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The Horizon effect: A counterfactual analysis of EU Research & Innovation grants

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The Horizon effect: A counterfactual analysis of EU Research & Innovation Grants

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Working Paper

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ABSTRACT

This paper evaluates the causal impact of the Horizon 2020 Framework Programme for Research and Innovation on financial firm-level outcomes using a Difference-in-Differences (DiD) approach. We use administrative data from CORDA and financial data from ORBIS spanning from 2010 to 2022, for a sample of approximately 40 thousand unique private companies that applied for Horizon 2020 funding. The findings suggest that firms receiving Horizon 2020 grants exhibit an average increase of 20% in employment and about 30% in total assets and revenues, compared to comparable companies in the control group, in the years after receiving their first grant. Positive effects persist even after 2.5 years, which is the average duration of a project in our sample. Companies in the "Information and communication" and "Professional, scientific and technical activities" NACE sectors are driving the results, while other sectors show insignificant effects.[*]

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1. Introduction

Understanding the impact of EU Research and Innovation (R&I) funding on socio-economic outcomes is of paramount importance. Rigorous evaluation is crucial to ascertain whether these investments have effectively fulfilled their intended objectives and to guide evidence-based policymaking for future funding allocations.

In the context of ex-post policy evaluation, it is crucial to understand the limitations of simplistic comparative approaches. Simply contrasting a treated unit before and after the implementation of a policy, or comparing a treated unit with an untreated unit post-treatment, can lead to inaccurate estimations of policy impact. This is primarily due to the oversight of confounding factors and the dynamic nature of external influences. For instance, in a before-and-after comparison, ascribing all observable changes in the treated unit solely to the policy disregards the role played by pre-existing trends. In the same vein, comparing a treated unit to an untreated counterpart post-treatment overlooks the pre-existing disparities between these units, which might independently affect outcomes, irrespective of the policy. Such simplistic comparisons do not effectively establish a reliable counterfactual scenario — a critical element for accurately discerning a policy's true effect. Absent this, any changes noted could be erroneously attributed to the policy, whereas they might have arisen from unrelated factors.

Counterfactual evaluation, a method used in research and policy analysis to assess the ex-post causal impact of a specific intervention, entails the examination of outcomes of interest among those who have benefited from a policy intervention or programme (referred to as the "treated group") in juxtaposition with those of a group that is similar in all pertinent respects to the treatment group but has not benefited from the programme (referred to as the "control group"). For such purpose, different statistical approaches and evaluation designs exist[1], which are applied based on the context and policy at stake.

Counterfactual evaluation is commonly used in fields such as medicine, economics, social sciences, and public policy to evaluate the effectiveness of various interventions or policies. This method represents a robust approach for quantifying the causal impact of EU R&I funding. By systematically analysing what would have happened in the absence of this funding, we can pinpoint the genuine contributions of these programs to scientific advancements, technological breakthroughs, economic growth, and societal well-being.

The Horizon 2020 Framework Programme for Research and Innovation was the European Union flagship funding programme aimed at supporting and promoting research and innovation projects across various scientific and

[1] Among the most common see randomized control trial, regression discontinuity design, difference in differences, synthetic control method, and propensity score matching.

technological fields. It operated from 2014 to 2020, financing not only companies across all EU member states, but also in other countries around the world.

The main aim of the paper is to investigate the causal impact of the Horizon 2020 Framework Programme for Research and Innovation on financial firm-level outcomes such as employment, assets, and revenue. Specifically, the paper explores:

- The causal impact of receiving Horizon 2020 funding as a whole
- The causal impact of receiving Horizon 2020 funding differentiating by sector

We use administrative data sourced from CORDA[2] and financial data obtained from ORBIS[3], covering the period from 2010 to 2022. The final sample comprehends roughly 40 thousand distinct privately owned companies that submitted applications for Horizon 2020 funding. To infer causality, we rely on Difference-in-Differences (DiD) approach, accounting for staggered treatment timing and heterogeneous treatment effect.

The paper brings novelty in two ways, first it provides novel evidence on the causal effect of the Horizon 2020 Framework Programme for Research and Innovation as a whole. Second, it identifies in which sectors of the economy EU R&I funding have been more effective. To the best of our knowledge, no other paper has to date attempted an analysis of such a broad and diverse R&I funding scheme like Horizon 2020, with most analysis focused on smaller, country specific, or field specific R&I sub-programmes.

2. Theoretical discussion

The primary argument for public support to innovation is that of market failure. Market failures occur due to the large positive externalities associated with Research & Innovation (R&I). There are benefits of the technological innovation created by the research that spill over to other agents who did not conduct the research. This makes the socially optimal level of innovation higher than the private one, translating into overall private underinvestment in innovation. Furthermore, due to asymmetry of information, innovative companies often face significant financial constraints that hamper innovation. Such externalities and financial frictions arise due to some intrinsic features of R&I activities, such as uncertainty, non-excludability and partly non rivalry.

[2] A database managed by the European Commission Directorate-General for Research and Innovation containing information on applicants to Horizon 2020 grants.

[3] Bureau van Dijk's flagship company database. It contains information on companies across the world.

Although market failure is the main justification for public sector action, there are additional arguments. Woolthuis et al. (2005) point to system failures, which relate to the smooth interaction among innovative agents, and may arise due to the interactive and non-linear nature of innovation processes, in which actors (such as firms) interact with a manifold of other organisations (research institutes, customers, financial organisations) and institutions (IPR, regulations). In this context, system failures can arise because of lack of communication, physical infrastructures (such as high-speed ICT infrastructure), science-technology infrastructures (such as availability of scientific and applied knowledge and skills) and institutional infrastructures (such as anti-trust regulations).

Since the 2010s, there has also been a call by academics and policymakers for R&I policies to address potential directionality failures by better aligning innovation effort toward the tackling of the social and environmental challenges. Directionality failures pertain to the direction in which innovative agents channel their innovation. Such new development is called “Mission-Oriented Policy” (Haddad et al., 2022). The idea is that on its own the market does not direct enough resources toward the right challenges that will ensure the survival of humanity (Mazzucato, 2013).

In principle, government R&I grants can address all the mentioned issues. They can be directed specifically to R&D activities with the greatest knowledge spillovers, like fundamental research, can promote communication through collaboration requirements, and can be precisely aimed at high-priority objectives, such as climate change, healthcare, or digital transformation.

Yet, there are also potential risks, first the government agency faces the challenge of identifying programmes with significant social value, a task complicated by substantial uncertainties and information disparities in the realm of innovation. These disparities are also present in the private sector; however, R&D-performing firms typically possess superior information compared to public funding entities. Additionally, even when the agency is well-informed, there is the inherent risk of political capture, potentially diverting public funds to technologies with political support or well-connected companies instead of the ones a well-intentioned planner might prefer to support.

Hence, empirically testing the causal impact of R&I grant funding is of high policy relevance. Research in this domain is currently limited but expanding, and it has so far produced mixed findings. Howell (2017) employs a regression discontinuity (RD) design and looks at R&D grants of the U.S. Department of Energy's SBIR grant programme, finding that R&D grants increased beneficiaries companies’ revenue and patenting activities. Howell et al. (2021) employs a regression discontinuity (RD) design and investigates the U.S. Air Force Small Business Innovation Research (SBIR) programme, finding a positive impact on patenting and additional venture capital funding only on those calls where the applicants could suggest new technologies, while no effect is found when the Airforce decides what technology it wants. Using a regression discontinuity design to analyse an Italian R&D grant programme,

Bronzini and Iachini (2014) find no overall impact on companies' investment spending, with the positive effects concentrated on small firms. Wang et al., (2017) employs regression discontinuity design to analyse China's Innofund innovation subsidy grants and find that firms possessing political connections are more likely to receive R&D grants, while receiving the grant does not boost firms' survival, patenting, or venture funding.

Regarding the EU framework programme, the counterfactual evidence is also scarce, and concentrated in specific sub-instruments of the programme. An overarching evaluation of the causal impact of the whole programme missing, with papers focusing on its mono beneficiary instruments[4], avoiding tackling the evaluation challenges posed by the multi beneficiary actions[5], which constitute its majority.

As an example, Santoleri et al. (2022) looks at a Horizon 2020's "SME instrument" under the Industrial Leadership pillar[6], with a budget of around EUR 3 billion over 2014-2020, accounting for around 3.75% of all Horizon 2020 budget. Differently from most of the Framework Programme, the SME instrument is mono-beneficiary and specifically targeted at small-medium enterprises. Using regression discontinuity design, Santoleri et al. (2022) finds positive effects on cite-weighted patents, investment, and firm growth.

Ghirelli et al. (2023) investigate a sub-section of the EU framework programme, focusing on the European Research Council (ERC) grants[7]. The ERC targets researchers and - like the SME instrument - is mono beneficiary. Ghirelli et al. (2023) employ Difference-in-Differences and do not find any statistically significant effect on research productivity and excellence as a consequence of winning the ERC funding. The finding adds to other studies that - using either Difference-in-Differences or regression discontinuity design and focusing on national researcher grant schemes - find either small or no impact on research productivity (Langfeldt et al. 2015, Baruffaldi et al. 2020, Carayol and Lanoe 2017), with larger positive impact concentrated on young researchers (Jacob et al. 2010).

3. Institutional setting and data

3.1 Horizon 2020

Horizon 2020 is a research and innovation funding programme launched by the European Union in 2014 and the last call for proposals was in January 2021. Horizon 2020 was the largest ever European Union (EU) research and

[4]Like the ERC or the SME instrument where applicants apply to the grant as sole beneficiaries (i.e., not in group as part of a consortia).
[5] Applicants apply to the grant in group as part of a consortia.
[6] See figure 1.
[7] See figure 1.

innovation programme, with a budget of approximately EUR 80 billion. The programme employed R&D grants to a wide range of organizations[8], from different sectors, targeting a diverse set of strategic priorities. The programme also promoted cooperation between organisations, with many calls being multi-beneficiary and requiring a team[9] of at least three partners, often of distinct class-type[10], and from different countries.

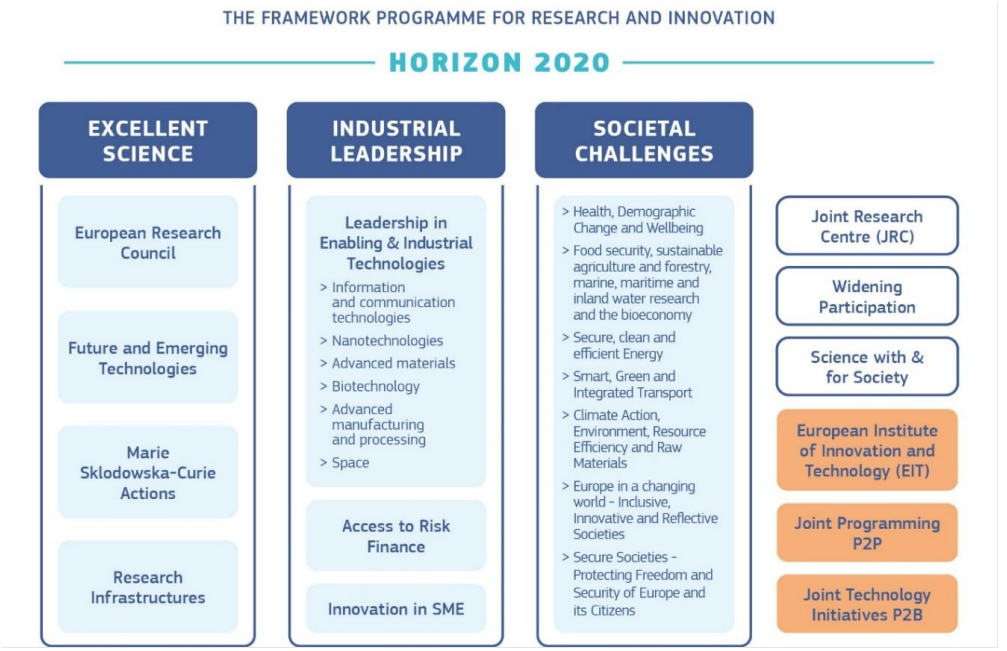
Seen as a means to drive economic growth and create jobs by coupling research and innovation (R&I), Horizon 2020 aimed at supporting EU industrial competitiveness, scientific excellence and helping to tackle societal challenges (European Commission 2017). Such a philosophy can be observed in its structure, built around three main pillars (Excellent Science, Industrial Leadership and Societal Challenges) and the various programme parts.

Grants were generally allocated through the publication of "calls for proposals" on both, the European Commission website and the EU's Official Journal. The calls were opened and closed periodically during the programme, and each call gave precise information on the questions that the Commission wanted the applicants to address in their proposals. After a call deadline, all proposals under the call were first checked by the European Commission for eligibility, and then underwent a pre-defined selection procedure. The selection process consisted of either a single-stage or two-stage procedure, with a panel of independent specialists in their fields evaluating each proposal against a list of criteria to see if it should receive funding.

All proposals above a pre-defined score were identified as worthy of funding and labelled as "high quality proposals". However, due to budget limitations[11], not all "high quality proposals" could be funded, making an argument for the need of additional programme funding. Because the calls described were not all opened simultaneously between 2014 and 2020, the resulting R&D grants were awarded at different points in time. This created variations in the timing of treatment (i.e., the receipt of a Horizon 2020 grant).

[8] Horizon 2020 was open to universities, private companies, non-governmental organizations, public sector organizations and international organizations.
[9] Also called "consortium".
[10] Such as public-private partnerships or universities and private companies' collaborations.
[11] The total amount of available budget for the specific call.

Figure 1: Horizon 2020's structure



Source: European Commission, 2017.

3.2 Data and summary statistics

Administrative data on Horizon 2020 successful and unsuccessful proposals and applicants are drawn from CORDA (COmmon Research DAta Warehouse), a database managed by the European Commission Directorate-General for Research and Innovation.

Firm-level financial data are obtained from the ORBIS company database. Given the absence of harmonized national business register data, ORBIS offers the most reliable source for consistent cross-country company data (Autor et al., 2020).

Using the VAT identification number and manual disambiguation, 80% of the unique EU beneficiary firms from CORDA were matched to the ORBIS database (118 212 out of 148 226 unique firms). This is in line with the matching precision achieved by previous literature using ORBIS data (e.g., Santoleri et al. 2022). Table 1 shows statistics of the original population (CORDA) compared to sample population (matched dataset with ORBIS). The standardized difference, as described in Austin (2009), is always bellow 0.05, well below Cohen's effect size index lowest bound of 0.2 (Cohen, 1998), in a wide array of common variables.

Table 1: Comparison between applicants' population and sample

	Population Mean	Sample Mean	Std. Diff.
Number of applicants per call	569.39	527.78	0.038
Number of applicants per proposal	3.50	3.34	0.031
Year of application	2017.13	2017.13	0.001
Share of high-quality proposals	0.51	0.52	-0.012
Share of grants to proposals	0.13	0.13	-0.006
Requested budget per applicant	585049.86	598183.00	-0.009
Share of applicants from Widening country[12]	0.16	0.15	0.017
Share of applicants from non-Widening country	0.67	0.69	-0.051
Share of applicants from Associated country[13]	0.08	0.07	0.040
Share of applicants from Third country[14]	0.10	0.09	0.023

The matched sample is restricted to companies with *unconsolidated* accounts, i.e. financial statements not integrating the statements of the possible controlled subsidiaries or branches of the concerned company. This ensures that a grant received by a subsidiary company is accounted only for the subsidiary and not for the holding (parent) company.

To ensure comparability between the unsuccessful and the successful applicants, as defined by the Difference-in-Difference approach used to infer causality, the sample is further restricted to include only applicants with proposals of high quality[15]. The final sample consists of 40 thousand unique companies, with balance sheet data spanning over 2010 to 2022.

Table 2 shows how many times the final sample of 40 000 unique firms applied to Horizon 2020 fundings, and across how many different programme parts. Since there is no limitation on the number of times the same company can apply to different calls for proposals, on average the same company applied for Horizon 2020 funding six times. Furthermore, companies do not apply only to calls for proposals under just one programme part: on average, a company applies to two different programme parts.

[12] Countries identified as 'low performing' in research and innovation, and thus eligible to apply for actions dedicated to spreading excellence and widening participation.

[13] Association to Horizon 2020 is governed by Article 7 of the Horizon 2020 Regulation. Entities from associated countries can participate under the same conditions as those from EU countries. A country becomes associated to Horizon 2020 through an international agreement.

[14] The third countries are those non-associated countries and international organisations that can participate in Horizon 2020 projects, unless specific limitations or conditions are laid down in the work programme and/or the call/topic text.

[15] As defined by the quality thresholds of each call for proposals.

Table 2: Tabulation of unique firms by the number of times they applied for grants

N. of times	Freq.	Percent	Cum.	N. of prog. parts	Freq.	Percent	Cum.
1	11023	27.52	27.52	1	19658	49.09	49.09
2	7194	17.96	45.49	2	9863	24.63	73.71
3	4814	12.02	57.51	3	4720	11.79	85.50
4	3565	8.90	66.41	4	2319	5.79	91.29
5	2548	6.36	72.77	5	1330	3.32	94.61
6	1903	4.75	77.52	6	745	1.86	96.47
7	1455	3.63	81.16	7	465	1.16	97.63
8	1164	2.91	84.06	8	286	0.71	98.35
9	930	2.32	86.39	9	223	0.56	98.90
10	672	1.68	88.06	10	121	0.30	99.21
More	4780	11.95	100	More	318	0.79	100
Total	40048	100.00		Total	40048	100.00	

Note: On the left-hand side, the table shows the tabulation of how many times the same companies have applied to different Horizon 2020 grants. On the right-hand side, the table shows the tabulation of to how many different program parts the same companies have applied within Horizon 2020. On average, a unique company applied to 6.1 different grants and 2.2 different program parts.

Table 3 shows if and when our 40 thousand unique companies won for the first time a Horizon 2020 grant. In other words, it represents how staggered is the treatment over time. Regardless of how many times the companies applied, around 50% of Horizon 2020 applicants never managed to win a grant. Only 10% of companies won their first Horizon 2020 grant in the first year of the programme, with numerous firms winning in each year of the programme from 2014 to 2021. Consequently, the treatment is distributed over all the Horizon 2020 years of implementation (2014-2022).

Table 3: Tabulation of unique firms winning a grant for the first time

	Freq.	Percent	Cum.
Never treated	20805	51.95	51.95
2014	4051	10.12	62.07
2015	2911	7.27	69.33
2016	2958	7.39	76.72
2017	2337	5.84	82.56
2018	2543	6.35	88.91
2019	2457	6.14	95.04
2020	1779	4.44	99.48
2021	207	0.52	100.00
Total	40 048	100.00	

Note: The table shows the number of unique companies that never won a Horizon 2020 grant, as well as the number of companies that won their first grant for each year. While the same unique company often apply many times in different years, here it is counted only in the first year that it succeeds in winning a grant. In other words, it is a tabulation of "staggered entry into to treatment".

Table 4 displays some descriptive statistics on the firm-level main outcome variables by year, from 2010 to 2021. Orbis financial data is not available for all firms and years analysed, i.e., for many years we have information on employment, assents, and revenue for a sub-set of all the firms participating in Horizon 2020 that we linked to ORBIS. Yet, we can follow the financials of most companies over time, and the reporting is relatively homogeneous across the years with no suspicious jumps in the observed averages of the financial variables. The higher the amount of financial information we have before and after the staggered treatment, the more statistical power our DiD will have. Overall, a small positive trend in the outcome variables among all companies is observed.

Table 4: Summary statistics of outcome variables by year

Variables	Ln employment		Ln total assets		Ln revenues	
Year	N	mean	N	mean	N	mean
2010	2161	4.29	4020	15.3	2761	15.603
2011	9659	4.739	15018	16.049	10739	16.474
2012	16441	4.718	25296	16.037	18778	16.469
2013	17734	4.704	27166	15.967	20073	16.383
2014	19158	4.656	28421	15.919	20818	16.329
2015	21518	4.602	30014	15.912	21880	16.312
2016	24266	4.548	31447	15.89	22852	16.248
2017	27577	4.486	33941	15.897	23910	16.26
2018	28121	4.489	34640	15.936	24227	16.295
2019	28180	4.509	34848	16.005	24268	16.346
2020	27934	4.477	33631	16.14	23344	16.363
2021	13081	4.433	15807	16.202	10949	16.59
2022	239	4.452	273	14.835	97	17.041

Note: The table shows the descriptive statistics for all available unique firm level financial information by year. Not all companies reported to ORBIS their financial status every year, hence there are fluctuations on the number of unique firms (N) reporting employment, total assets, and revenues by year.

Table 5 illustrates the distribution of distinct companies across various economic sectors. Notably, 31% of private enterprises that have sought funding through Horizon 2020 belong to the sector of “Professional, Scientific, and Technical Activities”, 25% to “Manufacturing”, and 19% to “Information and Communication”. Nevertheless, the sample exhibits substantial diversity in terms of represented sectors, with numerous sectors individually comprising more than five hundred unique companies. These sectors include “Agriculture, Forestry, and Fishing”, “Electricity, Gas, Steam, and Air Conditioning Supply”, “Construction”, “Wholesale and Retail Trade; Repair of Motor Vehicles”, “Transportation and Storage”, “Financial and Insurance Activities”, “Administrative and Support Service Activities”, as well as “Human Health and Social Work Activities”.

Table 5: Tabulation of unique companies by NACE sector

NACE Main Section	Freq.	Percent	Cum.
A - Agriculture, forestry, and fishing	622	1.57	1.57
B - Mining and quarrying	169	0.43	2.00
C - Manufacturing	10027	25.34	27.33
D - Electricity, gas, steam, and air conditioning supply	632	1.60	28.93
E - Water supply; sewerage, waste management	495	1.25	30.18
F - Construction	688	1.74	31.92
G - Wholesale and retail trade; repair of motor vehicles	2349	5.94	37.86
H - Transportation and storage	682	1.72	39.58
I - Accommodation and food service activities	67	0.17	39.75
J - Information and communication	7615	19.24	58.99
K - Financial and insurance activities	627	1.58	60.57
L - Real estate activities	220	0.56	61.13
M - Professional, scientific, and technical activities	12329	31.15	92.28
N - Administrative and support service activities	1154	2.92	95.20
O - Public administration and defence; comp. social security	99	0.25	95.45
P - Education	404	1.02	96.47
Q - Human health and social work activities	596	1.51	97.97
R - Arts, entertainment, and recreation	226	0.57	98.54
S - Other service activities	575	1.45	100.00
Total	39576	100.00	

4. Empirical strategy

The difference-in-difference (DiD) approach is used to identify the causal effect of Horizon 2020 on private companies, by comparing the changes in outcome before and after the grant for recipients (treated units) and non-recipients[16] (control units). DiD is one of the most popular methods of applied researchers aiming to analyse causal effects. Under the Parallel Trends Assumption (PTA), differences in those changes identify the Average Treatment Effects of the treated units (ATT)[17]. The difference-in-difference (DiD) approach is favoured over the Regression Discontinuity Design (RDD) due to differences in the threshold and scoring reliability across the different programme parts of Horizon 2020.

In recent years, the econometric literature on event-study and Difference-in-Difference approaches has undergone significant development, with numerous alternative algorithms emerging. These algorithms allow for accurate estimations in complex frameworks, such as those involving staggered treatment adoption, heterogeneous causal effects, multiple groups, and

[16] To increase the comparability between treatment and control group, the analysis excludes unsuccessful applicants with low quality proposals from the control group.

[17] The "Average Treatment Effects of the treated units" measures the average impact or change caused by a specific treatment on the group that received it, compared to those who didn't receive the treatment. It focuses on the causal effect, showing how much the treatment caused the difference or change in outcomes.

variations in treatment timing[18]. These developments are particularly important as these studies showed that even generalised DiD models (such as the Two-way Fixed Effects Model[19]) may not be adequate to identify an ATT when effects are heterogeneous[20] (Goodman-Bacon, 2021).

The analysis at hand follows the procedure proposed by Callaway and Sant'Anna (2021) for two main reasons: first, it allows to deal with variations in the treatment timing and heterogeneous treatment effects. Second, it allows to condition on covariates when the parallel trends assumption holds potentially only after conditioning on observed pre-treatment characteristics. In practice, this algorithm runs a series of 2 × 2 comparisons between periods in the future and the last period before treatment, using two-way fixed-effects models, and adjusting confidence intervals to avoid multiple-testing issues. This is estimated using the doubly robust DID estimator proposed by Sant'Anna and Zhao (2020) based on inverse probability of tilting and weighted least squares. Robust and asymptotic standard errors are obtained using influence functions, and clustered at the panel level.

With the presented method, we estimate the following equation:

$$y_{i,t,c} = \beta_1 \sum_{1}^{5} T_{i,t,c} \times (c-k) + \beta_2 \sum_{0}^{5} T_{i,t,c} \times (c+k) + \vartheta_i + \gamma_t + \epsilon_{i,t,c} \quad (1)$$

Where $y_{i,t,c}$ represents our outcome variables of interest for company i, measured in year t, applying in year c. As firm-level outcome variables we consider employment, total assets and revenues. β_1 is a vector of coefficients capturing the effect of the grant in each year *before* the call year c. This set of coefficients should not be statistically different from 0, for the common trend assumption to hold. The year of reference is c − 1, the year prior to the call. β_2 is a vector of coefficients estimating the effect of the grant in each year *after* the call year c. These constitute the primary coefficients of interest that signify the causal effect of the grant. We control for ϑ_i, firm fixed effects (which capture also call year c) and γ_t calendar year fixed effects. We condition the DiD parallel trend assumption on company NACE, country of origin and the number of times it has applied for Horizon 2020 calls. We check the pre-treatment period up to 5 years before winning the grant.

[18] See Callaway and Sant'Anna, 2021; Borusyak et al., 2021; Sun and Abraham, 2021; Arkhangelsky and Imbens, 2022; De Chaisemartin and d'Haultfoeuille, 2022.

[19] A two-way fixed effects (2FE) regression, or linear regression with unit and time fixed effects, is often seen as the default methodology for estimating causal effects from panel data. It is used to adjust for unobserved unit-specific and time-specific confounders at the same time, and it is equivalent to a difference-in-differences estimator under the simplest settings.

[20] Which is a likely case in a vast and diverse R&I programme such as Horizon 2020 (see Figure 1).

5. Results

5.1 The effects of the whole programme

This section presents and explores the outcomes derived from estimating Eq. 1 on the sample of companies applying to any part of the programme. In the context of the Difference-in-Differences (DID) framework, we first assess the validity of the common trend assumption by examining observations in the period *preceding* the treatment. We analyse data from the five years preceding their grant call deadline.

The DID coefficient quantifies the disparity in outcomes between the treated and control groups in a given year, relative to the same disparity in outcomes one year before the treatment (the reference year). The common trend assumption presupposes that the trajectories of outcomes for treated individuals and controls exhibit parallel patterns prior to the treatment. This implies that the DID coefficients should be zero in the pre-treatment period. If this condition is met, any divergence in trends between the treated and control groups after the treatment is indeed attributable to the treatment itself (i.e., receiving a Horizon 2020 grant) rather than other unobserved factors. To enhance comparability between grant recipients and non-recipients, we include all successful applicants and the highest-performing non-recipients[21].

Figure 2 plots the DiD estimates for the pre and post treatment periods.[22] Like with pre-treatment, a period of 5 years was examined also after the treatment, to the extent data was available. Firms receiving Horizon 2020 grants increased on average their employment level by about 20% (compared to non-funded firms), and their total assets and revenues by about 30%, in the years following the receipt of the first grant. Effects are present even after 2.5 years (the average duration of a project in our sample). Such result confirms the positive and causal impact of the Framework Programme on beneficiary companies' growth.

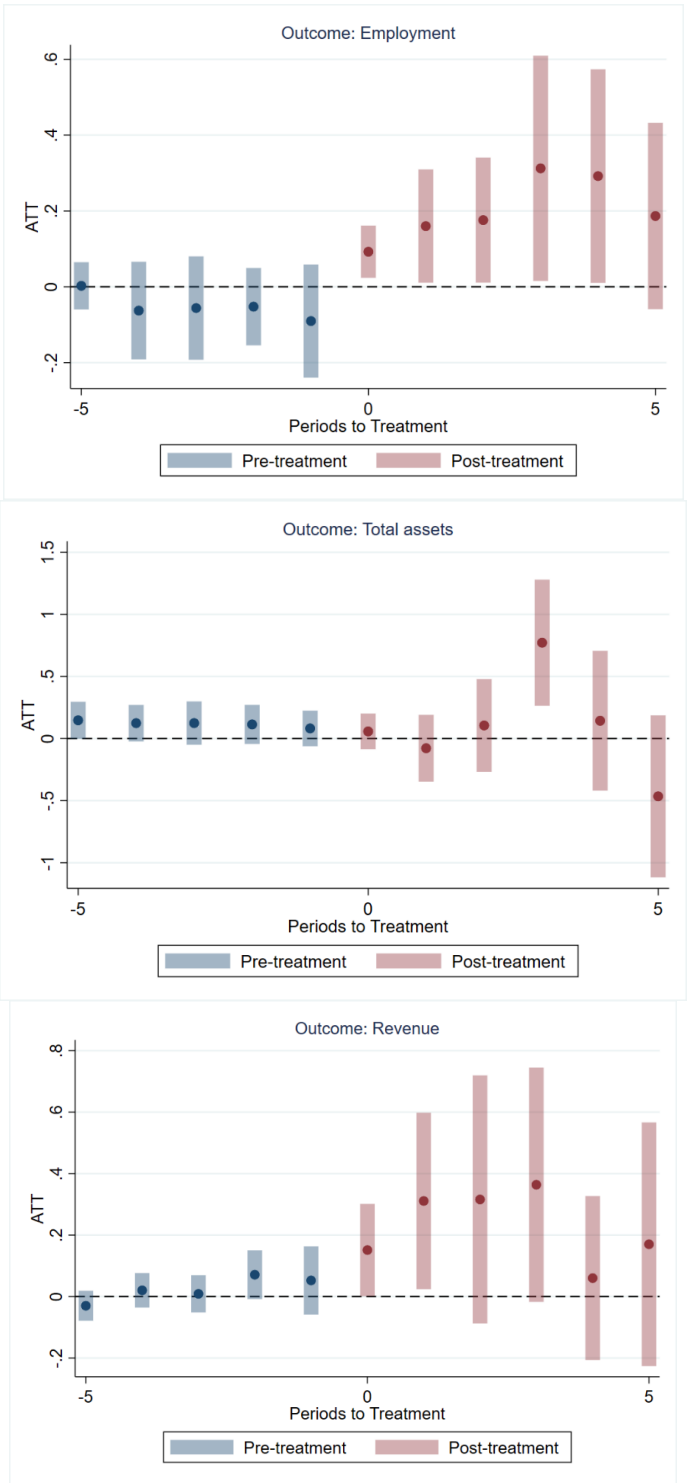
The DiD estimates during the five years preceding the receipt of the grant support the conditional parallel trend assumption[23], with pre-treatment coefficients failing to be statistically different from zero.

[21] We define high-performing non-recipients as those applicants whose proposals have feen defined as high quality by the evaluation committee, and yet did not rank high enough to secure funding.

[22] Confidence interval at 99%.

[23] To ensure the satisfaction of the parallel trend assumption, we condition the parallel trend assumption on a set of firm specific covariates such as the firm NACE, firm country of origin and the number of times the firm applied to Horizon 2020.

Figure 2: DiD coefficients plot on firm level financial outputs for whole Horizon 2020



5.2 Heterogeneous effects

This section presents and explores the outcomes derived from estimating Eq. 1 on the sub-sample of companies applying to any part of the programme by company NACE code. Even though Horizon 2020 attracts applicants from all economic activities, only some are positively impacted by receiving EU funding. The positive impact of Horizon 2020 funding on companies' financial performance is mostly coming from sectors *"NACE J - Information and communication"* and *"NACE M - Professional, scientific and technical activities"*. All other sectors show insignificant effects.

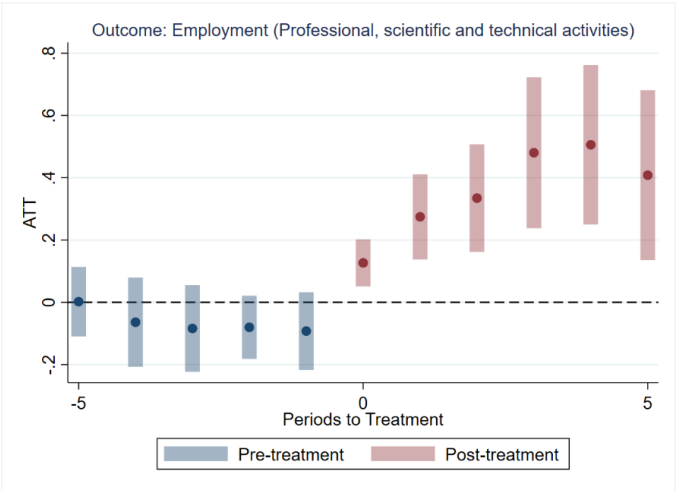
Figure 3 shows the causal impact of receiving Horizon 2020 grant for a firm working in the Professional, scientific, and technical activities sector. The impact is much larger than for any other sector, with an average increase of firm employment by about 30% (compared to non-funded firms), and their total assets and revenues by about 40%. Effects are present even after 2.5 years (the average duration of a project in our sample).

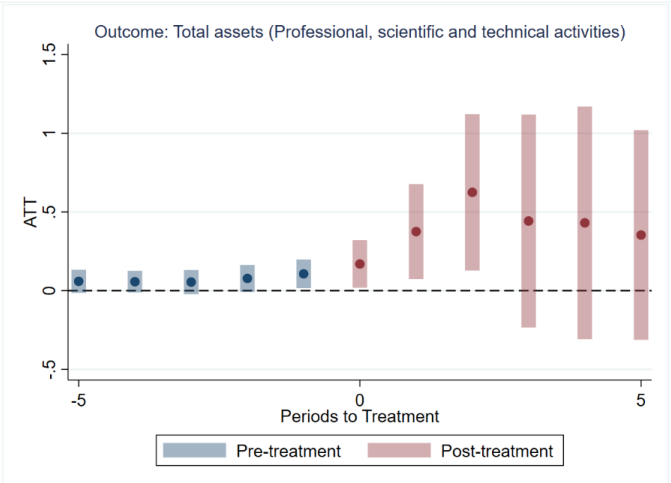
Figure 4 depicts the causal effect of Horizon 2020 fundings on firms in the Information and communication sector. Here the impact is limited to the total assets, while employment and revenues appear unaffected by the grants. A company in the Information and Communication sector, on average, increases its total assets by about 40% (compared to non-funded companies).

On the other hand, EU funding seems to be ineffective in boosting the financial variables observed for companies in the sectors: NACE A - Agriculture, forestry, and fishing, NACE B - Mining and quarrying, NACE C - Manufacturing, NACE D - Electricity, gas, and steam, NACE E - Water supply; sewerage, waste maintenance, NACE F - Construction, NACE G - Wholesale and retail trade, NACE H - Transportation and storage, NACE I - Accommodation and food service, NACE K - Financial and insurance activities, NACE L - Real estate activities, NACE N - Administrative and support services, NACE O - Public administration and defence, NACE P - Education, NACE Q - Human health and social work activities, NACE R - Arts, entertainment and recreation, NACE S - Other service activities (see Figures A1-A3 in Appendix).

Such results call for further analysis to investigate the sectoral effects, with the view to redesign the programme to improve effectiveness of EU R&I fundings. It is important to highlight that the financial variables used in the presented analysis may not be equivalently adequate to measure the success of the EU programme across all sectors of the economy, with some sectors for which other outcome variables, such as patents and publications, could be more suited. Yet labour and assets being two of the main components of production, their relevance should not be underestimated.

Figure 3: DiD coefficients plot on firm level financial outputs for Professional, scientific, and technical activities





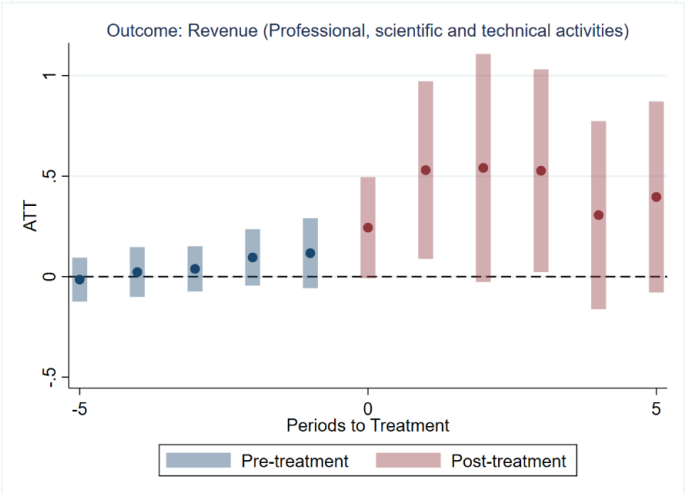
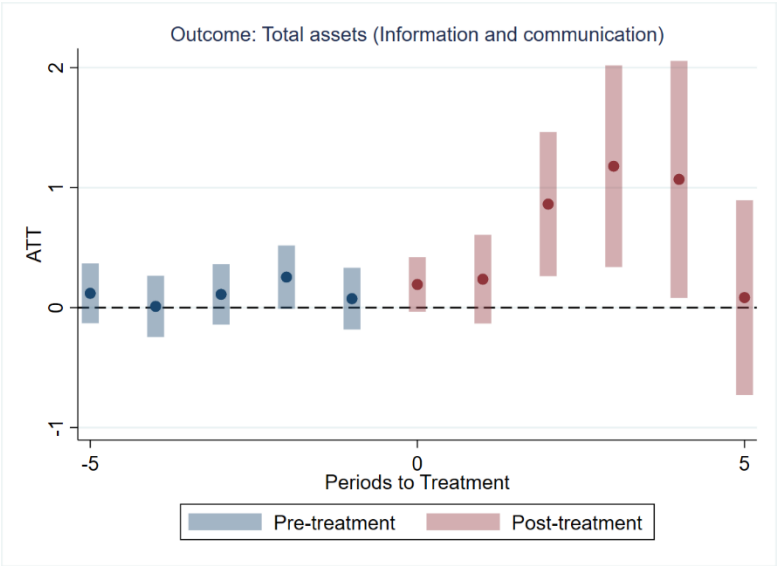


Figure 4: DiD coefficients plot on firm level financial outputs for Information and communication



6. Caveats and future research

The analysis reported presents some limitations that need to be taken into account when interpreting the results. First, we are only considering the causal effect of winning a Horizon 2020 grant, and not the cumulative effect of winning two or more grants. Future extensions and analysis could investigate how the return of winning EU funding vary based on the number of grants a company is awarded.

Second, we measure the impact of EU R&I funding on the firms' financial variables, but other outcome variables such as patents and publications classified by technology and scientific field could be interesting to investigate. Further research could extend the present analysis looking at the impact of Horizon 2020 on scientific and innovation output.

Third, the open design of EU Framework Programme for Research and Innovation allows companies to apply multiple times and to multiple programme parts with different objectives, this imply that a company could be treated in many programme parts while at the same time un-treated in others. Our results apply regardless of the Horizon 2020 programme part to which a company has applied for. Future research could restrict the sample to applicants treated in one single programme part and explore the impact heterogeneity across the different programme parts, as well as investigate on potential gains of being treated horizontally, across different programme parts.

Finally, alternative novel DiD estimation methods such as those proposed by Lee, S. J., & Wooldridge, J. M. (2023) and De Chaisemartin, C., &

d'Haultfoeuille, X. (2023) could be implemented to further confirm on the soundness of the findings.

7. Conclusions

The paper investigates the causal impact of Horizon 2020 Framework Programme for Research and Innovation on financial firm-level outcomes using a Difference-in-Differences (DiD) approach. We estimate the causal impact of winning EU R&I funding on private companies' employment, total assets and revenue, further exploring the heterogeneity of the effect across economic sectors, and taking into account the staggered and heterogeneous nature of the treatment.

The paper brings novelty to the literature in two ways. Firstly, this study offers original insights into the causal impact of the Horizon 2020 Framework Programme for Research and Innovation as a comprehensive entity. Secondly, it pinpoints the sectors of the economy in which EU research and innovation funding has exhibited greater effectiveness. To the best of our knowledge, there is no existing research paper that has undertaken a comprehensive analysis of a broad, diverse, and interconnected research and innovation funding initiative like Horizon 2020. Most existing analyses have primarily concentrated on smaller, country-specific, or field-specific sub-programs within the realm of research and innovation.

We find that EU R&I funding deliver EU added value, fulfilling its "additionality" objectives[24]. Receiving Horizon 2020 grants causes a subsequent increase of approximately 20% in companies' employment levels, as well as approximately 30% growth in their total assets and revenues in the years following the receipt of their initial grant. The effect is mostly coming from firms in the "Information and communication" and "Professional, scientific and technical activities" sectors, while other companies seem to be unaffected.

Our findings confirm the pivotal role played by EU Research & Innovation funding in enhancing EU competitiveness and fostering growth. Moreover, they prompt reflection regarding potential resource reallocation towards more suitable areas. As our results have underscored, EU R&I funding has demonstrated its greatest efficacy in domains closely aligned with research and innovation, such as ICT and scientific and technical activities.

Finally, the analysis provides a sound base and point of reference for future ex-post evaluations of EU Framework Programmes for Research and Innovation. As well as indicating promising future shores of research to further develop and improve the quantitative evidence on the effectiveness of collaborative, cross-county and interdisciplinary Research & Innovation funding in the EU.

[24] Not displacing or replacing national funding but bringing added value that would not take place in absence of EU intervention

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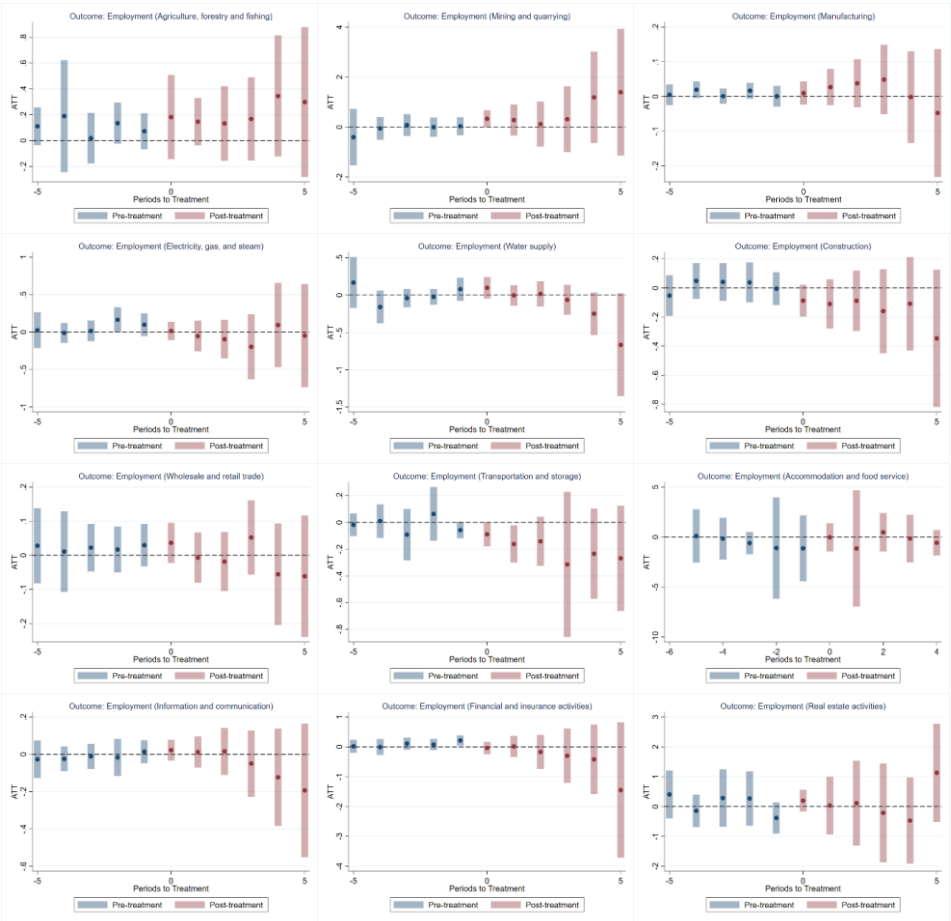
9. Appendix

Figure A1: DiD coefficients plot on firm level employment by NACE code



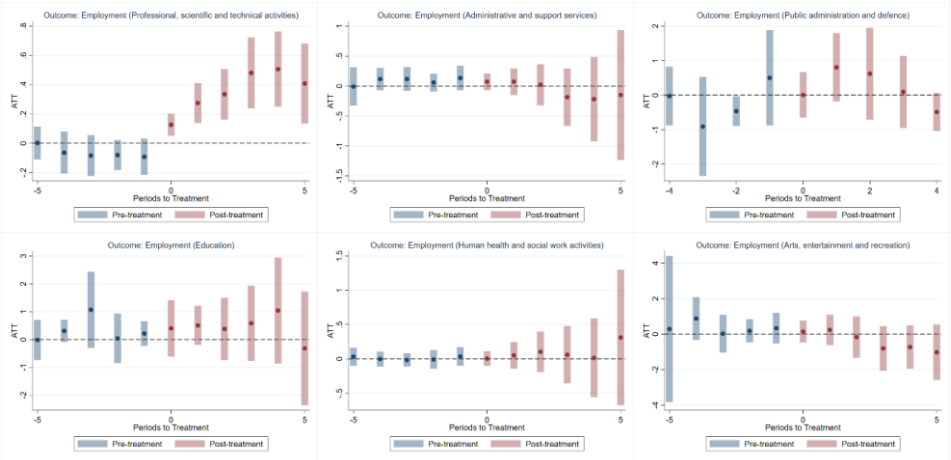
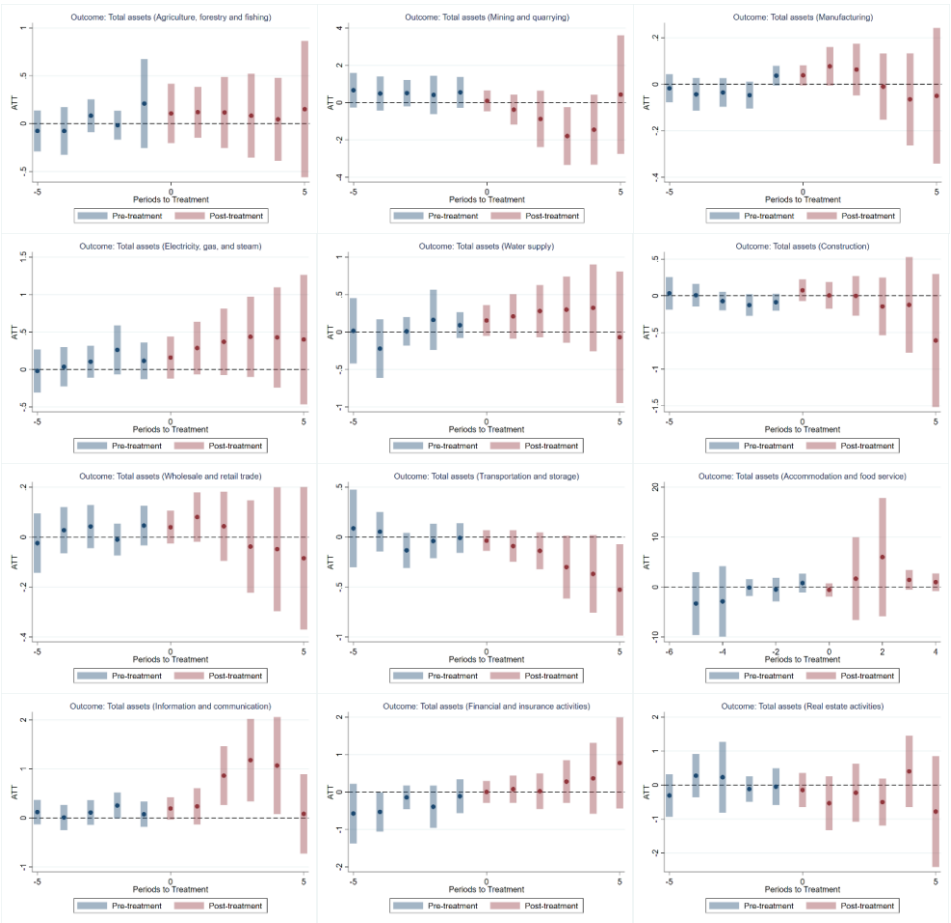


Figure A2: DiD coefficients plot on firm level total assets by NACE code



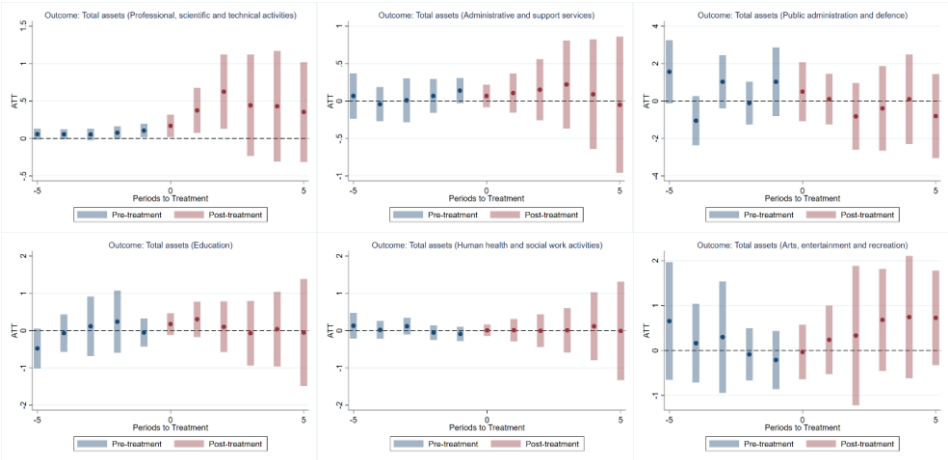
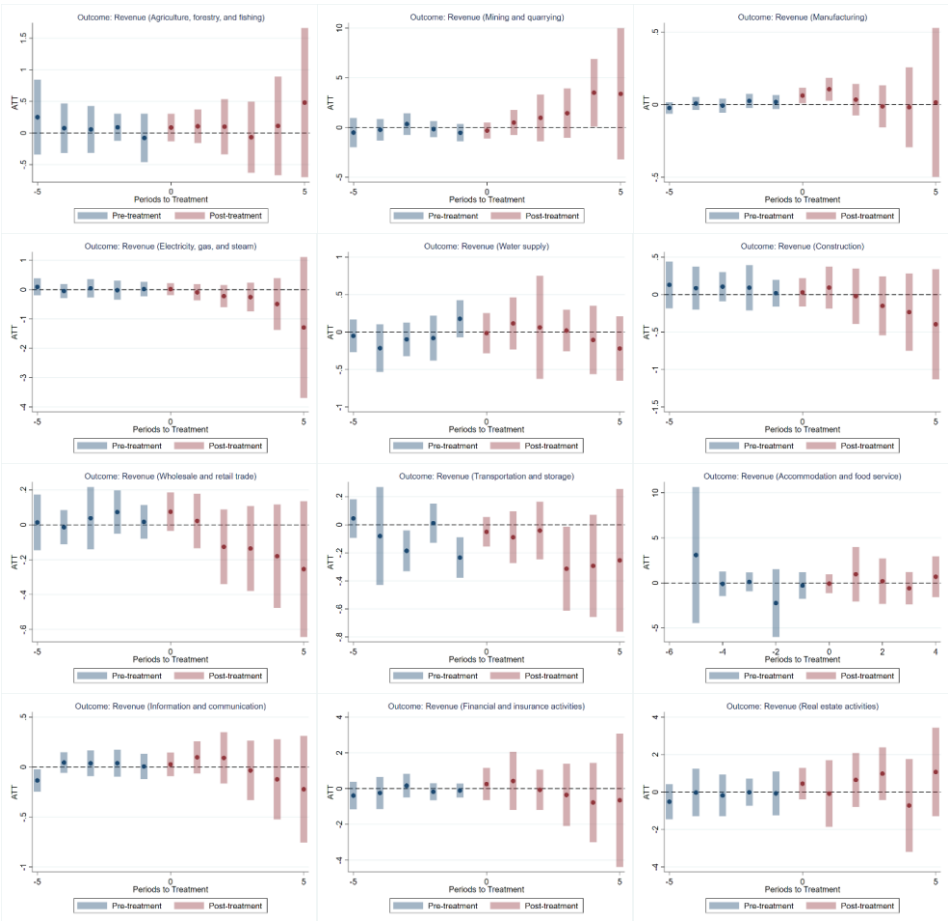
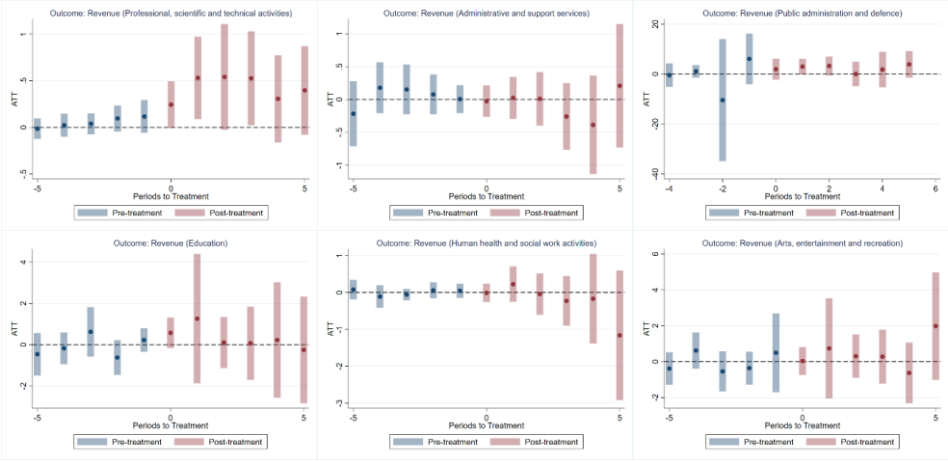


Figure A3: DiD coefficients plot on firm level revenue by NACE code




Outcome: Revenue (Professional, scientific and technical activities)
Outcome: Revenue (Administrative and support services)
Outcome: Revenue (Public administration and defence)
Outcome: Revenue (Education)
Outcome: Revenue (Human health and social work activities)
Outcome: Revenue (Arts, entertainment and recreation)
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This paper evaluates the causal impact of the Horizon 2020 Framework Programme for Research and Innovation on financial firm-level outcomes using a Difference-in-Differences (DiD) approach. We use administrative data from CORDA and financial data from ORBIS spanning from 2010 to 2022, for a sample of approximately 40 thousand unique private companies that applied for Horizon 2020 funding. The findings suggest that firms receiving Horizon 2020 grants exhibit an average increase of 20% in employment and about 30% in total assets and revenues, compared to comparable companies in the control group, in the years after receiving their first grant. Positive effects persist even after 2.5 years, which is the average duration of a project in our sample. Companies in the “Information and communication” and “Professional, scientific and technical activities” NACE sectors are driving the results, while other sectors show insignificant effects.

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