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The Impact of EU Grants for Research and Innovation on Firms' Performance *

(A kutatási és innovációs célú uniós támogatások hatása a vállalatok teljesítményére)

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Contents

Abstract

The paper evaluates the impact of the European Commission's Seventh Framework Programme (FP7) grants on profit-oriented firms' post-treatment performance. Using a quasi-experimental design and a dataset covering applicants from 46 countries, we find that FP7 grants increase firms' sales and labour productivity by about 18%. However, there is no significant impact on employment levels, pointing to potential growth barriers that prevent firms from scaling production despite improved productivity. The effectiveness of these grants varies significantly based on factors such as financial constraints, project risk profiles, market structure, and the innovation environment. Smaller, less productive firms with tighter financial constraints in technology-intensive sectors operating in concentrated markets and favourable innovation environments, particularly those undertaking longer and riskier projects, tend to benefit more.

JEL: C31, G28, H57, O31.

Keywords: EU funds for research and innovation; firm productivity; regression-discontinuity design.

Összefoglaló

A tanulmányban az Európai Bizottság hetedik keretprogram (FP7) támogatásainak a profitorientált vállalatok teljesítményére való hatását vizsgáljuk. A 46 ország pályázóira kiterjedő mikroadatbázis alapján azt találjuk, hogy az FP7 támogatásai mintegy 18%-kal növelték a cégek árbevételét és munkatermelékenységét. A foglalkoztatási szintre azonban nem volt jelentős hatása, ami arra utal, hogy a termelékenység javulása ellenére a termelés csak korlátozottan skálázható. A támogatások hatékonysága jelentősen eltér olyan tényezők függvényében, mint a pénzügyi korlátok, a projekt kockázati profilja, a piac szerkezete és az innovációs környezet. A támogatásoknak nagyobb hatása volt a koncentrált piacokon és kedvező innovációs környezetben, technológiaintenzív ágazatokban működő, kevésbé termelékeny, pénzügyi korlátokkal rendelkező, kisebb cégekre, különösen azokra, amelyek hosszabb és kockázatosabb projekteket kiviteleztek.

1 Introduction

It has been long recognised that without public support, private investment in research and development (RD) falls short of the socially optimal level (Nelson (1959)). As argued by Arrow (1962), innovation-related knowledge intrinsically entails non-divisibility (half the knowledge of a technology is not worth half of the full knowledge), “non-probabilisable” uncertainty regarding economic outcomes, and incomplete appropriability even with patent protection. These factors discourage firms from pursuing innovation projects. Additionally, financial frictions caused by uncertainty associated with RD and information asymmetries between borrowers and lenders further reduce private sector engagement in RD (Griliches (1986), Hall (2002)). In these circumstances, the social return on RD spending exceeds the private return, making direct or indirect subsidies an effective means to address this market failure and enhance social welfare (Spence (1984)).

To reduce the costs of innovation and stimulate RD investments, governments in many countries and supranational authorities have implemented policies to support private innovation activities. These policies include direct support through grants and subsidies, as well as indirect support through tax credits. One of the largest such funding programmes worldwide is the European Commission’s (EC) Framework Programmes (FP) for Research and Technological Development. The first FP was launched in 1984, and subsequent programmes covered five-year periods until FP7, which extended to seven years (2007-2013). The current FP9, known as Horizon Europe, spans from 2021 to 2027. The budget for these programmes has steadily increased, from approximately 4 billion EUR for FP1 to over 50 billion EUR for FP7 and 95 billion EUR for FP9.

This paper evaluates the impact of FP7 grants on the post-treatment performance of profit-oriented firms. Our focus is on private companies participating in the core programme called Cooperation, which represents two-thirds of the budget. Using a unique dataset that includes both successful and unsuccessful FP7 applicants, along with balance-sheet data from firms in 46 countries, we employ a quasi-experimental research design to assess the programme’s effectiveness. Specifically, we utilise the external experts’ scores assigned to each project proposal to compare the average post-treatment performance of “marginal beneficiaries” (firms that received grants with scores slightly above the threshold for funding) and “marginal non-beneficiaries” (unsuccessful firms with scores just below the threshold) within a regression discontinuity framework (see e.g. G. W. Imbens and Lemieux (2008)). In this framework, the score serves as a proxy for the “quality” of the project; higher scores indicate better and more viable research projects with a higher probability of success and, therefore, a greater expected impact on firms’ outcomes. The estimation of the fund’s impact relies on the discontinuity of the post-treatment outcome variable around the threshold. If an abrupt shift in the average values of outcome variables is identified precisely at the threshold, it suggests that firms receiving the grant performed better than those with research projects of similar quality but without the financial support of the grant.[1]

A crucial – and often neglected – step in our identification strategy is defining appropriate treated and control units using a “clean control approach.” Our sample selection ensures that the control group, i.e. firms participating in research consortia whose projects scored just below the threshold, remains unaffected by the potential impact of other awarded projects the firm may be running in parallel. In other words, we ensure that observations influenced by the intervention related to the overlapping awarded project are not used as counterfactuals. Additionally, we ensure that our outcome variables – specifically, the logarithm of sales, number of employees, and productivity – are not directly influenced by the receipt of funds. Since the funds may temporarily boost productivity and lead firms to hire additional temporary employees for project-related tasks, we define the post-treatment period as the time following the project’s completion and the final payment by the EC.

Studies relying on quasi-experimental methods have only emerged relatively recently in empirical literature. Early studies, using data restricted to successful applicants, primarily employed matching methods based on observable characteristics to

[1] It is important to note that FP7 is very heterogeneous in terms of objectives, particularly regarding whether they finance RD projects (systematic and scientific work undertaken to create new knowledge, improve existing processes, products, or services, or solve specific problems) or innovation activities (translating ideas, inventions, or scientific knowledge into commercially viable products, processes, or services). Broadly speaking, Cooperation calls were mainly given for RD projects, but there were also some calls with innovation purposes. For simplicity, we use RD and innovation interchangeably throughout the paper.

build control groups. The main limitation of this approach is that the unobserved characteristics of firms applying for financing their research projects may differ significantly from those of the firms used as counterfactuals. Most importantly, firms applying for and securing research grants are known to have feasible research projects. In contrast, the counterfactual group constructed using matching methods may not even be committed to research and development (RD) during the same period. Therefore, the observed difference in post-treatment performance between the treated and the counterfactual group could merely be a result of the positive success probability of the RD activity initiated by the former group, even in the absence of the grant. This translates into better expected firm performance following the research conducted, compared to the counterfactual group, which may not have embarked on any RD projects. As documented by Zúñiga-Vicente et al. (2014) in a comprehensive review of the topic, early empirical studies on the effectiveness of such programmes yielded mixed results.[2] Empirical evidence varies depending on several factors, including the time period examined, the type of RD projects covered, the amount of subsidy, and the history of grants received.

More compelling impact evaluations have emerged with the availability of data on both successful and rejected applicants within the same support programme. Only a few relatively recent studies exploit the difference between successful and unsuccessful applicants to identify the impact of research grants. Among these, Bronzini and Iachini (2014) use a regression discontinuity design (RDD) to assess the impact of a regional programme in northern Italy. They find a positive effect of the funds on RD investments for small enterprises, in both tangible and intangible assets, approximately equal to the amount of the subsidy received. However, the programme did not generate additional investment for larger firms. The authors suggest that this result indicates tighter financial constraints faced by small firms, whereas larger firms substitute public funds for privately financed RD. In a follow-up study, Bronzini and Piselli (2016) report a significant effect of the programme on the number of patents and the probability of patenting innovations, with larger impacts for smaller firms. Similarly, Howell (2017), using the same identification strategy, examines the impact of the Small Business Innovation Research (SBIR) grant programme in the US. The findings show that grants positively influence revenues, the citation-weighted number of patents, survival, and the probability of receiving venture capital financing in subsequent phases of innovation. In a subsequent paper, Howell and Brown (2020) finds that SBIR grants increase the average earnings of incumbent employees who were with the firm before the award, with the effect intensifying with worker tenure. However, newly hired employees do not benefit from the additional cash flow provided by the research grant. This suggests a backloaded wage contract channel, where employees of financially constrained firms initially accept lower wages, expecting higher pay when funds become available. Wang et al. (2017), also using RDD, evaluate a similar grant programme targeting early-stage technological ventures of Small and Medium-Sized Enterprises (SMEs) in China. They find that firms with observable merits and political connections are more likely to receive Innofund grants. The authors also provide evidence of bureaucratic intervention, as applicants' evaluation scores are non-randomly missing. Their study finds no evidence that receiving the grant increases survival, patenting, or venture funding. Finally, Widmann (2024) reports a significant impact of Austrian Research Promotion Agency grants on the propensity of Austrian firms to file patent applications. More established firms perform better in this area, appearing to use research grants to undertake ambitious, unconventional RD projects.

Despite its strategic and budgetary importance for the EU, the effectiveness of the EU Framework Programmes has never been rigorously assessed using quasi-experimental techniques. Previous efforts to quantify the impact of the EC's framework programmes for RD, or parts thereof, primarily fall into the category of early studies that rely on matching techniques or Heckman corrections (Heckman (1979)) to mitigate selection bias and create control groups. These studies include Barajas et al. (2012), which analyses the impact of FP4, FP5, and FP6 on Spanish firms; Aguiar and Gagnepain (2017), which examines the impact of the FP5 "User-friendly Information Society" thematic programme; and more recently, Szücs (2020), who investigates the effects of FP6, FP7, and Horizon 2020. While the first two studies find significant impacts of the grants, notably by increasing investments in intangible assets (a proxy for the generation of new knowledge, see Barajas et al. (2012)) and improving firms' productivity (Barajas et al. (2012), Aguiar and Gagnepain (2017)), the findings by Szücs (2020) suggest that, on average, subsidies did not lead to increased private research budgets. However, they did have a positive impact on smaller firms, smaller projects, and more RD-intensive companies. The only study using a quasi-experimental identification technique to analyse part of the EC's RD grants was conducted by Santoleri et al. (2020). The study focuses on the segment of the Horizon 2020 programme specifically targeted at SMEs. With a budget of approximately 3 billion EUR for the years 2014-2020, the SME Instrument mimics the US SBIR programme. Unlike the core of the FPs, it features a two-phase grant scheme. In the first phase, firms receive a lump sum grant for concept and feasibility assessment, while the second phase funds product development.

[2] See also Becker (2015) for a survey focusing also on tax credits.

The authors find that RD grants to SMEs have substantial positive effects on cite-weighted patents, investment, firm growth, the likelihood of obtaining external equity, and firm survival.

We contribute to the recent literature employing quasi-experimental methods by examining the effectiveness of one of the world's largest RD funding programmes. This programme is the largest of its kind previously analysed, both in terms of total budget, number of applicants and awarded firms, characteristics of the applicants, scope and characteristics of the research projects, as well as sectoral and country coverage. This diversity presents a unique opportunity to delve into the multifaceted impacts of research and innovation funding across various dimensions. By examining factors such as firm and project characteristics, sectoral differences, and the diverse attributes of different countries or markets, this exploration can substantially enhance our understanding of the mechanisms driving the benefits of these funds. This deeper comprehension is essential for strategically allocating resources to ensure the optimal utilisation of available funds.

Our findings reveal compelling evidence that EU research and innovation funding significantly boosts awarded firms' post-treatment sales by 18.2 percentage points and labour productivity by 18.5 percentage points on average. However, these grants do not significantly affect employment levels. This indicates that while the grants enhance firms' productivity and consequently their sales even after the completion of the projects, firms are unable to scale up their production in the medium or long term following a successful innovation project partially financed by European funds.

Our heterogeneity analysis reveals a nuanced landscape of the effectiveness of research grants. First, financial constraints emerge as a pivotal factor. Our results show that SMEs, often limited by insufficient collateral and consequently restricted access to financial markets, benefit significantly from such grants. In contrast, larger firms, with their broader access to financial markets, do not show a significant long-term impact from public funding. The role of financial constraints is also evident at a more aggregate level: firms in countries with greater capital market imperfections experience a stronger treatment effect.

The second factor determining the effectiveness of public funding for RD is the inherent risks associated with research projects. According to Arrow's arguments about the discouraging effects of these risks, public funding should yield more beneficial outcomes for riskier projects. Our results support this reasoning, as firms in technologically or knowledge-intensive sectors, which typically engage in frontier research and make high-risk investments, benefit more from public RD funding. Manufacturing RD projects, being more technology-based and inherently riskier than innovation in the service sector (Morrar (2014)), experience a greater impact from FP7, as confirmed by our results. The length of a project is also closely tied to the underlying risk of RD, and since longer projects represent riskier investments, it is not surprising that we observe a larger treatment effect for these projects. From a different perspective, the heterogeneous impact of grants for RD based on the initial productivity of firms may also be partly related to the risks associated with innovation projects. Our results indicate that less productive firms derive significantly greater benefits from grants compared to their more productive counterparts. Less productive firms might be reluctant to invest in risky projects due to fear of failure. Additionally, less productive firms often face tighter financial constraints, further hindering their ability to engage in research activities. In this context, grants act as a safety net by covering a portion of the costs, encouraging these firms to undertake riskier research activities.

Third, the market structure that firms are operating in also determines their incentive of engaging in risky innovation activities and, consequently, the beneficial effect of public funding for RD. In particular, the relationship between competition and innovation has been a long-standing debate in industrial economics, with theories from Schumpeter (1942) and Arrow (1962) providing foundational perspectives. Schumpeter argued that increased competition reduces the profitability of innovation, while Arrow contended that high competition forces firms to innovate to maintain their market position. Public RD funding complicates this dynamic by offsetting lower private incentives, potentially being more effective in markets with lower private incentives for RD. Our results, which align more closely with Arrow's theory, indicate that public RD funding helps offset lower private incentives in more concentrated markets.

In addition to encouraging firms to engage in research activities to varying degrees based on firm characteristics, project specifics, and the operating environment, the benefits of public funding also depend on the success probability of the awarded projects. Our results indicate that firms located in favourable innovation environments, as measured by the county-level ”capacity to innovate” indicator from the World Economic Forum's Global Competitiveness Index, experience amplified benefits from FP7 funding.

Finally, we investigate whether the size and composition of consortia applying for FP7 funds affect the effectiveness of the programme. FP7 aims to foster collaborative research among profit-oriented enterprises and partnerships between industry, academia, and public institutions. Collaborative efforts within FP7 may help overcome RD cost barriers by pooling resources and sharing expenses, thereby enhancing project efficiency and reducing redundancy. However, challenges like free-riding and increased coordination costs can emerge, particularly in larger consortia. For the most part, our results are inconclusive regarding the importance of consortium composition. We observe no significant differences in effectiveness based on consortia size, indicating that the number of participants does not significantly impact the outcomes of public funds on RD. Additionally, we find no clear evidence that collaborations with universities, research institutions, or partners from non-EU countries influence FP7 grant effectiveness. However, we do find that firms in consortia without public institutions tend to achieve better post-treatment outcomes. This could be because projects involving public institutions often pursue broader objectives beyond improving private firms' performance, possibly encompassing social goals.

The remainder of this paper unfolds as follows. First, Sections 2 provides a detailed overview of the FP7 programme for Research and Technological Development. Section 3 introduces the various datasets used in our analysis, detailing the steps taken for data preparation, sample selection, defining "clean controls", and presenting descriptive statistics for both successful and unsuccessful firms and projects. Section 4 outlines the econometric strategy employed, followed by Section 5, which presents the findings regarding the impact of FP7 grants on firms' post-treatment performance. Section 6 examines the validity and the robustness of our results. The heterogeneity analysis is presented in Section 7. Finally, Section8 provides concluding remarks.

2 The 7th EU Framework Programme for Research and Technological Development

Since the European Commission launched the First Framework Programme (FP) for Research and Technological Development (RTD), its strategic objectives have included strengthening science and technology in support of European industry interests and promoting research activities aligned with other EU policies. The programme fosters the development of European scientific community, providing it with the requisite skills and expertise while supporting high quality scientific and technical work conducted through transnational projects.[3] The first FP set the precedent for subsequent framework programmes, each spanning five-year periods until FP7, which marked the first instance of a seven-year duration (2007-2013). Presently, the ongoing FP9, also known as Horizon Europe, covers the period between 2021 and 2027. The budget allocated to FPs gradually increased from about 4 billion EUR for FP1 to over 50 billion EUR for FP7 and 95 billion EUR for FP9.

The FP7 comprises five principal building block Programmes. This paper focuses on the core programme known as *Cooperation*, which represents two-thirds of the overall budget. Its primary objective is to catalyse transnational collaborative research consortia, encompassing both partnerships between profit-oriented enterprises and collaborations between industry and academia in particular thematic areas. The remaining four blocks include the *Ideas* programme, supporting "frontier research" based on excellence across various scientific domains; the *People* programme, facilitating researchers' mobility and career development; the *Capacities* programme, aimed at reinforcing research capacity activities such as research infrastructure, regions of knowledge, and research for the benefit of SMEs; and lastly, the *Nuclear research* programme, which funds activities such as nuclear research, technological development, radiation protection, and nuclear safety.

The funding governing FP7 projects is co-financing. The standard reimbursement rate for research and technological development projects is set at 50%. This rate can increase to 75% for non-profit public bodies, SMEs, research organisations, or higher education institutions. In the case of frontier research actions, the reimbursement rate may even reach 100%.

The funding in the form of grants is generally allocated through the publication of "calls for proposals". These calls are open for application to various entities, including universities, research institutions, companies, governmental administrations, and individual researchers from EU Member States, as well as associate countries (Norway, Switzerland, Israel, Albania) and candidate countries (Iceland, Macedonia, Serbia, Turkey). Additionally, participants from international cooperation countries have the opportunity to apply in collaboration with entities from Member States or associate countries. Project proposals must be submitted within specified deadlines, adhere to clearly defined themes, and establish the necessary partnership structures to be eligible for consideration.

Following the application deadline, the European Commission (EC) conducts an initial eligibility check on all proposals submitted under a specific call, after which they undergo a pre-defined selection procedure. The selection process typically takes the form of either a single-stage or two-stage process, with the former being the more commonly utilised method, encompassing 376 out of 446 calls. In the single-stage process, each detailed project proposal submitted to a specific call undergoes an initial assessment by a minimum of three independent external experts. These experts assign a score to the project, generally ranging from 0 to 5, evaluating its quality based on predefined criteria such as potential impact, financial and technical feasibility, and other pertinent aspects. Subsequently, in a second round, the experts collaboratively discuss the proposals and jointly assign a final score to each project, typically between 0 and 15. All evaluated proposals are then ranked based on these final scores. Finally, The EC sets a threshold for project acceptance based on the total budget available for the specific call. Projects above

[3] Decision No 1982/2006/EC of the European Parliament and of the Council of 18 December 2006 concerning the Seventh Framework Programme of the European Community for research, technological development and demonstration activities (2007-2013)

the threshold are main-listed, and applicants are invited to engage in negotiations for the grant agreement. In the course of the negotiation process, the EC may seek additional clarifications or modifications, such as adjustments to the budget structure or proposed actions. If adjustments are necessary for the successful implementation of a project, the EC may also consider and approve modifications proposed by the applicants, including potential changes to the composition of the consortium. Unsuccessful applicants are either rejected or placed on a reserve list. Should main-listed projects withdraw before the contract is signed, replacements can be drawn from the reserve list. Additionally, the EC may select consortia from the reserve list if there is a decision to augment the allocated funds for the call.

As implied by its name, the distinctive feature of the two-stage selection method is that the submission of proposals takes place in two stages. The process can unfold in various ways, but in the most prevalent two-stage submission scheme, applicants are initially requested to submit a concise, partially developed technical proposal, outlining their solution for achieving the objectives specified in the call. These initial proposals undergo evaluation, scoring, and ranking by external experts, mirroring the process employed in single-stage calls. Subsequently, applicants possessing the highest-ranked first-stage technical proposals are invited to submit their comprehensive proposals for the second stage. The full proposal is expected to align with the short outline proposal and should not deviate substantially. Ultimately, the full proposals undergo another round of evaluation, following a similar process to that of single-stage calls.

In a streamlined two-stage selection framework, the EC selects applicants to advance to the second stage without the involvement of external experts. Consequently, no expert scores are assigned during the first stage. The second stage closely mirrors the single-stage procedure. In a minority of cases, the main selection takes place in the first stage. This approach resembles the single-stage process with a full expert evaluation, followed by discussions with the pre-selected applicants aimed at reaching a final agreement.[4]

[4] While calls for proposals, followed by either a single-stage or two-stage selection procedure, serve as the primary means for fund allocation, certain exceptions exist. For instance, specific FP funds designated for complex or highly specialised tasks can be allocated through direct invitations.

3 The data

3.1 CORDA AND ORBIS

The project involves using two distinct databases that are linked together. First, data pertaining to applicants and signed grants for research funding are extracted from *Corda*, a database managed by the EC's Directorate-General for Research and Innovation (DG-RTD). The Corda database is constructed from three separate datasets. The Corda's *proposals* part gathers details on both successful and unsuccessful applications, including the project's proposed start and end dates, claimed project cost, requested funds, the amount of grant proposed by the Commission, and various company details such as name, address, and contact person. Additionally, it records application process information, such as the expert evaluators' scores and the final decisions from both the experts and the EC. Once the evaluation is complete and all information is registered, the database is no longer updated. The Corda *projects* part, on the other hand, holds continuously updated data on successful projects after the signature of the contract. This includes the final grant amount received by successful applicants and the final schedule of the innovation project. A third dataset, the so-called *h20* is also used for harmonisation purposes. Also managed by the EC's DG-RTD, it provides centralized, harmonised metadata on all applicants since the beginning of FP7, offering detailed applicant-level information, including firms' VAT numbers, duplications, and transfer of rights.

Second, firms' balance-sheet and financial information are sourced from Orbis, the richest available international dataset at the individual firm level. Maintained by Bureau van Dijk (BvD), a subsidiary of Moody's Analytics, Orbis compiles data from various sources, including official business registers, annual reports, webpages, disclosure documents, and newswires. This diverse data stream is then structured into key financial and balance sheet variables, encompassing almost all pertinent aspects of firms' activities. Each firm in Orbis is uniquely identified by a code assigned by BvD (referred to as the BvD Number), allowing for the tracking of a firm's dynamics over time. The most recent year included in our sample is 2016.

Following a meticulous pre-cleaning and harmonisation of the three Corda datasets and Orbis, the various datasets are linked using a combination of direct merging based on the company's VAT number and a similarity score matching approach (described in details in Raffo and Lhuillery (2009)) based on company name, along with other company details such as postal and email addresses, and webpage information. Additional details about the databases and the matching procedure used is provided in Appendix A.

3.2 HARMONISATION AND STANDARDISATION OF FINAL SCORES

One of our key variables of interest is the scores assigned by expert evaluators to the project. In the vast majority of cases, scores are documented within the standard range of 0 to 15. Nonetheless, for certain calls, scores are recorded in Corda as a percentage of the maximum attainable score, spanning from 0 to 100. In a few exceptional instances, the recorded maximum achievable score in the database deviates, mainly settling at 5 (refer to Section 2 for additional information on experts' scores). To ensure comparability of the final scores across different calls, an initial harmonisation process is conducted, ensuring that all scores fall within the common range of 0 to 15.

Subsequently, the final scores, which ultimately determine the applicants' final rankings, are normalised by setting the technical cut-off thresholds to 0. Successful applicants are thus assigned a normalised score indicating the number of points above the threshold, while unsuccessful applicants receive a negative normalised score representing the points below the threshold.

3.3 SAMPLE SELECTION AND DEFINITION OF CLEAN CONTROLS

After generating project-level variables, such as a dummy indicating the presence of a research institute, higher education, public institution, or various country groups in the project, we retain information solely on profit-oriented applicants to FP7 grants. The reduced database contains 61,029 firms, submitting 48,492 project proposals through 446 calls, resulting in a total of 172,199 observations (refer to the first line of Table 1). The final estimation sample is further narrowed down based on specific call, project, or applicant-related criteria.

Table 1 illustrates the elimination steps, detailing the number of calls, project proposals, firms, and observations directly or indirectly excluded from the sample based on specific criteria. The last column indicates the share of FP7 funds allocated to profit-oriented applicants associated with each elimination step.

First, 165 calls are excluded for call-specific reasons, such as being announced for individuals (e.g., Marie Skłodowska-Curie actions), invitation-based calls, or calls targeting non-research actions (support coordination, networks of excellence, etc.). This step leads to the exclusion of 6,050 firms from the sample (see rows a-c of 1).[5] Second, 3,639 first-stage applications of a two-stage selection process, along with 716 ineligible project proposals, are removed from the sample (rows d and e). Third, 2,743 observations are eliminated because some participants in a winning project left before signing the contract (row f).

These steps reduce the sample to 281 calls, with 32,884 project proposals submitted by 50,619 firms, resulting in a total of 134,462 observations. This sample is referred to as relevant for the purpose of this study (see the penultimate row of the table). The final estimation sample is further reduced due to missing observations. Specifically, we exclude 9 calls because the scores obtained during the selection procedure are not recorded (row g of the table); 9 calls because all proposals are either accepted or rejected (h); 9,067 projects which (are expected to) end after 2016, rendering post-treatment data unavailable (i), 11,064 firms that could not be matched with Orbis (j), and an additional 4,825 firms with missing financial information in Orbis.

A crucial last step of the sample selection defines clean controls for the identification of the impact of the grants. As detailed in Section 4, identifying the effects of FP7 funds on firms' performance relies on comparing awarded firms with a counterfactual group of unsuccessful applicants. If a firm participates in at least one successful project, any other project which runs (or would run) in parallel with the awarded project must be removed from the sample, and the firm must be considered treated. This ensures that observations influenced by the intervention related to the overlapping awarded project are not used as counterfactuals. In cases of several overlapping successful or unsuccessful applications, we retain only the one with the highest normalised final score.

Since projects are typically long, spanning several years, it is rare to observe two consecutive non-overlapping projects in the sample. In such cases, where there is at least one post-treatment year without any project between the end of the first project and the start of the second, both projects are retained in the sample. For example, if a firm has an unsuccessful project followed by a successful project, the unsuccessful project is considered a valid counterfactual only if the expected end date of the unsuccessful project leaves at least one post-treatment year before the successful project begins.

Furthermore, we ensure that our outcome variables — namely, the logarithm of sales, number of employees, and productivity — are not directly influenced by the receipt of funds. The funds received may temporarily boost productivity, and firms might opt to hire additional temporary employees to fulfill project-related tasks. Consequently, we solely consider observations after the conclusion of the project, referred to as the post-treatment period. In the same vein, the pre-treatment values of the outcome variable pertain to those realised prior to the start of the project. In cases of overlapping successful projects, we adjust the ending date of the project with the highest score among several overlapping successful applications to coincide with the latest ending date of the projects. For similar reasons, the starting date of such a project is also adjusted to match the starting date of the first overlapping successful application.

After removing unusable observations, the size of the considered sample is reduced to 23,953 observations, corresponding to 12,321 projects and 22,686 firms. While the reduction in sample size may seem substantial, even compared to the relevant sample (see the last two rows of Table 1), the drop primarily stems from long projects ongoing in 2016 (43% of all FP7 funds awarded to profit-oriented firms). In contrast, only about 11% of FP7 funds are dropped from the relevant sample for all other reasons combined, with 6.6 percentage points corresponding to the necessary elimination of overlapping projects. This highlights that, aside from projects still in progress in 2016, most of the sample size reduction is attributed to the exclusion of unsuccessful applicants belonging to the control group. Indeed, out of the 15,889 firms dropped due to a lack of financial information from Orbis (rows j and k of Table 1), 13,272 have never been awarded.

[5] The elimination of Marie Skłodowska-Curie Actions and calls targeted to individuals (line (a)) also results in the exclusion of 3,227 firms, as the institutions that the researchers are affiliated with are involved in the application process.

Table 1
Summary of the sample selection

	Calls	Project proposals	Firms	Obs.	Amount (%)
FP7 profit-oriented applicants	446	48,492	61,029	172,199	100.0
Excluded calls:					
(a) Marie Curie & individuals	88	7,044	3,227	14,162	7.9
(b) Ad-hoc invitations	1	7	2	36	0.0
(c) Not research	76	4,183	2,821	11,060	5.3
Excluded project proposals:					
(d) First stage	0	3,639	2,480	7,657	0.0
(e) Ineligible	0	716	708	2,079	0.0
Excluded firms:					
(f) Firm left the project	0	19	1,172	2,743	0.0
Excluded for other reasons:					
(g) No score available for the call	9	902	710	4,166	2.7
(h) No awarded or rejected in the call	9	37	25	148	0.3
(i) Project ends $>$ 2016	32	9,067	11,309	40,259	43.0
(j) Not matched w/ Orbis	0	936	11,064	16,121	0.6
(k) No financial data in Orbis	0	930	4,825	11,314	1.2
(l) Overlapping projects	11	8,691	0	38,501	6.6
Relevant sample *(FP7 without a-f)*	281	32,884	50,619	134,462	86.8
Final sample	220	12,321	22,686	23,953	32.3

Notes: The table summarises the sample selection process for FP7 grants from the Corda database. The columns display the number of calls, project proposals, firms, and observations directly or indirectly excluded from the original sample, derived from the Corda database, when considering only profit-oriented applicants. The last column indicates the share of FP7 funds allocated to profit-oriented applicants associated with each elimination step. Rows (a) to (f) specify the number of observations removed from the sample based on the criteria outlined in the paper. The penultimate row presents the remaining relevant sample for the purpose of this study after the exclusion of rows (a) to (f). The relevant estimation sample is subsequently further reduced due to other reasons outlined in rows (g) to (l). The last line displays the final sample considered after all exclusions.

3.4 DESCRIPTIVE STATISTICS

Table 2 outlines key characteristics of projects in both the relevant (first three columns) and final estimation samples (last three columns). The success rate is approximately 20% in both samples, calculated from either the total number of projects (first row of the table) or the number of projects per call (second row). Primarily due to the inevitable elimination of overlapping and long-term projects with an expected end date beyond 2016, the final sample exhibits a significant reduction in both the number of projects per call (second row) and the number of firms per project (third row) compared to the relevant sample. The third and the fourth rows of the table reveal that awarded projects generally involve slightly more firms and are, on average, somewhat longer than rejected applications. The average grant size for research and development ranges from 3.3 to 3.9 million euros, depending on the considered sample (as indicated in the fifth row of Table 2).

The involvement of small and medium-sized enterprises (SMEs) in FP7 is substantial, with over 90% of consortia featuring at least one SME (see the bottom part of Table 2). The European Commission has indeed prioritised SME funding, aiming for at least 15% of the Cooperation programme funding under FP7 to be allocated to SMEs.[6] In pursuit of this objective, SMEs were actively encouraged to engage in the programme by offering elevated funding rates (75% instead of the standard 50%) and a broader array of funding schemes. The involvement of SMEs was consistently monitored through a series of SME Progress Reports.

The subsequent sections of the table highlight that research or higher education institutions are prevalent in around 80% of consortia, and approximately one-fifth involve public institutions. Old member states are represented in nearly all submitted applications, while about half of the consortia also include new member state countries that joined the EU after 2004. The participation of non-EU countries is less common, with associate countries involved in about one-third of the projects, and approximately 10% of applications include third countries.

Table 3 provides descriptive statistics for firms participating in FP7 based on the final estimation sample. The first column of the table displays statistics for all firms, while the second column represents the sample of firms participating in at least one awarded project. The last column presents the sample of unsuccessful applicants. The sample includes 22,686 firms, with 10,209 being awarded at least once. On average, firms in the final sample participate in one project only, a result largely influenced by excluding overlapping projects (see Subsection 3.3). Awarded firms are, on average, larger and more productive, with pre-treatment (i.e. before signing the contract or grant agreement) sales approximately 3.6 times greater than those of the control group (third row of Table 3). Successful firms employ on average over twice as many people and demonstrate about an 18% higher level of productivity compared to non-successful firms (rows 5 and 7 of Table 3).[7]

On average, both firms' sales and productivity experienced an increase during the investigated period. On the other hand, the average number of employees decreased slightly. These average trends are predominantly driven by awarded firms, as depicted in the second column of Table 3. Notably, while unsuccessful applicants also managed to augment their sales, albeit to a lesser extent, their labour productivity exhibited an opposite trend.

The significance of SMEs and old member states in our sample is evident even at the firm level. While new member states are involved in approximately half of the submitted projects (see Table 2), they only account for about 11% of the total number of firms in the sample. Concerning funds allocated for the Cooperation Programme, old member states received 24.5 billion euros, contrasting with the 1.1 billion euros received by new member states.[8] Lastly, only 6% of the firms are from associate countries, while the presence of candidate and tiers countries is negligible.

[6] Decision No 1982/2006/EC of the European Parliament and the Council of 18 December 2006 concerning the Seventh Framework Programme of the European Community for research, technological development and demonstration activities (2007-2013).

[7] Productivity is measured as the ratio of sales to the number of employees, a simple and straightforward measure that ensures the widest data availability in Orbis, allowing us to maximise the sample size.

[8] Country level funding amounts for the 2007-2014 FP7 Cooperation programme are reported in Fresco et al. (2015). The picture is similar if we consider the difference in population between old and new member states: the former countries received 608 euros per capita, compared to 105 euros per capita in the new member states. The population data to calculate per capita figures are taken from Eurostat.

Table 2
Descriptive statistics on projects

	Relevant sample			Final sample		
	All	Awarded	Rejected	All	Awarded	Rejected
Number of projects	32,884	6,840	26,044	12,321	2,995	9,326
Number of projects per call	117	24.3	92.7	56	13.6	42.4
	(220)	(36.9)	(188)	(108)	(25.1)	(84.7)
	[42]	[12]	[29]	[18.5]	[5]	[13]
Nb. of firms per project	4.1	5	3.9	1.9	2.6	1.7
	(3.1)	(4.1)	(2.7)	(1.5)	(2.1)	(1.1)
	[3]	[4]	[3]	[1]	[2]	[1]
Project duration (years)	3.8	4.6	3.5	3.6	4.4	3.3
	(1.1)	(1.1)	(1)	(1.1)	(1)	(.9)
	[4]	[4]	[4]	[4]	[4]	[3]
Grant size ('000 euros)		3,887			3,305	
		(4,382)			(3,544)	
		[2,950]			[2,682]	
Presence of SME (%)	90.6	90.1	90.7	95.3	93.1	95.9
– of research institute (%)	79.2	85	77.6	78.8	84.6	76.9
– of higher education (%)	85.8	83.5	86.4	81.3	80.7	81.5
– of public institution (%)	19.7	17.1	20.4	18.6	14.8	19.8
– of old member state (%)	99.7	99.8	99.7	99.7	99.7	99.7
– of new member state (%)	48.1	43.8	49.2	51.5	48.2	52.5
– of associate country (%)	35.1	40.3	33.7	34.5	38.2	33.3
– of candidate country (%)	10.3	9	10.7	10.6	9.1	11.1
– of tiers country (%)	11.3	11.5	11.2	10.6	11	10.5

Notes: The table provides descriptive statistics for both the relevant sample (first three columns) and the final sample (last three columns) of projects. The first and fourth columns, labelled as "All", present statistics for the entire sample. The second and fifth columns display statistics for successful applications, while the third and sixth columns present data for rejected project proposals. In the sample we consider, associate countries encompass Norway, Switzerland, and Israel; candidate countries include Albania, Iceland, Macedonia, Serbia, and Turkey; and tiers countries comprise Australia, Belarus, Canada, China, Japan, India, New-Zealand, Russia, Ukraine, and the United States of America. Standard deviations are in parentheses, and medians are in brackets.

Table 3
Descriptive statistics on firms

	All	Awarded	Rejected
Number of firms	22,686	10,209	12,477
Average number of applications by a firm	1.1	.3	.7
	(.2)	(.5)	(.5)
	[1]	[0]	[1]
Pre-treatment sales (millions of euros)	209	437	119
	(2,192)	(3,750)	(1,091)
	[3.07]	[5.1]	[2.39]
Post-treatment sales (millions of euros)	279	583	152
	(3,401)	(5,668)	(1,521)
	[3.86]	[6.16]	[2.97]
Pre-treatment number of employees	816	1,359	592
	(9,996)	(12,433)	(8,653)
	[26]	[40]	[22]
Post-treatment number of employees	789	1,188	607
	(10,401)	(12,050)	(9,288)
	[25]	[36]	[21]
Pre-treatment productivity (sales per employee)	.53	.64	.54
	(12.9)	(12.6)	(14.9)
	[.13]	[.15]	[.13]
Post-treatment productivity (sales per employee)	.63	1.06	.46
	(23.1)	(37.6)	(10.3)
	[.15]	[.16]	[.14]
SME (%)	73.9	68.2	76.5
Old member state (%)	76.4	69.9	79.8
New member state (%)	10.9	8.9	11.8
Associate country (%)	6.4	5.5	6.8
Candidate country (%)	.5	.4	.5
Tiers country (%)	.6	.6	.6

Notes: The table provides descriptive statistics for firms participating in FP7 based on our final estimation sample. The first column displays statistics for all firms, the second column represents the sample of firms participating in at least one awarded project, and the last column presents the sample of unsuccessful applicants. In the sample we consider, associate countries encompass Norway, Switzerland, and Israel; candidate countries include Albania, Iceland, Macedonia, Serbia, and Turkey; and tiers countries comprise Australia, Belarus, Canada, China, Japan, India, New-Zealand, Russia, Ukraine, and the United States of America. Standard deviations are in parentheses, and medians are in brackets.

4 Identification strategy

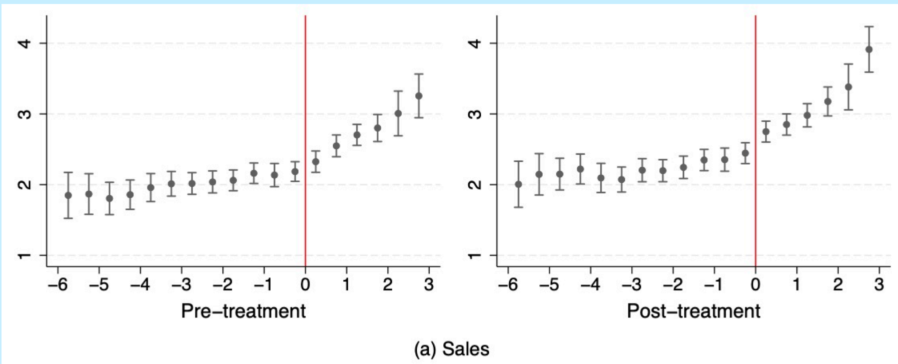
To assess the effectiveness of the FP7 funding scheme, we rely on the Regression Discontinuity Design (RDD) technique. First introduced by Thistlethwaite and Campbell (1960), the RDD is a powerful quasi-experimental method for estimating causal effects of interventions by comparing observations that are closely situated above or below a fixed cutoff or threshold along a "running variable". In our analysis, this running variable is the project's normalised score, with zero being the threshold (refer to Section 3.2 for detailed information).

The estimation of the average treatment effect hinges upon the discontinuity of the post-treatment outcome variable around the threshold. The core concept of the RDD is well illustrated in Figure 1, 2 and 3. These "regression discontinuity plots" visually depict the potential abrupt shift in the average values of outcome variables - such as sales, number of employees and productivity - precisely at the specific threshold on the running variable, providing valuable insights into causal effects near this threshold value.

The graphs on the left-hand side reveal that larger firms, both in terms of sales and number of employees, tend to secure higher scores for their project proposals. However, the correlation between firms' pre-treatment productivity and the average score they obtain for their project proposals appears less evident. Notably, for all three outcome variables, there is no discernible discontinuity around the threshold (the value zero on the X-axis). Conversely, on the right-hand side graphs, a clear discontinuity is observable precisely around the cutoff for both sales and productivity, providing a visual evidence of the positive impact of FP7 funds. However, for the number of employees, this discontinuity is either absent or noticeably less pronounced.

The estimation method of RDD is detailed in G. W. Imbens and Lemieux (2008). *Sharp* RDD approach is employed when treatment assignment is strictly determined by the threshold, such that D=1 if $S \geq S^*$, where D is the treatment dummy, S represents the score (running variable) and S^* denotes the threshold. However, in our case, this condition isn't entirely met. As explained in Section 2, main-listed consortia with scores above the threshold are not automatically guaranteed to receive the grant. In certain instances, grants may be denied to main-listed firms exceeding the technical cutoff following negotiation of the grant agreement, or some consortia may withdraw their applications for various reasons. At the same time, consortia on a reserve list might be awarded.

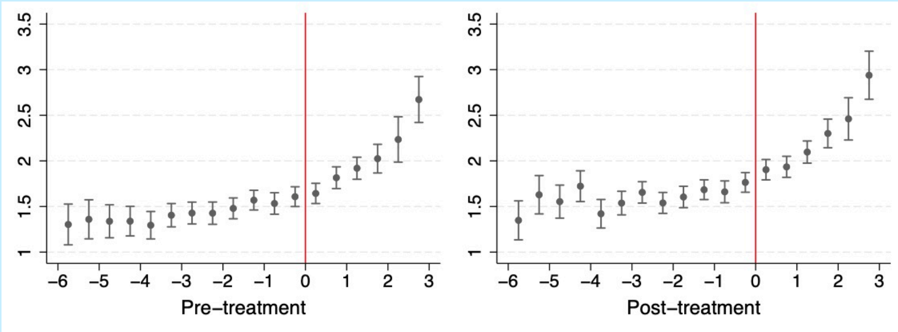
Figure 1
Regression discontinuity plot (sales)



Notes: The graph plots the average values of the logarithm of sales variable, for different values of the running variable, separately for pre-treatment (left-hand side graph) and post-treatment periods (right-hand side graph). For comprehensive technical and methodological insights into regression discontinuity plots, refer to Calonico et al. (2015).

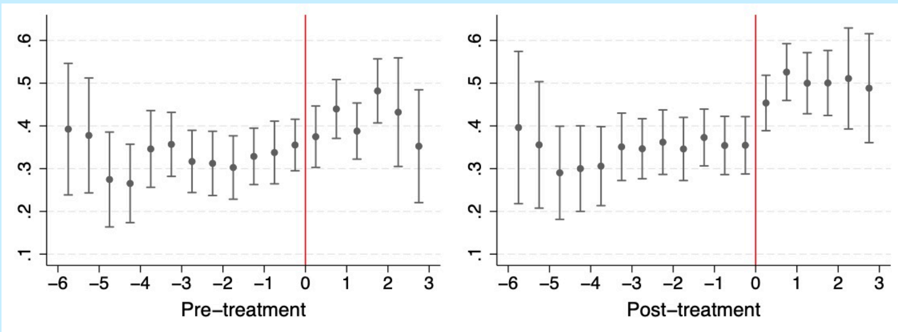
Table 4 illustrates the extent of this confounding process in our study: 3.29% of projects that scored below the technical threshold for funding are nonetheless awarded grants by the EC committee, while 3.23%, despite achieving higher scores, are ultimately rejected or withdrawn.

Figure 2
Regression discontinuity plot (number of employees)



Notes: The graph plots the average values of the logarithm of number of employees variable, for different values of the running variable, separately for pre-treatment (left-hand side graph) and post-treatment periods (right-hand side graph). For comprehensive technical and methodological insights into regression discontinuity plots, refer to Calonico et al. (2015).

Figure 3
Regression discontinuity plot (productivity)



Notes: The graph plots the average values of the logarithm of productivity variable, for different values of the running variable, separately for pre-treatment (left-hand side graph) and post-treatment periods (right-hand side graph). For comprehensive technical and methodological insights into regression discontinuity plots, refer to Calonico et al. (2015).

This confounding process in the treatment selection mechanism necessitates the employment of a *fuzzy* regression discontinuity (FRD) estimation technique. In this framework, the treatment assignment is probabilistic, and consortia just above and just below the threshold have different probabilities of receiving the grant:

$$\lim_{s\uparrow S^*} P(D=1|S=s) \neq \lim_{s\downarrow S^*} P(D=1|S=s) \tag{1}$$

As argued by G. W. Imbens and Lemieux (2008), in a FRD framework, the unconfoundness assumption is fundamentally violated. Treated and control units, despite being closely situated around the cutoff, diverge in some significant aspect related to the assignment of treatment. Despite this violation of unconfoundedness, it remains feasible to estimate a local average treatment effect (LATE). By exploiting the treatment discontinuity at the cutoff point, a consistent estimator can be derived:

$$\tau_{FRD} = \frac{\lim_{s\downarrow S^*} E(Y|S=s) - \lim_{s\uparrow S^*} E(Y|S=s)}{\lim_{s\downarrow S^*} E(D|S=s) - \lim_{s\uparrow S^*} E(D|S=s)} \tag{2}$$

The ratio in eq. 2 represents the average treatment effect on *compliers*, i.e. firms that are awarded when their project proposals score above the threshold, and those that do not receive grants if their score falls below it.

Table 4
Expert scores, granted and non-granted projects

	Not granted	Granted	Total
Score $<$ threshold	8,928	405	9,333
	(72.46)	(3.29)	(75.75)
Score $>$ threshold	398	2,590	2,988
	(3.23)	(21.02)	(24.25)
Total	9,326	2,995	12,321
	(75.69)	(24.31)	(100.00)

Notes: The table displays the count and the frequency (parentheses) of both awarded and not awarded project proposals categorized according to whether their score exceeded or fell below the threshold. Own calculations based on the Corda database.

The LATE in a FRD is obtained through a two stages procedure. In the first stage, the treatment dummy (D_i) is regressed on an indicator denoting whether the project in which firm i participates receives a score above the threshold ($1[S_i \geq S^*]$), a polynomial of the obtained score ($\sum_{j=1}^{J} \mu_j S_i^j$), their interaction term, and a set of firm and project-level covariates likely to influence treatment assignment (X_i'):

$$D_i = \alpha 1[S_i \geq S^*] + \sum_{j=1}^{J} \mu_j S_i^j + \sum_{j=1}^{J} \phi_j S_i^j * 1[S_i \geq S^*] + \delta X_i' + \epsilon_i \tag{3}$$

Once the vector of propensity scores is obtained, the outcome variable (Y_i) is regressed on the propensity score ($\hat{D}_i$) and the same covariates as in the first stage (excluding the dummy indicating that the score obtained exceeds the threshold):

$$Y_i = \beta \hat{D}_i + \sum_{j=1}^{J} \nu_j S_i^j + \sum_{j=1}^{J} \varphi_j S_i^j * 1[S_i \geq S^*] + \lambda X_i' + u_i \tag{4}$$

In this framework, the dummy variable indicating whether the score is above the threshold ($[S_i \geq S^*]$) effectively serves as an instrument for treatment assignment. As such, the FRD can be interpreted as a type of Wald estimator, where the causal effect is identified using this instrumental variable approach.

We fit the model in eq. 3 and 4 using local-polynomial regressions. The optimal order of the polynomial (J) is based on the estimated Average Mean Squared Error (AMSE) for the bias-corrected fuzzy estimator.

The estimation sample is restricted to observations with scores lying within a specified bandwidth around the threshold. The selection of the optimal bandwidth is a trade-off between bias and variance. Too narrow a bandwidth can lead to high variance and instability in estimates, while an excessively wide bandwidth can introduce bias by including observations too far from the threshold. In our baseline specification, we apply the two-sided version of the Mean Squared Error optimal (MSE-optimal) bandwidth selector proposed by G. Imbens and Kalyanaraman (2012), allowing for different bandwidths on the two sides of the cutoff point. Within this range of scores, we apply a triangular weighting function, whereby observations receive linearly decreasing weights depending on their proximity to the threshold. As robustness checks, we use alternative bandwidth selection and weighting methods (see Section 6).

In our heterogeneity analysis, we stratify the sample based on specific firm and project characteristics to assess the effectiveness of FP7 for these selected subgroups. Let G_i a binary variable indicating whether firm i belongs to a subgroup, such as SMEs, the service sector, or projects with durations exceeding the median. In both the first and second stage equations, we interact all controls (excluding covariates X_i'), with G_i and $(1-G_i)$. For instance, the indicator for "above the threshold" in eq. 3 ($\alpha 1[S_i \geq S^*]$) is substituted by $\alpha_0 1[S_i \geq S^*]G_i + \alpha_1 1[S_i \geq S^*](1-G_i)$. We adopt the same approach for the polynomial of the obtained score, its interaction with the "above the threshold" indicator, and the corresponding explanatory variables in the second stage regression. The estimated parameters stemming from the interaction term $\hat{\beta}_0\hat{D}_i + \hat{\beta}_1(1-\hat{D}_i)$ reflect the heterogeneous impact of FP7 on the two subgroups $G_i = 0$ and $G_i = 1$.

However, this strategy does not guarantee that the two subgroups separated by a specific criterion are homogeneous according to other confounding factors. For instance, longer projects might primarily be undertaken by larger and more productive firms. Therefore, the heterogeneous impact attributed to project length might inadvertently reflect the heterogeneous impact associated with firm size and productivity rather than the intended variability based on project characteristics.

To mitigate this concern, we combine the FRD approach with an inverse propensity score weighting (IPW) method. This enhanced identification strategy involves an additional preliminary step, in which a binary probit model is estimated to determine the conditional probability that firm i belongs to the subgroup under investigation given a set of covariates:

$$P\left(G_i = 1 | X_i, Z_i\right) = \Phi\left(\eta X_i + \upsilon Z_i\right) \tag{5}$$

where X_i is the same set of controls as previously defined, Z_i is a vector of binary variables covering all subgroups considered *except the one under examination*, and Φ stands for the Cumulative Distribution Function (CDF) of the standard normal distribution. This estimation is performed on the restricted sample close to the threshold using predetermined bandwidths as described earlier.

Subsequently, we estimate the FRD model in eq. 3 and 4 by weighting the observations with the inverse of the propensity scores obtained from the probit equation. Specifically, firms belonging to the specific subgroup receive weights of $1/\hat{P}$, while those in the other group are assigned weights of $1/(1-\hat{P})$.[9] This inverse propensity weighting (IPW) scheme mitigates confounding by assigning greater weight to observations that were challenging to predict, thereby enhancing covariate balance between the subgroups $G_i = 0$ and $G_i = 1$ (Rosenbaum and Rubin (1985)). Importantly, this strategy ensures that the estimated heterogeneous effects are attributable to the subgroups under investigation, independent of other confounding factors (including other subgroups) that are controlled for.[10]

[9] Due to the sampling variability inherent in propensity score re-weighting, standard errors are computed using bootstrap estimation.

[10] The conventional IPW method does not necessitate adjustment for the same set of covariates (X_i and Z_i) in eq. 3 and 4. By incorporating these controls into the FRD equations, we account for the same covariates via two channels. This method is commonly referred to in the literature as "doubly robust". One of its primary advantages lies in its ability to yield consistent estimates even if either the first model (probit) for the propensity scores or the outcome regression model (FRD), or both, are correctly specified (Glynn and Quinn (2010)).

5 Estimation results

We fit the FRD model outlined in eq. 3 and eq. 4 using local-polynomial regressions. The definition of the post-treatment and pre-treatment periods, along with the selection criteria for the treated and control groups (as detailed in Section 3.3) ensure two crucial conditions: (i) the outcome and pre-treatment variables remain unaffected by the direct impact of the fund; and (ii) the control group is free from the influences of any prior or concurrent awarded projects.

The main outcome variables of interest are the logarithm of sales, number of employees, and productivity after the end of the project. To have comparable output variables we first remove aggregate shocks by regressing out the effects of country×sector×year dummies using OLS on the whole sample of firms in Orbis. Subsequently, we compute the three-year average value of the outcome variables clean from aggregate effects during this post-treatment period.[11] Likewise, the pre-treatment values of the outcome variables are computed as the three-year averages of these variables prior to the start of the project.

Additional controls (X_i') in eq. 3 and eq. 4 include various firm- and project-level variables. The inclusion of covariates in RDD does not compromise the validity of the identification strategy (G. W. Imbens and Lemieux (2008), Lee and Lemieux (2010)). However, it can significantly enhance estimation precision. This is particularly true for pre-treatment realisations of the outcome variable, which are usually highly correlated with the dependent variable. Additionally, we account for whether the consortium includes research institutions, higher education centers, or public institutions, as well as whether at least one of the participants is from New Member States or countries categorised as associate, candidate, or tiers countries.

Table 5 presents the FRD estimates, where the odd columns show the results of the first-stage regressions, and the even columns display the results of the second-stage regressions for different output performance variables.

The first-stage regression is a linear probability model, with the dependent variable representing a binary indicator for winning a research grant. Given that over 93% of project proposals surpassing the threshold are awarded, it is unsurprising that the dummy variable indicating whether the score exceeds the threshold significantly influences the probability of receiving the grant. Other control variables in the regression reflect their combined impact on the likelihood of dropping out from the main-listed group and the systematic choices of the EC when selecting projects from the reserve list in scenarios where main-listed projects are replaced by reserve-listed ones, or if the EC increases the number of selected projects. Results suggest that involvement of a research institution, higher education, an associate country, or a new member state in the consortium slightly decreases the dropout probability and increases the probability of being selected from the reserve list, while participation of a public institution or a candidate country slightly have the opposite effect. Nonetheless, all coefficients are small in magnitude, indicating that the economic significance of these systematic dropouts or EC choices is minimal.

The second-stage results of the FRD estimations are displayed in the even columns of Table 5. The estimated coefficients of pre-treatment variables are statistically significant, indicating the persistence of firm performance measures over time. The coefficient of the treatment variable ”award” represents the Local Average Treatment Effect (LATE), reflecting the influence of the fund. The findings offer compelling evidence that receiving EU funds for research and innovation boosts post-treatment sales by 18.2 percentage points and labour productivity by 18.5 percentage points on average. However, the grant appears to have no significant effect on the number of employees. In other words, the results suggest that grants enhance firms' productivity and consequently their sales even after project completion. However, firms appear to face growth barriers that prevent them from scaling up production in the medium term, even after completing a successful innovation project partially financed by European funds.

Table 6 explores the impact of FP7 RD grants on additional performance measures, including added value, material costs, wage bill, total assets, and leverage. The table includes three specifications: the baseline model (row a), a model without pre-treatment variables (row b), and a model excluding all covariates (row c). The first three variables — added value, material

[11] In instances where a full three-year period is unavailable due to missing data or because our sample ends, we utilise the maximum number of years for which data are available.

Table 5
Impact of FP7 research grants on firms' post-treatment performance

	Sales		Nb. of employees		Productivity	
	First stage	Second stage	First stage	Second stage	First stage	Second stage
Award		0.182***		-0.073		0.185***
		(0.053)		(0.054)		(0.044)
Above thold. (score $\geq$ 0)	0.757***		0.814***		0.788***	
	(0.011)		(0.014)		(0.014)	
Cooperation with:						
Research inst.	0.057***	0.029	0.077***	0.016	0.074***	0.048*
	(0.009)	(0.033)	(0.013)	(0.030)	(0.012)	(0.026)
Higher edu.	0.017**	0.055**	0.017*	0.090***	0.018*	0.013
	(0.007)	(0.027)	(0.009)	(0.025)	(0.009)	(0.022)
Public inst.	-0.030***	0.018	-0.038***	0.066**	-0.033***	-0.054**
	(0.009)	(0.032)	(0.012)	(0.033)	(0.012)	(0.026)
Associate country	0.027***	0.027	0.031***	0.020	0.033***	-0.008
	(0.007)	(0.027)	(0.009)	(0.026)	(0.009)	(0.021)
Candidate country	-0.031***	0.016	-0.027*	-0.003	-0.026*	0.023
	(0.012)	(0.036)	(0.015)	(0.038)	(0.015)	(0.029)
Tiers country	-0.015	0.089*	-0.018	0.077*	-0.020	0.040
	(0.012)	(0.046)	(0.015)	(0.044)	(0.015)	(0.035)
New member state	0.022***	0.021	0.031***	-0.036	0.028***	0.007
	(0.007)	(0.024)	(0.008)	(0.023)	(0.008)	(0.019)
Additional covariates:						
Pre-treatment variables	Yes	Yes	Yes	Yes	Yes	Yes
Polynomial of the score	Yes	Yes	Yes	Yes	Yes	Yes
Effective number of obs.		9,519		6,197		6,668
Bandwidth		5.0		2.4		2.8
Order of the polynomial		1		1		1

*Notes: The table presents the results derived from FRD estimates. The data is drawn from Corda and Orbis. Odd columns exhibit the outcomes of the first-stage regressions, while even columns depict the results of the second-stage regressions for various output variables (sales, number of employees, and productivity, all expressed in logs). For a detailed explanation of the dependent variables and the regressors, please refer to the paper. Associate countries include Norway, Switzerland, and Israel; candidate countries include Albania, Iceland, Macedonia, Serbia, and Turkey; while tiers countries comprise Australia, Belarus, Canada, China, Japan, India, New-Zealand, Russia, Ukraine, and the United States of America. The table also provides information on the optimal bandwidth around the threshold, the effective number of observations within the optimal bandwidth, and the optimal order of the local polynomial used in the model. Significance levels are denoted as follows: *** significant at 1%, ** significant at 5%, * significant at 10%.*

costs, and wage bill — are derived from detailed firm income statements, which have more missing observations compared to basic variables such as sales and employment. Consequently, the sample size, particularly near the treatment threshold, is smaller, limiting the precision of the estimates. Despite this limitation, the results reveal a significant positive impact of the grants on added value, material costs, and the wage bill, underscoring the role of public funding in expanding resource utilisation and operational scale. Additionally, we observe a significant increase in firms' total assets, indicating that grant recipients make investments during the research project. However, there is no significant effect on leverage ratios, suggesting that firms do not increase their reliance on external financing. These findings provide further evidence that the productivity improvements associated with the grants are driven by tangible upgrades and resource expansions rather than mechanisms such as increased markups.

Table 6
Impact of FP7 research grants on other performance measures

	Added value	Material cost	Wage bill	Total assets	Leverage
(a) Baseline	0.131**	0.225**	0.063	0.224***	0.013
	(0.066)	(0.102)	(0.061)	(0.061)	(0.031)
(b) W/o pre-treatment variables	0.303**	0.348*	0.302**	0.317**	0.049
	(0.153)	(0.184)	(0.127)	(0.143)	(0.035)
(c) W/o covariates	0.279*	0.355*	0.288**	0.306**	0.049
	(0.154)	(0.184)	(0.128)	(0.143)	(0.035)

*Notes: The table presents the second-stage regression results derived from FRD estimates for other performance measures (added value, material cost, wagebill, total assets, leverage, all expressed in logs). The data is drawn from Corda and Orbis. Significance levels are denoted as follows: *** significant at 1%, ** significant at 5%, * significant at 10%.*

6 Validation and Robustness

Table 7 presents various robustness checks with alternative specifications and technical assumptions, as well as placebo regressions aimed at assessing the validity of the FRD approach.

The first row (a) replicates the baseline estimate presented in Table 5, incorporating linear impacts of the score on the probability of being awarded in eq. 3, and on the outcome variable in eq. 4. In the subsequent two rows (b) and (c), we depart from the AMSE-optimal polynomial order and manually set the order of the polynomial J to 2 and 3, respectively. Increasing the polynomial order J diminishes the precision of estimation. With J=3, while the point estimates remain close to those obtained with lower polynomial orders, the estimated impact of the grants on sales is no longer statistically significant at the 10% level.

Rows (d) and (e) present FRD estimates using alternative kernel specifications, specifically Epanechnikov or uniform, instead of the triangular kernel used in the baseline specification. Specification (f) uses the bias-corrected optimal bandwidth selector proposed by Calonico et al. (2014) (CCT) rather than the version proposed by G. Imbens and Kalyanaraman (2012) (IK). Results from these alternative specifications closely align with our baseline findings.

Row (g) reports the results of a specification without pre-treatment variables, while row (h) omits any covariate X_i'. Eliminating the pre-treatment values of the outcome variable from the equations yields less precise estimates, especially for sales. The other controls show no substantial impact on the results. Nonetheless, even for sales, the estimated impact of the funds remains statistically significant at the 10% level, with the point estimate being close to the baseline result.

The remaining rows (i) to (m) of Table 7 are dedicated to validating whether our research design is appropriate for an RDD (and FRD) approach. The first fundamental assumption we investigate is whether there is any sign of deliberate manipulation of the running variable near the cutoff point. Such manipulation can take various forms, such as strategic behaviour of firms or individuals to manipulate the scores to ensure they fall on a specific side of the cutoff.[12]

This requirement appears to be satisfied within our framework for several reasons. Firstly, the precise threshold is not predetermined, preventing applicants from strategically aiming for a particular score above or below the threshold. Secondly, applicants are motivated to achieve the highest score possible as their primary incentive is to secure the award. Thirdly, the scoring and selection process involves independent external experts, ensuring impartiality in the evaluation.

To further investigate potential manipulation of the scores, we visually depict and formally test the discontinuity in the density function of the scores around the threshold. The underlying reasoning is that if manipulation is present, we expect an abnormal concentration of observations just above or below the cutoff point. The histogram of normalised scores is depicted in Figure 4.

The left-hand side graph (a) shows that although there is no prescribed rounding rule for scores, experts tend to assign scores that are multiples of 0.5. In a few exceptional cases, experts provide scores within the 0 to 100 range. However, after the normalisation process, these scores are converted into fractional numbers (see Section 3.2), resulting in smaller bars on the graphs, primarily clustered around the 0 threshold. These smaller bars also include scores assigned by experts seeking to differentiate points around the thresholds, particularly in situations involving numerous competitive participants in a call. Most importantly, however, we do not observe a clustering of observations around the threshold, indicating that manipulation is not a significant concern. The right-hand side graph (b) illustrates the same histogram, where scores are rounded to the nearest multiple of 0.5, effectively mitigating discrepancies between scoring methods across different calls.[13] Notably, the adjusted scores also demonstrate an absence of concentration around the threshold.

[12] An illustrative example of manipulation occurs when households intentionally underreport their income or reduce their work hours (and therefore their revenues) to qualify for a welfare programme offering financial aid to households with incomes below a specific threshold.

[13] With these alternative normalized scores, the threshold of 0 still effectively distinguishes between main-listed projects and those either placed on a reserve list or rejected.

Table 7
FP7 research grants and post-treatment performance: alternative specifications

	Sales	Nb. of employees	Productivity
Robustness checks			
(a) Polynomial order: 1	0.182***	-0.073	0.185***
	(0.053)	(0.054)	(0.044)
(b) Polynomial order: 2	0.243***	-0.075	0.216***
	(0.076)	(0.062)	(0.054)
(c) Polynomial order: 3	0.254	-0.139*	0.230***
	(0.188)	(0.078)	(0.070)
(d) Epanechnikov kernel	0.172***	-0.075	0.182***
	(0.053)	(0.053)	(0.044)
(e) Uniform kernel	0.149***	-0.101*	0.193***
	(0.054)	(0.059)	(0.047)
(f) CCT Bandwidth	0.206***	-0.056	0.158***
	(0.059)	(0.046)	(0.036)
(g) W/o pre-treatment variables	0.210*	0.006	0.164***
	(0.108)	(0.103)	(0.060)
(h) W/o covariates	0.194*	-0.008	0.162***
	(0.109)	(0.103)	(0.060)
(i) Score rounded	0.202***	-0.043	0.151***
	(0.058)	(0.046)	(0.035)
Placebo regressions			
(k) Cut-off point: -0.5	0.216	2.308	-0.037
	(0.200)	(5.394)	(0.607)
(l) Cut-off point: 0.5	-0.199	0.430	-0.453
	(0.180)	(0.311)	(0.930)
(m) Pre-treatment dep. var.	0.120	-0.191	0.023
	(0.125)	(0.209)	(0.054)

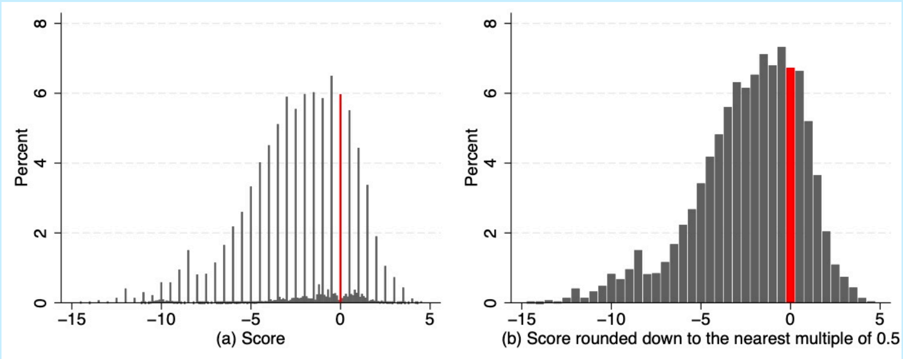
*Notes: Each row represents results from a distinct FRD regression. Dependent variables are in log. Row (a) corresponds to the baseline estimate in Table 5. Rows (b) and (c) alter the local polynomial order from the baseline of 1 to 2 and 3, respectively. Rows (d) and (e) present FRD estimates using different kernel specifications. Row (f) uses the bias-corrected optimal bandwidth selector proposed by Calonico et al (2014). Row (g) reports results from a specification without pre-treatment variables, while row (h) omits any covariates. In specification (i), the score is rounded down to the nearest multiple of 0.5. Rows (k) and (l) display two placebo regressions with discontinuity thresholds set at -0.5 and 0.5. Lastly, row (m) presents an additional placebo regression performed on pre-treatment output variables. Significance levels are denoted as follows: *** significant at 1%, ** significant at 5%, * significant at 10%.*

We formally test the manipulation of the running variable using the method proposed by Frandsen (2017). This test remains consistent even when the running variable is discrete. In contrast to the standard test by McCrary (2008) for continuous running variables, Frandsen (2017) indirectly examine the smoothness condition of the discrete running variable by analysing its probability mass function. A bandwidth parameter, denoted as *k*, the degree to which we scrutinise the density function around the cutoff. Even with a bandwidth as low as 0.02, we find no evidence to reject the null hypothesis of a smooth density function at the cutoff value, with a p-value of 0.105. As we increase *k*, the p-value rises further, reaching 0.322 when $k = 0.03$, and continuing to increase with higher *k* values. Consequently, the formal test confirms the absence of manipulation in the scores.

As a robustness check, we conduct the same FRD regressions using the scores rounded to the nearest multiple of 0.5. The results, outlined in row (i) of Table 7, corroborate our baseline findings.

The second crucial requirement for a valid RDD setup is the occurrence of a discontinuity in the outcome variable precisely at the threshold, without any other disruptions along the running variable. This condition ensures the integrity of the design's causal inference. Rows (k) and (l) formally examine the presence of discontinuities at fictitious thresholds. In these placebo regressions, we manually set the cutoff points to -0.5 and 0.5 of the normalised score and perform the same FRD regressions. For all outcome variables, the estimated treatment effects are not statistically significant at these alternate thresholds, offering compelling evidence supporting the validity of our research design.

Figure 4
Score



Notes: The graph depicts the histogram of scores obtained for the project proposals. In both graphs, scores are normalised, with the technical cutoff threshold set to 0. Additionally, on the right graph, scores are rounded to the nearest multiple of 0.5.

The final falsification tests examine the impact of the treatment on variables not expected to be influenced by it, such as the pre-treatment values of the outcome variables. Visual evidence in Figure 1, 2 and 3 in Section 4 illustrates the absence of discontinuity around the threshold for the pre-treatment variables. Additionally, we formally test this by applying our baseline specification to the pre-treatment output variables as dependent variables. The results, displayed in row (m) of Table 7, reveal no discontinuity for these falsification outcome variables. Alongside the robustness checks and other placebo regressions previously presented, our analysis provides robust evidence that European research grants significantly impact awarded firms' post-treatment sales and labour productivity.

7 Heterogeneity analysis

Table 8 presents the heterogeneity analysis of FP7 grants' impact on firms' post-treatment performance measures. Each row of the table displays results obtained from distinct fuzzy RDD regression specifications for various dimensions of heterogeneity. The estimation approach, outlined in detail in Section 4, guarantees that the heterogeneous effects attributed to the subgroups under examination are isolated from other potential confounding factors, including those related to other subgroups. In the left panel of the table, the dependent variable is sales, while in the right panel, it is productivity.[14] The first two columns in each panel display the estimated treatment effects separately for the two groups distinguished by the specific dimension, while the third column presents the difference between these two treatment effects.

Our results indicate that research and innovation grants are notably effective in enhancing the performance of SMEs (see row (a) of Table 8). Conversely, the treatment effect of research grants on large firms is statistically insignificant, with the point estimate approaching zero. This pattern aligns with established research in the field (Lach (2002), González et al. (2005), Bronzini and Iachini (2014), Bronzini and Piselli (2016), Pereira et al. (2018)), which consistently shows that public funding has a greater influence on small firms' research and innovation activities due to their typically tighter financial constraints. Small firms often lack the collateral required to secure loans, making grants crucial in facilitating their pursuit of otherwise financially challenging research and innovation endeavours. In contrast, large firms are generally better positioned to access funding from financial markets for risky innovation projects. As argued by Lach (2002), large firms frequently receive grants or subsidies for projects that they would have pursued even in the absence of public funding.[15]

Apart from firm size, the pre-treatment productivity of firms is also a crucial factor influencing the effectiveness of research grants. Consistent with prior research (e.g., Vanino et al. (2019)), we observe that less productive firms derive significantly greater benefits from research and innovation grants compared to more productive firms (as shown in row (b) of Table 8).[16] Less productive firms may exhibit reluctance to invest in risky projects due to financial constraints or fear of failure. Grants serve as a safety net by covering a portion of costs, thereby encouraging these firms to pursue riskier yet potentially high-reward research activities. This engagement enables them to narrow the productivity gap with more successful firms over time.

The significant impact of financial constraints on the effectiveness of public RD support is also evident at the systemic level. In rows (k) and (l) of Table 8, we explore country-level heterogeneity using two measures of credit accessibility. The first measure, "Easier access to funds," is based on the "Ease of access to loans" indicator from the World Economic Forum's Global Competitiveness Index. The second measure, "Easier access to credit," is derived from the "Getting credit" indicator in the World Bank's Doing Business Report. In both cases, we divide the sample based on whether the access to credit is below or above the median value of the indicator. Consistent with previous research (Hyytinen and Toivanen (2005), Czarnitzki and Licht (2006)), our analysis highlights a greater treatment effect for firms operating in countries characterised by more substantial capital market imperfections.

The second block of Table 8 examines the sectoral dimension of the effectiveness of research grants. Specifically, in row (c), we explore the difference between the manufacturing and the service sector. From a theoretical standpoint, the potentially diverse impact of public RD support can be viewed from two perspectives. On one hand, based on the credit constraint argument discussed earlier, manufacturing firms may find it easier to secure private financing due to their substantial tangible assets that

[14] We refrain from presenting results for the number of employees, as the effects are statistically insignificant across all cases.

[15] It is important to highlight that SMEs receive a larger share of the total project cost compared to larger firms (75%, instead of the standard 50%), which may partly drive the observed heterogeneous effect. Additionally, larger firms may have more concurrent research projects, so the financing of a single project by EU grants might have a relatively lower impact on their overall performance. Unfortunately, our dataset does not allow us to control for the exact grant amounts received by individual firms. While the total cost of each research project is included in the dataset, this amount is allocated at the consortium level and not distributed among the individual participants. Therefore, we lack detailed information on how much specific firms received from the grants and how much they contributed from their own budgets.

[16] We classify a firm as highly productive if its pre-treatment productivity exceeded the median.

Table 8
Heterogeneity in the impact of FP7 research grants on firms' post-treatment performance

	Sales			Productivity		
	No	Yes	Diff.	No	Yes	Diff.
Firm charactersistics						
(a) SME	0.038	0.267***	0.228**	0.037	0.245***	0.207**
	(0.089)	(0.067)	(0.108)	(0.073)	(0.060)	(0.095)
(b) High productivity	0.307***	0.077	-0.230**	0.280***	0.059	-0.221**
	(0.082)	(0.073)	(0.109)	(0.075)	(0.064)	(0.102)
Sector						
(c) Services†	0.252***	0.089	-0.164	0.170**	0.107	-0.063
	(0.091)	(0.093)	(0.128)	(0.074)	(0.086)	(0.112)
(d) Technology intensive†	0.064	0.266***	0.202	0.031	0.217***	0.186
	(0.110)	(0.078)	(0.133)	(0.101)	(0.063)	(0.118)
Project characteristics						
(e) Longer project	0.075	0.244***	0.168	0.136	0.168**	0.032
	(0.097)	(0.082)	(0.124)	(0.089)	(0.069)	(0.113)
(f) Lot of participants	0.205**	0.151**	-0.055	0.203***	0.161***	-0.042
	(0.084)	(0.073)	(0.110)	(0.070)	(0.062)	(0.093)
(g) Incl. research institute	0.240	0.180***	-0.060	0.253*	0.186***	-0.067
	(0.174)	(0.058)	(0.184)	(0.138)	(0.050)	(0.147)
(h) Incl. higher education	0.281**	0.201***	-0.080	0.157	0.187***	0.030
	(0.135)	(0.064)	(0.148)	(0.120)	(0.054)	(0.130)
(i) Incl. public institution	0.224***	-0.022	-0.246*	0.199***	0.151	-0.048
	(0.063)	(0.131)	(0.144)	(0.053)	(0.115)	(0.127)
(j) Incl. non-EU firms‡	0.246***	0.151*	-0.095	0.184***	0.132*	-0.053
	(0.072)	(0.085)	(0.111)	(0.064)	(0.068)	(0.093)
Country / market characteristics						
(k) Easier access to funds	0.193***	0.084	-0.109	0.201***	0.080	-0.121
	(0.062)	(0.101)	(0.118)	(0.055)	(0.094)	(0.110)
(l) Easier access to credit (DBI)	0.259***	0.088	-0.171	0.205***	0.174*	-0.031
	(0.068)	(0.100)	(0.121)	(0.053)	(0.097)	(0.110)
(m) Capacity to innovate	0.116	0.289**	0.173	0.159***	0.317***	0.159
	(0.075)	(0.123)	(0.143)	(0.058)	(0.094)	(0.111)
(n) High market concentration	0.190***	0.356***	0.166	0.145**	0.332***	0.188*
	(0.066)	(0.108)	(0.127)	(0.060)	(0.093)	(0.109)

*Notes: The table displays the heterogeneity analysis of the impact of FP7 research grants on firms' post-treatment log sales and log productivity. See Section 4 for methodological details. Standard errors are bootstrapped with 1,000 replications. † Only manufacturing and services. ‡Only firms from EU countries are considered. *** significant at 1%, ** significant at 5%, * significant at 10%.*

can serve as collateral (Almeida and Campello (2006)). Therefore, we anticipate a higher treatment effect on research and innovation funds for the service sector, where collateral is scarcer. On the other hand, since manufacturing RD projects tend to be more technology-based and inherently riskier (Morrar (2014)), the presence of public funding should yield more beneficial outcomes for manufacturing firms. Our findings support the predominance of the latter argument, as only manufacturing firms exhibit a positive and statistically significant treatment effect on both sales and productivity. This suggests that the riskier innovation landscape in the manufacturing sector amplifies the impact of public RD support.

The link between technology, the inherent risks associated with RD, and the availability of public funds is also evident when considering the heterogeneity associated with the technological intensity of the industry. We define sectors as technology-intensive if they belong to high or medium-high technology manufacturing or high-tech or other knowledge-intensive service sectors, according to the classification by De-Miguel-Molina et al. (2012). Past research has yielded mixed results on this topic. Earlier studies, such as González and Pazó (2008) and Becker and Hall (2013), found that RD subsidies are more effective for firms operating in low-tech sectors. The authors argue that high-tech firms are more capable of replacing public funding with internal resources, allowing them to continue their research activities even in the absence of public funding. However, a more recent study by Vanino et al. (2019) contradict these findings, demonstrating that public RD funding is more effective for more technology- or knowledge-intensive firms. Our findings align with this latter perspective. As depicted in row (d) of Table 8, the treatment effect is positive only for more technologically-intensive firms. This is likely due to the inherently riskier nature of the research projects these firms undertake. High-tech firms typically engage in frontier research and make investments that carry higher risks. These projects are also more prone to asymmetric information problems when seeking external financing. As a result, public funding for RD enables these high-risk projects to be launched, which would otherwise be abandoned.

Examining the heterogeneity in treatment effects across various project-level variables reveals several dimensions of interest. In row (e), we analyse the differences in treatment effects related to the project's duration. The length of a project is closely tied to the notion of underlying risk associated with RD. RD typically involves a long, multi-stage time lag between initial cash outlays and eventual returns (Bakker (2013)). Generally, longer projects represent riskier investments, making them more challenging to finance through capital markets. Consequently, public financing is expected to have a greater impact on longer (and riskier) projects compared to smaller-scale ones. Our evidence supports this theoretical prediction, as projects exceeding the median duration display a larger treatment effect.

The remainder of the heterogeneity analysis based on project characteristics examines various dimensions related to the size and composition of consortia applying for FP7 funds. As discussed in Section 2, the cooperation programme of FP7 primarily aims to foster collaborative research among profit-oriented enterprises, as well as between industry and academia or public institutions. A major advantage of collaborative research is the ability to overcome significant cost barriers that might otherwise hinder RD investment. Collaborative efforts allow firms to pool resources and share costs, reducing redundancy by avoiding duplication of similar RD activities. Partnerships also enhance opportunities for learning from partners, thereby improving RD project outcomes and subsequently firm performance (Belderbos et al. (2004), Okamuro (2007)). However, there are potential downsides, such as the risk of free-riding, where firms benefit from each other's RD without contributing equally (Kesteloot and Veugelers (1995)). Additionally, a large number of partners can negatively impact the outcome of RD collaborations by increasing coordination, monitoring, and control costs (Morandi (2013)). Against this background, we assess, in row (f) of Table 8, whether public funding for RD is more effective for larger consortia. Our findings show positive and statistically significant treatment effects both below and above the median number of participants, with no significant difference between these effects. Consistent with Vanino et al. (2019), we conclude that the number of participants does not significantly influence the effectiveness of public funds for RD.

Previous studies indicate that research cooperation with universities, research institutions, or public bodies fosters knowledge spillovers and enhances firms' RD capabilities. These collaborations provide firms with access to valuable external knowledge, thereby boosting their innovation potential and market competitiveness (Cassiman and Veugelers (2002), Belderbos et al. (2004)). Contrary to expectations, however, Vanino et al. (2019) find that public funds for RD have a larger impact on firms participating in projects without a university partner. The authors suggest that non-university projects may be closer to market, leading to stronger commercial impacts on participating firms in the short and medium term. For the most part, our results are inconclusive regarding the importance of consortium composition. The treatment effect is consistently statistically significant for both sales and productivity in projects involving a research institute or a higher education institute (rows (g) and (h)). However, the LATE for projects without a research institute is also significant at the 10% level for productivity, and the point estimate is higher than for projects with a research institute, although the difference is not statistically significant. Similarly, projects without the involvement of a higher education institute are significantly impacted by research funding, with point estimates higher than those for projects involving a higher education institute, but again, the difference is not statistically significant. The only clear result related to consortium composition concerns the inclusion of a public institution. Results shown in row (i) suggest that firms in consortia without a public institution tend to perform better in terms of post-treatment outcomes. This may be because projects involving a public institution often pursue broader objectives beyond merely improving private firms' performance, potentially encompassing social purposes.

The FP7 programme encouraged the inclusion of non-EU countries to foster global collaboration (see Section 2). Including non-EU partners in FP7 projects provides EU firms with valuable opportunities to access diverse pools of knowledge, innovative practices, and new markets, ultimately enhancing their long-term competitiveness and innovation capacity. Such international collaborations are also seen as crucial for addressing global challenges and driving technological advancements on a broader scale. While this cooperation is generally seen as beneficial, our findings indicate that the impact of EU funds on private firms' performance tends to be higher when the consortium does not include non-EU partners, although the difference is not statistically significant (row (j) of Table 8). One potential reason for this could be the increased costs associated with coordinating and monitoring projects involving non-EU countries. These additional logistical and administrative burdens can dilute the effectiveness of the funding and slow the pace of research and development activities. Furthermore, differing regulatory environments and strategic priorities between EU and non-EU countries might create friction, making it harder to achieve project goals efficiently. However, it is difficult to pinpoint the precise cause of the somewhat lower impact of EU funds for consortia including non-EU firms from our data, so this interpretation remains speculative.

Lastly, we delve deeper into the heterogeneity of the impact of FP7 funds at the systemic level, focusing on two additional dimensions. The first dimension is related to the probability of project success. Specifically, we examine whether being located in a country with a high propensity for innovation influences firms' post-treatment performance differently. Using data from the World Economic Forum's Global Competitiveness Index, we split the sample into countries below and above the median score on the "capacity to innovate" indicator. Theoretically, being in a favourable innovation environment could amplify the benefits for FP7 recipients due to positive knowledge spillovers (Feldman (1999)). Our results, presented in row (m) of Table 8, highlight the significance of the environment in which FP7 beneficiaries operate. We observe a positive and significant treatment effect on sales only for firms in countries more conducive to innovation. For productivity, the impacts are positive and significant in both more and less favourable locations, but the treatment effect is significantly greater in areas more prone to innovation. This indicates that in environments favourable to research, where the probability of success is higher, FP7 funds are more effective.

The second dimension of interest at the systemic level is the interaction between market structure and the effects of public funding for RD. The relationship between competition and innovation has long been a central topic in industrial economics, with economic theories and empirical findings often contradicting each other. Foundational theories on this relationship date back to Schumpeter (1942) and Arrow (1962). Schumpeter argued that increased competition reduces the profitability of innovation because the incentive depends on the rent a firm can collect, which decreases as competition accelerates the arrival of subsequent innovations from rival firms. Conversely, Arrow contended that high competition forces firms to innovate to maintain or improve their market position. Aghion et al. (2005) complement this theory with the "escape competition effect," suggesting that stronger competition increases the incremental profit from innovating, prompting firms to boost RD spending to outpace their competitors.

Public funding for RD adds complexity to an already intricate problem. By offsetting lower private incentives, public RD support is anticipated to be more effective in markets with generally lower private incentives for RD. Consequently, we should expect a higher impact in more competitive markets according to Schumpeterian theory, and a more substantial impact in concentrated markets as per Arrow's model. Although our empirical model's indirect nature prevents us from determining which theory better describes the interaction between market structure and innovation incentives, our results appear to align more closely with Arrow's theory, where public RD funding helps offset lower private incentives in more concentrated markets. Results are shown in the last row of Table 8. Markets are divided into those with low or high levels of concentration based on the Herfindahl-Hirschman indices (HHI) calculated separately for each country, sector, and year using the full sample of firms in Orbis. Markets with an HHI above the median are classified as highly concentrated. Our estimates indicate a positive and significant treatment effect of FP7 funds on both sales and productivity in both concentrated and non-concentrated markets, with a more pronounced impact in highly concentrated markets.

8 Conclusion

This paper provides a rigorous evaluation of the impact of EC's FP7 grants for Research and Technological Development on profit-oriented firms' post-treatment performance. Building on a robust quasi-experimental approach, namely a fuzzy regression discontinuity design, and a comprehensive dataset covering both successful and unsuccessful applicants from 46 countries, our findings underscore significant positive effects of FP7 grants on firms' sales and labour productivity, increasing by 18.2% and 18.5%, respectively. However, we find no discernible impact on employment levels, indicating that growth barriers may hinder firms' ability to scale production despite enhanced productivity.

The paper reveals several key factors influencing the effectiveness of research grants. First, financial constraints likely play a crucial role. Accordingly, SMEs benefit significantly from grants due to their limited access to financial markets, unlike larger firms. For the same reason, the effect of grants for RD is more pronounced in countries with greater capital market imperfections.

Second, the inherent risks associated with innovation projects significantly influence the effectiveness of research grants. Our findings are consistent with Arrow's argument that uncertainty is a major factor preventing firms to engage in risky innovation activities. Supported by our results, firms in technologically or knowledge-intensive sectors, which engage in high-risk investments, gain more from public RD funding. Manufacturing RD projects, generally riskier than those in the service sector, see a greater impact from FP7 funding. Longer RD projects, closely correlated with higher risks, also show larger treatment effects. Additionally, less productive firms benefit more from grants due to their reluctance to invest in risky projects because of fear of failure and tighter financial constraints.

Third, market structure significantly influences the effectiveness of public funding for RD. Our findings, which align closely with Arrow's theory on the relationship between competition and innovation, suggest that public RD funding effectively counteracts lower private incentives in concentrated markets.

Fourth, the impact of public funding also hinges on the likelihood of success for the awarded projects. Our findings reveal that firms in conducive innovation environments derive enhanced benefits from these grants.

Lastly, our findings suggest that consortium size does not significantly impact the outcomes of public funds on RD effectiveness. Similarly, collaborations with universities, research institutions, or partners from non-EU countries do not clearly influence FP7 grant effectiveness. Interestingly, consortia without public institutions tend to achieve better post-treatment outcomes, potentially because projects involving public institutions often pursue broader objectives beyond enhancing private firms' performance, possibly encompassing social goals.

Our results highlight the trade-offs policymakers face when designing the optimal allocation of RD funds. Ideally, relatively small and less productive enterprises with tighter financial constraints in technology-intensive manufacturing sectors should be targeted, especially when engaging in longer, riskier projects and operating in highly concentrated markets and favourable innovation environments. However, these factors often contradict each other. For instance, longer and riskier projects are more likely to be undertaken by larger, more productive enterprises. Additionally, innovation-friendly environments are often found in countries or regions with more developed financial markets, creating further trade-offs to consider. Balancing these competing factors is crucial for maximizing the effectiveness of public RD funding.

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Appendix A Matching Corda with Orbis

A.1 THE CORDA DATABASE

The various parts of Corda and the h20 dataset are linked using both direct matches based on exact identifiers (firms, projects) and similarity score matching based on company names and other details. First, projects present in both the FP7 proposal and FP7 project datasets are linked based on identical firm identifiers, legal names, websites, or postal addresses. Subsequently, the combined FP7 database is linked to the h20 dataset. A harmonized Corda dataset is then created, incorporating information from all available databases.

As a general rule, exact matches are initially sought based on VAT codes and then on company names. When exact identifiers are missing or inconsistent between datasets, similarity score matching is employed based on company names. The algorithm, detailed in Raffo and Lhuillery (2009), assigns a set of potential matches from one database to each company in another. A similarity score ranging from 0 to 1 reflects the distance between firms' name entries in the two datasets.This step is performed using the Stata command reclink2. The threshold for considering two firms a potential match is set at 0.5. The final match is selected from possible alternatives using additional information on firms, such as postal addresses (city, postal code, and street), websites, and email addresses.

After each linkage step, all variants of discrepant information on firms are retained and utilised in subsequent steps. For instance, after linking records with the same VAT number but different company names or postal addresses, the new linked record includes both name or address variants and is used for finding exact matches in subsequent steps.

A.2 MATCHING WITH ORBIS

After standardizing firm-level information for homogeneity and comparability with Corda, such as adding the country abbreviation at the beginning of the VAT code and removing the web domain from webpage addresses, the matching procedure between Orbis and Corda is conducted on a country-by-country basis using the same method as the matching process within different parts of Corda. First, a direct merge between datasets is performed based on VAT codes and company names. Second, a similarity score matching technique identifies potential matches based on company names. Third, a selection criterion, considering various combinations of secondary variables (postal address, website, and email address), is applied to identify the correct match among multiple alternatives. Finally, false potential matches are manually excluded from the final sample.

The success rate of the matching process is significantly influenced by the quality of the Orbis and Corda data, particularly the availability of VAT codes. Across all considered countries, 78% of firms in the relevant sample for our analysis (39,555 out of 50,619 firms) were successfully matched.

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