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ABSTRACT

Investment Grants and Firms' Productivity: How Effective Is a Grant Booster Shot?*

This paper investigates the effect of awarding a second investment grant to the same firm. We implement a Regression Discontinuity Design strategy using a very rich firm-level administrative database, which allows us to link applications to grants and their scores to firms' performance. Overall, our results show a positive and significant impact of an investment grant booster shot on firms' labour productivity. This effect is significantly larger than the effect of a single grant. A more granular analysis shows a strong impact of awarding a second grant to small-sized firms. However, we found no effect on micro, medium and large-sized firms. Our results suggest that the characteristics of the targeted firms, namely firm size, matter for the effectiveness of awarding a second grant to the same firm.

JEL Classification: D22, H25, L25, L52

Keywords: industrial policy, investment grants, multiple treatments, productivity

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1 Introduction

There is little consensus among economists on the effectiveness of investment grants, namely on firms' productivity (e.g., Cerqua and Pellegrini, 2014, Bronzini and Iachini, 2014, Bronzini and Piselli, 2016, Criscuolo et al., 2019 and Dvouletý et al., 2021). The empirical literature on the impact of public subsidies is ambiguous in part due to incomplete and non-representative data samples and identification issues (e.g., Bronzini and Piselli, 2016, Criscuolo et al., 2019, Criscuolo et al., 2022). These limitations are even more pertinent in the case of the assessment of the impact of allocating multiple grants to the same firm (e.g., Howell, 2017 and Muraközy and Telegdy, 2022).

This paper aims to shed light on this debate by implementing an effective identification strategy using a very rich firm-level administrative database that includes the population of Portuguese firms that have applied to the European Regional Development Fund (ERDF) in 2007-2018. In that period, a high concentration of grants in a small group of firms, that have received multiple grants, stands out. Around 30% of the supported firms were awarded multiple grants, representing about 65% of the total ERDF. Among those, a group of 2,167 firms received almost 50% of the total funds. Our database comprises 54,765 applications by 24,627 firms, 16,428 funded projects of 10,980 firms, corresponding to 5.9 billion euros. We have information about the application scores for selected and non-selected firms, which a committee of independent experts awards, the applications' and the project's implementation dates. The combination of that data with detailed balance sheet information on the financial and operational status of firms allows us to assess the impact on productivity of awarding multiple grants to the same firm. This data allows us to implement a Regression Discontinuity Design (RDD) strategy to identify the effects of allocating multiple subsidies to the same firm, namely on its productivity.

Public subsidies to support firms' investment have been a common practice around the world – see, for example, Cheng et al. (2019), Fang et al. (2018), and Lim et al. (2018) on public subsidies in China, or Brown and Earle (2017) on the public support to small firms by Small Business Administration in the United States, or the European Commission NextGenerationEU (European Commission and Directorate-General for Budget, 2022). The context of a global wave of public subsidies urges a better understanding of the effectiveness of this type of industrial policy. Several factors have contributed to bringing public subsidies back to the limelight: vast amounts of subsidies to firms and banks following the international financial crisis and the COVID-19 pandemic; trade wars between the US and China; the war in Ukraine; disruption in global supply chains that resulted in shortages of crucial components, namely semiconductors. From East to West, all economic powers elected technology sovereignty as a national goal – see, for example, The Economist's Special Report, on the 13th January 2022 edition, on the new interventionism wave. In this context, where significant financial resources are allocated to public subsidies worldwide, it is crucial to design effective policies (e.g., Criscuolo et al., 2022).

Investment grants aim to address the presence of market failures, namely financial constraints (e.g., Fang et al., 2018 and Hall and Lerner, 2010), knowledge spillovers and disincentives for socially optimal levels of investment, namely in R&D (e.g., Arrow, 1972 and Bloom et al., 2019). However, the mixed evidence on the benefits of grants to firms' performance shows the limitations of industrial policy. Ehrlich and Overman (2020) emphasize that public subsidies may wreak havoc due to two risks: a deadweight and a displacement effect. In the case of a deadweight effect, public support may be allocated to firms that would have undertaken the projects anyway. This risk implies that public support is not given to the firms in greatest need but to those that could have found alternative financing sources. The displacement effect occurs when public subsidies stimulate investment in targeted areas at the cost of reducing investment in other areas. In this case, public subsidies have a crowding-out effect (e.g., Bronzini and de Blasio, 2006 and Kline and Moretti, 2014). The effectiveness of investment grants also depends on design issues: sectors and firms to be targeted (e.g., Jugend et al., 2020); the type of subsidy, that is, grants or subsidized loans (e.g., Huergo and Moreno, 2017); the optimal amount of funds to allocate to each firm (e.g., Görg and Strobl, 2007); or firms' characteristics such as size or their participation in international trade (e.g., Rotemberg, 2019).

The design and implementation of these programs are crucial to attaining their economic and social goals. The assessment of applications by independent experts, based on objective criteria, is a necessary condition for a transparent and effective allocation of investment grants. Otherwise, the industrial policy may favour specific firms over others, breaking competition rules and, thus, distorting the level playing field and hindering efficiency (e.g., Akcigit et al., 2018). The expansion of selected firms at the cost of their competitors might wreak havoc impact on aggregate output (e.g., Rotemberg, 2019). This may be the case when multiple subsidies are allocated to the same firm, which is the focus of our analysis.

The evidence on the effectiveness of investment grants, namely on productivity, is scarce (e.g., Criscuolo et al., 2022). Several papers have investigated the impact of public subsidies on firms' investment, employment and turnover. A systematic review by Becker (2015) shows that subsidies typically stimulate private R&D investment. Cerqua and Pellegrini (2014) evaluate the impact of subsidies to private firms in Italy and found a positive effect on employment, investment and turnover. Cingano et al. (2022) analyzing investment subsidies across Italian firms found that investment subsidies generate a significant impact on employment growth. Vanino et al. (2019) analyzed the effect of public support for R&D and innovation on firms in the United Kingdom and found a positive impact on employment and turnover growth.

The results by firm size show that investment grants have a greater impact on small-sized firms. Criscuolo et al. (2019) investigating the impact of investment grants from the Regional Selective Assistance program in the United Kingdom found a positive effect on employment, but only for small-sized firms. Analyzing an R&D subsidy program implemented in Italy, Bronzini and Iachini (2014) found that the subsidies increase investment by small-sized firms, whereas there is no impact on larger firms. González et al. (2005), using data for Spain, concluded that subsidies stimulate R&D expenditures, particularly in small-sized firms. Bronzini and Piselli (2016) evaluating the impact of R&D grants in Italy also found a positive impact of the program on the number of patent applications, but the effect was greater for smaller firms. Those results suggest that the impact of investment grants on investment, employment and turnover is more pronounced in small-sized firms (e.g., Criscuolo et al., 2022).

The empirical literature on the impact of public subsidies on a firm's productivity is ambiguous. Crespi et al. (2020) and Cin et al. (2017), analyzing grants for R&D to firms in Chile and South Korea, respectively, found a positive impact on firms' productivity. Muraközy and Telegdy (2022), in an analysis of ERDF grants for Hungary, found a positive impact of subsidies on labour productivity but no effect on total factor productivity. However, the most common result in the empirical literature is the absence of an impact on firms' productivity. Cerqua and Pellegrini (2014), investigating the impact of the main Italian regional policy, found a negligible effect. Hall and Maffioli (2008), analyzing technological subsidies in Latin American economies, found no clear evidence of a positive effect on firms' productivity. However, Criscuolo et al. (2019) found no evidence of a positive impact of investment grants on productivity. Cheng et al. (2019), using data for innovation grants in China, and Karhunen and Huovari (2015) analyzing the R&D subsidies to SMEs in Finland, found no positive impact on firms' productivity. Gabriel et al. (2022) and Santos (2019) investigate the impact of ERDF grants in the Portuguese economy and found no effect on productivity.

The empirical evidence of the impact of multiple grants allocated to the same firm is scarce and mixed. Muraközy and Telegdy (2022) investigate the impact of multiple ERDF grants for Hungarian firms. Those authors concluded that firms receiving multiple grants grow faster than those receiving only one and that multiple grants may favour the efficiency of the European Union's Structural and Cohesion Funds. Howell (2017) use an extensive database of ranked applications to the US Department of Energy's Small Business Innovation Research to evaluate a two-stage R&D grant program. In this program, only the winners of grants in phase 1 could apply to phase 2. The author considers different competitions and centers the ranks around zero to implement a sharp RDD by comparing firms in the neighbourhood of the cutoff. Howell (2017) concluded that the first treatment strongly affected innovation and financial and commercial success. On the other hand, the author found no effects for the grant awarded in phase 2, which may be due to eligibility criteria and adverse selection. Moreover, the author concluded that a single grant is more effective for firms facing financial constraints.

Our paper contributes to the literature on the effectiveness of investment grants, namely on the effectiveness of awarding multiple grants to the same firm. The contributions of our evaluation are twofold. First, our analysis assesses the effectiveness of awarding multiple investment grants to a firm, a topical issue scarcely explored in the literature. The concentration of multiple grants in a small number of firms raises concerns about the effectiveness of allocating public subsidies. In this paper, we evaluate the impact of a second ERDF grant on firms' performance by implementing an RDD strategy. We conclude that, overall, an investment grant booster shot has a positive and statistically significant impact on value-added and labour productivity, but no effect on total factor productivity. Our results also show that the impact of the booster shot on those variables is significantly larger than the effect of a single grant. These results suggest that allocating multiple subsidies to the same firm may be an effective strategy to improve firms' performance.

Our second contribution is to show that the impact of an investment booster shot hinges on the firm's characteristics, namely, on firm size. Micro and small-sized firms are expected to face more stringent financial constraints (e.g., Fazzari et al., 1988). Therefore, we investigate the role of firm size in the effectiveness of single and multiple investment grants. Our results show that an investment grant booster shot has no positive impact on micro-sized firms. On the other hand, our estimates for small-sized firms show that investment grants may be very effective in fostering firms' performance. Our estimates show that the impact of an investment grant booster shot on value-added and labour productivity may be much larger than the one of a single grant. No positive and significant effects were found for medium- and large-sized firms, both in the case of a single grant and of a grant booster shot.

Our results suggest that the characteristics of the targeted firms are relevant to the effectiveness of awarding multiple grants to the same firm. In particular, eligibility criteria concerning firm size and firms' growth between the first and second grants should be considered when awarding a second grant to the same firm.

The remainder of this paper is organized as follows. Section 2 describes the ERDF investment grants program and describes the database. Section 3 presents the empirical strategy. Section 4 presents and discusses the results of the RDD analysis. Section 5 provides a robustness check analysis. Section 6 concludes and discusses the implications for eligibility criteria of allocating multiple subsidies to the same firm.

2 Program description, data and multiple subsidies

In our empirical analysis, we use data from the ERDF to support Portuguese firms' investment. This data includes two multiannual financial frameworks: the National Strategic Reference Framework, 2007-2013 (NSRF), and PT2020, 2014-2018. The ERDF aims at strengthening economic and social cohesion in the EU and is one of the five funds settled by the European Structural Investment Funds (ESIF), managed by the European Commission and the EU member states, to promote job creation, and a more competitive and sustainable economy.

ERDF subsidies to firms aim at increasing firms' productivity and competitiveness, improving economic specialization, regional development, and the economy's internationalization. These objectives are of utmost importance in the context of the Portuguese economy, which has lived through a long period of low growth, protracted productivity stagnation and economic divergence in the 21st century (e.g., Blanchard and Portugal, 2017 and Eichenbaum et al., 2017).

ERDF has been an important instrument for Portuguese policymakers' toolkit to promote competitiveness and productivity growth. The ERDF program has three instruments to support firms' investment. The Innovation Incentive System, which aims at promoting investment in innovation and the firms' internationalization, accounts for over 65% of total ERDF in NSRF and PT2020. The Qualification Incentive System aims at increasing SME productivity and internationalization through investment in intangibles, accounting for around 20% of total ERDF. The third instrument is the Research and Development Incentive System which aims at increasing investment in R&D and the development of new products and services, accounting for around 15% of total ERDF.[1] In our analysis, we consider investment grants awarded to firms in those three programs.

The application to subsidies for firms' investment projects by ERDF follows calls for tender. The selection criteria are made available in the call that announces the opening of the tender. Applications are evaluated by a group of independent experts of recognised merit and suitability. Applications' scores vary between 0 and 5. The best-scored projects are granted a subsidy until the program specified budget line. Selected projects receive subsidies according to the project's specifications, investment implementation and goals contracted.

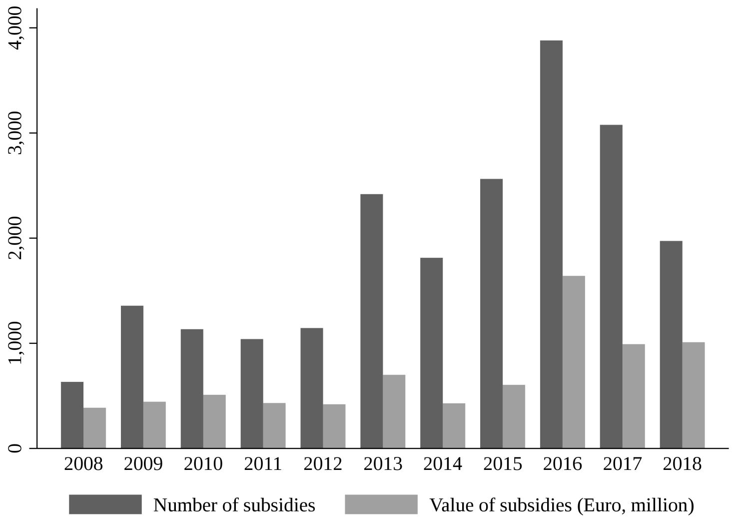
In our empirical analysis, we use two very rich longitudinal firm-level administrative databases for the Portuguese economy. The database from the Portuguese Agency for

[1] In fact, the designation of those three ERDF instruments is slightly different in NSRF and in PT2020. In NSRF the incentive systems were the following: Innovation; SME Qualification; and Research and Technological Development. In PT2020, the three instruments were the following: Entrepreneurial Innovation and Entrepreneurship; Qualification and Internationalization of SME; and Research and Technological Development.

Development and Cohesion (AdC) includes information for the population of applications to ERDF grants, including the firm identification, the application evaluation score for selected and non-selected firms, the application and contract dates, the amount of the ERDF benefit and total investment, both for NSRF and PT2020 (the data has been used at the Banco de Portugal Microdata Research Laboratory (BPLIM), 2019). The database from AdC comprises 24,627 firms and 16,428 funded projects corresponding to 10,980 firms. The AdC database allows us to identify the number and timing of subsidies allocated to each firm in the period 2007-2018.

The second dataset used in our analysis is the Central Balance Sheet (CBS) from the Bank of Portugal (see Banco de Portugal Microdata Research Laboratory (BPLIM), 2020). The CBS database provides annual economic and financial information on non-financial corporations operating in Portugal, since 2006. The CBS database contains firm-level administrative data, including balance sheets and other accounting data, such as the turnover, value-added, labour costs, leverage, total assets or the number of employees. This information allows us to compute labour productivity and total factor productivity. These data are available yearly for the population of non-financial private sector firms, from 2006 to 2018 (about 390 thousand firms per year).

Those two datasets can be linked at the firm-level as they use the same (anonymised) firm identifier. By linking the two longitudinal databases we can apply adequate identification strategies to gauge the impact of multiple grants on firms' performance.[2]



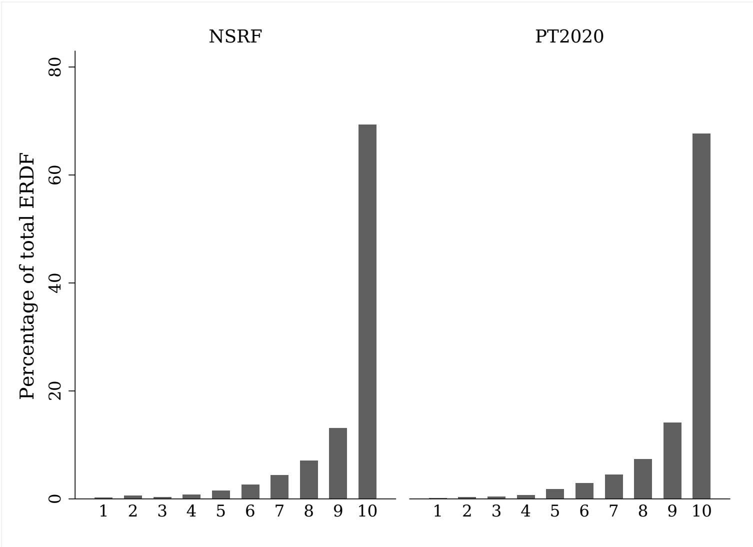
Source: Own computations using data from the *Portuguese Agency for Development and Cohesion.*

Figure 1: Number and value of subsidies by year

In the NSRF, ERDF grants to firms' investment reached an amount of 3.3 billion euros, corresponding to a total investment of 8.3 billion euros, allocated to 6487 firms.

[2]A full description of the variables used in our empirical analysis is presented in Table A.1 in the Appendix.

In PT2020, ERDF subsidies amounted to 4.2 billion euros contracted until 2018, the period of our analysis, corresponding to a total investment of 9.2 billion euros, allocated to 7243 firms. Figure 1 presents the number and value of subsidies by year. Since 2012, the number of subsidies to firms has increased substantially and 2016 was the year with the highest amount of projects contracted (around 4,000) and the highest amount of subsidies awarded (over 1,5 billion euros).



Source: Own computations using data from the *Portuguese Agency for Development and Cohesion*

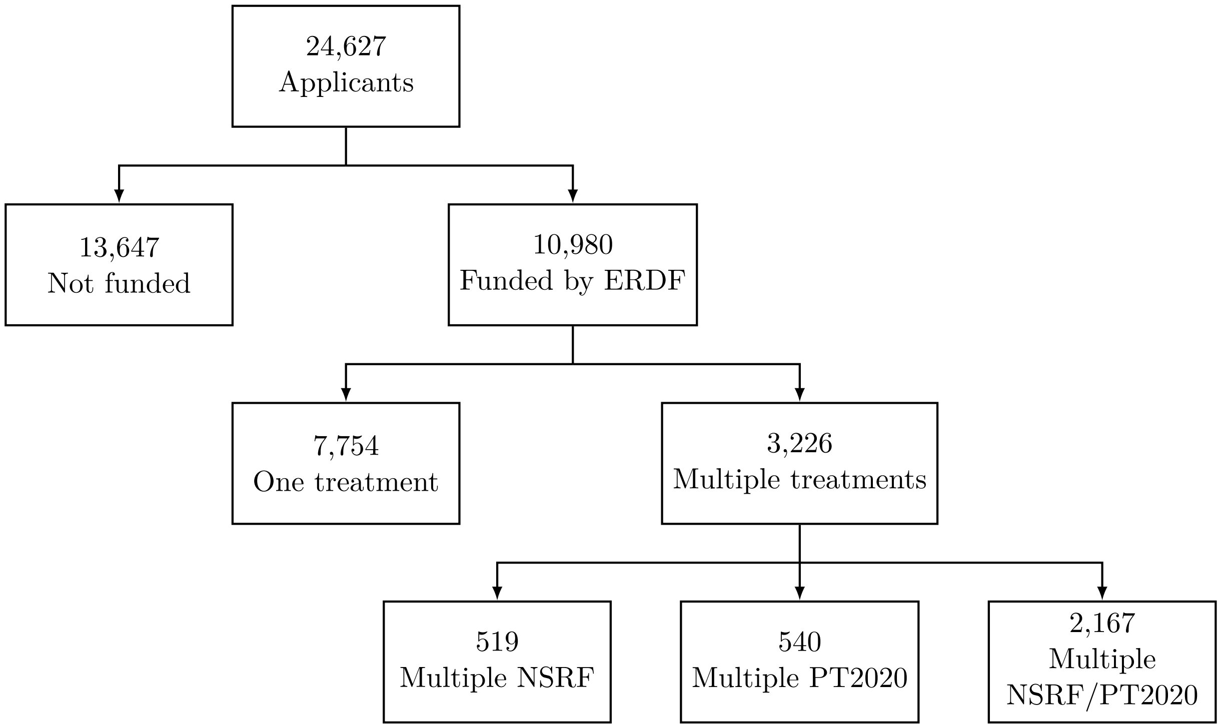
Figure 2: Decile distribution of ERDF subsidies to firms' investment in the NSRF (2007-2013) and in PT2020 (2014-2018)

The analysis of the distribution of ERDF subsidies to firms' investment shows a high concentration in a small number of firms, both in the NSRF (2007-2013) and in PT2020 (2014-2018). Figure 2 presents the decile distribution of ERDF subsidies to firms' investment in both programs. Figure 2 shows a high concentration of ERDF subsidies, where 10% of the firms which received the highest grants account for 69% and 66% of total ERDF subsidies to firms' investment in the NSRF and in PT2020, respectively.

Figure 3 presents an overview of the distribution of the ERDF subsidies to firms' investment. In the period 2007-2018, 24,627 firms applied to ERDF grants, 10,980 received ERDF subsidies, and 13,647 were not selected to receive a grant. Thus, 55% of the firms that applied to receive ERDF subsidies were not supported.

From the analysis of the data in Figure 3 a feature stands out in both ERDF programs: a significant share of firms have received more than one grant; that is, 3,226 firms of the awarded firms (29%) received more than one subsidy. From the group of firms that have received multiple treatments, 2,167, were awarded a grant, both in the NSRF and PT2020. That group of firms received around 1,6 billion euros in the NSRF (47.7% of total ERDF) and 1,9 billion euros in PT2020 (43.8% of total ERDF). On the other hand, 519 and 540 firms received multiple grants in the NSRF and in PT2020, respectively.

The availability of detailed information on the timing of subsidies and the application scores allows us to investigate in a more effective way the effectiveness of allocating multiple subsidies to the same firm, that is, the effectiveness of investment grants booster shots.



Source: Own computations using data from the *Portuguese Agency for Development and Cohesion*

Figure 3: Overview of the distribution of the ERDF grants to firms' investment in 2007-2018 (NSRF and PT2020)

Table 1 shows the distribution of firms by the number of grants and the corresponding share of ERDF. The one-off treatment, that is, firms that received only one grant, accounts for 7,754 firms (around 70% of the total supported firms), corresponding to 35% of total ERDF subsidies. On the other hand, around 30% of the awarded firms received multiple subsidies, which accounted for 65% of the total ERDF subsidies to firms. For example, 1,900 firms received two grants, accounting for 22% of total ERDF.

3 Empirical strategy

In this section, we describe our empirical strategy to evaluate the impact of an investment grant on firms' performance. The empirical literature on the impact of public subsidies is ambiguous in part due to incomplete and non-representative data samples and identification issues (e.g., Bronzini and Piselli, 2016, Criscuolo et al., 2019, Criscuolo et al., 2022). We implement a sharp RDD to identify a causal relationship

Table 1: Number of firms and share of grants by the number of treatments (2007-2018)

Grants	Firms	Share (%)
0	13,647	0
1	7,754	35
2	1,900	22
3	732	15
4	292	11
5 or more	302	18

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion.*

between grants and firms' performance, namely on firms' productivity. The availability of the scores of both non-selected and funded applications allows us to carry out a robust identification strategy to evaluate the impact of a grant booster shot on firms' investment, employment, value-added and productivity. In our analysis, we consider two measures of productivity. Labour productivity is computed as the ratio of value-added over the number of workers. Total Factor Productivity (TFP) is computed following Ackerberg et al. (2015). We use intermediate inputs as a proxy estimator (to control for correlation between input levels and the unobserved firm) as in Levinsohn and Petrin (2003). We also include the assets and the wage bill as control variables – see Fox and Smeets (2011) and De Loecker and Syverson (2021).

In our econometric specification, the dependent variable is generically defined as Y_i and can take two possible values, $Y_i(1)$, under the treatment, and $Y_i(0)$ in its absence. The running variable which defines the treatment assignment is the application's (standardized) score (S_i) – see Angrist and Rokkanen (2015).[3] The treatment indicator (T_i) is a binary variable that assumes the value 1 if the firm receives the grant (score equal to or above zero, $S_i \geq 0$) and 0 otherwise (score below zero, $S_i < 0$). Equation (1) presents firms' two potential outcomes:

$$Y_i = (1 - T_i) \cdot Y_i(0) + T_i \cdot Y_i(1) = \begin{cases} Y_i(0) & \text{if } S_i < 0 \\ Y_i(1) & \text{if } S_i \geq 0 \end{cases} \tag{1}$$

The average treatment effect is estimated as the difference in the outcomes between the treated and the control group at the cutoff (c) – see equation (2).

[3] In our analysis, when firms have applied more than once per year, we assumed two criteria to select one application per year per firm. Firstly, we prioritize the selected applications. Secondly, we prioritize the ones with the highest scores.

$$\tau_{RDD} = E\left[Y_i(1) - Y_i(0) | S_i = c\right] \tag{2}$$

The key assumption underlying our identification strategy is that firms with scores in the neighbourhood of the cutoff are similar and have the same potential outcome. Thus, the causal effect is identified by comparing both groups in the neighbourhood of the cutoff – see Lee and Lemieux (2010) and Cattaneo et al. (2020) for a detailed discussion of the RDD strategy.

The application scores vary between zero and five. In the period 2007-2018, we consider 668 calls. Each call has a cutoff, separating funded from non-selected applications. We pool all calls in a single dataset, considering only one observation per firm. To standardize the pool of applications we set the cutoff at zero by computing the difference between the scores and cutoffs of each call.

We exclude from the analysis the calls without a cutoff, that is, the calls in which all applicants were selected for funding or all applicants were non-selected. When a firm applies several times for ERDF grants, we choose the selected application. When all applications are non-selected, we choose the first one.

Figure 4 describes our two-step RDD empirical strategy. Firstly, we evaluate the impact of a Single grant versus No grant on firms' performance – the sample corresponding to Box A in the diagram. Secondly, we evaluate the impact on firms' performance of having a Second grant. In this step, our sample comprises firms that have received one grant and applied for a second grant. The sample used to evaluate the booster shot effect corresponds to Box B in the diagram.

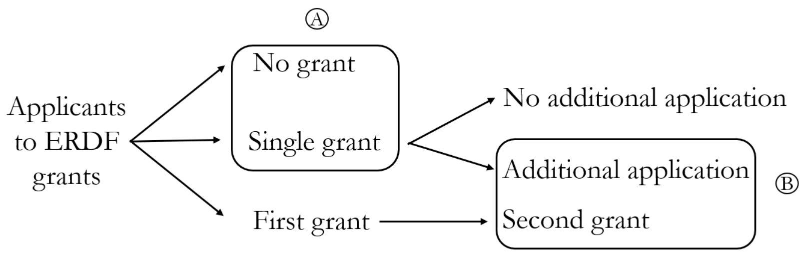
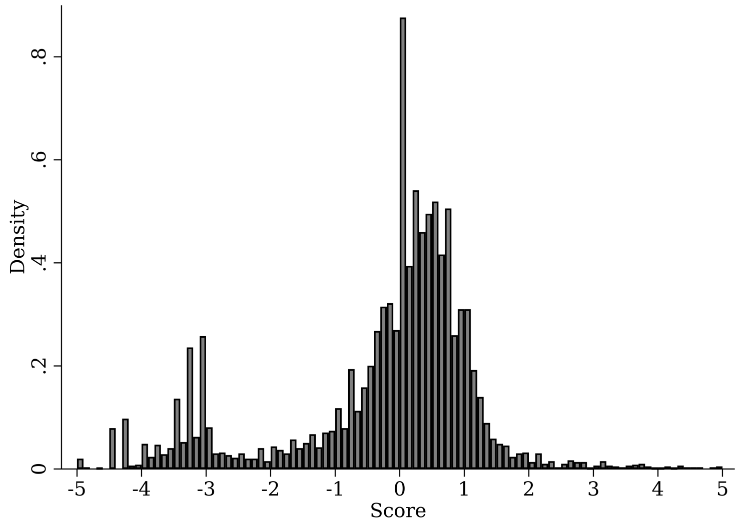


Figure 4: Control and treatment groups

The sample used in the first step of our empirical strategy includes 5,934 firms from 473 calls, wherein 2,386 firms were not selected, and 3,548 firms received a single grant. Figure 5 presents the distribution of the scores after standardizing the cutoff of all calls to zero. The scores equal to or above zero correspond to firms that received a single grant, while those below zero correspond to non-selected firms. The standardization implies that the scores vary between minus five and five.

In our RDD estimates, we make use of the application scores of the firms that were not awarded a grant – 'No grant' – and the scores of the firms that received one grant – 'Single grant'.



Source: Own computations using data from the *Portuguese Agency for Development and Cohesion*

Figure 5: Scores distribution, no treatment versus one treatment

Table 2 presents the descriptive statistics for 2007 for non-selected and selected firms that applied for a grant in 2008. In panel A, we present the descriptive statistics for the full sample, while in Panel B we look at the firms inside the bandwidth around the cutoff.[4] Considering the full sample, the average labour productivity and TFP statistically differ between the control and treated groups. In contrast, investment, employment and value-added are not statistically different across the two groups. On the other hand, comparing the control and treated groups inside the bandwidth, we observe that the control and treated groups are statistically identical, as shown by the t-test results - except for TFP at a 10% significance level.

In the second step of our empirical strategy, we assess the impact of awarding a second grant to firms. We select the group of firms that received one grant and have applied for a second grant. As in the first step, we use an RDD to compare firms awarded a second grant with those that were not successful in their application.

This sample includes 700 firms and 195 calls, where 209 firms were not selected to receive a second grant, and 491 firms were awarded a second grant. Additionally, we do not consider non-selected applications when in that year a firm receives a grant from a previous call. Finally, we drop firms that received a third treatment until three years after receiving the second grant. Figure 6 presents the distribution of the scores for firms that have received a single grant (scores below zero) and firms that have received two grants (scores equal to or above zero).

[4]The cutoff is computed according to Calonico et al. (2014). It corresponds to the set of estimations presented in Section 4.1, Table 4.

Table 2: Descriptive Statistics in 2007: no treatment versus single treatment

Panel A: Full sample									
	Control				Treated				T-Test
	N	Mean	Median	s.d.	N	Mean	Median	s.d.	
Investment	467	220.62	36.78	550.30	267	226.90	58.09	573.05	-0.15
Employment	467	32.28	12	54.68	267	30.20	14	48.30	0.52
Value-Added	467	1073.29	299.88	2216.87	267	1025.39	402.35	1939.84	0.29
Labour Productivity	467	29.24	22.99	22.30	267	32.74	25.28	22.39	-2.04**
TFP	466	1.72	1.69	0.62	266	1.83	1.73	0.69	-2.20**
Panel B: Inside bandwidth									
Investment	95	348.50	38.50	810.08	182	251.33	50.23	634.28	1.10
Employment	95	36.17	13	65.29	182	31.37	12	51.96	0.67
Value-Added	95	1410.66	374.75	2900.18	182	1094.41	357.56	2107.55	1.04
Labour Productivity	95	33.16	24.09	25.71	182	32.59	25.70	22.45	0.19
TFP	95	1.67	1.66	0.66	181	1.83	1.71	0.71	-1.88*

Notes: Investment, value-added and labour productivity in thousands of euros. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.

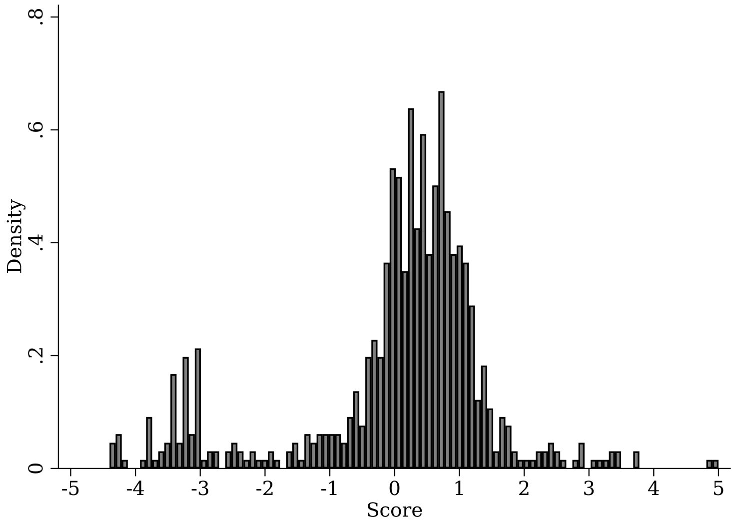
Table 3 reports the descriptive statistics in 2012 for the group of firms that applied for a second grant in 2013. Table 3 shows the descriptive statistics for the full sample and for the group of firms with scores inside the bandwidth around the cutoff. Due to a smaller number of observations, we define the bandwidth as 50% of applications in the neighbourhood of the cutoff. In the full sample, the averages of employment and value-added are different comparing the control and treated groups while for investment, labour productivity, and TFP the mean values are not statistically different. Inside the bandwidth, the groups are statistically identical except for employment as shown by the t-test results.

Table 3: Descriptive Statistics in 2012: one treatment versus two treatments

Panel A: Full sample									
	Control				Treated				T-Test
	N	Mean	Median	s.d.	N	Mean	Median	s.d.	
Investment	63	519.97	35.72	1653.37	86	367.50	93.95	690.94	0.77
Employment	63	24.35	16	44.22	86	83.44	37	147.01	-3.09***
Value-Added	63	863.57	316.04	1972.92	86	2817.21	995.50	6841.86	-2.20**
Labour Productivity	63	31.07	24.45	27.44	86	33.69	28.79	23.87	-0.62
TFP	63	1.54	1.45	0.69	86	1.62	1.58	0.56	-0.71
Panel B: Inside bandwidth									
Investment	32	407.33	20.88	1641.22	51	269.18	82.65	623.66	0.54
Employment	32	16.28	8	18.52	51	42.78	16	65.38	-2.23**
Value-Added	32	1053.84	268.15	2696.83	51	1463.55	577.31	2790.25	-0.66
Labour Productivity	32	36.28	25.31	34.49	51	32.33	27.82	23.32	0.62
TFP	32	1.73	1.52	0.74	51	1.55	1.53	0.55	1.24

Notes: Investment, value-added and labour productivity in thousands of euros. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.



Source: Own computations using data from the *Portuguese Agency for Development and Cohesion*

Figure 6: Scores distribution, one treatment versus two treatments

In our empirical analysis, we also evaluate how the impact of a single grant and a grant booster shot hinges on firm-size. We consider three firm-size classes: micro, small, and medium/large-sized firms.[5] The descriptive statistics by firm size are presented in Tables A.2 and A.3 in the Appendix.

4 Results

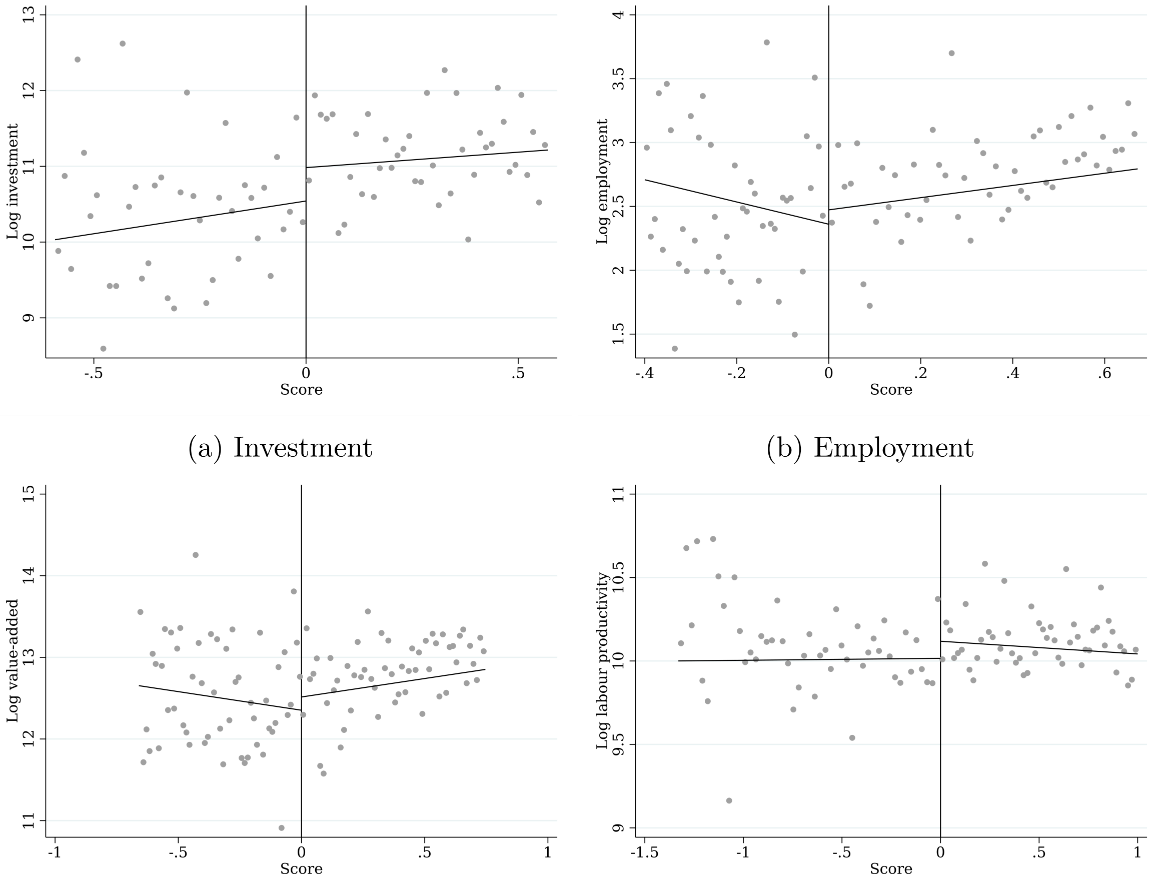
This section presents the results of the RDD estimations for our two-step empirical strategy: the impact of a single grant and of an investment grant booster shot on firms' performance. We present the results for the whole sample and by firm-size.

4.1 No grant versus a single grant

In Figure 7, presenting the RDD plots, we show the differences in investment, employment, value-added, and labour productivity at the neighbourhood of the cutoff between non-selected firms and those that received a single grant. Those representations suggest that a discontinuity might exist between the control and treated groups, mainly

[5]For the classification of firm size, we follow the classification defined in the Official Journal of the European Union, L 124 , 20/05/2003 P. 0036 - 0041, Annex, Article 2: "1.the category of micro, small and medium-sized enterprises (SMEs) is made up of enterprises which employ fewer than 250 persons and which have an annual turnover not exceeding EUR 50 million, and/or an annual balance sheet total not exceeding EUR 43 million. 2. Within the SME category, a small enterprise is defined as an enterprise which employs fewer than 50 persons and whose annual turnover and/or annual balance sheet total does not exceed EUR 10 million. 3. Within the SME category, a microenterprise is defined as an enterprise which employs fewer than 10 persons and whose annual turnover and/or annual balance sheet total does not exceed EUR 2 million." For more details see the information at http://data.europa.eu/eli/reco/2003/361/oj.

on investment, value-added, and labour productivity, supporting the RDD estimations that we present below.



(a) Investment

(b) Employment

(c) Value-added

(d) Labour Productivity

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*

Figure 7: No treatment versus single treatment

Table 4 presents the RDD estimates of the overall impact of a single investment grant on firms' performance. Each set of lines corresponds to a regression where the dependent variable, defined in logs, is identified in the first column. For investment, employment, and value-added we evaluate the impact of the grant one year after the firm has received the subsidy. For labour productivity and TFP we access the impact three years after the firm has received the subsidy, because the effect may take longer to materialize (e.g., Cerqua and Pellegrini, 2014).

For each dependent variable, we report two estimates, corresponding to the two definitions of the kernel function underlying each regression. In column two, we report the estimates using a triangular kernel function, where observations are assigned a weight that declines symmetrically and linearly with the distance to the cutoff. In contrast, in column three, we use an Epanechnikov kernel to set the weight as a quadratic decaying – see Cattaneo et al. (2020). In both cases, observations outside the bandwidth have a

Table 4: No treatment versus single treatment

Dependent variable (in logs)	Kernel function		Sample size
	Triangular	Epanechnikov	
Investment $_{t+1}$	0.442***	0.415***	5,025
	(0.164)	(0.160)	
Employment $_{t+1}$	0.111*	0.097*	5,919
	(0.064)	(0.057)	
Value-Added $_{t+1}$	0.161**	0.150**	5,787
	(0.068)	(0.065)	
Labour Productivity $_{t+3}$	0.103***	0.102***	4,304
	(0.032)	(0.030)	
TFP $_{t+3}$	-0.011	0.026	4,284
	(0.045)	(0.055)	

Notes: The dependent variable of each regression is defined in the first column. In the second and third columns we report the RDD estimates based on the kernel function identified in the respective column. All regressions include the following control variables: profitability, leverage, sales growth, assets, size and industry. Robust standard-errors clustered at the application/year level in parentheses. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.

zero weight. We allow the bandwidth to differ on each cutoff side.[6] Following Gelman and Imbens (2019), we use local linear RDD estimators.

Our estimations follow a non-parametric approach that includes covariates - see Calonico et al. (2019) for a detailed discussion of the methodology and Greenstone et al. (2022) for an application showing that it provides consistent results. We consider the following control variables: profitability, leverage, sales growth, assets, size and for sectors defined by the one letter code. We exclude sectors with 50 or fewer observations and firms created in the application year. In line with Cattaneo et al. (2020), we clustered the standard errors. As the application year is different according to the calls, we cluster at the application/year level.

For the different regressions, the control and treatment groups inside the bandwidth represent between [12%,25%] and [31%,44%] of the sample, respectively. For example, the sample underlying the analysis of the impact of a single grant on employment comprises 5,919 observations – see Table 4. The control group has 2,378 firms, while the treated group has 3,541 firms. Inside the bandwidth of the Triangular kernel estimation the control group has 714 firms, and the treated group has 2,130 firms. The number of observations across the different regressions differs because we drop the observations with zero values on the respective dependent variable. In productivity estimates we

[6]We replicated the estimations discussed below using a symmetric bandwidth and the results are consistent. The analysis is available upon request.

drop an additional set of observations because we evaluate the impact of a grant over a three-year lag.

In the following analysis, we will focus the discussion on the estimates and statistical significance of the Triangular kernel, as the results show a high degree of similarity with the Epanechnikov kernel estimations. The results reported in Table 4 show that a single grant has a positive impact on firms' performance, except for the TFP. Our results suggest that the impact of a single grant on investment is about 44% and statistically significant at the 1% level. The effect of a single grant is also positive and statistically significant for employment (11%), value-added (16%), and labour productivity (10%).

The impact of investment grants may change with firm-size. The economic rationale for public subsidies to firms is based on liquidity constraints, that may affect more micro and small-sized firms – see, for example, Fazzari et al. (1988) and Zwick and Mahon (2017). Public subsidies may foster firms' investment by reducing the cost of capital. Therefore, we expect the impact of grants to be stronger for micro- and small-sized firms. This result has been corroborated in the empirical literature (e.g., Criscuolo et al., 2022).

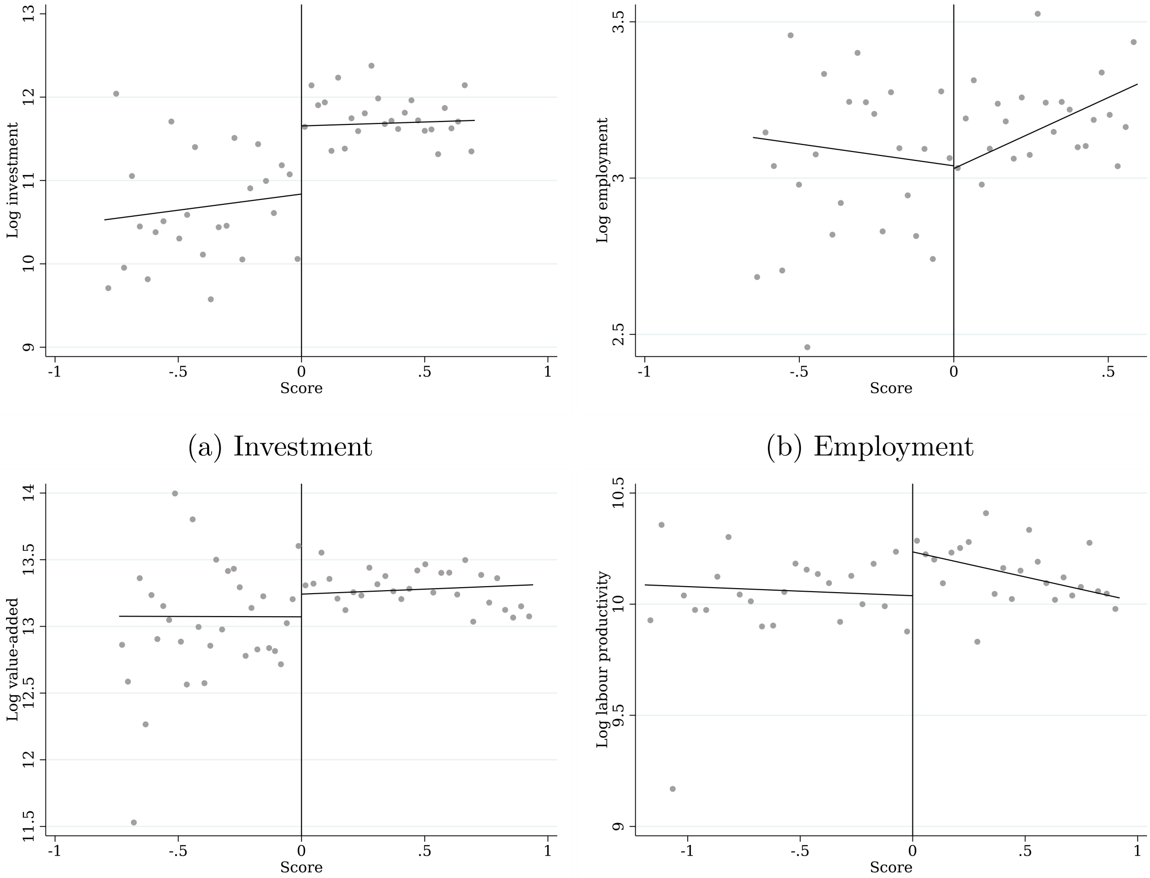
The results for micro-sized firms, Table 5, show that a single grant has a positive and statistically significant effect on value-added at the 10% level. However, we found no impact on investment, employment, labour productivity, and TFP.

Table 5: No treatment versus single treatment: micro-sized firms

Dependent variable (in logs)	Kernel function		Sample size
	Triangular	Epanechnikov	
Investment $_{t+1}$	0.220	0.205	1,598
	(0.267)	(0.263)	
Employment $_{t+1}$	0.075	0.090*	2,325
	(0.051)	(0.053)	
Value-Added $_{t+1}$	0.158*	0.177**	2,240
	(0.092)	(0.089)	
Labour Productivity $_{t+3}$	0.092	0.108	1,750
	(0.075)	(0.084)	
TFP $_{t+3}$	0.057	0.088	1,730
	(0.059)	(0.063)	

Notes: The dependent variable of each regression is defined in the first column. In the second and third columns we report the RDD estimates based on the kernel function identified in the respective column. All regressions include the following control variables: profitability, leverage, sales growth, assets and industry. Robust standard-errors clustered at the application/year level in parentheses. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.



(a) Investment

(b) Employment

(c) Value-added

(d) Labour Productivity

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*

Figure 8: No treatment versus single treatment, small-sized firms

Concerning small-sized firms, the RDD plots presented in Figure 8 show discontinuities at the cutoff on investment, value-added, and labour productivity, which are larger than the ones observed in Figure 7 for the whole sample. The RDD estimates are presented in Table 6. Compared to the evidence for micro-sized firms, the results show that the impact of a single grant is more effective for small-sized firms. Our estimates show that a single grant has a positive and statistically significant impact on investment and value-added. While the effect for value-added is similar to the one found for the whole sample, the effect on investment is twice as large (about 82%). The effect of a single grant on the labour productivity of small-sized firms is about 20%, twice the effect found for the whole sample – see Table 4. The stronger impact of subsidies on small-sized firms is in line with the studies of Decramer and Vanormelingen (2016), Howell (2017), Criscuolo et al. (2019), Bronzini and Iachini (2014) and Dechezlepretre et al. (2018).

For medium- and large-sized firms, we found no positive impact on firms' performance – see Table 7. The impact of a single treatment is only positive and statistically

Table 6: No treatment versus single treatment: small-sized firms

Dependent variable (in logs)	Kernel function		Sample size
	Triangular	Epanechnikov	
Investment $_{t+1}$	0.818***	0.841***	2,410
	(0.209)	(0.207)	
Employment $_{t+1}$	-0.010	0.008	2,667
	(0.072)	(0.074)	
Value-Added $_{t+1}$	0.170**	0.170**	2,635
	(0.080)	(0.080)	
Labour Productivity $_{t+3}$	0.196**	0.187**	1,888
	(0.091)	(0.089)	
TFP $_{t+3}$	0.029	0.029	1,888
	(0.067)	(0.063)	

Notes: The dependent variable of each regression is defined in the first column. In the second and third columns we report the RDD estimates based on the kernel function identified in the respective column. All regressions include the following control variables: profitability, leverage, sales growth, assets and industry. Robust standard-errors clustered at the application/year level in parentheses. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.

significant on investment. On the other hand, a single grant has a negative and statistically significant impact on productivity.

4.2 A single grant versus two grants

In this section, we implement the second step of our empirical strategy, which aims at evaluating the impact of an investment grant booster shot. In this analysis, we follow a similar approach to the one discussed in the previous section. As before, we evaluate the impact on investment, employment, and value-added one year after the firm has received a second grant. For labour productivity and TFP we assess the impact three years after the firm has received a second grant. We consider the same kernel functions and control variables used in Section 4.1. We now add as a control variable the amount of subsidy received in the first treatment. As before, we drop the sectors with less than 50 observations, and the standard-errors are clustered at the application/year level. A smaller number of observations lead us to define the bandwidth as 50% of applications in the neighbourhood of the threshold.[7]

Table 8 presents the estimates of the impact of a second grant on firms' performance.

[7]We estimated the impact of a grant booster shot defining the bandwidth according to the optimization techniques discussed in Calonico et al. (2014). The results, available upon request, are consistent with the ones presented in this section but show a lower statistical significance.

Table 7: No treatment versus single treatment: medium and large-sized firms

Dependent variable (in logs)	Kernel function		Sample size
	Triangular	Epanechnikov	
Investment $_{t+1}$	0.524**	0.551**	663
	(0.248)	(0.238)	
Employment $_{t+1}$	0.019	-0.036	699
	(0.172)	(0.152)	
Value-Added $_{t+1}$	-0.063	-0.079	687
	(0.132)	(0.128)	
Labour Productivity $_{t+3}$	-0.224*	-0.184	498
	(0.119)	(0.124)	
TFP $_{t+3}$	-0.222**	-0.203*	498
	(0.110)	(0.104)	

Notes: The dependent variable of each regression is defined in the first column. In the second and third columns we report the RDD estimates based on the kernel function identified in the respective column. All regressions include the following control variables: profitability, leverage, sales growth, assets and industry. Robust standard-errors clustered at the application/year level in parentheses. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.

The control and treatment groups inside the bandwidth for the different regressions vary between [12%,16%] and [35%,39%] of the sample, respectively. For example, for the estimation of the impact of a booster shot on employment considering a triangular kernel function, the sample includes 696 observations – see Table 8. The control group has 207 firms, and the treated group has 489 firms. Considering the firms with scores in the neighbourhood of the cutoff, the control group has 114 firms, while the treated group has 247 firms.

The results of Table 8, column Triangular, show that a grant booster shot has a positive and statistically significant impact on value-added and labour productivity, 29% and statistically significant at the 1% level. The magnitude of the coefficients is much higher for an investment grant booster shot than for a single grant – see Table 4. The impact of a booster shot on value-added is twice as large as the one of a single grant, while for labour productivity is almost three times as large.

The results of the estimations of the effect of an investment booster shot by firm size are presented in Tables 9 to 11. In these estimations, we define the firm's size at the moment it applies for a second grant. We found no positive and statistically impact of an investment booster shot on micro-sized firms – see Table 9. Furthermore, we observed a negative impact on investment. Firms that are micro-sized when applying for the second grant do not seem to benefit from a booster shot. The majority of firms

Table 8: One treatment versus two treatments

Dependent variable (in logs)	Kernel function		Sample size
	Triangular	Epanechnikov	
Investment $_{t+1}$	0.304	0.310	630
	(0.202)	(0.191)	
Employment $_{t+1}$	0.052	0.065	696
	(0.061)	(0.060)	
Value-Added $_{t+1}$	0.293***	0.292***	683
	(0.102)	(0.102)	
Labour Productivity $_{t+3}$	0.293***	0.301***	628
	(0.110)	(0.116)	
TFP $_{t+3}$	0.154	0.153	626
	(0.112)	(0.115)	

Notes: The dependent variable of each regression is defined in the first column. In the second and third columns we report the RDD estimates based on the kernel function identified in the respective column. All regressions include the following control variables: profitability, leverage, sales growth, assets, amount of subsidy in the first grant, size and industry. Robust standard-errors clustered at the application/year level in parentheses. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.

included in this set of regressions remained micro-sized firms after receiving the first grant (92.2%), while others decreased their size after getting the first grant (7.8%) – see Table A.4. This result may be due to the fact that firms' growth between the first and the second grant is not taken into account by the eligibility criteria for awarding a second grant.

Our estimates for small-sized firms, presented in Table 10, show that an investment grant booster shot leads to an increase in investment of about 79%, statistically significant at the 1% level. A booster shot also has a positive and statistically significant impact on value-added, 56%, and on labour productivity, 39%. The magnitude of the coefficients is significantly higher for small-sized firms than for the whole sample – see Table 8. Therefore, an investment grant booster shot seems to be an effective tool for fostering the performance of small-sized firms. The opposite results for micro-sized firms compared to small-sized firms hint that an investment grant booster shot is effective only if firms reached some critical size.

Finally, our estimates, presented in Table 11, show that an investment grant booster shot has no impact on the performance of medium and large-sized firms.

Table 9: One treatment versus two treatments: micro-sized firms

Dependent variable (in logs)	Kernel function		Sample size
	Triangular	Epanechnikov	
Investment $_{t+1}$	-1.461**	-1.248**	116
	(0.613)	(0.522)	
Employment $_{t+1}$	-0.259	-0.252	150
	(0.178)	(0.179)	
Value-Added $_{t+1}$	-0.254	-0.283	141
	(0.237)	(0.230)	
Labour Productivity $_{t+3}$	0.108	0.086	133
	(0.252)	(0.248)	
TFP $_{t+3}$	0.201	0.190	132
	(0.251)	(0.246)	

Notes: The dependent variable of each regression is defined in the first column. In the second and third columns we report the RDD estimates based on the kernel function identified in the respective column. All regressions include the following control variables: profitability, leverage, sales growth, assets, amount of subsidy in the first grant and industry. Robust standard-errors clustered at the application/year level in parentheses. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.

Table 10: One treatment versus two treatments: small-sized firms

Dependent variable (in logs)	Kernel function		Sample size
	Triangular	Epanechnikov	
Investment $_{t+1}$	0.789***	0.775***	340
	(0.295)	(0.285)	
Employment $_{t+1}$	0.074	0.073	368
	(0.124)	(0.125)	
Value-Added $_{t+1}$	0.559**	0.554**	364
	(0.261)	(0.258)	
Labour Productivity $_{t+3}$	0.386*	0.377*	328
	(0.216)	(0.220)	
TFP $_{t+3}$	0.128	0.100	327
	(0.188)	(0.187)	

Notes: The dependent variable of each regression is defined in the first column. In the second and third columns we report the RDD estimates based on the kernel function identified in the respective column. All regressions include the following control variables: profitability, leverage, sales growth, assets, amount of subsidy in the first grant and industry. Robust standard-errors clustered at the application/year level in parentheses. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.

Table 11: One treatment versus two treatments: medium and large-sized firms

Dependent variable (in logs)	Kernel function		Sample size
	Triangular	Epanechnikov	
Investment $_{t+1}$	-0.381	-0.279	136
	(0.299)	(0.308)	
Employment $_{t+1}$	0.414	0.462	138
	(0.390)	(0.398)	
Value-Added $_{t+1}$	0.239	0.241	138
	(0.278)	(0.279)	
Labour Productivity $_{t+3}$	0.667	0.749	131
	(0.792)	(0.848)	
TFP $_{t+3}$	0.720	0.781	131
	(0.627)	(0.654)	

Notes: The dependent variable of each regression is defined in the first column. In the second and third columns we report the RDD estimates based on the kernel function identified in the respective column. All regressions include the following control variables: profitability, leverage, sales growth, assets, amount of subsidy in the first grant and industry. Robust standard-errors clustered at the application/year level in parentheses. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.

5 Robustness checks

In this section, we present the results of the robustness check to our empirical analysis by considering the estimations for the manufacturing sector and by distinguishing among the three ERDF programs described in Section 2.

First robustness check The manufacturing sector is the most representative in our sample. For the estimations discussed in Section 4.1, no grant versus a single grant, the main sectors in the sample are manufacturing (37%), retail (24%), and consulting services (15%) – see Table A.5 in the Appendix. For the analysis of the grant booster shot, Section 4.2, most firms are also from the manufacturing (56%), retail (16%), and consulting services (15%) – see Table A.6 in the Appendix.

For the manufacturing sector, the results on the impact of a single grant on investment and value-added, Table A.7 in the Appendix, column Triangular, are consistent with the estimates discussed in Section 4.1, Table 4. We highlight the magnitude of the impact on both outcomes, which is larger by about 10 percentage points in the manufacturing sector. However, the effect of a single grant on employment and labour productivity is not statistically significant.

The estimates for micro-sized firms, Table A.8, confirm the positive impact of a single grant on value-added, which is now about 38%, more than twice the effect estimated

Table 12: One treatment versus two treatments: manufacturing sector

Dependent variable (in logs)	Kernel function		Sample size
	Triangular	Epanechnikov	
Investment $_{t+1}$	0.195	0.260	372
	(0.492)	(0.481)	
Employment $_{t+1}$	0.172	0.173	392
	(0.129)	(0.119)	
Value-Added $_{t+1}$	0.292**	0.288**	388
	(0.137)	(0.142)	
Labour Productivity $_{t+3}$	0.241*	0.275**	354
	(0.137)	(0.133)	
TFP $_{t+3}$	0.156*	0.183	354
	(0.093)	(0.120)	

Notes: The dependent variable of each regression is defined in the first column. In the second and third columns we report the RDD estimates based on the kernel function identified in the respective column. All regressions include the following control variables: profitability, leverage, sales growth, assets, amount of subsidy in the first grant and size. Robust standard-errors clustered at the application/year level in parentheses. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.

for the sample with all sectors – see Table 5. A second insight is that, for manufacturing micro-sized firms, a single grant has a positive impact on investment, contrary to what we found for the sample considering all sectors.

Regarding manufacturing small-sized firms, the results for productivity are consistent with the ones reported in Section 4.1, *i.e.*, a positive and significant impact of about 20% – see Table 6 and Table A.9 in the Appendix. However, we now conclude that there seems not to exist a positive impact on value-added, while the previous effect on investment is cut by a third.

Our estimates of the impact of an investment grant booster shot are presented in Table 12. The results for value-added and labour productivity confirm the findings of our main estimations; *i.e.*, for firms in the manufacturing sector, a second investment grant has a positive impact – see Table 8. The magnitude of the impacts is in line with the estimates reported in Section 4.2. Contrary to the result for the whole sample, we now find a positive effect of an investment grant booster shot on TFP (statistically significant at the 10% level). The estimated effect is about 16%.

Breaking the analysis by firm size, and looking at small-sized manufacturing firms, the estimates reported in Table 13 corroborate the previous finding of a positive and significant impact on investment and value-added.[8] However, the results do not confirm

[8]Due to a small number of observations for micro, medium and large sized-firms, we could not estimate the effect on those groups of firms.

Table 13: One treatment versus two treatments: small-sized firms in the manufacturing sector

Dependent variable (in logs)	Kernel function		Sample size
	Triangular	Epanechnikov	
Investment $_{t+1}$	0.877*	0.896	214
	(0.529)	(0.550)	
Employment $_{t+1}$	0.108	0.102	226
	(0.176)	(0.173)	
Value-Added $_{t+1}$	0.464**	0.439**	223
	(0.193)	(0.199)	
Labour Productivity $_{t+3}$	0.228	0.207	201
	(0.190)	(0.189)	
TFP $_{t+3}$	-0.059	-0.076	201
	(0.129)	(0.138)	

Notes: The dependent variable of each regression is defined in the first column. In the second and third columns we report the RDD estimates based on the kernel function identified in the respective column. All regressions include the following control variables: profitability, leverage, sales growth, assets and amount of subsidy in the first grant. Robust standard-errors clustered at the application/year level in parentheses. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.

our previous finding of a positive impact on labour productivity – see Table 10.

The following takeaways deserve a highlight. First, regarding our baseline estimates, we observe a positive impact of an investment booster shot on TFP in the manufacturing sector. Second, for manufacturing small-sized firms, the impact of a booster shot on labour productivity is not statistically significant.

Second robustness check In our main estimations, we included the three systems of incentives: the Innovation Incentive System, the Qualification Incentive System, and the Research and Development Incentive System – see Section 2. The goals and the specificities of R&D investment projects are expected to take longer to impact on firms' performance. Therefore, as a robustness check, we exclude the applications to the Research and Development Incentive System and replicate our estimations as defined in our empirical strategy.

The estimates for this new sample corroborate the findings of the baseline estimates, namely the positive impact of an investment grant booster shot on value-added and labour productivity – see Tables 14 and 15. The magnitude of the estimates for value-added and labour productivity is in line with our previous findings – see Table 8. However, we now find a positive effect of an investment grant booster shot on firms' investment – see Table 14. The impact on investment is about 43%. Focusing on

Table 14: One treatment versus two treatments: without grants to R&D

Dependent variable (in logs)	Kernel function		Sample size
	Triangular	Epanechnikov	
Investment $_{t+1}$	0.432*	0.446*	497
	(0.250)	(0.248)	
Employment $_{t+1}$	0.005	0.026	550
	(0.065)	(0.062)	
Value-Added $_{t+1}$	0.243**	0.252**	539
	(0.102)	(0.104)	
Labour Productivity $_{t+3}$	0.298**	0.305**	482
	(0.119)	(0.127)	
TFP $_{t+3}$	0.114	0.110	480
	(0.119)	(0.123)	

Notes: The dependent variable of each regression is defined in the first column. In the second and third columns we report the RDD estimates based on the kernel function identified in the respective column. All regressions include the following control variables: profitability, leverage, sales growth, assets, amount of subsidy in the first grant, size and industry. Robust standard-errors clustered at the application/year level in parentheses. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.

Table 15: One treatment versus two treatments: small-sized firms without grants to R&D

Dependent variable (in logs)	Kernel function		Sample size
	Triangular	Epanechnikov	
Investment $_{t+1}$	0.685**	0.675**	275
	(0.332)	(0.323)	
Employment $_{t+1}$	0.007	0.020	297
	(0.119)	(0.122)	
Value-Added $_{t+1}$	0.578**	0.566**	294
	(0.255)	(0.256)	
Labour Productivity $_{t+3}$	0.507***	0.480**	257
	(0.180)	(0.188)	
TFP $_{t+3}$	0.161	0.124	256
	(0.188)	(0.181)	

Notes: The dependent variable of each regression is defined in the first column. In the second and third columns we report the RDD estimates based on the kernel function identified in the respective column. All regressions include the following control variables: profitability, leverage, sales growth, assets, amount of subsidy in the first grant and industry. Robust standard-errors clustered at the application/year level in parentheses. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.

small-sized firms, Table 15, our robustness check corroborates the previous finding of a positive impact on investment, value-added and labour productivity. We highlight the positive effect of about 51% on labour productivity, compared to 39% reported in Table 10.

6 Concluding remarks

A new global wave of public policies aiming to increase the resilience of global supply chains and strengthen technological sovereignty or other national strategic goals is in place in the US, the European Union, and China. In this context, improving our understanding of the best approaches to allocating public subsidies is crucial. This paper contributes to this topical issue by evaluating the effectiveness of awarding multiple investment grants to the same firm.

In the Portuguese economy, a high share of total ERDF has been allocated to a small number of firms that have received multiple grants. Awarding multiple grants to the same firm, instead of allocating grants to firms that have never received a public subsidy to finance an investment plan, raises concerns about the effectiveness of such a strategy in enhancing firms' performance and on the eligibility criteria. It is, therefore, of the utmost importance to evaluate the impact of investment grant booster shots on firms' performance.

Overall, our RDD estimates show a positive impact of a single grant on firms' investment, employment, value-added and labour productivity. On the other hand, our estimates show that awarding a second grant to the same firm only affects its value-added and labour productivity. The magnitude of the impact of the booster shot is twice as stronger for value-added and three times the effect on labour productivity. These results suggest that the allocation of multiple subsidies to the same firm may be an effective strategy to improve firms' performance. However, we should stress that we found no impact on total factor productivity, both for single and multiple grants.

Our results also suggest that the effectiveness of an investment grant depends on the targeted firms' characteristics, namely firm size. In the first place, we show that the allocation of single and multiple grants to micro-sized firms does not have a positive and significant effect on productivity. Regarding employment and value-added, a single grant seems to have an impact on micro-sized firms. However, an investment grant booster shot does not have any positive effect on the performance of micro-sized firms.

The estimates for small-sized firms show that investment grants may be very effective in fostering firms' performance. Our results show that both a single grant and a grant booster shot have a positive and significant impact on investment, value-added and labour productivity. Additionally, we conclude that the impact of an investment grant booster shot is three times larger in value-added and twice as large in labour productivity than the one of a single grant. However, the results for labour productivity are not robust across sectors, namely in manufacturing.

Finally, our estimates found no positive impact of investment grants, both in the case of a single and of multiple grants, on the performance of medium- and large-sized firms.

Summing up, our results suggest that an investment grant booster shot might be more effective when targeted at small-sized firms. This result corroborates previous findings in the literature: because small-sized firms may be financially constrained, they are the ones that benefit the most from public subsidies. Additionally, our results for micro-sized firms suggest that, even for financially constrained firms, a critical minimum firm size may exist for an investment grant booster shot to improve firms' performance effectively. The absence of effects of an investment grant booster shot in the performance of micro-sized firms suggests that the eligibility criteria for a second grant should consider the performance of firms since the first grant.

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Appendix

Table A.1: Variables description and sources

Variable	Description	Source
Gross Capital Formation	Investment (€)	CBS
Employment	Employment = number of workers	CBS
Value-Added	Value-Added (€)	CBS
Labour Productivity	Productivity = Value added / workers (€)	CBS
TFP	Total Factor Productivity	CBS
Profitability	Profit = EBITDA / Total assets	CBS
Turnover	Turnover = Growth rate of sales (%)	CBS
Assets	Assets = Total assets (€)	CBS
Leverage	Leverage = total liabilities / total assets	CBS
Score	Score = application evaluation score	AdC

Note. The computation of the TFP follows Ackerberg et al. (2015).

Table A.2: Descriptive Statistics by firm size, 2007: no treatment versus single treatment

	Panel A: Micro							
	Control				Treated			
	N	Mean	Median	s.d.	N	Mean	Median	s.d.
Investment	185	33.94	7.57	72.59	87	50.39	16.66	123.05
Employment	185	4.46	4	2.65	87	5.17	5	2.62
Value-Added	185	100.12	76.93	85.13	87	136.16	125.03	89.60
Productivity	185	22.63	17.96	15.91	87	28.54	22.22	22.75
TFP	184	1.57	1.54	0.63	87	1.73	1.64	0.77
	Panel B: Small							
Investment	203	167.14	65.31	262.16	135	163.17	76.75	226.73
Employment	203	24.62	20	22.15	135	24.38	19	20.40
Value-Added	203	677.65	490.03	592.46	135	748.66	569.64	660.01
Productivity	203	30.05	25.39	18.13	135	33.35	26.11	20.55
TFP	203	1.83	1.77	0.62	134	1.85	1.80	0.61
	Panel C: Medium and large							
Investment	79	795.21	204.95	1092.84	45	759.31	160.13	1197.96
Employment	79	117.09	98	85.46	45	96.04	66	83.74
Value-Added	79	4368.84	3032.58	3844.65	45	3574.73	1925.51	3600.18
Productivity	79	42.63	29.89	35.16	45	39.03	30.71	25.62
TFP	79	1.78	1.74	0.54	45	1.94	1.84	0.75

Notes: Investment, value-added and labour productivity in thousands of euros.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet.*

Table A.3: Descriptive Statistics by firm size, 2012: one treatment versus two treatments

	Panel A: Micro							
	Control				Treated			
	N	Mean	Median	s.d.	N	Mean	Median	s.d.
Investment	24	27.42	22.97	26.20	21	61.18	18.85	124.11
Employment	24	5.04	6	2.22	21	4.10	4	2.70
Value-Added	24	122.48	99.50	103.03	21	114.97	72.40	105.75
Productivity	24	23.71	19.47	14.49	21	31.16	24.13	31.20
TFP	24	1.58	1.53	0.59	21	1.38	1.33	0.71
	Panel B: Small							
Investment	29	153.77	33.06	346.70	37	137.53	90.11	144.58
Employment	29	24.93	19	14.91	37	39.73	34	33.68
Value-Added	29	643.03	514.72	528.79	37	1110.12	794.28	842.09
Productivity	29	26.03	25.62	13.55	37	34.17	29.78	23.21
TFP	29	1.42	1.43	0.62	37	1.65	1.69	0.40
	Panel C: Medium and large							
Investment	10	2764.06	1379.59	3432.40	28	901.13	353.00	1011.38
Employment	10	69.00	43	97.75	28	200.71	153	211.53
Value-Added	10	3281.74	1954.01	4218.86	28	7099.68	3160.05	10850.00
Productivity	10	63.34	39.09	51.91	28	34.96	30.19	18.64
TFP	10	1.82	1.59	1.04	28	1.75	1.64	0.58

Notes: Investment, value-added and labour productivity in thousands of euros.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*

Table A.4: The firms' size on the first treatment for firms that received a booster shot (%)

Panel A: Micro	
Size on the first grant	%
Micro	92.2
Small	7.8
Panel B: Small	
Micro	8.9
Small	85.7
Medium	5.0
Large	0.4
Panel C: Medium and large	
Small	17.2
Medium	58.6
Large	24.1

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet.*

Table A.5: The firms' sector (%): no treatment versus single treatment

Sector	%
Manufacturing	36.7
Construction	6.8
Retail	24.1
Transport services	2.7
Accommodation and food services	5.1
Telecommunications services	6.7
Consulting, scientific and technical services	14.6
Administrative services	3.4

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.

Table A.6: The firms' sector (%): one treatment versus two treatments

Sector	%
Manufacturing	56.1
Retail	16.0
Telecommunications services	12.4
Consulting, scientific and technical services	15.4

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.

Table A.7: No treatment versus single treatment: manufacturing sector

Dependent variable (in logs)	Kernel function		Sample size
	Triangular	Epanechnikov	
Investment $_{t+1}$	0.554***	0.631***	1966
	(0.171)	(0.171)	
Employment $_{t+1}$	0.126	0.137	2175
	(0.085)	(0.084)	
Value-Added $_{t+1}$	0.252***	0.250***	2129
	(0.084)	(0.082)	
Labour Productivity $_{t+3}$	0.120	0.127	1411
	(0.086)	(0.086)	
TFP $_{t+3}$	0.011	0.018	1409
	(0.089)	(0.088)	

Notes: The dependent variable of each regression is defined in the first column. In the second and third columns we report the RDD estimates based on the kernel function identified in the respective column. All regressions include the following control variables: profitability, leverage, sales growth, assets and size. Robust standard-errors clustered at the application/year level in parentheses. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.

Table A.8: No treatment versus single treatment: micro-sized firms in the manufacturing sector

Dependent variable (in logs)	Kernel function		Sample size
	Triangular	Epanechnikov	
Investment $_{t+1}$	0.701*	0.715**	361
	(0.367)	(0.359)	
Employment $_{t+1}$	0.265	0.275	442
	(0.187)	(0.185)	
Value-Added $_{t+1}$	0.378*	0.367*	424
	(0.207)	(0.190)	
Labour Productivity $_{t+3}$	0.213	0.157	288
	(0.239)	0.222)	
TFP $_{t+3}$	0.150	0.168	286
	(0.181)	(0.186)	

Notes: The dependent variable of each regression is defined in the first column. In the second and third columns we report the RDD estimates based on the kernel function identified in the respective column. All regressions include the following control variables: profitability, leverage, sales growth and assets. Robust standard-errors clustered at the application/year level in parentheses. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.

Table A.9: No treatment versus single treatment: small-sized firms in the manufacturing sector

Dependent variable (in logs)	Kernel function		Sample size
	Triangular	Epanechnikov	
Investment $_{t+1}$	0.526*	0.539*	1,216
	(0.316)	(0.321)	
Employment $_{t+1}$	0.043	0.045	1,324
	(0.102)	(0.102)	
Value-Added $_{t+1}$	0.132	0.105	1,307
	(0.094)	(0.086)	
Labour Productivity $_{t+3}$	0.208*	0.219*	841
	(0.116)	(0.113)	
TFP $_{t+3}$	-0.045	-0.049	841
	(0.118)	(0.113)	

Notes: The dependent variable of each regression is defined in the first column. In the second and third columns we report the RDD estimates based on the kernel function identified in the respective column. All regressions include the following control variables: profitability, leverage, sales growth and assets. Robust standard-errors clustered at the application/year level in parentheses. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Own computations using data from the *Portuguese Agency for Development and Cohesion* and *Central Balance Sheet*.