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Unlocking Growth? EU investment programmes and firm performance

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Abstract

This study evaluates the effectiveness of EU Cohesion Policy as an investment programme, employing a novel dataset that links firm-level data from Orbis with project-level information from the Kohesio database. It focuses on two key questions: (1) Which firms receive EU funding? (2) How does receiving EU funding affect firm performance? By applying a logit model and a local projection difference-in-differences approach, we provide new insights into the allocation mechanisms of EU Cohesion Policy funds and their firm-level impact. Our findings show that funding tends to be allocated to firms that already perform relatively well, and that firms receiving EU funding experience a persistent productivity increase of approximately 3% after 4 years, with smaller and more financially constrained firms experiencing relatively greater improvements. Moreover, funding targeting "SME investment" tends to enhance firm performance disproportionately more than other categories, whereas projects directed the "green transition" appear comparatively less beneficial.

Keywords: European Structural and Investment Funds, Productivity, Corporate Investment, Fiscal Policy, Place-based Policy.

JEL classification: E22, D24, H54, O38, O52

Non-technical summary

Productivity is a key driver of long-term economic growth and living standards. In recent decades, however, Europe has experienced a marked and persistent slowdown in productivity growth, raising concerns among policymakers and bringing the topic to the centre of the policy debate. Against this backdrop, EU Cohesion Policy, delivered primarily through the European Structural and Investment Funds (ESIF), represent one of the EU's main instruments for promoting economic development, productivity, and regional convergence.

This paper evaluates the impact of the 2014–2020 ESIF on firm-level outcomes across the EU. Using a novel dataset that links firm-level information from the Orbis database with project-level data from the European Commission's Kohesio dataset, the study examines (1) which firms receive EU funding and (2) how receiving funding affects their investment and productivity.

The analysis shows that EU funding is typically directed toward relatively well-performing firms, that are less capital-intensive and face some degree of financial constraints. Firms receiving funding increase their capital by around 15% within one year and experience a gradual productivity growth, reaching approximately 3% after four years. These effects are more pronounced for small and medium-sized enterprises (SMEs) and for firms facing financing constraint, suggesting that EU funding helps to unlock investment by easing access to capital.

Moreover, the study finds that not all categories of funding yield the same outcomes. Projects aimed at supporting "SME investment" have stronger positive effects on capital accumulation and productivity growth, while projects targeting green transition objectives show more limited gains.

The findings highlight the important role of EU programmes in enhancing firm-level investment and productivity. They also suggest that targeted allocation—especially towards SMEs and financially constrained firms—can improve the policy's effectiveness. These insights are especially relevant as the EU continues to channel investments during the ongoing Cohesion Policy programming period—and the Recovery and Resilience Facility—, while also preparing to revamp the EU budget for the 2028–2034 cycle.

1 Introduction

Productivity is a fundamental driver of long-term economic growth and improvements in living standards.[1] While productivity performance has long been a priority for policymakers, it has recently taken centre stage in the EU policy debate amid the pronounced and persistent slowdown observed in Europe over the past three decades (Draghi, 2024). In this context, assessing the effectiveness of existing policy instruments aimed at fostering investment and productivity is essential, not only to evaluate their impact, but also to inform future policy design by identifying what works, for whom, and under what conditions.

An example of such instruments is the EU Cohesion Policy. While the EU's fiscal capacity remains limited, the Cohesion Policy—operationalized through the European Structural and Investment Funds (ESIF)—stands as one of the Union's most significant instruments for promoting economic development. Over the past 25 years, the EU has invested approximately one trillion euros through these funds, with the objective of reducing regional disparities and promoting economic and social cohesion. For the current programming period (2021-2027), the EU has allocated around €392 billion for Cohesion Policy initiatives, confirming its commitment to promoting convergence and growth through this instrument.[2]

This paper contributes to the growing literature on the effectiveness of place-based policy by evaluating the impact of EU structural funds on firm-level outcomes, focusing in particular on firms' investment and productivity. To do so, we construct a novel dataset that links firm-level information from the Orbis database with project-level data from the European Commission's Kohesio dataset, covering the entire EU.

We address two main questions: (1) What are the characteristics of firms that receive EU funding? (2) What are the effects of receiving EU funding on firm performance? To address the first question, we use a logistic regression model to identify the firm characteristics that most influence the likelihood of receiving funding. In addition, to prevent over-fitting and isolate the most relevant predictors, we also apply lasso penalization to select a key subset of firm-level variables. This allows us to uncover structural differences between treated and never-treated firms, and informs our subsequent identification strategy. For the second question, we employ a local projection difference-in-differences (LP-DiD) approach following Dube et al. (2023). Our identification strategy relies on including covariates and restricting the sample only to firms that eventually received EU funds,

[1] As Paul Krugman wrote, in a now famous quote, *"productivity isn't everything, but in the long run it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker"* (Krugman, 1990).

[2] For more details on the 2021-2027 programming period see the European Commission website.

leveraging variation in the timing of treatment across firms to pin down the effects of receiving funding. In other words, we exploit the fact that firms first receive funding in different years to use not-yet (but eventually) treated firms as controls for already treated firms.

Our results indicate that EU funding is typically granted to firms that are growing, less capital intensive, and financially constrained. Following the receipt of funds, these firms increase investment sharply — as capital rises by 15% within one year — and expand their leverage, suggesting improved access to external finance. The effects on productivity materialize more gradually, with total factor productivity (TFP) increasing cumulatively by up to 3% four years after the intervention. We also find modest but statistically significant increases in intangible intensity, pointing to a shift in capital composition.

Importantly, the benefits are concentrated among smaller firms and those with greater financial constraints, underscoring the value of targeted support for small and medium-sized enterprises (SMEs). Moreover, we explore heterogeneity by policy priority and find that funding allocated to "SME investment" yields more robust firm-level gains, while funding directed towards the "Green transition" improves firm outcomes to a lesser extent.

Overall, this paper provides new empirical evidence that EU Cohesion Policy funds enhance firm performance and productivity, with significant differences by firm size, financial conditions, and funding category. These findings highlight the importance of designing targeted funding mechanisms—that balance support for high-performing firms with interventions that alleviate financing constraints—to maximize the impact of EU investment programmes.

The remainder of the paper is structured as follows: section 2 reviews the relevant literature and outlines the paper's contribution, section 3 presents the data, section 4 describes the research design and discusses the results, and section 5 concludes.

2 Literature review

Our work relates to the growing literature aiming to measure the impact of public policies by employing micro data. Our findings largely corroborate prior research, which consistently showed that EU funds help firms invest and grow. Our first contribution relates to the novelty of the dataset, which allows us to study productivity at the firm-level and in all EU countries. Previous studies tend to find mixed results on firms' productivity. For example, Bachtrögler et al. (2019) analyse the effects of Cohesion Policy funding for the 2007-2013 programming period on a sample of manufacturing firms, finding positive employment and capital impacts but limited productivity improvements. Single-country studies reveal similar patterns. Beņkovskis, Tkačevs and Yashiro (2019) show that Latvian firms receiving funds from The European Regional Development Fund (ERDF) increase employment and turnover immediately, but achieve productivity gains only after two years. Cabral and Manuel Campos (2023) find positive and persistent effects across multiple performance indicators, including productivity, for Portuguese firms using dynamic difference-in-differences methodology. Bernini and Pellegrini (2011) analyse Italian regional policy, finding higher growth in output and employment but negative long-term productivity impacts.

We believe that our positive results on productivity are partly due to our large sample of firms, as well as our methodological choices, which allow time for the productivity effects to emerge, by studying firm outcomes up to four years after receiving funds. Lastly, the empirical methodology we employ addresses the issues highlighted by the new Difference-in-Differences literature (de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021). These concerns have put into question the findings of applied papers—including some prior work on the effects of EU funds on firm performance—that used the now discredited two-way fixed effects regressions in settings with staggered treatment and heterogeneous, dynamic treatment effects.

Moreover, our findings that smaller firms benefit disproportionately from public support are largely consistent with prior evidence. Criscuolo et al. (2019) show that productivity enhancing effects of subsidies exist solely for small firms, while large companies do not display improvements. Alexandre, Chaves and Portela (2025) also find that only micro- and small-sized firms benefit from single grants. However, Beņkovskis, Tkačevs and Yashiro (2019) show that initially less productive, larger, and more leveraged ERDF beneficiaries achieve larger productivity gains.

We find that Cohesion funds are allocated to financially constrained firms, helping them increase leverage and capital. This can explain why we see larger productivity improvements for financially constrained firms. These findings are broadly consistent with literature that examines the role of publicly funded banks and development institution in mitigating firms' financing constraints. Akcigit et al. (2024) analyse Turkey's large credit guarantee program and find that supported firms preserved 17% percent more employment and achieved 70% percent higher sales. However, the program did not spur productivity-enhancing investment, such as R&D, and resulted in increased firm indebtedness. The gains were most pronounced for medium-sized firms and labour-intensive sectors. Zecchini and Ventura (2009) find causal relationships between Italian public credit guarantees and higher debt leverage with lower costs for SMEs. An impact evaluation of European Investment Bank (EIB) supported credit in the Western Balkans (EIB, 2023) finds EIB-funded firms achieved about 15% higher employment growth than comparable non-beneficiaries, translating to roughly 15 additional jobs per €1 million of EIB loans. Beneficiary firms also substantially increased their capital stock – on average total assets grew 20% and fixed assets 35% relative to control firms – suggesting that EIB credit enabled firms to undertake investments they otherwise could not finance.

Our paper is also related to studies that use regional data to estimate the multipliers of EU structural funds. Canova and Pappa (2021) find that the ERDF has positive short-term effects on regional variables, though gains dissipate within three years. Coelho (2019) estimates regional multipliers of 1.8 contemporaneously and 4.1 three years after shocks, while Durand and Espinoza (2021) find short-term multipliers of 1.2-1.8 percent with some evidence of private investment crowding-in. De Santis and Vinci (2025) find strong crowding-in effects. Gabriel, Klein and Pessoa (2021) estimate a government spending multiplier of around 2 for output and 1.4 for employment in the eurozone. Fiuratti et al. (2023) provide a more cautious assessment, finding little evidence of large GDP multipliers despite strong regional investment responses.

3 Data

Our empirical analysis is based on three main datasets: 1) Orbis by Bureau van Dijk, which contains firm-level balance sheet information at annual frequency; 2) Kohesio dataset from the European Commission, which provide project-level data on Cohesion Policy for the programming period 2014-2020 for the 27 EU member states; 3) Eurostat, from which we obtain aggregate variables at sectoral (NACE) and regional (NUTS) level.

3.1 Orbis

Our Orbis sample runs from 2010-2022 for the 27 member states of the European Union. The raw data requires intensive cleaning to deal with data-quality issues and to construct a nationally representative dataset. The cleaning steps we implement follow closely Díez, Fan and Villegas-Sánchez (2021) and Şebnem Kalemli-Özcan et al. (2024). The data cleaning process begins by removing observations with basic reporting errors (e.g. negative sales or missing industry information). It also includes checks based on ratios of key balance-sheet variables, and excludes firms reporting implausible annual growth rates in sales, revenues, or number of employees. After cleaning the data, we deflate the nominal variables using country level GDP deflators from Eurostat, so that all monetary variables are expressed in real terms (with base year 2015).

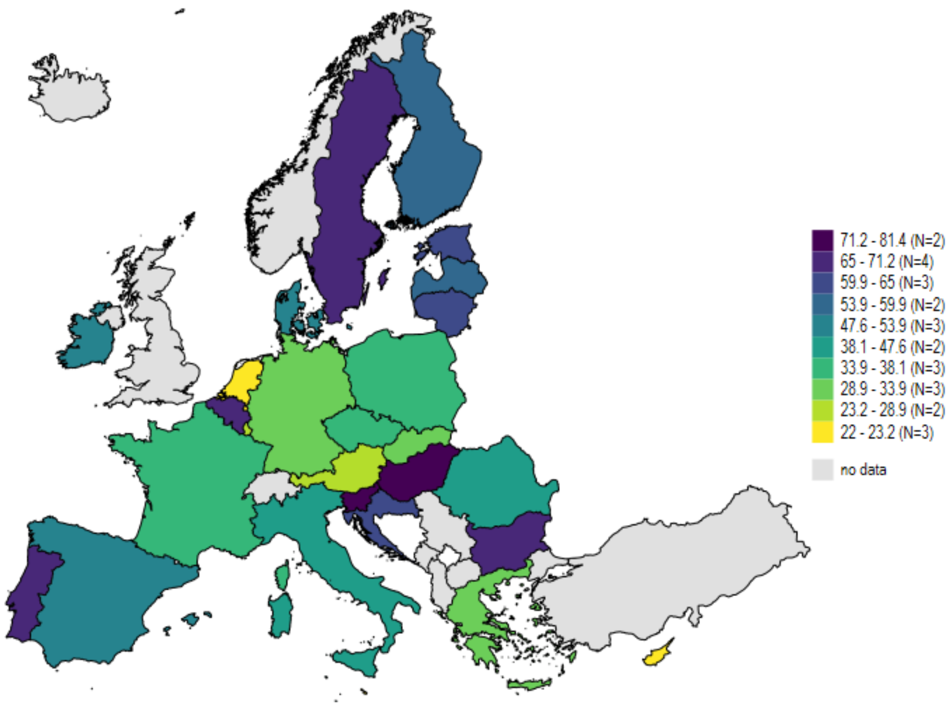

Figure 1: Average Gross Output coverage over the period 2010-2022 in our cleaned Orbis sample. Coverage is computed by summing for each country in each year the operating revenue of all the firms and then dividing the sum by the country's gross output data from Eurostat. We then average the coverage for each country across the years from 2010 to 2022.

The map in figure 1 shows the average coverage for the EU27 countries for the period we use in our analysis (2010-2022). Coverage varies considerably across the countries ranging from around 20% to 80% of total gross output.

Figure 2 shows the evolution of average coverage across EU27 countries in our cleaned Orbis sample. We report the coverage for the period 2000-2022, but in our analysis we only use data from 2010 onwards. In the period of interest (2010-2022), firms in our sample cover on average roughly 50% of total gross output and 25% of employment.

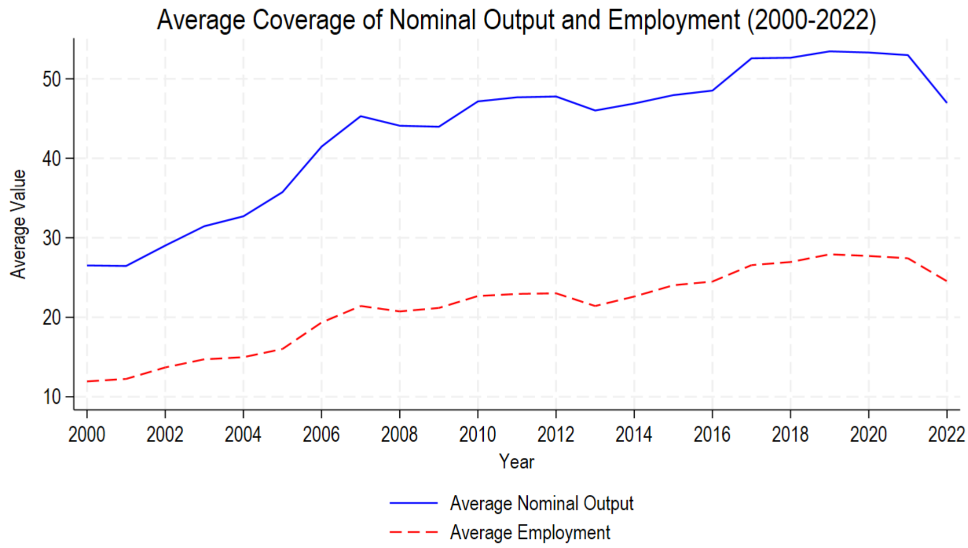

Figure 2: Average coverage for the EU27 countries in the cleaned Orbis sample. Coverage is first computed for each country by year, followed by an unweighted average across countries for each year to construct the time series. The denominators for nominal output and employment are sourced from Eurostat.

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3.2 EU Cohesion Policy

The EU Cohesion Policy aims at reducing regional disparities and foster job creation, business competitiveness, economic growth, sustainable development and improvements to citizens' quality of life across the European Union. [3]

Concretely, the EU Cohesion Policy is delivered through specific funds, whose names, composition, amounts and objectives can change between programming periods. In the programming period 2014-2020, funding was delivered through the European Structural and Investment Funds (ESIF), which comprises the following funds: the European Regional Development Fund (ERDF), the European Agricultural Fund for Rural Development (EAFRD), the European Social Fund (ESF), the Cohesion Fund (CF), the Youth Employment Initiative (YEI) and the European Maritime and Fisheries Fund (EMFF). Table 1 displays the breakdown of ESIF by sub-funds, highlighting the relative size of each of them, as well as the amount of the EU and national contribution.

Figure 3 display the regional distribution of ESIF per capita by NUTS2 regions, showing that less developed regions receive relatively more funding per capita, in line with the policy's objectives.

[3]For more details see the European Commission website.

Fund	EU Amount	% of Total	National Amount	Total Amount
ERDF	230,005,563,849	42%	78,117,360,847	308,122,924,696
EAFRD	136,042,437,812	25%	56,904,949,527	192,947,387,339
ESF	104,402,027,966	19%	35,980,887,543	140,382,915,509
CF	61,434,784,152	11%	10,946,167,365	72,380,951,517
YEI	8,960,645,385	2%	1,504,778,494	10,465,423,879
EMFF	5,616,815,235	1%	2,168,988,675	7,785,803,910
Total	*546,462,274,399*	*100%*	*185,623,132,451*	*732,085,406,850*

Table 1: Planned financing under the different EU Cohesion Policy funds. Columns represent: (1) the fund name, (2) EU amount of planned financing under each fund, (3) percentage share of each fund in the total EU contribution, (4) national co-financing amount, and (5) the total amount of planned financing. Source: European Commission.

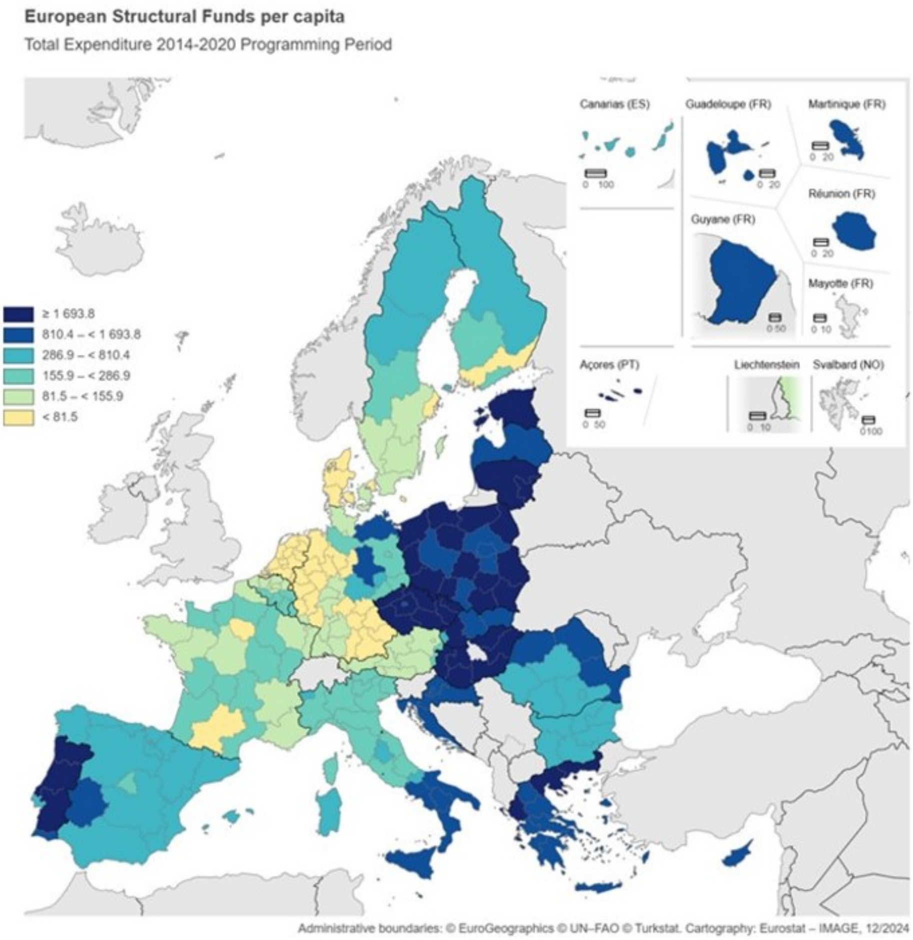


Figure 3: Map showing the total Cohesion Policy per capita spending in the 2014-2020 programming period. The numbers are based on a regional dataset provided by the European Commission.

The mechanism by which ESI funds are allocated is relatively complex and involves multiple stages and authorities. From a firm's perspective, the process starts by identifying funding opportunities, which are often advertised on platforms such as the EU Funding & Tenders Portal[4] or

[4]For more information see the EU Funding & Tenders Portal website.

on national and regional portals. Once a suitable opportunity is identified, firms must check their eligibility. This involves ensuring that their project aligns with EU priorities and verifying their capacity to co-finance the project. Interested firms need to compile a comprehensive set of documents, including a project proposal, budget, impact assessments, and necessary legal and financial documents.[5] Submitted applications are subject to evaluation and decision-making processes conducted by Managing Authorities and independent experts. If the application is successful, the firm moves into the implementation and reporting phase, during which it must adhere to EU reporting standards and undergo regular audits.

Key stakeholders in this process include the European Commission, which sets priorities and approves programs, and Managing Authorities, which are national or regional bodies that oversee project selection, for example, Poland's Ministry of Development Funds and Regional Policy or regional governments in Spain. Independent experts evaluate the technical and financial viability of projects, while civil society participates in consultations and monitoring.

Decision-makers and evaluation criteria vary depending on the funding source. For EU programs, decisions are made by European Commission panels and external experts. For regional funds, national or regional Managing Authorities are responsible. Evaluation criteria focus on the project's alignment with EU priorities like climate action and digitalization, as well as factors such as innovation, feasibility, scalability, economic, social, or environmental impact, cost-effectiveness, and sustainability.

Data on Cohesion Policy projects for the 27 EU member states are sourced from the Kohesio dataset[6] provided by the European Commission.[7] For the 2014-2020 programming period, the Kohesio dataset contains detailed information at project level, [8] including the total expenditure, co-financing rates, project duration, and strategic priority addressed.[9] Crucially, for each project the dataset provides the name of the beneficiary, which we use to identify the corresponding firm in Orbis.

The Kohesio dataset also has some limitations. First, the data contains some missing values

[5] Applicants are required to meet specific criteria and provide detailed documentation. A clear project proposal detailing objectives, timelines, and deliverables is essential. The budget breakdown should include proof of co-financing and detailed cost estimates. Impact assessments are necessary to quantify the anticipated social, environmental, or economic benefits of the project. Additionally, legal and financial documents such as company registration, financial statements, and partnership agreements, if applicable, must be submitted.

[6] The data is available on the European Commission website.

[7] We focus on the 2014-2020 programming period because the current one (2021-2027) is not yet completed and, to our knowledge, data on previous programming periods are not publicly available at project level.

[8] The data were updated to the end of 2022 at the time of download.

[9] The Cohesion Policy framework entails a grace period of up to 3 years resulting in projects being completed beyond the end of the programming period. For more details see A modernised Cohesion Policy: The mid-term review.

	mean	p25	p50	p75	sd
Total funds awarded	232,790	1,767	7,570	58,094	3,741,000
Total project size	329,251	2,306	10,967	91,737	4,588,000
Project duration	2.18	1.00	2.00	3.00	1.22
Cofinance rate	0.72	0.50	0.75	0.85	0.21

Table 2: Summary statistics for the Cohesion Policy projects for the programming period 2014-2020 for which project level data is available. Monetary values are in 2015 EUR and are deflated using the value of the deflator at the start year of the project. p25 refers to the 25th percentile, p50 is the median and p75 is the 75th percentile, sd is the standard deviation.

and occasional reporting errors. Second, the dataset only provides information on the start dates and the completion dates of projects, without the full time profile of the expenditures. To address this issue, we distribute the total amount of each project evenly across its duration.[10] Figure 4 compares the aggregate regional expenditure data provided by the European Commission with the time series we construct aggregating project level information from the Kohesio dataset. The two lines display the similar patterns and strong co-movement. Our measure of total annual spending shows a somewhat more front-loaded expenditure profile than the regional level data, where a higher share of spending takes place towards the end of the programming cycle. Moreover, the total spending in the aggregate regional expenditure data is larger than the project level Kohesio data, partly as a result of the missing data in the project-level dataset.

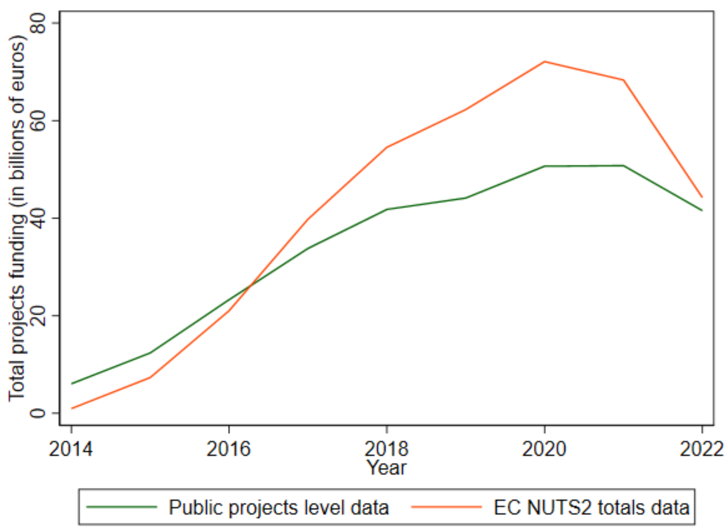


Figure 4: The orange line represents aggregate regional ESIF expenditure, as reported by the European Commission, while the green line shows the aggregate expenditure from the Kohesio dataset, calculated by distributing each project's total amount evenly over its duration.

[10]This is the same approach used, for example, in Auerbach, Gorodnichenko and Murphy (2020).

3.3 Eurostat

We obtain country and sector level indicators on output, investments, employment and price levels from Eurostat. These indicators are used to deflate Orbis variables and to assess coverage against aggregate data.

3.4 Merging Orbis firm-level data with Cohesion funds data

A key challenge in linking the project-level Cohesion Funds dataset with the firm-level Orbis dataset is the absence of a common identifier. To overcome this limitation, we match firm names, which are available in both datasets. To reduce the likelihood of false positive matches that would compromise the treatment group, the matching procedure is designed with a conservative approach. As only the beneficiary name and country are available, matches are restricted to entities located within the same country. The matching algorithm proceeds in four steps:

1. names are cleaned of spaces, punctuation, accents, all letters are capitalized and common acronyms, such as *"LLC"* for *"Limited Liability Company"*, are harmonized using a dictionary of acronyms specific for each country; [11]

2. the cleaned names are used as if they were IDs and an exact matching is performed;

3. firms that were part of one-to-one matches are considered valid treatment group firms, while firms that were part of many-to-one or one-to-many matches are flagged and are excluded from further analysis;

4. finally, firms for which the total amount of project exceeds their total assets are also flagged and excluded.

Table 3 presents the number of beneficiaries with available project data by country (first column), alongside the number of firms included in valid matches (second column) and those excluded (third column). It is important to note that not all beneficiaries are firms; many are public or non-profit entities such as schools, hospitals, or charities. In addition, several data quality issues affect both the coverage and the success rate of the matching algorithm. For instance, in the Cohesion dataset, beneficiary names are occasionally missing, making it impossible to match certain projects to firms in Orbis. In some cases, information on project funding amounts is also absent. Firms that are matched only to projects with missing funding data are therefore included in the excluded

[11] The dictionary of acronyms has been developed in-house and is available upon request.

Country	All Beneficiaries	Treatment Group	Excluded Group
Austria	2,557	367	203
Belgium	2,215	-	-
Bulgaria	35,179	-	-
Cyprus	4,055	-	-
Czechia	36,600	2,153	2,043
Germany	117,289	8,492	7,835
Denmark	193	5	1
Estonia	9,484	7	5
Spain	72,072	16,268	2,816
Finland	5,503	2,241	696
France	20,209	721	2,525
Greece	36,379	9	-
Croatia	7,741	861	426
Hungary	24,592	1,506	160
Ireland	310	-	4
Italy	129,872	10,216	35,179
Lithuania	9,677	2,924	634
Luxembourg	60	-	-
Latvia	897	45	6
Malta	2,192	-	123
Netherlands	13,447	393	519
Poland	57,419	1,760	1,263
Portugal	124,265	38,174	13,289
Romania	10,256	2,811	3,086
Sweden	1,158	61	34
Slovenia	4,543	46	9
Slovakia	5,215	198	63
EU27 Total	**733,379**	**89,258**	**70,919**

Table 3: The table shows the numbers of unique Cohesion Beneficiaries for the 2014-2020 programming period by country. All Beneficiaries is counting the number of unique beneficiaries that we attempt to merge with the firms in the Orbis dataset. The treatment group column shows the number of firms that were valid matches with Cohesion projects. The excluded group shows the number of firms that were part of non-valid matches (mostly due to being part of one-to-many or many-to-one matches).

group. Importantly, the treatment group used in the regression analysis is smaller than the number of valid matches reported in table 3, as some firms are dropped from the regressions due to missing values in one or more explanatory variables or insufficient coverage over time.

3.5 Productivity estimation

One of the key variables we analyse is firm level total factor productivity (TFP). Since TFP is not directly observable we need to estimate it from the firm level data. We follow the approach of Levinsohn and Petrin (2003) and use Orbis data to estimate the production functions separately for each country and two digit NACE sector pair. Further details are provided in Appendix A.2.

4 Empirical Analysis

4.1 Summary Statistics

We match approximately 90,000 firms in Orbis to projects data from the Cohesion Policy. The total EU funding allocated to the firms in our dataset accounts for approximately 16 billion euros, which accounts for 34% of the total of 47 billion euros directly allocated to firms under the Cohesion Policy for the 2014-2020 programming period[12].

Based on current Commission reporting, 47 billion had been allocated to firms by 2022, entirely under the ERDF, accounting for roughly 22% of the fund's total allocation. Hence, while our dataset covers a substantial share of the funds directly matched to firms, our analysis focuses on a specific component of the overall Cohesion Policy.

Consistently with reporting by the Commission, most of the firms matched (approximately 81%) and assigned to our treatment group receive funding from the European Regional Development Fund. However, we also find that 17% of firms receive funding from the European Social Fund and under 2% from the Youth Employment Initiative. This discrepancy is not unexpected, as Commission reporting is subject to ongoing updates and has not yet been finalised. The policy objectives under which firms receive funding are: Smarter Europe – 75% of firms, Social Europe – 19%, and Greener carbon-free Europe – 6%. The most common thematic objectives are: Competitiveness of SMEs – 63% of firms, Sustainable and quality employment – 15%, Research and innovation – 11%, and Low-carbon economy – 5%.

Figure 5 illustrates a word cloud derived from the descriptions of funded projects involving firms in our treatment group. The visualization prominently features key terms such as "development," "business," "knowhow," "permanent," "new," "structural," "competitiveness," "implementation," "overcome," and "difficulties." These words indicate a strong focus on promoting sustainable and enduring business growth, emphasizing structural changes, and enhancing firms' competitiveness.

Moreover, the frequent appearance of terms such as "innovation," "internationalisation," "expansion," "modernisation," and references to "SMEs" underline the intent of funding transformative investments. These terms collectively suggest EU Cohesion funding is primarily aimed at addressing structural and operational challenges, facilitating innovation, and boosting long-term productivity and competitiveness.

[12]The share of funds directly matched to firms comprises FIRMS: Private match grant aid, FIRMS: Private match non-grant, and RTDI: Private match investment, as reported in the ESIF 2014-2020 Achievement Details time-series dataset provided by the Commission. The latter shows that funds directly matched to firms mostly pertain to the ERDF fund, as confirmed by our matching exercise.

Figure 5: Word cloud of projects descriptions - matched firms.

For an average firm that we match to Cohesion projects, we see non-missing project funding for just over 2 years. Some firms receive more than one project in a given year in which case we sum the project amounts to keep our final dataset at firm-year level. Comparing tables 2 with 4 we can see that the projects matched to firms have similar co-financing rates and duration but are smaller in size. Table 4 also allows us to contextualize the size of the funding received by firms by comparing the project amounts with firms' total assets or annual sales figures. A median firm that receives funding under Cohesion Policy receives total funding of approximately 4% of total assets or 5% of annual sales.

	mean	p25	p50	p75	sd
Total funds awarded	176,924	3,750	12,499	60,375	2,399,000
Total project size	319,805	6,545	18,190	103,306	3,195,000
Co-finance rate	0.75	0.50	0.80	1.00	0.23
Funds awarded to assets ratio	0.11	0.01	0.04	0.13	0.21
Funds awarded to sales ratio	0.44	0.01	0.04	0.12	10.88
Project size to assets ratio	0.17	0.01	0.05	0.18	0.33
Project size to sales ratio	0.65	0.01	0.05	0.16	16.01
Active projects	1.25	1	1	1.125	7.39
Years with projects data	2.13	1	2	3	1.53

Table 4: Summary statistics relating to the Cohesion Projects that were successfully matched to the firm-level panel (i.e. our treatment group). p25 refers to the 25th percentile, p50 is the median and p75 is the 75th percentile, sd is the standard deviation. Monetary values are in 2015 euros. Total funds awarded and Total project size are at firm level (summing over the years the total amounts for each firm). Active projects is the number of projects under which a firm is receiving funding in a given year. Years with projects data is counting the number of non-missing observations of total funds per firm. The ratios of totals to assets and sales are computed using the total amounts pertaining to projects divided by firms' average total assets and average annual sales, Co-finance rate is the ratio of total funds awarded to total project size.

Table 5 reports summary statistics for key firm-level variables separately for the firms that were matched to Cohesion projects and those that were not matched. We can see that the firms that received funding under the Cohesion Policy are generally larger, growing faster, more leveraged, and more reliant on debt financing. These differences could be explained by composition effects (if for example firms receiving funding operate predominantly in sectors with larger, faster-growing, more leveraged firms). Moreover, as the means are based on the entire period (pre and post treatment) we cannot ascertain to what extent the differences are due to selection versus effects of the policy.

	Unmatched firms			Matched firms		
	mean	median	obs	mean	median	obs
Revenue	5,953,601	306,186	27,280,366	13,221,530	771,970	740,843
Sales	5,657,518	297,390	26,758,172	12,650,531	734,950	736,961
Assets	8,201,400	281,042	27,280,366	17,770,130	694,215	740,843
Capital to labour ratio	90,655	7,527	26,109,180	53,421	14,227	738,464
Employment	25.4	4	27,280,366	60.3	9	740,843
Producitivity growth	0.7%	0.1%	13,112,474	1%	1%	473,910
Employment growth	1.6%	0.0%	19,240,478	4%	0%	616,499
Sales growth	1.4%	1.0%	19,504,156	5%	4%	614,524
Gross profit margin	33.4%	57.6%	12,292,197	53%	54%	493,446
Capital growth	-0.9%	-7.2%	18,906,352	5%	-5%	603,926
Debt to equity ratio	0.11	0.00	19,940,642	0.18	0.11	573,387
Sales to assets ratio	1.68	1.25	26,758,172	1.43	1.13	736,961
Leverage ratio	0.11	0.00	19,940,804	0.18	0.11	573,389
Intangible intensity	0.03	0.00	27,028,142	0.03	0.00	739,376
Equity to assets ratio	0.45	0.43	27,257,884	0.43	0.40	740,839
Current ratio	122.7	1.7	26,923,680	11.4	1.7	732,842

Table 5: Summary statistics reported for the firms that were not matched to any Cohesionproject (unmatched firms) and firms that were matched to a project (matched firms). The "mean" and "median" are based on the entire 2010-2022 period, "obs" counts the number of non-missing observations for each variable. All monetary variables are expressed in 2015 euros. Growth rates are annual log growth rates, i.e. $ln(Y_t) - ln(Y_{t-1})$.

4.2 Which firms receive funding?

There is no single easy criterion to answer the question of which firms receive funding under the Cohesion Policy programmes. In this paper, we study the selection based on firm characteristics, and model this choice using a binary outcome model. In particular, we average firm level variables over the four year pre-treatment period (2010-2013) and use them to predict whether a firm received Cohesion Policy funding at any point between 2014-2022. The estimation equation is:

$$\text{logit}[P(Y_i = 1 \mid \bar{X}_i')] = \beta_0 + \sum_{j \in J} \beta_j \bar{X}_{i,j} + \sum_{s \in S} \gamma_s \text{nace}_{i,s} + \sum_{r \in R} \delta_r \text{region}_{i,r}$$

where Y_i takes value of 1 if firm i received funding and 0 otherwise, $\bar{X}_{i,j}$ are the firm-level variables, $\text{nace}_{i,s}$ is a dummy that takes value 1 is firm i is in sector s and 0 otherwise, $\text{region}_{i,r}$ is a dummy that takes value 1 if firm i is in country r and 0 otherwise, logit[ ] is the logistic function.

Our most parsimonious specification includes in $\bar{X}_i$ only a limited set of firm-level variables: total assets, capital to labour ratio, sales growth, and firm age. We also consider a more extended set of variables, including the leverage ratio, current ratio, sales to assets ratio, TFP growth, growth in employment, growth in capital, and intangible intensity.

We run three versions of each specification with varying levels of granularity of the sector level dummies and report the results in table 6. All specifications include region dummies (at NUTS2 level), and we control for: NACE letter, 2 digit or 3 digit sectors. We Z-Score normalize all the continuous variables so that the Odds Ratios reported in the regression table can be reported as the effects of increasing the variable by one standard deviation. The reported standard errors are clustered at the NUTS2 region level, as the selection of Cohesion Policy beneficiaries is conducted at the NUTS2 administrative level.

Logit: Odds Ratio

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Assets	1.65***	1.65***	1.67***	1.65***	1.64***	1.66***	1.65***	1.64***	1.66***
Capital/Labour	0.76***	0.77***	0.77***	0.64***	0.65***	0.65***	0.50***	0.52***	0.52***
Sales growth	1.19***	1.19***	1.19***	1.20***	1.19***	1.19***	1.15***	1.15***	1.15***
Age	1.05*	1.05*	1.04*	1.05**	1.05**	1.05**	1.04*	1.03*	1.03*
Leverage ratio				1.29***	1.29***	1.29***	1.27***	1.27***	1.27***
Current ratio				0.53	0.55	0.55	0.44	0.45	0.46
Sales/Assets							0.80***	0.78***	0.79***
TFP growth							1.02***	1.02**	1.02**
Employment growth							1.08***	1.08***	1.08***
Capital growth							1.07***	1.08***	1.08***
Intangible intensity							0.68***	0.67***	0.66***
Observations	1,568,454	1,568,228	1,565,966	1,379,406	1,379,230	1,377,074	1,379,108	1,378,932	1,376,776
Sector dummies	Letter	2 digit	3 digit	Letter	2 digit	3 digit	Letter	2 digit	3 digit
NUTS2 dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Logit regressions for whether firms receive funding in the 2014-2020 programming period based on 2010-2013 average firm characteristics. The dependent variable takes value 1 if a firm received Cohesionfunding in the 2014-2020 programming period and 0 otherwise. The explanatory variables are Z-score normalized. The coefficients are odds ratios (values above 1 mean positive effect, values below 1 negative effect on probability of receiving funds), Sector dummies are at either NACE Letter level, NACE 2 digit, or NACE 3 digit sector level. The standard errors used to compute statistical significance were clustered by NUTS2 region.

The results in table 6 show that firms with higher total assets have higher odds of receiving funding, while firms with higher capital-to-labour ratios are less likely to receive funding. Fast-growing firms show higher probabilities of selection, while a firm's age has a modest positive effect on receiving funding. The extended specifications reveal that more leveraged firms are more likely to receive funding, while firms with higher intangible intensity are less likely to be selected. Together, this suggests that larger, growing, more leveraged, less capital-intensive firms are favoured.

In addition to the model described above, we employ a data-driven approach to guide the selection of the most relevant predictors. We begin by estimating a lasso-penalized linear probability model for whether a firm is part of the treatment group. The model includes a wide range of firm-level predictors $X_{i,j}$, but not all of them are selected. Since lasso is a penalized regression we are not worried about over-fitting and can include many regressors knowing that only those with the most predictive ability will be selected. In other words, we can be agnostic about what variables are important in predicting if a firm receives funding and "let the data speak" about what is the relevant set of predictor variables. The variables we include that are subject to selection are: region dummies, sector dummies, total assets, employment, capital, value added, materials expenditure, productivity growth, employment growth, capital growth, value added growth, sales growth, debt to equity ratio, sales to assets ratio, leverage ratio, equity to assets ratio, capital to labour ratio, current ratio, intangible intensity, age, dummies for whether a firm is under 5 and under 10 years old, and a number of dummies capturing whether the firm is relatively productive/leveraged/capital intensive/liquid compared to peers within its' NACE 2-digit sector country year group. The "financially constrained" dummy takes the value of 1 if a firm is less than 15 years old and has above median leverage compared to other firms in its country and NACE 2-digit sector, in the spirit of Cloyne et al. (2023), Durante, Ferrando and Vermeulen (2022) and Anaya Longaric et al. (2025). The ">p90 TFP" dummy takes a value of 1 if a firms is in the top 10% of the TFP distribution in its country and NACE 2-digit sector, following the definition of a firm at the productivity frontier by Andrews, Criscuolo and Gal (2015).

The lasso regression minimizes the following objective function:

$$\text{Objective} = \frac{1}{2n}\sum_{i=1}^{n}\left(Y_i - \beta_0 - \sum_{j\in J}\beta_j \bar{X}_{i,j} - \sum_{s\in S}\beta_s \text{nace}_{i,s} - \sum_{r\in R}\beta_r \text{region}_{i,r}\right)^2 + \lambda\sum_{j=1}^{p}|\beta_j|,$$

where n is the number of observations, p is the number of predictors considered for selection, λ is the penalty parameter controlling the strength of the regularization. The ℓ_1-penalty term ($\lambda\sum_{j=1}^{p}|\beta_j|$) induces sparsity by shrinking some coefficients exactly to zero, effectively excluding the corresponding predictors from the model. A higher λ value increases the penalty, leading to more coefficients being set to zero. For a given λ, lasso minimizes the objective function, yielding a model with a subset $S \subset J$ of predictors included.

We use the Bayesian Information Criterion (BIC) to select the optimal penalty parameter (λ)

that balances goodness-of-fit and model complexity. The BIC is defined as:

$$\text{BIC} = -2\ln(\hat{L}) + p\ln(n),$$

where $\hat{L}$ is the maximum likelihood of the model, p is the number of non-zero model parameters, and n is the number of observations.

Our lasso procedure evaluates models across a grid of one hundred potential λ values, calculating the BIC for each model. The selected λ and its corresponding model is the one that minimizes the BIC. To compare the results from this procedure with the results from our Logit model, we estimate the Logit model as before but with the set $S \subset J$ of predictors determined by the lasso procedure just described. For interpretability we report the coefficients as Odds Ratios and we Z-score normalize all continuous variables.

The lasso logistic regression results in Table 7 reveal that allocation is concentrated among firms exhibiting larger size, faster growth, higher productivity, and moderate financial risk. Larger firms—measured by both employment and capital stock—are more likely to receive aid. At the same time, firms with less than 50 employees are more likely to receive funding, suggesting that funding is primarily allocated to relatively larger yet still small enterprises. Growth indicators are among the most robust drivers of selection. Firms with higher growth in productivity, employment, capital and value added enjoy higher odds of receiving funding. Productivity itself also matters. Firms above the 10^{th}, 50^{th} and 90^{th} percentiles of sector–country TFP exhibit higher odds. Financial risk profiles exhibit a non-linear selection function. Firms just above the 10^{th} percentile of leverage ratio and current ratio are disproportionately supported, whereas those at or above the median thresholds see lower odds. Continuous measures of sales-to-assets and intangible intensity carry significant negative effects, while higher equity-to-assets ratios have a positive effect. In combination, these results indicate that the policy is directing funds toward firms that are financially stretched—highly leveraged and relatively illiquid—yet not so overextended as to be deemed non-viable. Age plays virtually no role once other factors are controlled for. Higher capital-to-labour ratio is inversely related with the probability of receiving funding, suggesting that funding is allocated to less capital-intensive firms. Together, we see that funding is primarily allocated to larger, growing, less capital-intensive, and productive SMEs under moderate financial pressure.

	(1)	(2)	(3)
Labour	1.35***	1.44***	1.47***
Capital	1.27***	1.15**	1.16**
Value Added	1.09	0.97	0.97
Materials	1.06		
TFP growth	1.05***	1.04***	1.04***
Employment growth	1.09***	1.09***	1.09***
Capital growth	1.07***	1.07***	1.07***
Value Added growth	1.20***	1.19***	1.19***
Debt/Equity	0.60	0.69	1.53
Sales/Assets	0.63***	0.66***	0.67***
Leverage ratio	2.64	2.38	1.08
Intangible intensity	0.73***	0.72***	0.72***
Capital/Labour	0.76***	0.79***	0.78***
Equity/Assets	1.18***	1.18***	1.19***
Current ratio	0.73		
Age	1.00	0.99	0.99
<50 Employees	1.33***	1.39***	1.43***
Financially constrained	0.96**	0.96***	0.96
>p10 TFP	1.49***	1.52***	1.52***
>p10 Leverage ratio	2.63***	2.78***	2.70***
>p10 Current ratio	1.25***	1.27***	1.25***
>p50 TFP	1.35***	1.37***	1.35***
>p50 Leverage ratio	0.50***	0.47***	0.48***
>p50 Capital/Labour	0.85***		
>p50 Current ratio	0.93**	0.93*	0.93**
>p90 TFP	1.08**	1.10***	1.10***
>p90 Leverage ratio	0.45***	0.42***	0.43***
>p90 Current ratio	0.71***	0.70***	0.70***
>p90 Capital/Labour	0.78***	0.76***	0.77***
Less than 5 years old	0.96*	0.96**	0.97
Less than 10 years old	1.01	1.01	
Observations	1,382,291	1,382,114	1,380,609
Sector dummies	Letter	2 digit	3 digit
NUTS2 dummies	YES	YES	YES

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Logit regressions results for whether firms receive funding in the 2014-2020 programming period based on 2010-2013 average firm characteristics. The dependent variable takes value 1 if a firm received Cohesion funding in the 2014-2020 programming period and 0 otherwise. The set of explanatory variables was selected by the lasso regression using the optimal penalty parameter according to BIC. Continuous explanatory variables were Z-score normalized. The coefficients are odds ratios (values above 1 mean positive effect, values below 1 negative effect on probability of receiving funds), region and sector dummies are not reported. The sector dummies were at: NACE Letter level, NACE 2 digit, or NACE 3 digit sector level. The standard errors used to compute statistical significance were clustered by NUTS2 region.

4.3 How does EU funding affect firm performance?

To answer how funding affects firm performance, we rely on the Difference-in-Differences framework. However, as our setting differs from the canonical 2 groups in 2 periods design of Heckman, Ichimura and Todd (1998), we rely on novel estimators designed for settings with many periods and staggered treatment adaption. In particular, most of our analysis is based on the Local Projections Difference-in-Differences framework of Dube et al. (2023), but we also reproduce our main results using the Callaway and Sant'Anna (2021) Difference-in-Differences with multiple periods estimator (see Appendix A.3). We choose these estimators as they allow for heterogeneous and dynamic treatment effects, and for the "parallel trends assumption" to hold potentially only after conditioning on observed covariates.

Following the exposition in Dube et al. (2023), we define: outcome Y_{it} as observed for $i = 1, \dots, N$ firms over $t = 1, \dots, T$ years. Firms can receive a binary treatment (i.e. receive EU funds or not) denoted by the indicator variable $D_{it} \in \{0, 1\}$. We assume treatment is permanent[13], therefore we have $D_{is} \leq D_{it}$ for $s < t$. We let p_i denote the year in which firm i receives funding for the first time, with $p_i = \infty$ if firm i never receives funding.

We define the treatment groups (cohorts) $g \in \{0, 1, \dots, G\}$ as firms that first received funding in the same year, and we define group $g = 0$ as the never treated group (i.e. firms that never receive EU funding throughout the sample period). We denote the year in which firm g enters treatment as p^g.

Using the potential outcomes framework, we let $Y_{i,t}(0)$ denote the potential outcome that firm i would experience in year t if they were to remain untreated throughout the whole sample period. We let $Y_{i,t}(p)$ denote the outcome for firm i in year t, if firm i were to enter treatment at time $p \neq \infty$. Define the (unit- and time-specific) treatment effect at time t for a firm which enters treatment at year p_i as:

$$\tau_{it} = Y_{i,t}(p_i) - Y_{i,t}(0).$$

As we do not observe the counterfactual no-treatment path of outcomes for the treated firms, the above is not observable. This is the fundamental problem of causal inference. As such, we turn our attention to the average effect on the treated (ATT). We define the (group-specific and dynamic) ATT at horizon h for group g which enters treatment at time p as:

$$\tau_g(h) = E\left[Y_{i,p+h}(p) - Y_{i,p+h}(0) \mid p_i = p\right].$$

$\tau_g(h)$ represents the average dynamic effect, h periods after entering treatment, for all firms belonging to a group g that enter treatment at time p.

We allow for heterogeneous treatment effects across different cohorts, i.e. $\tau_g(h) \neq \tau_{g'}(h)$ for

[13] Although the projects firms undertake after receiving funds have a finite horizon we assume permanent treatment effects as we believe the effects of the projects on the firm persist beyond the completion of a project.

some horizons h and some pairs of groups $g' \neq g$. We also include covariates and region and sector fixed effects to allow for the parallel trends assumption to potentially hold only conditionally on $W'_{i,t-1} = \{X'_{i,t-1}, \gamma_s, \delta_r\}$, where $X'_{i,t-1}$ are lagged time-varying firm characteristics, γ_s and δ_r are sector and region dummies. To recover the ATT we make the following assumptions:

Assumption 1. Conditional no anticipation

$$E\left[Y_{it}(p) - Y_{it}(0) \mid W'_{i,t-1}\right] = 0, \quad \text{for all } p \text{ and } t \text{ such that } t < p.$$

Assumption 2. Conditional parallel trends

$$E\left[Y_{i,t+h}(0) - Y_{i,t-1}(0) \mid W'_{i,t-1}, p_i = p\right] = E\left[Y_{i,t+h}(0) - Y_{i,t-1}(0) \mid W'_{i,t-1}\right],$$

for all $t \in \{2, \dots, T\}$, all $h \in \{0, \dots, T-1\}$, and all $p \in \{1, \dots, T, \infty\}$.

Assumption 3. Linear conditional expectation function

$$E\left[Y_{i,t+h}(0) - Y_{i,t-1}(0) \mid W'_{i,t-1}\right] = \delta_t^h + W'_{i,t-1}\theta^h$$

Assumption 4. Treatment effects are independent of covariates[14]

Finally, we can define our main object of interest as the dynamic ATT at horizon h conditional on covariates as:

$$\text{ATT}^h(x) = E\left[Y_{i,p_i+h}(p_i) - Y_{i,p_i+h}(0) \mid p_i \neq \infty, w = W'_{i,t-1}\right].$$

Our main identification challenge in recovering the ATT is that firm characteristics predict receiving funding, as documented in the previous section. As such, the assumption of no treatment anticipation is unlikely to hold unconditionally. Moreover, as we only see the projects that got accepted, we cannot distinguish between selection into treatment due to firms' decision to apply versus the policy-makers decision of which applications to accept. We address this challenge by including covariates (including region and sector fixed effects) in our model and by restricting our sample to only the firms that did eventually receive funding. In other words, we use the not-yet (but eventually) treated firms as the control group for the already treated firms. Formally, for each $h = 0, 1, 2, 3, 4$ estimate:

$$Y_{i,t+h} - Y_{i,t-1} = \beta^h \Delta D_{i,t} + X'_{i,t-1}\gamma^h + \tau_t^h + \gamma_s^h + \delta_r^h + e_{i,t}^h, \tag{1}$$

[14] We drop this assumption by implementing the Regression Adjustment LP DiD estimator (see section A.3).

restricting at each h the sample only to firms that are either:

- newly treated at time t, i.e. $\Delta D_{i,t} = 1$,
- not-yet (but eventually) treated, i.e. $D_{i,t+h} = 0$ and $D_{i,T} = 1$.

τ_t^h, γ_s^h and δ_r^h are year, sector (NACE letter) and region (NUTS2) fixed effects respectively. We use region and sector fixed effects to absorb common sectoral and common regional variation in the growth rates of the dependent variables. In Appendix A.3 we verify that our results are robust to not including region and sector fixed effects and to including higher-dimensional region by sector fixed effects.

Under assumptions 1 - 4, the LP-DiD equation 1 consistently estimates the variance-weighted ATT:

$$E(\hat{\beta}^h) = \sum_{g \neq 0} \omega_{g,h} \, \tau_g^h.$$

The weights ($\omega_{g,h}$) assigned to each group-specific effect are given by:

$$\omega_{g,h} = \frac{N_{CCS_{g,h}} n_{g,h}(1 - n_{g,h})}{\sum_{g \neq 0} N_{CCS_{g,h}} n_{g,h}(1 - n_{g,h})}.$$

where $CCS_{g,h}$ is the clean control sample for cohort g at time horizon h (all firms that are newly treated or not-yet treated), $N_{CCS_{g,h}}$ is the number of observations in $CCS_{g,h}$, and $n_{g,h} = N_g / N_{CCS_{g,h}}$ is the share of treated units in $CCS_{g,h}$. This variance-weighted ATT aggregates the effects over the treatment cohorts and summarizes the dynamic treatment effect as a single weighted average per horizon (with the horizon being in relative time to treatment administration).

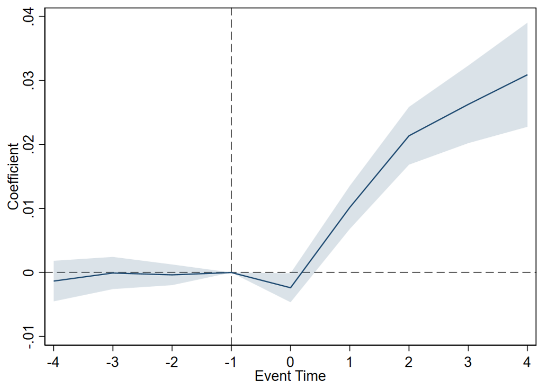
Furthermore, we control for the lagged values of: total assets, sales growth, current ratio, capital to labour ratio, sales to assets ratio, and age. We chose these variables based on the Logit model results from section 4.2. Conditioning on covariates that predicted receiving EU funds adds credibility to the conditional parallel trends assumptions we are relying on for identification. In the Appendix A.3, we report results without covariates and with a richer set of covariates. To test for treatment anticipation effects we estimate equation 1 for the pre-treatment horizons $h = -2, -3, -4$. Checking that $\hat{\beta}^h = 0$ for pre-treatment horizons ($h < -1$) ensures that there are no systematic differences in the pre-treatment growth rates of the outcome variable between the cohort of firms treated at t and the cohorts treated later. Rejecting the hypothesis that $\hat{\beta}^h = 0$ when $h < -1$ would indicate a violation of the assumption of no treatment anticipation and call into question our estimates of the treatment effects. To verify the no treatment anticipation assumption we plot these pre-treatment coefficients when reporting our results. Lastly, to ensure that our results are not affected by entry and exit of firms into the sample we only study firms that have non-missing productivity data for the whole sample period. [15]

Due to the additional restrictions to our sample, the results presented in this section are based on a smaller number of treated firms compared to the one reported in table 3 for the full treatment group. The number of firms that are treated over the period considered is 14,538, with the majority located in Portugal (7,246 firms), Spain (4,334 firms), and Italy (1,786 firms). These three countries together account for over 90% of the firms in our sample. This over-representation is partly due to the significant amount of Cohesion Policy funding directed to these countries, but it also reflects the relatively high coverage and data quality available for them in the Orbis dataset compared to other EU member states.

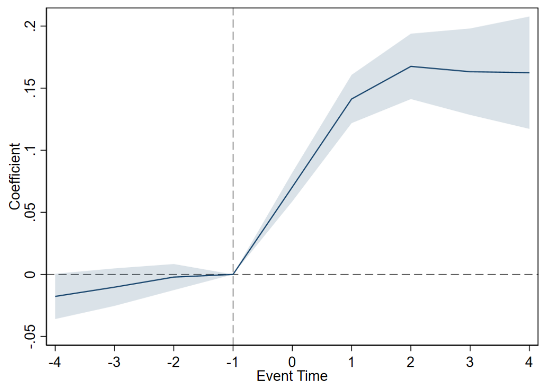
Our main variables of interest in the empirical analysis are: total factor productivity, leverage ratio, intangible intensity and capital. Our baseline results are plotted on figure 6, we also report these results in table format in the appendix section A.5. We find that firms that receive funding see their productivity increase gradually with a cumulative effect of 3% after 4 years (our maximum horizon). This effect is both statistically significant (at the 99% confidence level) and economically important. It implies that a firm that received funding after 4 years can produce almost 3% more value added with the same capital and labour inputs. We see no immediate effect on productivity at horizon 0 while capital and leverage ratio rise immediately. This is to be expected if capital investments take time to become productive. The fact that firms increase their leverage ratio after receiving EU funding suggests that they are able to attract additional financing after receiving the funds. In fact, they are likely borrowing in order to finance their project. [16] Firms quickly increase their capital by 1.5% by horizon 1. This shape and timing of the response suggests that firms invest immediately after receiving the funding, but do not appear to have higher investment rates past the 2 years horizon.

[15] Our results are robust to removing this restriction and keeping all firms with at least one year of data, see Appendix section A.3.

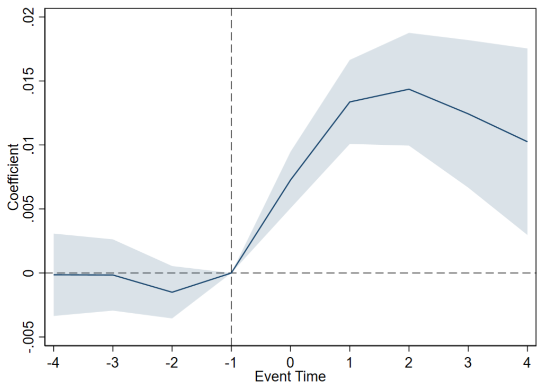
[16] While projects are co-financed by the EU, firms only receive a reimbursement of costs ex post, up to 85% of the total project amount.



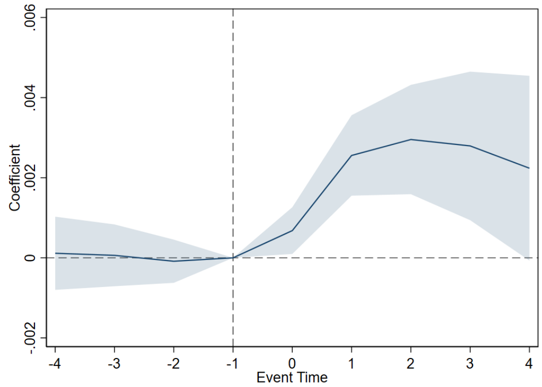
(a) TFP



(b) Capital



(c) Leverage Ratio



(d) Intangible Intensity

Figure 6: Cumulative effects of receiving Cohesion Policy funding on firms outcomes, plotted with 99% confidence intervals (robust standard errors clustered at firm-level). Coefficient shows the effect size, for panels (a) and (b) a coefficients of 0.1 means 10% cumulative growth effect. For panel (c) and (d) the effect is the change in the leverage ratio and the ratio of intangible capital in total assets respectively. Event time is in years.

4.4 Heterogeneity Analysis

To better understand the mechanisms underlying our baseline results, we investigate potential heterogeneity in the effects of EU funding across firms. First, in section 4.4.1 we look at the role of firms' characteristics. Secondly, in section 4.4.2 we examine the role played by the funding intended purpose. To this end, we extend our baseline LP-DiD specification by interacting the treatment variable with a binary indicator B_i that captures the relevant dimension of interest. This approach follows the state-dependent local projections methodology in Cloyne, Jordà and Taylor (2023), allowing us to assess how treatment effects vary conditional on firm-specific conditions and funding characteristics. Our regression equation becomes:

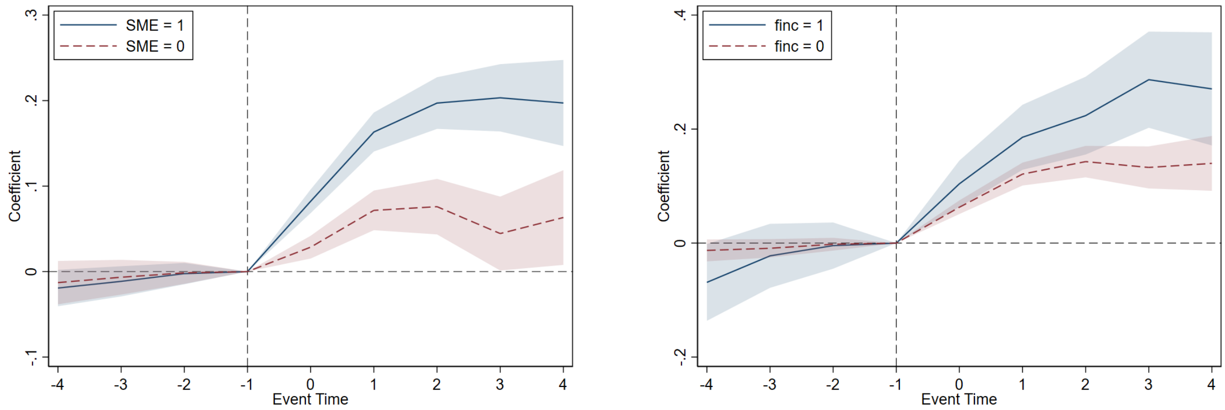
$$Y_{i,t+h} - Y_{i,t-1} = \beta_0^h + \beta_1^h B_i + \beta_2^h \Delta D_{i,t} + \beta_3^h \Delta D_{i,t} \times B_i + X'_{i,t-1}\gamma_1^h + \tau_t^h + \gamma_s^h + \delta_r^h + e_{i,t}^h, \qquad (2)$$

where now β_2^h is the effect on firms with $B_i = 0$ and $\beta_2^h + \beta_3^h$ is the effect on firms with $B_i = 1$. We focus on dummies B_i, which define either the category of EU funding received or specific firm characteristics.

4.4.1 Heterogeneity by firm characteristics

We study the differential impact of receiving funding on: 1) small and medium sized firms (< 50 employees) versus the rest and 2) financially constrained firms versus non-financially constrained firms. Financially constrained are defined as young firms (i.e. which are less than 15 years old) and with a leverage above median compared to other firms in their country and NACE 2-digit sector, in the spirit of Cloyne et al. (2023) Durante, Ferrando and Vermeulen (2022) and Anaya Longaric et al. (2025). We build dummies based on pre-2014 data, to rule out possible treatment effects on the state of the firm.

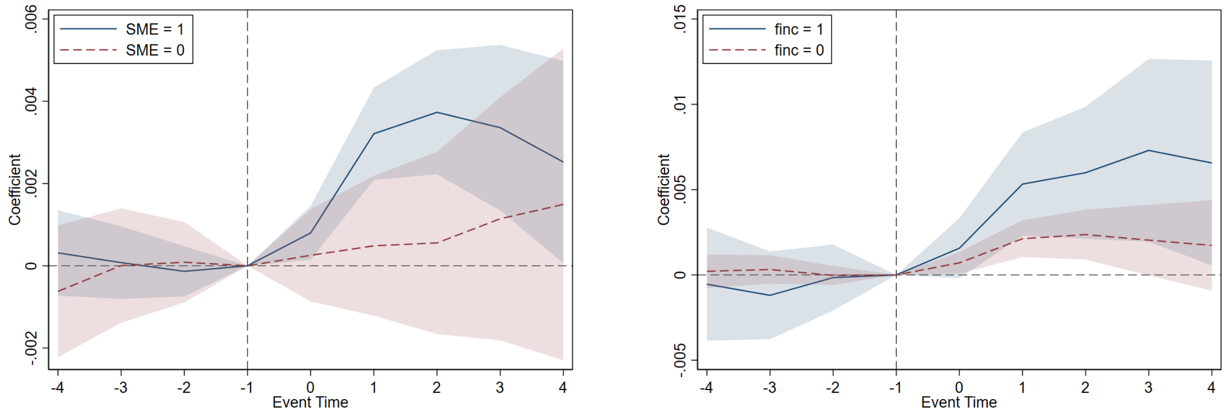
Figures 7, 8, 9, 10 show the effect of receiving EU funding for different dependent variables, namely capital, intangible intensity, TFP and leverage ratio. The effect is generally larger for smaller and for financially constrained firms (blue lines). The heterogeneity is less pronounced in the responses of TFP and intangible intensity. Financially constrained firms see a larger effect on their leverage ratio in response to receiving funding as compared with non-financially constrained firms. This suggests that receiving EU funding helps constrained firms access other forms of financing, possibly by serving as a good signal to banks or potential investors. Larger firms tend to increase their leverage only temporarily while SMEs see a permanent increase in their leverage ratio. SMEs and financially constrained firms see a larger growth in their capital stock.



(a) Size

(b) Financial Constraint

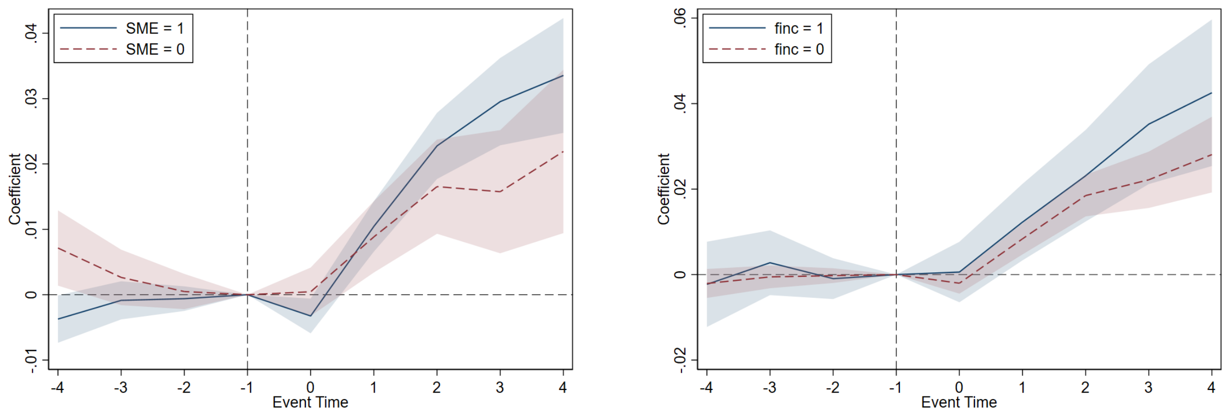
Figure 7: Cumulative effect on firm **Capital** with 99% Confidence Interval (SEs clustered at firm level). Coefficient of 0.01 means 1% growth effect. Time in years relative to when firm first received funding. Left panel: solid blue line plots effect for small firms, dashed red line for large firms. Right panel: solid blue line plots effect for financially constrained firms, dashed red line for non-constrained firms.



(a) Size

(b) Financial Constraint

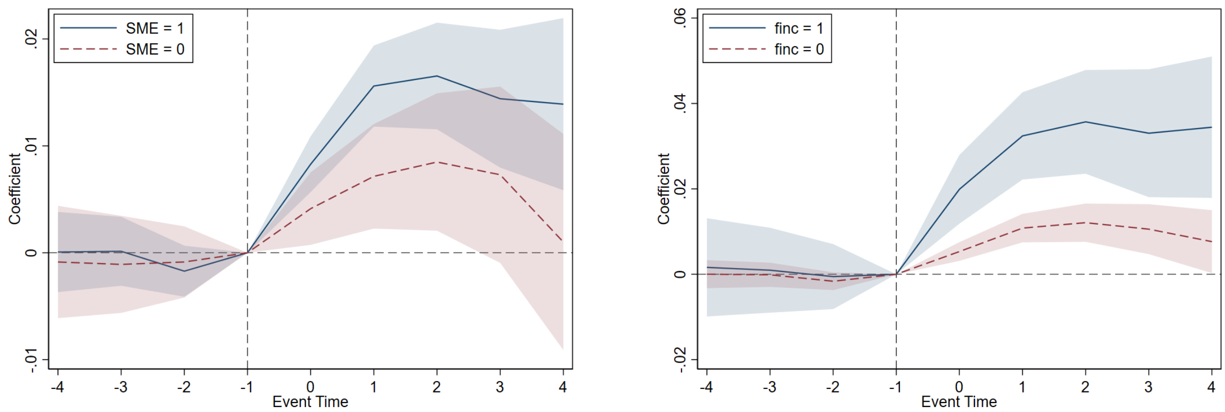
Figure 8: Cumulative effect on firm **Intangible Intensity** with 99% Confidence Interval (SEs clustered at firm level). Time in years relative to when firm first received funding. Left panel: solid blue line plots effect for small firms, dashed red line for large firms. Right panel: solid blue line plots effect for financially constrained firms, dashed red line for non-constrained firms.



(a) Size

(b) Financial Constraint

Figure 9: Cumulative effect on firm **TFP** with 99% Confidence Interval (SEs clustered at firm level). Coefficient of 0.01 means 1% growth effect. Time in years relative to when firm first received funding. Left panel: solid blue line plots effect for small firms, dashed red line for large firms. Right panel: solid blue line plots effect for financially constrained firms, dashed red line for non-constrained firms.



(a) Size

(b) Financial Constraint

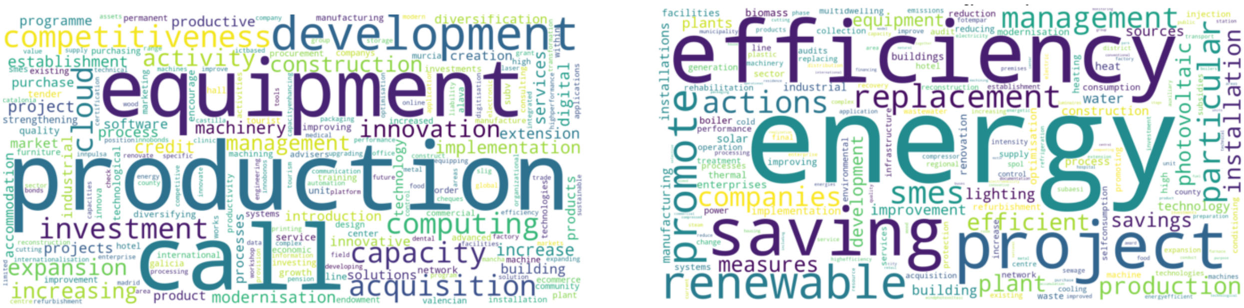
Figure 10: Cumulative effect on firm **Leverage Ratio** with 99% Confidence Interval (SEs clustered at firm level). Time in years relative to when firm first received funding. Left panel: solid blue line plots effect for small firms, dashed red line for large firms. Right panel: solid blue line plots effect for financially constrained firms, dashed red line for non-constrained firms.

4.4.2 Heterogeneity by funding category

Our data contains rich details on the projects for which firms received funding, extending beyond just the amounts and disbursement dates. In particular, we have project level data on the thematic category, policy priority and even a short project description. Leveraging this information, we categorize the funding based on the policy objective of the project. In particular, we group together funding for the following five broad categories: "Small and Medium Enterprise (SME) investment", "SME support, Research & Development", "Green transition", "Social and territorial cohesion".[17]

We find that while all funding categories support firm outcomes, the categories "SME investment" and "Green transition" offer the most interesting insights.[18] Projects categorized under "SME investment" (Figure 11a) prominently highlight terms such as "equipment", "production", "capacity", "investment," "acquisition," "modernisation", and "innovation". These keywords indicate a strong emphasis on capital expenditure, with funding directed towards tangible assets and production-enhancing investments aimed at improving the competitiveness, productivity, and innovation capabilities of SMEs.

On the other hand, the "Green transition" category (Figure 11b) features frequent references to "energy", "efficiency", "saving", "renewable", "replacement," "installation" and "management". These terms reflect a clear focus on sustainability, including measures to enhance energy efficiency, implement renewable energy solutions, and promote sustainable management practices within firms.



(a) SME investement

(b) Green transition

Figure 11: Word Clouds for projects pertaining to "SME investment" and "Green transition"

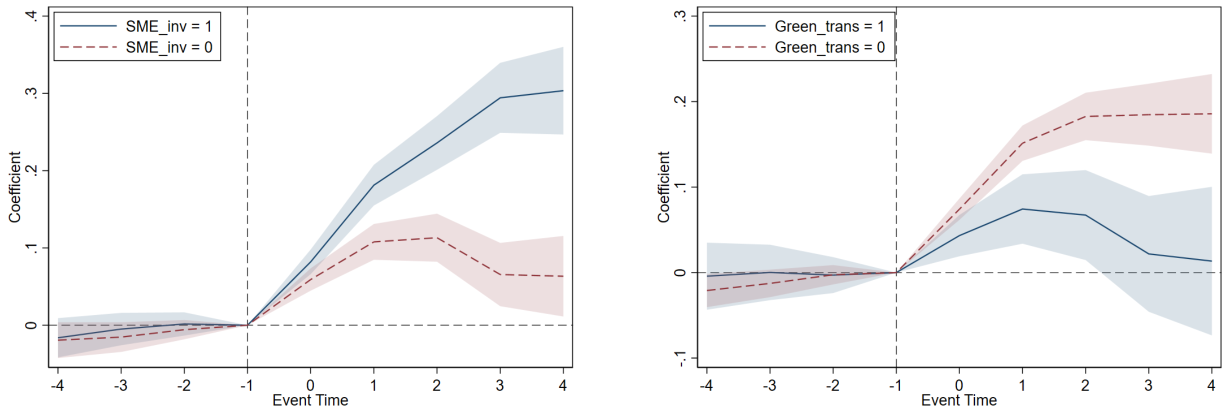
Results suggest that funding targeted specifically towards "SME investment" is more effective in facilitating firm investment and enhancing total factor productivity (TFP). Consistently, this targeted funding leads to a more pronounced increase in firms' leverage ratios.

In contrast, funding received for "Green transition" projects has a more modest and shorter-lived effect on increasing firm capital, with no significant effect beyond year 2, when compared to other projects. It also has little to no effect on productivity, intangible intensity, or the leverage ratio. This suggests that adopting green practices may not necessarily yield substantial productivity gains in the short term — for instance, when operational high-emitting equipment is replaced

[17]The 'SME investment" dummy is based on the descriptive data pertaining to the projects under which firms received funding, while in the previous section the "SME" dummy was based purely on the size of the firm. irrespective of the rationale for the funding it received.

[18]Results from the other categories are presented in the Appendix.

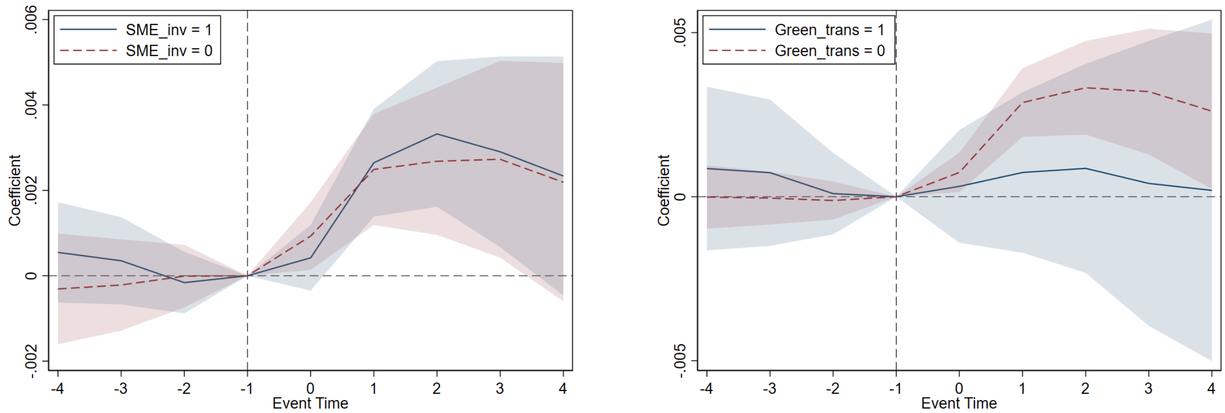
prematurely. Nevertheless, our findings indicate that green projects still positively influence firm outcomes overall. [19]



(a) SME investement

(b) Green transition

Figure 12: Cumulative effect on firm **Capital** with 99% Confidence Interval (SEs clustered at firm level). Coefficient of 0.01 means 1% growth effect. Time in years relative to when firm first received funding. Left panel: solid blue line plots effect from funding for "SME investment", dashed red line for other funding. Right panel: solid blue line plots effect for funding for "Green transition", dashed red line for other funding.

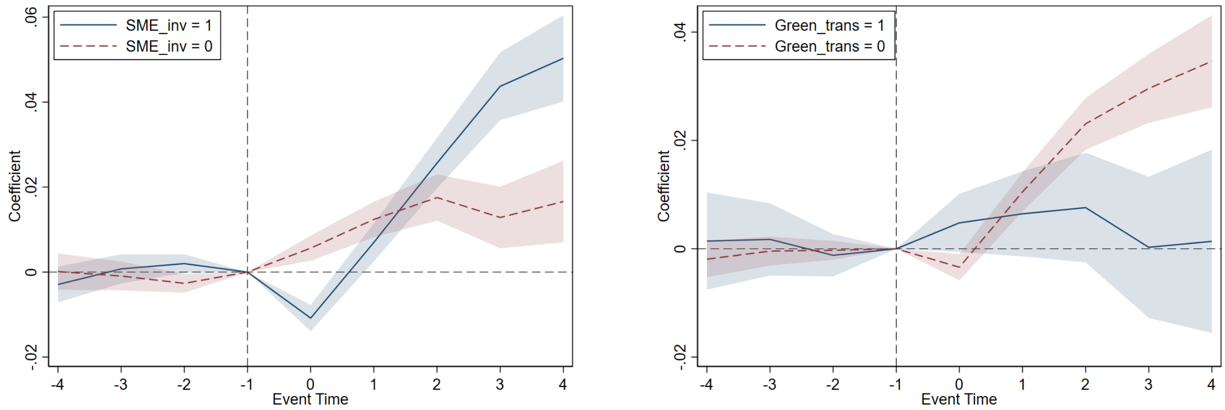


(a) SME investment

(b) Green transition

Figure 13: Cumulative effect on firm **Intangible Intensity** with 99% Confidence Interval (SEs clustered at firm level). Time in years relative to when firm first received funding. Left panel: solid blue line plots effect from funding for "SME investment", dashed red line for other funding. Right panel: solid blue line plots effect for funding for "Green transition", dashed red line for other funding.

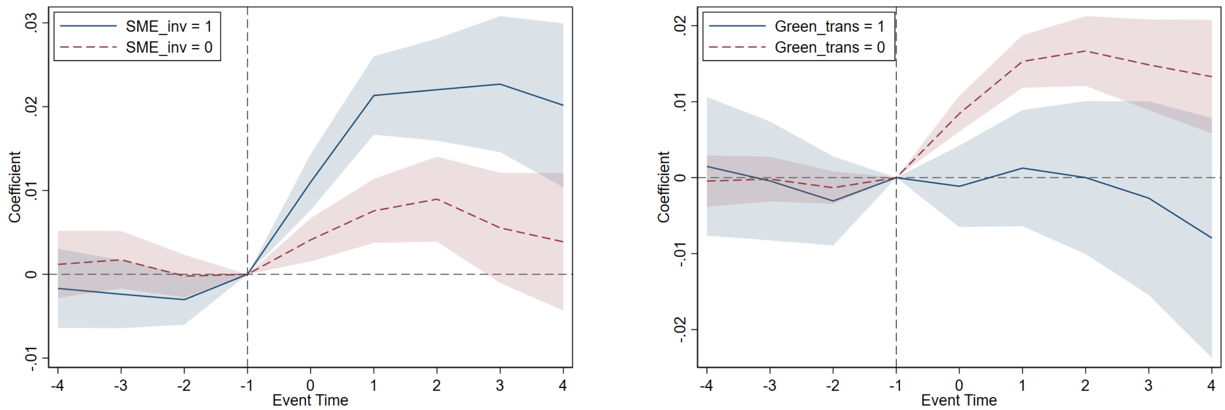
[19] The effectiveness of funds supporting green investments should not be evaluated solely—or even primarily—by their impact on productivity, but rather by their contribution to emission reductions and broader environmental outcomes. A full assessment of these effects lies beyond the scope of this study. Here, we simply note that green investments have a positive, albeit smaller, effect on firms' outcomes.



(a) SME investement

(b) Green transition

Figure 14: Cumulative effect on firm **TFP** with 99% Confidence Interval (SEs clustered at firm level). Coefficient of 0.01 means 1% growth effect. Time in years relative to when firm first received funding. Left panel: solid blue line plots effect from funding for “SME investment”, dashed red line for other funding. Right panel: solid blue line plots effect for funding for “Green transition”, dashed red line for other funding.



(a) SME investement

(b) Green transition

Figure 15: Cumulative effect on firm **Leverage Ratio** with 99% Confidence Interval (SEs clustered at firm level). Time in years relative to when firm first received funding. Left panel: solid blue line plots effect from funding for “SME investment”, dashed red line for other funding. Right panel: solid blue line plots effect for funding for “Green transition”, dashed red line for other funding.

5 Conclusions

This paper provides empirical evidence on the effects of the 2014-2020 EU Structural and Investment Funds on firm-level investment and productivity. By linking firm-level data from the Orbis database with project-level information from the European Commission’s Kohesio dataset, the study addresses two central questions: which firms receive EU funding? How does this funding affect firm performance?

The analysis shows that funding tends to be allocated to firms that are already performing relatively well, but are less capital-intensive and financially constrained. On average, firms receiving funding experience a sharp increase in capital, which grows by 15% after one year, and a gradual increase in total factor productivity, which goes from 1% after one year to approximately 3% after 4 years. Notably, smaller firms experience relatively greater improvements, indicating that EU funding plays a particularly important role in supporting productivity and capital growth in small and medium-sized enterprises (SMEs). Moreover, financially constrained firms increase their capital investment and leverage ratio more than non-financially constrained firms, suggesting that EU funds contribute to alleviate financial constraints. Lastly, we find that projects aimed at supporting "SME investment" bring the largest gains, while the gains form projects targeting the green transition are more modest.

Overall, the findings of this paper highlight the crucial contribution of the European Structural and Investment Funds to fostering firm growth and driving sustained improvements in productivity, in line with the overall objectives of the EU Cohesion Policy. Moreover, our findings suggest that crafting targeted funding strategies that balance support for high-performing firms with assistance to financially constrained ones could enhance the effectiveness of these investments.

The present analysis opens several avenues for future research. First, investigating the role of co-financing rates could offer insights into whether an "optimal" rate exists—one that maximizes the effectiveness of EU funds. Such analysis could help inform the design of more efficient funding mechanisms. Second, a natural extension would be to estimate firm-level fiscal multipliers in order to quantify the impact of each euro invested, for example, in terms of output and employment. Finally, this research provides a foundation for evaluating EU funding instruments, and a similar approach could be used to evaluate other programs, including the Next Generation EU.

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A Appendix

A.1 Orbis cleaning steps

Following Díez, Fan and Villegas-Sánchez (2021) our steps to clean the Orbis dataset prior to producitivty function estimation and subsequent empirical analysis are:

1. Basic variables and initial cleaning:
    1.1. Drop duplicate observations
    1.2. If available keep the unconsolidated (U1 or U2) company accounts, if not keep the consolidated (C1) account.
    1.3. Drop firm-year observations with missing information on total assets, operating revenues, sales, and employment
    1.4. Drop firms in all years if: a) Total assets are negative in any year, b) Employment is negative or greater than 2 million in any year, c) Sales are negative in any year, d) Tangible fixed assets are negative in any year
    1.5. Drop firm-year observations with missing, zero, or negative values for materials, operating revenue, and total assets
    1.6. Drop firm-year observations with missing industry information
    1.7. Keep only firm-year observations with 12-month reporting periods
    1.8. Filter outliers based on the following ratios, dropping firm-year observations outside the 0.1st to 99.9th percentile range: a) Employment per million of assets, b) Employment per million of revenue, c) Revenue to assets ratio.
    1.9. Drop firm-year observations with negative age.
    1.10. Drop firms in all years if calculated age is negative.
2. Further quality checks:
    2.1. Drop firm-year observations where the ratio of total shareholder funds and liabilities to total assets is outside the range of 0.9 to 1.1.
    2.2. Drop firm-year observations with negative or zero liabilities.
    2.3. Drop firm-year observations where the ratio of liabilities to current liabilities plus non-current liabilities is outside the range of 0.9 to 1.1.

2.4. Drop firm-year observations with zero or missing fixed assets.

2.5. Drop firm-year observations with missing or zero costs of employees.

2.6. Drop firm-year observations with negative values for various financial variables (e.g., current liabilities, non-current liabilities, current assets, loans, creditors, etc.

2.7. Drop firm-year observations where the ratio of short-term bank liabilities to total liabilities is greater than 1.1.

2.8. Drop firm-year observations where the ratio of long-term bank liabilities to total liabilities is greater than 1.1.

2.9. Drop firm-year observations with negative depreciation and amortization.

2.10. Drop firms in all years if the ratio of employee costs to capital is: a) greater than 1000, b) less than 0.1st percentile or greater than 99.9th percentile of the distribution.

2.11. Drop firm-year observations where the ratio of tangible fixed assets to total assets is greater than 1.

2.12. Drop firm-year observations with negative shareholder funds.

2.13. Filter outliers based on the ratio of other shareholder funds to total assets (dropping firm-year observations

2.14. Drop firm-year observations with negative value added.

2.15. Filter outliers based on the ratio of employee costs to value added: a) Drop if ratio greater than 1.1, b) Drop if ratio less than 1st percentile or greater than 99th percentile of the distribution, c) Drop if ratio less than 0.1 and number of employees is missing.

2.16. Filter outliers based on leverage ratios, dropping firm-year observations outside the 0.1st to 99.9th percentile range for: a) Capital to shareholder funds ratio, b) Total assets to shareholder funds ratio.

3. Growth-based filtering:

3.1. Filter outliers based on growth rates, dropping firms in all years if: a) For firms with 0-10 employees: growth rate $\geq$ 1000% (10 times), b) For firms with 11-20 employees: growth rate $\geq$ 500% (5 times), c) For firms with 21-50 employees: growth rate $\geq$ 300% (3 times), d) For firms with 51-100 employees: growth rate $\geq$ 200% (2 times), e) For firms with 101+ employees: growth rate $\geq$ 100% (1 time), f) For firms with missing lagged employment: growth rate $\geq$ 2000% (20 times). These conditions are applied separately for: Employment growth, Sales growth, Operating revenue growth.

4. Deflate nominal variables using country-specific GDP deflators from the World Bank World Development Indicators database (we use 2015 as base year so that all the nominal values are expressed in constant 2015 EUR).

A.2 Estimating firm-level productivity

We follow the approach of Levinsohn and Petrin (2003) to estimate firm level total factor productivity (TFP) as implemented in STATA by the prodest function written by Rovigatti and Mollisi (2016). We estimate the production functions separately for each country and two-digit NACE sector pair. We exclude NACE sector A (Agriculture, forestry and fishing) as for this sector the production function without land as a production input is misspecified.

We begin with a 3 inputs log-linear Cobb-Douglas production function:

$$y_{it} = \beta_0 + \beta_k\, k_{it} + \beta_l\, l_{it} + \beta_m\, m_{it} + \omega_{it} + \varepsilon_{it},$$

where y_{it} is the log of output for firm i at time t, k_{it} is capital, l_{it} is labour, m_{it} is materials (or other intermediate input), ω_{it} represents the firm's unobserved productivity (TFP), ε_{it} is an i.i.d. measurement error.

The key econometric challenge is that ω_{it} is observed by the firm when making input decisions but not by the econometrician, potentially leading to endogeneity problems.

The estimation is carried out in two stages, under the following assumptions:

1. **Monotonicity and Invertibility:** It is assumed that the material input m_{it} is chosen as a function of capital and the unobserved productivity shock. Formally, we assume

$$m_{it} = f\left(k_{it}, \omega_{it}\right),$$

where f is strictly monotonic in ω_{it}. This ensures that the function can be inverted so that productivity can be written as

$$\omega_{it} = h\left(k_{it}, m_{it}\right).$$

2. **Free Variables:** Firms are assumed to adjust their material and labour inputs flexibly after observing the productivity shock. These inputs are non-dynamic in the sense that they are decided within the period and do not affect future profits.

3. **State Variable:** Capital evolves according to the investment policy function $i()$, which is

decided at time $t-1$.

4. **Markovian Productivity Process:** The unobserved productivity shock follows a first-order Markov process:

$$\omega_{it} = g\left(\omega_{it-1}\right) + \xi_{it},$$

where ξ_{it} is an innovation term that is assumed to be uncorrelated with the inputs.

Stage 1:

In this first step, the idea is to remove the endogeneity induced by the unobserved productivity shock ω_{it}. Using the invertibility assumption, we replace ω_{it} with the control function $g(k_{it}, m_{it})$. The production function is re-written as:

$$y_{it} = \beta_0 + \beta_k\, k_{it} + \beta_l\, l_{it} + \beta_m\, m_{it} + h(k_{it}, m_{it}) + \varepsilon_{it}.$$

Letting

$$\phi(k_{it}, m_{it}) = \beta_0 + \beta_k\, k_{it} + \beta_m\, m_{it} + h(k_{it}, m_{it})$$

We can rewrite

$$y_{it} = \beta_l\, l_{it} + \phi(k_{it}, m_{it}) + \varepsilon_{it}.$$

which can be estimated non-parametrically (we use a third-order polynomial in m_{it} and k_{it} for $\phi(k_{it}, m_{it})$). This identifies β_l

Stage 2:

In the second stage, we estimate the remaining parameters β_m and β_k. To identify β_m and β_k, we use two moment conditions:

$$E[(\xi_{it} + \varepsilon_{it})k_{it}] = E[\xi_{it}k_{it}] = 0,$$

$$E[(\xi_{it} + \varepsilon_{it})m_{it-1}] = E[\xi_{it}m_{it-1}] = 0.$$

The first moment condition identifies β_k by assuming that capital is a state variable and does not respond to ξ_{it}. The second condition exploits the assumption that last period's material choice is uncorrelated with ξ_{it}, allowing us to identify β_m.

The estimate of the residual comes from the following relationship:

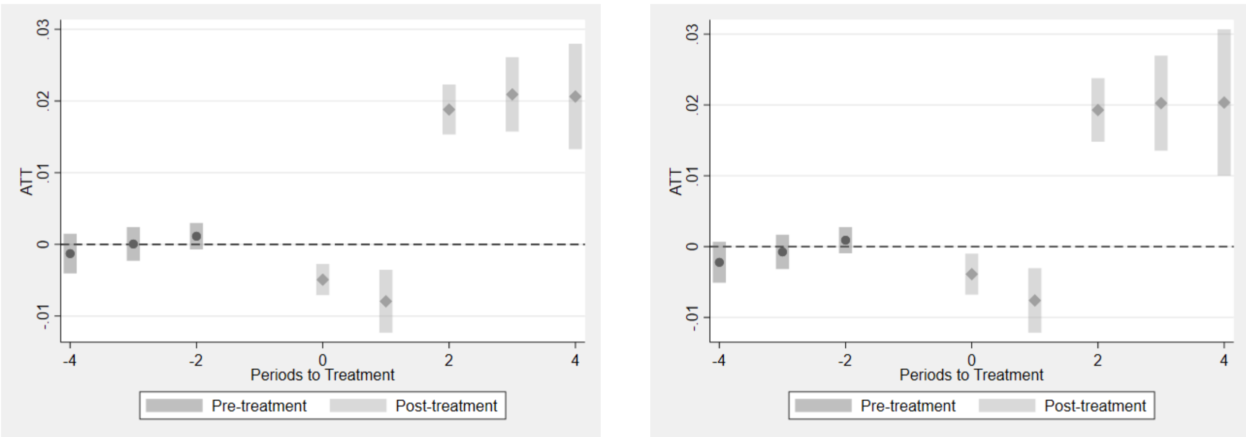
$$\xi_{it} + \widehat{\varepsilon_{it}}(\beta^*) = y_{it} - \hat{\beta}_l l_{it} - \beta^*_m m_{it} - \beta^*_k k_{it} - E[\widehat{\omega_{it}|\omega_{it-1}}].$$

Noting that the residual is a function of the two candidate parameters $\beta^* = (\beta^*_m, \beta^*_k)$, and that the estimates of ω_{it} are obtained from the first stage results combined (i.e. the estimate $\hat{\beta}_l$) with the candidate values (β^*_m, β^*_k).

A.3 Robustness of the empirical results

A.3.1 Using Difference-in-Differences with multiple time periods estimator.

Here we report our main result, but using the Callaway and Sant'Anna (2021) estimator instead of Dube et al. (2023) estimator. We replicate our main results showing the increase in firm productivity from receiving EU funds using the Callaway and Sant'Anna (2021) Difference-in-Differences with multiple periods estimator. We present the results both using the same set of controls as in the baseline specification and without any controls.

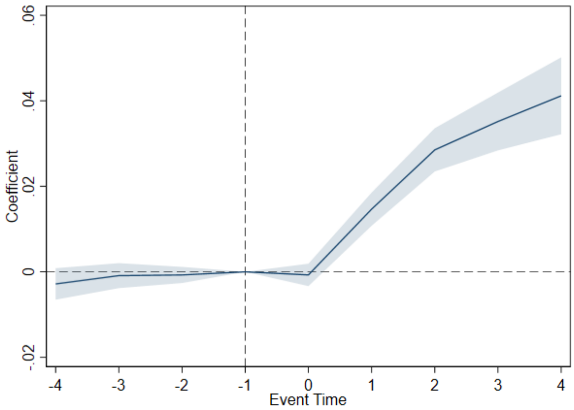


(a) TFP effect (no controls) (b) TFP (baseline)

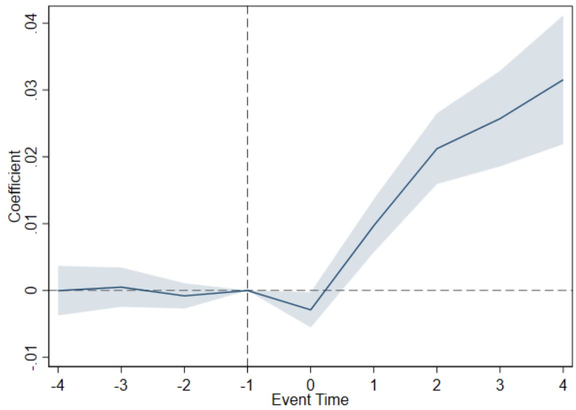
Figure 16: Cumulative effects of receiving Cohesion Policy funding on firms total factor productivity, plotted with 99% confidence intervals (robust standard errors clustered at firm-level). An ATT coefficient of 0.1 means 10% cumulative growth effect. Period to treatment are in years. Both panels are estimated using the estimator of Callaway and Sant'Anna (2021). The left panel is a model without controls. The right panel has the same controls as the baseline LP DiD specification.

A.3.2 Changing the fixed effects specification

We present the results of estimating the LP DiD model in equation 1 except without including region and sector fixed effects or with the inclusion of higher dimensional sector (NACE letter) by region (NUTS2) fixed effects.



(a) TFP effect (no region or sector FEs)



(b) TFP (region by sector FEs)

Figure 17: Cumulative effects of receiving Cohesion Policy funding on firms total factor productivity, plotted with 99% confidence intervals (robust standard errors clustered at firm-level). A coefficient of 0.1 means 10% cumulative TFP growth effect. Event time is in years. Both panels are estimated using the LP DiD estimator in equation 1, but the left panel removes region and sector fixed effects ($\gamma_s^h + \delta_r^h$), while the right panel replaces them with region by sector fixed effects ($\gamma_s^h + \delta_r^h$ becomes $\xi_{s,r}^h$)

A.3.3 Adding more time-varying controls

We present the results of estimating the LP DiD model in equation 1 but with a richer set of time varying firm level covariates in X'_{t-1}. In particular we include the first three lags of: capital growth, value added growth, sales growth, employment growth, (log) employment, (log) total assets, (log) capital, (log) materials, (log) value added,intangible intensity, sales to assets ratio, capital to labour ratio and age.

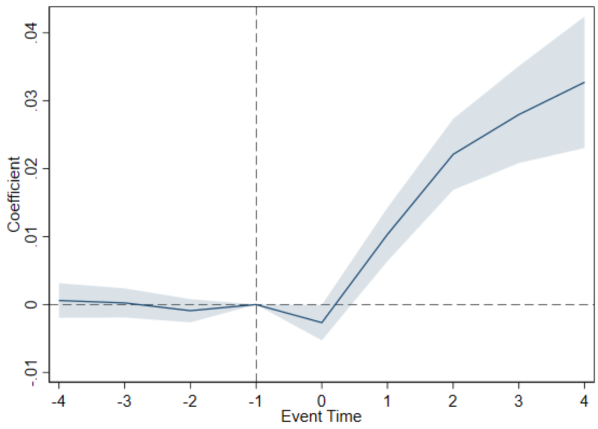


Figure 18: Cumulative effects of receiving Cohesion Policy funding on firms total factor productivity, plotted with 99% confidence intervals (robust standard errors clustered at firm-level). A coefficient of 0.1 means 10% cumulative TFP growth effect. Event time is in years. LP DiD model with a richer set of time varying firm level covariates.

A.3.4 Removing the coverage restriction on firms

We replicate the baseline results without the restriction that firms must have TFP data for the whole duration of the sample. Instead, we consider all eventually treated firms in the regression, no matter how many years of data coverage we have for them.

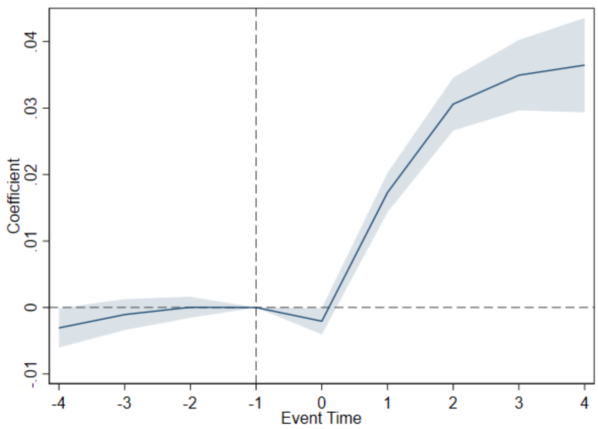
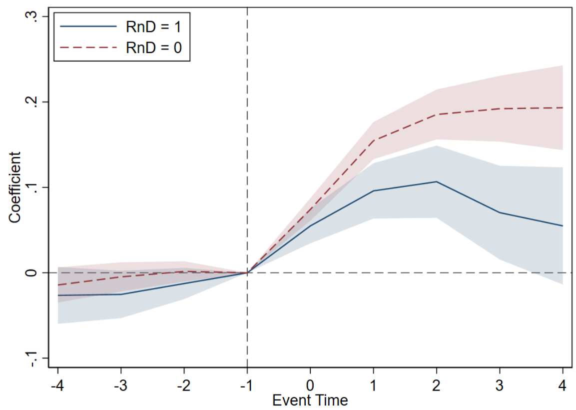
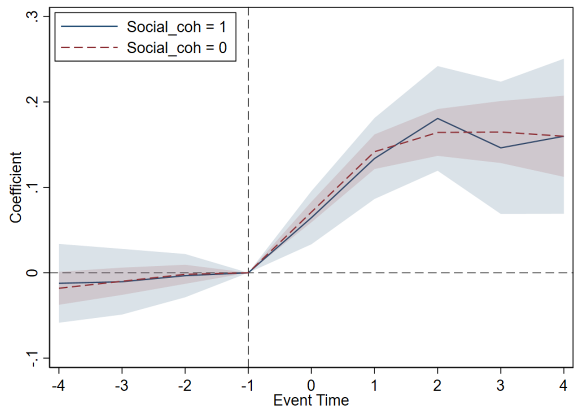


Figure 19: Cumulative effects of receiving Cohesion Policy funding on firms total factor productivity, plotted with 99% confidence intervals (robust standard errors clustered at firm-level). A coefficient of 0.1 means 10% cumulative TFP growth effect. Event time is in years. LP DiD model on a sample of all eventually treated firms (without a minimum coverage restriction, i.e. unbalanced panel).

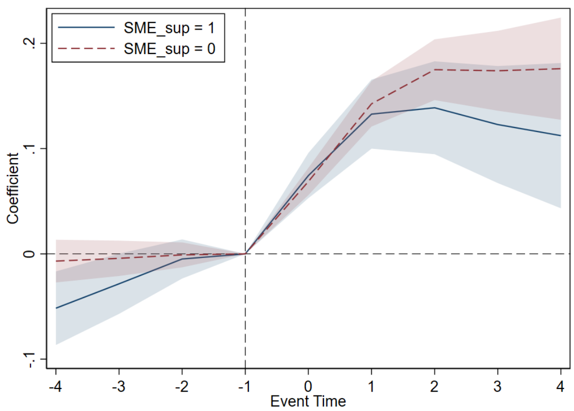
A.4 Heterogeneity analysis - additional funding categories



(a) R&D

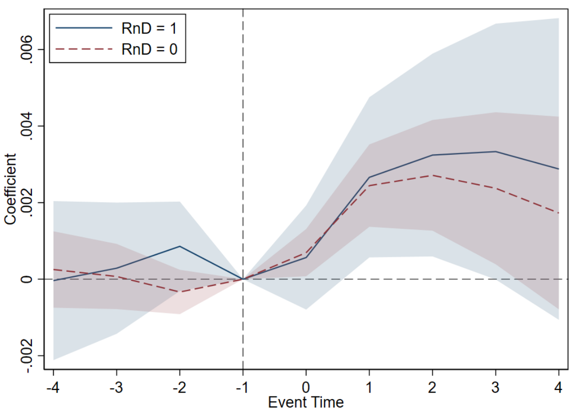


(b) Social cohesion

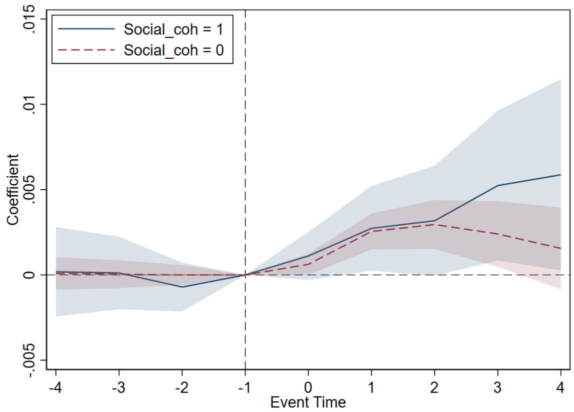


(c) SME support

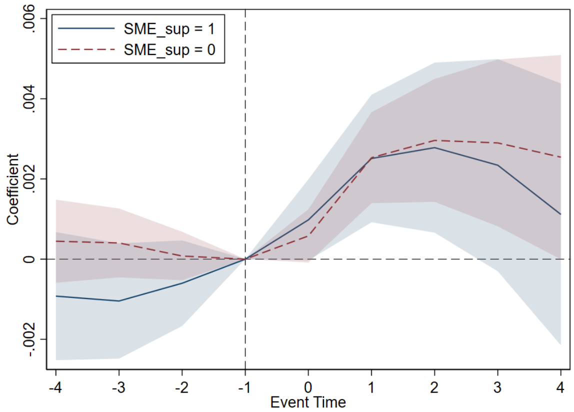
Figure 20: Cumulative effect on firm **Capital** with 99% Confidence Interval (SEs clustered at firm level). Coefficient of 0.01 means 1% growth effect. Time in years relative to when firm first received funding.



(a) R&D

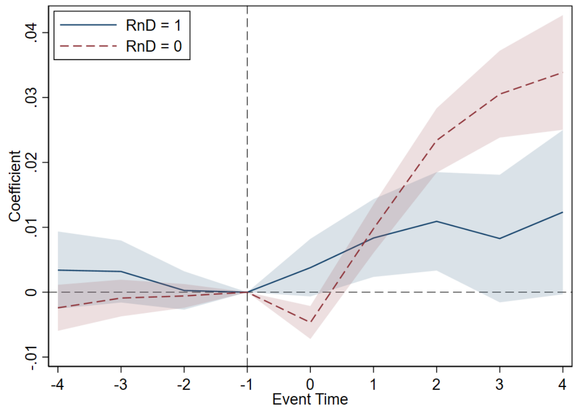


(b) Social cohesion

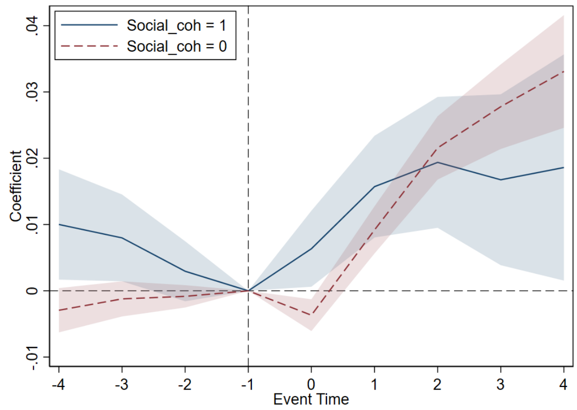


(c) SME support

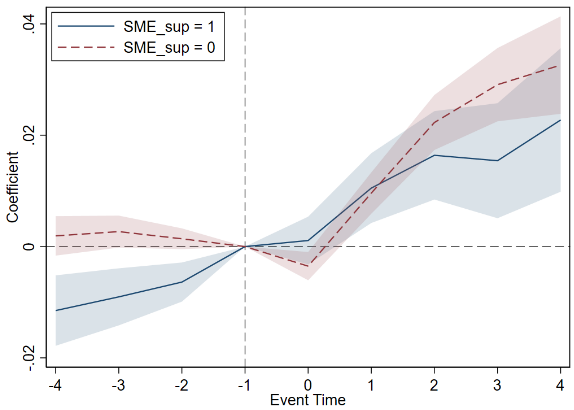
Figure 21: Cumulative effect on firm **Intangible Intensity** with 99% Confidence Interval (SEs clustered at firm level). Time in years relative to when firm first received funding.



(a) R&D

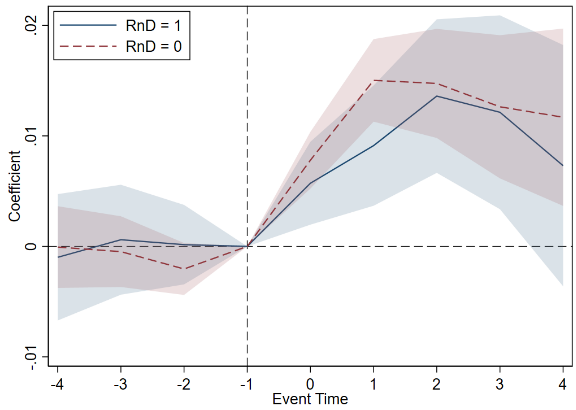


(b) Social cohesion

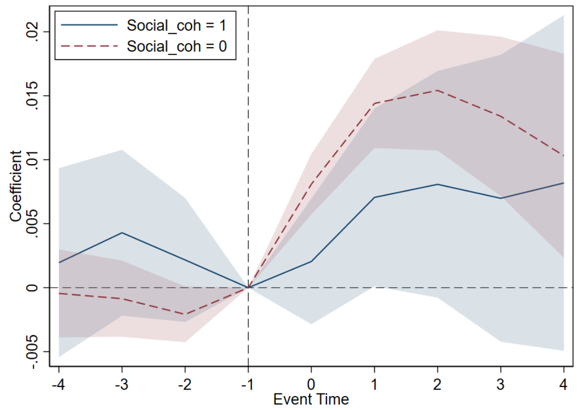


(c) SME support

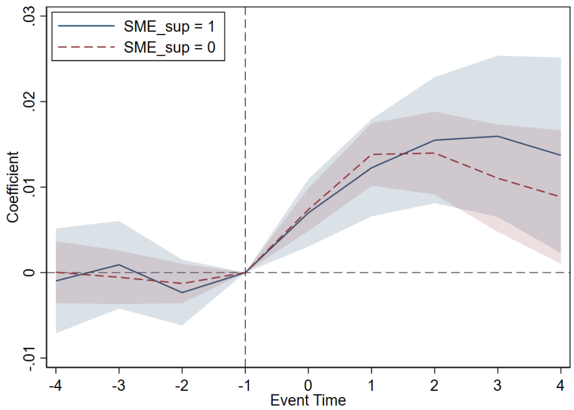
Figure 22: Cumulative effect on firm **TFP** with 99% Confidence Interval (SEs clustered at firm level). Coefficient of 0.01 means 1% growth effect. Time in years relative to when firm first received funding.



(a) R&D



(b) Social cohesion



(c) SME support

Figure 23: Cumulative effect on firm **Leverage Ratio** with 99% Confidence Interval (SEs clustered at firm level). Time in years relative to when firm first received funding.

A.5 Baseline results in table format

For completeness we present the main results presented in figure 6 from our LP-DiD regressions in table format.

Event-time estimates	Coefficient	S.E.	|t|	P >|t|	99 % C.I.		Observations
pre4	-0.0002	0.0014	-0.11	0.916	-0.004	0.004	89,033
pre3	0.0006	0.0011	0.48	0.630	-0.002	0.003	103,559
pre2	-0.0006	0.0007	-0.82	0.413	-0.002	0.001	118,068
pre1	0.0000	.	.	.	.	.	.
impact	-0.0025	0.0010	-2.44	0.015	-0.005	0.000	118,068
post1	0.0105	0.0015	6.87	0.000	0.007	0.014	103,261
post2	0.0224	0.0020	11.02	0.000	0.017	0.028	87,365
post3	0.0270	0.0027	9.88	0.000	0.020	0.034	68,400
post4	0.0326	0.0037	8.94	0.000	0.023	0.042	53,452
Pooled estimates	**Coefficient**	**S.E.**	**|t|**	**P >|t|**	**99 % C.I.**		**Observations**
Pre	-0.0004	0.0009	-0.43	0.667	-0.003	0.002	89,033
Post	0.0183	0.0025	7.44	0.000	0.012	0.025	53,452

Table 8: LP-DiD regressions results for the effect of receiving EU funding on firm's total factor productivity. A coefficient of 0.1 means a 10% growth effect. Event time is in years. Pooled estimates report average estimates for the pre and post treatment periods. Robust standard errors are clustered at firm level.

Event-time estimates	Coefficient	S.E.	|t|	P >|t|	99 % C.I.		Observations
pre4	-0.0215	0.0081	-2.64	0.008	-0.042	-0.001	89,033
pre3	-0.0091	0.0067	-1.36	0.173	-0.026	0.008	103,559
pre2	-0.0031	0.0047	-0.67	0.501	-0.015	0.009	118,068
pre1	0.0000	.	.	.	.	.	.
impact	0.0684	0.0051	13.31	0.000	0.055	0.082	118,068
post1	0.1457	0.0086	17.01	0.000	0.124	0.168	103,261
post2	0.1743	0.0117	14.95	0.000	0.144	0.204	87,365
post3	0.1746	0.0153	11.38	0.000	0.135	0.214	68,400
post4	0.1731	0.0199	8.7	0.000	0.122	0.224	53,452
Pooled estimates	**Coefficient**	**S.E.**	**|t|**	**P >|t|**	**99 % C.I.**		**Observations**
Pre	-0.0091	0.0058	-1.56	0.118	-0.024	0.006	89,033
Post	0.1487	0.0138	10.79	0.000	0.113	0.184	53,452

Table 9: LP-DiD regressions results for the effect of receiving EU funding on firm's capital. A coefficient of 0.1 means a 10% growth effect. Event time is in years. Pooled estimates report average estimates for the pre and post treatment periods. Robust standard errors are clustered at firm level.

Event-time estimates	Coefficient	S.E.	|t|	P >|t|	99 % C.I.		Observations
pre4	-0.0005	0.0015	-0.33	0.739	-0.004	0.003	64,728
pre3	-0.0009	0.0013	-0.68	0.496	-0.004	0.002	76,984
pre2	-0.0021	0.0009	-2.23	0.026	-0.004	0.000	90,052
pre1	0.0000	.	.	.	.	.	.
impact	0.0071	0.0010	7.11	0.000	0.005	0.010	91,969
post1	0.0136	0.0015	9.13	0.000	0.010	0.017	78,556
post2	0.0140	0.0020	6.98	0.000	0.009	0.019	65,238
post3	0.0113	0.0026	4.3	0.000	0.005	0.018	50,429
post4	0.0094	0.0033	2.83	0.005	0.001	0.018	38,786
Pooled estimates	**Coefficient**	**S.E.**	**|t|**	**P >|t|**	**99 % C.I.**		**Observations**
Pre	-0.0014	0.0011	-1.24	0.217	-0.004	0.001	60,534
Post	0.0124	0.0023	5.37	0.000	0.006	0.018	35,768

Table 10: LP-DiD regressions results for the effect of receiving EU funding on firm's leverage ratio (defined as the share of long term debt in total assets). Event time is in years. Pooled estimates report average estimates for the pre and post treatment periods. Robust standard errors are clustered at firm level.

Event-time estimates	Coefficient	S.E.	|t|	P >|t|	99 % C.I.		Observations
pre4	0.0002	0.0004	0.6	0.551	-0.001	0.001	89,016
pre3	0.0003	0.0003	0.8	0.427	-0.001	0.001	103,536
pre2	0.0000	0.0002	0.03	0.975	-0.001	0.001	118,043
pre1	0.0000	.	.	.	.	.	.
impact	0.0005	0.0003	1.79	0.073	0.000	0.001	118,049
post1	0.0024	0.0005	5.21	0.000	0.001	0.004	103,247
post2	0.0026	0.0006	4.17	0.000	0.001	0.004	87,351
post3	0.0028	0.0008	3.33	0.001	0.001	0.005	68,389
post4	0.0026	0.0010	2.5	0.012	0.000	0.005	53,445
Pooled estimates	**Coefficient**	**S.E.**	**|t|**	**P >|t|**	**99 % C.I.**		**Observations**
Pre	0.0001	0.0003	0.32	0.749	-0.001	0.001	89,000
Post	0.0022	0.0006	3.36	0.001	0.001	0.004	53,438

Table 11: LP-DiD regressions results for the effect of receiving EU funding on firm's intangible intensity (defined as a share of intangible fixed assets in total assets). Event time is in years. Pooled estimates report average estimates for the pre and post treatment periods. Robust standard errors are clustered at firm level.

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