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Article

Beyond the badge of honour: the effect of the academic excellence initiative on staff recruitment in Italy

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Abstract

Understanding how excellence-based funding affects academic recruitment is central to evaluating the broader implications of performance-oriented research policies. We study the Department of Excellence Initiative ("Dipartimenti di Eccellenza") in the Italian higher education system. Unlike other excellence initiatives in Europe, this programme was directed at departments rather than universities. We investigate the effect of the initiative on new faculty positions, distinguishing between external recruitment and internal promotion, as well as different career stages. We also analyse heterogeneity across departmental categories, differentiating between first-tier (top-rated) and second-tier (near-elite) departments. Our findings indicate a positive effect on the creation of new faculty positions within funded departments, particularly through external recruitment and across various career stages. Notably, we provide evidence of greater benefits accruing to second-tier departments relative to their first-tier counterparts, particularly with respect to entry-level tenure-track positions.

Keywords excellence initiatives, university departments, second-tier departments, staff recruitment, Italy
JEL classifications: I23, O38, H52

1. Introduction

The allocation of competitive research funding and 'excellence' titles to a limited number of universities or departments has become a prominent policy tool across countries (Agasisti et al. 2022; Dyrstad et al. 2024; Carayol and Maublanc 2025). This approach raises important questions about how incentives and resources influence academic behaviour and institutional outcomes. Prior studies indicate that such mechanisms can shape faculty careers (Faria and McAdam 2015), improve research visibility (Coupé et al. 2010), and contribute to disciplinary transformations (Svorenčík 2020). On the one hand, selecting a subset of university departments as 'excellent' and awarding them substantial funding aims at fostering competition and enhancing overall performance by spurring institutions to increase research productivity and international visibility (Agasisti et al. 2022). On the other hand, critics contend that these programmes may exacerbate inequalities and foster behaviour oriented more towards award acquisition rather than long-term positive outcomes (Moore et al. 2017). Understanding the effects of such policies makes a contribution to both the literature on academic incentives and to a more efficient allocation of public research funding—especially for talent attraction across institutions.

Against this backdrop, this article examines a specific policy within this domain—the Italian 'Departments of Excellence' initiative—and investigates whether receiving an excellence award, along with the associated funding, enables a university department to expand and recompose its academic staff, in terms of the balance between internal and external hires and across career stages, and whether this effect differs between first- and second-tier departments. Hence, this study adds to the literature by analysing the effect of excellence-based funding on academic staff recruitment at the departmental level, rather than the university level (i.e. at a more granular unit of responsibility and cost), and by focusing on a national context where scientific quality is more dispersed across institutions compared to countries such as the United Kingdom or France (Aghion et al. 2010; Abramo et al. 2012).[1]

Existing studies provide some insights but leave gaps regarding the link between funding received via a programme of excellence and human resource outcomes. Prior studies provide insights into how performance-based funding influences outputs such as publications and rankings. In Italy, earlier reforms (i.e. Law 240/2010) spurred productivity increases (Bratti et al. 2021), while broader international evidence highlights both positive effects and diminishing returns (Aagaard et al. 2020; Azoulay and Li 2021). Norway's experience confirms that performance-linked funding can drive institutional adjustments (Dyrstad et al. 2024), and Germany's Excellence Initiative has raised the profile of awarded institutions (Carayol and Maublanc 2025). However, a growing body of literature also points to potential adverse effects, such as cumulative advantage dynamics (Bol et al. 2018), lower probability to conduct risky research (Li and Agha 2015), and reduced efficiency due to excessive concentration (Bonaccorsi and Daraio 2005).

Despite these findings, little is known about how such schemes affect recruitment. Research has largely focused on outputs, overlooking internal organizational dynamics. It remains unclear whether excellence awards enhance departments' capacity to attract new staff, or whether exclusion leads to talent loss or reduced hiring. Moreover, the extent to which such policies differentially affect departments of different quality levels remains underexplored. For example, UK-based evidence shows that research evaluation affects labour markets, with hiring clustered around evaluation periods (Harris et al. 2025).

To address these gaps, we analyse academic hiring in Italy before and after the 2018 Italian 'Departments of Excellence' initiative. Since only a subset of departments received the award—based on research quality and proposals—we construct a quasi-experimental treatment-control setup. By comparing recruitment trends between awarded and non-awarded departments over time, we isolate the effect of additional funding on hiring, distinguishing between internal and external recruits, and among different career stages. We also investigate heterogeneity between first-tier (top-rated) and second-tier (near-elite) departments, assessing whether the initiative benefited top departments or catching-up ones. In doing so, our analysis sheds light on whether the initiative narrowed or widened pre-existing disparities among top-rated and near-elite departments.

[1] This is also supported by data on the ratio of PhD students to undergraduate students, which, compared to other European university systems, is relatively homogeneous across Italian institutions, reflecting a lower degree of vertical differentiation within the sector (see Huisman et al., 2015).

We find that the programme led to an overall increase in hiring, driven largely by second-tier departments. Awarded departments recruited more than their non-awarded counterparts, particularly through external hires. New positions were distributed evenly across temporary, tenure-track, and tenured contracts. Notably, second-tier departments accounted for most of the additional hiring, focusing especially on tenure-track roles and balancing internal and external recruitment. These findings suggest that the programme did not simply reinforce the dominance of leading departments but also provided a significant contribution to catching-up ones, helping them close the gap in academic recruitment. That is, under the specific conditions of this Italian scheme, excellence initiative helped to level the playing field rather than exacerbating inequality.

Our findings not only shed light on the micro-dynamics of academic hiring but also offer several broader lessons for Italy and for performance-based funding policies more generally. Firstly, the evidence that near-elite (second-tier) departments benefitted disproportionately from the additional funding shows that, under specific conditions, performance funding can act as an equalizer rather than merely reinforcing the position of already established institutions. This stands in contrast to critiques arguing that such funding mechanisms tend to exacerbate existing inequalities by disproportionately favouring top performers (e.g. Fadda et al. 2022). At the same time, it raises legitimate concerns about research policies that promote excessive concentration of resources in the hands of a limited number of institutions, potentially undermining the broader objectives of system-wide capacity building (e.g. Geuna and Martin 2003).

Second, our results imply that performance-oriented funding mechanisms can contribute not only to a short-term increase in hiring but also to longer-term capacity building. In the Italian context, the focus on tenure-track positions in near-elite departments points to a healthy expansion of human capital, suggesting that additional resources can enable second-tier departments to catch up with their elite counterparts, even in the long-term.

Third, these outcomes highlight the importance of considering heterogeneity in institutional contexts when designing performance-based funding programmes. The differential effect observed between first- and second-tier departments suggests that funding policies should be calibrated to account for diverse baseline capacities and resource endowments. This tailored approach is likely to be relevant not only for Italy but also for other higher education systems facing similar issues in relation to resource allocation and institutional inequality (Dougherty and Natow 2020).

Finally, by focusing on departments—the units directly responsible for recruitment, research coordination, and budget execution—this study uncovers granular organizational responses that broader university-level analyses have missed (Bonaccorsi and Daraio 2005; Carayol and Maublanc 2025).

The remainder of the article is structured as follows. Section 2 outlines the various rationales underpinning excellence-based funding and reviews the main findings from existing policy evaluations. Section 3 provides an overview of major excellence initiatives in Europe and describes the Italian 'Departments of Excellence' programme. Section 4 presents the empirical strategy and main results, including heterogeneity across department tiers. Section 5 discusses robustness checks, and Section 6 concludes.

2. Theoretical framework: rationales and critiques

From a theoretical perspective, programmes that reward excellence are grounded in incentive theory, which highlights competition as a key mechanism for enhancing performance within academic systems. A central conceptual framework in this regard is tournament theory, as articulated by Lazear and Rosen (1981), who argue that rank-order competitions with substantial rewards for top performers can effectively incentivize effort and productivity among agents. Participants are rewarded based on relative performance, prompting system-wide improvement as institutions compete for scarce resources. Excellence initiatives reflect this logic, with funding bodies allocating resources to a subset of institutions, thus creating an incentive for others to emulate top performers (Aghion et al. 2010). The underlying logic posits that the prospect of being excluded from funding or reputational benefits will spur lagging institutions to emulate the practices of leading ones, thereby generating dynamic efficiency gains across the system.

These policies also align with principal-agent models in the economics of science, where governments (principals) use performance-based incentives to steer academic institutions (agents) towards policy goals (Stephan 1996). In this framework, the government or funding body acts as the principal, deploying high-powered incentives to align research organizations' actions with the principal's objectives for higher research quality (Gomez-Mejia and Balkin 1992). Concentrating rewards on high achievers is intended to mitigate moral hazard and induce greater effort than an egalitarian funding model would. Empirical evidence shows such schemes can raise productivity (Cattaneo et al. 2016; Agasisti et al. 2022). Furthermore, channelling funds to high performers may create synergies, enabling them to attract talent, develop infrastructure, and foster knowledge spillovers to industry (Spinesi 2013). Recent findings from Carayol and Maublanc (2025) show that the adoption of excellence funding in Germany and France increases scientific output. However, effectiveness depends on the design of the evaluation process (Li 2017), selection transparency (Gläser and Laudel 2007), and the ability of lower quality institutions to adapt to the new setting (Aghion et al. 2010).

Reputational mechanisms are at play here too. Building on Merton's (1988) concept of the 'Matthew effect' in science, getting an 'excellence badge' makes research organizations more appealing to high productive scholars and more credible to external partners, improving recruitment and research collaboration. Hence, the initiative's intended impact is a blend of direct incentives (monetary awards) and reputational gains that increase academic performance (Johnes and Johnes 1993; Bol et al. 2018).

Despite these rationales, the existing literature has put forward some critiques to the excellence approach for allocation of research funding. A key concern is that excellence schemes may reinforce inequality, disproportionately benefiting already strong institutions (Merton 1988; Bol et al. 2018). Bol et al. (2018) show that grant winners often secure more funding later, partly due to reputational gains, thereby supporting the well-documented 'Matthew effect' (Azoulay et al. 2014). Similarly, competitive research funding at the institutional level may actually reduce competition in the long term, as the performance gap between high- and low-performing institutions becomes excessively high (Ortagus et al. 2023).

A second critique refers more closely to behavioural theory. High-stakes rewards can encourage strategic behaviour focused on metrics (e.g. publication counts) over substantive outcomes (Gomez-Mejia and Balkin 1992). Azoulay and Li (2021) argue that ex-post rewards may incentivize short-term research. Similarly, Checchi et al. (2019) find that while publication quantity rises under performance-based funding, quality gains are limited. This may result in an uncritical pursuit of an 'excellence' mantra, rather than fostering truly transformative scientific work, a phenomenon sometimes labelled the 'fetishization of excellence' (Moore et al. 2017).

A third critique concerns diminishing returns. Overfunding top departments can lead to inefficiencies if they approach capacity, while under-resourced but capable groups might yield higher returns with marginal support (Canton 2025). Moreover, the meritocratic assumptions behind such schemes are often contested. For example, Canton (2025) advocates for a portfolio-based model balancing excellence with diversity and impact.[2]

[2] Our analysis is grounded in a critical realist perspective, which guides our understanding of how performance-based funding shapes academic recruitment. We seek to uncover the causal mechanisms—such as departmental autonomy, funding design, and institutional bargaining power—that produce observed outcomes, while recognizing that these effects are contingent on specific institutional contexts. Although we acknowledge reputational and behavioural dynamics emphasized in interpretive and post-structuralist critiques, we treat these as interacting with, rather than replacing, structural and material drivers within a broader system of incentives and constraints.

Building on these theoretical insights, this article examines a specific policy within this domain—the Italian 'Departments of Excellence' (DoE) initiative—and investigates whether receiving an excellence award, along with the associated funding, enables a university department to recruit more academic staff, with particular attention to the composition of hires across different appointment types, and whether these effects differ between first- and second-tier departments. Our analysis is guided by two core research questions:

RQ1: Did the programme lead to a measurable change in staff recruitment for awarded departments relative to those not selected?
RQ2: Were these effects different between top-tier and second-tier departments?

These questions are directly linked to the framework discussed above, as they examine how incentive mechanisms, reputational boosts, and potential behavioural distortions collectively influence departmental outcomes in the higher education sector. In order to better contextualize these theoretical arguments, the next section first outlines the most important excellence initiatives implemented in Europe, illustrating their main design features and reported effects. Then, we provide the details of the Italian 'Departments of Excellence' initiative, which constitutes the programme evaluated in the empirical part of this manuscript.

3. Excellence initiatives in Europe and the Italian 'Departments of Excellence'

3.1 Major European excellence programmes

European governments have introduced several large-scale initiatives intended to promote research excellence by selectively allocating significant public funding to top-performing institutions. Although the specific goals and evaluation criteria vary, these programmes share a common rationale rooted in performance-based funding and reputational enhancement.[3]

In Germany, for instance, the Excellence Initiative (EI) awarded 4.6 billion euros in two phases (2007–2017) across three funding streams, with successful universities becoming 'universities of excellence'. Research on the EI shows mixed outcomes: Menter et al. (2018) report lower-than-expected development among selected institutions, and Lehmann and Stockinger (2019) show that top universities had a disproportionate advantage in industrial collaborations following the initiative. Gawellek and Sunder (2016) find no positive effect on efficiency once additional funding is excluded. Moreover, adopting Italy as a control group in a triple difference-in-differences (DiD) framework, Civera et al. (2020) show that while the EI significantly increased research quantity, it paradoxically led to a decline in average research quality, suggesting a trade-off between output and impact under competitive funding.

Similarly, Denmark's UNIK initiative put substantial resources into a few selected universities, aiming to improve strategic capacity and attract top researchers (Aagaard and de Boer 2016). However, critics argued that its relatively short five-year timeframe limited its effectiveness and that it unintentionally fostered competitive rather than collaborative approaches (Aagaard and de Boer 2016).

In France, the so-called 'Shanghai shock' (Dobbins 2012) prompted large investments to create 'world-class universities'. Under the 2008/2009 PIA ('Plan d'Investissements pour l'avenir'), programmes like IDEX (Initiative D'EXcellence) aimed to consolidate smaller institutions and improve their international visibility. Yet the number of French universities in leading global rankings has remained modest (European Commission 2016), indicating

[3] Appendix B, Table B1 (see online supplementary material), provides a comparative overview of the main characteristics of excellence initiatives implemented across European countries.

that resource concentration alone does not necessarily translate into substantial change in prestige.

Finally, Spain's Campus of Excellence Initiative (CEI) emerged in the late 2000s with goals such as encouraging alliances and addressing fragmentation. However, funding constraints introduced by the global financial crisis meant that the initiative had to rely heavily on loans , limiting its impact. Seeber (2017) shows that the scientific output of CEI-awarded universities increased, though the overall system also improved at a comparable pace.

3.2 The Italian policy 'Departments of Excellence'

The Italian higher education system is a unitary system comprising only universities and traditionally oriented towards institutional equality: the quality of teaching and research is expected to be relatively uniform across universities (i.e. low vertical differentiation). However, a heated debate persists between supporters (e.g. Boeri and Perotti 2021) and critics (e.g. Economia e Politica 2021) of a funding model that allocates resources based on research performance (Abramo et al. 2009; Civera et al. 2021; Capano 2023).

Starting in the 2000s, a small but growing share of resources for research funding has been allocated based on the results of ex-post evaluation exercises. Subsequently, following Law 232 of 11th December 2016, the Italian research system launched an initiative to provide additional funding for organizational excellence: the 'Dipartimenti di Eccellenza'—'Departments of Excellence' (henceforth DoE)—policy. This intervention funded 180 departments within Italian universities, selected from the 350 departments that achieved the highest scores in the 2010–2014 research evaluation exercise (Bertocchi et al. 2015), out of a total of approximately 800 departments.

At the beginning of 2018, each awarded department received between 1.06 and 1.8 million euros per year, depending on the department's size, for a 5-year period, concluding at the end of 2022.[4] Of this funding, between 50% and 70% was allocated to academic staff recruitment.[5] This policy initiative represents the sole grant scheme within the Italian system that allowed expenditure on the creation of permanent academic staff positions.[6] Notably, a quarter of the recruitment budget was earmarked for young researchers, with an additional quarter reserved for hiring individuals who had not been affiliated with the same university for at least three years.

The selection of the top 350 Italian departments eligible to compete for the award was based on a research quality indicator known as the ISPD (Departmental Performance Standardized Indicator).[7] By comparing each department's ranking relative to all departments with the same disciplinary composition, this indicator was designed to facilitate comparisons across different disciplines (CRUI-ANVUR 2015). It was derived from the outcomes of the 2010–2014 research evaluation exercise results. Once the ranking of all Italian departments had been established based on the ISPD, the top 350 were granted the opportunity to compete for the DoE award. The competition process assigned 70% of the evaluation weight to the ISPD indicator, while the remaining 30% was based on a 5-year

[4] Departments specializing in the hard sciences also received an additional yearly 250,000 euros each, designated for 'research infrastructures'.

[5] Although we lack specific data on the individual department's resource allocation, there is ample anecdotal evidence to suggest that all departments allocated the 70% funding to academic staff positions, encompassing both temporary and permanent personnel.

[6] Italian universities, in accordance with Law168/1989 and with Law 240/2010, autonomously establish their own regulations for academic staff recruitment and career progression, based on a three-year planning document, and constrained by the availability of state funding, while adhering to ethical guidelines and the principles set forth in the European Charter for Researchers.

[7] The methodological note explaining the ISPD calculation is available here: https://www.anvur.it/wp-content/uploads/2018/04/Nota_metodologica_ISPD_AN_.pdf, last accessed on July 2024.

development project proposed by each department.[8] An *ad hoc* committee, appointed specifically for this purpose, evaluated these development projects.

Unlike other comparable European initiatives, the DoE specifically promoted staff recruitment—particularly through permanent or long-term positions—making it a suitable setting in which to examine how targeted funding may affect a department's capacity to attract new academic staff. The distinctiveness of the Italian policy in relation to other European excellence initiatives is highlighted in Table B 1 in Appendix B (see online supplementary material), which offers a schematic comparison of their respective characteristics, differences, and similarities. Notably, the DoE initiative offers a particularly appropriate setting for our research questions as it is unique among other European excellence schemes because: (1) it operates at the departmental rather than university level, allowing us to capture variation in recruitment responses at the unit directly responsible for hiring decisions; (2) it allocated a substantial portion of funding explicitly for permanent academic staff recruitment, making it well suited to examine effects on hiring patterns across contract types and career stages and (3) it was implemented in a system with dispersed scientific excellence and low institutional stratification, creating the conditions to explore whether performance-based funding reinforces or reduces inequalities between first- and second-tier departments.

The following sections present our empirical strategy and findings, focusing on whether and how the DoE shaped hiring outcomes in awarded departments.

4. Empirical framework

4.1 Data

The creation of our dataset started with data sourced from the 'Cerca Università' website.[9] This platform offers comprehensive information, spanning from 2000 to 2021, for each Italian university, including the names, positions, affiliated departments, and scientific fields of academic staff, ranging from assistant professors to full professors, regardless of their permanent or non-permanent status. The list of Italian university departments obtained from 'Cerca Università' was subsequently merged with the list of the 350 departments participating in the DoE competition, available on the Ministry of Education website.[10]

In 2010, Law 240 initiated a reform within the university system, abolishing faculties and retaining only departments. Consequently, several new university departments emerged in the wake of this reform. Therefore, our analysis begins in 2013 when the majority of the 350 departments participating in the DoE had been established.

Initially, our list comprised 352 departments, as the 350th and 352nd departments achieved the same ISPD score. We excluded a total of 62 departments for the following reasons: (1) the department belongs to a special school (Sant'Anna Pisa, IUSS Pavia, IMT Lucca) where the available information did not permit the retrieval of personnel numbers for individual departments; (2) the department spanned across universities, making it impossible to determine precise personnel figures associated to each university; (3) the department was created after 2013; (4) the department experienced significant personnel transfers, either incoming or outgoing, with a transfer rate exceeding 20% of the department's size in a single year, which is a signal of departments merger or split; (5) we also

[8] While the top 350 departments participated in the open competition, some departments received the grant *de facto*, thanks to some prerequisites for eligibility. Notably, the highest-rated department within each university, based on the ISPD indicator, would receive the award provided that its development project met a minimum threshold, referred to as 'Phase 1'. In cases where a university had multiple departments with the same top ISPD score, the university itself determined which department would undergo the 'Phase 1' evaluation. Advancing to 'Phase 1' virtually guaranteed access to the funding.

[9] https://cercauniversita.cineca.it, last accessed on March 2023.

[10] https://www.miur.gov.it/dipartimenti-di-eccellenza, last accessed on March 2023.

excluded departments for which data at the university level were unavailable (specifically, the Ministry does not provide information on the public income of the University of Trento due to its special status within the region).

As a result, we established a balanced panel comprising 290 departments, observed from 2013 to 2020. We excluded the year 2021 because, in late 2020, the Ministry of Education initiated an extraordinary assistant professor recruitment programme set to commence in 2021. This initiative aimed to 'rebalance the presence of young researchers in various territories' (DM 16 November 2020, n. 856). However, the treated period still allows us to capture the policy's effects since, given the uncertainty regarding the availability of funding over time, universities focused nearly all their expenditure on new positions during the period considered in this study.

Of the 290 departments analysed, 148 received funding, while 142 did not. These departments were observed for four years before the treatment and three years after the treatment. For each department, we extracted data on the total number of academic staff, including both existing and newly recruited staff, classified by their career position and year. Additionally, we collected information at the university and provincial levels, pertaining to the location of the university/department.

To assess the representativeness of our sample relative to the Ministry's data on the population of departments participating in the call, we conducted a comparison across variables for the 2016 fiscal year. This analysis allows us to evaluate whether there are statistically significant differences between our sample and the population parameters provided by the Ministry.[11] Results of the t-test mean comparison show that our dataset does not report any statistically significant differences with respect to department size ($t=0.46$) and to ISPD score ($t=0.55$). Moreover, we also test the presence of any difference in the percentage distribution of departments across ERC sectors (Physical Engineering $z=0.16$, Life Science $z=0.4$, Social Sciences $z=0.21$), and geographical location within Italy (North: $z=0.32$, Centre: $z=0.56$, South and Islands: $z=0.24$), and any difference in the percentage of awarded departments ($z=0.03$). From this descriptive analysis, we can conclude that our estimating sample is representative of the overall population of departments along relevant dimensions.

For the purpose of our analysis, we also distinguish between first- and second-tier departments. To do so, we use the ISPD score, defining second-tier departments as those scoring below the ISPD median. The distribution of ISPD scores is left-skewed, with half of the departments attaining scores ranging from 98 to 100, and the other half falling within the range of 67.5 to 97.5. Robustness check with different thresholds to distinguish first- from second-tier departments are reported in Section 5.

To assess the effect of the DoE policy on recruitment patterns in departments receiving funding, we examine a range of dependent variables. These variables, which will be detailed subsequently, refer to overall new positions and also to different types of positions, ranging from temporary to tenure-track, and from external sourcing to internal promotions. The rationale behind this disaggregation is to reveal potential heterogeneity in the policy's effects across different types of academic positions and career stages and possibly to identify potential unintended consequences of the policy.

4.2 Method

Our empirical approach examines variations in the average number of positions filled in the departments that received the DoE grant compared to those in non-receiving departments before and after the program's official start in 2018. We employ a DiD approach within a non-staggered timing setting, as all departments received treatment in the same

[11] The DoE utilized the status of Italian Departments as of 1 January 2017 to construct the sample comprising the 350 eligible departments. Our data are recorded as of 31 December 2016; accordingly, we compare our 2016 data with that reported by the Ministry to verify the consistency of our dataset.

year. This approach enables us to assess the effect of receiving the grant on relative outcomes while accounting for inherent differences across departments and national trends over time.

Our estimation involves estimating the following canonical DiD model:

$$Y_{it} = \alpha \ + \beta_1 D_i + \beta_2 Post_t + \delta(D_i \ \times Post_t) + X_{it}\delta + \varepsilon_{it} \tag{1}$$

The dependent variables are measured in department i and year t, and can be summarized into two groups. The first group distinguishes between (1) all new positions, (2) new recruitments from outside the university, and (3) internal promotions. The second group pertains to different career stages and encompasses: (1) the number of new fixed-term (3-year) positions (RTD-A in Italian nomenclature), (2) the number of new tenure-track positions (RTD-B in Italian nomenclature), and (3) the number of tenured professor positions (i.e. associate and full professors). The choice of dependent variables serves to understand the multifaceted effect of the funding policy on departmental recruitment patterns, capturing a comprehensive picture of how departments allocate their resources. D_i equals one if the department has received the funding from the DoE, and 0 otherwise; $Post_t$ is a time dummy taking value 1 after the DoE award year 2018; X_{it} is a vector of time-varying covariates, which includes the number of department research staff at time $t-1$ and the number of research staff transfers from other departments. In addition, at the university level, we control for the income linked to the research evaluation exercise (in millions of euros). Furthermore, we include per capita value-added (in tens of thousands of euros) and the unemployment rate at the province level (NUTS-3) to control for territorial disparities influencing simultaneously the ability to win the DoE programme and the capacity to hire new researchers. The parameter of interest is represented by δ, which, under the three DiD assumptions of no anticipation, SUTVA, and parallel trends, captures the average treatment effect on the treated (ATT) of the programme's introduction in the treated group compared to the non-treated group. Standard errors are clustered at the department level.

We also investigate the heterogeneity of the treatment effect across departments' research quality. We do so by introducing an additional dummy variable (L_g) for the group of departments with research quality below the median value. We refer to these departments as 'second-tier departments'. Our objective is to explore the heterogeneity in the treatment effect on different types of departments, particularly distinguishing between top-rated (first-tier) and near-elite (second-tier) departments. The regression takes on the form:

$$\begin{aligned} Y_{it} = \alpha \ &+ \beta_1 D_i + \beta_2 Post_t + \beta_3 L_g + \ \delta(D_i \ \times Post_t) + \theta\left(D_i \ \times L_g\right) + \zeta\left(Post_t \times L_g\right) \\ &+ \omega \ \left(D_i \ \times \ Post_t \times L_g\right) + X_{it}\delta + \varepsilon_{it} \end{aligned} \tag{2}$$

where the parameter of interest is ω, which compares the effect of being awarded the DoE by the treated group relative to the non-treated one across first- vs second-tier departments.

Equations (1) and (2) presented above are estimated in a series of progressively more stringent specifications. The most restrictive specifications incorporate (1) university-by-post fixed effects to account for post-treatment shock, which can jointly affect departments in the same university, and (2) inverse probability weighting. The latter is particularly relevant to control for the bias induced by the inclusion of covariates in a DiD setting (Abadie 2005; Heckman et al. 1997; Sant'Anna and Zhou 2020). We follow Abadie (2005) and compute propensity scores during the pre-treatment period by predicting the value $\widehat{p}(x)$

through a logit regression of the treatment variable on a set of relevant covariates.[12] These covariates are aimed at controlling the selection process for the award and encompass the following variables: the number of department research staff at time $t-1$, the number of research staff transfers from other departments, the university income linked to the research evaluation exercise, provincial-level per capita value-added and unemployment rate, and NUTS 1 regional fixed effects. The weights employed in the most stringent specification are computed as $\frac{1}{\hat{p}}(x)$ for treatment group observations and $\frac{1}{1-\hat{p}}(x)$ for control group observations.[13] Subsequently, these weights are normalized to ensure that their mean equals 1 within their respective groups. This normalization is implemented to enhance robustness against potential violations of the positivity assumption (Brunell and DiNardo 2004).[14]

The DiD approach hinges on the parallel trend assumption, which posits that, in the absence of treatment, treated units would have followed a similar trajectory as untreated units. This assumption is untestable by definition, but examining whether pre-treatment effects significantly differ from zero provides insights into its plausibility in the current empirical setting. In the following section, we introduce dynamic pre-treatment effects and examine whether these lead variables significantly differ from zero, both separately and jointly (Roth 2022; Deryugina 2017). This is conducted both in the model incorporating covariates and without covariates. The latter approach aims to avoid issues arising from the inclusion of bad controls and to demonstrate that, in our empirical setting, it is plausible to assume unconditional parallel trends. This avoids the bias induced by assuming parallel trends conditional on a set of covariates (Sant'Anna and Zhao 2020). A failure to reject the null hypothesis indicates that, prior to treatment, adopters and non-adopters were subject to common trends, conditional on observable characteristics. However, Roth (2022) presents evidence suggesting that pre-trend testing is statistically underpowered, and relying on such tests for estimating treatment effects can inadvertently introduce bias.

In instances where parallel trends may be questionable, synthetic control (SC) methods have emerged as a potential solution. Pioneered by Abadie and Gardeazabal (2003) and further developed by Abadie et al. (2010, 2015), these methods construct an SC from a pool of control units, matching it as closely as possible to the treated unit in pre-treatment outcomes and other covariates. An innovative approach bridging DiD and SC is the synthetic difference-in-differences estimator (SDID) proposed by Arkhangelsky et al. (2021). This method combines the strengths of DiD and SC, allowing for treated and control units to have different trends prior to a reform and creating a matched control unit that lessens the reliance on parallel trend assumptions. SDID addresses limitations in standard DiD and SC methods, offering consistency and asymptotic normality, and can incorporate covariates. As a further extension for the model described in Equations (1) and (2), we implement the SDID estimator. This approach complements our results, which report on the treatment effects as delineated in Arkhangelsky et al. (2021), further incorporating their proposed bootstrap procedure for the computation of standard errors.

Summary statistics for our variables of interest and main controls for the full estimating sample and relevant sub-samples are presented in Table 1. Out of 290 departments, 51.03% received the DoE grant. Among the winning departments, 25.68% were second-tier. When comparing treated to untreated departments, the former show higher average

[12] Statistics relative to the propensity score procedure used to compute weights, showing a good performance in terms of bias reduction, are available from the authors upon request.

[13] To check the robustness of the results to alternative specification of the inverse probability weights, we stick to Abadie (2005) and we weight the control group only. Results are in line with those presented in the text and available from the authors upon request.

[14] In an additional robustness check, available from the authors upon request, we implement the double robust specification, which combines the inverse probability weighting and outcome regression methods as introduced by Sant'Anna and Zhao (2020). Our main results are confirmed by this additional robustness check as well.

values for all variables (columns 2–3). Conversely, when comparing second-tier to first-tier departments, the more research-productive departments show higher average values (columns 4–5). Interestingly, when the same comparison is made conditional on being treated, second-tier departments perform better compared to first-tier departments, and vice versa (columns 6–9). Together, these statistics suggest interesting patterns that warrant further testing in a more sophisticated setting, one that can control for confounding effects as per the estimation strategy outlined.

4.3 Results

4.3.1 Baseline results

Our findings related to Equation (1) are presented in Tables 2 and 3, each focusing on different outcome variables. For each outcome, we report results from three increasingly stringent specifications: the first includes department and post-treatment fixed effect along with time-varying control variables; the second adds university-by-post fixed effects; and the third incorporates propensity score weighting.[15] Table 2 displays results for the total number of new positions, the number of new positions excluding internal promotions (i.e. external hires) and the number of internal promotions. Considering the most stringent specification (columns 3, 6, and 9), we observe that receiving funding leads to an average increase of 0.89 additional positions overall and 0.78 additional positions from external sources, while there is no statistically significant effect for what concerns internal promotions.

Table 3 presents findings for temporary research contracts, tenure-track research positions, and tenured positions across the three specifications. The results indicate that receiving the award generates, on average, 0.28 additional temporary research contracts, 0.25 additional tenure-track researcher positions, and 0.22 tenured positions.

In summary, we can conclude that the policy had a substantial effect on departmental recruitment patterns, as expected. Funded departments have increased their hiring capacity compared to non-funded departments, with the effect primarily manifesting in external hires and across all stages of career. Notably, the funding was not employed for internal career advancement. This suggests a positive evaluation of the policy's effect on funded departments relative to unfunded ones.

Turning to Equation (2), we present our findings in Tables 4 and 5, again using the same three specifications for each dependent variable. Our focus here is on comparing the effect of the award on second-tier departments versus first-tier departments. Table 4 demonstrates that second-tier departments were able to hire 2.25 more individuals overall compared to first-tier departments, with 1.24 of these positions filled by external candidates. Moreover, we can also see that second-tier departments are able to make more internal promotions thanks to the policy compared to first-tier departments.

Table 5 indicates no significant difference between second- and first-tier departments in creating new temporary positions. However, we observe a substantial effect regarding tenure-track positions, with second-tier departments recruiting, on average, over 1 new tenure-track assistant professor more than first-tier departments. For what concerns tenured position, second-tier departments hire 0.4 additional figures, however the coefficient is significant only at the 10% level.

In conclusion, we observe that the benefits of the policy appear to be more pronounced for second-tier departments, which seem to report higher gains from this funding compared to their first-tier counterparts.

[15] To account for potential differential shocks across years between the treated and control groups, we replicate our baseline estimations including year fixed effects rather than a single post-treatment fixed effect. In the most restrictive specification, we also replace the university-by-post fixed effect with university-by-year fixed effects. The results are consistent with those presented in the paper and are available from the authors upon request.

Table 1. Summary statistics, full sample, and sub-samples.

	Overall (1)	Treated (2)	Untreated (3)	Second-tier (4)	First-tier (5)	Treated Second-tier (6)	Treated First-tier (7)	Untreated Second-tier (8)	Untreated First-tier (9)
Dependent variables									
New positions	8.23	8.64	7.81	7.86	8.59	9.16	8.46	7.39	8.93
	(5.35)	(5.54)	(5.11)	(5.61)	(5.06)	(6.51)	(5.16)	(5.17)	(4.77)
New positions (excl. promotions)	3.02	3.15	2.88	2.88	3.15	3.48	3.04	2.66	3.45
	(2.65)	(2.78)	(2.49)	(2.65)	(2.64)	(3.10)	(2.65)	(2.42)	(2.58)
Internal promotions	4.50	4.72	4.28	4.31	4.68	4.89	4.66	4.10	4.74
	(3.62)	(3.69)	(3.53)	(3.81)	(3.42)	(4.15)	(3.52)	(3.66)	(3.13)
Temporary	1.51	1.56	1.46	1.47	1.55	1.83	1.47	1.34	1.77
	(1.85)	(1.90)	(1.79)	(1.95)	(1.74)	(2.32)	(1.72)	(1.78)	(1.79)
Tenure track	1.56	1.66	1.45	1.46	1.65	1.72	1.64	1.36	1.68
	(1.64)	(1.71)	(1.57)	(1.57)	(1.70)	(1.84)	(1.66)	(1.46)	(1.81)
Tenured	0.83	0.89	0.76	0.77	0.88	0.98	0.86	0.70	0.92
	(1.11)	(1.17)	(1.03)	(1.12)	(1.09)	(1.39)	(1.08)	(0.99)	(1.11)
Control variables									
No. of researchers	68.04	69.10	66.95	67.27	68.77	72.08	68.07	65.51	70.74
	(26.32)	(25.94)	(26.67)	(27.67)	(24.96)	(30.15)	(24.26)	(26.51)	(26.79)
No. of transfers	0.30	0.32	0.28	0.27	0.33	0.31	0.32	0.26	0.34
	(1.11)	(1.26)	(0.93)	(1.04)	(1.17)	(1.49)	(1.18)	(0.82)	(1.16)
Research funding (mil €)	50.09	47.82	52.45	44.11	55.74	32.29	53.16	48.45	63.00
	(31.59)	(31.89)	(31.12)	(31.13)	(31.00)	(27.28)	(31.63)	(31.34)	(27.94)
Value added per capita	2.98	2.99	2.97	2.88	3.07	2.65	3.10	2.97	2.99
	(0.86)	(0.86)	(0.86)	(0.89)	(0.82)	(0.90)	(0.82)	(0.87)	(0.83)
Uunemployment rate	9.73	9.62	9.85	10.47	9.03	12.14	8.76	9.86	9.81
	(5.03)	(4.88)	(5.18)	(5.44)	(4.50)	(6.03)	(4.07)	(5.08)	(5.46)
Observations	2029	1035	994	986	1043	265	770	721	273

Table shows summary statistics for the full sample (column 1) and for several sub-samples. Sub-samples are treated (column 2) and untreated (column 3) departments, second- (column 4) and first-tier departments (column 5), treated second—(column 6) and treated first-tier departments (column 7), untreated second—(column 8) and untreated first-tier departments (column 9). Summary statistics are means and standard deviations (in parentheses).
Source: Authors' calculations.

Table 2. Effect of the Department of Excellence Programme on University Faculty Recruitment: new positions and internal promotions.

	New positions			New positions (excl. promotions)			Internal promotions		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat × After	0.954**	0.923**	0.886**	0.809**	0.786**	0.781**	−0.031	−0.006	0.004
	[0.314]	[0.299]	[0.301]	[0.205]	[0.202]	[0.202]	[0.233]	[0.204]	[0.205]
No. of researchers	−0.156**	−0.195**	−0.196**	−0.114**	−0.136**	−0.137**	−0.062**	−0.070**	−0.072**
	[0.025]	[0.031]	[0.031]	[0.012]	[0.016]	[0.016]	[0.020]	[0.022]	[0.022]
No. of transfers	−0.097	−0.150+	−0.143+	−0.039	−0.036	−0.039	−0.016	−0.064	−0.057
	[0.093]	[0.087]	[0.083]	[0.045]	[0.044]	[0.044]	[0.064]	[0.063]	[0.062]
Amount of research funding	0.033*	−0.004	−0.005	0.013	0.045**	0.046**	−0.009	−0.080**	−0.082**
	[0.014]	[0.020]	[0.021]	[0.009]	[0.013]	[0.013]	[0.010]	[0.017]	[0.017]
Value added per capita	1.753+	1.539	1.272	3.663**	3.866**	3.807**	−3.294**	−3.381**	−3.613**
	[0.902]	[1.007]	[1.130]	[0.509]	[0.538]	[0.555]	[0.704]	[0.810]	[0.902]
Unemployment rate	0.047	−0.023	−0.015	−0.127**	−0.055	−0.056	0.159*	0.040	0.044
	[0.088]	[0.098]	[0.099]	[0.046]	[0.057]	[0.057]	[0.067]	[0.084]	[0.085]
Department and post FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University-by-post FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Prop score weight	No	No	Yes	No	No	Yes	No	No	Yes
N (Departments)	290	290	290	290	290	290	290	290	290

This table displays the average treatment on the treated coefficient using 2014–2020 data. Regressions are based on 2,029 department-year observations. Estimates include controls for the number of employees at $t-1$, the number of staff transferred between departments, university income linked to the VQR, province-level per-capita value added and provincial unemployment rate. Department, post fixed effects are included in all specifications. Columns 2, 3, 5, 6, 8, and 9 also include university-by-post fixed effects. Regressions in columns 3, 6, and 9 are estimated using $1/(1-\widehat{p}(x_i))$ to weight untreated observations and $1/\widehat{p}(x_i)$ otherwise. $\widehat{p}(x_i)$ is the propensity score and is calculated controlling for the number of department research staff at time $t-1$, the number of staff transferred between departments, university income linked to the VQR, province-level per-capita value added, provincial unemployment rate and NUTS 1 regional fixed effects. Standard errors clustered at the department level are in parentheses.

$^{+}$ $P<0.1$, * $P<0.05$, ** $P<0.01$.

Source: Authors' calculations.

Table 3. Effect of the Department of Excellence Programme on University Faculty Recruitment: temporary and permanent positions.

	Temporary			Tenure track			Tenured		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat × After	0.338*	0.289*	0.283*	0.228*	0.261*	0.249*	0.192*	0.212*	0.219*
	[0.142]	[0.132]	[0.134]	[0.109]	[0.105]	[0.105]	[0.094]	[0.087]	[0.086]
No. of researchers	−0.046**	−0.064**	−0.063**	−0.045**	−0.059**	−0.061**	−0.014*	−0.018**	−0.018**
	[0.008]	[0.011]	[0.011]	[0.007]	[0.008]	[0.008]	[0.006]	[0.007]	[0.007]
No. of transfers	−0.065*	−0.060*	−0.060+	−0.026	−0.021	−0.017	−0.001	−0.017	−0.011
	[0.030]	[0.031]	[0.031]	[0.043]	[0.046]	[0.040]	[0.027]	[0.029]	[0.033]
Amount of research funding	0.011+	0.039**	0.038**	0.005	0.013+	0.013+	−0.004	−0.021**	−0.021**
	[0.007]	[0.012]	[0.012]	[0.005]	[0.007]	[0.007]	[0.004]	[0.006]	[0.006]
Value added per capita	1.282**	1.524**	1.500**	4.483**	4.594**	4.569**	−0.709**	−0.950**	−0.966**
	[0.407]	[0.420]	[0.436]	[0.318]	[0.343]	[0.343]	[0.251]	[0.271]	[0.280]
Unemployment rate	−0.150**	−0.082+	−0.082+	−0.002	0.023	0.024	0.070**	0.049+	0.049+
	[0.036]	[0.045]	[0.046]	[0.027]	[0.033]	[0.033]	[0.021]	[0.026]	[0.026]
Department and post FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University-by-post FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Prop score weight	No	No	Yes	No	No	Yes	No	No	Yes
N (departments)	290	290	290	290	290	290	290	290	290

This table displays the average treatment on the treated coefficients using 2014–2020 data. Regressions are based on 2,029 department-year observations. Estimates include controls for the number of employees at $t-1$, the number of staff transferred between departments, university income linked to the VQR, province-level per-capita value added and provincial unemployment rate. Department, post fixed effects are included in all specifications. Columns 2, 3, 5, 6, 8, and 9 also include university-by-post fixed effects. Regressions in columns 3, 6, and 9 are estimated using $1/(1-\widehat{p}(x_i))$ to weight untreated observations and $1/\widehat{p}(x_i)$ otherwise. $\widehat{p}(x_i)$ is the propensity score and is calculated controlling for the number of department research staff at time $t-1$, the number of staff transferred between departments, university income linked to the VQR, province-level per-capita value added, provincial unemployment rate and NUTS 1 regional fixed effects. Standard errors clustered at the department level are in parentheses.

$^{+}P<.1$, $^{*}P<.05$, $^{**}P<.01$.

Source: Authors' calculations.

Table 4. Effect of the Department of Excellence Programme on University Faculty Recruitment for second-tier university departments: new positions and internal promotions.

	New positions			New positions (excl. promotions)			Internal promotions		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat × After × Second-tier	2.250**	2.424**	2.249**	0.899*	1.312**	1.239*	1.390*	1.167*	1.060*
	[0.719]	[0.786]	[0.811]	[0.436]	[0.480]	[0.489]	[0.537]	[0.523]	[0.514]
No. of researchers	−0.159**	−0.199**	−0.200**	−0.115**	−0.140**	−0.140**	−0.064**	−0.072**	−0.073**
	[0.025]	[0.031]	[0.032]	[0.012]	[0.016]	[0.016]	[0.020]	[0.022]	[0.023]
No. of transfers	−0.099	−0.159+	−0.149+	−0.040	−0.042	−0.043	−0.018	−0.068	−0.059
	[0.097]	[0.090]	[0.085]	[0.046]	[0.045]	[0.045]	[0.067]	[0.064]	[0.062]
Amount of research funding	0.034*	−0.004	−0.005	0.013	0.045**	0.046**	−0.008	−0.080**	−0.082**
	[0.014]	[0.020]	[0.021]	[0.009]	[0.013]	[0.013]	[0.010]	[0.017]	[0.017]
Value added per capita	1.777*	1.491	1.235	3.670**	3.829**	3.775**	−3.284**	−3.394**	−3.619**
	[0.888]	[1.009]	[1.133]	[0.505]	[0.538]	[0.554]	[0.699]	[0.810]	[0.903]
Unemployment rate	0.059	−0.023	−0.015	−0.122**	−0.055	−0.056	0.166*	0.040	0.044
	[0.086]	[0.098]	[0.099]	[0.045]	[0.057]	[0.058]	[0.066]	[0.084]	[0.085]
Department and post FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University-by-post FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Prop score weight	No	No	Yes	No	No	Yes	No	No	Yes
N (Departments)	290	290	290	290	290	290	290	290	290

This table displays the average treatment on the treated coefficients for second tier departments using 2014–2020 data. Regressions are based on 2,029 department-year observations. Estimates include controls for the number of employees at $t-1$, the number of staff transferred between departments, university income linked to the VQR, province-level per-capita value added and provincial unemployment rate. Department, post fixed effects are included in all specifications. Columns 2, 3, 5, 6, 8, and 9 also include university-by- post fixed effects. Regressions in columns 3, 6, and 9 are estimated using $1/(1-\widehat{p}(x_i))$ to weight untreated observations and $1/\widehat{p}(x_i)$ otherwise. $\widehat{p}(x_i)$ is the propensity score and is calculated controlling for the number of department research staff at time $t-1$, the number of staff transferred between departments, university income linked to the VQR, province-level per-capita value added, provincial unemployment rate and NUTS 1 regional fixed effects. Standard errors clustered at the department level are in parentheses.

+ $P<.1$, * $P<.05$, ** $P<.01$.

Source: Authors' calculations.

Table 5. Effect of the Department of Excellence Programme on University Faculty Recruitment for second tier university departments: temporary and permanent positions.

	Temporary			Tenure track			Tenured		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat × After × Second-tier	0.158	0.343	0.296	1.101**	1.078**	1.045**	0.334	0.438+	0.430+
	[0.293]	[0.310]	[0.314]	[0.242]	[0.258]	[0.249]	[0.249]	[0.261]	[0.248]
No. of Researchers	–0.047**	–0.066**	–0.065**	–0.046**	–0.061**	–0.063**	–0.015*	–0.019**	–0.019**
	[0.008]	[0.011]	[0.011]	[0.007]	[0.008]	[0.008]	[0.006]	[0.007]	[0.007]
No. of transfers	–0.065*	–0.062*	–0.062*	–0.028	–0.025	–0.020	–0.002	–0.018	–0.012
	[0.029]	[0.031]	[0.031]	[0.045]	[0.049]	[0.042]	[0.027]	[0.030]	[0.034]
Amount of research funding	0.013+	0.039**	0.038**	0.005	0.013+	0.013+	–0.004	–0.021**	–0.021**
	[0.007]	[0.012]	[0.012]	[0.005]	[0.007]	[0.007]	[0.004]	[0.006]	[0.006]
Value added per capita	1.315**	1.501**	1.479**	4.485**	4.574**	4.554**	–0.710**	–0.957**	–0.972**
	[0.407]	[0.420]	[0.436]	[0.316]	[0.343]	[0.343]	[0.251]	[0.270]	[0.280]
Unemployment rate	–0.145**	–0.082+	–0.082+	0.003	0.023	0.024	0.071**	0.049+	0.049+
	[0.034]	[0.045]	[0.046]	[0.026]	[0.033]	[0.033]	[0.022]	[0.026]	[0.026]
Department and post FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University-by-post FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Prop score weight	No	No	Yes	No	No	Yes	No	No	Yes
N (Departments)	290	290	290	290	290	290	290	290	290

This table displays the average treatment on the treated coefficients for second-tier departments using 2014–2020 data. Regressions are based on 2,029 department-year observations. Estimates include controls for the number of employees at $t-1$, the number of staff transferred between departments, university income linked to the VQR, province-level per-capita value added and provincial unemployment rate. Department, post fixed effects are included in all specifications. Columns 2, 3, 5, 6, 8, and 9 also include university-by-post fixed effects. Regressions in columns 3, 6, and 9 are estimated using $1/(1-\widehat{p}(x_i))$ to weight untreated observations and $1/\widehat{p}(x_i)$ otherwise. $\widehat{p}(x_i)$ is the propensity score and is calculated controlling for the number of department research staff at time $t-1$, the number of staff transferred between departments, university income linked to the VQR, province-level per-capita value added, provincial unemployment rate and NUTS 1 regional fixed effects. Standard errors clustered at the department level are in parentheses.

$^{+}$ $P < .1$, * $P < .05$, ** $P < .01$.

Source: Authors' calculations.

4.3.2 Group effects

To better understand the sources of differential effects in hiring practices between first- and second-tier departments, we analyse the group effects derived from Equation (2). Table 6 shows the triple interaction coefficients (Treat × Post × Second-tier) from Equation (2) (column 1) as reference for each of our dependent variables. The triple interaction coefficients from Equation (2) can be obtained as two equivalent linear combinations. First, (1) the difference between funded and non-funded second-tier departments (column 2) minus (2) the difference between funded and non-funded first-tier departments (column 3). Second, (1) the difference between funded second- and first-tier departments (column 4) minus (2) the difference between non-funded second- and first-tier departments (column 5).

Our analysis reveals that the effects observed in Tables 4 and 5 are primarily driven by the enhanced recruitment capabilities of funded second-tier departments compared to their non-funded second-tier counterparts (Table 6, column 2). In contrast, funded first-tier departments do not significantly outperform non-funded first-tier departments in terms of recruitment (Table 6, column 3). Moreover, funded second-tier departments demonstrate greater recruitment activity than funded first-tier departments (Table 6, column 4). Notably, for tenure-track positions, which represent the entry-level academic appointments, non-funded first-tier departments exhibit a higher recruitment rate than non-funded second-tier departments (Table 6, column 5). This finding suggests that first-tier departments may possess greater bargaining power within their institutions, possibly due to their contributions to university funding through research quality.

In conclusion, our results indicate that second-tier departments benefit more substantially from this funding policy compared to first-tier departments. The policy appears to provide second-tier departments with additional resources for recruitment that they would not have obtained otherwise, whereas the effect on first-tier departments is less pronounced.

4.3.3 Parallel trends

The validity of the DiD methodology rests on the assumption that the trends in treated versus untreated departments were the same prior to the funding. Although parallel trends are by definition untestable because we do not observe what would have happened to the treated in case they would have not been treated, we can check whether the pre-trend between treated and control group remain the same, and so suggesting this would have happened also after the treatment period.

Tables 7 and 8 display the results of our analysis of pre-treatment effects to determine whether they significantly differ from zero, providing insights into the plausibility of the parallel trend assumption in our empirical setting.[16] Table 7 presents the dynamic pre-treatment effects, examining whether these lead variables differ significantly from zero, both separately and jointly, in models that include covariates. As the inclusion of covariates can introduce biases (Sant'Anna and Zhao 2020), we also present results without controlling for them to verify whether there are unconditional parallel trends prior to treatment (Table 8). The results from both tables show that the pre-treatment coefficients are not significantly different from zero at standard confidence levels, both individually and jointly. The only exception is the treatment in the year 2016 for internal promotions in the presence of control variables, which is positive and significant at the 10% level. However, the test of joint significance for all pre-treatment effects remains reassuringly not significant.

[16] We conduct the analysis for the model specified in Equation (1) only, as recent applied econometrics literature has shown that in nested models, it suffices to check for pre-treatment parallel trends in just one of the models (Olden and Møen, 2022). The results for the model in Equation (2), which also support parallel trends in the pre-treatment period, are available from the authors upon request.

Table 6. Group effects.

	Treat × Post × Second-tier (1)	Second-tier Funded vs Non funded (2)	First-tier Funded vs Non funded (3)	Funded Second-tier vs First-tier (4)	Non-funded Second-tier vs First-tier (5)	N (Departments)
New positions	2.249**	2.248**	−0.001	1.426*	−0.823	290
	[0.811]	[0.677]	[0.489]	[0.716]	[0.502]	
New positions (excl. promotions)	1.239*	1.655**	0.417	1.012**	−0.227	290
	[0.489]	[0.373]	[0.335]	[0.385]	[0.326]	
Internal promotions	1.060*	0.521	−0.539	0.444	−0.617	290
	[0.514]	[0.368]	[0.373]	[0.400]	[0.375]	
Temporary	0.296	0.643**	0.347	0.518*	0.222	290
	[0.314]	[0.230]	[0.223]	[0.234]	[0.238]	
Tenure track	1.045**	0.859**	−0.187	0.620**	−0.425*	290
	[0.249]	[0.188]	[0.169]	[0.198]	[0.174]	
Tenured	0.430+	0.464*	0.034	0.244	−0.186	290
	[0.248]	[0.196]	[0.151]	[0.207]	[0.158]	

This table displays group effect coefficients using 2014–2020 data. Regressions are based on 2,029 department-year observations. Columns 2–5 show the group effects for different comparison categories: second-tier funded vs second-tier non-funded departments (column 2), first-tier funded vs first-tier non-funded departments (column 3), funded second-tier vs funded first-tier departments (column 4), and non-funded second-tier vs non-funded first-tier departments (column 5). Column 1 reports coefficients from the fully saturated specifications in Tables 4 and 5 (specifically columns 3, 6, and 9 in each table). The coefficients in column 1 are obtained as linear combinations of coefficients in other columns (either column 2 minus column 3 or column 4 minus column 5). Estimates include controls for the number of employees at $t-1$, the number of staff transferred between departments, university income linked to the VQR, province-level per-capita value added and provincial unemployment rate. Department, post and university-by-post fixed effects are included in all specifications. All regressions are estimated using $1/(1-\widehat{p}(x_i))$ to weight untreated observations and $1/\widehat{p}(x_i)$ otherwise. $\widehat{p}(x_i)$ is the propensity score and is calculated controlling for the number of department research staff at time $t-1$, the number of staff transferred between departments, university income linked to the VQR, province-level per-capita value added, provincial unemployment rate and NUTS 1 regional fixed effects. Standard errors clustered at the department level are in parentheses.
$^{+}$ $P<0.1$, * $P<.05$, ** $P<.01$.
Source: Authors' calculations.

4.3.4 Synthetic difference in differences

The robustness of these findings is further substantiated by the application of a SDID. Results of this approach are reported for the models estimating the effect of being awarded a DoE grant as per Equation (1) (Fig. 1) and the heterogeneous effect across department research quality standing as in Equation (2) (Table 9).

Results in Fig. 1 confirm the significant increase in new faculty positions, new positions excluding promotions and new tenured positions. When comparing the results of the SDID estimator to the baseline DID, the magnitude and significance of the coefficients are largely consistent, although slightly lower for new positions. The analysis also highlights a marked increase in new positions in year 2019 and a subsequent decrease, suggesting that the effect of the DoE award on faculty recruitment was temporary at best.

Table 9 shows the results for the effect of the DoE grant on second-tier departments. These results are largely consistent with those from our baseline DID, with the only difference being a non-significant yet positive effect on the number of tenured positions.

The use of this estimator adds credibility to the findings, reinforcing the conclusion that the DoE programme had a substantive effect on academic faculty recruitment and career progression.

Table 7. Pre-treatment trends: parallel trend assumption.

	New positions	New positions (excl. promotions)	Internal promotions	Temporary	Tenure track	Tenured
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Year 2014	0.034	–0.107	0.266	–0.136	–0.008	0.221
	[0.495]	[0.237]	[0.436]	[0.187]	[0.158]	[0.179]
Treat × Year 2015	–0.400	–0.010	–0.262	0.049	–0.045	0.070
	[0.521]	[0.268]	[0.453]	[0.208]	[0.157]	[0.159]
Treat × Year 2016	0.303	–0.130	0.581+	–0.025	–0.043	–0.050
	[0.435]	[0.280]	[0.340]	[0.209]	[0.179]	[0.138]
Department and post FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
University-by-post FE	Yes	Yes	Yes	Yes	Yes	Yes
Prop score weight	Yes	Yes	Yes	Yes	Yes	Yes
Joint *P*-value	.518	.935	.224	.699	.981	.446
N (Departments X year)	1104	1104	1104	1104	1104	1104
N (Departments)	276	276	276	276	276	276

This table displays the pre-treatment event study coefficients using 2014–2016 data. Regressions are based on 1,104 department-year observations. Estimates include controls for the number of employees at $t-1$, the number of staff transferred between departments, university income linked to the VQR, province-level per-capita value added and provincial unemployment rate. Department, post and university-by-post fixed effects are included in all specifications. All regressions are estimated using $1/(1-\widehat{p}(x_i))$ to weight untreated observations and $1/\widehat{p}(x_i)$ otherwise. $\widehat{p}(x_i)$ is the propensity score and is calculated controlling for the number of department research staff at time $t-1$, the number of staff transferred between departments, university income linked to the VQR, province-level per-capita value added, provincial unemployment rate and NUTS 1 regional fixed effects. Standard errors clustered at the department level are in parentheses.

$^{+}P<.1$, $^{*}P<.05$, $^{**}P<.01$.

Source: Authors' calculations.

Table 8. Pre-treatment trends with no controls: unconditional parallel trend.

	New positions	New positions (excl. promotions)	Internal promotions	Temporary	Tenure track	Tenured
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Year 2014	0.275	0.002	0.406	–0.168	0.043	0.216
	[0.703]	[0.280]	[0.617]	[0.221]	[0.162]	[0.186]
Treat × Year 2015	0.309	0.211	0.211	0.154	0.019	0.043
	[0.623]	[0.322]	[0.560]	[0.245]	[0.182]	[0.168]
Treat × Year 2016	0.277	–0.152	0.575	–0.076	0.008	–0.068
	[0.492]	[0.297]	[0.366]	[0.204]	[0.211]	[0.136]
Department and post FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	No	No	No	No	No	No
University-by-post FE	No	No	No	No	No	No
Prop score weight	Yes	Yes	Yes	Yes	Yes	Yes
Joint *P*-value	.938	.715	.474	.343	.991	.463
N (Departments)	290	290	290	290	290	290

This table displays the pre-treatment event study coefficients using 2014–2016 data. Regressions are based on 1,160 department-year observations. Department and post fixed effects are included in all specifications. All regressions are estimated using $1/(1-\widehat{p}(x_i))$ to weight untreated observations and $1/\widehat{p}(x_i)$ otherwise. $\widehat{p}(x_i)$ is the propensity score and is calculated controlling for the number of department research staff at time $t-1$, the number of staff transferred between departments, university income linked to the VQR, province-level per-capita value added, provincial unemployment rate and NUTS 1 regional fixed effects. Standard errors clustered at the department level are in parentheses.

$^{+}P<.1$, $^{*}P<.05$, $^{**}P<.01$.

Source: Authors' calculations.

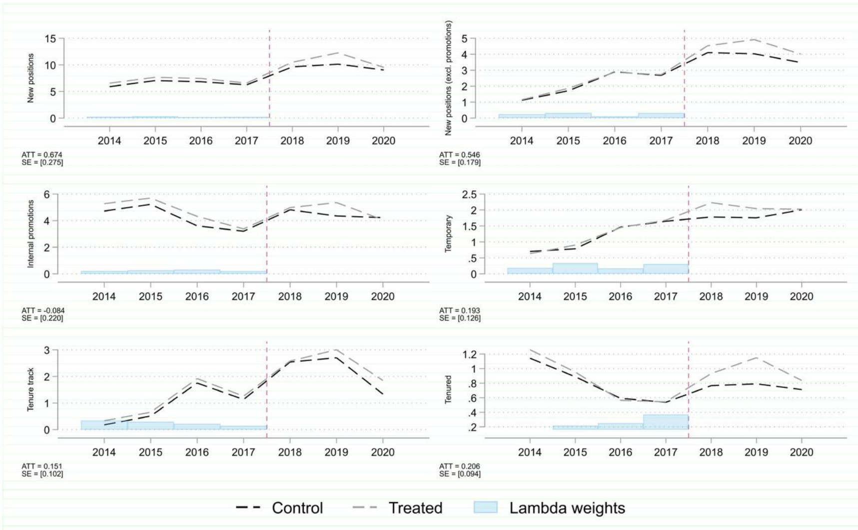

Figure 1. Effect of the Department of Excellence Programme on University Faculty Recruitment, Synthetic Diff-in-Diff estimator. Notes. Synthetic difference-in-difference estimator (Arkhangelsky et al. 2021). Estimates include controls for the number of employees at $t-1$, the number of staff transferred between departments, university income linked to the VQR, province-level per-capita value added and provincial unemployment rate. Lambda weights are defined as optimized time weights assigned to control units to construct the synthetic control that minimize the differences with the treated unit during the pre-treatment period. Standard errors are based on 500 bootstrap replications. *Source*: Authors' calculations.

Table 9. Effect of the Department of Excellence Programme on University Faculty Recruitment for second tier university departments: synthetic diff-in-diff estimator.

	New positions (1)	New positions (excl. promotions) (2)	Internal promotions (3)	Temporary (4)	Tenure track (5)	Tenured (6)
Treat × After × Second Tier	2.238**	0.890*	1.447**	0.196	0.895**	0.266
	[0.674]	[0.430]	[0.526]	[0.306]	[0.243]	[0.262]
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
N (departments)	289	289	289	289	289	289

This table displays results from the synthetic difference-in-difference estimator (Arkhangelsky et al. 2021), based on 2,023 department-year observations using 2014–2020 data. Estimates include controls for the number of employees at $t-1$, the number of staff transferred between departments, university income linked to the VQR, province-level per-capita value added and provincial unemployment rate. Standard errors are based on 500 bootstrap replications.

$^{+}P<.1$, $^{*}P<.05$, $^{**}P<.01$.

Source: Authors' calculations.

5. Robustness checks

To ensure the reliability of our findings, we conducted a series of robustness checks. We replicated our most stringent specification, incorporating department, post-treatment, and university-by-post fixed effects, as well as propensity score weighting. Firstly, we assess the robustness of our results against the issue of 'bad controls' as described by Angrist and Pischke (2009). There is a potential bias in our estimates of the effect of additional funding if the control variables only account for the benefits (or disadvantages) associated with the programme, but not both. In such cases, these variables are considered 'bad controls' and should be excluded. Specifically, we examine the programme's effect on the creation of new positions, accounting for the benefits (e.g. the ability to attract transfers) but not the drawbacks attributable to the programme. This selective control can lead to a biased estimation of the programme's effects. For this reason, we present results that exclude the controls in our regression analysis. Results offer comprehensive support for our findings both referred to Equation (1) as reported in Table A 1, and to Equation (2) reported in Table A 2, in Appendix A (see online supplementary material).

Second, in our main analysis, we employ a linear regression model incorporating multiple fixed effects. Considering that our dependent variables are non-negative count variables, an alternative model such as the Poisson pseudo-maximum likelihood (PPML) regression, as suggested by Gourieroux et al. (1984), may be more appropriate. The PPML model offers several advantages. It ensures the consistency of parameter estimates even when the distribution of the dependent variable deviates from a Poisson distribution. This is particularly relevant in scenarios of overdispersion, high incidence of zeros in the dependent variable, and significant cross-sectional variation (Silva and Tenreyro 2006; Bertanha and Moser 2016). Recent developments in applied research have extended the PPML model to include multiple fixed effects, thus enabling the control of diverse sources of heterogeneity (Correia et al. 2020). We incorporate this approach as a robustness check for our findings. Tables A 3 and A 4 in Appendix A (see online supplementary material) display the results, examining the effect of the DoE both generally and specifically within second-tier university departments, respectively. These findings are consistent with the estimates reported in the main analysis.

Third, we conduct our estimations on a restricted sample. Specifically, we exclude university departments that, despite being among the top 352, did not participate in the selection process due to the legal provision, which stipulated that at most 15 departments per university could partake in the competition. In other words, some large universities had to exclude certain departments from competing for the award when surpassing the maximum limit of 15. This method allows us to assess whether our estimates are influenced by the selection of departments participating in the competition. The results, as depicted in Tables A 5 and A 6 in Appendix A (see online supplementary material), continue to corroborate our primary findings.

Finally, our classification of university departments into first and second tiers is based on the median research quality score in the ISPD, set at 98 out of 100. To test the robustness of our findings, we conducted a series of analyses using alternative threshold values below 98. Specifically, we employed scores between 95 and 98 in increments of 0.5, with the value 95 corresponding to the 40th percentile in the research quality distribution of our sample. Table A 7 (see online supplementary material) presents the results for which first-tier departments are those with an ISPD higher to 95 (40th percentile). The outcome of this is in line with our main findings, indicating consistent results.[17]

6. Conclusions

The Italian 'Departments of Excellence' initiative presents a unique case study among excellence-based funding mechanisms in higher education. Unlike European counterparts that focused on university-level interventions, this policy targeted individual departments—rather than universities—providing substantial funds for recruitment and promotion. Moreover, this initiative was implemented in a country where public expenditure on

[17] Results for other ISPD values, ranging between 97.5 and 95.5, are not included in the paper. However, they are consistent with the findings presented and can be made available by the authors upon request.

research is significantly below the European average, and where top scientists tend to be dispersed across various institutions (e.g. Abramo et al. 2012).

Our results show that excellence-based funding programmes can increase the number of researchers recruited by universities. However, this effect varies by recruitment type—early-career researchers and external recruits benefit most—and by the quality of the host department, with second-tier departments in terms of research quality benefitting more than 'superstar' units.

Our analysis offers several key insights for both academics and policy makers. First, the initiative significantly increased departmental recruitment capacity, particularly through external hires across all career stages, thereby achieving its primary objective of strengthening human capital within the Italian university system. This underscores the effectiveness of selective funding mechanisms (e.g. Stephan 1996), especially when departments have control over recruitment. From a policy perspective, other countries may in the future adopt similar two-stage quality models—peer review followed by a selective funding mechanism—as implemented under the European Commission's Seal of Excellence (European Commission 2022).

Second, we identify heterogeneous impacts across departments. Second-tier departments, which rank well nationally but below the elite, gained disproportionately –recruiting on average two additional academic staff members compared to top-tier departments. This likely reflects differences in bargaining power vis-à-vis university management. While top departments may secure resources irrespective of excellence-based initiatives, second-tier departments appear more responsive to such instruments. Our findings suggest that performance-based funding, under certain conditions, can foster convergence rather than increase inequality (cf. Bol et al. 2018). Accordingly, EU-level excellence programmes might consider allocate resources to mid-ranked departments to broaden the base of research excellence (European Commission 2021).

Finally, by examining a system with relatively weak institutional stratification, our results contribute to the literature on excellence schemes (e.g. Aagaard et al. 2020; Carayol and Maublanc 2025), highlighting how both the level of intervention and the structure of the funding mechanism crucially shape outcomes.

Nevertheless, some important limitations set the stage for future research endeavours. First, the second-tier departments in our analysis still outperform a large share of Italian departments in terms of research quality, as according to the research evaluation exercise they fall within the top 50% of approximately 800 departments nationwide. Future studies should investigate the potential effects of funding on third- or fourth-tier departments (bottom 50%) and their subsequent recruitment patterns. Second, due to data limitations no analysis was carried out regarding the scientific productivity of researchers hired or promoted in both first- and second-tier departments. Finally, the Italian higher education system remains characterized by profound territorial disparities, particularly between the North and South. While similar differences exist in other European countries, they are often addressed through federal or decentralized governance structures—unlike Italy's more centralized approach. This creates a persistent tension between the principle of equality and uneven institutional capabilities. The Department of Excellence initiative, by funding a relatively large number of departments, may reflect an attempt to promote excellence while the effects on geographical disparities remain unclear. Future research should examine whether the initiative affected the North–South divide in the recruitment patterns identified in this study, and in the quality of hiring.

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Supplementary material

Supplementary material is available at *Oxford Economic Papers Journal* online. These are the online appendices, and data and replication files. The data and replication files are also available at https://github.com/frarent/dpt_of_excellence

Conflicts of interest

The authors declare that they have no conflicts of interest.

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