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EXCELLENCE FUNDS, EXCELLENT OUTCOMES? LESSONS FROM ITALIAN UNIVERSITY DEPARTMENTS

by Niccolò Cattadori*, Edoardo Frattola** and Elena Lazzaro***

Abstract

This paper investigates the causal effects of a competitive excellence initiative financing Italy's top twenty-five per cent university departments. We exploit a novel linkage of administrative data regarding faculty careers, publications, departmental activities, and student enrollment to estimate the effects of the policy in a dynamic difference-in-differences framework. In direct terms, the additional financial resources allowed funded departments to increase their faculty size but had a limited impact on course offerings. Indirectly, the excellence designation led to higher student enrollment, particularly among high-achieving ones, suggesting a positive quality signal. The funding boosted scientific output but not productivity, except in large STEM and Life Sciences departments, which benefited from agglomeration effects and improved research infrastructure.

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Keywords: excellence funding, scientific productivity, student enrollment, STEM.

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1 Introduction[1]

Scientific knowledge is a key input for innovation and long-run economic growth (Romer, 1990). Because it often exhibits the characteristics of a public good, economists have argued that it would be underprovided by the private sector, thereby providing a rationale for government and non-profit institution funding (Azoulay and Li, 2020). In recent years, an increasing amount of public funding to university research has been allocated competitively (Geuna, 2001; Wang et al., 2018), using peer-reviewed competitions such as research grant programs. Likewise, donors and foundations typically finance the best departments and institutions. Among these forms of competitive funding allocation, over the past twenty years, several countries have implemented various university excellence initiatives (Fu et al., 2018). Examples of such initiatives include Germany's *Exzellenzinitiative*, France's *Initiatives d'Excellence*, China's 985 project, and South Korea's BK21 program. These policies aim to identify the most promising institutions and allocate substantial additional research funding to them. The objectives include enhancing the concentration of talented scientists, providing resources for advanced research, and achieving global competitiveness. To avoid inefficient use of public resources, it is essential to determine whether these funds are spent effectively. However, it is hard to quantify their returns since the best institutions and researchers are more likely to be financed, and a positive selection effect would, therefore, bias the estimates (Jaffe, 2002). Beyond direct financial support, competitive funding mechanisms can also generate indirect effects that amplify their impact. The recognition associated with receiving "excellence" funding may serve as a quality signal, enhancing the institution's reputation. This, in turn, can increase its attractiveness to prospective students or faculty. Understanding both the direct and indirect effects of competitive funding is therefore crucial for policymakers seeking to maximize the returns on public investments in higher education.

This study examines the impact of the Italian excellence initiative *Dipartimenti di Eccellenza* on several key outcomes, including faculty size, educational offerings, student attraction, and scientific production and productivity. Started in 2018, this program selects and funds the top 180 (approximately 25%) departments in public universities, providing them with substantial resources for five years. These resources can be utilized for faculty hiring,

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performance-based incentives, investments in research infrastructure, and the provision of high-quality educational activities. We use a unique combination of rich longitudinal data on the careers and publications of all Italian academics, departments' educational offerings (in terms of degree and PhD programs), and university student enrollment. To address the issue of endogeneity in department selection, we exploit the longitudinal nature of our data and perform a dynamic difference-in-differences (DiD) analysis, comparing outcomes before and after the first year of the program between funded and non-funded applicant departments.

Specifically, our analysis distinguishes between the direct and indirect effects of the policy. Direct effects refer to the impact on the outcomes the policy was explicitly designed to support through the provision of excellence funds, i.e., faculty hiring and the enhancement of educational activities. Indirect effects capture instead other downstream relevant responses that can further benefit winning departments beyond the immediate policy goals, such as student attraction or scientific production and productivity.

When examining direct effects, we find that the policy resulted in a significant increase in faculty hiring. By 2023, departments that received funding had, on average, nearly six more faculty members compared to non-funded departments, representing an 8.4% increase relative to the mean department size in 2017. On the other hand, the impact on educational offerings was limited: there was only a mild and marginally significant increase in the number of degree programs, and no creation of new PhD programs. We do observe a temporary rise in PhD enrollments, suggesting that departments used part of the funds to offer more scholarships, but this effect faded after five years, likely due to uncertainty about future resources.

In terms of indirect effects, we document that excellence funding led to a significant increase in student enrollment. After three years, the number of students enrolling in the first year of bachelor's, master's, and single-cycle programs increased by 13.3% relative to the pre-treatment mean. This effect was especially strong among high-achieving students. The excellence designation likely acted as a quality signal, making the departments more attractive to students seeking better academic opportunities and career prospects. Moreover, the increase in enrollment was similar for both local and out-of-province students, suggesting that the recognition had an impact both at the local and national levels.

Excellence funding also had a positive impact on scientific production: funded departments experienced a 12.5% increase in publications and a 15.3% rise in journal articles. The increase in output was mostly due to the larger faculty size, since our aggregate results show no significant rise in scientific production per faculty member. However, when examining different academic fields separately, we find an increase in productivity in STEM and Life

Sciences (STEM-LS) departments, particularly in larger ones, suggesting that investments in research infrastructure and positive agglomeration externalities have played a role in enhancing individual productivity. No such effect was observed instead in Social Sciences and Humanities departments.

This paper contributes to three main strands of the literature. The first focuses on the effects of excellence funding programs. Evidence on such initiatives is relatively limited, and the effects vary across countries. For instance, positive effects on scientific output have been observed for France (Carayol and Maublanc, 2025) and Russia (Matveeva et al., 2021). In Germany, while Carayol and Maublanc (2025) estimate an increase in the number of publications, Cantner et al. (2023) conclude that teaching and research productivity did not significantly improve in funded universities. Null or negative effects have also been reported for other non-European countries (see, e.g., Shin, 2009 on South Korea; Zhang et al., 2013 on China; Fu et al., 2018 on Taiwan). Most existing studies do not leverage credible exogenous variation in the likelihood of receiving funding but instead compare funded and unfunded institutions. Therefore, a primary contribution of this paper is to enhance the identification strategy relative to previous research. By using a difference-in-differences methodology, we can more reliably causally identify the average treatment effect of receiving funding on the treated. Additionally, we estimate the impact of excellence funding on several outcomes that were not previously considered in the literature, such as faculty hiring, the expansion of educational offerings, and student attraction, and we show that some of them can be significantly affected by the program. Evaluating the benefits of excellence funding requires a comprehensive assessment of these various dimensions to provide policymakers with a thorough understanding of the policy's overall impact. Finally, by looking at the Italian excellence program, we focus on a country characterized by relatively low expenditures in R&D and where the effect of additional funds may be stronger (Benavente et al., 2012; Ganguli, 2017).[2]

The second stream of literature to which this project contributes studies, more generally, the impact of public funding on scientific productivity. Most research in this area has focused on two main units of analysis: universities and individual researchers. Studies focusing on universities usually find a positive relationship between funding and researchers' output (see, among others, Aghion et al., 2010; Whalley and Hicks, 2014; Rosenbloom et al., 2015; Popp, 2016), whereas those looking at grants for individual researchers tend to find mixed evidence, with the effect varying across countries, institutional contexts, and the seniority

[2]For instance, in 2017, before the introduction of the excellence program, R&D expenditures were just 1.4% of GDP in Italy, against 2.1% in China, 2.2% in France, 3.1% in Germany, and 4.3% in South Korea (source: World Bank).

of the researchers (see, for example, Jacob and Lefgren, 2011; Arora and Gambardella, 2005; Azoulay et al., 2011; Howell, 2017; Azoulay et al., 2019; Ayoubi et al., 2019; Ghirelli et al., 2023; Gush et al., 2018; Langfeldt et al., 2015; Wang et al., 2019; Carayol and Lanoë, 2017). Our paper contributes to the existing literature by analyzing the impact of funds competitively allocated to departments rather than universities or individual researchers. Examining the effects at the department level enables us to better understand the potential channels through which resources can impact scientific productivity and provide new insights. On the one hand, we show that public funds can have heterogeneous effects on productivity depending on the academic field you are considering, something that university-level analyses may be too broad to detect. In particular, we highlight the likely relevance of investments in research infrastructure as a productivity-enhancing tool in STEM-LS departments. On the other hand, by focusing on a more aggregate unit of analysis, we can capture potential agglomeration externalities that seem to play a role in our context and are often overlooked in researcher-level studies.

Finally, we also relate to the literature on the supply-side determinants of university students' enrollment decisions. Based on economic models of human capital investment (Becker, 1964; Toutkoushian and Paulsen, 2016), empirical studies in this field have mostly focused on costs of attendance and geographical proximity as key factors explaining how students choose where to enroll (see, among others, Long, 2004; Skinner, 2019; Drewes and Michael, 2006; Kelchtermans and Verboven, 2010; Wilkins et al., 2013; Mitze et al., 2015). Fewer papers have also considered the role of university quality (e.g., Long, 2004; Drewes and Michael, 2006; Griffith and Rask, 2007; Pigini and Staffolani, 2016; Ciriaci, 2014; Biancardi and Bratti, 2019), typically using different proxies to measure it, such as newspapers' university rankings, students-to-teacher ratios, total instructional expenditures, students' test scores, or quality of research output. Our work exploits instead a direct signal of quality that is easily understandable for prospective students (the "excellence department" certification) to provide new evidence on how an institution's perceived status positively affects student enrollment decisions and, therefore, on how public policies can indirectly influence the attractiveness of universities.

The remainder of the paper is structured as follows. In Section 2, we describe the institutional setting, the data, and the estimation sample. Section 3 outlines our empirical strategy. Section 4 presents and discusses the results. Section 5 concludes.

2 Institutional setting and data

2.1 The Italian university system

The higher education system in Italy is predominantly public, with over 93% of faculty employed in public universities as of 2022 (ANVUR, 2023). Departments are the primary units through which universities are organized. They were first introduced by Law No. 28 of February 21, 1980, with the task of promoting and coordinating research activities. In 2010, Law No. 240 of December 30 assigned to departments both functions related to scientific research and those related to teaching and training.

The primary source of funding for universities is the Ordinary Fund (*Fondo Finanziamento Ordinario*, FFO), allocated annually by the Ministry of University and Research.[3] It is intended to cover institutional expenses, including staff and operational costs. The distribution of the FFO among universities is based on each university's historical expenses, number of students, research performance, and on equity objectives. Recent regulatory changes have modified the allocation methods, introducing criteria that gradually reduce the emphasis on historical funding in favor of performance-based incentives and standard costs per student. Each university is then responsible for deciding how funds are distributed internally among its departments. The amount of the FFO for 2017, prior to the introduction of the Italian excellence initiative, was approximately €7 billion.

2.2 The Italian excellence program

We analyze the first edition of the *Dipartimenti di Eccellenza* initiative, approved by the Italian parliament in December 2016 (Law No. 232 of December 11, 2016), under which 180 departments in public Italian universities were selected and funded based on merit. This fund was added as a specific and separate item to the targeted quota of the FFO, and not as a replacement for other resources.[4] The policy aimed to incentivize excellence in research and department development.

In the first stage of the selection process, all the 766 departments in public universities were ranked according to a standardized index (ISPD[5]) that measured research performance over

[3]The second major source of funding comes from students' enrollment fees. Over the last decade, its weight has fluctuated between 15 and 20% of the FFO.

[4]Between 2017 and 2018, the FFO increased even excluding the newly introduced excellence funds, from €7.02 to €7.07 billion.

[5]*Indicatore Standardizzato di Performance Dipartimentale* (Standardized Departmental Performance Indicator), defined by ANVUR, the Italian National Agency for the Evaluation of the University and Research

the period 2011-2014. The 350 departments with the highest research index were eligible to apply for funding in one of 14 academic fields[6] by submitting a development plan, with the constraint that a maximum of 15 departments per university could apply.[7] The development plan should include a financial program for a five-year period outlining how resources would be allocated for staff recruitment, staff incentives, research infrastructure, and high-level teaching and scientific activities. The number of funding slots in each academic field was defined by the government, taking into account the size of each field and criteria aimed at enhancing specific sectors of Italian research.

Subsequently, a commission of seven experts[8] evaluated the development plans of the 314 applying departments from 61 universities. Within each of the 14 fields, funding slots were allocated by ranking the departments based on a weighted average of the ISPD research index and the evaluation of their development plans.[9]

Starting in 2018, the 180 winning departments were awarded a baseline transfer of €1,350,000 per year for a period of five years. This amount varied depending on the academic field and the size of the department that awarded it. Specifically, the transfer for departments in the fourth (fifth) dimensional quintile increased by 10% (20%), whereas the amount for departments in the second (first) quintile decreased by 10% (20%). Additionally, for departments operating in STEM and Life Sciences (STEM-LS[10]), the annual amount was increased by €250,000, to be used exclusively for investments in research infrastructure. The average transfer was substantial, amounting to approximately 18% of the annual department funds

System. The ISPD ranges from 0 to 100 and takes into account the quantity and quality of research produced by faculty members of each department, standardized by academic field.

[6]In Italy, there are 14 "academic fields", as officially designated: Mathematics and Computer Science; Physics; Chemistry; Earth Science; Biology; Medicine; Agricultural Science and Veterinary; Civil Engineering and Architecture; Industrial and Information Engineering; Science of the Antiquities, Philology, Literature and Art; History, Philosophy, Pedagogy and Psychology; Law; Economics and Statistics; and Social and Political Sciences. If faculty members from different academic fields were affiliated with the same department, that department had to apply for funding in the field that achieved the best results in the most recent ANVUR evaluation of research quality.

[7]If there are more than 15 departments in a qualifying position on the ranking, the university proceeds with a selection, justifying the choice based on the ISPD and additional criteria that may be established by the individual university. Due to this constraint, the number of departments that submitted the development plan was 314, rather than 350.

[8]Two members were chosen by the Minister of University and Research, one appointed by the Prime Minister, and four designated by the Minister of University and Research from two lists of three members each, respectively provided by ANVUR and the National Committee of Research Guarantees (CNGR).

[9]The final score was determined as the sum of $0.7\times$ISPD and the evaluation of the development plan, which ranges from 0 to 30. Within a given field with K available funding slots, the threshold for receiving funds was not fixed *ex ante*, but endogenously determined as the K^{th} final score in decreasing order.

[10]The STEM-LS group includes 9 out of 14 academic fields: Mathematics and Computer Science; Physics; Chemistry; Earth Science; Biology; Medicine; Agricultural Science and Veterinary; Civil Engineering and Architecture; and Industrial and Information Engineering.

in 2017.[11] No more than 70% of the total funding amount can be used for staff recruitment, with a minimum of 25% allocated for hiring professors external to the university and 25% for assistant professors. In particular, the cost of each new hire to be covered through the excellence funds was computed as 15 years of salary.[12]

By the end of the last year of funding (i.e., 2022), each university had to submit a report on the use of resources and results to the evaluation commission. The commission reviewed the report and provided feedback. If the evaluation was negative, the university could not apply for excellence funding for the same department in the following edition (2023-2027).

2.3 Data

To estimate the effects of excellence funding on several outcomes, we combined for the first time the following datasets on the Italian university system:

- *Excellence funding allocation.* For each department that applied for funding, we know the dimensional quintile, the scores received in the selection process (both ISPD and evaluation of the development plan), the field of application, the outcome of the selection process, and the resources allocated. This information was provided to us by CINECA, an Italian interuniversity consortium that provides IT support and research infrastructure services to universities.

- *Faculty employment.* We reconstruct the universe of Italian higher education professors by exploiting publicly accessible faculty lists.[13] These lists are compiled annually by CINECA and are based on mandatory administrative reports submitted by all universities. They represent the end-of-the-year total faculty employment, from 2013 to 2023. The lists include each faculty member's full legal name, gender, rank (assistant, associate, or full professor[14]), university and department affiliation, and academic field. However, they do not contain unique identifiers.

[11] To estimate the annual department funds in 2017, we assume that universities allocate their annual budget (their FFO share) to departments proportionally to their employment size. We then took the average across the winning departments of the ratio between excellence funds and the estimated 2017 department funds.

[12] For instance, this cost amounted to around €1.7 million for a full professor, €1.2 million for an associate professor, and between €0.9 and €1.1 million for an assistant professor (MIUR, Nota n.8414, July 11, 2017).

[13] Data can be found at the following link `https://cercauniversita.mur.gov.it/php5/docenti/cerca.php`.

[14] In this paper, the academic ranks are mapped to the Italian system as follows: full professor corresponds to *professore ordinario*, associate professor to *professore associato*, and assistant professor to *ricercatore a tempo determinato* (both RTD-A and RTD-B) and *ricercatore a tempo indeterminato*, which were the relevant entry-level academic positions during our period of analysis.

- *Research output.* We collect rich research output data from institutional repositories (IRs), which are maintained by almost all Italian public universities. These online platforms offer a comprehensive record of academic activities, encompassing journal articles, books, chapters, conference materials, and other relevant publications. Each entry contains information about the authors, publication year, and the type of contribution. We restrict our focus to the period from 2013 to 2023. To link faculty members to their publications, we match faculty and output datasets based on names, surnames, abbreviations, and various permutations of these. This method is necessary due to the lack of a common individual identifier in faculty lists and IR data. Despite this limitation, our match is very good: we were able to match more than 98% of our faculty employment data with the corresponding faculty publications in the IRs.[15]
  Our preferred metric of scientific output is the number of fractional articles (publications), defined as the number of research items divided by the number of authors.[16] For a given department and year, this metric aggregates the number of author-adjusted articles (publications) written by researchers affiliated with the department. Similarly, for each researcher and year, this metric aggregates the author-adjusted articles (publications) written by the researcher.[17]

- *Educational offerings.* For each department, we know how many degree programs (at the bachelor's, master's, and single-cycle levels) were offered in a given academic year, from 2013 to 2023. This information was provided to us by the Ministry of University and Research, thanks to an agreement with the Bank of Italy. In addition, we utilize publicly accessible databases[18] managed by CINECA to retrieve the number of PhD programs offered by each department between 2013 and 2023.

- *Student enrollment.* Using data provided by the Ministry of University and Research, thanks to an agreement with the Bank of Italy, we can compute the number of students who enroll in the first year of a degree program (bachelor's, master's, or single-cycle) between 2013 and 2021. By exploiting the link between degree programs and the

[15]Around 40% of the unmatched observations come from one single small university, which does not maintain its own IR. The departments of this university are therefore excluded from our analysis of research output.

[16]For several reasons, including the need for normalized indicators across fields of research, fractional counting is often preferred in an aggregate-level analysis. From an aggregate perspective, fractional counting adds up to the same number of articles as are in the data, which provides balance, consistency, and precision (Sivertsen et al., 2019).

[17]Our analysis considers both overall scientific publications and, more specifically, academic articles to account for the varying significance that different types of research output hold across academic fields.

[18]Data can be found at the following link: `https://cercauniversita.mur.gov.it/php5/dottorati/cerca.php`.

departments where they are offered, we can then aggregate the student count at the department level. Moreover, for each student, we know their province of residence, province of study, and INVALSI score obtained in grade 10.[19] With this information, we can define some subgroups of students enrolling in the first year of a degree program, such as out-of-province students (those studying in a province different from where they reside) or students above or below a given percentile of the INVALSI score distribution (which we use as a proxy for student quality).

- *PhD researchers.* CINECA also provided us with data on the end-of-the-year number of PhD students enrolled in each department, from 2013 to 2023.

2.4 Sample and descriptive statistics

Table A1 summarizes some baseline pre-treatment characteristics of the 314 departments in our estimation sample, namely the ones that applied for funding. Departments that were awarded funding were larger, with an average of around three more faculty members (two female), and had a higher proportion of senior faculty. Additionally, these departments produced more research output, with approximately 25 more fractional publications, offered around 0.26 more PhD programs, had more PhD researchers, and were more likely to be placed in the North of Italy. Consistent with their funding awards, they scored higher on both the research performance index (ISPD) and the evaluation of the development plan, suggesting that both components of the final score played a relevant role in determining the selection outcome. Finally, the average funding awarded was over €1.5 million per year.

3 Empirical strategy

As mentioned in Section 1, to identify the effects of the Italian excellence initiative, we employ a difference-in-differences (DiD) approach, leveraging the time-series dimension of our data. The idea behind the DiD estimation is to compare outcomes before and after the first year of excellence funding between recipient and non-recipient departments. Specifically, in our department-level analysis, we estimate the following dynamic TWFE equation:

$$Y_{d,t} = \alpha_d + \lambda_{f(d),t} + \sum_{j \neq -1} \beta_j \mathbb{1}[E_{d,t} = j] + \epsilon_{d,t} \tag{1}$$

[19]INVALSI is the Italian National Institute for the Evaluation of the Education and Training System. Among its many activities, it is responsible for implementing a standardized test on core skills in Italian and mathematics every year for students in grades 2, 5, 8, 10, and (since the 2018-2019 school year) 13.

where $Y_{d,t}$ denotes the outcome for department d observed in year t, α_d are department fixed effects, and $E_{d,t}$ is the distance from the first funding year (i.e., from 2018). Since each department could apply to a single field (see Section 2.2), we denote the field×year fixed effects as $\lambda_{f(d),t}$, where $f(d)$ indicates the field associated with department d. We choose 2017 as the baseline period and cluster standard errors at the department level.

This event-study specification allows us to evaluate the post-treatment dynamics of the funding effects, as it may take time for the impact to fully materialize. Our main parameters of interest are β_j's for $j \geq 0$, which capture the average treatment effect on the treated (ATT) j years after the introduction of the policy. As usual in these settings, we have two underlying identification assumptions (Roth et al., 2023).[20] The first one is that, in the absence of excellence funding, the average outcome for the treated and untreated groups would have evolved in parallel (parallel trends assumption). Although we cannot directly test this assumption, we can examine whether the trends in the outcome variables were similar between treated and controls in the pre-treatment periods by looking at the estimates of β_j's for $j < -1$. Reassuringly, this is true for all our outcomes (Figures 1-7), supporting the plausibility of parallel trends in the post-treatment.[21] The second assumption requires that departments did not change their behavior before the introduction of the policy in anticipation of their future treatment status (no-anticipation assumption). Since the law was approved in December 2016 and departments could submit their applications for excellence funds until July 2017, it is unlikely that they correctly anticipated whether they would be funded or not, and that treated and controls started to behave differently before 2018.[22]

For all the outcomes, in order to obtain a summary measure of the treatment effect, we also estimate the following static difference-in-differences equation:

$$Y_{d,t} = \alpha_d + \lambda_{f(d),t} + \delta(Funded_d \times Post_t) + \epsilon_{d,t} \tag{2}$$

where $Funded_d$ is an indicator variable that equals 1 for funded departments, $Post_t$ is an indicator variable for the funding period, and δ is our aggregate ATT of interest (under the

[20]Difference-in-differences settings always implicitly encode also the stable unit treatment value assumption (SUTVA), i.e., that unit i's outcomes do not depend on the treatment status of unit $k \neq i$, which rules out spillover and general equilibrium effects.

[21]Since the parallel trends assumption seems to hold unconditionally, we do not need to include covariates in our DiD regressions (Roth et al., 2023).

[22]Another possible concern is the presence of time-varying unobserved confounders. To be relevant, an unobserved confounder would have to differentially affect our two groups of departments, whose treatment status was the outcome of a complex assignment mechanism, as explained in Section 2.2. To the best of our knowledge, it is unlikely that such a confounder exists, especially since the introduction of the *Dipartimenti di Eccellenza* was the only policy change implemented at the department level during our period of analysis.

same two identification assumptions discussed above).[23]

4 Results

In this section, we present our results by distinguishing between direct and indirect effects. We define as direct effects those referring to the outcomes explicitly mentioned by the law, that is, to the actions that winning departments could directly finance with the new resources. We therefore first analyze the policy impact on faculty size and educational offerings.[24] Conversely, we define as indirect effects other potentially relevant consequences that can emerge as a response to excellent departments' new environment and status, beyond the immediate policy goals. In particular, we analyze two key outcomes: student attraction and scientific research.

4.1 Direct effects

One of the most immediate ways departments could use excellence funding is through faculty expansion. Figure 1 shows that receiving excellence funds led to a significant increase in faculty hiring. The total faculty count rose by an average of two positions in 2018, immediately following the receipt of funds. By 2023, funded departments employed almost six more faculty members than non-funded departments, an 8.4% increase relative to the mean department size in 2017 (Table A2, column 1). As anticipated in Section 2.2, the law allowed winning departments to cover up to 15 years of salary for each new hire, thus limiting the uncertainty about future financial resources, at least in the medium term.

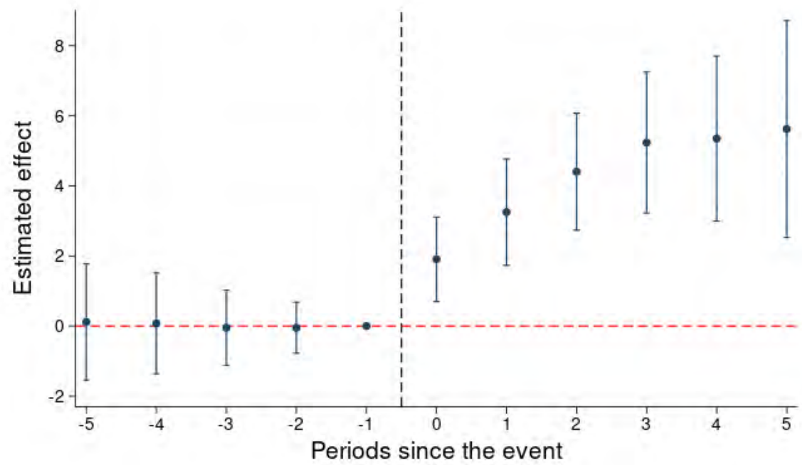
To better understand this effect, we can examine the impact across different faculty ranks. Out of the six additional faculty members hired by 2023, almost three were assistant professors, two were associate professors, and one was a full professor (Figure A1). This pattern suggests that departments used the additional funds to expand all ranks of their faculty

[23]Since most of our outcomes (e.g., faculty size, offered degree or PhD programs, enrolled students) are count variables, we performed a robustness check estimating also a non-linear Poisson model with fixed effects: $\mathbb{E}[Y_{d,t} \mid \cdot] = \exp\Big(\alpha_d + \varphi_t + \lambda_{f(d),t} + \sum_{j\neq -1} \beta_j \, \mathbb{1}[E_{d,t} = j]\Big)$. For each outcome, the average marginal effects estimated using the Stata command `ppmlhdfe`, which implements Poisson pseudo-maximum likelihood (PPML) regressions with multiple levels of fixed effects, closely match the corresponding OLS coefficients from Equation 1. These results are available upon request.

[24]Unfortunately, we do not have data to study the effect on the other two items that could have been financed through excellence funds (see Section 2.2), namely investments in research infrastructure and performance-based incentives for faculty.

(Table A2, columns 2-4).[25]

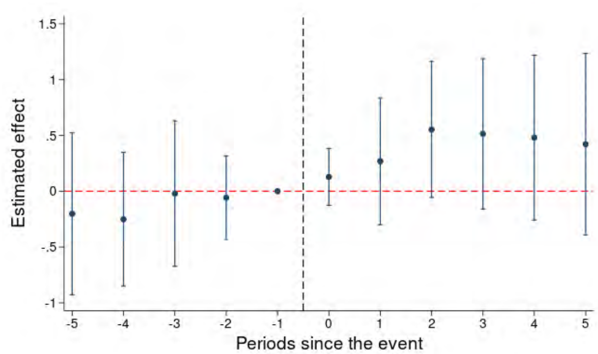
Figure 1: **Effect on total faculty count**



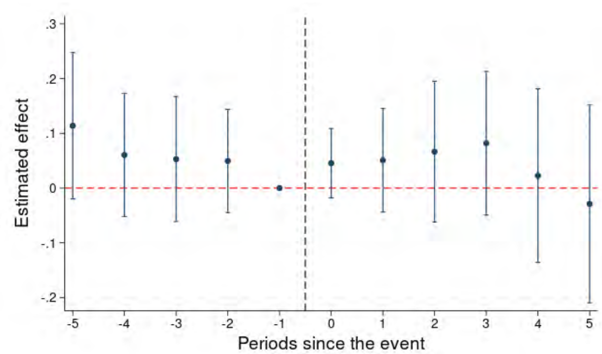
Notes: The graph shows point estimates and 95% confidence intervals for the parameters β_j's of Equation (1), using as the outcome variable the total faculty count. Standard errors are clustered at the department level.

Figure 2: **Effect on educational offerings**

(a) Degree programs



(b) PhD programs



Notes: The graphs show point estimates and 95% confidence intervals for the parameters β_j's of Equation (1), using as the outcome variable the number of degree programs (Panel a) or PhD programs (Panel b). Standard errors are clustered at the department level.

Another way departments could leverage excellence funding is by enhancing their offer of academic programs. The additional resources could, in principle, facilitate the launch of

[25]This expansion among funded departments did not cause meaningful negative spillovers on non-funded control departments, with less than 5% of new hires in the treated group coming from departments in the control group. Around 6% were instead hired from other treated departments, 62% from outside our sample (e.g., non-applicant departments in public universities, private or foreign institutions, non-university research centers), and the remaining 27% were internal promotions from non-faculty (e.g., PhDs or post-docs) to faculty positions within the same department.

new degree or PhD programs by covering startup costs, attracting faculty, and improving infrastructure. As shown in Figure 2 and Table A3 (columns 1-2), we estimate a mild and marginally significant effect on the number of degree programs, but no impact at all on the creation of new PhDs. Since the excellence initiative operated on a limited time horizon, departments may have hesitated to launch new educational programs, preferring instead to support existing ones. For instance, although the number of PhD programs remained unchanged, we observe a temporary increase in PhD enrollments (Figure A2). Within three years of receiving excellence funding, the number of PhD researchers increased by almost six units, corresponding to a 16.6% rise relative to pre-funding levels; after five years, this increase had faded (Table A3, column 3). Given the typical length of PhD programs in Italy (three years), this evidence suggests that funded departments may have allocated part of their resources to temporarily increase the number of PhD scholarships available to prospective researchers, before reverting to the pre-treatment mean due to uncertainty about future funding.

4.2 Indirect effects

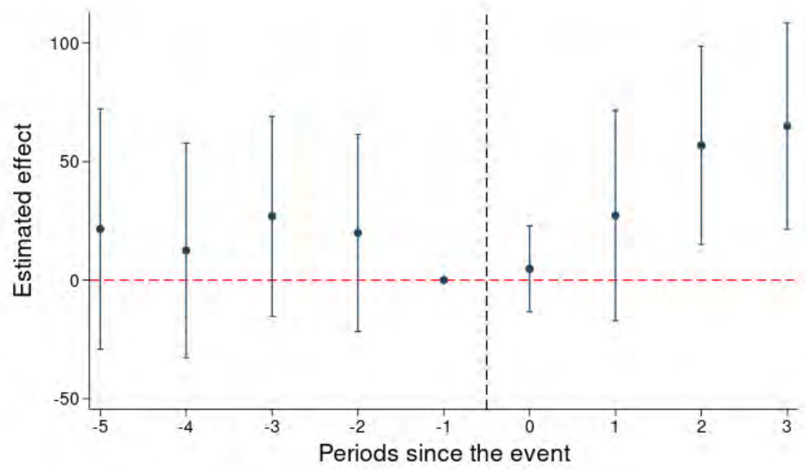
4.2.1 Attractiveness

The way funds were assigned, targeting departments officially recognized as “excellent”, could enhance their attractiveness to prospective students. In an environment where information about a department’s true quality is imperfect, external signals play a crucial role in shaping perceptions. The excellence program designation may serve as a certification of quality, with students interpreting it as a signal of better learning opportunities, stronger academic networks, and improved career prospects, factors that are central to enrollment decisions. This recognition can, therefore, generate a positive reputation effect, increasing the visibility and perceived status of winning departments and making them more appealing to incoming students.

As shown in Figure 3 and Table A4 (column 1), after three years,[26] the number of students who enroll in the first year of a bachelor’s, master’s, or single-cycle program increased by almost 65, corresponding to a 13.3% rise relative to the pre-treatment mean. The magnitude of this effect is more than proportional to the expansion of the choice set of prospective students seen in Section 4.1, thus supporting the idea that being awarded the *Dipartimento di Eccellenza* status improved the department’s attractiveness.

[26] 2021 is the last year for which data is available for this outcome.

Figure 3: **Effect on student enrollment**



Notes: The graph shows point estimates and 95% confidence intervals for the parameters β_j's of Equation (1), using as the outcome variable the number of students enrolling in the first year of a degree program. Standard errors are clustered at the department level.

To gain a deeper understanding of this effect, we further investigate the characteristics of incoming students. Specifically, we analyze whether the enrollment increase was driven primarily by high-achieving students or if it extended across the entire academic spectrum. To do so, we separately examine students belonging to the top and bottom 10% of the INVALSI score distribution in grade 10.[27] Distinguishing between these groups allows us to determine whether the excellence designation attracts stronger students, potentially enhancing the department's overall academic profile, or if it appeals more broadly, suggesting a general reputational boost that influences students at all performance levels.

Additionally, to assess the strength of the reputation effect, we replicate the analysis separately for local and out-of-province students (i.e., those relocating from other provinces). While the former are more likely to have pre-existing knowledge of a department's quality through local networks, direct interactions, or word of mouth, the latter typically have lower prior knowledge and rely more heavily on external indicators when making enrollment decisions. Therefore, out-of-province students should be more responsive to the signal conveyed by the excellence award, but if this new signal is strong enough, a reputation effect may materialize even for local students.

[27] To define the two groups of students, we consider for each individual the average INVALSI score between the Italian test and the Math test taken at the end of grade 10. For each year, we then take the distribution of those scores for the subpopulation of students who will enroll in the first year of a degree program in our period of analysis, and compute the 10th and 90th percentiles. This information is available only for students who enrolled between 2015 and 2021.

The results, presented in Figure 4 and Table A4 (columns 2-5), reveal that the excellence award had a particularly strong impact on high-achieving students, with a significant and large increase (over 50% by 2021 relative to the pre-treatment mean) in enrollment among those in the top 10% of the INVALSI score distribution. Conversely, we do not observe a comparable effect for lower-achieving students. This pattern is further confirmed when examining all quartiles of the distribution (Figure A3): the effect is strongest for students in the top quartile and gradually diminishes as we move toward lower school performance levels, becoming negligible for those in the bottom half of the distribution. This suggests that the program's reputation primarily attracted stronger students rather than generating a broad-based appeal across all academic levels. The award likely served as a signal of quality, drawing in students who are more responsive to academic prestige and future career prospects. On the other hand, the increase in enrollment was similar among out-of-province and local students, which suggests a strong increase in the department's reputation at both the local and national levels. Even local students, despite having higher pre-existing knowledge about department quality, updated their information and significantly changed their enrollment decisions accordingly.

To summarize, these findings suggest that winning departments experienced a reputation boost, making them more competitive in attracting students, particularly high-achieving ones.

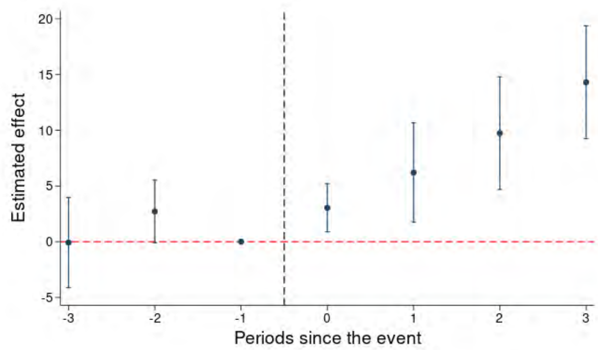
4.2.2 Research output and productivity

As highlighted in Section 4.1, winning departments allocated a share of the funds to hire additional researchers, which in turn could improve their capacity to produce scientific output. Figure 5 and Table A5 (columns 1-2) show that treated departments experienced a significant increase in the total number of publications. Specifically, by 2023, the number of publications increased by 18 (a 12.5% rise), out of which 10 were articles published in academic journals (15.3% more than in 2017).

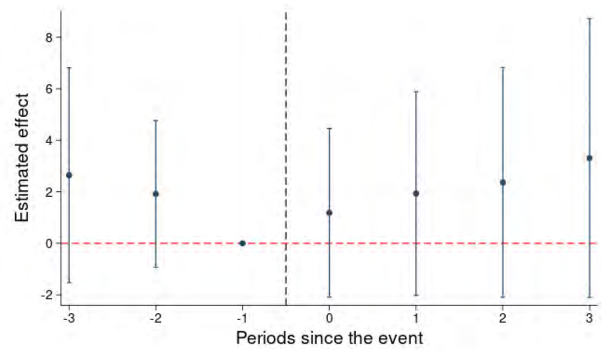
Given the expansion in faculty size, it is not entirely surprising that total research output increased, as a larger number of researchers should naturally translate into a greater volume of publications. However, beyond this mechanical effect, the excellence program could also have had an impact on research productivity, i.e., on the number of publications per faculty member. In principle, several mechanisms may contribute to this outcome. First, the presence of agglomeration externalities could play a role. A larger academic environment may facilitate collaboration, the exchange of ideas, and peer effects, ultimately enhancing indi-

Figure 4: **Effect on student enrollment by group**

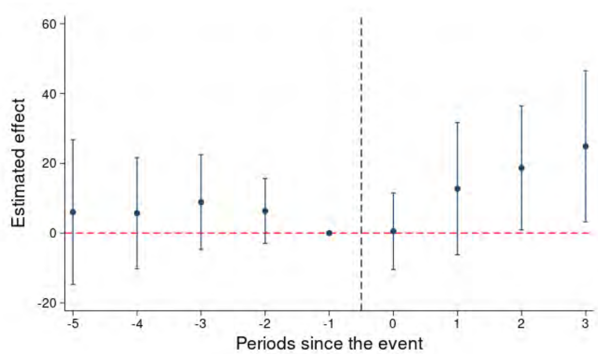
(a) Top 10% students



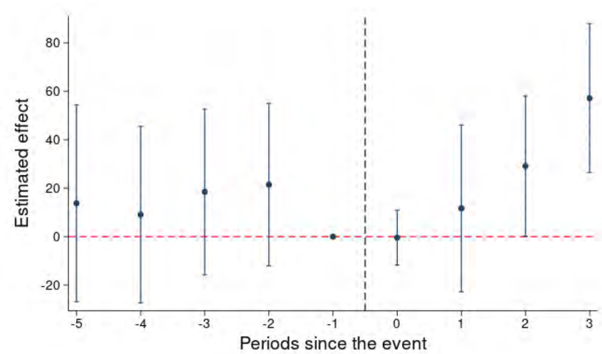
(b) Bottom 10% students



(c) Local students



(d) Out-of-province students



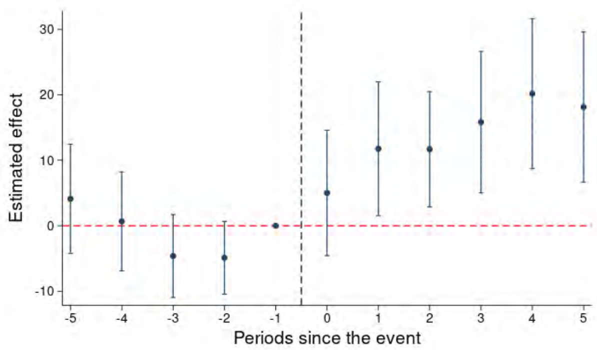
Notes: The graphs show point estimates and 95% confidence intervals for the parameters β_j's of Equation (1), using as the outcome variable the number of top-10% (Panel a), bottom-10% (Panel b), local (Panel c), or out-of-province (Panel d) students enrolling to the first year of a degree program. Standard errors are clustered at the department level.

vidual productivity. Second, the productivity of new hires could influence department-wide research performance. If newly recruited faculty members are, on average, more productive than the incumbents, their contribution could lead to an overall improvement in research output per capita within the department. Third, financial incentives could provide an additional boost if departments were allowed to use part of the funding to reward particularly productive researchers. Finally, investments in research infrastructure, such as laboratories or advanced equipment, can create a more conducive environment for high-quality research, particularly in academic fields that rely heavily on specialized infrastructure.

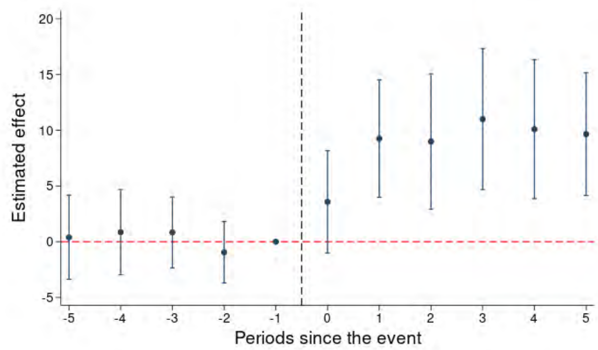
Although our setting does not permit us to directly test the relative importance of these mechanisms, we can draw some inferences based on the characteristics of the excellence program and the observed results. First, the evidence presented in Section 4.1 confirms that winning departments expanded their faculty base, suggesting that at least an agglomeration

Figure 5: **Effect on research output**

(a) Publications



(b) Articles



Notes: The graphs show point estimates and 95% confidence intervals for the parameters β_j's of Equation (1), using as the outcome variable the number of fractional publications of any type (Panel a) or the number of fractional articles published in academic journals (Panel b). Standard errors are clustered at the department level.

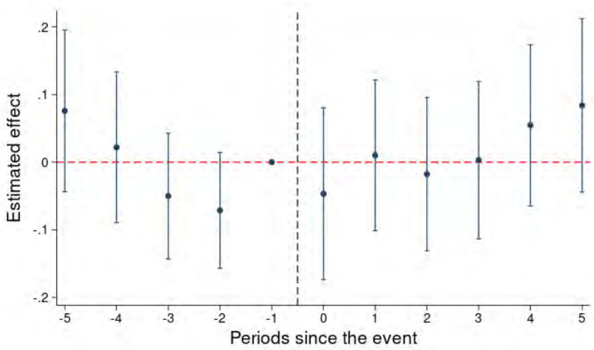
effect may be at play. Second, our analysis shows that newly hired professors were not, on average, more productive than researchers already employed in funded departments.[28] As reported in Table A8, new hires tended to have slightly fewer publications compared to their colleagues, even when controlling for their academic rank. This finding suggests that any improvements in department productivity, if they occur, are unlikely to be driven by the hiring of more productive faculty, ruling out this channel as a key mechanism. Third, financial incentives are more difficult to assess directly. While the program allowed departments to allocate part of the funding to performance-based rewards, we lack detailed information on whether and how these incentives were implemented. However, if this mechanism were at play, its effects would likely be similar across disciplines, as there is no clear reason why departments in different fields would differ systematically in their use of financial incentives. Finally, the impact of the excellence program on research productivity could instead vary across disciplines if the fourth channel mentioned above, i.e., investments in research infrastructure, was the most relevant. Fields in which research depends heavily on infrastructure and equipment, such as STEM and medicine, are more likely to benefit from productivity-enhancing investments. Conversely, disciplines with lower infrastructure needs may not experience the same boost. To explore this heterogeneity, we split our sample into two groups of departments: those operating in STEM and Life Sciences (STEM-LS) and those active in Social Sciences and Humanities (SSH).[29]

[28]Because of data limitations, in this comparison, newly hired professors are only those who were already within the Italian university system before joining a funded department after 2018.

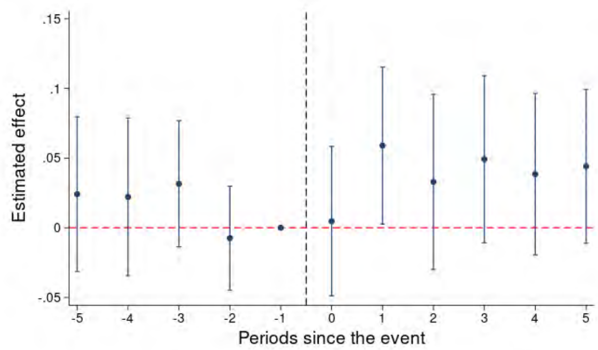
[29]The SSH group includes 5 academic fields: Science of the Antiquities, Philology, Literature and Art; History, Philosophy, Pedagogy and Psychology; Law; Economics and Statistics; and Social and Political

Figure 6: **Effect on productivity**

(a) Publications per faculty member



(b) Articles per faculty member



Notes: The graphs show point estimates and 95% confidence intervals for the parameters β_j's of Equation (1), using as the outcome variable the number of per-capita fractional publications of any type (Panel a) or the number of per-capita fractional articles published in academic journals (Panel b). Standard errors are clustered at the department level.

Figure 6 and Table A5 (columns 3-4) present the overall effect of the policy on scientific productivity, showing no significant impact when considering all disciplines together, regardless of the chosen outcome (any type of publication or just academic articles). In other words, on average, the increase in the number of scientific outputs shown in Figure 5 was just proportional to the corresponding rise in faculty size, with no effect in per-capita terms. However, when we distinguish between STEM-LS and SSH departments, we find a non-negligible increase in productivity only for the former (Figure 7 and Tables A6-A7, columns 1-2): by 2023, productivity rose by 7.5% (7.8% for articles only), with the estimated coefficient being significant at the 5% level.[30] Given the lack of any productivity response in SSH departments,[31] this heterogeneity suggests that monetary incentives may not have been a driving factor. While the law permitted departments to allocate part of the excellence funds to reward highly productive faculty, it is unclear to what extent this opportunity was exploited or which departments chose to implement such incentives. Without detailed information on how these funds were allocated, it remains challenging to fully assess their potential impact on individual research efforts.

To deepen our understanding of the mechanisms driving the positive effect on STEM-LS departments, and in particular to better assess the relevance of agglomeration externalities

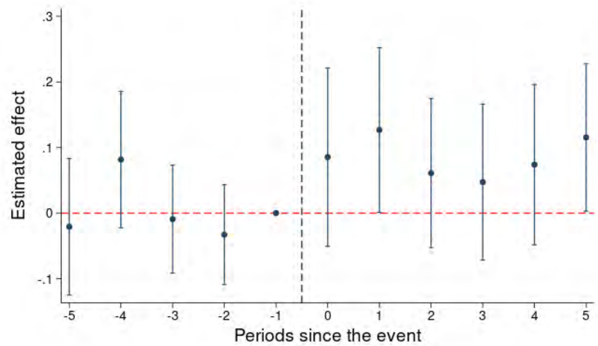
Sciences.

[30]These results remain consistent even when considering only faculty members who were already employed in the department in 2017 (Figure A4).

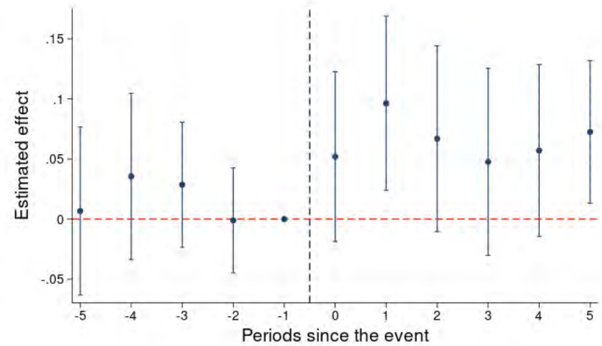
[31]In these fields, publication cycles tend to be, on average, longer than in STEM-LS areas. Therefore, we cannot exclude the possibility that the absence of a statistically significant effect on productivity in SSH departments may partly reflect research times that exceed our five-year post-treatment analysis period, in addition to considerations regarding the effectiveness of monetary incentives.

Figure 7: **Effect on productivity by department field**

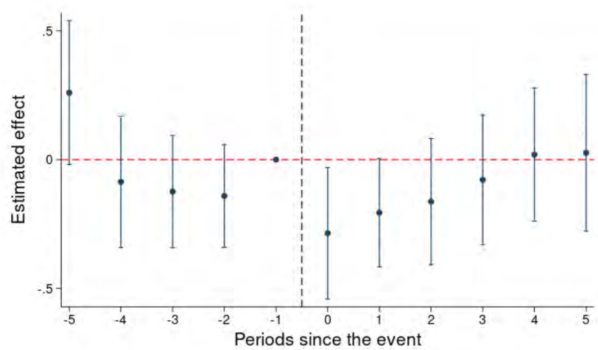
(a) Publ. per faculty member - STEM-LS



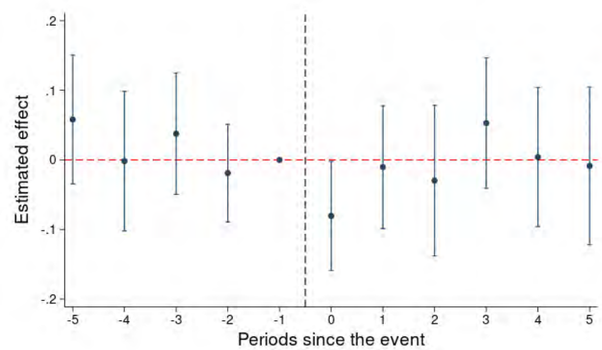
(b) Articles per faculty member - STEM-LS



(c) Publ. per faculty member - SSH



(d) Articles per faculty member - SSH



Notes: The graphs show point estimates and 95% confidence intervals for the parameters β_j's of Equation (1), using as the outcome variable the number of per-capita fractional publications or articles for departments operating in STEM and Life Sciences (STEM-LS; Panels a and b, respectively) or in Social Sciences and Humanities (SSH; Panels c and d, respectively). Standard errors are clustered at the department level.

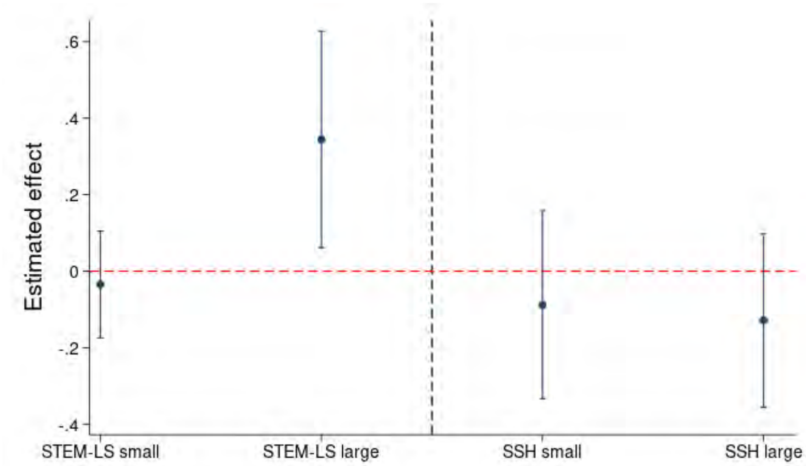
and infrastructural investments, we extend our analysis by considering the size of the departments. Size may play a crucial role for two main reasons. First, as discussed in Section 2.2, the funding formula allocated more resources to larger departments. Second, larger departments may have a greater capacity to attract a higher number of researchers, thereby amplifying the benefits of agglomeration effects.

As shown in Figure 8 and Table A6 (columns 3-6), our findings reveal that the effect was strong and significant only for larger departments in STEM-LS, where productivity increased by 20.1% relative to 2017.[32,33] This suggests that two key mechanisms—investments

[32]We consider as larger departments those belonging to the fourth and fifth quintiles of the distribution of department size in 2017.

[33]In Figure A5 and Table A7, we replicate the same heterogeneity analysis by looking at the number of fractional articles (instead of any type of publication) per capita. Results are consistent with those reported in Figure 8 and Table A6.

Figure 8: **Effect on productivity by department field and size (publications)**



Notes: The graph shows the point estimate and the 95% confidence interval for the parameter δ of Equation (2), using as the outcome variable the number of per-capita fractional publications for small and large departments operating in STEM and Life Sciences (STEM-LS) or in Social Sciences and Humanities (SSH). Small departments are defined as those belonging to the first three quintiles of the department size distribution in 2017, while large departments are those in the fourth and fifth quintiles. Standard errors are clustered at the department level.

in research infrastructure and agglomeration externalities—are driving the observed increase. On the one hand, the absence of any effect in large SSH departments highlights that while substantial funding is a necessary condition for productivity gains, it is not sufficient on its own. Simply receiving more resources due to a larger size does not necessarily translate into higher productivity, unless these resources can be utilized to enhance working conditions and research infrastructure, as is the case in STEM-LS departments. On the other hand, infrastructural investments alone may not be sufficient to generate a productivity increase: smaller departments, even those operating in STEM-LS, do not report any effect, as they may lack the density of researchers needed to trigger positive agglomeration externalities through the exchange of ideas, expertise, and methodologies.

Summarizing, while in SSH departments, the rise in scientific outputs was directly proportional to faculty expansion, in STEM-LS departments, the policy also led to a significant increase in research productivity, particularly in the largest ones. This finding suggests that the availability of excellence funds was not sufficient on its own. Instead, the combination of agglomeration effects and investments in research infrastructure appears to have played a decisive role in generating productivity gains.

5 Conclusion

Over the past twenty years, several countries have implemented university excellence initiatives, through which the most promising research institutions have been given additional resources to become more competitive on the global level. In this study, we evaluate the Italian excellence initiative (*Dipartimenti di Eccellenza*), launched in 2018, which selects and funds the top-25% departments in public universities. We adopt a dynamic difference-in-differences empirical strategy and find both direct and indirect significant effects on funded departments. In particular, the policy led to an increase in faculty size (across all faculty ranks), the attraction of more students through a reputational effect (especially strong among high-performing ones), and a boost in aggregate scientific production. STEM and Life Sciences departments, particularly larger ones, also experienced an improvement in productivity, suggesting that investments in research infrastructure and positive agglomeration externalities played a relevant role. On the other hand, we find only a mild and imprecise impact of excellence funds on the creation of new degree programs, and no impact at all on PhD programs.

While we were able to assemble rich longitudinal information on academic careers, publications, educational offerings, and student enrollment for the first time, we recognize some data limitations in this work. First, when measuring the effect on scientific production and productivity, we can only examine the quantity of publications and articles, rather than their quality (which could be proxied, for instance, by citations). Second, we lack data on how funded departments actually spent their additional resources, particularly on whether and to what extent they introduced monetary incentives to reward highly productive researchers. This prevents us from directly testing some of the potential channels that could affect productivity, as discussed in Section 4.2.2. Finally, we cannot check whether winning departments experienced any crowding out of other resources (as shown, e.g., by Buenstorf and Koenig, 2020 for Germany), with universities adjusting the internal distribution of their ordinary funds to partly compensate for losing departments. However, if this were the case, we could still conclude that our estimates are lower bounds for the true ATTs.

We believe that our findings bear important policy implications. First, when assessing the benefits of excellence funding, it is crucial to jointly consider both direct and indirect effects of the policy. In this paper, for instance, we show that excellence funding can have a positive impact on student attraction. Given that student tuition fees are a major source of university funding, this increased enrollment may initiate a virtuous cycle for winning departments, thereby enhancing financial stability and enabling them to sustain and expand their resources over time. Without considering this channel, the benefits of excellence funding would have been underestimated.

Second, the gains from excellence funding may not be homogeneous across academic fields. We find evidence that productivity gains are larger for departments in STEM and Life Sciences, which require investments in infrastructure to produce research. This result, which would have been overlooked in an aggregate university-level analysis, is crucial for policy-makers seeking to more effectively target excellence funds. Additionally, this heterogeneity may extend to other outcomes not considered in our project. For instance, researchers in funded STEM-LS departments may have also filed more patents or created more businesses through public-private partnerships. Future research is needed to further explore this issue.

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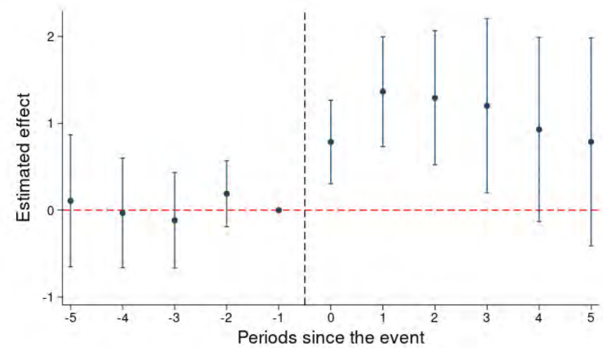
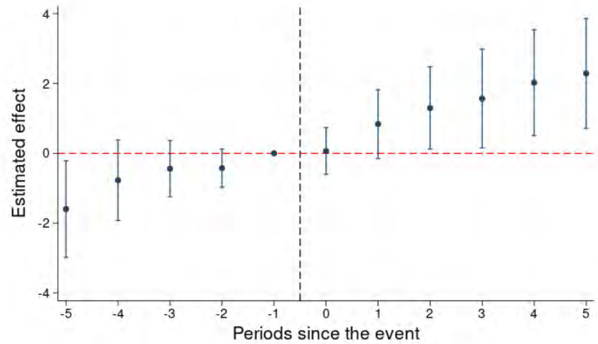
A Appendix: Additional Figures and Tables

Figure A1: **Effect on total faculty count by seniority**

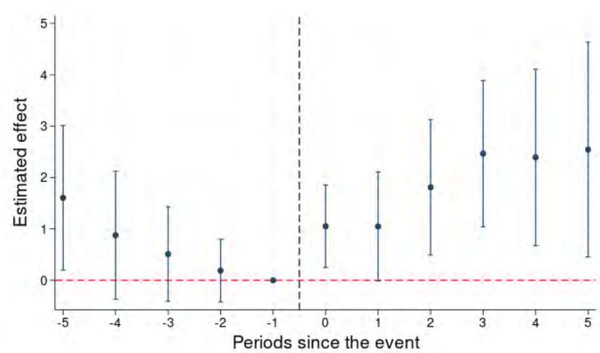
(a) Full professors



(b) Associate professors

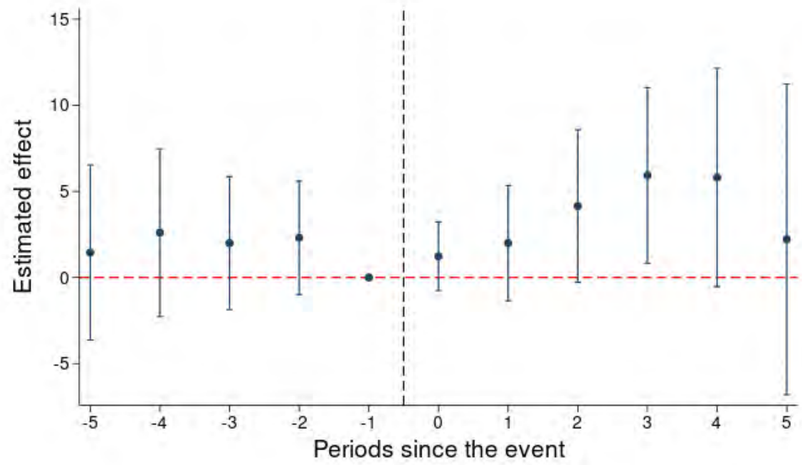


(c) Assistant professors



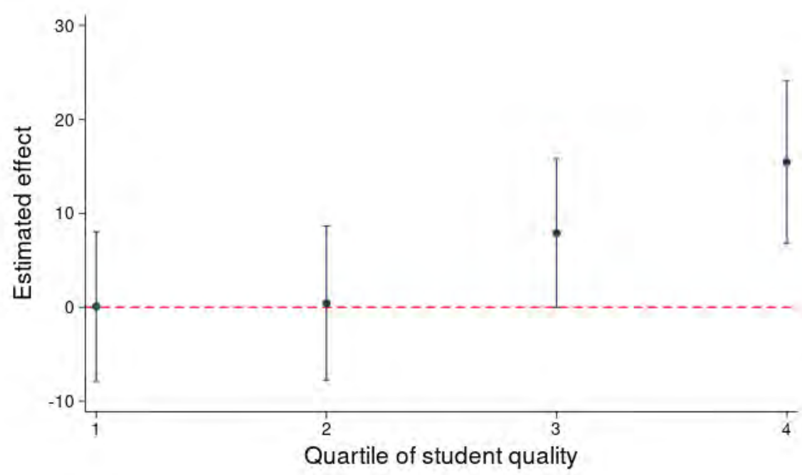
Notes: The graphs show point estimates and 95% confidence intervals for the parameters β_j's of Equation (1), using as the outcome variable the number of full (Panel a), associate (Panel b), or assistant (Panel c) professors. Standard errors are clustered at the department level.

Figure A2: **Effect on PhD researchers**



Notes: The graph shows point estimates and 95% confidence intervals for the parameters β_j's of Equation (1), using as the outcome variable the number of PhD researchers. Standard errors are clustered at the department level.

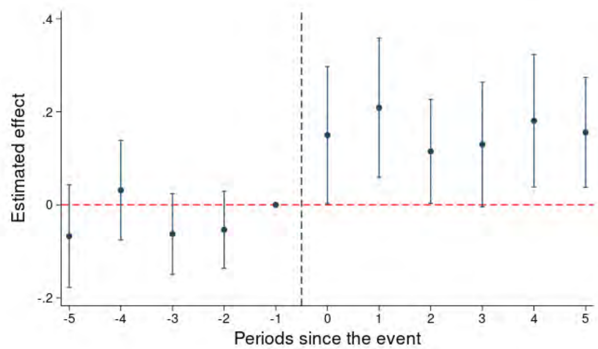
Figure A3: **Effect on student enrollment by quartile of school performance**



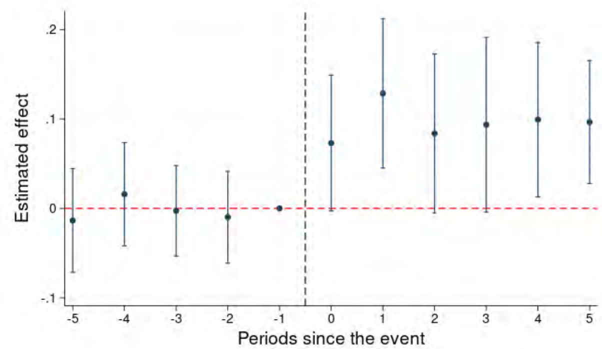
Notes: The graph shows the point estimate and the 95% confidence interval for the parameter δ of Equation (2) estimated across quartiles of the distribution of students' INVALSI scores in grade 10, using as the outcome variable the number of students enrolling to the first year of a degree program. Standard errors are clustered at the department level.

Figure A4: **Effect on productivity by department field - Incumbent faculty**

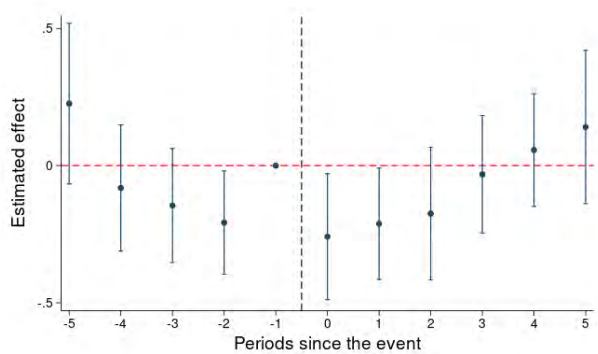
(a) Publications - STEM-LS



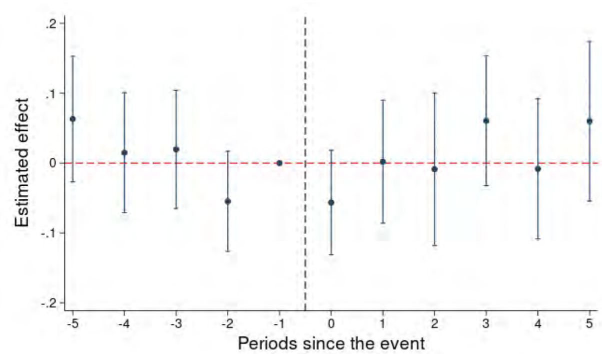
(b) Articles - STEM-LS



(c) Publications - SSH

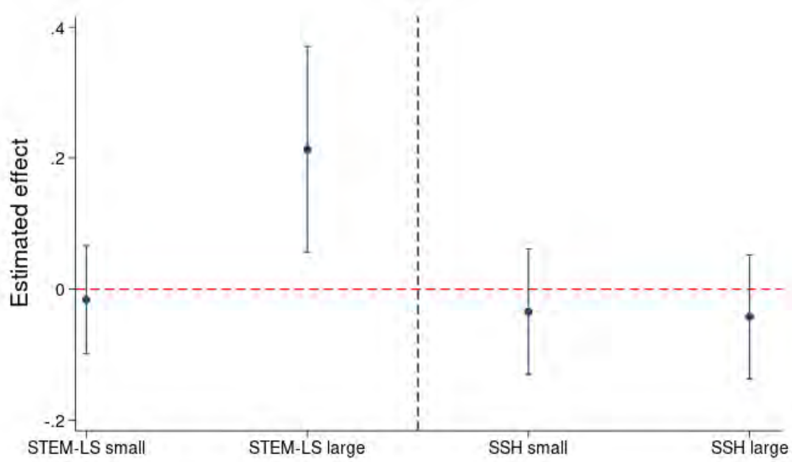


(d) Articles - SSH



Notes: The graphs show point estimates and 95% confidence intervals for the parameters β_j's of the following individual-level equation: $Y_{i,t} = \alpha_i + \lambda_{f(i),t} + \sum_{j \neq -1} \beta_j \mathbb{1}[E_{d(i),t} = j] + \epsilon_{i,t}$, where α_i are individual fixed effects and the other variables have the same meaning as in Equation 1. In this regression, we consider only faculty members who were already employed in the department in 2017 and use as the outcome variable the number of fractional publications or articles for departments operating in STEM and Life Sciences (STEM-LS; Panels a and b, respectively) or in Social Sciences and Humanities (SSH; Panels c and d, respectively). Standard errors are clustered at the 2017 department level.

Figure A5: **Effect on productivity by department field and size (articles)**



Notes: The graph shows the point estimate and the 95% confidence interval for the parameter δ of Equation (2), using as the outcome variable the number of per-capita fractional articles for small and large departments operating in STEM and Life Sciences (STEM-LS) or in Social Sciences and Humanities (SSH). Small departments are defined as those belonging to the first three quintiles of the distribution of department size in 2017, while large departments are those in the fourth and fifth quintiles. Standard errors are clustered at the department level.

Table A1: **Summary statistics**

	(1) All Sample Mean	(2) Funded Mean	(3) Non-funded Mean	(4) Difference (2) - (3)
Total faculty	65.58	66.98	63.69	3.30
Female faculty	23.88	24.74	22.72	2.02
Assistant professors	23.19	22.78	23.75	-0.96
Associate professors	25.37	26.43	23.95	2.48
Full professors	17.01	17.77	15.99	1.78*
Fractional publications	134.38	145.29	119.97	25.31*
Fractional articles	60.83	63.33	57.52	5.80
Fractional publications by faculty member	2.03	2.13	1.89	0.24
Fractional articles by faculty member	0.92	0.93	0.90	0.03
Degree programs	7.93	8.28	7.46	0.82
Single-cycle degree programs	0.34	0.34	0.34	0.00
Bachelor's degree programs	3.38	3.44	3.31	0.12
Master's degree programs	4.35	4.65	3.93	0.72
Students enrolled (first year)	472.81	486.52	454.16	32.37
PhD programs	1.26	1.37	1.12	0.26*
PhD researchers	32.17	35.67	27.50	8.17*
STEM-LS	0.64	0.61	0.67	-0.06
North	0.54	0.59	0.46	0.13*
Center	0.29	0.27	0.32	-0.05
South	0.17	0.14	0.22	-0.08
ISPD	93.73	97.77	88.30	9.47***
Development plan evaluation	23.39	25.44	20.63	4.82***
Annual funding (€ million)	0.86	1.51	0.00	1.51***
N	314	180	134	314

Notes: Statistics for variables in the first panel of the table are measured in 2017, the last year before treatment. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table A2: **Results: Faculty count**

	(1) Total Faculty	(2) Assistant Professors	(3) Associate Professors	(4) Full Professors
β_{-5}	0.12	1.61**	-1.60**	0.11
	(0.84)	(0.72)	(0.70)	(0.39)
β_{-4}	0.08	0.88	-0.77	-0.03
	(0.73)	(0.63)	(0.59)	(0.32)
β_{-3}	-0.05	0.51	-0.44	-0.12
	(0.54)	(0.47)	(0.41)	(0.28)
β_{-2}	-0.05	0.19	-0.43	0.19
	(0.37)	(0.31)	(0.28)	(0.19)
β_0	1.91***	1.05**	0.07	0.79***
	(0.61)	(0.41)	(0.34)	(0.24)
β_1	3.25***	1.05*	0.84*	1.36***
	(0.77)	(0.54)	(0.50)	(0.32)
β_2	4.40***	1.81***	1.30**	1.29***
	(0.85)	(0.67)	(0.60)	(0.39)
β_3	5.24***	2.46***	1.57**	1.20**
	(1.02)	(0.72)	(0.72)	(0.51)
β_4	5.35***	2.39***	2.03***	0.93*
	(1.20)	(0.87)	(0.77)	(0.54)
β_5	5.62***	2.54**	2.29***	0.79
	(1.57)	(1.06)	(0.80)	(0.61)
δ	4.26***	1.25*	1.97***	1.03**
	(1.04)	(0.67)	(0.61)	(0.44)
$\bar{y}_{2017}$	66.98	22.78	26.43	17.77
N	3409	3409	3409	3409

Notes: The sample includes all departments that applied to the excellence program. β_j denotes the event-study estimates of equation (1). δ denotes the difference-in-difference estimate of equation (2). $\bar{y}_{2017}$ denotes the average of the outcome variable in the treatment group measured in 2017. All regressions include department and academic field x year fixed effects. Robust standard errors clustered at the department level are shown in parentheses. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table A3: **Results: Educational offerings**

	(1) Degree Programs	(2) PhD Programs	(3) PhD Researchers
β_{-5}	-0.20	0.11*	1.45
	(0.37)	(0.07)	(2.58)
β_{-4}	-0.25	0.06	2.60
	(0.30)	(0.06)	(2.48)
β_{-3}	-0.02	0.05	1.99
	(0.33)	(0.06)	(1.96)
β_{-2}	-0.06	0.05	2.30
	(0.19)	(0.05)	(1.67)
β_{0}	0.13	0.05	1.23
	(0.13)	(0.03)	(1.01)
β_{1}	0.27	0.05	1.99
	(0.29)	(0.05)	(1.70)
β_{2}	0.55*	0.07	4.15*
	(0.31)	(0.07)	(2.25)
β_{3}	0.51	0.08	5.93**
	(0.34)	(0.07)	(2.59)
β_{4}	0.48	0.02	5.81*
	(0.38)	(0.08)	(3.22)
β_{5}	0.42	-0.03	2.22
	(0.41)	(0.09)	(4.58)
δ	0.50*	-0.01	1.87
	(0.30)	(0.05)	(2.60)
$\bar{y}_{2017}$	8.28	1.37	35.67
N	3167	3343	3337

Notes: The sample includes all departments that applied to the excellence program. β_j denotes the event-study estimates of equation (1). δ denotes the difference-in-difference estimate of equation (2). $\bar{y}_{2017}$ denotes the average of the outcome variable in the treatment group measured in 2017. All regressions include department and academic field x year fixed effects. Robust standard errors clustered at the department level are shown in parentheses. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table A4: **Results: First-year student enrollment**

	(1) Total Enrollment	(2) Top 10% Enrollment	(3) Bottom 10% Enrollment	(4) Local Enrollment	(5) Out-of-province Enrollment
β_{-5}	21.54			6.02	13.77
	(25.75)			(10.54)	(20.63)
β_{-4}	12.54			5.71	9.11
	(22.98)			(8.11)	(18.50)
β_{-3}	26.91	-0.08	2.64	8.87	18.49
	(21.40)	(2.05)	(2.12)	(6.92)	(17.39)
β_{-2}	19.93	2.72*	1.91	6.34	21.47
	(21.14)	(1.43)	(1.45)	(4.72)	(17.02)
β_0	4.74	3.04***	1.18	0.52	-0.41
	(9.20)	(1.10)	(1.66)	(5.58)	(5.72)
β_1	27.27	6.21***	1.93	12.74	11.68
	(22.56)	(2.26)	(2.01)	(9.64)	(17.48)
β_2	56.86***	9.74***	2.36	18.67**	29.13**
	(21.23)	(2.57)	(2.27)	(9.02)	(14.71)
β_3	64.90***	14.31***	3.31	24.88**	57.14***
	(22.09)	(2.57)	(2.75)	(11.01)	(15.58)
δ	22.21	7.36***	0.71	8.82	11.69
	(17.87)	(2.00)	(1.68)	(8.39)	(11.24)
$\bar{y}_{2017}$	486.52	28.21	18.88	206.96	277.07
N	2543	1977	1977	2492	2492

Notes: The sample includes all departments that applied to the excellence program. β_j denotes the event-study estimates of equation (1). δ denotes the difference-in-difference estimate of equation (2). $\bar{y}_{2017}$ denotes the average of the outcome variable in the treatment group measured in 2017. All regressions include department and academic field x year fixed effects. Robust standard errors clustered at the department level are shown in parentheses. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table A5: **Results: Research output**

	(1) Production (Publications)	(2) Production (Articles)	(3) Productivity (Publications)	(4) Productivity (Articles)
β_{-5}	4.12	0.40	0.08	0.02
	(4.24)	(1.92)	(0.06)	(0.03)
β_{-4}	0.67	0.86	0.02	0.02
	(3.84)	(1.94)	(0.06)	(0.03)
β_{-3}	-4.61	0.84	-0.05	0.03
	(3.21)	(1.62)	(0.05)	(0.02)
β_{-2}	-4.89*	-0.95	-0.07	-0.01
	(2.82)	(1.40)	(0.04)	(0.02)
β_0	5.01	3.58	-0.05	0.00
	(4.87)	(2.33)	(0.06)	(0.03)
β_1	11.76**	9.25***	0.01	0.06**
	(5.19)	(2.68)	(0.06)	(0.03)
β_2	11.68***	8.99***	-0.02	0.03
	(4.47)	(3.08)	(0.06)	(0.03)
β_3	15.82***	11.00***	0.00	0.05
	(5.48)	(3.21)	(0.06)	(0.03)
β_4	20.16***	10.09***	0.05	0.04
	(5.81)	(3.17)	(0.06)	(0.03)
β_5	18.12***	9.66***	0.08	0.04
	(5.83)	(2.80)	(0.07)	(0.03)
δ	14.71***	8.51***	0.02	0.02
	(5.14)	(2.92)	(0.05)	(0.03)
$\bar{y}_{2017}$	145.29	63.33	2.13	0.93
N	3376	3376	3376	3376

Notes: The sample includes all departments that applied to the excellence program. β_j denotes the event-study estimates of equation (1). δ denotes the difference-in-difference estimate of equation (2). $\bar{y}_{2017}$ denotes the average of the outcome variable in the treatment group measured in 2017. All regressions include department and academic field x year fixed effects. Robust standard errors clustered at the department level are shown in parentheses. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table A6: **Heterogeneity: Productivity (publications)**

	(1) STEM-LS All	(2) SSH All	(3) STEM-LS Small	(4) STEM-LS Large	(5) SSH Small	(6) SHH Large
β_{-5}	-0.02	0.26*	0.00	-0.13	0.31*	0.21
	(0.05)	(0.14)	(0.07)	(0.10)	(0.18)	(0.25)
β_{-4}	0.08	-0.09	0.15**	-0.05	-0.10	0.12
	(0.05)	(0.13)	(0.07)	(0.09)	(0.18)	(0.15)
β_{-3}	-0.01	-0.12	0.04	-0.12	-0.10	-0.15
	(0.04)	(0.11)	(0.05)	(0.08)	(0.13)	(0.19)
β_{-2}	-0.03	-0.14	-0.01	-0.10	-0.10	-0.14
	(0.04)	(0.10)	(0.05)	(0.07)	(0.13)	(0.14)
β_0	0.09	-0.29**	0.00	0.27**	-0.23	-0.42*
	(0.07)	(0.13)	(0.09)	(0.13)	(0.17)	(0.21)
β_1	0.13**	-0.21*	0.05	0.32**	-0.13	-0.26**
	(0.06)	(0.11)	(0.08)	(0.15)	(0.15)	(0.13)
β_2	0.06	-0.16	-0.01	0.19**	-0.03	-0.32**
	(0.06)	(0.12)	(0.08)	(0.09)	(0.15)	(0.14)
β_3	0.05	-0.08	-0.04	0.24*	-0.02	-0.14
	(0.06)	(0.13)	(0.07)	(0.13)	(0.17)	(0.20)
β_4	0.07	0.02	-0.07	0.36***	-0.02	0.16
	(0.06)	(0.13)	(0.08)	(0.12)	(0.13)	(0.28)
β_5	0.12**	0.03	0.07	0.20*	-0.08	0.20
	(0.06)	(0.15)	(0.08)	(0.10)	(0.20)	(0.19)
δ	0.08	-0.09	-0.03	0.34**	-0.09	-0.13
	(0.06)	(0.10)	(0.07)	(0.14)	(0.13)	(0.12)
$\bar{y}_{2017}$	1.59	2.91	1.50	1.69	2.80	3.09
N	2161	1215	1278	883	806	409

Notes: The sample includes all departments that applied to the excellence program. β_j denotes the event-study estimates of equation (1). δ denotes the difference-in-difference estimate of equation (2). $\bar{y}_{2017}$ denotes the average of the outcome variable in the treatment group measured in 2017. All regressions include department and academic field x year fixed effects. Robust standard errors clustered at the department level are shown in parentheses. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table A7: **Heterogeneity: Productivity (articles)**

	(1) STEM-LS All	(2) SSH All	(3) STEM-LS Small	(4) STEM-LS Large	(5) SSH Small	(6) SHH Large
β_{-5}	0.01	0.06	0.02	-0.03	0.08	0.03
	(0.04)	(0.05)	(0.05)	(0.05)	(0.07)	(0.08)
β_{-4}	0.04	-0.00	0.06	-0.03	-0.01	0.07
	(0.04)	(0.05)	(0.05)	(0.06)	(0.07)	(0.07)
β_{-3}	0.03	0.04	0.03	-0.01	0.08	-0.01
	(0.03)	(0.04)	(0.04)	(0.05)	(0.06)	(0.07)
β_{-2}	-0.00	-0.02	-0.00	-0.03	0.00	-0.04
	(0.02)	(0.04)	(0.03)	(0.05)	(0.04)	(0.06)
β_0	0.05	-0.08**	0.01	0.15**	-0.08	-0.07
	(0.04)	(0.04)	(0.04)	(0.07)	(0.05)	(0.06)
β_1	0.10***	-0.01	0.05	0.21**	-0.01	0.03
	(0.04)	(0.04)	(0.05)	(0.08)	(0.06)	(0.08)
β_2	0.07*	-0.03	0.03	0.16*	-0.02	-0.08
	(0.04)	(0.05)	(0.05)	(0.09)	(0.06)	(0.10)
β_3	0.05	0.05	-0.03	0.23**	0.09	-0.02
	(0.04)	(0.05)	(0.04)	(0.09)	(0.06)	(0.07)
β_4	0.06	0.00	-0.03	0.23***	0.01	-0.02
	(0.04)	(0.05)	(0.04)	(0.08)	(0.07)	(0.07)
β_5	0.07**	-0.01	0.00	0.19***	-0.01	-0.05
	(0.03)	(0.06)	(0.04)	(0.06)	(0.07)	(0.06)
δ	0.05	-0.03	-0.02	0.21***	-0.03	-0.04
	(0.04)	(0.04)	(0.04)	(0.08)	(0.05)	(0.05)
$\bar{y}_{2017}$	0.90	1.06	0.88	0.94	1.03	1.12
N	2161	1215	1278	883	806	409

Notes: The sample includes all departments that applied to the excellence program. β_j denotes the event-study estimates of equation (1). δ denotes the difference-in-difference estimate of equation (2). $\bar{y}_{2017}$ denotes the average of the outcome variable in the treatment group measured in 2017. All regressions include department and academic field x year fixed effects. Robust standard errors clustered at the department level are shown in parentheses. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table A8: **New hires productivity**

	(1)	(2)	(3)	(4)	(5)	(6)
	Lagged publications (per year)			Average publications (2013-2017)		
	Incumbents	New hires	Diff.	Incumbents	New hires	Diff.
All faculty	2.23	2.01	0.22**	2.19	2.20	-0.01
N	75741	1222	76963	75741	1222	76963
Assistant profs	1.80	1.64	0.15	1.47	1.73	-0.27
N	19756	372	20128	19756	372	20128
Associate profs	2.16	1.95	0.21*	2.03	2.11	-0.08
N	33864	532	34396	33864	532	34396
Full profs	2.74	2.55	0.19	2.82	2.69	0.12
N	22121	318	22439	22121	318	22439

Notes: All means are computed on the sample of funded departments in the funding period (2018-2023). In each year, incumbents are defined as researchers who belonged to the department the year before, while new hires are researchers who did not belong to the department the year before. Because of data limitations, new hires are only researchers who were already within the Italian university system before joining a funded department. In each year, lagged publications denote the number of publications in the previous year, whereas average publications denote the average number of publications in the period 2013-2017. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.