0.049 | -0.031 | 0.016 | 0.074 | -0.142 | 0.077 | 0.168 | 0.196 | 0.039 | 0.142 | 0.036 |
| Ln(EU-ITA fund lab+1) | 4.74 | 5.35 | 0.00 | 14.15 | 0.072 | 0.057 | 0.120 | 0.060 | 0.058 | -0.000 | -0.010 | 0.010 | 0.042 | -0.121 | -0.062 | 0.131 | -0.038 | -0.006 | 0.190 | -0.013 |
| PhD Student hours | 4.56 | 4.73 | 0.00 | 24.50 | 0.275 | 0.115 | 0.202 | 0.173 | 0.155 | -0.109 | 0.057 | 0.037 | 0.03 | -0.051 | 0.018 | 0.145 | 0.130 | 0.018 | 0.108 | 0.189 |
| Postdoc hours | 2.59 | 3.98 | 0.00 | 48.00 | 0.124 | 0.152 | 0.191 | 0.136 | 0.116 | -0.120 | 0.021 | 0.055 | 0.028 | 0.042 | 0.126 | -0.089 | 0.130 | 0.024 | -0.059 | 0.149 |
| *Initial performance* | | | | | | | | | | | | | | | | | | | | |
| Zero initial publications | 0.09 | 0.29 | 0.00 | 1.00 | -0.175 | -0.156 | -0.189 | -0.044 | -0.092 | 0.147 | 0.045 | -0.033 | 0.001 | -0.077 | -0.125 | 0.131 | -0.271 | -0.044 | 0.115 | -0.101 |
| Ln(initial adj. pub) | 0.42 | 0.86 | -2.48 | 2.30 | 0.411 | 0.148 | 0.233 | 0.216 | 0.278 | -0.208 | 0.103 | 0.120 | -0.069 | 0.141 | 0.291 | 0.062 | 0.023 | 0.099 | 0.047 | 0.235 |
| Zero initial citations | 0.09 | 0.29 | 0.00 | 1.00 | -0.175 | -0.156 | -0.189 | -0.044 | -0.092 | 0.147 | 0.045 | -0.033 | 0.001 | -0.077 | -0.125 | 0.131 | -0.271 | -0.044 | 0.115 | -0.101 |
| Ln(initial year norm. cit) | 0.57 | 0.94 | -3.70 | 2.52 | 0.218 | 0.341 | 0.380 | 0.090 | 0.104 | -0.088 | -0.028 | 0.037 | 0.139 | -0.055 | 0.128 | 0.030 | 0.367 | 0.024 | 0.026 | 0.097 |
| Zero initial CiteScore | 0.09 | 0.29 | 0.00 | 1.00 | -0.186 | -0.166 | -0.207 | -0.046 | -0.097 | 0.165 | 0.034 | -0.038 | -0.005 | -0.063 | -0.134 | 0.141 | -0.294 | -0.046 | 0.123 | -0.108 |
| Ln(initial CiteScore) | 1.81 | 0.83 | -2.02 | 3.36 | 0.262 | 0.272 | 0.363 | 0.112 | 0.137 | -0.184 | -0.002 | 0.090 | 0.042 | 0.067 | 0.268 | -0.054 | 0.385 | 0.040 | -0.049 | 0.121 |

Note: Due to space restrictions, correlations amongst lab measures are reported in Appendix Table A3. No. of observations is 2,097, no. of academics is 262, observation period is 2001-2010. The citation variables refer to the numbers of citations received to autumn 2013. We applied the average CiteScore for 2011-2014. The initial performance variables refer to the pre-sample period 1998-2000. All independent variables are 1-year lagged.

more recent years. Finally, we calculate the average yearly CiteScore of publications, corresponding to the average journal impact of the published work.

*4.3 Independent Variable*

Our main explanatory variable is competitive funding, applied for to and received from national and regional funding bodies. While this funding can be used by the entire lab, the Principal Investigator (PI) is responsible for drafting proposals, managing the funding and making research decisions. Therefore, we consider funding application and receipt at PI level. Funding *application* takes the value 1 if an application was submitted; research funding received (*Italian funding)* is split across the award period (typically 3 years).[14] Due to the large size and infrequency of EU funding, and the multiple researchers involved, we consider it at the lab level (see Section 4.4). In our sample, 62% of academics submitted at least one application during the observation period. Most academics made only one application, resulting in a sample mean of 23%. Funding success is highly skewed, with a few successful applicants (36% of academics). The average amount of funding received was just over €10k.

We consider the academic's gender to measure any potential gap in research activity. In our sample, 38% are women, and the *female* variable is weakly negatively correlated to applying for funding, funding amount and productivity (see Table 1). Mean comparisons reported in Table 2 show that the difference between men and women for publication numbers is high, with women producing a third fewer publications. The difference for the quality/impact measures is weaker and insignificant in the case of Citescore. However, differences in applications for funding are very large with women applying just over half as many times as men and receiving just a third of the funding amount, providing some first indication of primary gender effects.

**Table 2: Mean differences between men and women for core variables**

| *Main variables* | Men<br>Obs = 1307 | Women<br>Obs = 790 | Mean difference<br>(t-test) |
|---|---|---|---|
| Adj. publications | 0.874 | 0.486 | 0.388*** |
| Norm. citations | 0.847 | 0.756 | 0.091** |
| CiteScore (average) | 2.699 | 2.568 | 0.131 |
| Ln(Italian funding+1) | 2.309 | 0.748 | 1.560*** |
| Application | 0.279 | 0.149 | 0.130*** |
| Teaching hours | 3.899 | 3.552 | 0.347*** |
| Administrative role | 0.142 | 0.080 | 0.063*** |
| Small child (0-3yrs) | 0.096 | 0.148 | -0.052*** |
| *Other variables* | | | |
| (Age-50)/10 | 0.246 | -0.368 | 0.614*** |
| Professor | 0.431 | 0.210 | 0.221*** |

*** (**,*) indicate a significance level of 1% (5%, 10%).

[14] The results are confirmed in unreported tests using a funding dummy instead of funding amount. Results available upon request.

We consider teaching, administration and child-care as secondary gender effects and include these as main variables which we interact with *female*. We measure teaching as the number of *teaching hours* per week, a measure rarely included in empirical analyses. Missing values in this measure were imputed using the individual's mean number of teaching hours in other years and mean number of teaching hours of other staff of the same rank, from the same department in the same year. In the final estimation, taking account of missing values in other measures, about 45% of observations were linked to imputed teaching hours. The number of teaching hours per week is 3.8 and varies between zero and 10.9 (a maximum of 330 hours per year, with a mean of approximately 110 hours and a standard deviation of 48 hours). We included a measure for each year that the academic held an *administrative* position within the department, which applied to 61 academics in the sample period (or 12% of observations). The women in our sample, who, on average, are of lower academic ranking, are less likely to hold administrative positions as only full professors can have leadership roles. Women, also, provide slightly fewer hours of classroom teaching (see Table 2). Our expectation is that women would devote more 'real' time to these tasks and that the effect would differ between men and women, generating a secondary gender effect.

To capture parental responsibilities we include a dummy measuring whether the academic cares for a child aged between 0 and 3 years (small child).[15] Since we expect the effect of child care to differ between men and women, we interact these two variables. The share of academics with young children during the observation period is 24%, accounting for 11.5% of observations (10% for men and 15% for women)

*4.4 Controls*

For each academic staff member, we were able to obtain the academic's *age* and *professor* status. We centre age on 50 (the mean) and divide it by 10 to ease reading of the coefficients. Both measures are time-variant. We include a field dummy for *chemistry* staff (reference is *physics*). All these data were available for the full population of academics. In the estimations for average citation numbers, we control for the average number of *coauthors* since the literature suggests there is a strong correlation between number of authors and citations received (Tahamtan et al., 2016; Wuchty et al., 2007).

Each academic is assigned to one of the 89 identified research labs or groups. Research lab assignment allows us to calculate the size of each lab (*lab size*) in terms of number of permanent academic staff. Some labs consist only of a single permanent member of staff, others comprise 10 or more. Mean lab size is 5 and the median is 4. We follow Carayol and Matt (2006) and compute lab group characteristics based on all permanent members of the group excluding the focal academic. We measure average age (centring age on 40 and dividing by 10) of research lab colleagues (*mean age lab*) and the share of full professors (*professors lab*) in each research group. We also include group members' average publication performance (*publication lab*) after

[15] We assume the effect of children will be strongest during the first 3 years of the child's life when state care is not readily available. This is a stricter assumption than in Stack (2004), which considers all pre-schoolers. In additional tests we found that the effect of having an older child (aged 4-6) is insignificant, which supports our assumption.

correcting for co-authorship, and average citations (*citation lab*), or CiteScore (*CiteScore lab*) in the CiteScore equations. These group measures are not available for labs with just one permanent member of staff so we included a dummy for single person lab (*single person lab*) and set all group characteristics to zero. This applies to 17% of labs, accounting for 14% of observations. Academics receive competitive funding, mostly from national sources, and some from international (EU) sources. During the 2004 to 2009 period, 17 academics received EU funding. Given the large size of these projects they cannot be considered individual projects; thus, we split them across the whole lab with the result that EU funding is combined with national and regional Italian funding, to obtain a measure of total funding received by other members of the research lab. Again, we split the research funding across the award period and calculate the average amount of funding (*EU-ITA funding lab*) received per lab member (not including the focal researcher) per year. Finally, we include data on PhD students (*PhD student hours*). We calculated the number of person months per year available to each lab and divided this by the number of lab members. Data on PhD students are available from year 2004 and were imputed for earlier years.[16] The mean number of PhD student months is 4.6. An additional lab variable is post-doc hours, which is included in the selection model predicting selection into funding (see section 5.3). The mean number of postdoc months available to each academic per year is 2.6.

## 5. Estimation model

We conduct a step-wise empirical analysis estimating three different models of scientific productivity. The first considers a model of funding and productivity, taking into account the endogeneity of award of funding, but not selection. We expand this model to account for reverse causality between productivity and parenthood. Finally, in the full model we consider selection into funding competition, thus, estimating all three stages of the funding-productivity chain. At each stage we consider primary and secondary gender effects.

### *5.1 Instrumental variable model*

First we estimate a model assessing the impact of individual competitive funding on the new research being produced, with funding lagged one year in line with the literature.[17] Research productivity is measured as the number and quality or impact of published journal articles. There are a number of biases in the estimation of this relationship, the most relevant being the endogeneity of competitive funding, which means that Ordinary Least Square (OLS) models would overestimate the effect of funding on research performance. Therefore, we need to find a way to isolate the variation in funding success.

To this end, since national and regional competitive funding budgets differ by year, we exploit the exogenous variation in timing of funding by including year fixed effects. In addition, we make use of an Instrumental Variable (IV) model. We define an instrument, namely, the

[16] Results for PhD student hours are robust in the reduced sample estimations not reported here.
[17] Results are robust to a 2 year lag.

academic's national socio-political capital, with the expectation that it will affect the probability of success in obtaining national competitive funding. In several countries, there is evidence of some form of an elite or alumni (e.g., old boy) network effect (Feinberg and Price, 2004; Viner et al., 2004; Shibayama and Geuna, 2016; 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 is expected to be particularly dominant if resources are scarce. Here, we measure academic national socio-political capital as occupying leading management roles in the Italian Physics and Chemistry Societies. Whilst we acknowledge that some level of scientific excellence is required for appointment to such positions,[18] we claim that such influential roles are the result, mainly, of a socio-political process. More importantly, we expect the socio-political capital associated to these types of positions to be correlated to a higher probability of receiving funding from either national or regional funding agencies. Such local social capital would not give priority access to the international publication system and, thus, should not directly affect publication performance. Clearly, using the same instrument for the UK and US could potentially be problematic.

In our sample, 14 academics were elected for at least one year (maximum 6 years non-continuous) to one of these top leadership positions. They were mostly senior men, with women systematically underrepresented in positions of power (Morley, 2014). However, due to the low overall number of observations, the difference between men and women is insignificant (see Table 2). A dummy variable measuring socio-political capital takes the value 1 for the first year of top leadership responsibility and the three succeeding years, to account for the expected longer term effects.[19]

Although this instrument varies across the time window considered, the variance is small, so we include a second instrument. Organizational studies show that human behaviour is affected by isomorphism (Dacin, 1997; Boxenbaum and Jonsson, 2017), that is, individuals tend to behave similar to how other people in the organization behave. In science, academics in the same field will be affected by the fund-raising behaviour of peers (Tartari et al., 2014), they will tend to perform similar activities to their peers and accumulate skills in these activities, which we describe as isomorphism. While we cannot consider the funding received by close peers, we exploit information on the funding success of academics in unconnected research labs in the same discipline (in our sample we consider 82 research labs and two disciplines; see data description above). This considers the fundraising of academics that do not work in the same area of research expertise as the focal academic, but would be working in close proximity to the focal academic and be subject to the same research evaluation mechanisms. In other words, the more funding raised by academics in labs other than the focal one, the greater the likelihood that an academic in the focal lab will receive individual funding without this impacting directly on his or her publication performance. We further tested the statistical appropriateness of the two instruments

[18] In our sample, 4 chemists received a prestigious Italian medal award; only 2 had held major administrative roles in the Italian Chemical Society. In auxiliary regressions, we confirmed that this is not correlated to the outcome variables.
[19] The effects hold, also, if we consider other time windows, such as limiting the effect to the membership period or the 5 years following it. This consistency shows that the socio-political capital built through these memberships is not lost in the short or medium term.

in auxiliary regressions which confirmed that they are not individually or jointly significant in the outcome equations.

We consider the differential effect for women in the first and second stage of the IV model to estimate primary gender effects and the existence of a gender gap. Further, if, as applies to universities in continental Europe, funding cannot be used to free up time from teaching or administrative tasks, and academics experience competing demands on their time, then funding may not always lead to higher performance. Commitments related to having a young child can also compete with research time and, therefore, are considered. All three effects are expected to be stronger for women compared to men (secondary gender effects) and, therefore, are interacted with the *female* dummy.

We need to consider a second source of endogeneity - promotion to a higher academic rank. Mairesse and Pezzoni (2015: 83) note that "career advancement and scientific productivity are strongly related" with high-performing academics more likely to be promoted to professor and higher-ranked academics having greater access to resources and networks, resulting in performance advantages. The authors use 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 the academic's research productivity in year *t-1*, whether they are female, age and its squared term, and year and department dummies. We then include the predicted promotion value in the first stage IV regression and run the productivity equations. The complete model is:

$$P_{it}(\varphi) = \varphi[\widehat{ICF}_{it-1} + \widehat{Pr}_{it-1} + OIC_{it-1} + LR_{it-1} + Te_{it-1} \times Fe_i + Ad_{it-1} \times Fe_i + C_{it-1} \times Fe_i] + \epsilon_{it}$$
$$\widehat{ICF}_{it}(\gamma) = \gamma[IV_{it} + \widehat{Pr}_{it} + OIC_{it1} + LR_{it1} + Te_{it} \times Fe_i + Ad_{it} \times Fe_i + C_{it} \times Fe_i] + \vartheta_{it}$$
$$\widehat{Pr}_{it}(\delta) = \delta[P_{it-1} + OIC_{it}] + \mu_{it} \qquad (1)$$

where $\varphi, \gamma \; and \; \delta$ are the vectors of the parameters to be estimated. *P* measures research productivity, *ICF* individual competitive funding and *Pr* promotion to a higher academic rank. *OIC* measures other individual characteristics, such as age, *LR* measures lab characteristics, *Te* is teaching, *Ad* is administration and *C* denotes existence of a young child. Interactions with *Fe*, indicating that the academic is a woman, are included. *IV* are instrumental variables and the error term $\epsilon$ is uncorrelated to the fitted values of $\widehat{ICF}$ and $\widehat{Pr}$.

### *5.2. Reverse causality and unobserved heterogeneity*

To explore the possibility that the effect of child care is not determined by scientific productivity prior to having children, we follow the suggestion in Wooldridge (2002) to include the logarithm of the academic's 'initial productivity' in the outcome equations in the 2SLS model. This complements the predicted promotion measure which already captures a dynamic second order past research performance effect. The initial productivity variables capture path dependence and cumulative advantage effects in research productivity. They proxy, also, for the otherwise unobserved permanent heterogeneity of individual academics such as their cognitive capability, motivation and talent (Fernández-Zubieta et al., 2016; Mairesse and Pezzoni, 2015). This measure has the advantage that it enables 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, that is, 1998 to 2000, as the initial value and include the logged average as well as a dummy to indicate the ‘zero’ initial value in the model. These also enter the first stage of the IV model.

### *5.3. Modelling selection into funding*

Equation (1), while correcting for multiple sources of bias, does not correct for potential selection into applying for funding. As noted in Section 2, the decision to apply for funding is not random, but is determined endogenously, with academics making the decision to opt in or out of the competition for grants. A modelling approach that accounts for selection has the advantage that we can estimate the propensity to apply for funding. Thus, a selection stage equation can be very informative for understanding who applies for funding. In the selection equation, we include the activities that compete for academics’ time and, thus, may affect proposal writing time. We include predicted promotion, which captures career stage and performance, and past applications since we expect persistence in applying for funding (Bol et al., 2018). As an exclusion restriction, we include the number of postdoc hours available in the academic’s lab. Postdocs are often asked to prepare funding proposals for the lab and, therefore, their availability should have a direct impact on the ability to apply. We test the appropriateness of the restriction in auxiliary regressions and confirm that the variable is insignificant in the funding and outcome equations.

The selection is estimated as:

$$Pr(apply)_{it} = \theta[ER_{it} + \widehat{Pr}_{it} + OIC_{it1} + Te_{it} \times Fe_i + Ad_{it} \times Fe_i + C_{it} \times Fe_i + apply_{it-1}] + \sigma_{it} \qquad (2)$$

where $\theta$ is the parameter being estimated and $ER$ is the exclusion restriction. We next estimate the 2SLS model in equation (1). To do this, we estimate separate equations for those who applied and those who did not apply for funding. We set the selection to 1 for the three years after a funding application since this is the usual funding window and, therefore, the period when we would expect to see an effect of funding. We include the inverse Mills ratio ($\alpha^{\rho}$) in the IV model equation (1). A statistically significant $\alpha^{\rho}$indicates that selection bias would be ignored if we did not model the decision to apply.

## 6. Empirical Analysis

### *6.1 2SLS IV regression*

We estimate equation (1) as a 2SLS, taking logs plus the units of the publication and funding measures to correct for their skewness.[20] All explanatory variables are lagged one year, which means that publications in 2010 are estimated based on 2009 individual and lab characteristics. Year fixed effects are included in all the models and standard errors are clustered at the individual and laboratory levels (nested). Table 3 reports the promotion equation and first and second stages of the 2SLS model

[20] Unreported tests using a count publication measure rather than a log dependent variable, confirm the overall results.

The promotion equation in Table 3 column 1 shows that being a professor is linked to prior performance, but, unlike Mairesse and Pezzoni (2015), we find no evidence of a significant promotion disadvantage for women (the female dummy is negative, but not significant). The predicted professor effect is positive and significant in both the first stage funding equation and the second stage productivity equation. This is due to second order past research performance effects, which determine future productivity while, at the same time, determining the likelihood of obtaining funding. These effects are particularly strong in the first stage, where the amount of funding awarded to professors is almost four times higher than that awarded to more junior members of staff. The first stage instrument equation shows, also, that our instruments are good predictors of funding. The effects can be interpreted as elasticities and show that members of esteemed organizations receive two-and-a-half times more funding than non-members.[21] Funding by other labs in the same field is also positive, predicting an increase in the focal academic's funding of more than 50% for a 100% increase in funding to other labs. Both instruments are jointly significant and satisfy the test for exogeneity.

In terms of gender differences, we find a strongly significant negative correlation between female researcher and amount of competitive funding, with funding being 90% less for women compared to men, suggesting serious gender differences in access to resources. Since the model includes a promotion equation that controls for past performance and other individual and lab characteristics, the gender difference might be driven by either gender biased funding allocation or differences in proposal quality, drafting or selling skills between women and men.

Concerning secondary gender effects, we found no evidence of a negative effect of teaching on the probability of raising money. Taking an administrative position has a negative coefficient for women, albeit insignificant. In auxiliary regressions that include only leading administrative posts, we observe a negative, significant interaction effect suggesting that female top administrators may have less time to develop successful grant applications and, thus, receive significantly less funding. However, we should highlight that the high coefficient may due to the small number of women holding such top administrative posts.

Further, there is no negative effect of being female with young children on the probability of raising money, which suggests that parental duties likely do not correlate with the quality of proposal writing and, thus, the probability of winning a competitive grant.

In terms of control variables, we find that the share of full professors in the lab has a strong negative sign, which indicates that individuals in a lab with a higher share of full professors will raise less funding. For example, an increase in the share of full professors in the lab from 31%, the mean, to 50%, decreases the amount of individual funding by about a third. PhD student hours are strongly positive, underlining the relevant support role provided by doctoral students in either having good research ideas, drafting good quality research proposals or freeing time for the PI to write research proposals.

[21] The log includes a unit that was added so as not to lose observations with zero funding. This unit can be ignored in the case of funding where €1 more makes little difference to the overall amount received, and the effects can be interpreted as elasticities.

**Table 3: Results of two-stage least square regression on research outcomes**

| | Probit | | 1st Stage | | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Professor | | Ln(Italian funding+1) | | Ln(adj.publications+1) | | Ln(norm.citations+1) | | Ln(CiteScore+1) | |
| | b | se | b | se | b | se | b | se | b | se |
| Ln(Italian funding+1) | | | | | 0.003 | 0.022 | 0.004 | 0.017 | 0.020 | 0.034 |
| Female | -0.148 | 0.248 | -0.957** | 0.485 | -0.178*** | 0.049 | -0.040 | 0.060 | -0.023 | 0.091 |
| Teaching hours | | | 0.064 | 0.106 | -0.007 | 0.009 | -0.007 | 0.010 | -0.001 | 0.017 |
| Female#Teaching hours | | | 0.050 | 0.120 | 0.017 | 0.011 | 0.008 | 0.013 | 0.006 | 0.020 |
| Administrative post | | | 0.784 | 0.539 | 0.083 | 0.052 | -0.019 | 0.039 | 0.077 | 0.063 |
| Female#Administrative post | | | -1.164 | 0.736 | -0.069 | 0.071 | 0.100 | 0.075 | -0.101 | 0.107 |
| Small child (0-3) | | | 0.294 | 0.560 | 0.037 | 0.069 | 0.138** | 0.056 | 0.156** | 0.063 |
| Female#small child | | | 0.021 | 0.619 | -0.120* | 0.067 | -0.151** | 0.067 | -0.228** | 0.093 |
| *Controls* | | | | | | | | | | |
| (Age-50)/10 | 1.641*** | 0.149 | -0.394 | 0.241 | -0.199*** | 0.028 | -0.132*** | 0.029 | -0.359*** | 0.047 |
| (Age-50)/$10^2$ | -0.345*** | 0.097 | -0.264** | 0.119 | -0.046*** | 0.014 | -0.017 | 0.011 | -0.016 | 0.019 |
| Pr(professor) | | | 3.596*** | 1.052 | 0.627*** | 0.135 | 0.323** | 0.132 | 0.917*** | 0.194 |
| Ln(coauthors+1) | | | | | | | 0.095*** | 0.012 | | |
| *Lab measures* | | | | | | | | | | |
| Single person lab | | | -1.507*** | 0.576 | -0.148** | 0.068 | -0.004 | 0.055 | -0.172* | 0.092 |
| Lab size | | | -0.075* | 0.041 | -0.010*** | 0.004 | -0.007* | 0.004 | -0.002 | 0.007 |
| Mean age lab | | | 0.287 | 0.291 | -0.019 | 0.029 | -0.037 | 0.032 | -0.103** | 0.044 |
| Professors lab | | | -1.844** | 0.730 | -0.033 | 0.074 | 0.081 | 0.081 | 0.228** | 0.116 |
| Publications lab | | | -0.365 | 0.232 | 0.043 | 0.034 | 0.031 | 0.034 | -0.049 | 0.040 |
| Citations lab | | | 0.000 | 0.006 | -0.001 | 0.001 | 0.004*** | 0.001 | | |
| CiteScore lab | | | | | | | | | 0.053** | 0.022 |
| Ln(EU-ITA funding lab+1) | | | 0.022 | 0.029 | -0.001 | 0.002 | 0.001 | 0.002 | -0.004 | 0.003 |
| PhD Student hours | | | 0.104*** | 0.033 | 0.015*** | 0.005 | 0.007 | 0.005 | 0.017** | 0.008 |
| Chemistry | | | -0.446 | 0.374 | -0.011 | 0.040 | -0.044 | 0.039 | -0.063 | 0.056 |
| *Instruments* | | | | | | | | | | |
| Social capital | | | 2.596** | 1.297 | | | | | | |
| Ln(Italian funding other labs+1) | | | 0.504*** | 0.156 | | | | | | |
| Ln(l.adj.pub+1) | 0.517** | 0.231 | | | | | | | | |
| Ln(l.citations+1) | 0.217*** | 0.065 | | | | | | | | |
| Joint sign. of department dummies (6) | 7.61 | | | | | | | | | |
| Constant | -1.527*** | 0.362 | -5.221*** | 1.840 | 0.349*** | 0.072 | 0.159** | 0.067 | 0.630*** | 0.101 |
| Pseudo/Adjusted $R^2$ | 0.497 | | | | 0.244 | | 0.219 | | 0.228 | |
| Hansen J-test (p-value) | | | | | 0.154 | | 0.132 | | 0.921 | |
| Underidentification test (p-value) | | | | | 0.00137 | | 0.00142 | | 0.00150 | |
| ***dydx(Female)*** | -0.027 | 0.044 | -0.900*** | 0.276 | -0.138*** | 0.038 | -0.015 | 0.031 | -0.040 | 0.050 |

Note: N = 2097; clusters = 262 in individual id, 86 in lab. *** (**,*) indicate a significance level of 1% (5%, 10%). Year dummies included; robust clustered standard errors. Publication counts are co-author adjusted. Citations are year normalized. First stage regression for adjusted publication count is reported. First stage estimations for normalized citations and CiteScore are similar and available upon request.

Table 3 Models 1 to 3 respectively report the results for co-author adjusted publication count, normalized average number of citations and average CiteScore. After instrumenting, we find no significant link between funding and publications, citations or CiteScore. These results show that, after removing potential sources of endogeneity, funding does not have a significant effect on performance, although this should be contextualized to the Italian system where national competitive funding plays a marginal role (less than 10% of total university research funding). [22]

We next look at primary and secondary gender effects. In Model 1 (adjusted publications), the female dummy exerts the strongest influence among these variables, entering negatively, in line with prior research. When we calculate elasticities, we find that, on average, women produce 14% fewer publications than men. The primary gender effect is insignificant for citations and Citescore, suggesting that after controlling for other factors, women do not publish lower quality/impact research.

Teaching hours are negative in the publication and citation models, but the coefficients are small and non-significant. [23] Women's teaching responsibilities are positive, but insignificant, which suggests that, in the Italian case, teaching is not correlated to scientific productivity for either men or women. Administrative roles enter insignificantly; their interaction with gender is negative but also insignificant. However, due to convention and regulation of the Italian system only full professors can be appointed to the most senior administrative positions and, therefore, any effect may be captured by the professor variable.

The marginal effects of the interaction between female and having a child are depicted in Figure 2. The interaction between being female and having small children is negative, and weakly significant in the publications count model, indicating that women caring for a small child publish less than those without children. In the citation model (Table 3 Model 2), the female dummy is insignificant, but the interaction with children is significant and negative, while the children dummy for men is positive. The CiteScore model in Table 3 Model 3, confirms the positive effect of young children for men and the negative effect for women. This indicates that women academics with young children receive fewer citations than men with children, which might be explained by the parental role separation in childcare. While fathers take on the role of breadwinner and their partners assume domestic responsibilities, women do not benefit from this separation; they tend to have to perform both work and domestic roles and their performance in terms of citation numbers reduces. Thus, when women are caring for young children, a citations performance gap emerges between men and women. This might be because women are unable to devote enough time to developing or promoting research with a high impact (Acker and Armenti, 2004; Rafnsdóttir and Heijstra, 2013; Myers et al. 2020). For instance, women may not be able (due to physical and psychological strain) to devote the time required for extensive revisions or may be unable to attend international meetings to present their research, which reduces its visibility. We tested for visibility by checking whether single-authored publications from women authors receive fewer citations than those authored by men;

[22] A base OLS model that does not account for endogeneity of funding is presented in Appendix Table A4. The base model, in line with prior research, shows a positive, albeit small, effect of individual competitive public funding.

[23] This is confirmed in models that do not include the imputed values.

however, we found no evidence that this was the case. Nevertheless, we cannot rule out loss of visibility during child caring years as a possible explanation for reduced publications impact.

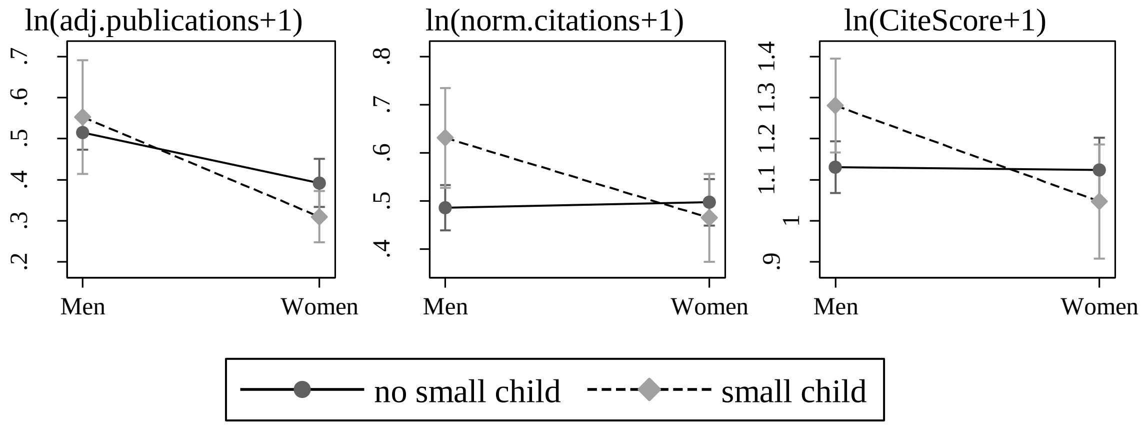


**Figure 2:** Predicted outcome variables by gender and parenthood
(full estimation results presented in Table 3)

The control variables provide some interesting insights. Publications, citations and CiteScore are associated to higher academic rank, but generally decrease with age. The citations model confirms the positive correlation to co-author numbers, in line with prior research. Lab size is correlated negatively to publications and citations numbers, but seem not to be related to article CiteScore. Average age of lab members has a negative effect in the CiteScore model, suggesting that academics working in groups that include older members, on average, produce lower quality research compared to those whose colleagues are younger. The share of full professors in the lab has a positive sign in the CiteScore model, but has no effect in the publications and citations count models. Lab performance in terms of quality/impact is correlated strongly to citations and CiteScore, while lab funding is insignificant in all the models. We found, also, that the number of PhD student hours is linked positively to publications and CiteScore. This highlights the relevant role played by postgraduate students in the successful operation of labs in Italy; the larger the number of PhD students in the PI's lab, the higher the number (and the impact) of papers they produce.

*6.2 Controlling for reverse causality*

Figure 2 shows that a productivity gap in terms of publication quality/impact emerges between men and women with the presence of young children. While we can assume that men are encouraged and are more able to focus on their research work, we cannot rule out a positive citation and CiteScore effect for men stemming from their opting for fatherhood once a performance advantage is achieved. In other words, we cannot rule out reverse causality.

In the descriptive analysis depicted in Figure 3, we observe that men who become fathers outperformed male peers with no children prior to their becoming fathers and this performance advantage increases further once the child is born. The analysis is limited to academics under the age of 45, which covers the main period for becoming parents among both the men and women in the sample. Women who decide to have a child show slightly above average performance compared to women who never have children, but this performance advantage disappears once the child is born.

To investigate further whether this gender effect is determined by performance prior to having a child, we control for initial performance, as described in Section 5.2. This allows us to control, also, for overall time-invariant unobserved heterogeneity and cumulative publication advantage. The results of the outcome equation of the 2SLS model reported in Table 4, show that the initial value enters positively in the outcome equations and reduces the positive child effect for men, rendering it insignificant for citations, while the negative child effect for women remains almost unchanged. This suggests that the female effect is causal, while we cannot reject the hypothesis of reverse causality for male researchers, that is, that they decide to become fathers once they are become established on a high performance path.

In the first stage equations, the negative correlation between female researcher and amount of competitive funding is confirmed with funding being 77% less for women compared to men. Also, in terms of secondary gender effects, the administrative position effect for women turns significant, confirming that female administrators suffer a time substitution effect with fund raising. At the same time, administration now enters significantly positive in Model 1 (adjusted publications), suggesting that researchers taking administrative responsibilities tend to be more productive.

Most control variables lose some magnitude after controlling for initial performance, although the signs remain largely unchanged. Lab effects turn largely insignificant with the exception of PhD hours, which remains positive and significant in the publication and CiteScore models.

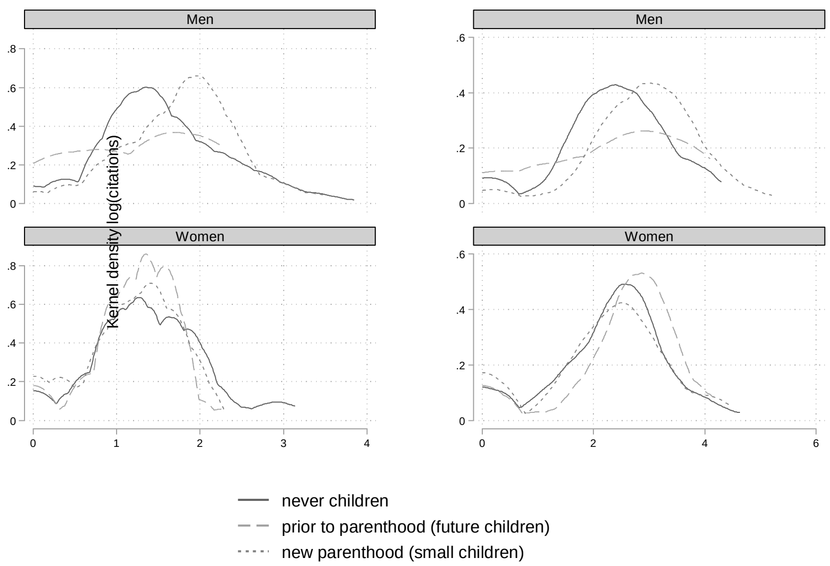


**Figure 3:** Kernel density of publications and citations for men and women and by parenthood status

**Table 4: Results of two-stage least square regression on research outcomes controlling for initial condition**

| | 1st stage Ln(Italian funding+1) b/se | (1) Ln(adj.publications+1) b/se | (2) Ln(norm.citations+1 b/se | (3) Ln(CiteScore+1) b/se |
|---|---|---|---|---|
| Individual Italian funding | | -0.010 | 0.002 | 0.015 |
| | | (0.023) | (0.016) | (0.026) |
| Female | -0.628 | -0.110** | 0.029 | 0.083 |
| | (0.518) | (0.053) | (0.053) | (0.074) |
| Teaching hours | 0.054 | -0.006 | 0.001 | 0.008 |
| | (0.105) | (0.009) | (0.009) | (0.010) |
| Female#Teaching hours | -0.000 | 0.005 | -0.005 | -0.009 |
| | (0.130) | (0.013) | (0.011) | (0.016) |
| Administrative post | 0.829 | 0.105** | 0.005 | 0.074 |
| | (0.525) | (0.052) | (0.035) | (0.055) |
| Female#Administrative post | -1.352* | -0.109 | 0.029 | -0.104 |
| | (0.774) | (0.070) | (0.070) | (0.084) |
| small child (0-3) | 0.276 | 0.034 | 0.070 | 0.089 |
| | (0.512) | (0.068) | (0.057) | (0.057) |
| Female#small child | 0.061 | -0.115* | -0.137** | -0.223** |
| | (0.582) | (0.067) | (0.068) | (0.088) |
| *Controls* | | | | |
| (Age-50)/10 | -0.217 | -0.169*** | -0.126*** | -0.335*** |
| | (0.225) | (0.028) | (0.024) | (0.044) |
| $(Age-50)/10^2$ | -0.164 | -0.024* | -0.005 | 0.019 |
| | (0.107) | (0.012) | (0.010) | (0.015) |
| Pr(Professor) | 2.651*** | 0.471*** | 0.267** | 0.753*** |
| | (1.016) | (0.124) | (0.107) | (0.160) |
| Ln(Coauthors+1) | | | 0.050*** | |
| | | | (0.014) | |
| Chemistry | -0.502 | -0.005 | -0.069** | -0.038 |
| | (0.353) | (0.036) | (0.034) | (0.047) |
| Zero initial adj.pub \| norm.cit \| | -0.075 | -0.143*** | -0.117*** | -0.025 |
| CiteScore | (0.446) | (0.037) | (0.032) | (0.085) |
| Ln(initial adj.pub \| norm.cit \| | 0.718*** | 0.141*** | 0.125*** | 0.262*** |
| CiteScore) | (0.191) | (0.028) | (0.018) | (0.032) |
| *Instruments* | | | | |
| Social capital | 2.400* | | | |
| | (1.255) | | | |
| Ln(Italian funding other | 0.520*** | | | |
| labs+1) | (0.159) | | | |
| Constant | -5.559*** | 0.307*** | 0.205*** | 0.111 |
| | (1.917) | (0.071) | (0.074) | (0.090) |
| Lab controls | YES | YES | YES | YES |
| Adjusted $R^2$ | | 0.291 | 0.282 | 0.334 |
| Hansen J-test (p-value) | | 0.439 | 0.139 | 0.860 |
| Underidentification test (p-value) | | 0.00126 | 0.00155 | 0.00146 |
| ***dydx(Female)*** | -0.774*** | -0.119*** | -0.003 | 0.011 |
| | (0.272) | (0.037) | (0.022) | (0.040) |

Note: N = 2097; clusters = 262 in individual id, 86 in lab. *** (**,*) indicate a significance level of 1% (5%, 10%). Year dummies are included; robust clustered standard errors in parentheses. Publication counts are co-author adjusted. Citations are year normalized. First stage regression for adjusted publication count is reported. First stage estimations for normalized citations and CiteScore are similar and available upon request.

*6.3 Controlling for selection*

The estimations reported above may suffer from selection bias. We address this by accounting for selection into applying for funding (equation (2)). The number of observations is reduced to 1,846 since we include a lagged application variable in the selection model to account for the Matthew effect in applying for funding (Bol et al., 2018).

Table 5 Model 1 reports the results of the selection stage. It shows that the decision to apply is linked to the predicted professor effect, which also captures second order past research performance effects, and to prior funding applications. The exclusion restriction, post-doc hours, is positive and significant. We find no evidence of a gender or child effect. However, we do find a positive effect of teaching hours and administrative position. While we would assume that these activities could be substitutes in the academic's time allocation, it appears that this is not the case. Anecdotal evidence for the Italian system confirms polarization, with a group of most productive researchers engaging in all academic activities (Bianchini et al. 2013). We do not find strong evidence of secondary gender effects in the selection, though for women having an administrative position is negative albeit insignificant.

Table 5 Model 2 shows the results of the first stage of the 2SLS model on publications for those that selected into funding. Taking account of selection is crucial for estimating funding success as indicated by the strongly significant inverse Mills ratio ($\alpha^{p}$) in the first stage of the 2SLS. The social capital IV is no longer significant in this model. This suggests that there is some level of self-selection taking place at the application stage, with those lacking social capital not applying for funding. However, both instruments are jointly significant ($p$ = 0.0220). Due to the selection, the negative marginal effect for women increases in this estimation compared to the model without selection. Calculation of elasticities suggests that after accounting for selection, the negative gender effect becomes stronger and that men receive 120% more funding compared to women. This indicates that a gender biased funding allocation and/or differences in proposal quality, drafting or selling skills may be influencing award of funding (e.g., Steinþórsdóttir et al., 2020).

Teaching hours enter negatively, suggesting that lack of proposal writing time may lead to lower quality proposals. The effect is significant only at the 10% level and is insignificant in the first stage equation for citations count or CiteScore. Holding an administrative post remains positive but insignificant while the gender interaction stays negative and insignificant. Once selection is taken into account, all the lab controls become insignificant, with the exception of a negative effect of professors in the lab.

Table 6 Model 1 shows the results of the 2SLS model on publications for those that selected into funding competition. In addition, Model 2 shows separate results for those that did not apply for funding. Therefore, we have two sets of outcome estimations for those actively seeking funding and those not doing so. The equivalent estimations for citations and CiteScore are presented in Models 3 and 4, and 5 and 6 respectively.

The outcome equations confirm the insignificant funding effect in Tables 3 and 4. The marginal effect shows that women, regardless of whether or not they applied for funding, have fewer publications than men. However, they do not produce lower quality research. Teaching and administrative roles are insignificant for almost all outcomes; administration entering positively in Model 1 (publications of those that select into funding) and Model 6 (CiteScore of those that select out of funding).

In the research quality equations, a negative female-child interaction effect is found only for those that did not apply for funding. Instead, women that select into applying for competitive funding do not differ from men in terms of their publication performance, regardless of whether or not they have children. This result may be indicative of the career priorities and ambitions of the women and men in the two sub-samples. The other coefficients are largely consistent between the two sub-samples, with secondary gender effects for teaching and administration (mostly negative) not significant.

We are aware that our results might be sensitive to changes in the dependent variables. To check the sensitivity of our results, we tested them in alternative regressions, reported in Appendix 2. They confirmed our overall findings.

**Table 5: Results of selection and first stage of two-stage least square regression on accounting for selection**

| | Selection Application | | 2SLS 1$^{st}$ stage Ln(Italian funding+1) | |
|---|---|---|---|---|
| | b | se | b | se |
| Female | -0.174 | 0.219 | -0.975 | 1.284 |
| Teaching hours | 0.057$^{*}$ | 0.031 | -0.238$^{*}$ | 0.138 |
| Female#Teaching hours | 0.008 | 0.050 | -0.059 | 0.295 |
| Administrative post | 0.219$^{*}$ | 0.122 | 0.268 | 0.610 |
| Female#Administrative post | -0.210 | 0.252 | -0.040 | 1.631 |
| Small child (0-3) | 0.101 | 0.230 | 0.499 | 0.771 |
| Female#small child | -0.041 | 0.285 | 0.255 | 1.106 |
| *Controls* | | | | |
| (Age-50)/10 | -0.107 | 0.089 | 0.539 | 0.435 |
| (Age-50)/10$^2$ | -0.124$^{***}$ | 0.039 | -0.160 | 0.309 |
| Pr(professor) | 0.993$^{***}$ | 0.291 | -1.087 | 1.400 |
| Chemistry | 0.066 | 0.099 | -2.463$^{*}$ | 1.417 |
| Postdoc hours | 0.032$^{***}$ | 0.009 | | |
| Lagged Application | 0.734$^{***}$ | 0.097 | | |
| Zero initial adj.pub | | | 1.814 | 1.104 |
| Ln(initial adj.pub) | | | 1.612$^{***}$ | 0.371 |
| *Instruments* | | | | |
| Social capital | | | 1.275 | 1.257 |
| Ln(Italian funding other labs+1) | | | 2.056$^{***}$ | 0.767 |
| $\alpha^{\rho}$ | | | -0.399$^{***}$ | 0.071 |
| Constant | -1.529$^{***}$ | 0.188 | -20.026$^{**}$ | 9.638 |
| Lab controls | NO | | YES | |
| Observations | 1846 | | 753 | |
| IDs | 257 | | 162 | |
| Pseudo $R^2$ | 0.144 | | | |
| ***dydx(Female)*** | -0.047$^{*}$ | 0.026 | -1.200$^{**}$ | 0.569 |

Note: *** (**,*) indicate a significance level of 1% (5%, 10%). Year dummies included; robust standard errors, clustered at individual and lab. First stage estimations for citations and CiteScore are similar and available upon request.

**Table 6: Results of two-stage least square and OLS regressions accounting for selection**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Ln(adj.publications+1) | | Ln(norm.citations+1) | | Ln(CiteScore+1) | |
| | 2nd Stage 2SLS | Not selected | 2nd Stage 2SLS | Not selected | 2nd Stage 2SLS | Not selected |
| | b/se | b/se | b/se | b/se | b/se | b/se |
| Ln(Italian funding+1) | -0.034 | | -0.001 | | -0.020 | |
| | (0.027) | | (0.019) | | (0.028) | |
| Female | -0.284** | -0.055 | 0.140 | -0.003 | 0.219 | 0.139* |
| | (0.113) | (0.053) | (0.118) | (0.067) | (0.185) | (0.074) |
| Teaching hours | -0.008 | -0.015 | 0.004 | 0.002 | 0.012 | -0.003 |
| | (0.014) | (0.010) | (0.017) | (0.010) | (0.016) | (0.015) |
| Female#Teaching hours | 0.030 | -0.005 | -0.033 | 0.004 | -0.053 | -0.012 |
| | (0.027) | (0.012) | (0.025) | (0.015) | (0.042) | (0.019) |
| Administrative post | 0.101** | 0.055 | 0.006 | 0.051 | 0.027 | 0.169** |
| | (0.049) | (0.083) | (0.039) | (0.069) | (0.057) | (0.077) |
| Female#Administrative post | -0.008 | -0.058 | -0.072 | 0.078 | -0.159 | -0.157 |
| | (0.090) | (0.094) | (0.086) | (0.105) | (0.107) | (0.108) |
| Small child | 0.108 | -0.028 | -0.007 | 0.088 | 0.115 | 0.069 |
| | (0.086) | (0.073) | (0.046) | (0.066) | (0.089) | (0.060) |
| Female#small child | -0.127 | -0.064 | -0.050 | -0.195*** | -0.067 | -0.296** |
| | (0.110) | (0.079) | (0.104) | (0.073) | (0.136) | (0.134) |
| *Controls* | | | | | | |
| (Age-50)/10 | -0.173*** | -0.173*** | -0.100* | -0.142*** | -0.299*** | -0.390*** |
| | (0.040) | (0.030) | (0.052) | (0.025) | (0.050) | (0.053) |
| (Age-50)/$10^2$ | -0.003 | -0.012 | -0.006 | 0.004 | 0.041 | 0.024 |
| | (0.027) | (0.013) | (0.022) | (0.014) | (0.026) | (0.019) |
| Pr(Professor) | 0.368*** | 0.412*** | 0.201 | 0.271*** | 0.613*** | 0.824*** |
| | (0.123) | (0.119) | (0.138) | (0.099) | (0.154) | (0.161) |
| Ln(Coauthors+1) | | | 0.068* | 0.044*** | | |
| | | | (0.035) | (0.014) | | |
| Chemistry | 0.044 | -0.042 | -0.050 | -0.089** | 0.086 | -0.113** |
| | (0.052) | (0.043) | (0.053) | (0.036) | (0.066) | (0.056) |
| Zero initial adj.pub \| norm.cit \| CiteScore | 0.006 | -0.144*** | -0.070 | -0.142*** | 0.168 | -0.046 |
| | (0.097) | (0.035) | (0.084) | (0.033) | (0.115) | (0.091) |
| Ln(initial adj.pub \| norm.cit \| Citescore | 0.261*** | 0.104*** | 0.133*** | 0.111*** | 0.295*** | 0.243*** |
| | (0.065) | (0.024) | (0.028) | (0.018) | (0.034) | (0.035) |
| $\alpha^{\rho}$ | -0.024* | -0.003 | -0.002 | -0.001 | -0.022* | -0.009** |
| | (0.013) | (0.002) | (0.013) | (0.004) | (0.013) | (0.005) |
| Constant | 0.562*** | 0.278*** | 0.216 | 0.206*** | 0.327* | 0.184* |
| | (0.176) | (0.090) | (0.198) | (0.067) | (0.198) | (0.105) |
| Lab controls | YES | YES | YES | YES | YES | YES |
| Observations | 753 | 1087 | 753 | 1087 | 753 | 1087 |
| IDs | 162 | 205 | 162 | 205 | 162 | 205 |
| Adjusted $R^2$ | 0.155 | 0.257 | 0.195 | 0.333 | 0.206 | 0.371 |
| Hansen J-test (p-val.) | 0.479 | 0.407 | 0.338 | 0.900 | 0.255 | 0.696 |
| Underidentification test (p-value) | 0.0342 | | 0.0497 | | 0.0285 | |
| ***dydx(Female)*** | -0.173** | -0.087** | -0.011 | -0.009 | -0.032 | 0.040 |
| | (0.061) | (0.031) | (0.040) | (0.031) | (0.079) | (0.040) |

Note: *** (**,*) indicate a significance level of 1% (5%, 10%). Year dummies are included; robust standard errors in parentheses, clustered at individual and lab. Publication counts are co-author adjusted. Citations are year normalized.

## 7. Conclusions

In this study, we revisited the funding-productivity nexus looking, in particular, at primary and secondary gender effects. We add to existing studies by considering all stages of the research process from the decision to apply for funding, success in being awarded funding for research, and producing the research output. We further considered the role of gender at each stage, examining direct effects and effects mediated by other academic and non-academic activities, such as teaching, administration and parental responsibilities, to shed new light on the 'productivity puzzle'. We proposed and implemented a new estimation model, employing 2SLS, with a promotion equation and an IV equation for individual competitive funding, to address potential endogeneity concerns. We controlled, also, for performance differences ex-ante, allowing us to validate the direction of causality of the gender effects. In accounting for selection into applying for funding, we provide unique insights into differences between applicants and non-applicants. Further, we include information on teaching, administration and child care commitments, which might compete with academics' efforts to raise funding or publish their research, effects we expect to be stronger for women. Given the problems associated to correct measurement of the production of new knowledge, in this paper we proxy research output using a large set of measures to capture output quantity and quality/impact. All the robustness checks confirmed our main results.

To address selection and endogeneity concerns not dealt with sufficiently in the existing literature, we developed a 2SLS IV based model to account for selection into funding, in which we showed that individual competitive funding is linked inherently to individual characteristics such as career stage, prior performance, gender and socio-political capital. These findings are in line with the existence of a Matthew effect related to accumulated advantage in applying for and receiving funds, as suggested in the prior literature (e.g., Laudel, 2006; Perc, 2014; Steinþórsdóttir et al., 2020). Women were found to raise less funding than men, an effect that was larger after accounting for selection, which could be an indication of gender biased funding allocation (as suggested by van der Lee and Ellemers, 2015 and Witteman et al., 2019) or differences in proposal quality, drafting or selling skills (due, possibly, to gendered language; van der Lee and Ellemers, 2015).

Taking account of these differences in access to research funding, we have shown that competitive research funding does not translate into higher numbers of publications or higher quality/impact. We shed new light, also, on the relationship between gender and research productivity. We showed that women produce fewer, but not lower quality research papers, which is consistent with the previous literature (e.g. Lynn et al. 2018). When we examined the impact of caring for a young child, we found that women produce lower impact research (motherhood penalty). This suggests that women who have responsibility for young children are unable to devote enough time to developing or promoting high impact research. Indeed, prior studies suggest that women encounter more difficulties managing work and family life, in effect limiting the time they can allocate to extensive revisions or to promoting their research compared to men (Acker and Armenti, 2004; Rafnsdóttir and Heijstra, 2013). The current COVID-19 pandemic has increased this burden further, which may amplify gender differences in the coming years (Myers et al. 2020). We found that the child-care effect is driven by those that do not apply for funding, suggesting some level of self-selection in terms of career and research ambitions between the subsamples of applicants and non-applicants. The group producing the most highly cited research is men with young children, which points to their embrace of the role of breadwinner, in line with Stack (2004). However, if we control for past performance level, this effect becomes insignificant, which suggests that the decision to have children is a strategic one for men.

We found evidence, also, of a rather complex interaction between gender and other academic activities. Teaching seems not to be a relevant constraint on the conduction of research (no significant correlation with our productivity measurements); however, we found some evidence that those active in applying for grants are also more involved in teaching, but that the quality of the proposals could suffer from the time devoted to teaching commitments, resulting in lower funding success. As for teaching, we found that researchers involved in administration are more inclined to apply for funding and some are also more productive. These results provide some support to the view of a system in which there is a subgroup of highly active researchers able to perform on each of the three main tasks of university life (teaching, research and administration) for which time substitution effects seem to be less relevant. We found no significant second level gender effect associated to teaching, while we found some weak evidence that female academics involved in administrative duties (especially at the highest level) are less prone to submit new research proposals and raise funding. This could be due to women devoting more time to these tasks or having more difficulty in managing time between competing tasks, resulting in lower propensity to apply for and obtain funding, publications and citations.

There are some limitations we need to acknowledge. Our results are specific to a national research system where grant-based funding is low and teaching buy-outs are not the norm. This situation could be comparable to other countries in Europe, where block funding still dominates. However, the results might be different for countries where competitive funding is favoured, such as in the UK and the US, or is indispensable such as in Russia. Also, in the period considered, national competitive funding suffered some discontinuity. Therefore, lack of a relationship between caring for children and raising competitive money might have been affected by the co-occurrence of having children and lack of opportunities to apply for competitive funds, yet, this would have affected all academics. The dataset used for this study is small, is limited to one university and covers only a 10 year window. While our results are robust, we would encourage further studies using larger datasets.

We found that a leading management position in the Italian Physics and Chemistry Societies more than doubles the amount of funding received, which is concerning from a policy perspective. This situation is not unique to Italy; there is evidence of it in China and the US (Feinberg and Price, 2004; Fisman et al., 2017). However, appointment to an esteemed position in such societies is not always linked to merit and, even if merit plays a part, other networks should receive the same funding preferences. In Italy, where funding is particularly scarce, this dominance of elite networks could impede research progress seriously. The socio-political capital effect vanishes when we account for selection into applying for funding. We argue that this is due to self-selection out of the funding race, by academics who lack these network links.

In terms of further policy implications of our study, we can conclude that unless support systems are put in place for women with childcare responsibilities, funding will not translate into more or more highly-cited publications. In the current pandemic, women with children have experienced even stronger limitations on their work time (Myers et al. 2020); therefore, addressing these disparities and providing additional support is ever more critical.

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## Appendix

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

All the professors in a department were arranged in an $n \times n$ matrix, where $n$ is the number of professors. Given funding structure of the Italia system, full professors were identified as PIs. All publications of the 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 have been built around one, or in few cases two, full professor. 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: Robustness Checks

We conduct a number of robustness checks that test if our results hold for alternative measures of the dependent variable. Firstly, we report the results for the normal publications count, not adjusted for co-author numbers (descriptive statistics in Table A5). Before estimating these models, we exclude researchers in the three applied physics labs who tend to work in large teams of up to 300 authors and could skew the results; this leaves a sample of 250 academics. The estimations accounting for selection and reverse causality are reported in Table A6 Columns 1 and 2. The results confirm the insignificant funding effect. The female dummy, however, loses significance and the marginal effect turns insignificant for the sub-sample of non-applicants. At the same time the female-child dummy enters negative and significant, suggesting that, not accounting for co-author numbers, overall, women produce fewer publications following the arrival of a child in both the applicant and non-applicant samples.[24]

In a second robustness check (Table A6 Columns 3 and 4), we regress on a citation count that is not year-normalized (descriptive statistics in Table A5). For the non-normalized citation measure the instruments cannot fully solve endogeneity and the Hansen J-test cannot reject overidentification of the instruments. Consequently, funding enters significantly. The negative child effect for women remains strong and significant in the sample of those that do not apply for funding.

We conducted additional robustness checks using alternative quality/impact measures provided by Elsevier, Source-Normalized Impact per Paper (SNIP) and the SCImago Journal Rank (SJR) (descriptive statistics in Table A5). These results are reported in Table A7 and confirm the insignificant primary gender effect and the motherhood penalty found in the CiteScore estimations. Further, for a subset of publications, we were able to record Thomson Reuters JIF and the Article Influence Score (AIS). Results not reported here confirmed the overall findings of the Elsevier measures.

[24] The robustness of the results was also confirmed in an IV/GMM Poisson model on the publication count outcome. The estimation is available upon request.

## Appendix 3: Appendix Tables

**Table A1: 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 A2: 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 A3: Correlations amongst lab variables**

| Variables | (17) | (18) | (19) | (20) | (21) | (22) | (23) | (24) | (25) | (26) |
|---|---|---|---|---|---|---|---|---|---|---|
| (17) Single person lab | 1.000 | | | | | | | | | |
| (18) Lab size | -0.483 | 1.000 | | | | | | | | |
| (19) (Mean age lab-50)/10 | 0.033 | -0.105 | 1.000 | | | | | | | |
| (20) Professors lab | -0.463 | 0.150 | 0.569 | 1.000 | | | | | | |
| (21) Publications lab | -0.472 | 0.060 | -0.071 | 0.249 | 1.000 | | | | | |
| (22) Citations lab | -0.365 | 0.064 | -0.062 | 0.223 | 0.267 | 1.000 | | | | |
| (23) CiteScore lab | -0.641 | 0.298 | -0.113 | 0.305 | 0.518 | 0.543 | 1.000 | | | |
| (24) Ln(EU-ITA fund lab+1) | -0.387 | 0.356 | 0.012 | 0.229 | 0.305 | 0.173 | 0.293 | 1.000 | | |
| (25) Postdoc hours | -0.089 | -0.099 | 0.073 | 0.141 | 0.209 | 0.123 | 0.167 | 0.177 | 1.000 | |
| (26) PhD Student hours | -0.081 | 0.026 | -0.010 | 0.050 | 0.349 | 0.141 | 0.153 | 0.282 | 0.344 | 1.000 |

Note: Complementing correlations reported in Table 1.

**Table A4: Results of OLS regression on research outcomes**

| | (1) Ln(adj.publications+1) | | (2) Ln(norm.citations+1) | | (3) Ln(CiteScore+1) | |
|---|---|---|---|---|---|---|
| | b | se | b | se | b | se |
| Ln(Italian funding+1) | 0.014*** | 0.004 | 0.006** | 0.003 | 0.013*** | 0.004 |
| Female | -0.167*** | 0.054 | -0.038 | 0.059 | -0.030 | 0.115 |
| Teaching hours | -0.008 | 0.009 | -0.007 | 0.009 | -0.001 | 0.015 |
| Female#Teaching hours | 0.016 | 0.014 | 0.008 | 0.013 | 0.007 | 0.029 |
| Administrative post | 0.074* | 0.042 | -0.021 | 0.036 | 0.082 | 0.053 |
| Female#Administrative post | -0.058 | 0.061 | 0.102 | 0.081 | -0.108 | 0.102 |
| Small child (0-3) | 0.033 | 0.057 | 0.137** | 0.055 | 0.159*** | 0.055 |
| Female#small child | -0.119* | 0.070 | -0.151** | 0.066 | -0.229** | 0.101 |
| *Controls* | | | | | | |
| (Age-50)/10 | -0.195*** | 0.023 | -0.131*** | 0.025 | -0.362*** | 0.040 |
| (Age-50)/$10^2$ | -0.043*** | 0.012 | -0.016* | 0.009 | -0.018 | 0.017 |
| Pr(professor) | 0.587*** | 0.085 | 0.315*** | 0.087 | 0.941*** | 0.124 |
| Ln(coauthors+1) | | | 0.095*** | 0.014 | | |
| *Lab measures* | | | | | | |
| Single person lab | -0.131** | 0.056 | -0.001 | 0.046 | -0.181** | 0.085 |
| Lab size | -0.010** | 0.004 | -0.007** | 0.003 | -0.002 | 0.010 |
| Mean age lab | -0.021 | 0.024 | -0.037 | 0.025 | -0.101** | 0.040 |
| Professors lab | -0.014 | 0.065 | 0.085 | 0.064 | 0.217** | 0.099 |
| Publications lab | 0.047* | 0.024 | 0.032 | 0.024 | -0.051 | 0.033 |
| Citations lab | -0.001 | 0.001 | 0.004*** | 0.001 | | |
| CiteScore lab | | | | | 0.053*** | 0.015 |
| Ln(EU-ITA funding lab+1) | -0.001 | 0.002 | 0.001 | 0.002 | -0.004 | 0.003 |
| PhD Student hours | 0.014*** | 0.004 | 0.007** | 0.003 | 0.018*** | 0.004 |
| Chemistry | -0.016 | 0.030 | -0.044 | 0.033 | -0.061 | 0.045 |
| Constant | 0.337*** | 0.064 | 0.157** | 0.067 | 0.636*** | 0.109 |
| Adjusted $R^2$ | 0.254 | | 0.219 | | 0.229 | |
| ***dydx(Female)*** | -0.128*** | 0.028 | -0.015 | 0.027 | -0.044 | 0.045 |

Note: N = 2097; clusters = 262 in individual id, 86 in lab. *** (**,*) indicate a significance level of 1% (5%, 10%). Year dummies included; robust clustered standard errors, clustered at the individual and lab levels. Publication counts are co-author adjusted. Citations are year normalized.

**Table A5: Additional descriptive statistics**

| | mean | sd | p50 | min | max |
|---|---|---|---|---|---|
| Publications (normal count) | 4.58 | 6.58 | 3.00 | 0.00 | 73.00 |
| Citations (average) | 16.54 | 21.31 | 10.67 | 0.00 | 262.00 |
| 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 A6: Results of two-stage least square and OLS regression accounting for selection on research outcomes, robustness tests**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Ln(publications+1) | | Ln(citations+1) | |
| | 2nd Stage 2SLS | Not selected | 2nd Stage 2SLS | Not selected |
| | b/se | b/se | b/se | b/se |
| Ln(Italian funding+1) | -0.079 | | 0.156** | |
| | (0.051) | | (0.076) | |
| Female | -0.247 | 0.070 | 0.507 | 0.125 |
| | (0.258) | (0.118) | (0.392) | (0.199) |
| Teaching hours | 0.002 | -0.007 | 0.055 | 0.022 |
| | (0.026) | (0.023) | (0.055) | (0.029) |
| Female#Teaching hours | 0.014 | -0.020 | -0.058 | -0.016 |
| | (0.060) | (0.028) | (0.081) | (0.044) |
| Administrative post | 0.110 | 0.138* | 0.075 | 0.297* |
| | (0.102) | (0.073) | (0.100) | (0.169) |
| Female#Administrative post | 0.073 | -0.061 | -0.334 | -0.065 |
| | (0.202) | (0.111) | (0.246) | (0.250) |
| Small child | 0.167 | 0.080 | -0.006 | 0.210 |
| | (0.152) | (0.141) | (0.183) | (0.133) |
| Female#small child | -0.351* | -0.317** | -0.217 | -0.566** |
| | (0.201) | (0.157) | (0.240) | (0.225) |
| (Age-50)/10 | -0.471*** | -0.455*** | -0.549*** | -0.669*** |
| | (0.074) | (0.067) | (0.159) | (0.077) |
| $(\text{Age-50})/10^2$ | 0.018 | 0.013 | 0.063 | 0.005 |
| | (0.051) | (0.025) | (0.069) | (0.038) |
| Pr(professor) | 1.166*** | 1.062*** | 1.102** | 1.475*** |
| | (0.217) | (0.236) | (0.498) | (0.286) |
| Ln(coauthors+1) | | | 0.397*** | 0.162*** |
| | | | (0.120) | (0.046) |
| Chemistry | 0.054 | -0.189** | -0.135 | -0.258** |
| | (0.110) | (0.089) | (0.155) | (0.106) |
| Zero initial adj.pub \| | 0.532* | 0.077 | 0.612* | 0.359* |
| norm.cit \| CiteScore | (0.309) | (0.111) | (0.363) | (0.185) |
| Ln(initial adj.pub \| | 0.496*** | 0.337*** | 0.343*** | 0.338*** |
| norm.cit \| Citescore | (0.099) | (0.052) | (0.066) | (0.049) |
| $\alpha^{\rho}$ | -0.057** | -0.013** | 0.040 | -0.004 |
| | (0.026) | (0.006) | (0.033) | (0.011) |
| Constant | 0.414 | 0.091 | -1.376** | -0.188 |
| | (0.290) | (0.208) | (0.643) | (0.231) |
| Lab controls | YES | YES | YES | YES |
| Observations | 732 | 1024 | 753 | 1087 |
| Adjusted $R^2$ | 0.108 | 0.378 | -0.055 | 0.420 |
| Hansen J-test (p-val.) | 0.448 | 0.547 | 0.0618 | 0.176 |
| Underidentification test (p-value) | 0.0456 | | 0.0526 | |
| ***dydx(Female)*** | -0.205* | -0.051 | 0.192 | -0.017 |
| | (0.105) | (0.065) | (0.167) | (0.091) |

Note: *** (**,*) indicate a significance level of 1% (5%, 10%). Year dummies included; robust clustered standard errors in parentheses, clustered at the individual and lab levels. High energy physics and other areas of physics relying on large coauthor teams are excluded in the publication model. First stage regressions are available upon request.

**Table A7: Results of two-stage least square regression with selection on research outcomes, robustness test**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Ln(SNIP+1) | | Ln(SJR+1) | |
| | 2nd Stage 2SLS | Not selected | 2nd Stage 2SLS | Not selected |
| | b/se | b/se | b/se | b/se |
| Ln(Italian funding+1) | -0.002 | | -0.005 | |
| | (0.015) | | (0.021) | |
| Female | 0.100 | 0.073 | 0.199 | 0.108* |
| | (0.098) | (0.051) | (0.142) | (0.063) |
| Teaching hours | 0.012 | 0.002 | 0.013 | 0.006 |
| | (0.010) | (0.009) | (0.014) | (0.012) |
| Female#Teaching hours | -0.022 | -0.002 | -0.051* | -0.011 |
| | (0.023) | (0.012) | (0.028) | (0.015) |
| Administrative post | 0.005 | 0.064 | 0.002 | -0.015 |
| | (0.029) | (0.049) | (0.045) | (0.114) |
| Female#Administrative post | -0.052 | -0.057 | -0.108 | 0.076 |
| | (0.060) | (0.069) | (0.089) | (0.134) |
| Small child (0-3) | 0.078 | 0.039 | 0.114 | 0.079* |
| | (0.057) | (0.032) | (0.076) | (0.042) |
| Female#small child | -0.034 | -0.167** | -0.021 | -0.259*** |
| | (0.076) | (0.069) | (0.107) | (0.083) |
| *Controls* | | | | |
| (Age-50)/10 | -0.174*** | -0.234*** | -0.195*** | -0.260*** |
| | (0.028) | (0.032) | (0.041) | (0.036) |
| $(Age-50)/10^2$ | 0.022 | 0.019* | 0.030* | 0.023 |
| | (0.014) | (0.010) | (0.018) | (0.015) |
| Professor | 0.386*** | 0.517*** | 0.349*** | 0.580*** |
| | (0.084) | (0.092) | (0.134) | (0.111) |
| Chemistry | -0.022 | -0.124*** | -0.021 | -0.140*** |
| | (0.039) | (0.030) | (0.055) | (0.039) |
| Zero initial SNIP \| SJR | 0.020 | -0.107** | -0.026 | -0.089 |
| | (0.076) | (0.050) | (0.074) | (0.058) |
| Ln(initial SNIP \| SJR) | 0.197*** | 0.172*** | 0.240*** | 0.202*** |
| | (0.029) | (0.031) | (0.030) | (0.028) |
| $\alpha^{\rho}$ | -0.009 | -0.007** | -0.013 | -0.009*** |
| | (0.007) | (0.003) | (0.011) | (0.003) |
| Constant | 0.297** | 0.230*** | 0.365** | 0.207*** |
| | (0.121) | (0.064) | (0.158) | (0.079) |
| Lab controls | YES | YES | YES | YES |
| Observations | 753 | 1087 | 753 | 1087 |
| Adjusted $R^2$ | 0.189 | 0.362 | 0.213 | 0.382 |
| Hansen J-test (p-value) | 0.465 | 0.457 | 0.411 | 0.491 |
| Underidentification test (p-value) | 0.0379 | | 0.0365 | |
| ***dydx(Female)*** | -0.001 | 0.036 | -0.031 | 0.040 |
| | (0.041) | (0.024) | 0.056 | (0.031) |

Note: *** (**,*) indicate a significance level of 1% (5%, 10%). Year dummies included; robust standard errors in parentheses, clustered at individual and lab. First stage regressions are available upon request.