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The Effect of PhD Funding on Post-degree Research Career and Publication Productivity[⑦]

Roberto Nisticò*

Abstract
In this paper, I explore to what extent the receipt of funding during PhD encourages post-degree research career and publications. Using novel data on new PhD graduates from all Italian universities, I document a strong effect of funding on both the probability of entering a research profession and the publication productivity within a few years after graduation. I provide additional evidence that funded students invest more in research- oriented activities (e.g., visiting research programs abroad) and spend less time working part-time during the PhD, thus adding to the mechanisms that potentially account for the effect of funding.

Keywords: PhD, Research Career, Publication Productivity.

JEL classification: H52, I22, I23, J24

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1 Introduction

Understanding the determinants of Ph.D. student outcomes has long been an issue of interest among economic scholars. Most of the existing research has focused on the importance of faculty quality and the quality of the thesis supervisor (Waldinger, 2010; Cardoso, Guimaraes and Zimmermann, 2010; Hilmer and Hilmer, 2007; Grove and Wu, 2007; van Ours and Ridder, 2003) and has found that students receiving their Ph.D. from higher quality universities are more likely to succeed later in life. Other studies, analysing students in Economics only, have documented that scores in first-year core exams (Athey et al., 2007) or in GRE tests (Krueger and Wu, 2000) are important predictor of Ph.D. student professional success. This paper investigates the role of the financial support received during Ph.D. to explain short-run student performance after graduation.

The effect of financial support on student outcomes has been widely investigated in literature, though mainly in relation to students in schools (Bartik and Lachowska, 2012; Fryer, 2011; Andrews *et al.*, 2010; Kremer *et al.*, 2009; Angrist and Lavy, 2009; Angrist *et al.*, 2006) and in undergraduate programs (Gunnes *et al.*, 2013; De Paola *et al.*, 2012; Garibaldi *et al.*, 2012; Leuven *et al.*, 2010; Cornwell *et al.*, 2005; Dynarsky, 2003). Related studies for students in Ph.D. programs paid most of the attention to the impact of financial support on the Ph.D. production process, i.e., on times-to degree and completion rates (Mangematin, 2000; Ehrenberg and Mavros, 1995; Booth and Satchell, 1995; Bowen and Rudenstine, 1992). Some have examined the impact of research grants on subsequent publication outcomes of postdoctoral fellows (Jacob and Lefgren, 2011) and researchers in Economics (Arora and Gambardella, 2005). However, little is known about whether financial support is also an important driver for Ph.D. student outcomes after graduation.

This paper investigates whether the receipt of funding during Ph.D. encourages a post-degree research career and to what extent it also affects publication productivity within a few years after graduation. Yet, it contributes to the existing research in two different perspectives: i) it extends the empirical evidence on the effect of financial support on Ph.D. student outcomes - which, to date, typically focused on one particular field of study or university - by taking advantage of a novel dataset on new Ph.D. graduates from all Italian universities that also allows to distinguish across different fields of study; ii) it adds to the debate on the role of public investment in promoting research, by examining a graduate education system that is mostly publicly subsidized, a peculiar characteristic of the Italian system as well as of that of many other European countries.

Addressing empirically the causal relationship between funding and Ph.D. student outcomes after graduation is complex. The crucial problem is controlling for the potential endogeneity due to the omission of unobserved characteristics that are correlated with both funding and student outcomes. In the estimation of the effect of funding on research outcomes, a possible omitted factor might be student research orientation, which is difficult to observe. Indeed, if funded students are likely those more research oriented, then, failure to control for this correlation would bias the OLS estimates of the effect of funding. To deal with this issue, I exploit the variation in the supply of scholarships financed by the Italian Ministry of Education (MIUR) across Ph.D. programs in different universities and fields of study. I therefore construct IV estimates of the effect of funding by estimating a two-equation model in which I use the number of positions covered by MIUR scholarship over the total number of open positions in each Ph.D. program, hereafter called scholarship ratio (SR), to instrument for funding in the main outcome equation.

I explore the possibility that SR has a direct effect on research outcomes, thus violating the exclusion restriction assumption required for the instrument to be valid. This possibility may arise when changes in SR influence the quality composition of students entering a Ph.D. program, or, to put it differently, if a higher SR is systematically associated with a higher fraction of more academically inclined students across Ph.D. programs. Using a falsification exercise, I show that changes in SR do not significantly alter students' quality composition at the access to the Ph.D., hence providing some confidence on the identification strategy implemented in the empirical analysis.

There are other plausible concerns that could undermine the identification of the effect of funding. First, applicants may move towards places with higher SR before enrolment to the Ph.D. in order to increase their chances to get funding. This would cause a geographical sorting bias. To deal with this issue, in the research outcomes equation I account for cross-regional mobility before enrolment to Ph.D. Moreover, to further account for potential selective mobility, in the sensitivity analysis I use as alternative instrumental variable the home region SR, i.e., the exposure to MIUR scholarships in the region of the B.A. university. Second, a higher SR may be associated with higher quality of the university and, in turn, university quality may affect student research outcomes. To capture this aspect, I control for an indicator of university quality as measured by the Italian Research Assessment Exercise.

Results from the empirical analysis uncover significant and positive effects of funding on a variety of student research outcomes after three to five years from graduation. The research outcomes reflect both the likelihood of entering a research profession and the early research productivity in terms of scientific articles. In particular, I find that funding increases the probability of entering a profession in research institutions by around 60 percentage points and the likelihood of having more than 3 scientific articles by around 50 percentage points. It is however worth clarifying that these results have a LATE interpretation, reflecting the causal effect of funding for a part of the support of the instrument. They would indeed capture the effect of funding for the marginal students whose likelihood of receiving funding is affected by changes in SR, that is, students that received funding but that would have not received it if SR were slightly lower (i.e., the compliers). I argue that these are students with high academic ability, though not outstanding, for whom funding can make most of the difference in terms of early research outcomes.

Consistent with this argument, I show indeed that funding has a heterogeneous effect, depending on student academic ability. In particular, I find that the first-stage estimates of SR are positive and strongly significant for students with very high B.A. grades and turn out to be not significant for students with low-middle B.A. grades. Intuitively, indeed, while "bad" students would never get funding and "brilliant" students would always do so, regardless of SR, the likelihood of getting funding for "good-quality" students, instead, increases with SR.

One possible criticism when using IV estimation strategy is the possibility that the instrument is weak, resulting in very large confidence intervals. Following Staiger and Stock (1997), I therefore estimate some of the models using LIML procedure and I find that LIML estimates are larger than 2SLS and, consistent with Blomquist and Dahlberg (1999), have greater standard errors. I also explore the possibility of non-linear effects either in the observables or in the instrument and I show that results do not significantly change when adding non-linear terms either in the main outcome equation or in the first-stage regression, respectively. Moreover, to ensure that results are not driven by the specific outcome variable used in the analysis, I replicate the baseline model using alternative outcome variables both for research career and productivity and I show that estimates are not sensitive to the way I measure the outcome variable.

Finally, this paper investigates the mechanisms through which funding would affect research outcomes. Besides being an important signal of academic ability, funding may provide students with strong incentives to invest in research-oriented activities while writing the dissertation, such as visiting research programs, summer schools, courses, conferences/workshops. Alternatively, funding may induce students to increase their time spent on studying, thus reducing their time spent on working while studying, e.g., teaching activities or part-time work. I find empirical evidence that funded students invest more in visiting research programs abroad and spend less time on part-time work while studying. Furthermore, I document that funding stops being relevant once channel variables are included in the main outcome equation as additional controls.

The remainder of the paper is organized as follows: section 2 describes the data and provides some descriptive statistics. Section 3 presents the empirical strategy and explains the identification strategy. Section 4 discusses the empirical findings on the effect of funding on research outcomes and presents robustness checks, followed by results on the underlying mechanisms. Section 5 concludes and discusses policy implications.

2 Data

I use data from the first survey on the professional careers of Italian Ph.D. graduates carried out by the Italian National Institute of Statistics (ISTAT). The survey was conducted between December 2009 and February 2010 and interviewed all Ph.D. graduates at Italian universities in 2004 and 2006 with the aim of detecting their vocational integration and employment conditions about five and three years after graduation, respectively. This is a total survey as it refers to the universe of Ph.D. graduates in 2004 and 2006, which consists of 18568 individuals (8443 for 2004 and 10125 for 2006), though the response rate was about 70%, thus reporting information on 12964 observations (5689 for 2004 and 7275 for 2006).[1] Because of this, ISTAT used an estimation procedure based upon the definition of weights to correct the data for the total missing response and avoid that non respondents systematically differ from respondents.[2] The survey questionnaire consists of 5 sections. The first section refers to the curriculum studiorum and all training activities and characteristics related to the Ph.D. program, besides the subjective opinions on the educational experience. The second section refers to the labor market and is devoted to those who reported to have a job or a post-doc position at the date of the interview. In particular, this section asks information about numerous

[1] The response rate was higher for the 2006 cohort (72%) than for the 2004 cohort (67%).

[2] In general, when conducting a survey on a population of N units, if respondents are only $N_1 (N_1 < N)$ then estimates are produced by assigning each of the N_1 units a weight $\gamma = N_1/N$. For greater details about the correction procedure see the online note on the methodology of the survey on the ISTAT website.

job characteristics including sector, position held, type of contract, working time, salary, working place (whether in Italy or abroad), and about access to the labor market and job satisfaction. It also reports detailed information about the scientific productivity (in terms of journal and conference articles, monographs and patents) and research or teaching activities. The third section refers to the job searching and is dedicated to those, employed or not, who reported to be searching for a job. The fourth section is about mobility experiences after Ph.D., especially towards other countries. Finally, the fifth section refers to characteristics of either the family of origin or the current family at the time of the interview.

One potential issue in using these data is the sample selection. Indeed, since data are on students who earned the Ph.D., they do not allow to observe the attrition rate, i.e., how many students dropped out from the Ph.D. The attrition rate can represent a problem in the extent to which the proportions of funded and unfunded students that earned the degree differ systematically from their relative counterparts at the access to the Ph.D. To put it differently, if those dropping out of the Ph.D. were more likely to be students without funding, then the analysis would be suffering of selection bias.[3] To address this issue, I compare ISTAT survey data with MIUR administrative data on the access to Ph.D., such as the number of enrolled students with and without MIUR scholarship by year, field of study and university. Table 1 compares, for both the 2004 and 2006 cohort, the percentage of students who have officially entered the Ph.D. with and without MIUR scholarship (columns 1 and 2 , respectively) with the relative percentage of Ph.D. graduates who reported to have and have not a MIUR scholarship (column 4 and 5, respectively) in the ISTAT survey. Because the survey data do not report the year of enrolment to the Ph.D., I restrict the comparison to those that completed the Ph.D. on time (about 90% of the whole sample). By matching this information with that on the duration of the program, I am able to identify the

[3] The intuition behind this relies on the fact that funding makes it easier to complete the Ph.D. and, therefore, those who completed in spite of not having funding are likely to be more motivated on average than the average student without funding. This implies that, if anything, attrition would bias downwards the OLS estimates.

entry academic year for each cohort.[4] In the upper panel I restrict the analysis to the 3-year Ph.D. programs while in the lower panel I also include the 4-year Ph.D. programs. In the latter, statistics are weighted averages where the weights (35% and 65%, respectively) reflect the relative proportions of 4-year and 3-year Ph.D. programs observed in the sample. Table 1 shows that the percentages of entrants with and without scholarship reported by MIUR statistics are very similar to their relative counterparts reported by ISTAT data. This would suggest that potential attrition from Ph.D. would have not altered the composition of funded and unfunded students, and that selection bias might be considered as negligible.

Table 1: Addressing sample selection

	(1)	(2)		(3)	(4)
	MIUR data			**ISTAT data**	
Enrolment year	SCH	NO SCH	Completion year	SCH	NO SCH
Upper panel: 3-year PhD programs only					
2000-01	70%	30%	2004	69%	31%
2002-03	60%	40%	2006	63%	37%
Lower panel: 3-year and 4-year PhD programs					
1999-00 (4-year PhD programs) 2000-01 (3-year PhD programs)	71%	29%	2004	68%	32%
2001-02 (4-year PhD programs) 2002-03 (3-year PhD programs)	60%	40%	2006	63%	37%

Notes: here the ISTAT sample includes all fields of study and is restricted to those that completed the Ph.D. on time in order to identify exactly the enrolment year for each cohort and make the comparison with the MIUR administrative data on access to Ph.D. Columns 1-2 report the official percentage of students who entered the Ph.D. with (SCH) and without (NO SCH) MIUR scholarship, respectively. Columns 3-4 report the percentage of graduates in the sample who reported to have (SCH) and have not (NO SCH) a MIUR scholarship, respectively. In the lower panel, these percentages represent weighted averages with weights 0.35 and 0.65 for 4-year and 3-year PhD programs, respectively (weights reflect the relative fractions of 4-year and 3-year PhD programs in the ISTAT sample).

The main advantage of using ISTAT data is the possibility to exploit information on Ph.D. graduates in all fields of study and from all Italian universities. However, due to confidential matters, data allow to know the province of the university awarding the Ph.D. but not the exact university.[5] So each observation

[4]For example, with respect to the 2004 cohort the entry academic year is 2000-2001 for those that completed a 3-year Ph.D. program on time and 1999-2000 for those that completed a 4-year program on time.

[5]Although the information on the exact university woud be ideal to account for university specific characteristics within the same province, it is worth noting that the vast majority of the Italian provinces has just one university, with the exception of the very large ones such as Rome,

in the sample is identified by a specific field of study and a specific university province. Data are on 14 different fields of study and 110 university provinces. For the purpose of this paper (i.e., to investigate the effect of funding on pursuing a post-degree research career and on early research productivity in terms of scientific articles), some fields of study, namely medicine (and related fields) and humanities, have no value added in the empirical analysis. Indeed, while Ph.D. students in medicine and related fields tend to enter medical occupations, those in humanities are more oriented towards teaching-based rather than research-based professions and tend to publish monographs rather than scientific articles. Therefore, I exclude these fields from the sample and restrict the analysis to graduates in the remaining 10 fields, which can be grouped in three macro-fields: Social sciences, Engineering and Natural sciences.[6] After this exclusion, the restricted sample consists of 7892 graduates, 3437 of the 2004 (44%) and 4455 of the 2006 (56%), distributed across the three macro-fields with the following proportions: Social sciences (26%), Engineering (31%) and Natural sciences (43%).

Summary statistics for the variables of interest are reported in table A.1 in the appendix. The main variable of interest is Funding, a dummy taking value 1 if students received any type of funding during the Ph.D., i.e., a scholarship or fellowship or research/teaching assistantship. It is worth noting that the mean value of Funding is in general 89% and differs significantly between students that have carried out a research career after graduation (92%) and students that, at the date of interview, do not work in research institutions. The outcome variables measure either whether students undertake a post-degree research career or their research productivity after graduation. With respect to the research career, I

Milan, Naples and few others. Furthermore, unlike the US one, the Italian university system is far more homogeneous, and differences across universities within the same province might not be notable. Therefore, for the purpose of the present analysis, this should not represent a big issue.

[6]Social sciences includes 3 fields of study, namely Law, Economics and Statistics, Sociology and Political Science. Engineering includes 2 fields of study, namely Civil Engineering and Architecture, Industrial and Information Engineering. Natural sciences includes 5 fields of study, namely Maths, Physics, Chemistry, Hearth Science, Biology. The 4 excluded fields of study are Medicine, Agricultural and Veterinarian Sciences, Antiquity-Linguistics-Art Hystory, Hystory-Phylosophy-Education-Psycology.

use as main outcome variable a dummy that takes value 1 if a graduates, at the date of interview, work in research institutions. Alternatively, I use a dummy indicating whether, in their job at the date of interview, they carry out research activities at least in part. With regard to the research productivity, the preferred outcome variable is a dummy equal to 1 if graduates, at the date of interview, have more than 3 scientific journal articles. As alternative measure of research productivity, I use a dummy that takes value 1 if they have more than 3 conference and proceedings articles.[7] The correlations among all the considered outcome variables are reported in table 2.

Table 2: Correlations among outcome variables

	Work in research institutions	Research at least in part	More than 3 journal articles	More than conference articles
Work in research institutions	1			
Research at least in part	0.3876	1		
More than 3 journal articles	0.4274	0.4152	1	
More than 3 conference articles	0.3695	0.3646	0.5452	1

Descriptive statistics indicate that 56% of the sample works in research institutions and this percentage substantially differs among funded (58%) and unfunded students (40%). Yet, 74% of Ph.D. graduates carries out research activities at least in part and this percentage is significantly lower for unfunded students (67%). Regarding research productivity, 57% of Ph.D. graduates have more than 3 scientific journal articles and this fraction is 58% and 47% for students with and without funding, respectively. Also, 47% of the sample have more than 3 conference and proceedings articles but this percentage significantly differs across the two subgroups, being 49% for funded and 36% for unfunded students, respectively. For

[7] There could be other ways of measuring research productivity, such as wages or different labor market outcomes, however, because of the particular structure of the Italian labor market - which is characterized by very slow career and low variation in salary, especially in academic and other research institutions - this type of measures are not very good proxies for the research productivity of the Italian Ph.D. graduates.

what concerns the activities undertaken during the Ph.D. experience, 31% spent at least a period of 4 consecutive weeks in a visiting research programme abroad, 35% attended summer schools, 38% carried out teaching activities on a regular basis and 13% worked part-time while studying. All these percentages significantly diverge across funded and unfunded students. In particular, visiting programmes are much more common among funded students (33%) than unfunded ones (14%) and the same applies to summer schools (37% versus 18%). This gap is far more pronounced in the case on part-time work: only 8% of funded students report to have worked part-time during Ph.D. while this percentage jumps to 57% for unfunded ones.

The last three variables reported in table A1 require specific attention. The first two - RAE score and mean professor age - serve as measures of university quality while the third one - Scholarship ratio (SR) - serves as instrumental variable in the empirical analysis. The RAE score variable is drawn from the Three-year Research Evaluation (VTR) conducted in 2006 by the Committee for Evaluation of Research (CIVR) in collaboration with CINECA - a non-profit consortium of Italian universities and research institutions - and referring to the period 2001-2003. The RAE score indicator measures, for each department, the percentage of scientific articles evaluated as excellent, discounted for the department's property degree of the examined articles. To match this measure with the ISTAT survey data, I compute, for each field of study, the RAE indicator at the province level by averaging over universities within the same province. The resulting indicator is continuous, varying from 0 to 1 (larger values indicating better research quality), with a mean of 0.19 and a standard deviation of 0.12. Data on professor age and scholarship ratio are instead drawn from the MIUR statistics. While the former measures the mean professor age in each department, the latter measures the ratio between the number of MIUR scholarships and the total number of Ph.D. open positions per department by year. Again, both variables are computed at the university province level. Over the considered sample, the mean professor age is

57 (standard deviation is 2.7) but it varies from a minimum of 38 to a maximum of 64.

Finally, SR displays a mean of 0.6 (standard deviation of 0.09), meaning that MIUR scholarships cover, on average, 60% of the total Ph.D. positions. This value varies from a minimum of 29% to a maximum of 100% across different provinces and fields of study. To understand what explains this variation, more background on the Italian PhD funding system is provided in the next section.

3 The Italian PhD funding system

In the context of the present analysis, the Italian PhD system is regulated by the Law 3 July 1998 no. 210.[8] This Law establishes that each university institutes the PhD courses, in compliance with the general requirements and criteria imposed by the MIUR. In particular, each university defines:

- the number of open positions in each course, provided that this number is not less than 3;
- the number of scholarships in each course, provided that this number covers at least half of the total positions in each course.

The scholarships are allocated by each department according to an entry test, coupled with an interview. In general, the MIUR scholarship amounts to 800 euro per month and covers the entire duration of the program, conditional on the positive evaluation at the end of each year. Also, it is increased by the 50% for a maximum of 18 months during visiting research periods abroad, besides being associated to other benefits, such as reimbursement of the expenses for summer schools, conferences and workshops.

It is important to note that most of the scholarships (75%) are subsidized by the MIUR, who defines the criteria according to which resources are redistributed across universities. In particular, the MIUR establishes that:

[8] This system has been recently reformed by the Law 30 December 2010, no. 240.

- 80% of the total resources must be allocated, for a 50%, in proportion to the total number of BA graduates and, for the other 50%, in proportion to the total number of PhD graduates in the past two academic years;

- the remaining 20% must be redistributed proportionally to the current number of PhD students in each cohort, provided that the faculty consists of at least 10 tenured teachers and that at least 9 positions in the last three academic years have been covered by scholarships.

Overall, this indicates that the variation in SR across universities mainly depends on the size of the university, hence lending support to the identification strategy outlined in the next section.

4 Empirical Strategy

I assume that Ph.D. graduates' research outcomes (Y) depend on whether they had any type of funding during the Ph.D. (F) and a set of observable (X) and unobservable characteristics. Each graduate i is identified by a specific field of study (indexed by f) and university province (indexed by p). I also assume that Funding depends on the same set of characteristics as research outcomes and on the Scholarship Ratio (SR), specific to each graduate i's field of study f and university province p. The latter measures the number of Ph.D. positions covered by MIUR scholarship over the total number of open positions for each pair (f, p). It reflects the likelihood of getting funding and serves as instrumental variable. I therefore propose to instrument the endogenous variable F with SR and estimate the following two-equation model:

$$Y_{ifp} = \beta_0 + \beta_1 F_{ifp} + X^{'}\delta + \varepsilon_{ifp} \tag{1}$$

$$F_{ifp} = \alpha_0 + \alpha_1 SR_{fp} + X^{'}\sigma + \mu_{ifp} \tag{2}$$

where equation 1 is the research outcomes regression and equation 2 the corresponding first-stage regression. X' is a vector of observables including individual characteristics, parental background, individual ability based on the undergraduate studies and a number of characteristics of the Ph.D. including an indicator of the university research quality, measured at the province level. The vector X' also includes dummy variables (that serve as fixed effects) for graduate cohort, field of study and university province. The parameter of interest is β_1 which indicates the impact of funding on early research outcomes after graduation. As discussed later, the IV estimate of β_1 has a Local Average Treatment Effect (LATE) interpretation.[9] It would capture the effect of funding for the subpopulation of "compliers", that is, the subgroup of students whose likelihood of getting funding changes with variations in SR.

The identification of β_1 relies on two conditions. First, SR must be correlated with F but uncorrelated with Y other than through its effect on F (exclusion restriction assumption). In other words, variations in SR should not directly influence student ability. To address this point, I implement a falsification exercise by regressing student academic ability on SR and a set of observables, including dummies for cohort, field of study and university province. Results are reported in table 3 and suggest that changes in the scholarship ratio do not significantly affect student ability, regardless of how regression model is specified (when using OLS, Probit or Logit). The B.A. grade in the Italian university system varies from a minimum of 66 to a maximum of 110, with greater values indicating higher grades. Because there might be potentially different grading standards across universities and fields of study, I also use, as alternative proxy for student ability, parental education and, in particular, a dummy indicating whether at least one parent had a B.A. degree at the time of his children's enrolment to the B.A. Taken together, estimates in table 3 suggest that results are not driven by the way student ability is measured. Yet, the magnitude of the coefficient for SR is very close to zero.[10]

[9] See Imbens and Angrist (1994)

[10] As diagnostic test, I show that even if the 95% confidence interval upper bound was the

Table 3: Falsification exercise: Scholarship ratio and student ability

	(1) OLS	(2) PROBIT	(3) LOGIT	(4) OLS	(5) PROBIT	(6) LOGIT
	Student ability					
	BA grade ≥ 106			**At least one parent with BA degree**		
Scholarship ratio (SR)	0.015	0.003	0.008	0.016	0.015	0.015
	(0.080)	(0.082)	(0.084)	(0.083)	(0.082)	(0.082)
Female	0.018*	0.016	0.018	-0.002	-0.002	-0.001
	(0.010)	(0.010)	(0.010)	(0.014)	(0.014)	(0.014)
Age at graduation 29 or less	0.251***	0.256***	0.266***	0.160***	0.159***	0.159***
	(0.018)	(0.017)	(0.018)	(0.015)	(0.015)	(0.015)
Age at graduation 30	0.147***	0.127***	0.125***	0.107***	0.107***	0.108***
	(0.018)	(0.015)	(0.015)	(0.020)	(0.020)	(0.020)
Age at graduation 31	0.091***	0.075***	0.072***	0.038**	0.039**	0.039**
	(0.022)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)
Age at graduation 32	0.076***	0.061***	0.059***	0.044**	0.045**	0.046**
	(0.018)	(0.014)	(0.013)	(0.019)	(0.020)	(0.020)
At least one parent	0.018	0.020*	0.020*			
with BA degree	(0.011)	(0.011)	(0.011)			
At least one parent	0.005	0.007	0.006			
with managerial job	(0.010)	(0.009)	(0.010)			
Regional mobility pre-PhD	0.013	0.011	0.015	0.080***	0.080***	0.079***
	(0.017)	(0.016)	(0.016)	(0.013)	(0.013)	(0.013)
4-year PhD program	0.014	0.016	0.015	-0.028*	-0.030*	-0.031*
	(0.015)	(0.016)	(0.015)	(0.015)	(0.016)	(0.016)
RAE score of PhD university	0.005	0.011	-0.004	-0.174**	-0.169**	-0.167**
	(0.075)	(0.077)	(0.080)	(0.073)	(0.072)	(0.073)
Mean professor age	0.004	0.003	0.003	0.003	0.003	0.003
of PhD university	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Observations	7892	7888	7888	7892	7892	7892

Notes: robust standard errors, clustered by field of study*university province, are reported in parentheses. * p<0.05 ** p<0.01 *** p<0.001. Estimated marginal effects are reported when using PROBIT and LOGIT models. Control dummies for cohort, field of study and university province are included in all specifications. Reference category is "Age at graduation 33 or more".

Second, *SR* must be uncorrelated with Y, conditional on covariates. One potential concern is the bias due to geographical sorting, i.e., if individuals move towards regions with higher *SR* in order to increase their chances of getting funding. I capture this aspect by including a dummy for cross-regional mobility before enrolment to Ph.D. as well as controlling for university province fixed effects. Yet, to further account for selective mobility issues, in the sensitivity analysis, I use, as alternative instrumental variable, the *home region SR*, which reflects the supply of MIUR scholarships in the region of the B.A. university. Another potential

"true" coefficient, it would still not cause a significant bias. In this case, one standard deviation increase in *SR* (0.09) would increase the probability to have a B.A. grade greater than 105 by less approximately 1 percentage point (0.09*0.11). Overall, results indicate that changes in *SR* do not alter the quality composition of students enrolled to Ph.D., hence reinforcing the exclusion restriction assumption.

concern is that, in principle, SR may have an independent effect on Y because higher values of SR may be associated with higher university quality and as result with higher research outcomes. I avoid the bias due to this channel by controlling for two distinct indicators of university research quality: the RAE score and the mean professor age, both measured at the university province level by field of study.[11] Moreover, figures 1-2 in the appendix plot SR against both the RAE score and the mean professor age, respectively, and show that differences in SR are not systematically correlated with differences in quality. This result holds either when including all fields of study or when focusing on each specific field at one time (social sciences, engineering and natural sciences, respectively).

Although the outcome variables are binary, to estimate the effect of funding, I use a linear probability model as it enables a LATE interpretation of the IV estimator. I initially treat both equations 1 and 2 as linear and estimate the model using the standard 2SLS estimator with SR serving as instrument for F. Then, since F in equation 1 is also binary, I proceed using the two-step estimation strategy with binary endogenous regressor as discussed in Windmeijer and Santos Silva (1997) and Wooldridge (2002). This procedure consists of estimating first a probit for F on SR and a set of covariates, and then using the fitted probabilities to instrument for F in the outcome equation.[12] The robustness of this estimator, which I refer to as 2SIV, does not depend on a correct specification of the equation for F, i.e., estimator is robust to misspecification of such equation as probit (Wooldridge, 2002, p. 623).

Results from the empirical analysis are discussed in the next section.

[11] Mean professor age can be thought as proxy of university research quality given that research performance decreases with age.

[12] This procedure has been recently implemented also by Finlay and Neumark (2010) to estimate the causal effect of never-married motherhood on child educational outcomes.

5 Results

5.1 The Effect of Funding on Research Outcomes

Before turning to IV estimates, I first present OLS estimates, which are reported in table 4. Although OLS estimates of β_1 in equation 1 might be potentially inconsistent because of the omitted variable bias, they still provide a useful piece of information about the funding-research outcomes link. They show a positive and strongly significant correlation between funding and research outcomes, either at the extensive or intensive margins. Interestingly, this correlation hardly changes when enlarging the set of controls (columns 1 to 6) while keeping accounting for cohort, field of study and university province fixed effects. In particular, it is worth emphasizing how coefficients remain strongly stable after controlling for student ability (as measured by the B.A. grade), and for Ph.D. university quality (as measured by the RAE score and the mean professor age). Furthermore, these estimates are robust to alternative measures of the outcome variable (column 7), either when focusing on research career (upper panel) or on research productivity (lower panel).

Overall, the OLS estimates would suggest that, conditional on all other covariates, the probability to pursue a research career after graduation is about 14 percentage points higher for funded students than for unfunded ones. Also, the likelihood of having more than 3 journal articles at the date of interview, which reflects the probability of being an active researcher, is about 8 percentage points higher for funded students than for unfunded ones.

Table 4: Funding and early research outcomes: OLS estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Upper panel: Research career						
	Work in research institutions						**Research at least in part**
Funding	0.146***	0.140***	0.140***	0.140***	0.141***	0.141***	0.055***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.018)
	Lower panel: Research productivity						
	More than 3 journal articles						**More than 3 conference articles**
Funding	0.091***	0.079***	0.081***	0.080***	0.082***	0.083***	0.067***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Control variables							
Dummies for cohort, field of study and university province	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual traits	No	Yes	Yes	Yes	Yes	Yes	Yes
Parental backgroung	No	No	Yes	Yes	Yes	Yes	Yes
BA-related traits	No	No	No	Yes	Yes	Yes	Yes
Regional mobility pre-PhD	No	No	No	No	Yes	Yes	Yes
PhD-related traits	No	No	No	No	No	Yes	Yes
Observations	7892	7892	7892	7892	7892	7892	7892

Notes: robust standard errors, clustered by field of study*university province, are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Individual traits variables are "Female", "Age at graduation 29 or less", "Age at graduation 30", "Age at graduation 31", "Age at graduation 32" ("Age at graduation 33 or more" is the reference category). Parental background variables are "At least one parent with BA degree at enrollment to BA" and "At least one parent with managerial job at enrollment to BA". BA-related traits variables are "BA grade 110", "BA grade in [106,106]", "BA grade in [101,105]", "BA grade in [91,100]" ("BA grade in [66,90]" is the reference category), "BA university in the north", "BA university in the centre" ("BA university in the south" is the reference category). PhD-related traits variables are "4-year PhD program", "RAE score of PhD university" and "Mean professor age of PhD university". The outcome variable mean is 0.56 for "Work in research institutions", 0.74 for "Research at least in part", 0.57 for "More than 3 journal articles" and 0.47 for "More than 3 conference articles", respectively.

I then move to discuss IV results, which are reported in table 5.[13] Column 1 reports estimates obtained using the standard 2SLS estimator, with funding (F) being instrumented by SR. Results from first-stage regression suggest that SR is a strong predictor of funding (F-statistic is around 16, larger than the rule-of-thumb threshold of 10 proposed by Staiger and Stock, 1997). However, the second-stage estimate for β_1 is not statistically significant at conventional levels, neither in the upper nor in lower panel, and has large standard errors, suggesting that is very imprecise. Column 2 reports estimates resulting from the 2SIV estimator outlined above. First-stage results confirm the strong predictive power of the instrument, which now reflects the predicted value of funding obtained from a probit model of F on SR and other covariates. Differently from column 1, second-stage estimates for funding are now strongly statistically significant (at the 1% and 5% level for the extensive and intensive margins, respectively). They have smaller standard errors, indicating that they are also more precise.[14] Yet, they have very large coefficients in magnitude (much larger than corresponding OLS).[15]

Overall, the IV results in column 2 document that funding significantly affects both the likelihood of entering a research profession and the publication outcomes after graduation. In particular, I find that, for the marginal student, funding increases the probability of entering an occupation in research institutions by about 64 percentage points, and the likelihood of being a productive researcher after graduation (i.e., having more than 3 scientific publications) by about 54 percentage points.

[13]Equations 1 and 2 are jointly estimated using the stata command "ivregress 2sls".

[14]This suggests that precision increases when threating the endogenous variable F as binary in first-stage regression.

[15]Even if point estimates in column 2 may not be considered as informative about the magnitude of the effect of funding, looking at the confidence intervals helps getting an idea of how important is funding to explain differences in research outcomes among Ph.D. graduates. The 95% CI for the estimate in column 2 in the upper panel, for instance, ranges from 0.2 to 1.1. This demonstrates that the effect of funding is certainly positive and statistically different from zero. Moreover, even if the lower bound estimate (0.2) was the true coefficient, funding would still have a positive effect on pursuing a research career after graduation. In particular, funding would increase the probability of entering a research occupation after graduation by at least 20 percentage points.

Table 5: Funding and early research outcomes: IV estimates

	(1) 2SLS using SR as instrument	(2) 2SIV using F-hat as instrument	(3) 2SIV using SR & F-hat as instruments	(4) LIML using SR & F-hat as instruments	(5) 2SIV adding non-linear covariates	(6) 2SIV adding SR^2 in probit	(7) 2SIV adding SR^2 & SR^3 in probit	(8) 2SIV using home region SR as instrument	(9) 2SIV using alternative outcome
Upper panel: Research career									
	Work in research institutions								**Research at least in part**
Funding	0.194	0.643***	0.610***	0.629***	0.304	0.621***	0.575***	0.834***	0.415**
	(0.397)	(0.228)	(0.227)	(0.237)	(0.187)	(0.235)	(0.216)	(0.282)	(0.207)
Lower panel: Research productivity									
	More than 3 journal articles								**More than 3 conference articles**
Funding	0.532	0.545**	0.542**	0.542**	0.467**	0.480*	0.422*	0.524**	0.532**
	(0.481)	(0.263)	(0.271)	(0.271)	(0.197)	(0.270)	(0.251)	(0.276)	(0.224)
First stage									
Scholarship Ratio (SR)	0.222***		0.045	0.045					
	(0.056)		(0.060)	(0.060)					
Predicted Funding (F-hat)		0.822***	0.773***	0.773***	0.894***	0.819***	0.828***	0.812***	0.822***
from probit		(0.152)	(0.171)	(0.171)	(0.140)	(0.151)	(0.138)	(0.171)	(0.152)
F-test statistics	15.922	29.161	15.358	15.358	40.851	29.446	36.143	20.827	29.161
Hansen test p-value			0.515	0.515					
Observations	7892	7853	7853	7853	7840	7853	7853	7768	7853

Notes: robust standard errors, clustered by field of study*university province, are reported in parentheses. * p<0.05 ** p<0.01 *** p<0.001. The whole set of control variables is included in all specifications. "Home region SR" measures, for each field of study, the number of MIUR scholarships in the region of the B.A. university, relative to the overall number of PhD open positions in the same region. The outcome variable mean is 0.56 for "Work in research institutions", 0.74 for "Research at least in part", 0.57 for "More than 3 journal articles" and 0.47 for "More than 3 conference articles", respectively.

However, it is worth clarifying what the estimated model identifies and how the IV estimates should be interpreted. Following Imbens and Angrist (1994)'s LATE interpretation, they would reflect the causal effect of funding for the marginal student whose likelihood of getting funding is affected by changes in *SR*. This is likely to be a student with high academic ability, though not outstanding, that received funding but that would have not received it if *SR* were slightly lower; a student for whom funding can, therefore, make most of the difference in terms of research outcomes.

This interpretation would also reasonably motivate why I find the IV estimates to be notably larger, in magnitude, than the OLS ones. This is consistent with Imbens and Angrist (1994) who show that, in the presence of heterogeneous effects, the IV estimates may well exceed the OLS estimates - they would pin down the effect on the marginal individual which can be greater than the average effect -, though this requires a suitable monotonicity assumption. In the context of the present application, this monotonicity assumption would mean that even if *SR* may have no effect on the likelihood of getting funding for some students, all those students whose likelihood is influenced by changes in *SR* are influenced in the same manner. In other words, while changes in *SR* may affect only students with high ability (though not outstanding), all these students are affected in the same way.

In keeping with the LATE interpretation, in table 6 I show that first-stage estimates of the instrumental variable *SR* are positive and strongly significant for the sub-sample of students with B.A. grade ≥ 106 and turn out to be not significant for the sub-sample of those with B.A. grade < 106.[16] This would suggest that variations in *SR* strongly influence the chances of getting funding of high-quality students but not the chances of low-middle students. Intuitively, indeed, it is reasonable to think that, while low-middle quality students would never get funding (on average), regardless of *SR*, high-quality students' likelihood of getting

[16] According to Imbens and Angrist (1994), the IV estimator is a weighted average of local average treatment effects with higher weights attributed to those parts of the support of the IV for which changes in the instrument have greater effects on the endogenous variable.

funding increases with SR.

Table 6: First-stage estimates by student ability measured by BA grade

	(1) All	(2) BA grade ≥ 106	(3) BA grade < 106	(4) All	(5) BA grade ≥ 106	(6) BA grade < 106
				Funding		
Scholarship Ratio (SR)	0.222***	0.237***	0.089			
	(0.056)	(0.065)	(0.120)			
Predicted Funding (F-hat)				0.822***	0.956***	0.690*
from probit				(0.152)	(0.149)	(0.371)
F-test statistics	15.92	13.11	0.55	29.16	41.09	3.46
Observations	7892	6353	1539	7853	6304	1492

Notes: robust standard errors, clustered by field of study*university province, are reported in parentheses. * p<0.05 ** p<0.01 *** p<0.001. The whole set of control variables is included in all specifications. The outcome variable mean is 0.89.

5.2 Sensitivity Analysis

Here I investigate the sensitivity of the main IV results presented above. Columns 3 to 8 of table 5 show the sensitivity of the 2SIV estimates in column 2 to a number of robustness checks. First, in column 3 I augment the 2SIV model specification using both the predicted F from probit and SR as instrumental variables for F and also test the overidentifying restrictions.[17] Results are very similar to those in previous column.

Second, in column 4 I check whether the still large confidence intervals associated with estimates in column 3 reflect potential weak-instruments issues. Following Staiger and Stock (1997), I re-estimate the model in column 3 using the LIML estimator.[18] Results do not change, hence suggesting that they are not driven by weak instruments problems.

Third, I explore the possibility that IV results are driven by nonlinearities in the control variables rather than by variation in the instrumental variable SR. To account for this, in column 5 I re-estimate the baseline 2SIV specification by adding a large number of nonlinear terms. In particular, I include the quadratic term of all continuous control variables and all two-way interactions between the control

[17] First-stage F-statistic is around 15 and the test for overidentifying restrictions fails to reject the null hypothesis of valid instruments (the p-value of the Hansen test is 0.19).

[18] I use the stata command "ivregress liml"

dummies for female, age, B.A. grade and parental background. Estimates slightly change, especially in the upper panel with the estimate of funding becoming not statistically significant, but they remain similar in magnitude (in both panels, coefficients are not statistically different from those in column 2).

Forth, I also address the presence of nonlinearities in the effect of SR on funding. So far, I assumed that SR has a linear effect on F in equation 2, i.e., SR has the same effect on F, regardless of the value of SR. However, it might well be that such an effect increases when SR is higher. To examine potential non-linear functions of the instrument, I replicate the baseline model by including polynomials of SR in first-stage regression, SR^2 in column 6 and either SR^2 or SR^3 in column 7. Results in both columns 6-7 indicate that introducing nonlinearities in the first stage does not alter the main IV results.

Fifth, to further account for geographical sorting bias, I use a different instrumental variable, i.e., the *home region SR*, which measures, for each field of study, the number of MIUR scholarships in the graduates' home region (the latter being the region of the university where they obtained the B.A. degree), relative to the overall number of PhD open positions in the same region. In doing so, I follow the approach in Parey and Waldinger (2011). This would, more plausibly, take care of the selective mobility bias and, because mobility is low overall in the sample, would not make the instrument much weaker. Results are reported in column 8. The 2SIV estimates of Funding are still strongly significant and do not qualitatively differ from those in column 2 (also the standard errors are very similar). The F-statistic is still above 20 - though it drops compared to that in column 2 - hence suggesting that I can rule out weak-instrument issues.

Finally, in column 9 I check whether results are robust to alternative measures of the outcome variable. To measure the likelihood of pursuing a research career I use a dummy indicating if the occupation at the date of interview involves research activities at least in part. Instead, to measure research productivity I use a dummy taking value one if graduate has more than 3 conference and proceedings articles.

In both cases, estimates are strongly significant and substantially identical to those obtained using main outcome variable measures.

5.3 The Mechanisms

Funding might influence Ph.D. student early research career and productivity in different ways. Being an important signal of academic ability, it might play a relevant role in the Ph.D. job market. Also, it might affect students' study effort and efficiency while writing the thesis and, as result, their later research performance. When financed, students might be more motivated to invest in a number of training activities generally provided for doctoral students, such as visiting research programs or summer schools. Yet, they might be more encouraged to attend courses, seminars, conferences or workshops. However, in addition to increasing investment in research-oriented activities, funding might induce students to reduce time spent on working while studying, including teaching activities or part-time work.

To explore the channels mediating the effect of funding, I use the two-equation model described in section 4 and estimate the impact of F on a number of outcome variables reflecting either the likelihood of investing in research-oriented activities during Ph.D. or the time spent on working while studying. Results are reported in table 7. In the upper panel, the outcome variable is a dummy indicating whether students have participated to visiting research programs or summer schools or seminars/workshops, respectively. In the lower panel, the outcome is a dummy variable for students that have carried out regular teaching or part-time work, respectively. Overall, both OLS and IV estimates document that students with funding spend less time working part-time and invest more in visiting research programmes abroad. This would suggest that funding effects could work, not only through an increased investment in research-training activities, but also through an increased time devoted to studying, that is, less time dedicated on working during the Ph.D.

Table 7: Mechanisms potentially accounting for the effect of funding: OLS and IV estimates

	(1) OLS	(2) 2SLS	(3) 2SIV	(4) OLS	(5) 2SLS	(6) 2SIV	(7) OLS	(8) 2SLS	(9) 2SIV
Upper panel: Investment in research-oriented activities									
	Visiting research			**Summer schools**			**Seminars/Workshops**		
Funding	0.161***	1.150**	0.689***	0.131***	0.093	-0.253	0.043***	0.120	0.044
	(0.017)	(0.534)	(0.218)	(0.017)	(0.492)	(0.251)	(0.011)	(0.214)	(0.115)
Lower panel: Time spent on working while studying									
	Regular teaching			**Part-time work**					
Funding	0.120***	-0.397	0.175	-0.459***	-0.486**	-0.658***			
	(0.018)	(0.389)	(0.223)	(0.022)	(0.239)	(0.134)			
Observations	7892	7892	7853	7892	7892	7853			

Notes: robust standard errors, clustered by field of study*university province, are reported in parentheses. * $p<0.05$ ** $p<0.01$ *** $p<0.001$. The whole set of control variates is included in all specifications. The outcome variable mean is 0.31 for "Visiting research programs", 0.35 for "Summer school programs", 0.93 for "Seminars/Workshops", 0.38 for "Regular teaching", and 0.13 for "Part-time work", respectively.

I also re-estimate the baseline model by including the channel-related dummies (Visiting research, Summer schools, Seminars/workshops, Regular teaching and Part-time work) to the set of controls in the research outcomes equation. The caveat of doing this is that, being the channel variable strongly affected by the treatment (i.e., Funding), I do not properly address the endogeneity issue introduced with the inclusion of these outcomes. Estimates are reported in table A.2 in the appendix and show that, especially when using the 2SIV estimator, the effect of funding disappears once channel variables are accounted for. Despite the aforementioned econometric concerns, these estimates provide further empirical evidence that the effect of funding may work through the mechanisms outlined above.

6 Conclusions

This paper addresses whether the receipt of funding during Ph.D. encourages students to pursue a career in research after graduation and whether it also affects their research productivity. The IV results uncover a significant positive effect of funding on either the likelihood of entering a research occupation or the probability of having more than 3 scientific articles within a few years after graduation. Sensitivity checks show that results are robust to different model specifications and alternative measures of both the instrumental and the outcome variables.

The results in this analysis are qualitatively related to those in Jacob and Lefgren (2011) and Arora and Gambardella (2005) who document positive, though modest, effects of NIH and NFS research grants on publication outcomes of postdoctoral fellows and young economists, respectively. In addition, results are in line with those in De Paola *et al.* (2012) and Leuven *et al.* (2010) who find that financial rewards improve undergraduate student outcomes, though for high-ability students only. Similarly, consistent with the LATE interpretation, I show that my IV estimates reflect the causal effect of funding for the marginal student (i.e., a student with high academic ability, though not outstanding) whose likelihood of getting funding is affected by changes in the instrument.

I also explore the mechanisms through which the effect of funding might work. I document that students with funding are more likely to invest in research-oriented activities, such as visiting research programs abroad, suggesting that students might respond to financial support by increasing effort. However, I find also evidence that funded students spend less time working while studying, indicating that the effect of funding might operate also through an increase in time spent on studying. This is consistent with Gunnes *et al.* (2013) who show that, if rewarded for completing their degree on time, students in Higher Education reduce their part-time work while studying.

Overall, the results presented in this paper have an important policy implication in that public investment is crucial in promoting research. Where graduate education is mostly publicly financed, policy makers are particularly interested in the extent to which financial support to doctoral students encourages research. The main IV results presented above would suggest that, if the Italian Ministry of Education (MIUR) were to increase by two the number of positions covered by scholarship out of the total number of open positions per Ph.D. program, at least one additional candidate, at margins, would pursue a research career after graduation. Although the present study uses data on Italian Ph.D. graduates, results might be relevant for the policy-making of many other European countries which have graduate education systems similar to the Italian one. Further, in contrast with the recent European governments' tendency to cut resources to research, they would suggest that more public money should be diverted to graduate programs if the objective is to enhance research and, through this, boost the economy.

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Appendix A

Table A.1: Summary statistics

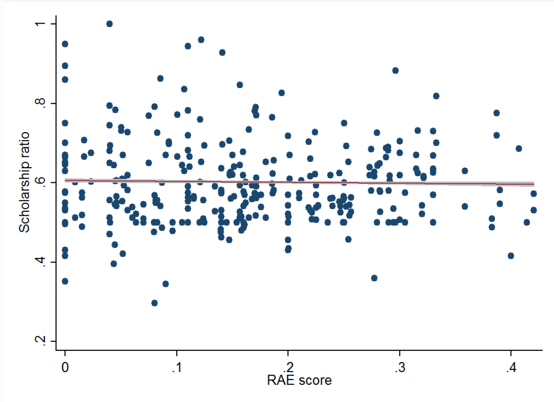
	All	Funding		Work in research institutions		Field of study		
		Yes	No	Yes	No	Social sciences	Engineering	Natural sciences
Funding	0.89	-	-	0.92	0.85	0.82	0.88	0.93
Work in research institutions	0.56	0.58	0.40	-	-	0.53	0.48	0.63
Research at least in part	0.74	0.74	0.67	0.89	0.54	0.74	0.74	0.73
More than 3 journal articles	0.57	0.58	0.47	0.76	0.33	0.56	0.53	0.61
More than 3 conference articles	0.47	0.49	0.36	0.64	0.27	0.35	0.51	0.53
Visiting research	0.31	0.33	0.14	0.35	0.25	0.32	0.29	0.31
Summer schools	0.35	0.37	0.18	0.42	0.26	0.29	0.34	0.39
Seminars/Workshops	0.93	0.94	0.89	0.95	0.91	0.92	0.93	0.94
Teaching	0.38	0.39	0.30	0.38	0.38	0.43	0.47	0.28
Part-time job	0.13	0.08	0.57	0.09	0.19	0.19	0.17	0.07
On-time graduation	0.88	0.89	0.82	0.91	0.85	0.80	0.89	0.93
Social sciences	0.26	0.24	0.41	0.25	0.28	-	-	-
Engineering	0.31	0.31	0.34	0.27	0.37	-	-	-
Natural sciences	0.43	0.45	0.25	0.48	0.36	-	-	-
Female	0.47	0.47	0.43	0.47	0.46	0.48	0.34	0.55
Age at graduation 29 or less	0.31	0.33	0.17	0.34	0.28	0.31	0.28	0.34
Age at graduation 30	0.16	0.17	0.11	0.16	0.16	0.16	0.16	0.17
Age at graduation 31	0.14	0.15	0.11	0.14	0.15	0.14	0.14	0.15
Age at graduation 32	0.11	0.11	0.13	0.11	0.11	0.12	0.11	0.10
Age at graduation 33 or more	0.27	0.24	0.48	0.25	0.29	0.28	0.31	0.24
At least one parent with BA degree	0.41	0.41	0.42	0.41	0.40	0.49	0.44	0.34
At least one parent with managerial job	0.40	0.40	0.43	0.41	0.40	0.47	0.43	0.35
BA grade 110	0.65	0.66	0.62	0.67	0.63	0.72	0.61	0.64
BA grade in [106,109]	0.15	0.15	0.16	0.15	0.15	0.12	0.17	0.16
BA grade in [101,105]	0.13	0.12	0.14	0.12	0.14	0.09	0.14	0.14
BA grade in [91,100]	0.06	0.06	0.08	0.06	0.07	0.06	0.08	0.05
BA grade in [66,90]	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.00
BA university in the north	0.41	0.41	0.36	0.42	0.39	0.37	0.39	0.44
BA university in the centre	0.26	0.25	0.30	0.25	0.27	0.29	0.24	0.25
BA university in the south	0.33	0.33	0.33	0.32	0.33	0.33	0.36	0.31
Regional mobility pre-PhD	0.18	0.17	0.27	0.19	0.18	0.31	0.13	0.14
4-year PhD program	0.22	0.23	0.13	0.25	0.18	-	-	0.51
RAE score of PhD university	0.19	0.19	0.18	0.20	0.19	0.16	0.16	0.23
Mean professor age of PhD university	56.57	56.63	56.08	56.66	56.44	55.26	56.97	57.07
Scholarship ratio (SR)	0.60	0.60	0.58	0.60	0.60	0.59	0.61	0.60
Observations	7892	6997	895	4408	3484	2068	2458	3366
Percentage	100	89	11	56	44	26	31	43

Table A.2: Funding, mechanism variables and early research outcomes: OLS and IV estimates

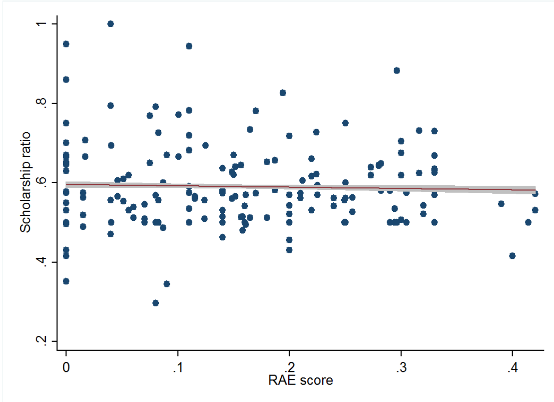
	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS	(5) 2SIV	(6) 2SIV
Upper panel: Research career						
Work in research institutions						
Funding	0.141***	0.057***	0.194	0.082	0.643***	0.128
	(0.017)	(0.017)	(0.397)	(0.494)	(0.228)	(0.123)
Visiting research		0.053***		0.052**		0.051***
		(0.014)		(0.026)		(0.015)
Summer schools		0.120***		0.120***		0.118***
		(0.014)		(0.019)		(0.014)
Seminars/workshops		0.068***		0.067***		0.065***
		(0.020)		(0.025)		(0.020)
Teaching regularly		0.012		0.011		0.009
		(0.012)		(0.022)		(0.012)
Part-time work		-0.118***		-0.109		-0.089*
		(0.017)		(0.195)		(0.048)
Lower panel: Research productivity						
More than 3 journal articles						
Funding	0.083***	0.044**	0.532	0.542	0.545**	-0.035
	(0.019)	(0.021)	(0.481)	(0.619)	(0.263)	(0.131)
Visiting research		0.101***		0.080***		0.105***
		(0.014)		(0.030)		(0.015)
Summer schools		0.117***		0.101***		0.119***
		(0.012)		(0.024)		(0.013)
Seminars/workshops		0.076***		0.060**		0.077***
		(0.022)		(0.028)		(0.022)
Teaching regularly		0.031**		0.012		0.035***
		(0.012)		(0.027)		(0.013)
Part-time work		0.003		0.198		-0.026
		(0.019)		(0.244)		(0.051)
First-stage						
Scholarship Ratio (SR)			0.222***	0.170***		
			(0.056)	(0.050)		
Predicted Funding (F-hat)					0.822***	0.976***
from probit					(0.147)	(0.096)
F-test statistics			15.92	11.93	29.16	79.02
Observations	7892	7892	7892	7892	7853	7853

Note: robust standard errors, clustered by field of study*university province, are reported in parentheses. * p<0.05 ** p<0.01 *** p<0.001. The whole set of control variables is included in all specifications.

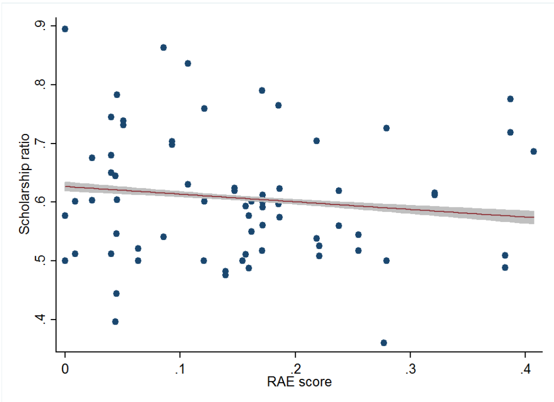
Figure 1: Correlation between SR and RAE score



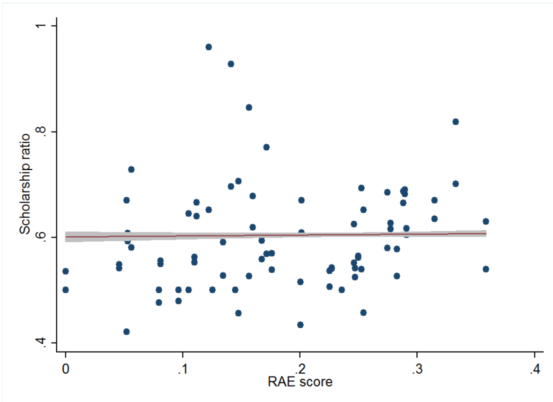
(a) All fields of study



(b) Social sciences

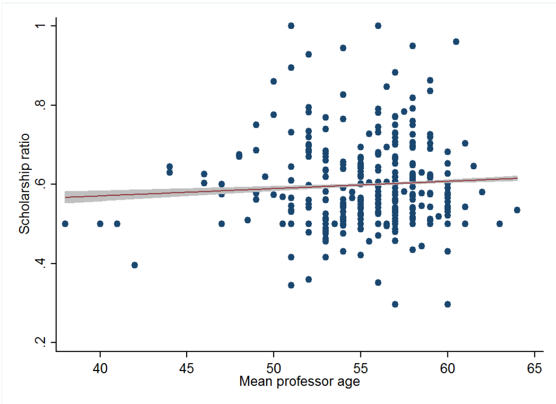


(c) Engineering

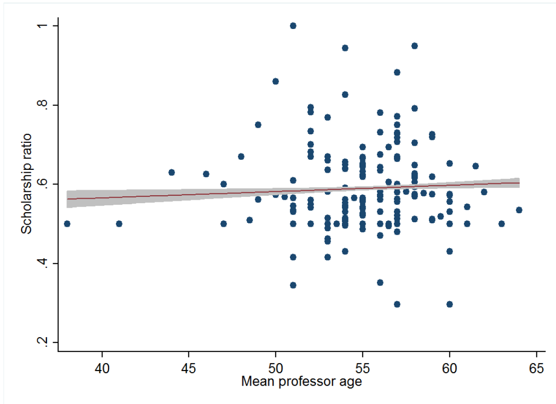


(d) Natural sciences

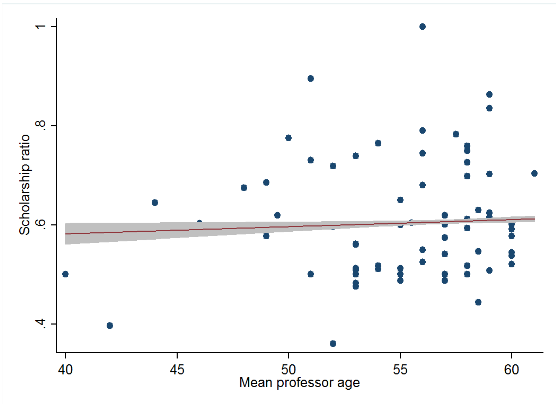
Figure 2: Correlation between SR and mean professor age



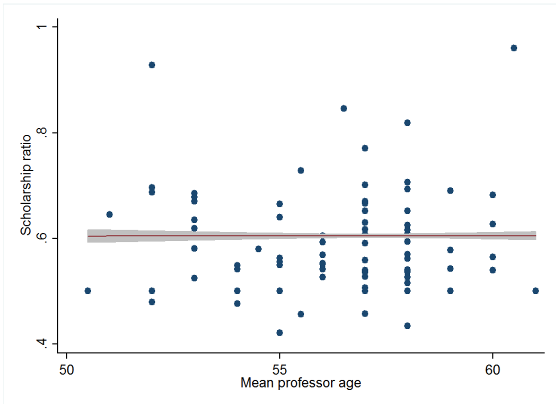
(a) All fields of study



(b) Social sciences



(c) Engineering



(d) Natural sciences