Funding and Research Outcomes in PhD Programs

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Abstract

This paper explores to what extent the receipt of funding during Ph.D. encourages post-degree research career and influences research productivity after graduation. Using novel data on new Doctorate recipients from Italian universities, I construct IV estimates of the effect of funding on both the likelihood to enter a research profession (extensive margins) and the early research productivity (intensive margins), respectively. The identification strategy exploits 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. Results uncover a significant and positive impact of funding on early research outcomes at both margins and are robust to different model specifications and outcome measures. About the underlying mechanisms, the analysis finds empirical evidence that, while studying, funded students invest more in research-oriented activities, i.e., visiting research programs, and spend less time working part-time than unfunded students do. Policy implications are discussed.

Keywords: Funding, PhD Graduates, Research Outcomes, IV

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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 focuses on the importance of faculty quality and the quality of the thesis supervisor (Waldinger, 2010; Cardoso, Guimaraes and Zimmermann, 2009; Hilmer and Hilmer, 2007; Grove and Wu, 2007; van Ours and Ridder, 2003) and find that students receiving their Ph.D. from higher quality universities are more likely to succede later in life. Other studies, analysing students in Economics only, document 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, DesJardins and Ranchhod, 2010; Kremer et al., 2009; Angrist and Lavy, 2009; Angrist et al., 2006) and in undergraduate programs (Gunnes et al., 2013; De Paola, Scoppa and Nistico', 2012; Garibaldi et al., 2012; Leuven et al., 2010; Cornwell, Lee and Mustard, 2005; Dynarsky, 2003). Related relevant 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). However, little is know about whether financial support is also an important driver for Ph.D. student outcomes after completion. This paper intends to reduce this lack of information and explores whether the receipt of funding during Ph.D. influences students' early research outcomes after graduation, in particular, to what extent it encourages post-degree research career and affects research productivity. It also contributes to extend up-to-date empirical evidence on the effect of funding on Ph.D. student outcomes, which typically focuses on one particular field of study or university, by taking advantage of a novel dataset on new Doctorate recipients from Italian universities that allow to distinguish across different fields of study and universities.

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 per Ph.D. program, hereafter 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 sistematically associated with a higher fraction of more academically inclined students across Ph.D. programs. As a falsification exercise, I estimate the effect of SR on students' academic ability measured by their performance in undergraduates studies and, in particular, on the proportion of students with very high B.A. grade. Results indicate that there is no significant effect, suggesting that changes in SR would not significantly alter students quality composition at the access to Ph.D. However, one possible criticism with using the B.A. grade is that it may not correctly measure student academic ability because of thepotentially different grading standards across universities and fields of study. Therefore, I replicate the exercise using as alternative measure 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 Ph.D. Results are in keeping with the previous ones, 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 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. 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 on student research outcomes in the aftermath of the graduation. The research outcomes cover both the likelihood to enter a research profession and the early research productivity in terms of scientific articles, the former being related to the extensive margins and the latter to the intensive ones. In particular, I find that funding increases the probability of entering a profession in research institutions by around 60 percentage points and the likelihood to have 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, whose motivation strongly depends on the receipt of funding and for whom therefore 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, if "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. Morevoer, 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 beeing an important signal of academic ability, funding may provide students with strong incentices to invest in research-oriented activities while writing the dissertation, such as visiting research periods, 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 and spend less time on part-time work while studying. In addition, I document that funding has no longer relevance once channel variables were 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. The survey is part of a system of surveys focusing on the study-to-work-transition, which also includes the surveys on university and upper secondary school graduates and provide a comprehensive picture on the education-to-work transition patways for the young. All surveys are carried out every three years and use the C.A.T.I. technique (Computer Assisted Telephone Interviewing) to interview each single group of students about three years after their graduation.

Differently from the other two which are sample survey, the survey on Ph.D. graduates refers to the universe of Ph.D. graduates in 2004 and 2006, which consists of 18568 doctorates: 8443 for 2004 and 10125 for 2006, though the response rate was about 70%, thus reporting information on 12964 doctorates, 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 systematicaly 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 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 that are 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 sample selection. Indeed, regarding students who completed the Ph.D., these data 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 sistematically from their relative counterparts at the access to the Ph.D. 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 register 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 that had or not a MIUR scholarship (column 4 and 5, respectively) in the ISTAT survey. Given that, from the survey data, I do not observe in which year Ph.D. started, 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 entry academic year for each cohort.[4] In the upper panel I restrict the analysis to the 3-year Ph.D.

[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_1units 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.

[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.

[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.

programs while in the lower panel I also include the 4-year Ph.D. programs. In the latter, statistics are weithed averages where the weights (35% and 65%, respectively) reflect the relative proportions of 4-year and 3-year Ph.D. courses 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, thus suggesting that pontential attrition from Ph.D. would have not altered the composition of funded and unfunded students and that selection bias might be considered as negligible.

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 universitites. However, for privacy matters, data allow to know the province of the university awarding the Ph.D. but not the exact one. So each observation 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, which is 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 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 doctorates in the remaining 10 fields, which can be grouped in three macro-fields: Social sciences, Engineering and Natural sciences. After this exclusion, the restricted sample consists of 7892 doctorates, 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 2. 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 cover both the extensive and the intensive margins of Ph.D. students' research performance after graduation. With respect to the extensive margins, the outcome variable measures whether students undertake a research career after graduation. In particular, it is a dummy variable indicating whether graduates, at the date of interview, work in research institutions. Alternatively, I also 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 intensive margins, the outcome measures students' research productivity in the aftermath of graduation. In this case, the main outcome variable is a dummy indicating whether students, after graduation, publish more than 3 scientific journal articles. As alternative outcome measure, I use a dummy taking value one if they have more than 3 conference and proceedings articles.[5] The correlations among all the outcome variables are reported in

[5]Note that the number of scientific articles would have been a more suitable measure of research productivity, but unfortunately data only allow me to know whether, at the date of interview, they have no articles, up to 3 or more than 3. Thus, the best I could do to measure

table 3. Descriptive statistics indicate that 56% of the sample work in research institutions and this percentage substantially differs among funded (58%) and unfunded students (40%). Yet, the 74% carries out research activities at least in part and this percentage is significantly lower for unfunded students (67%). Regard research productivity, graduates with more than 3 scientific journal articles are, on average, 57% of the sample and this fraction is 58% and 47% for students with and without funding, respectively. Also, those with more than 3 conference and proceedings articles are, on average, 47% of the sample but this percentage differs across the two subgroups, 49% for funded and 36% for unfunded students. For what concerns the activities undertaken during the Ph.D. experience, 31% spent at least a period of 4 consecutive week in a visiting research programme abroad, 35% attended summer schools, 38% carried out teaching activities on a regular base 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 2 requires subjective calls. 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 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 (bigger 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. The former measures the mean professor age in each department while 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. It is important to note that most of the scholarships

productivity is to consider whether they have more than 3 as opposed to less than 3 articles at the date of interview. Yet, because of the particular structure of the Italian labor market, characterized by very slow career and low variation in salary, especially in academe and other research institutions, labour market outcomes are not very good proxies for the research productivity of Italian doctorates.

in the Italian Ph.D. programs are financed by the MIUR. In particular, the MIUR scholarships represent the 75% of the total funding. In addition, it is worth noting that the MIUR scholarship is allocated according to an entry test. It amounts to 800 euro per month and covers the entire duration of the program. 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.

3 Empirical strategy

I assume that Ph.D. graduates' research outcomes (Y) depend on whether they had any type of funding during 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 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:

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

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

where equation (1) is the research outcomes regression and equation (2) the corrisponding 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.[6] It captures funding effects 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 ability is measured (when considering B.A. grade in columns 1-3 or parental education in columns 4-6) and of how regression model

[6]See Imbens and Angrist (1994)

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. One may question on using B.A. grade as measure student ability because of potential different grading standards across universities and fields of study. To overcome this issue, 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 Ph.D. Taken together, estimates in table 4 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.[7]

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. Another potential 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 CIVR indicator and the mean professor age, both measured at the university province level by field of study.[8]

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 and provides consistent estimates regardless of the assumption on the distribution of the error terms. 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, pag. 623). 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.[9] 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 mispecification of such equation as probit.

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

[7]As diagnostic test, I show that even if the 95% confidence interval upper bound was the "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 approsimately 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.

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

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

4 Results

4.1 The effect of funding on research outcomes

Before turning to IV estimates, I first present OLS estimates, which are reported in table 5.[10] They show a positive and strongly significant correlation between funding and research outcomes, either at the extensive and 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 FE. In particular, it is worth emphasizing how coefficients remain strongly stable after controlling for student ability, measured by B.A. grade, and for Ph.D. university quality, measured by the RAE score and the mean professor age. Furthermore, these estimates are robust to alternative measures of the outcome variable (column 7), both when considering research career (upper panel) and research productivity (lower panel). Interpreting OLS estimates, they 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 resercher, is about 8 percentage points higher for funded students than for unfunded ones.

I then move to discuss IV results, which are reported in table 6.[11] Column 1 reports estimates obtained using the standard 2SLS estimator, instrumenting funding (F) with SR. Results from first-stage regression suggest that SR is a strong predictor of funding (F-statistics is around 16, larger than the rule-of-thumb threshold of 10). 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, although now the instrument is 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.[12] Yet, they have very large coefficients in magnitude (much larger than corrisponding OLS).[13]

However, it is worth clarifying what the estimated model identifies and how the

[10]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.

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

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

[13]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 careert after graduation. In particular, funding would increase the probability of entering a research occupation after graduation by at least 20 pecentage points.

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 ability but not outstanding that received funding but that would have not received it if SR were slightly lower. Also, this is likely to be a student whose research motivation strongly depends on funding; 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 IV estimates to be notably larger, in magnitude, than OLS ones.[14] In keeping with this interpretation, in table 7 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 $B.A.grade < 106$.[15] 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, on average, low-middle quality students would never get funding, regardless of SR, whilst high-quality students' likelihood of getting funding increases with SR.

Overall, the IV results in column 2 document that funding significantly affects research outcomes either at the extensive or intensive margins. About the extensive margins, I find that, for marginal students, funding increases the probability of entering an occupation in research institutions by about 64 percentage points. Regard the intensive margins, I show that the likelihood to have more than 3 scientific publications, i.e., to be a productive researcher, increases by about 54 percentage points for the marginal student that received funding.

4.2 Sensitivity analysis

Here I investigate the robustness of the main IV results presented above. Columns 3 to 8 of table 6 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.[16] 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.[17] 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

[14]And this is consistent with Imbens and Angrist (1994) who show that, in the presence of heterogeneous effects and under suitable monotonicity assumptions, IV estimates may well exceed OLS estimates as they pin down the effect on the marginal individual which can be greater than the average effect.

[15]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.

[16]First-stage F statistics 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).

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

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 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, coeffients 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 squared in column 6 and either SR squared or SR cubed 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, I investigate whether results reflect the effect of graduating on stipulated time instead of the real effect of funding. In principle, indeed, funding might increase on-time graduation and, as consequence, influence research performance. To net out the effect of funding from potential on-time completion effects, I include as additional control a dummy for on-time graduation. Results, in column 8, are robust to this inclusion. 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 (coefficients are not statistically different from each other).

Overall, robustness checks confirm that the IV estimates of this analysis provide credible evidence of the causal effect of funding on research outcomes. In the reminder of this section, I focus on the mechanisms through which such an effect might operate.

4.3 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 perfomance. 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, besides 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 3 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 8. In the upper panel, the outcome variable is a dummy indicating whether students have participated to either 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 either 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. I also re-estimate the baseline model by including the channel-related dummies (Visiting, Summer schools, Seminars/workshops, Regular teaching and Part-time work) to the set of controls in the research outcome equation. Estimates are reported in table 9 and show that, especially when using the 2SIV estimator, the effect of funding disappears once channel variables are accounted for. Taken together, results in tables 8-9 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 Ph.D.

5 Conclusions

In this paper I use novel data on the 2004 and 2006 cohort of Italian Ph.D. graduates to study the effect of funding on early research outcomes both at the extensive and intensive margins. In particular, I investigate the extent to which the receipt of funding during Ph.D. influences either the likelihood of pursuing a research career or research productivity after graduation. To identify the effect of funding I use the variation in the supply of Ph.D. scholarships financed by the Italian Ministry of education (MIUR) across fields of study and university province. IV results uncover significantly positive funding effects on either entering a research occupation or having more than 3 scientific articles few years after graduation. Sensitivity checks show that results are robust to different model specifications and alternative outcome measures. These results, especially for what concerns the effect of funding on research productivity, are closely related to those found by Jacob and Lefgren (2011) who show that receipt of NIH postdoctoral training grant strongly increases research productivity. Further, results are in line with those in De Paola, Scoppa and Nistico' (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 (with high-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 funding effects 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.

These results 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 in this analysis 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 this analysis uses data on Italian doctorates, 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.

References

[1] Andrews, Rodney J., Stephen DesJardins, and Vimal Ranchhod (2010). "The Effects of the Kalamazoo Promise on College Choice", Economics of Education Review, 29(5): 722–737.

[2] Angrist, Joshua, Eric Bettinger, and Michael R. Kremer (2006). "Long-Term Educational Consequences of Secondary School Vouchers: Evidence from Administrative Records in Colombia", American Economic Review, 96(3): 847–862.

[3] Angrist, Joshua, and Victor Lavy (2009). "The Effects of High Stakes High School Achievement Awards: Evidence from a Randomized Trial", American Economic Review, 99(4): 1384–1414.

[4] Athey, Susan, Laerence F. Katz, Alan B. Krueger, Steven Levitt, and James Poterba (2007). "What Does Performance in Graduate School Predict? Graduate Economics Education and Student Outcomes", American Economic Review, 97(2): 512-518.

[5] Bartik, Timothy J. and Marta Lachowska (2012). "The Short-Term Effects of the Kalamazoo Promise Scholarship on Student Outcomes", Upjohn Working Papers and Journal Articles 12-186, W.E. Upjohn Institute for Employment Research.

[6] Blomquist, Soren and Matz Dahlberg (1999). "Small Sample Properties of LIML and Jackknife IV Estimators: Experiments with Weak Instruments", Journal of Applied Econometrics, 14: 69–88.

[7] Booth, Alison L., and Stephen E. Satchell (1995). "The Hazard of Doing a Ph.D.: An Analysis of Completion and Withdrawal Rates of British Ph.D. Students in the 1980s", Journal of the Royal Statistical Society A, 158(2): 297-318.

[8] Bowen, William G. and Neil L. Rudenstine (1992). "In Pursuit of the Ph.D.", Princestone, NJ: Princestone University Press.

[9] Breneman, David W. (1976). "The PhD Production Process", in J. T. Fromkin, D.T. Jamison, and R. Radner (Eds.), "Education as an Industry", Cambridge, MA: Ballinger.

[10] Cardoso, Ana Rute, Paulo Guimaraes, and Klaus F. Zimmermann (2010). "Comparing the Early Research Performance of PhD graduates in Labor Economics In Europe and the USA", Scientometrics, 84(3): 621-637.

[11] Cornwell, Christopher and Lee K. Mustard (2005). "Student Responses to Merit Scholarship Retention Rules", Journal of Human Resources, XL(4): 895-917.

[12] De Paola, Maria, Vincenzo Scoppa, and Rosanna Nistico' (2012). "Monetary Incentives and Student Achievement in a Depressed Labor Market: Results from a Randomized Experiment", Journal of Human Capital, 6(1): 56-85.

[13] Dynarsky, Susan M. (2003). “Does Aid Matter? Measuring the Effect of Student Aid on College Attendance and Completion”, American Economic Review, 93(1): 279-288.

[14] Ehrenberg, Ronald G. and Panagiotis G. Mavros (1995). “Do Doctoral Students, Financial Support Patterns Affect Their Times-to Degree and Completion Probabilities?”, Journal of Human Resources, 30(3): 581-609.

[15] Fryer, Roland G. (2011). “Financial Incentives and Student Achievement: Evidence from Randomized Trials”, Quarterly Journal of Economics, 126(4): 1755–1798.

[16] Garibaldi, Pietro, Francesco Giavazzi, Andrea Ichino and Enrico Rettore (2012). “College Cost and Time to Complete a Degree: Evidence from Tuition Discontinuities”, The Review of Economics and Statistics, 94(3): 699-711.

[17] Grove, Wayne A., and Steven Wu (2007). “The Search for Economics Talent: Doctoral Completion and Research Productivity”, American Economic Review, 97(2): 506-511.

[18] Gunnes, Trude, Lars J. Kirkebøen, and Marte Rønning (2013). “Financial Incentives and Study Duration in Higher Education”, Labour economics, 25: 1-11.

[19] Hilmer, Christina and Michael Hilmer (2007). “Women Helping Women, Men helping Women? Same-Gender Mentoring, Initial Job Placements, and Early Career Publishing Success for Economics PhDs”, American Economic Review, 97(2): 422-426.

[20] Jacob, B. and Lefgren, L. (2011). “The Impact of Research Grant Funding on Scientific Productivity” Journal of Public Economics. 95(9-10): 1168-1177.

[21] Kremer, Michael R., Edward Miguel, and Rebecca Thornton (2009). “Incentives to Learn”, Review of Economics and Statistics, 91(3): 437–456.

[22] Krueger, Alan B. and Steven Wu (2000). “Forecasting Job Placements of Economics Graduate Students”, Journal of Economics Education, 31(1): 81-94.

[23] Leuven, Edwin, Hessel Oosterbeek, and Bas van der Klaauw (2010). “The Effect of Financial Rewards on Students’ Achievement: Evidence from a Randomized Experiment”, Journal of the European Economic Association, 8(6): 1243–1265.

[24] Mangematin, Vincent (2000). “PhD Job Market: Professional Trajectories and Incentives During the PhD”, Research Policy, 29(6): 741-756.

[25] Staiger, Douglas and James H. Stock (1997). “Instrumental Variables Regression with Weak Instruments”, Econometrica, 65: 557-586.

[26] van Ours, Jan C. and Geert Ridder (2003). “Fast Track or Failure: A Study of Graduation and Dropout Rates of Ph.D. Students in Economics”, Economics of Education Review, 22: 157-166.

[27] Waldinger, Fabian (2010). "Quality Matters: The Explulsion of Professors and The Consequencesfor PhD Student Outcomes in Nazi Germany", Journal of Political Economy, 118(4): 787-831.

[28] Windmeijer, Frank and Joao Santos Silva (1997). "Endogeneity in Count Data Models: An Application to Demand for Health Care", Journal of Applied Econometrics, 12(3): 281-294.

Tables of Results

Table 1: Addressing sample selection

	(1)	(2)	(3)		(4)	(5)	(6)
	MIUR DATA				**ISTAT SURVEY**		
Enrolment year	SCH	NO SCH	TOTAL	Completion year	SCH	NO SCH	TOTAL
Upper Panel	*3-year PhD programs only*						
2000-01	5864	2507	8371	2004	2202	975	3177
	70%	*30%*			*69%*	*31%*	
2002-03	7006	4688	11694	2006	2524	1469	3993
	60%	*40%*			*63%*	*37%*	
Lower Panel	*3-year and 4-year PhD programs*						
1999-00 (4y PhD)	5658	2344	8002	2004	3479	1634	5113
2000-01 (3y PhD)	*71%*	*29%*			*68%*	*32%*	
2001-02 (4y PhD)	6687	4470	11157	2006	3989	2365	6354
2002-03 (3y PhD)	*60%*	*40%*			*63%*	*37%*	

Notes: here ISTAT sample includes all fields of study and is restricted to those that have completed the Ph.D. on time in order to exactly identify the enrolment year for each cohort and, thus, make the comparison with MIUR data on access to Ph.D. Columns 1-2 report the number and percentage of students who have officially entered Ph.D. with (SCH) and without (NO SCH) MIUR scholarship, respectively. Columns 4-5 report the number and percentage of graduates in the sample who have reported that had (SCH) and had not (NO SCH) MIUR scholarship, respectively. In the lower panel, these numbers and percentages represent weighted averages with weights 0.35 and 0.65 for 4y PhD and 3y Phd, respectively (weights reflect the relative proportions of 4y PhD and 3y PhD observed in ISTAT sample.

Table 2: Summary statistics

	All sample	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_res inst	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
Journal articles_3+	0.57	0.58	0.47	0.76	0.33	0.56	0.53	0.61
Conference articles_3+	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 completion	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_29-	0.31	0.33	0.17	0.34	0.28	0.31	0.28	0.34
Age_30	0.16	0.17	0.11	0.16	0.16	0.16	0.16	0.17
Age_31	0.14	0.15	0.11	0.14	0.15	0.14	0.14	0.15
Age_32	0.11	0.11	0.13	0.11	0.11	0.12	0.11	0.10
Age_33+	0.27	0.24	0.48	0.25	0.29	0.28	0.31	0.24
Parental edu_BA	0.41	0.41	0.42	0.41	0.40	0.49	0.44	0.34
Parental job_manag	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_[106,109]	0.15	0.15	0.16	0.15	0.15	0.12	0.17	0.16
BA grade_[101,105]	0.13	0.12	0.14	0.12	0.14	0.09	0.14	0.14
BA grade_[91,100]	0.06	0.06	0.08	0.06	0.07	0.06	0.08	0.05
BA grade_[66,90]	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.00
BA uni_north	0.41	0.41	0.36	0.42	0.39	0.37	0.39	0.44
BA uni_centre	0.26	0.25	0.30	0.25	0.27	0.29	0.24	0.25
BA uni_south	0.33	0.33	0.33	0.32	0.33	0.33	0.36	0.31
Regional mobility	0.18	0.17	0.27	0.19	0.18	0.31	0.13	0.14
PhD program_4years	0.22	0.23	0.13	0.25	0.18	-	-	0.51
RAE score	0.19	0.19	0.18	0.20	0.19	0.16	0.16	0.23
Professor age	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 3: Correlations among outcome variables

	Work in res institutions	Research at least in part	Journal articles_3+	Conference articles_3+
Work in research institutions	1			
Research at least in part	0.3876	1		
Journal articles_3+	0.4274	0.4152	1	
Conference articles_3+	0.3695	0.3646	0.5452	1

Table 4: SR and student ability

	(1) OLS	(2) PROBIT	(3) LOGIT	(4) OLS	(5) PROBIT	(6) LOGIT
	Student ability					
	BA grade>=106			**Parental edu_BA**		
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_29-	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_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_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_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)
Parental edu_BA	0.018	0.020*	0.020*			
	(0.011)	(0.011)	(0.011)			
Parental job_manag	0.005	0.007	0.006			
	(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)
PhD program_4years	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	0.005	0.011	-0.004	-0.174**	-0.169**	-0.167**
	(0.075)	(0.077)	(0.080)	(0.073)	(0.072)	(0.073)
Professor age	0.004	0.003	0.003	0.003	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
N	7892	7888	7888	7892	7892	7892

Notes: robust standard errors, clustered by field of study*uni 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 categories is Age_33+.

Table 5: Funding and early research outcomes: OLS estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Upper panel	*Extensive margins: 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	*Intensive margins: Research productivity*						
	More than 3 journal articles						**More than 3 conf 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 uni province	+	+	+	+	+	+	+
Individual traits	-	+	+	+	+	+	+
Parental backgroung	-	-	+	+	+	+	+
BA-related traits	-	-	-	+	+	+	+
Regional mobility pre-PhD	-	-	-	-	+	+	+
PhD-related traits	-	-	-	-	-	+	+
Observations	7892	7892	7892	7892	7892	7892	7892

Notes: robust standard errors, clustered by field of study*uni province, are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Individual traits variables are Female, Age_29-, Age_30, Age_31, Age_32 (Age_33+ is the reference category). Parental background variables are Parental edu_BA and Parental job_manag. BA-related traits variables are BA grade_110, BA grade_[106,106], BA grade_[101,105], BA grade_[91,100] (BA grade_[66,90] is the reference category), BA uni_north, BA uni_centre (BA uni_south is the reference category). PhD-related traits variables are PhD_4y, RAE score and Professor age. The outcome variable mean (standard deviation) is 0.56 (0.50) and 0.74 (0.44) in the upper panel, respectively and 0.57 (0.49) and 0.47 (0.50) in the lower panel, respectively.

Table 6: Funding and early research outcomes: IV estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	2SLS	2SIV	2SIV	LIML	2SIV	2SIV	2SIV	2SIV	2SIV
	SR as instrument	F-hat as instrument	SR, F-hat as instruments	SR, F-hat as instruments	non-linear covariates	SR^2 in probit	SR^2, SR^3 in probit	On-time completion as control	alternative outcome var
Upper panel	*Extensive margins: 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***	0.594***	0.415**
	(0.397)	(0.228)	(0.227)	(0.237)	(0.187)	(0.235)	(0.216)	(0.227)	(0.207)
Lower panel	*Intensive margins: Research productivity*								
	More than 3 journal articles								**More than 3 conf articles**
Funding	0.532	0.545**	0.542**	0.542**	0.467**	0.480*	0.422*	0.491*	0.532**
	(0.481)	(0.263)	(0.271)	(0.271)	(0.197)	(0.270)	(0.251)	(0.260)	(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***	0.816***	0.822***
from probit		(0.152)	(0.171)	(0.171)	(0.140)	(0.151)	(0.138)	(0.147)	(0.152)
F-test statistics	15.922	29.161	15.358	15.358	40.851	29.446	36.143	28.611	29.161
Hansen test p-value			0.515	0.515					
Observations	7892	7853	7853	7853	7840	7853	7853	7853	7853

Notes: robust standard errors, clustered by field of study-uni 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 (standard deviation) is 0.56 (0.50) and 0.74 (0.44) in the upper panel, respectively and 0.57 (0.49) and 0.47 (0.50) in the lower panel, respectively.

Table 7: 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) from probit				0.822***	0.956***	0.690*
				(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-uni 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 (standard deviation) is 0.89 (0.32).

Table 8: Mechanisms underlying the effect of funding: OLS and IV estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	2SLS	2SIV	OLS	2SLS	2SIV	OLS	2SLS	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-uni 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 (standard deviation) is 0.31 (0.46) for "Visiting research programs", 0.35 (0.48) for "Summer school programs", 0.93 (0.25) for "Seminars/Workshops", 0.38 (0.49) for "Regular teaching", and 0.13 (0.34) for "Part-time work", respectively.

Table 9: Funding, mechanism variables and early research career: OLS and IV estimates

	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS	(5) 2SIV	(6) 2SIV
			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)
First-stage						
Scholarship ratio (SR)			0.222***	0.170***		
			(0.056)	(0.050)		
Predicted Funding (F-hat) from probit					0.822***	0.976***
					(0.147)	(0.096)
F-test statistics			15.92	11.93	29.16	79.02
Observations	7892	7892	7892	7892	7853	7853

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