Publication Outcome of Public Funding in Science: A Panel Data Analysis of Grant Attribution, Scaling and Bundling Issues

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Preliminary

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ABSTRACT

Using detailed transaction level data from a small highly selective university for the period 2000-2010, we first estimate the link between public research funding and research output at the grant level, taking into account the effect of the presence of overlapping grants in the principal investigator's (PI) grant portfolio. We measure grant research output in terms of publication quantity and quality, as represented by the number of articles and the average impact factor of the journals in which they are published. We then consider the economic implications of our grant level results, aggregated across all grants at the PI level. We estimate the effects of both the size of total funding and the composition (bundling) of total funding on the PI's publication quantity and quality. At the grant level, after addressing the two main challenges of the attribution of publications to grants and the endogeneity of funding, we find that the elasticities of quantity and quality of publications attributed to a focal grant with respect to its size (as measured by the yearly flow of funds) are respectively 0.43 and 0.27, holding constant the flow of funds from other grants. We also find negative elasticities of -0.19 and -0.20 for the quantity and quality of publications attributed to the focal grant with respect to the size of other grants. When we aggregate these estimates to the PI level, we find that publication output increases with respect to total funding in terms of quantity with an elasticity of 33%, but decreases in terms of quality with an elasticity of -11%. We find no evidence of negative marginal returns. We also find that results, are sensitive to the way funding is bundled and the number of overlapping of grants. Specifically, holding total funding constant, more grants are associated with more articles but articles of lower average quality, clearly suggesting that the bundling of grants matters and that there is a quantity quality trade-off. These results, which concern the scientific productivity of highly successful researchers at one of the US's top research institutions, should be investigated for other less highly-selective research institutions. Our prior is that the tradeoff we observe would be stronger if we were to study a more heterogeneous group of researchers than a highly selective group whose ability and expertise arguably attenuate the tradeoff.

JEL: C23; I23; J40; O30

Research Public Funding; Scientific Productivity; Competitive Grant; Returns to Funding; Quantity-Quality Tradeoff.

1. INTRODUCTION

Competitive research grants are the principal means for distributing public research funding to principal investigators (PIs). Increasing costs of conducting scientific research require that scientists often have multiple grants. Yet program officers, when asked to document the impact of funding, often draw a direct link between the grants they award and research output, ignoring the twin issue associated with multiple grants of attribution of research output to a specific grant and the extent to which the PI's productivity related to one grant is affected by the presence of other grants.

Policy makers, such as those in the Office of Science and Technology Policy (OSTP) of the White House, are concerned with the "bigger picture" of returns to total funding, rather than returns to a specific grant. They are also concerned with whether there is an optimal amount of funding to distribute to an individual and the degree to which the composition of a researcher's funding portfolio affects output. The first concern relates to scaling: is there evidence of decreasing or negative marginal returns? The second relates to the way in which grants are bundled: does the division of an individual's total funding into several grants affect these returns?

In this paper we respond first to the Program Officers' need to measure the effectiveness of their awarding grants by estimating the relationship between grant funding and research output at the grant level. We address the issue of multiple grants by controlling for the flow of funds from other grants. We then respond to the Policy Makers' needs to evaluate the returns to public funding and concerns with the scaling and bundling issues. We do so by aggregating the estimates obtained at the grant level to the PI level.

In our empirical analysis we measure grant research outcome in terms of publication quantity and quality, as represented by the number of articles and the average impact factor of the journals in which they are published. Crucial to conducting this analysis is establishing a direct link of publications to specific grants. Previous work has not had access to the data necessary to address this attribution challenge, using only data from one funding agency (see the numerous references to Berg and to Lorsch). Assessing causality is another major challenge, because grant funding and research output are endogenously determined. Researchers who receive grants are likely to differ in terms of ability, creativity and persistence from those who receive no or few grants. We can control for such unobserved differences in so far as they are largely permanent by taking advantage of the panel structure of our data to include PI fixed effects in the relation of publication to grant flow of funds. Introducing fixed effects can, however, aggravate estimation biases due to potential errors in variables and to other sources of endogeneity, in particular those arising from the correlation of researchers' publication productivity over time, largely reflecting the process of cumulative advantage that Robert Merton called the Matthew Effect (Merton, 1968). We address this further difficulty by relying on an instrumental variable (IV) approach.

Our basic results are qualitatively the following. We find that the larger the yearly flow of grant funds the higher is grant productivity, both in terms of quantity and quality of publications. However, the presence of other grants in a PIs' portfolios is detrimental to productivity related to the focal grant. At the aggregate level, we find that the PIs' overall productivity in terms of number of publications is augmented with the total amount of public grant funding received but, at least for sums under $1million, at a decreasing marginal rate. This result is congruent with the observation that funding does not cover all costs associated with research, such as equipment and infrastructure, which are invariant with the size of the grant. We find no significant evidence that publication productivity in total declines with scale at some high level of total of grant funding. Indeed, our results suggest just the opposite. Productivity in terms of average impact factor publications, on the other hand, diminishes with the size of total funding at a constant marginal rate. The explanation for the striking contrast of the positive and negative effects of grant funding on PI's productivity in terms of publication quantity and quality lies in the fact that bundling results in a significant and robust tradeoff between quality and quantity. Specifically, we show that increasing the concentration of funding in one grant for a PI with two grants enhances PI's productivity both in terms of quantity and quality for a given amount of total funding. At the same time, we show that increasing the number of grants for PIs with grants of equal size impacts their productivity positively in terms of quantity but negatively in terms of average quality, for a given amount of total funding.

The paper is organized as follow. Section 2 describes the literature on research funding from the perspective of scholars and practitioners studying the returns to grant funding, Section 3 describes the data used in our econometric analysis, Section 4 presents the model, the estimation strategy, and the simulation exercises, Section 5 reports the estimates obtained at the grant level. Section 6 compares the estimates directly obtained at the PI level with those predicted at the PI level by aggregation of the grant level estimates, while Section 7 and 8 develop the implications of the latter with regards to the scaling and bundling issues. Conclusions are drawn in section 9

2. LITERATURE REVIEW

The size of the research enterprise is well documented. In the United States, the *National Institutes of Health* (NIH) awards over 9,000 *research project grants* (RPGs) annually to over 25,000 US researchers working in health-related research. The US *National Science Foundation* (NSF) makes about 11,000 grants. In Europe, the European Union awards about 7,000 grants a year to 42,000 researchers working in a wide array of areas, while national and regional agencies fund many more. However, the impact of these research investments is less well understood (Lane, 2010; MacIlwain, 2010).

Two literature strands investigate the impact of funding on research productivity. The first strand, aimed at estimating the effect of award funding on individual productivity, derives from scholars working in the field and is often published in peer-reviewed journals. The second strand, focused on determining the effectiveness of specific funding programs, includes contributions by program officers and research directors, and is often published in editorials and blogs.

Contributions in peer-reviewed articles

The increasing availability of data from national funding agencies allows economists and sociologists of science to study the impact of being awarded a grant on researchers' outcomes and, in particular, publications. Most of this literature, which focuses on publication productivity, finds that the specific impact of being awarded a grant is rather limited. Arora & Gambardella (2005), for example, examine *National Science Foundation* (NSF) grant applications, and find that awarded scientists show modest productivity gains, except for young scientists, who benefit more from the funding decision. More recently, other work which has contributed using different methodological approaches, confirms that the impact of being awarded a grant has a limited effect. Jacob & Lefgren (2011), for example, find that being awarded a *National Institutes of Health*

(NIH) research grant increases the recipients' publication productivity by 7% over 5 years after the grant is awarded. Gush, Jaffe, Larsen, & Laws (2015) find that being awarded a grant from the *New Zeeland Marsden Fund* is associated with a 3 to 5% increase in annual publications and a 5 to 8% increase when publication counts are citation-weighted.

Other work considers additional dimensions of researcher's productivity. Defazio, Lockett, & Wright (2009), for example, find that the effect of being awarded a grant supporting collaboration by the *European Union* does not impact publication productivity during the funding period; however, it enhances productive collaborations in the post-funding period. Carayol & Lanoë (2017) find that receiving a grant from the French *Agence Nationale de la Recherche* (ANR) has a positive effect on the collaboration and turnover of co-authors. Similarly, Ayoubi, Pezzoni, & Visentin (2017) find that being awarded a grant primarily promotes scientific collaboration.

A common characteristic of this strand of literature is that it does not assess the outcome effects of public funding in terms of its monetary amount, which is what we do in this paper, but rather in terms of whether or not the researcher has received support. In one of the rare attempts to assess the monetary effects, Arora, David, & Gambardella (2000), on the basis of a sample of scientists applying to a biotechnology research program sponsored by the *Italian National Research Council* (CNR), obtain an elasticity of research output to research funding of 0.6.

Contributions in editorials and blogs

In one of the most commented attempts to link research funding and grant output, Jeremy Berg (Berg, 2010a), director at the time of the *National Institute of General Medical Sciences* (NIGMS) tied the amount of direct funding investigators received in fiscal 2006 from NIH grants to the number of articles published during the period 2007-2010 and found a correlation coefficient of 0.14 between the two. He plotted the average number of publications of grant recipients, and their impact factor, to bins of funding and found that researcher productivity began to diminish as grant size exceeded $600,000 to $750,000. He refers to this as evidence of "diminishing returns" to funding. He addressed the issue of attribution by assuming that all articles published by the investigator during the period could be attributed to NIH funding, even though many investigators have funding from more than one agency. The assumption that all articles published during the period 2007-2010 relate to funding received in 2006 ignores the fact that some of the research undoubtedly relates to funding received in an earlier or later period. The Berg posting generated considerable discussion about its methodology as well as the appropriateness of the output measure. Some postings also questioned the potential for conflating funding levels with lab characteristics, implicitly addressing the fact that Berg's methodology did not address issues of endogeneity.

In subsequent work Berg (Berg, 2010b) examined productivity associated with the number of grants, not the amount of funding. He found that researchers with one NIH grant produced a median of 11.5 articles; those with 2 produced a median of 23.5; the median for those with 3 was higher but with a marginal impact considerably lower than 11.5, as was the marginal impact of going from the 4th to 5th to 6th grants. The analysis, however, does not hold funding constant as the number of grants vary, and thus, by conflating the number of grants with total funding, ignores the bundling issue, namely the concentration of funding in many or few grants of different sizes.

Jon Lorsch, Berg's successor as director of NIGMS, built on Berg's research (Lorsch, 2015a), and a much earlier piece by Bruce Alberts (Alberts, 1985) outlining inefficiencies that can arise as labs become larger, to make the case that efficiencies are created when research funds are distributing more evenly. The argument is based on two different empirical studies. One (Fortin & Currie, 2013) compared the publications of university researchers funded by the *Natural Science and Engineering Research Council* (NSERC) of Canada with those who also received funds from another Canadian funding agency. The study found the latter to be no more productive in terms of article counts than those who received only funds from NSERC. The other (Danthi, Wu, DiMichele, Hoots, & Lauer, 2015) compares outputs attributed to NIH *American Recovery and Reinvestment Act* grants (ARRA) with outputs attributed to regular NIH grants and found that "despite shorter durations and lower budgets, ARRA grants had comparable citation outcomes per $million spent to that of contemporaneously funded NIH grants."

In more recent work, Lorsch and coauthors reexamined the relationship between research funding and output for NIGMS investigators. Attribution is determined by citations to funding sources found in publication acknowledgements. Funding in 2010 is related to publications in the four-year period 2011-2015 (Dorsey, Basson, & Lorsch, 2016). The authors find that publications increase with funding up to $300,000 but thereafter do not. They also report that the average number of citations per publication tends to be constant or very slightly decreasing.

More recently, Michael Lauer, the deputy director for extramural research at NIH, and coauthors analyzed the relationship of publications to an index measuring number of grants (Lauer, Roychowdhury, Patel, Walsh, & Pearson 2017). The index, christened the Grant Support Index (GSI), assigns points to R01 grants as well as other types of grants, which depend on how much time the investigator's research requires (Kaiser 2017). Lauer then related the GSI score to number of publications, measured in terms of an article's citations relative to those of other articles in the same field, referred as the Relative Citation Ratio (RCR). The relationship between the two variables was estimated using a double log form relating the log of weighted relative citations to the log of the GSI score. The resulting double log relationship increased at a decreasing rate. It was interpreted by Lauer and others to indicate the presence of diminishing marginal productivity. On the basis of their analysis, NIH proposed to cap an investigator at a given GSI score, using the resulting savings to fund early career and midcareer investigators. The proposal met considerable push back and was quickly abandoned by NIH in favor of creating the Next Generation Researchers Initiative with set asides for early career and midcareer investigators.[1]

The conclusions of the NIH analyses by Lauer and his colleagues are questionable econometrically for at least two reasons. First, and most importantly, like the earlier investigations by Berg, these analyses do not address the issue of endogeneity. In particular they do not control for the fact that individuals with higher scores may be inherently more productive than those with lower scores.[2] Second, as pointed out by many critics, a double log specification between two variables can be misleading. It does not translate directly to the usual log relation or simple linear relation between two variables. Thus, it does not follow directly from the analysis (or the figure that was widely

[1] See Michael Lauer: https://nexus.od.nih.gov/all/2017/05/02/nih-grant-support-index/ and Jocelyn Kaiser: http://www.sciencemag.org/news/2017/06/updated-nih-abandons-controversial-plan-cap-grants-big-labs-creates-new-fund-younger for the responses that the proposal solicited.

[2] In this respect, see also Shane Crotty: https://medium.com/@shane_52681/the-new-nih-rule-of-21-threatens-to-give-up-on-american-preeminence-in-biomedical-research-based-c40060bd3022 .

circulated) that smaller labs or teams are more efficient than larger ones, or in economic terms that returns to size or scale are marginally decreasing and eventually negative.[3]

3. DATA

A small highly selective university in the US provided us grant data on public funding for all faculty from 2000 to 2010, available to us only through remote access for reasons of confidentiality. Data include the identity of all the university faculty who are also principal investigators (PIs) on at least one public research grant. The available information includes both grant and PI biographic characteristics. We complement this information with the PI's publications collected from the Web of Science (WOS) bibliometric dataset (Institute for scientific information, Thomson Reuters). Before presenting our sample, variables and important descriptive statistics, we explain how we deal with the challenge of attributing publications to grants.

The issue of attribution

We address the issue of the attribution of publications to different grants by developing a new approach, referred to as PhD/PD attribution. We prefer this method to a purely chronological approach leading to very noisy and unreliable attribution.[4] The level of detail of our data enable us to know whether a PhD or postdoctoral researcher is supported on a grant of a given PI. We then trace all joint publications between the PI and the PhD and/or the postdoctoral researcher and consider it a dependable signal for attributing publications to a given grant. To be more specific, we attribute a publication to a grant when grant funds are used by the PI, in a reasonable period, to support PhDs or postdoctoral researchers with whom the PI co-authored the publication. We choose to attribute articles to the grant flow of funds in year t if they are published in the three-

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[3] See for example Carl Bergstrom and Javin West: http://callingbullshit.org/case_studies.html ,and Jocelyn Kaiser: http://www.sciencemag.org/news/2017/06/critics-challenge-nih-finding-bigger-labs-aren-t-necessarily-better .

[4] We have also tried to implement topic modelling to link publications to grants on the basis of a large corpus of grant abstracts. We found it to be impractical in our case, but certainly a method to develop in the future. We also considered using citations to funding sources reported in the publication acknowledgements, but the information was often either missing or overly vague (Rigby, 2011).

year window of publications covering year t and the two following years (t+1) and (t+2). The lag between the flow of funds and published articles reflects the fact that a period of one to two years often occurs between the performance of research and its publication. We also considered other publication windows (t, t+1), (t+1, t+2), (t, t+1, t+2, t+3) for determining attribution. We find that our econometric estimates are robust to different choices of windows.

Concerning the yearly use of grant funds by the PIs, we note that, even though funding is obligated in a given year, simple attribution of activity to the year of obligation is likely to be misleading, since the disbursement of funds and the associated work occurs over the period of the grant. Therefore, we compute the flow of funds associated with a grant in any year to be the total direct costs of the grant divided by the number of years of funding provided by the grant. We calculate the flow of funds from each focal grant over its length, and the flow of funds from all other overlapping grants in the PI's grant portfolio over their respective lengths. Appendix 1 reports a detailed explanation of our attribution method in which we discuss the important question of publication weighting in order to avoid double counting. We describe in detail the cases when multiple articles are the result of the research activity funded over different years by the flow of funds from multiple grants.

Sample, variables and descriptive statistics

After a minimum amount of data cleaning, and relying on our PhD/PD attribution method, we end up with a study panel with 3796 observations at the grant-PI-year level, corresponding to 240 PI's and 1544 grants over 10 years from 2000 to 2010.

Table 1 shows the descriptive statistics (mean, standard deviation, min and max) of the key variables of our grant-PI-year panel for the PhD/PD attribution method. The mean of the number of publications (NP) per grant-PI-year equals 1.49, varying between 0.04 and 24.48, and the corresponding mean of average journal impact factor (AIF) equals 3.79 varying between 0.02 and 36.10. Note that AIF is computed as the mean of the ratio of the impact factor weighted number of publications (WNP) by the number of publications NP.

The average flow of funds equals \$110,000 for the focal grant and \$380,000 for the other grants. The five last rows of Table 1 show the disciplinary composition of the university in terms of departments or "divisions". The largest is Engineering and Applied Sciences (28%), followed by Chemistry and Chemical Engineering (21%) and Geological and Planetary Sciences (21%), then Biology and Biological Engineering (17%) and Physics, Mathematics and Astronomy (13%). We have excluded Humanities and Social Sciences, which is a small division different from the others in terms of both funding practices and publications norms. On average, 1.49 publications are associated with each grant-year, having an average impact factor AIF of 1.98. The flow of funds from the focal grant is on average $110,000; the yearly average from other grants is $380,000.

Table 1: Descriptive statistics for the PI-Grant-year panel (3796 obs.)

	mean	sd	min	Max
Grant outcomes				
Number of publications	1.49	1.76	0.04	24.48
Average Impact Factor	1.98	2.37	0.02	36.10
Grant/PI characteristics				
X flow of focal grant [in M$]	0.11	0.09	0.01	0.52
Z flows from other grants [in M$]	0.38	0.33	0.00	2.01
Department of Biology (Dummy)	0.17	0.38	0.00	1.00
Department of Chemistry (Dummy)	0.21	0.41	0.00	1.00
Department of Engineering (Dummy)	0.28	0.45	0.00	1.00
Department of Geology (Dummy)	0.21	0.41	0.00	1.00
Department of Physics, Maths, Astronomy (Dummy)	0.13	0.34	0.00	1.00

Table 2 shows the corresponding descriptive statistics when we aggregate our data at the PI-year level from the PI-grant-year level. To do so, we sum the flows of funds from each grant and we obtain the flow of individual funding available each year to the 240 PIs included in our study sample. Similarly, we obtain the PI's annual total number of publications (NP) associated with all funds and the corresponding average impact factor (AIF). We see that on average the PIS have 3.62 publications a year that can be attributed to specific grants with an average impact factor of 2.37. The annual flow of funds from all grants at the PI level is $360,000 and the maximum is just over $2M.

Table 2: Descriptive statistics at PI-year level

	Mean	sd	Min	Max	N
Number of publications (according to the PhD/PD attribution)	3.62	4.10	0.05	44.71	1564
Average impact factor (according to the PhD/PD attribution)	2.37	2.47	0.18	31.02	1564
Individual flow of funds [M$]	0.36	0.30	0.01	2.03	1564
Department of Biology	0.17	0.37	0.00	1.00	240
Department of Chemistry	0.15	0.35	0.00	1.00	240
Department of Engineering	0.30	0.46	0.00	1.00	240
Department of Geology	0.18	0.38	0.00	1.00	240
Department of Physics, Mathematics, Astronomy	0.20	0.40	0.00	1.00	240

4. MODEL AND ESTIMATION

In our empirical analysis we proceed in two steps. In the first step, *grant level analysis*, presented in Section 5, we examine the relationship linking the grant flow of funds to publication output, both in terms of quantity and quality. In the second step, *principal investigator level analysis*, presented in Sections 6, 7 and 8, we document the quality of fit of our grant level estimates aggregated at the PI level and consider their economic implications. We first address the hotly debated issue of returns of funding to size or scale, and, second, the still largely neglected issue of bundling, or the grant composition of the PIs' total research funding. An overview of our main results at the PI level on these two issues is helpful since they may appear, erroneously, as incompatible with our estimation results at the grant level. To wit, we find that publication output with respect to total funding increases in terms of quantity with no substantive evidence of negative marginal returns but decreases in terms of quality. We also find that, holding total funding constant, the bundling of grants matters with a quantity-quality trade-off between more articles of lower-impact and less articles of higher impact-factor.

In the present section, we start by explaining our choice of a log-linear regression model specification of the relation between publication and the flow of funds of both the focal grant and the other grants. We next justify our choice of instrumental variables (IV) to control for the endogeneity of both types of flow of funds. We also consider the question of aggregation at the PI level in Appendix 5, which would have been straightforward if we could have used a linear regression specification, but is somewhat intricate with a log-linear regression.

Choice of specification

We consider the following Cobb–Douglas type regression:

$$y_{g,i,t} = \alpha x_{g,i,t} + \beta z_{g,i,t} \qquad \text{(Equation 1)}$$

where the subscript g stands for grant, i for PI, and t for year; $y_{g,i,t}$ denotes the logarithm of $Y_{g,i,t}$, the number of articles attributed to the grant or the corresponding average five year impact factor (IF); $x_{g,i,t}$ and $z_{g,i,t}$ are respectively the logarithms of $X_{g,i,t}$ and $Z_{g,i,t}$, the flows of funds of the focal grant and the other grants.

The Cobb–Douglas type regression has an elasticity of substitution equal to one, reflecting the fact that PIs in practice use funds from other grants to complement the funds from the focal grant. The choice of a linear regression would be unrealistic since it would assume an infinite elasticity of substitution. At the other extreme, a fixed proportion or Leontief production function would also be unrealistic by assuming a null elasticity of substitution. Furthermore, the choice of a Cobb-Douglas functional form appears as an excellent approximation. When we tested the more general Constant Elasticity of Substitution (CES) production function, we found an estimated elasticity of substitution very close to one (See Appendix 2).

The coefficient α in Equation 1, is the elasticity of focal grant productivity with respect to the focal grant flow of funds, holding the flow of funds of other grants constant. The coefficient β is the elasticity of focal grant productivity with respect to the flow of funds from other grants, holding the flow of funds from the focal grant constant. We expect a positive relationship between the flow of funds from the focal grant and its research output given that grant funds permit the PI to devote additional resources to the focal research grant, such as the PI's time and the time of research assistants and postdoctoral fellows. Funds also provide access to some materials and equipment that, in the absence of the grant, would not be available.

We also expect output associated with a focal grant potentially to be related to funds received from other grants because funds from other grants provide resources which can be shared across research projects. However, other grants also come with administrative tasks such as the preparation of proposals and the submission of progress reports that might negatively affect focal grant productivity. This administrative burden is well documented. A 2007 report of the Faculty Standing Committee of the *Federal Demonstration Partnership* (FDP) found that faculty working on federally supported research spent 42% of their research time on pre-and post-grant award administration activities—not on research (Decker, Wimsatt, Trice, & Konstan, 2007).

Overall, we expect the elasticity of publication attributed to the focal grant with respect to the flow of funds from the focal grant (α) to be positive while the elasticity of publication attributed to the focal grant with respect to the flow of funds from other grants (β) to be either positive or negative, but likely smaller in absolute value than (α).

The Cobb-Douglas type regression also has the advantage that it can be rewritten as Equation 2, strictly equivalent to Equation 1, if we re-normalize it by using in the equation the logit share of the focal grant flow of funds with respect to the total flow of fund: $s_{g,i,t} = log\left(S_{g,i,t}/(1 - S_{g,i,t})\right)$ with $S_{g,i,t} = \left(X_{g,i,t}/(X_{g,i,t} + Z_{g,i,t})\right)$. We thus obtain:

$$y_{g,i,t} = \alpha x_{g,i,t} + \beta\left(z_{g,i,t}\right) = (\alpha + \beta)x_{g,i,t} + \beta\left(z_{g,i,t} - x_{g,i,t}\right)$$

$$\text{or} \qquad y_{g,i,t} = (\alpha + \beta)x_{g,i,t} - \beta s_{g,i,t} \qquad \text{(Equation 2)}$$

We use Equation 2 in Section 7 to perform an interpretative simulation of our results, which we illustrate by a graphical representation. We also do the same by rewriting Equation 2 in terms of number of grants ($n_{i,t}$), which is convenient but only equivalent to Equations 1 and 2 if the grants of PIs in year *t* are all of equal size.

$$y_{g,i,t} = (\alpha + \beta)x_{g,i,t} - \beta\log(n_{i,t} - 1) \qquad \text{(Equation 3)}$$

Choice of instrumental variables

As noted in the introduction, a major concern for our analysis is endogeneity between researcher productivity attributed to the focal grant and success in being funded. We address the endogeneity issue by adopting a two-pronged approach. First, because the data are sufficiently rich to provide repeated observations on each faculty member with different grants over time, we are able to include PI fixed effects in our analysis. These fixed effects control largely for unmeasurable productivity related PI characteristics, such as ability, creativity and persistence, that are mostly invariant over time. Second, to deal with the "dynamic" dimension of endogeneity, we rely on an instrumental variable approach. We instrument the flow of funds of the focal grant (x) and the flow of funds of other grants (z) with four variables. First, the growth rate, smoothed over the three years (t-2) to current year t, of the total flow of research funds at the national level computed separately for PIs working in the departments of biology, chemistry, engineering, geology, and physics, mathematics and astronomy (*Growth rate of national funding*). We consider these variables as a proxy for the aggregated availability of funds at the national level that is expected to be correlated with the grant size. Second, a set of dummy variables indicating the public funding agency awarding the focal grant: *National Institute of Health* (NIH), *National Science Foundation* (NSF), *Department of Energy* (DOE), *Department of Defense* (DOD), and *Other Funding Agency*. Because different funding agencies award, on average, grants of different size, the source of funding is expected to be correlated with the size of the grant awarded to the scientist. Third, a dummy indicating that grants have been awarded by at least two other distinct funding agencies as a proxy of the PI's ability to raise funds (*More than 2 funding agencies*). The dummy *More than 2 funding agencies* is expected to be positively correlated with the flow of funds from other grants in the PI's portfolio. Fourth, the number of PI grants active in the current year *t* (*Number of grants*). The grant flow of funds is affected by a number of measurement errors, due in particular to some backward and forward flexibility in corresponding payments, while the number of grants, which a priori must not belong to our estimated regression, is observed without such errors as well as correlated with the flow of funds. It can thus be used together with the other three instruments as a proper instrument to correct for the flow of funds measurement errors.

We present in Table 3 some descriptive statistics for our four instrumental variables. We also document their relevance in Appendix 4, where we report the first stage regressions of the flow of funds of the focal grant (x) and of the other grants (z) on them.

Table 3: Summary statistics for the instruments (3796 obs.)

	Mean	sd	min	Max
Growth rate of national funding	0.05	0.11	-0.12	0.43
Number of grants	5.03	3.09	1.00	17.00
NSF	0.33	0.47	0.00	1.00
NIH	0.26	0.44	0.00	1.00
DOE	0.04	0.19	0.00	1.00
DOD	0.07	0.25	0.00	1.00
Other Funding Agency	0.30	0.46	0.00	1.00
More than 2 funding agencies	0.55	0.50	0.00	1.00

5. RESULTS AT GRANT LEVEL

The estimations of Equation 1 are shown in Table 4 without PI fixed effects and in Table 5 with PI fixed effects. We give in columns 1 and 4 the OLS estimates respectively for the number of publications and the average journal impact factor, while in column 2 and 5 we report the IV estimates instrumenting only the focal grant flow (*x*), and in columns 3 and 6 the IV estimates instrumenting both the focal grant flow (*x*) and other grant flow variables (z). All the specifications include year dummies and division dummies. Note also that for the sake of simplicity and since it

Table 4: OLS and IV estimates at grant level without PI fixed effects

VARIABLES	log(number of publications)			log(average impact factor)		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV(x)	IV(xz)	OLS	IV(x)	IV(xz)
x (log focal grant flow of funds)	0.27***	0.17**	0.34***	0.10***	0.61***	0.54***
z (log other grants flow of funds)	-0.11***	-0.11***	-0.062***	-0.10***	-0.11***	-0.13***
BIOLOGY DIVISION	-0.11*	-0.057	-0.18**	0.75***	0.50***	0.55***
CHEMISTRY and CHEMICAL ENGINEERING	0.45***	0.46***	0.40***	0.48***	0.42***	0.44***
ENGINEERING and APPLIED SCIENCE	-0.051	-0.043	-0.067	-0.45***	-0.49***	-0.48***
GEOLOGICAL and PLANETARY SCIENCES	-0.055	-0.093	-0.039	-0.12**	0.071	0.05
PHYSICS, MATH and ASTRONOMY	ref.	ref.	ref.	ref.	ref.	ref.
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
PI Fixed effects	No	No	No	No	No	No
Observations	3,796	3,796	3,796	3,796	3,796	3,796
R-squared	0.101	0.095	0.095	0.241	0.072	0.115

does not affect our slope estimates, we do not include a dummy for the 7% of the observations for which at time *t* there is only the focal grant and no other grants. Instead we prefer to assume that in this case there is a second one-year grant of $10,000, a minimum amount, in addition to the focal grant.

Our preferred estimates are those reported in columns 3 and 6 of Table 5, where we include PI fixed effects and instrument the flow of funds of both the focal grant and the other grants. We find that a 10% increase in the dollar flow of the focal grant increases the quantity and quality of attributed publications by respectively 4.3% and 2.7%, conditional on holding the size of the other grants constant. We also find a negative elasticity of the quantity and quality of the publications attributed to the focal grant with respect to other grants of respectively of 1.9% and 2.0%, conditional on holding the flow of funds from the focal grant constant. The intuition underlying the negative effect is that although other grant funds may contribute to covering some of the research costs of the focal grant, they also carry expectations of research, additional administrative costs and time (Lorsch, 2015b). If we compare these results with those obtained by instrumenting only the focal grant flow variable (columns 2 and 5), we find rather similar estimations.

Table 5: OLS and IV estimates at grant level with PI fixed effects

VARIABLES	log(number of publications)			log(average impact factor)		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV(x)	IV(xz)	OLS	IV(x)	IV(xz)
x (log focal grant flow of funds)	0.33***	0.38***	0.43***	0.028	0.17*	0.27***
z (log other grants flow of funds)	-0.15***	-0.14***	-0.19***	-0.13***	-0.11***	-0.20***
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
PI Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,796	3,796	3,796	3,796	3,796	3,796
R-squared	0.324	0.323	0.319	0.506	0.497	0.475

We use the estimations reported in Table 5, columns 3 and 6 to illustrate graphically in Figures 1 and 2 our results at the grant level. These figures represent respectively the grant publication quantity and quality isoquants varying the focal grant flow of funds ($X_{g,i,t}$) and its share with respect to the PI's total grant portfolio ($sh_{g,i,t}$). They both show similar effects: for a given flow

Figure 1: Grant publication quantity vs. focal grant flow of funds and share of focal grant with respect to the PI's grant portfolio

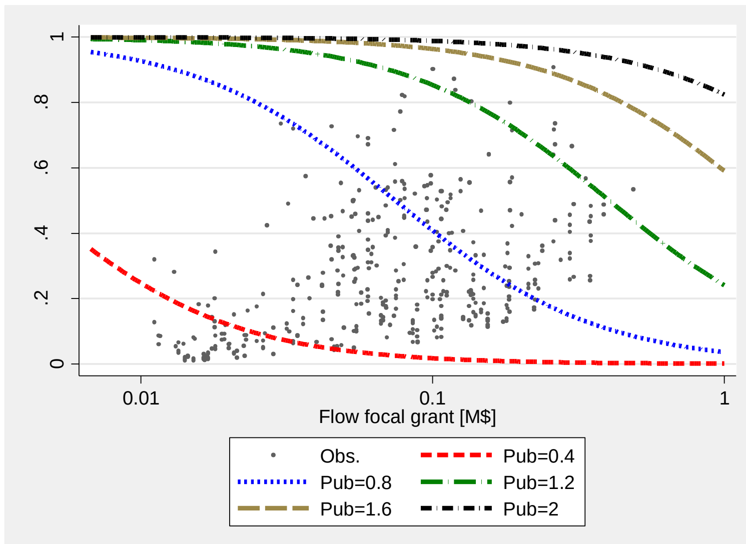
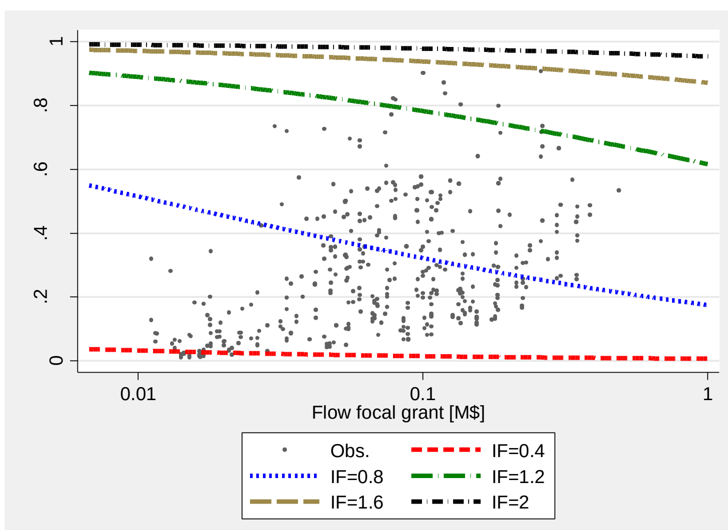


Figure 2: Grant publication quality vs. focal grant flow of funds and share of focal grant with respect to the PI's grant portfolio



of funds from the focal grant, the higher the share of the focal grant with respect to the PI's portfolio, the higher is the publication quantity and quality associated with it. For example, consider a grant with an annual flow of 0.1 million dollars. According to Figure 1, when the grant accounts for about 40% of the PI's grant portfolio the grant produces 0.8 publications per year, while if it accounts for the 90% it produces 1.2 publications per year. We find similar evidence with regard to Impact Factor in Figure 2.

6. COMPARING DIRECT AND INDIRECT ESTIMATES AT THE PI LEVEL

It is important to compare the estimates we would have obtained if we had performed our analysis directly at the PI level, instead of aggregating the results found at the grant level to the PI level. This is what we do in this section. We first consider the estimates (γ) resulting from the regression $y_{i,t} = \gamma x_{i,t}$ of the observed PI level publication quantity and quality $y_{i,t}$ on total funding $x_{i,t}$. Next, we compare these estimates to the corresponding estimates ($\bar{\gamma}$) resulting from the comparable regression $\bar{y}_{i,t} = \bar{\gamma} x_{i,t}$ on total funding, where the dependent variable $\bar{y}_{i,t}$ is computed by aggregating at the PI level the predicted publication quantity and quality $\hat{y}_{g,i,t}$ based on our preferred grant level estimates given in the previous section (the IV estimates without and with PI fixed effects from columns 2 and 3 and 5 and 6 of Tables 4 and 5). We show these direct and indirect estimates in Tables 6 and 7, and, in order to provide an intuitive understanding, we illustrate some of the results in Figures 3 and 4.

We see in Tables 6 and 7 (columns 1 and 2) that the direct elasticities of the PI's number of publications on funding are positive and equal to 0.44 without fixed effects and 0.33 with fixed effects, while the elasticity of average impact factor publication quality is positive and 0.13 without fixed effects and a negative -0.11 with fixed effects. The corresponding indirect estimates (columns 3 and 4) show the same pattern, being only slightly different. It is interesting to note that, as could be expected, they tend to be higher than the related grant level elasticity estimates of (α) or ($\alpha + \beta$) in Tables 4 and 5 (columns 2 and 3 or 5 and 6).

Table 6: Direct and indirect estimates at PI level without PI fixed effects

	(1)	(2)	(3)	(4)
	Observed	Observed	Predicted	Predicted
VARIABLES	log(PI's number of publications)	log(PI's Average impact factor)	log(PI's number of publications)	log(PI's Average impact factor)
log(PI flow of funds)	0.44***	0.13***	0.39***	0.063***
Constant	1.37***	0.65***	1.15***	0.38***
PI fixed effects	No	No	No	No
Observations	1,564	1,564	1,564	1,564
R-squared	0.134	0.015	0.375	0.048
Number of PIs	240	240	240	240

Table 7: Direct and indirect estimates at PI level with PI fixed effects

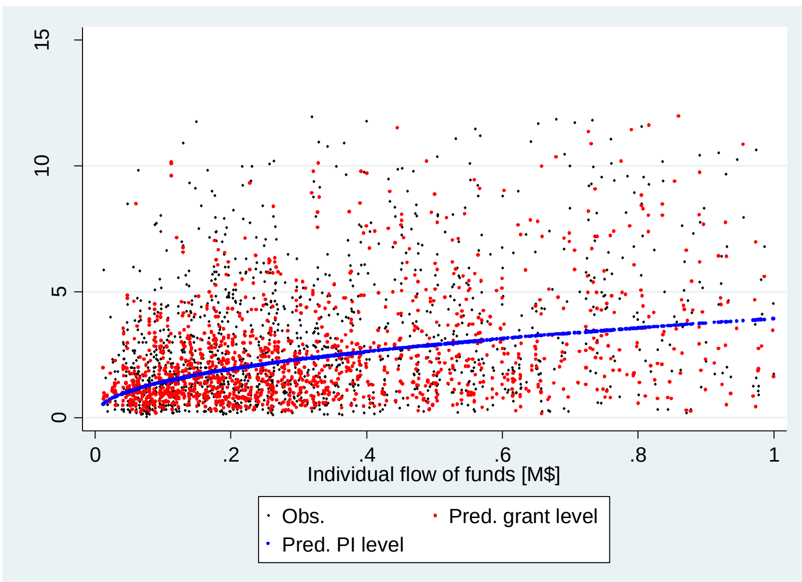
	(1)	(2)	(3)	(4)
	Observed	Observed	Predicted	Predicted
VARIABLES	log(PI's number of publications)	log(PI's Average impact factor)	log(PI's number of publications)	log(PI's Average impact factor)
log(PI flow of funds)	0.33***	-0.11***	0.29***	-0.089***
Constant	1.22***	0.33***	0.99***	0.17***
PI fixed effects	Yes	Yes	Yes	Yes
Observations	1,564	1,564	1,564	1,564
R-squared	0.050	0.008	0.140	0.140
Number of PIs	240	240	240	240

We illustrate the regressions with fixed effects of Table 7 (columns 1 and 2) in Figures 3 and 4. On the x-axis is the PI flow of funds and on the y-axis the PI number of publications or average impact factor. The black dots are the observed data points at the PI level, while the blue line is the curve of the fitted data points from the direct regression based on these observations. The red dots which form a cloud are the predicted data points at the PI level which are obtained by aggregation of the grant level predictions based on the regressions of Table 5 (columns 3 and 6).[5]

[5] Note that we do not show the curve of the fitted data points from the indirect regression with fixed effects of Table 7 (columns 3 and 4). This is because it is practically the same as the blue curve, since the estimates of the direct and indirect regressions are very close.

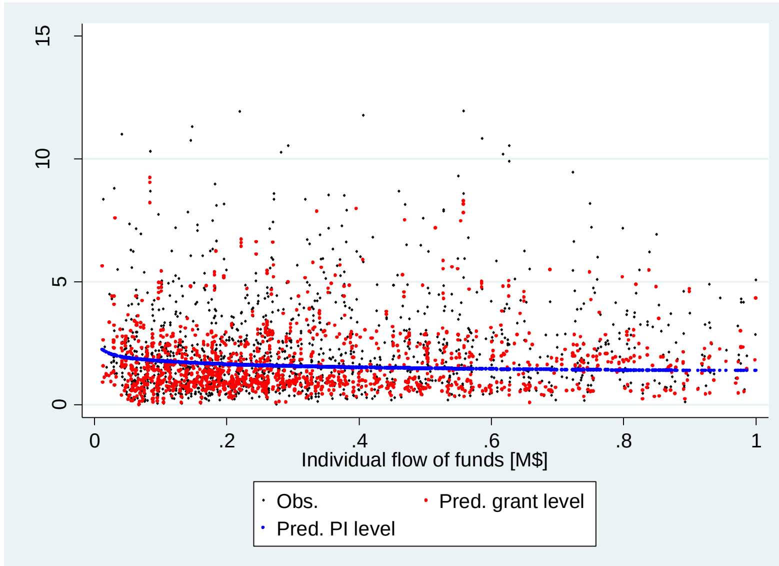
Below Figures 3 and 4 we also report the three correlations between number of publications (NP) and average impact factor (AIF) observed and predicted at the PI and grant level. We see that the correlations of the PI level observed values with their grant level predicted values are much higher than with their PI level predicted values: for NP 0.81 versus 0.39, and for AIF 0.67 versus 0.07. This is consistent with the fact that the latter are practically the same as the correlations between predicted values at the PI level and at the grant level for both NP and AIF.

Figure 3: Publication quantity and total flow of funding at PI level:



Correlation Observed PI level and Predicted PI level:	0.39
Correlation Observed PI level and Predicted Grant level:	0.81
Correlation Predicted PI level and Predicted Grant level:	0.41

Figure 4: Publication quality and total flow of funding at PI level



Correlation Observed PI level and Predicted PI level:	0.07
Correlation Observed PI level and Predicted Grant level:	0.67
Correlation Predicted PI level and Predicted Grant level:	0.05

7. EVIDENCE ON SCALING

In this section we investigate the robustness of our findings with regard to scaling. In view of the ongoing debate regarding the NIH analyses by Lauer and colleagues, it is important to assess to what extent our finding of decreasing marginal returns to PI total funding are an artifact of the log-linear form of our regressions, and in particular whether we can or cannot reject the presence of diminishing marginal returns at high levels of PI funding.

A simple and effective way to do so is to consider the residuals of the estimated regressions of the actual PI level data without and with PI fixed effects reported in Tables 6 and 7 of the preceding section, and to regress these residuals on a set of nine dummies (*Funding class 1-9*) identifying nine different classes (or bins) of individual funding in millions dollars, ranging from 0.1 $M to 2.0$M. Specifically, the first six classes correspond to an increase of 0.1 $M with respect to the preceding class; the last three classes with an increase respectively of 0.4, 0.5 and 0.5 $M with respect to the preceding class. If the logarithmic transformation is appropriate, we expect that we will not find significant effects of these dummies.

Tables 8 and 9, which are in the same format as Tables 6 and 7, show the results without and with fixed effects, for the residuals of the regressions on PI level observed and grant level predicted number of publication (NP) and average impact factor (AIF). In the absence of fixed effects, we find for both NP and AIF statistically significant evidence of less decreasing marginal returns than implied by the log-linear specifications. The effect is particularly notable for the two highest levels of funding. It is somewhat less striking for the predicted residuals than the observed ones. As could be expected, such evidence practically disappears with the inclusion of fixed effects. With their inclusion we find that most of the nine funding dummies in all four residuals regression are not statistically different then the lowest funding class taken as reference, even at a 10% confidence level. We can thus conclude that if we control for PI fixed effects the log-linear regressions appears to be an appropriate approximation, that the evidence for decreasing marginal returns is quite robust, and that the presence of diminishing returns to scale, even at very high amounts of total funding, is clearly rejected.

Table 9: Regression on the residuals of publication quantity and quality without PI fixed effects

	(1) Observed	(2) Observed	(3) Predicted	(4) Predicted
VARIABLES	Residuals log(PI's number of publications)	Residuals log(PI's Average impact factor)	Residuals log(PI's number of publications)	Residuals log(PI's Average impact factor)
Funding class 1 (less than 0.1M$)	ref.	ref.	ref.	ref.
Funding class 2 (from 0.1 to 0.2 M$)	0.11	0.19**	0.088	0.14**
Funding class 3	0.054	0.36***	-0.0043	0.21***
Funding class 4	0.098	0.44***	0.091	0.30***
Funding class 5	0.21*	0.44***	0.13	0.25***
Funding class 6	0.31***	0.65***	0.17**	0.48***
Funding class 7 (from 0.6 to 1M$)	0.33***	0.67***	0.23***	0.42***
Funding class 8 (from 1 to 1.5M$)	0.31**	0.71***	0.19*	0.48***
Funding class 9 (from 1.5 to 2 M$)	1.41***	0.75**	1.00***	0.59**
Constant	1.07***	-0.036	0.89***	-0.065
Observations	1,564	1,564	1,564	1,564
R-squared	0.019	0.062	0.016	0.042
Number of Pis	240	240	240	240

Table 10: Regression on the residuals of publication quantity and quality with PI fixed effects

VARIABLES	(1) Observed Residuals log(PI's number of publications)	(2) Observed Residuals log(PI's Average impact factor)	(3) Predicted Residuals log(PI's number of publications)	(4) Predicted Residuals log(PI's Average impact factor)
Funding class 1 (less than 0.1M$)	ref.	ref.	ref.	ref.
Funding class 2 (from 0.1 to 0.2 M$)	-0.070	0.0091	-0.044	0.039***
Funding class 3	-0.096	0.12	-0.096**	0.053***
Funding class 4	-0.13	0.045	-0.056	0.0098
Funding class 5	0.042	0.068	0.018	0.0077
Funding class 6	0.054	0.018	0.017	0.0011
Funding class 7 (from 0.6 to 1M$)	0.086	0.14	0.026	0.0045
Funding class 8 (from 1 to 1.5M$)	0.25*	0.062	0.071	-0.033
Funding class 9 (from 1.5 to 2 M$)	0.65*	0.013	0.22	-0.026
Constant	1.23***	0.27***	1.01***	0.15***
Observations	1,564	1,564	1,564	1,564
R-squared	0.009	0.005	0.010	0.027
Number of Pis	240	240	240	240

8. EVIDENCE ON BUNDLING AND QUALITY-QUANTITY TRADEOFF

Recall that our preferred results at the PI level show a robust and positive relationship between total funding and the number of articles and a negative and significant relationship between total funding and quality. To investigate the extent to which this relates to the way in which grants are bundled we consider two types of counterfactual simulations based on rewriting our log-linear Cobb-Douglas type regression in terms of logit shares of focal grant to total funding, and in terms of numbers of grants of equal size (see equation 2 and 3 in Section 4). These simulations confirm the importance of bundling and the existence of a publication quantity-quality tradeoff. We can best illustrate them by Figure 6 to 9.

Figure 6. Number of publications and total flow of funding at PI level in simulation with two grants of varying shares

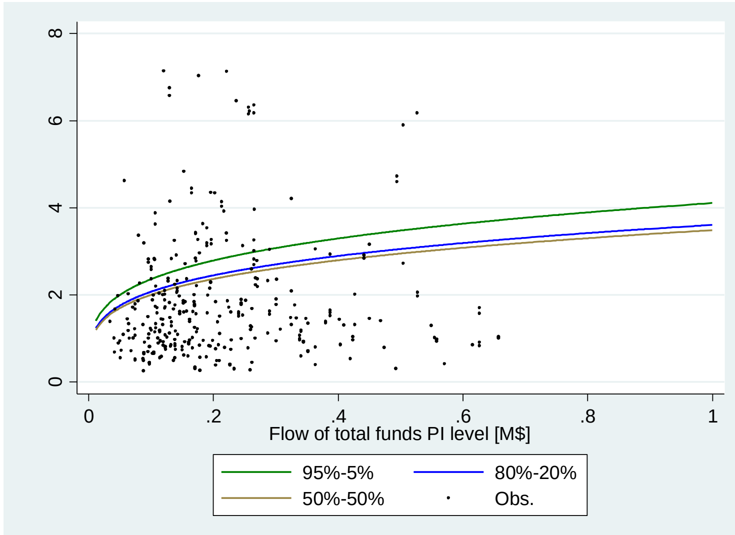
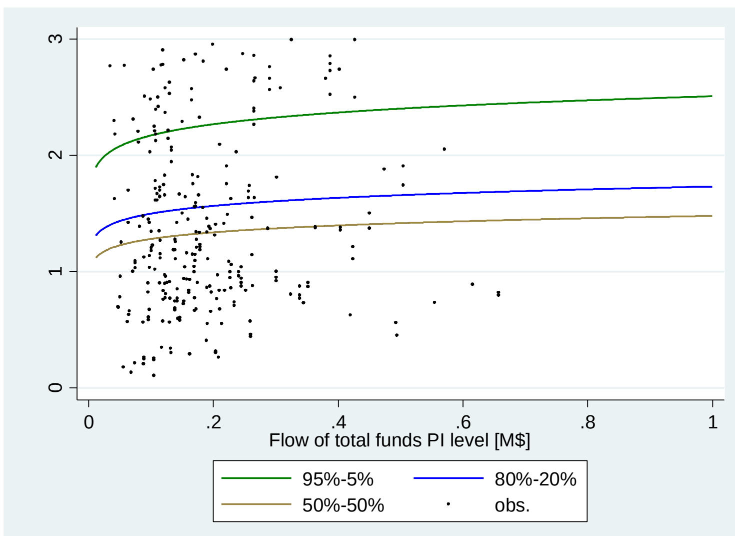


Figure 7. Average impact factor IF of publications and total flow of funding at PI level in simulation with two grants of varying shares



The first set of simulations reported in Figures 6 shows the relationship between PI publication quantity and total funding, if we assume that the PI has only two grants of different size for three different configurations: the two grants are of equal size (50%-50%), one is much larger than the other (80%-20%), and one is practically equal to total funding (95%-5%). Figure 7 shows the same thing for quality.

The second set of simulations reported in Figures 8 and 9 illustrate the same relationship if we assume that the PI has a varying the number of grants of equal size ranging from 2 to 9 grants.

Figure 8. Number of publications and total flow of funding at PI level in simulation with a varying number of grants of equal size

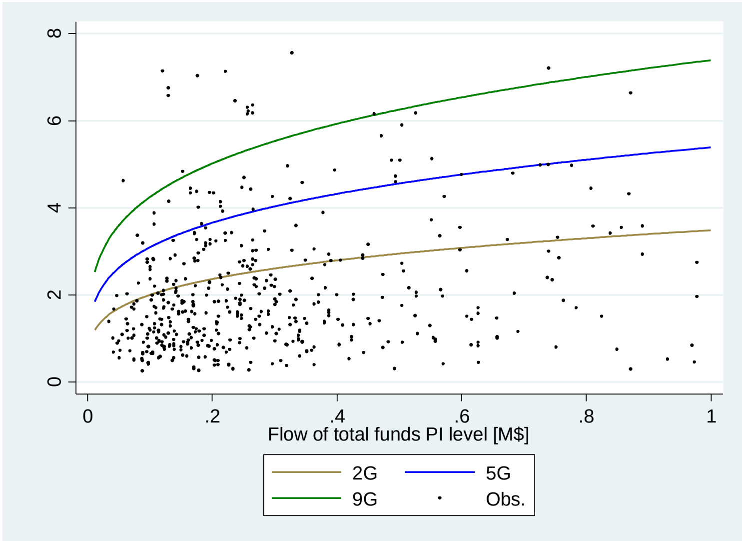
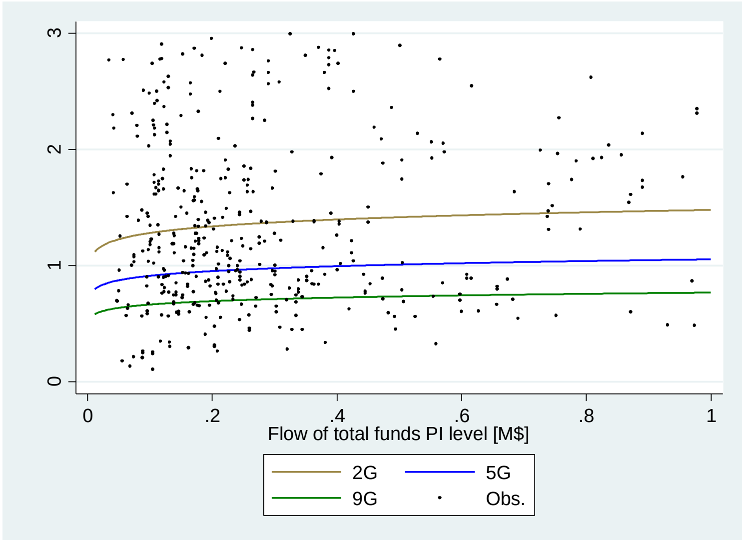


Figure 9. Average impact factor IF of publications and total flow of funding at PI level in simulation with a varying number of grants of equal size



Figures 6 and 7 show that for any size of PI total funds, the number of publications and average impact factor increase as the share of one grant increases relatively to the other grant. For instance, consider a PI with a flow of public research funds of 0.5 million dollars per year. Per year the PI has an average of 2.91 publications with two grants of 0.25 M$ each (50%), practically the same with one grant of 0.4 M$ (80%) and the other of 0.1 M$ (20%), and 3.44 publications, half a paper more on average, with a much larger primary grant of 0.475 M$ (95%) and a much smaller one of 0.025 M$ (5%). In parallel, the average impact factor increases from an average of 1.4 citations per publication per year, to 1.6 and 2.5, an increase of nearly 80%. Overall, this first counterfactual simulation exemplifies clearly that bundling matters.

Figures 8 and 9 show that, holding the flow of total funds constant, the number of publications increases as the number of grants of equal size increase, while the average impact factor decreases. By way of example, if we consider again a PI with a flow of 0.50 M$ of public research funds per year, the PI has 2.91 publications with two grants of 0.25 M$ each, 4.5 publications with five grants of 0.10 M$ each, and 4.5 publications with nine grants of 0.55 M$ each. In parallel, and in contrary to the count of publications, the average impact factor decreases from 1.3 per publication per year, to 1.0 and 0.8.

This second counterfactual simulation is consistent with the expectation that PIs are under pressure to produce at least one paper to justify a grant to the funding agencies, whatever its size. It also shows that holding funding constant more grants comes at the expense of quality. Overall, it clearly confirms the importance of a tradeoff between publication quality and quantity.

9 CONCLUSION

Using a novel method to attribute publications to grants we estimate the elasticity of publications to the flow of funds at the grant level. In order to control for endogeneity, we include fixed effects and instrument the focal grant flow of funds as well as the flow of funds from other grants. We find a significant and positive relationship between the publications attributed to the focal grant and the corresponding flow of funds, implying that, holding the flow of funds from the other grants constant, an increase of 10% in a focal grant leads to a 4.3% increase in the number of publications coming from the grant. Holding the flow of funds from the focal grant constant, a 10% increase in the flow of funds of the other grants results in a 1.9% decline of the number of publications attributed to the focal grant. We find similar, although slightly muted results, with regard to quality of publications as measured by the average impact factor of the journals in which articles are published.

We aggregate funds across grants at the PI level to examine the relationship between number of publications and their average impact factor and total PI funding. We observe decreasing marginal returns to funding for the former and negative returns for the latter. Specifically, at the PI level a 10% increase of total funding comes with a 3.3% boost to publication quantity, while it brings about a 1.1% reduction on publication quality. Alternative and more flexible specifications of our regressions show the robustness of our finding of decreasing marginal returns to scale. They clearly reject the existence of diminishing returns for high and very high levels of total funding.

The positive effect of funding on publication quantity and the negative effect on publication quality suggest a tradeoff between publication quantity and quality and that the way in which grants are bundled matters. We confirm this interpretation by considering two sets of counterfactual simulations. They show respectively that for the same amount of individual funding it is more efficient to have two grants of very unequal size for both quantity and quality of publications, while more grants of the same size are associated with more publications but of a lesser average impact factor. In short, in the case of multiple grants of equal size, a tradeoff exists between quantity and quality. These findings are congruent with the MIRA pilot initiative announced by NIGMS in July 2014 that supports an investigator's research through a single grant rather than through separate projects (NIGMS, 2014) and which was extended in 2017 to all NIGMS investigators, be they early stage, new or established.[6]

There are three main policy implications from our findings. First, program officers who want to increase the effectiveness of the grants awarded by their funding agencies should consider the negative effects of the presence of grants from other funding agencies. Second, policy makers designing research policies at national level should remember that marginal decreasing returns are

[6] See https://www.nigms.nih.gov/Research/mechanisms/MIRA/Pages/default.aspx.

to be expected. Third, that the bundling of grants matters: a publication quality-quantity tradeoff exists.

It is our hope that our approach to estimate the relationship between research inputs and research outputs will be adopted and improved upon by researchers using the UMETRICS data that are becoming available at the IRIS institute at the University of Michigan. There is a clear need to know whether our findings are unique to a small, selective, institution with exceedingly high standards or apply to larger institutions with a bit more heterogeneity. Our prior is that the tradeoff we observe would be stronger if we were to study a more heterogeneous group of researchers rather than a highly selective group whose ability and expertise arguably attenuate the tradeoff.

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Appendix 1: PhD/PD attribution methodology

This section describes the *PhD/PD attribution* methodology applied to attribute PI's publications to grant flows of funds.

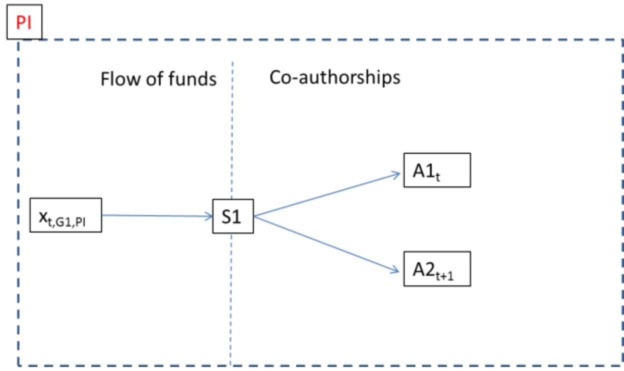
We attribute an article A to the flow of funds $X_{t,G}$, where t is the year of the flow and G is the grant, by complementing the information on payment of researchers with the bibliographic information reported in the article A. Precisely, we attribute the article A to the flow of funds $X_{t,G}$ if at least one PhD or PostDoc is supported by the funds $X_{t,G}$ in year t and, at the same time, the same PhD or Postdocs is a coauthor of the publication A with the PI awarded grant G. The articles that can be attributed to $X_{t,G}$ are limited to those published in t, $t+1$, and $t+2$, where t is the year of payment of the PhD / PD. For instance, if the PhD is paid in 2000, we consider her publications co-authored with the PI in 2000, 2001, and 2002.

In what follows we provide two examples of attribution of publications to grant flow of funds. In the first example, we apply our method to attribute multiple publications to a unique flow of funds in a given year. In the second example, we attribute multiple publications to multiple flow of funds from different grants. The PhD/PD attribution methodology allows us to share the credit of one article among different flow of funds avoiding article double counting.

Example 1. Attribution of multiple publications to a unique grant

Figure A1.1 shows how two articles, A1 and A2, are attributed to the flow of funds $X_{t,G1}$ of the grant *G1* awarded to the principal investigator PI. PhD student *S1* receives a salary in year t paid by the PI using funds from grant *G1*. At the same time *S1* is a co-author of PI in the publications A1 and A2. According to the PhD/PD attribution method, the full credit of both articles is assigned to the flow of funds of the grant *G1* in year t, namely $X_{t,G1}$.

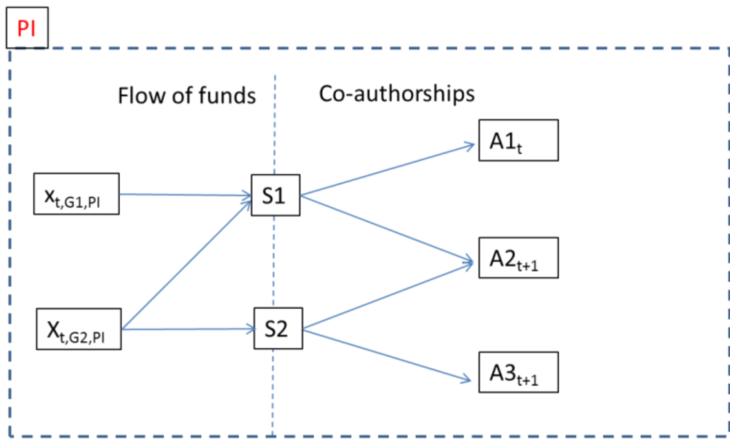
Figure A1.1: PhD/PD attribution method, example 1



Example 2. Attribution of multiple publications to multiple grants

The example reported in Figure A1.2 shows how the PhD/PD attribution method assigns the credit of three articles A1, A2, and A3 to two flows of funds ($X_{t,G1}$ and $X_{t,G2}$) of two different grants (*G1* and *G2*) both awarded to the same principal investigator PI. The salary of the PhD student *S1* is paid in year *t* by the PI on both grants *G1* and grant *G2*, while the salary of the PhD student *S2* is paid only on grant *G2*. *S1* is co-author of PI on the articles A1 and A2, while *S2* is co-author of PI on the articles A2 and A3. The credit of the article A1 is shared equally by $X_{t,G1}$ and $X_{t,G2}$, namely half of the credit of article A1 is attributed to each of the two flows of funds since S1 is paid both by G1 and G2. One third of the article A2 is attributed to $X_{t,G2}$ through S2, one third of A2 is attributed to $X_{t,G2}$ through S1, and one third of the A2 is attributed to $X_{t,G1}$ through S1. The article A3 is fully attributed to the flow of funds $X_{t,G2}$. In sum, the flow of funds $X_{t,G1}$ has a publication credit of 5/6 (1/2 (A1)+1/3 (A2)), while the flow of funds $X_{t,G2}$ has a publication credit of 13/6 (1/2 (A1)+1/3 (A2)+1/3 (A2)+1 (A3)). The sum of the credit attributed to both grants equals to 3 publications (5/6+13/6).

Figure A1.2: PhD/PD attribution method, example 2



According to the PhD/PD method, we attribute 8,990 publications to 3,796 flows of funds of the grants included in our study sample. Table A1.1 shows the proportion of publications that are fully attributed to one flow of funds $X_{t,G}$ (unique grant and unique year), to multiple flows of funds of the same grant in different years (unique grant and multiple years), to multiple grants with simultaneous flow of funds in the same year *t* (Multiple grants and a unique year), and to multiple grants and multiple flows of funds in different years (Multiple grants and multiple years). We find that the credit of more than half of the publications included in our study sample (52%) is shared by multiple grants and cannot be attributed to the research expenses of a unique year.

Table A1.1: Proportion of publications according to their attribution

Publication credit attributed to:	Mean	Std. Dev.	Min	Max
A unique grant and a unique year	21%	0.41	0	1
A unique grant and multiple years	22%	0.44	0	1
Multiple grants and a unique year	5%	0.49	0	1
Multiple grants and multiple years	52%	0.50	0	1
	100%			

Appendix 2: CES functional form

Equation A2.1 represents the Constant Elasticity of Substitution (CES) functional form. Differently from the Cobb-Douglas functional form used in the main text (Equation 1), CES allows for values of the elasticity of substitution different from one. Equation A2.1 reports CES function after its logarithmic transformation.

$$y = -\frac{\nu}{\rho}\ln(\delta X^{-\rho} + (1-\delta)Z^{-\rho}) \qquad \text{(Equation A2.1)}$$

Table A2.1 shows the results of the estimation of the parameters of the CES function both for the model having as dependent variable the number of publications (Column 1) and for the model having as dependent variable the average impact factor of the journals in which articles are published (Column 2). The elasticity of substitution estimated by the CES function can be calculated according to Equation A2.2 and is reported in Table A2.1.

$$\sigma = \frac{1}{1-\rho} \qquad \text{(Equation A2.2)}$$

Table A2.1: CES estimation

Parameters Estimated	Log(Number of publications)	Log(Average impact factor)
ν	0.20***	0.19***
	(0.026)	(0.024)
ρ	-0.16***	-0.073
	(0.039)	(0.094)
δ	1.27***	1.06***
	(0.072)	(0.077)
Constant	0.44***	0.73***
	(0.057)	(0.052)
σ (Elasticity of substitution)	*1.18*	*1.08*
Observations	3,796	3,796
R-squared	0.056	0.034

We conclude that the elasticity of substitution equal to one assumed when adopting the Cobb-Douglas functional form in the main text is appropriate.

Appendix 3: Instrumental Variable estimation, excluded instruments

This appendix describes four excluded instruments used in the first step of the IV estimation: (1) *Growth rate of national funding*, (2) *Number of grants*, (3) a dummy variable *More than 2 funding agencies*, and (4) a set of dummies identifying the *funding agency* of the focal grant.

1. *Growth rate of national funding*

We expect growth rate of national funding to be positively correlated with the amount of the grants awarded to the PI in our study sample. To calculate the *Growth rate of national funding* variable we proceed in three steps. First, we consider five categories of flow of funds at national level as reported in the official statistics[7]: NIH life sciences; other life sciences; physical sciences; engineering; mathematics and computer science. We match at least one category to each department of the university where we conducted our study. The matching criterion is based on the relevance of the funding category at national level for the department. For instance, we expect funds in the category Engineering to be relevant for the PIs affiliated to the Department of engineering and to be not relevant for the other departments. Table A2.1 shows the result of the matching. Second, we calculate the growth rate (positive of negative) of the funds for each department smoothed over three years, from t-2 to t. Figure A2.1 shows the values of the growth rate for each department. Third, we calculate the variable *Growth rate of national funding* by assigning a growth rate value to each focal grant according to the department of affiliation of the awarded PI.

Table A2.1: Matching between the department of affiliation of the PI and the classes of nation funds that are considered relevant for the department.

University departments	Categories of flow of funds at national level
Department of Biology	NIH life sciences + other life sciences
Department of Chemistry	Physical sciences
Department of Engineering	Engineering
Department of Geology	Physical sciences

[7] see https://www.aaas.org/page/historical-trends-federal-rd

Department of Physics, Math, Astronomy	Physical sciences + math & computer science

Table A2.2 shows the correlation between *Growth rate of national funding*, the focal grant flow of funds, and the other grant flow of funds. We expect also the *Growth rate of national funding* to be uncorrelated with the error term in the grant productivity equation.

Figure A2.1: Growth of the funds at national level for each department

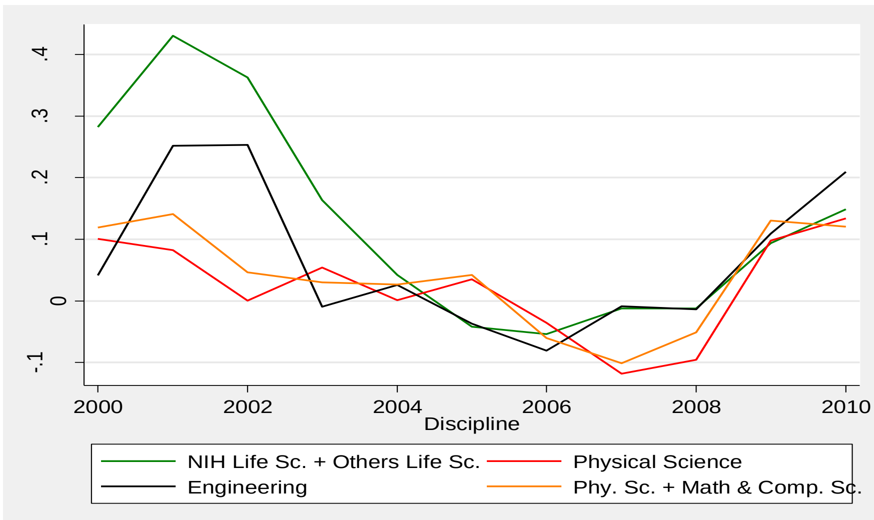


Table A2.2: Correlation between growth and flow focal /other grants

	Growth rate of national funding	x	z
Growth rate of national funding	1		
x (Focal grant flow of funds)	0.14	1	
z (Other grant flow of funds)	0.04	0.12	1

2. *The number of grants*

The number of "active" grants in year *t* is expected to be positively correlated with the PI's other grant flow of funds in year *t*, i.e., the more the grants awarded the more the funds available. The number of active grants is a good instrument to correct for the measurement error problem affecting the flow of funds in year *t*. Table A2.3 shows the correlation between the number of active grants in year *t*, the flow of funds of the focal grant, and the PI's other grant flow of funds.

Table A2.3: Correlation between the number of grants in year t and the flow of funds of the focal grant and the PI's other grant flow of funds

	Number of grants	x	z
Number of grants	1		
x (Focal grant flow of funds)	-0.16	1	
z (Other grant flow of funds)	0.43	0.12	1

3. Dummy *More than 2 funding agencies*

The number of distinct funding agencies awarding the PI's other grant flow of funds, i.e., *z*, is a proxy for the ability of the PI to raise funds from different sources. Table A2.4 shows the co-occurrence of different funding agencies in the PI's grant portfolio for our study sample. The values reported in the table represent the proportion of observations where, conditional on observing a focal grant awarded by a funding agency A, there is another grant in the PI's portfolio awarded by a funding agency B. For instance, when we consider a focal grant awarded by NIH, in 37% of the cases there is another grant awarded by NSF in the PI's grant portfolio. We define the variable *More than 2 funding agencies* as a dummy that equals one if there are two or more distinct agencies awarding the funds of the PI's other grants. Table A2.5 shows the correlation between the dummy *more than 2 funding agencies*, the flow of funds of the focal grant, and the PI's other grant flow of funds.

Table A2.4: Co-occurrence of the funding agencies in the PI's grant portfolio

		Other grant funding agency (B)					
		Only focal grant	NSF	NIH	DOE	DOD	OTHER
Focal grant Finding agency (A)	DOD	0.07	0.56	0.22	0.10	0.54	0.52
	DOE	0.08	0.69	0.26	0.30	0.19	0.64
	NIH	0.07	0.37	0.84	0.07	0.10	0.21
	NSF	0.11	0.67	0.20	0.10	0.18	0.51
	OTH	0.04	0.68	0.13	0.10	0.16	0.80

Table A2.5: Correlation between the dummy more than two funding agencies, the flow of funds of the focal grant, and the PI's other grants' flow of funds

	More than 2 agencies	x	z
More than 2 agencies	1		
x (Focal grant flow of funds)	-0.08	1	
z (Other grant flow of funds)	0.26	0.11	1

4. *Dummy variables for each funding agency (NSF, NIH, DOE, DOD, others)*

Dummies identifying the funding agencies awarding the focal grants are expected to be correlated with the size of the focal grants (x). For instance, DOE and NIH tend to award grants of larger size than NSF and DOD. Table A2.6 shows the average size of the grants included in our study sample by funding agency. The funding agency dummies are expected to be uncorrelated with the error term in the grant productivity equation.

Table A2.6: Average grant size by funding agency

Funding agency	flow of funds of the focal grant [M$]
DOD	0.12
DOE	0.13
NIH	0.16
NSF	0.09
OTHERS	0.08

Appendix 4: First stage equation, IV estimation

Table A4.1 shows the estimation of the first stage equation of the instrumental variable approach. The model reported in Column 1 includes as dependent variable the flow of funds of the focal grant, while the model reported in Column 2 includes as dependent variable the flow of funds of the other grants.

Table A4.1: First stage equation in the IV-2SLS estimation

	(1) OLS x (log focal grant flow of funds)	(2) OLS z (log other grant flow of funds)
Growth rate of national funding	0.53***	-0.11
Number of grants	-0.025***	0.25***
More than 2 funding agencies	-0.068**	0.35***
NSF	0.25***	-0.026
NIH	0.21***	-0.093**
DOE (Dep. of Energy)	0.61***	-0.045
DOD (Dep. of Defense)	0.27***	0.010
Other funding agencies	-	-
PI Fixed effects	Yes	Yes
PI-Grant-year obs.	3,796	3,796
R^2	0.412	0.579

Appendix 5: Aggregation from grant level to principal investigator level

In Section 6, we calculate the individual publication outcome and individual flow of funds by aggregating the grant publication outcome and the grant flow of funds for each PI in our sample. Specifically, we calculate individual flow of funds $F_{i,t}$ for each period *t* as the aggregated sum of flows of funds $X_{g,i,t}$ of the $n_{i,t}$ grants in the PI's portfolio in year *t* (Equation A5.1). Similarly, we calculate individual publication outcome as in Equation A5.2, where $PI's\ outcome_{i,t}$ equals to the count of articles attributed to the PI in year t with the PhD/PD attribution method or to the average impact factor of the journals in which these articles are published.

$$F_{i,t} = \sum_{g=1}^{n_{i,t}} X_{g,i,t} \qquad \text{(Equation A5.1)}$$

$$PI's\ outcome_{i,t} = \sum_{g=1}^{n_{i,t}} Y_{g,i,t} \qquad \text{(Equation A5.2)}$$

We investigate the presence of diminishing or negative marginal returns to funding by estimating the elasticity of individual funding to individual outcome, i.e., $\beta_1$in Equation A5.3. In Equation A5.3 we include also a vector γ_i of PI fixed effects and he model constant β_0.

$$\log(PI's\ outcome_{i,t}) = \beta_0 + \beta_1 \log(F_{i,t}) + \beta_2 \gamma_i \qquad \text{(Equation A5.3)}$$

We expect individual funding ($F_{i,t}$) to show diminishing (0<β_1<1) or negative marginal returns (β_1<0). The presence of the diminishing returns, implies that awarding additional funds to researchers already endowed with funds diminishes their effectiveness. The presence of negative returns, implies that increasing the amount of funding to a researcher already endowed with funds might be harmful her productivity.

After estimating the marginal returns to funding, we investigate the effect of different grant portfolio compositions on PI's publication outcome by conducting two sets of simulations using the results of the estimations of the elasticities α and β at grant level (see Equation 1, in Section 4).

The first simulation assumes that the PI has only two grants of different size and allows us to investigate the relationships between the predicted PI's publication outcome and the flow of individual funding ($F_{i,t}$), varying the relative size of the two grants. For instance, PI *i* in year *t* has available a total amount $F_{i,t}$ of funding for her research. $F_{i,t}$ is the sum of the flow of funds of two grants, A and B. A contributes to the individual funding $F_{i,t}$ with the share *s*, while B contributes with the remaining share, i.e. (*1-s*). The estimated PI's publication outcome is reported in Equation A5.4.

$$PI's\ outcome_{i,t} = e^{y_{A,i,t}} + e^{y_{B,i,t}} = e^{\alpha \cdot s \cdot F_{i,t}} \cdot e^{\beta \cdot (1-s) \cdot F_{i,t}} + e^{\alpha \cdot (1-s) \cdot F} \cdot e^{\beta \cdot s \cdot F_{i,t}} \quad \text{(Equation A5.4)}$$

We expect that the concentration of resources in one of the two grants, i.e. when *s* is very large or very small, to have positive effect on the PI's productivity. The results of this simulation are reported in Figure 5 and 6 in the main text.

The second simulation assumes that the PI has multiple grants of equal size and allows us to investigate the relationships between the predicted PI's outcome and the flow of individual funding, varying the number of grants. For instance, PI i in year *t* has a total amount $F_{i,t}$ of individual funding. $F_{i,t}$ is the sum of the amount of $n_{i,t}$ grants of equal size $F_{i,t}/n_{i,t}$. The PI's publication outcome is reported in Equation A5.5.

$$PI's\ outcome_{i,t} = n_{i,t} * e^{y_{.,i,t}} = n_{i,t} \cdot e^{\alpha \cdot (F_{i,t}/n_{i,t})} \cdot e^{\beta \cdot (n_{i,t}-1) \cdot (F_{i,t}/n_{i,t})} \quad \text{(Equation A5.5)}$$

We expect that an increased number of grants for a given amount of individual funding might lead to the increase of administrative costs for the PI. For instance, the PI's outcome might have a lower publication outcome when having four grants a year that sum to \$0.5 million rather than one grant of \$0.5 million. The results of this simulation are reported in Figure 7 and 8 in the main text.