
WORKING PAPER

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productivity”**

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The elusive impact of R&D grants on firm productivity¹

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August 4, 2023

Abstract

This paper evaluates the effectiveness of R&D subsidies, provided by the European Regional Development Funds, on firms' productivity. Using detailed longitudinal firm-level data covering the period 2007-2019, we employ state of the art differences-in-differences estimators to evaluate the impacts of R&D grants. Positive causal effects on gross value added and labour productivity are discernible for micro- and small-sized firms participating in co-promotion but not in individual projects. However, these effects seem to be elusive. No evidence of a positive effect of these grants on firm performance for medium- and large-sized firms or for individual R&D projects is found. This investigation contributes to a more comprehensive understanding of the relative effectiveness of productivity enhancement programs.

Keywords: R&D grants; productivity; European funds; co-promotion.

JEL Classification: D22, H25, L25, L52.

¹ Acknowledgements. The authors are grateful for the comments and suggestions of the participants at the 16th Annual Meeting of the Portuguese Economic Journal. The authors acknowledge the funding by National Funds of the FCT - Portuguese Foundation for Science and Technology, project UIDB/03182/2020.

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1 Introduction

This paper aims to evaluate the impact of research and development (R&D) grants on the performance of firms, namely focusing on productivity improvements. Several factors – the Covid-19 pandemic, trade wars, disruptions in global supply chains – have brought public subsidies back to the limelight. Those events generated a new wave of industrial policy aiming to guarantee technological sovereignty or a fast transition to renewable energies. In order to reach those goals, the European Union and the United States have allocated significant amounts of public resources to public subsidies. In this context, it is crucial to evaluate the effectiveness of public subsidies to firms.

R&D plays a pivotal role in driving competitiveness, productivity, and economic growth (e.g., Freeman, 1982; Romer, 1990; Coe & Helpman, 1995; Adams & Jaffe, 1996; Aghion & Howitt, 1998). As such, R&D investment has gained significant importance in the creation of intangibles-intensive and knowledge-based economies. To foster this investment, a variety of programs have been established, often experimenting with different incentive schemes and implementation mechanisms (Antonelli & David, 2016). The inherent uncertainty and non-rival nature of R&D lead to an underinvestment problem in the economy due to market failures, creating a wedge between social and private benefits (e.g., Arrow, 1962; Feldman & Kelley, 2003). This wedge provides a rationale for institutional intervention, such as public subsidies to R&D (e.g., Almus & Czarnitzki, 2003; Nelson, 2006; Czarnitzki and Lopes-Bento, 2014; Aristei et al., 2016; Bloom et al., 2019; Bryan & Williams, 2021; Ho et al., 2021). However, evidence on the effectiveness of those policies remains elusive.

The empirical evidence on the effects of R&D grants remains ambiguous due to incomplete and non-representative data samples and, on the other hand, identification issues (e.g., Bronzini & Iachini, 2014; Bellucci et al., 2019; Criscuolo et al., 2022). The identification problems arise due to the non-random nature of firms' decisions to apply for funds (e.g., David et al., 2000; Klette et al., 2000; Blanes & Busom, 2004) and the non-random grant awarding processes (Klette et al., 2000). In general, progress has been made in the R&D evaluation agenda, however there are gaps in our knowledge in terms of the design, deployment, and evaluation of innovation policy (Grillitsch et al., 2019; Criscuolo et al., 2022).

Our work addresses the challenge of measuring the impact of R&D incentives using richer data and state of the art Differences-in-differences (DiD) estimators. Regarding data we have the population of Portuguese firms that applied for R&D grants in the period 2007-2019. We apply the novel estimators proposed by de Chaisemartin & D'Haultfoeuille (2020), Borusyak et al. (2021) and Callaway & Sant'Anna (2021), which allow for the identification of dynamic heterogeneous effects of public subsidies, attributed at different moments in time. Our empirical strategy enables us to systematically compare the benefits of individual and co-promotion R&D projects, allowing for firm-size dependency in effects.

This study contributes to a more comprehensive understanding of the relative effectiveness of productivity enhancement programs. By explicitly assessing outcomes accounting for differences among treatment mechanisms and treated entities, it adds to the growing body of work that investigates the causal effects of R&D subsidies on firms' performance (e.g., Bronzini & Iachini, 2014; Karhunen & Huovari, 2015; Becker, 2015; Vanino et al. 2019; Bellucci et al., 2019; Berruti & Bianchi, 2020; Crespi et al., 2020). Furthermore, it provides nuanced guidance with respect to future R&D grant allocation approaches.

In what follows, section 2 presents the literature review and the positioning of the paper. Section 3 describes the program, our data and provides descriptive statistics on the R&D individual and co-promotion projects. Section 4 presents the empirical strategy and discusses the results. Section 5 concludes.

2. Literature Review

Public funding for R&D

Resource constraints, higher uncertainty and higher risk of failure insert a discrepancy between public and private returns in R&D that discourages firms from investing in innovation. Micro-sized firms, small and medium-sized enterprises (SMEs) and new entrants face further constraints on R&D investments due to asymmetric information in financial markets and their higher risk of default (e.g., Fazzari et al., 1988; Beck & Demirguc-Kunt, 2006; Freel, 2007; Czarnitzki & Hottenrott, 2011; Cin et al., 2017).

Public funding programs for R&D step in to alter firms' choices and enhance the chances of success in learning processes (Clarysse et al., 2009; Corredoira et al., 2018) by encouraging firms to innovate. The logic of such supporting programs spans from “negative motivations” of compensating firms for the losses triggered by obstacles to innovation, such as appropriability conditions, investment shortcomings and capability mismatches, all the way to “positive motivations” aimed at accelerating R&D activities and fostering the accumulation of quasi-public knowledge (Antonelli, 2020; Berrutti & Bianchi, 2020; Choi & Lee, 2017).

This rationale behind conventional innovation funding programs is broadly accepted across various schools of thought. It is acknowledged that private investment in innovation generates external spillovers that surpass the firm's individual gains (Antonelli & Crespi, 2013; Becker, 2015). As R&D is a non-rival good, it can lead to potential knowledge spillovers where other firms benefit from the innovation efforts of others (Katz, 1986; Nelson, 1959).

The policy instruments can be designed or combined with institutional reform to leverage collective and coordination aspects of innovation and productivity growth (Alexandre et al., 2022). The effectiveness of policy might depend on the specific types of funding schemes (i.e., pro-individual or pro-collaborative funding) and on the characteristics of the recipients (i.e., firm dimension) (Afcha & Chu, 2023). In terms of funding schemes, R&D grants may be awarded to individual projects, if one assumes R&D uncertainties mostly afflict firms in their stand-alone strategies, or to co-promotion projects, where interactions and relationships between innovators are considered essential in the learning process (Rakas & Hain, 2019).

R&D co-promotion and individual-based programs

As firms' constraints are not exclusively financial ones, entities may be more willing to apply for programs if they can access complementary capabilities, dampen uncertainties and achieve higher efficiencies. In this context, cooperative R&D and the embeddedness in knowledge networks have been shown to be essential for innovation (Boshma & Ter Wal, 2007) and are increasingly being supported by public programs (Broekel, 2013).

Firms tend to engage in co-promotion projects to mitigate the risks associated with innovation, share costs, avoid wasteful duplications of research, overcome financial hurdles, and access external resources, both monetary and knowledge-based, that would otherwise be inaccessible. These collaborative initiatives are particularly beneficial when developing new technologies where appropriation is difficult (Katz, 1986; Tether, 2002; Feldman & Kelley, 2003; Barajas et al., 2012; Ferrino et al., 2021; Mani et al., 2022). Evidence suggests that subsidised research cooperation can enhance innovation efficiency (Broeker & Graaf, 2012; Min et al., 2020) and foster learning (Subramanian et al., 2018).

Several studies also confirm a positive impact of co-promotion projects on firm productivity (Benfratello & Sembenelli, 2002; Belderbos et al., 2004; Barajas et al., 2012; Aguiar & Gagnepain, 2017). Crespi et al. (2020) found that R&D co-promotion projects positively influenced productivity among Chilean companies from 1990 to 2006, with significant spillovers to geographically proximate and untreated firms. Aguiar & Gagnepain (2017) observed a 44.4% average increase in labour productivity among 961 firms participating in R&D partnerships funded by the 5th European Framework between 1998 and 2002. Similarly, Benfratello & Sembenelli (2002) reported a positive association between participation in research joint ventures, under the Eureka program, and labour productivity, based on their analysis of 101 firms from 1992 to 1996. Belderbos et al. (2004) also found productivity increases in innovative Dutch firms engaged in R&D cooperation from 1996 to 1998, but only in partnerships with competitors and suppliers, not with customers or scientific institutions.

However, the evidence is not entirely consistent. Cannone & Ugheto (2014) found no impact of joint ventures on productivity in their evaluation of public support for R&D in Italy. Similarly, Barajas et al. (2012) did not find a direct effect of joint ventures on labour productivity in Spanish firms between 1995 and 2005; yet, they did identify an indirect effect through intangible fixed assets, which generated productivity growth.

Co-promotion projects, while beneficial, may also entail costs, such as management expenses, potential free-riding, and trust-building needs (Katz & Martin, 1997; Benfratello & Sembenelli, 2002; Feldman & Kelley, 2003; Barajas et al., 2012; Crespi et al., 2020). These can lead to coordination issues, potentially endangering shared benefits, as effective knowledge transfer requires strong organization, making

coordination and governance crucial in co-promotion projects. Thus, the effectiveness of co-promotion projects in R&D schemes may depend on the recipient firms' specific characteristics as firms will only participate when the expected benefits surpass these costs (Aschhoff & Schmidt, 2008; Crespi et al., 2020). In this context, some firms may prefer to undertake individual R&D investments.

Concerning individual R&D investments, several studies have explored the impact of R&D subsidies on firm productivity. Dai & Wang (2019) found positive effects on productivity among Chinese listed firms from 2006-2016. Similarly, Cin et al. (2017) reported positive impacts on value-added productivity in Korean manufacturing SMEs from 2000-2007. Okamura & Nishimura (2021) also found positive effects on SMEs' productivity in Japan from 2004-2016. However, the evidence is not consistent across all studies. Merito et al. (2010) found no significant effects on labour productivity in Italian manufacturing firms subsidized with R&D grants in 1999 or 2000. Karhunen & Huovari (2015) also found no significant positive effects on labour productivity in Finnish firms financed between 2002 and 2007, with potential for negative impacts depending on the type of the firm and the period in analysis.

Bellucci et al. (2019) compared the impacts of co-promotion and individual projects on Italian SMEs, from 2003 to 2012. They found that public subsidies for co-promotion projects were less effective than those allocated to individual research projects. Specifically, individual projects showed clear effects on investments and employment, while co-promotion projects demonstrated weaker and mixed effects, including slower employment growth and a negative impact on investment. Similarly, Crespi et al. (2020) compared individual and joint research projects in Chile, concluding that, while the benefits were broadly similar, research collaborations were preferable for generating spillovers. This study will contribute to this discussion by comparing the effects of each R&D modality on firms' productivity.

Many studies have also focused on characteristics of participating entities and tried to relate those to the impacts of R&D grants. There is a wide range of studies supporting that subsidies to small-sized firms do indeed result in higher benefits compared with the ones registered for larger firms (this is a conclusion from Zúñiga-Vicente et al. 2014 in a survey of 77 studies). This conclusion is consistent across multiple works on the impact of grants in private R&D investment and productivity (Busom, 2000; Benfratello

& Sembenelli, 2002; Lach, 2002; Hyytinen & Toivanen, 2005; Lööf & Heshmati, 2005; González & Pazó, 2008; Sissoko, 2011; Bronzini & Iachini, 2014). The logic behind these differences relates to the previously mentioned financial constraints of smaller firms. By providing R&D subsidies, the government effectively alleviates these constraints, enabling smaller firms to undertake projects they would not take otherwise (Criscuolo et al., 2019; Altomonte et al., 2016; Castellaci & Lie, 2015). Our paper also contributes to this discussion by evaluating the impact of R&D grants on smaller and larger-size firms.

Summing-up, it is not clear-cut whether R&D grants lead to productivity growth. The various assessments presented so far are not easily comparable given the heterogeneity of the results, which can vary based on numerous factors such as the country, institutional framework, the design of the program, and characteristics of the firms involved.

The identification problem and contribution of this study

Evaluating the effects of public policies on R&D is complex, notably, the autonomous decision-making process, wherein firms independently determine whether to apply and the terms of their application (either individually or in partnership), presents a significant challenge. This complexity stems from the non-random nature of the sample (e.g., David et al., 2000; Klette et al., 2000; Blanes & Busom, 2004), where low-promise organisations, that allocate more effort to grant-seeking, may indeed end up receiving the funds (Gustafsson et al., 2020). Such phenomenon implies clear issues of potential self-selection (David et al., 2000; Klette et al., 2000; Blanes & Busom, 2004). Furthermore, this non-randomness extends to the grant awarding process (Klette et al., 2000), implying the consideration of treatment selection (Imbens & Wooldridge, 2009) to avoid potential biases in the outcomes (Bellucci et al., 2019).

Econometric studies have employed various methods to identify and gauge the size and duration of impacts, but new and richer sources of data and more robust econometric techniques originated new waves of empirical estimates of the impact of R&D subsidies to firms (Benfratello & Sembenelli, 2002; Belderbos et al., 2004; Aguiar & Gagnepain, 2017; Crespi et al., 2020; Roth et al., 2023). One strategy highlighted in the literature to address potential selection bias involves using Propensity Score

Matching (PSM). This technique enables the selection of a subsample from the control group of firms, assuring, under strict assumptions, no statistical differences between the treatment and control groups. This procedure ensures comparability and effectively mitigates potential selection bias, as detailed by Clò et al. (2022).

A subsequent alternative is a robust two-step process, which combines PSM with a Differences-in-Differences (DiD) approach (PSM-DiD) and has also been employed in the literature. This methodology, thoroughly discussed in the works of Blundell & Costa Dias (2000) and Imbens & Wooldridge (2009), posits that by integrating PSM with DiD, it's possible to capture the effects of both observable and non-observable time-invariant variables on the outcomes. Table A.1 in the Appendix synthesizes recent empirical literature that applies the PSM-DiD method to evaluate R&D subsidies.

More recently, the traditional DiD approach has been subject to further scrutiny, especially in staggered design cases, where the treatment is not simultaneously introduced for all units under analysis but at different points in time for different sample subsets. This critique has been put forth by authors such as de Chaisemartin & D'Haultfoeuille (2020) (dC&DH), Borusyak et al. (2021) (BJS), and Callaway & Sant'Anna (2021) (C&S), among others. A staggered design can occur, for example, in policy interventions that are gradually rolled out across different firms, as in our study.

The estimators proposed by dC&DH, BJS, and C&S represent a significant advancement in identifying dynamic effects within a staggered design (see Chaisemartin & D'Haultfoeuille, 2022, or Roth et al., 2023, for a detailed discussion of this recent trend in the literature). Consequently, in our empirical analysis, we will adopt these three identification strategies to address the staggered design that underlies our research question. In doing this, we aim to build upon and enhance the staggered difference-in-difference empirical strategy first utilized by Clò et al. (2022) for the analysis of R&D grant impacts.

This paper contributes to the existing literature in three ways. Firstly, it contributes to the ongoing discussion on the impact of R&D support on performance by employing state-of-the-art DiD methods on high-quality data. This allows us to execute a robust identification strategy and gain valuable insights into the results of pro-innovation

public interventions. Secondly, we explore the benefits of both individual and co-promotion R&D projects. Lastly, we delve into how the impact of R&D grants varies based on the size of the firm.

3. Program and data

This section describes the R&D program funded by the European Regional Development Fund (ERDF) and the databases used in our empirical estimates. We also present statistics on the R&D individual and co-promotion projects and on the characteristics of the firms that applied to those grants.

The program

In this study, we evaluate the impact of the two typologies of R&D grants, grants to a single firm, and grants to co-promotion projects, backed by the European Regional Development Fund (ERDF) and financed via the System of Incentives for Innovation and Technological Development program. The primary objective of this program is to augment R&D investments, thereby strengthening firms' competitiveness. This is achieved by encouraging collaborations between businesses and entities within the scientific and technological system, fostering knowledge-intensive activities, and creating value through innovation. Santos et al. (2023) provide a description of that program and its impact on the productivity of the Portuguese regions.

Our analysis encompasses two multiannual frameworks: the National Strategic Reference Framework (NSRF, 2007-2013) and the Partnership Agreement Portugal 2020 (PT2020, 2014-2020). Under the NSRF (2007-2013), R&D initiatives were primarily focused on industrial research and experimental development activities, yielding new products, processes, or systems, or effecting substantial enhancements in existing ones. The R&D program under the PT2020 framework incorporates five project types: R&D projects developed by firms, involving industrial research and experimental development activities; projects targeting the demonstration of novel technological solutions; initiatives promoting the registration of industrial property protection such as patents; projects aimed at internationalizing R&D; and initiatives

fostering scientific and technological competencies with broad-ranging impacts at a multisector, regional, or cluster level, conducted through partnerships between businesses and entities of the scientific and technological system.

As discussed above, R&D projects can be undertaken by firms individually or via co-promotion. Co-promotion initiatives require the designation of a project leader to ensure seamless coordination among stakeholders and with the managing authority (usually the member with the greatest investment share). A contract outlining the partnership's critical aspects, such as cooperation scope, joint responsibility declaration, property rights allocation, and others, is required. It is also essential to establish each project member's significant contributions to the R&D activities. R&D projects' approval follows a "call for tenders" model where proposals are evaluated based on their merits. The selection criteria, reflecting the policy objectives of the funding award are provided in the call. Independent experts of acknowledged merit assess these projects, and those earning the highest scores are granted public funding.

Data

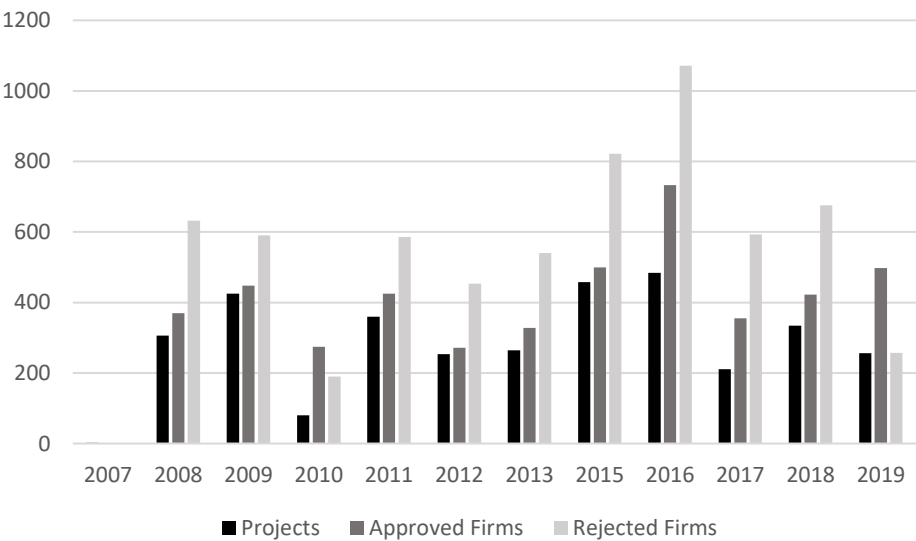
In our empirical analysis, we use a very detailed and comprehensive administrative database made available by the Portuguese National Innovation Agency (ANI), including all R&D applications, selected and non-selected for funding, carried out individually or in co-promotion. Our analysis covers the period 2007-2019, in which 2,106 firms participated in 3,254 R&D projects funded by ERDF, amounting to 1,038 million euros in grants and corresponding to a total investment of 2,268 million euros. The data for each project identifies all the entities (firms and organizations from the scientific and technological system) involved in the project, the value of the grant, total value of the R&D investment, the period of the project, the industry and the region.

The information from the ANI dataset was merged with the Central Balance Sheet Database (CB), a firm-level database made available by Banco de Portugal with yearly economic and financial information of all the non-financial Portuguese companies between 2007 and 2019. From the CB database we retrieved information on the number of total workers, value-added, tangible and intangible assets, firm size and age. Across the sample period of 13 years, the CB database includes information on

around 390 thousand firms per year. These data allow us to characterize the population of applicants to R&D grants over time, in mainland Portugal, that is to say, cases from the autonomous islands of Azores and Madeira are omitted thereby minimizing the presence of outliers. The merger of those two databases allows for the construction of a comprehensive dataset and for the application of adequate identification strategies to gauge the impact of R&D grants on firms' performance.

Figure 1 shows the number of R&D projects and the number of firms that had applications approved and rejected in the period 2007-2019. There is a significant variation in the number of projects and applications through the period under analysis, which is related to the transition between the two multiannual frameworks. The year 2016 stands out with the highest number of projects and applications. In terms of approval rate, 2019 stands out with the highest rate (66% of the firms applying to an R&D grant were approved; in the years 2008, 2012, 2013, 2015, 2017, and 2018 the approval rate ranged between 37% and 38%).

Figure 1: Number of R&D projects, approved and rejected firms, by year, 2007-2019



Source: Own computations based on data provided by ANI.

Table 1 presents the number of firms that participated in at least one R&D project from 2007-2019. From the NSRF to PT2020, there was a relative balance between the frameworks. In aggregate terms, we observe a slight decrease in the number of projects (from 1,675 to 1,579) and a slight increase in the number of firms (from 1,192 to 1,380). The most significant change is observed in the total amount of grants, which

increased from 477 to 561 million euros. This increase is primarily due to a substantial rise in awarded grants for co-promotion projects, which increased by almost 100 million euros, despite a smaller number of projects.

Table 1: R&D projects by multiannual framework, 2007-2019

	Number of projects	Number of firms	Grants (M €)	Total investment (M €)
NSRF (2007-2013)	1.675	1.192	477,19	1.111
PT2020 (2014-2019)	1.579	1.380	560,65	1.156
Total (2007-2019)	3.254	2.106	1.038	2.268
Panel A - R&D individual projects				
NSRF (2007-2013)	1.047	737	287,99	776,36
PT2020 (2014-2019)	1.012	833	277,15	623,12
Panel B - R&D co-promotion projects				
NSRF (2007-2019)	628	648	189,20	335,58
PT2020 (2014-2019)	567	710	283,49	532,71

Source: Author's computations based on data provided by ANI.

Table 2 distinguishes R&D projects by firm size, specifically between micro- and small-firms, and medium- and large-sized firms. We observe that micro- and small-sized firms are more engaged in R&D projects, whether in co-promotion or individually. However, medium- and large-firms receive a higher value in grants, despite participating in fewer projects and being fewer in number. The only exception is co-promotion projects in the NSRF.

Table 2: R&D projects by the multiannual framework and firm size, 2007-2019

	NSRF (2007-2013)			PT2020 (2014-2019)			Total (2007-2019)		
	Firms	Projects	Grants (M €)	Firms	Projects	Grants (M €)	Firms	Projects	Grants (M €)
R&D individual projects									
Micro-small firms	516	671	117,81	569	645	117,03	992	1316	234,84
Medium-large firms	227	376	170,18	276	368	160,13	421	744	330,31
R&D co-promotion projects									
Micro-small firms	385	428	103,62	401	353	113,27	664	701	216,89
Medium-large firms	270	334	85,58	324	353	170,22	481	687	255,80

Source: Author's computations based on data provided by ANI.

Sample construction

Our analysis examines three distinct treatments and creates corresponding samples for each. As previously mentioned, we will differentiate between individual and co-promotion projects, but we will also regard participation in any R&D project as a separate treatment, without distinguishing between the two types.

To establish the control groups for our regressions, we adopt the methodology of Bernini & Pellegrini (2011), Meuleman & De Maeseneire (2012), and Bronzini & Piselli (2016). These researchers consider firms that applied for R&D grants but were unsuccessful as the most suitable control group. Having proposed an R&D investment plan and demonstrated a willingness and need for funding, these firms provide an ideal comparison.

Additionally, to investigate potential variations in effects based on firm size, we split the samples for each treatment into two groups: one comprising only micro- and small-sized firms, and the other consisting solely of medium- and large-sized firms. This method results in nine distinct samples, divided among three different treatments (overall R&D, individual, and co-promotion projects), and three groups of firms differentiated by size (all sizes, micro-small firms, and medium-large firms). Table 3

provides a summary of all the samples considered, detailing the number of firms within both the treated and control groups.

Table 3: Samples descriptions by type of treatment and firm dimension

	All firms		Micro and small firms		Medium and large firms	
	Treated	Controls	Treated	Controls	Treated	Controls
Overall R&D	590	287	362	210	123	49
R&D individual	322	93	223	70	47	10
R&D co-promotion	207	195	113	141	59	39

Source: Authors' computations based on data provided by ANI.

Our analysis includes only firms listed in the CB database that have valid financial data for the variables of interest. We exclude observations with missing values in these variables. To accurately isolate the effect of the R&D projects from any other potential awarded grant, we exclude from our samples any firm that has received grants from incentive schemes other than R&D projects. This exclusion also applies to the control groups, where we remove firms from industries that lack a counterpart in the treated group within the same industry.

Table 4 presents descriptive statistics for firms that were awarded an R&D grant, either in the context of a partnership or individually. We also present descriptive statistics for micro-small firms that conducted co-promotion projects, as this will be one of the primary samples presented in the results section. The statistics reveal that firms applying for an R&D grant in the context of a co-promotion project are larger, have higher sales, exhibit higher productivity, and export more than firms applying individually for an R&D grant. Furthermore, we observe that the micro-small firms involved in co-promotion projects are larger than the average micro-small Portuguese firm.

Table 4: Descriptive statistics of all candidate firms for co-promotion projects and individual projects in the year 2019

	Sales (€ th.)	Assets (€ th.)	Employment	Gross Value- Added	Labour Productivity (€ th.)
Firms involved in R&D projects					
Average	23.400	18.100	127	9.184	102
SD	110.000	161.000	533	58.400	1.384
P10	165	25,47	5	78,45	15,19
Median	2.518	784	27	873	31,98
P90	30.600	9.918	243	9.690	69,29
Firms involved in R&D individual projects					
Average	12.400	3.896	67,58	4.127	39,39
SD	59.900	21.800	164	25.100	31,91
P10	198	25,96	5	78,81	15,90
Median	2.122	650	23,5	713	31,40
P90	21.600	6.906	205	7.366	68,03
Firms involved in R&D co-promotion projects					
Average	41.400	43.400	216	17.900	214
SD	167,000	266.000	856	92.200	2.319
P10	109	18,01	4	62,74	14,70
Median	3.160	962	37	1.061	31,25
P90	37.100	18.400	358	12.300	69,19
Micro and small firms involved in R&D co-promotion projects					
Average	2.272	821	14,67	582	35,60
SD	4.467	1.541	12,25	781	23,26
P10	61,04	6,59	3	32,20	15,19
Median	6.237	195	10	283	30,73
P90	64.263	2.531	37	1.731	56,69

Notes. P10 stands for percentile 10 (likewise for the other statistics). Min and Max represent the minimum and the maximum, respectively. V.A. represents the value added by the company. Source: Author's computations based on data provided by ANI merged with CB.

4. Empirical strategy and results

In this section, we outline our compared empirical approach and present the results of our assessment of the impact of R&D grants on firm productivity using the three DiD estimators discussed above: C&S, dC&DH and BJS; and the sensitivity analysis for (robust) inference of Rambachan & Roth (2023). We examine the impacts of R&D grants on individual projects, co-promotion projects as well as in either modality of R&D project. Additionally, we conduct the analysis separately for two distinct size categories

of firms: micro- and small-sized firms on one side, and medium- and large-sized firms on the other. In the discussion, we follow closely Roth et al. (2023).

4.1 Econometric model

Our econometric model is built around the following specification:

$$y_{i,t} = \gamma Treat_{i,t} + \beta X_{i,t} + \alpha_i + \vartheta_t + \varepsilon_{i,t} \quad (1)$$

Here, $y_{i,t}$ denotes the dependent variable for the firm i at time t . The focus of our analysis is the impact of R&D grants on firms' productivity. For the dependent variables, we consider two measures of productivity: labour productivity (LP) and Total Factor Productivity (TFP). LP is computed as the ratio of value-added over the number of workers. TFP is computed following Akerberg et al. (2015). Following Levinsohn & Petrin (2003), we use intermediate inputs as a proxy estimator to control for correlation between input levels and the unobserved firm. We also include the assets and the wage bill as control variables as in Fox & Smeets (2011) and de Loecker & Syverson (2021). In our empirical analysis, and as a benchmark, we will first consider a model for Gross Value Added (GVA).

The set of covariates, $X_{i,t}$, includes the firm's assets, profitability, liquidity, and financial autonomy, as well as a series of dummies to account for the firm's industry. The terms α_i and ϑ_t are firm-specific and time-specific fixed effects, respectively. The variable ε_{it} represents a white noise error term.

The regression analysis is implemented for the whole sample of firms involved in R&D projects funded by the European Regional Development Fund and by differentiating between R&D individual and co-promotion projects. Additionally, all the estimations are implemented by firm size, by defining a group of 'smaller' firms composed by micro- and small-sized firms, and a group of 'larger' firms composed by medium- and large-sized firms.

Under this setup, one form of the DiD that can be used is the Two-Way Fixed Effects (TWFE) model, which controls for time-invariant unobserved factors that could confound the estimated treatment effect and common shocks at each time period. However, and despite the simplicity and elegance of this model, it is based on two

major restrictive assumptions. It relies on the validity of the parallel trends and on the homogeneity of treatment effects, which might not hold in our case, where the timing of the treatment varies across firms, or the treatment effects change over time. In response to our staggered design, we employ three alternative estimators: C&S, dC&DH, and BJS. These methodologies, accommodate a treatment effect that fluctuates over time, offering insights into whether this effect intensifies or wanes, and whether it is a permanent or temporary phenomenon. These advanced methodologies are better equipped to estimate different treatment timings and dynamic treatment effects, thereby providing a more accurate analysis of the causal impact of interventions.

C&S propose a DiD estimator for settings with multiple time periods. Their estimator extends the classical DiD estimator, which assumes that the treatment effect is constant over time, to allow for time-varying treatment effects. They demonstrate that their estimator can consistently estimate the average treatment effect when treatment effects are heterogeneous and evolve over time. At the core of the estimator lies the group-time average treatment effect on the treated:

$$ATT(g, t) = E[y_{i,t}(g) - y_{i,t}(\infty) | G_i = g]$$

where $G_i = g$ is the period when firm i was first treated and $G_i = \infty$ if the unit was never treated. The estimator will be a weighted average of the predicted ATT of all periods t for each group of firms (cohort) treated at time g .

C&S propose three possible methods to compute the weights: the “Outcome Regression” (OR) approach, which necessitates accurate modelling of the outcome evolution in the comparison group; the “Inverse Probability Weighting” (IPW) approach, which requires a precise model for the conditional probability of unit i being in group g given some covariates; and the “Doubly-robust” (DR) approach, which combines both the OR and IPW approaches. We compute the weights using the DR method due to its increased robustness against model misspecifications. The C&S estimator only requires that the parallel trends assumption holds for periods past the treatment has begun. Imposing parallel trends for all groups and all periods is a stronger assumption and thus may be less plausible.

The estimator proposed by dC&DH, while similar to the C&S estimator, varies in its computation of weights. Both the treatment and control groups are weighted by the inverse of their probability of receiving treatment, enhancing comparability in pre-treatment trends. However, the potential for negative weights could present a challenge with this estimator, an issue that did not arise in our evaluation.

Finally, BJS proposes a similar approach but imposes a stricter parallel trends assumption. It creates a counterfactual for each treated firm based on a weighted average of all the preceding periods before the treatment. This approach requires that the parallel trends assumption holds for the entire period, which could yield more precise estimates. However, it is more susceptible to biased results in cases where the assumption does not hold.

4.2 Empirical results

In our main estimations we exclude any control variables from the vector $X_{i,t}$. These will be accounted for in later robustness checks. We will perform the ensuing analysis sequentially for GVA, LP, and TFP.

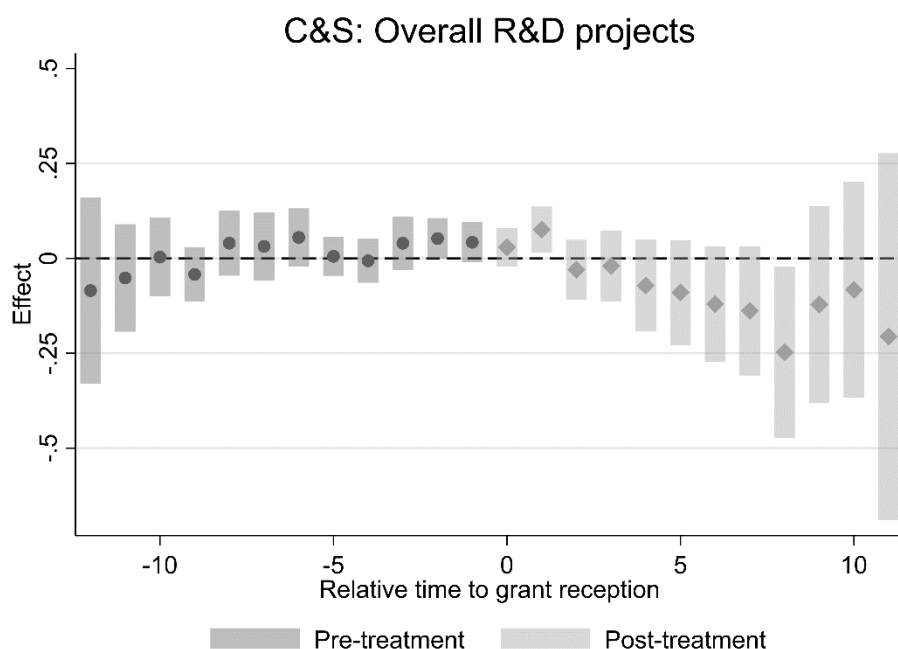
Gross-Added Value

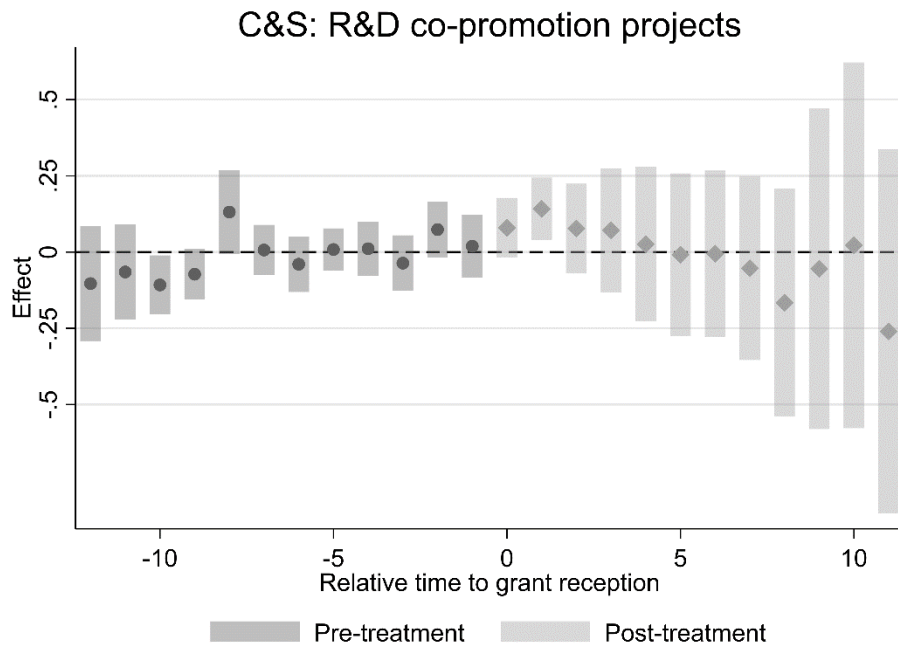
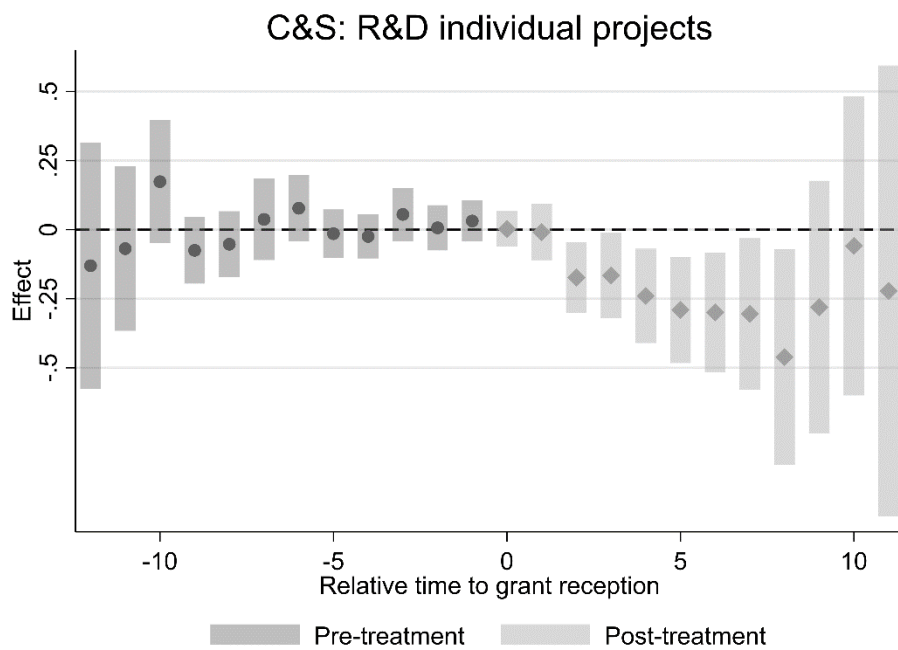
In this section, we present our estimation results concerning the impact of public grants on GVA. We detail the effects of each treatment examined for the three groups described above: overall R&D projects, R&D individual projects, and R&D co-promotion projects. We disclose the outcomes for event studies based on regression models that do not include additional controls. Figure 2 exhibits the estimates derived from the C&S estimator, while Figure 3 displays the results obtained using the dC&DH method. Figure 4 shows the estimates for the group ‘smaller’ firms that have benefited from R&D co-promotion grants.

In considering R&D projects and firms of all sizes, as seen in the top panel of Figure 2, we note a short-term positive impact of public grants on GVA, dissipating after one year post-treatment. The effect after one year is approximately 7.6%, statistically significant at the 5% significance level. Turning to R&D co-promotion projects, illustrated in Figure 2's middle panel, this conclusion is reinforced, with an observed effect of 14.2% one year post-treatment, statistically significant at 1%. However, when

assessing the effects of R&D individual projects, presented in the bottom panel, we find that R&D grants fail to generate a positive impact on GVA, instead contributing to negative effects beyond the second period. In all instances, when considering a three-period pre-treatment time interval and a 5% significance level, we fail to reject the null hypothesis that there are no treatment effects on the treated group's pre-treatment time. Overall, the estimates by dC&DH presented in Figure 3 corroborate these findings (we do not reject the null hypothesis that all placebos are equal to zero). These results suggest that public grants appear to have an immediate positive impact on GVA, particularly for co-promotion projects.

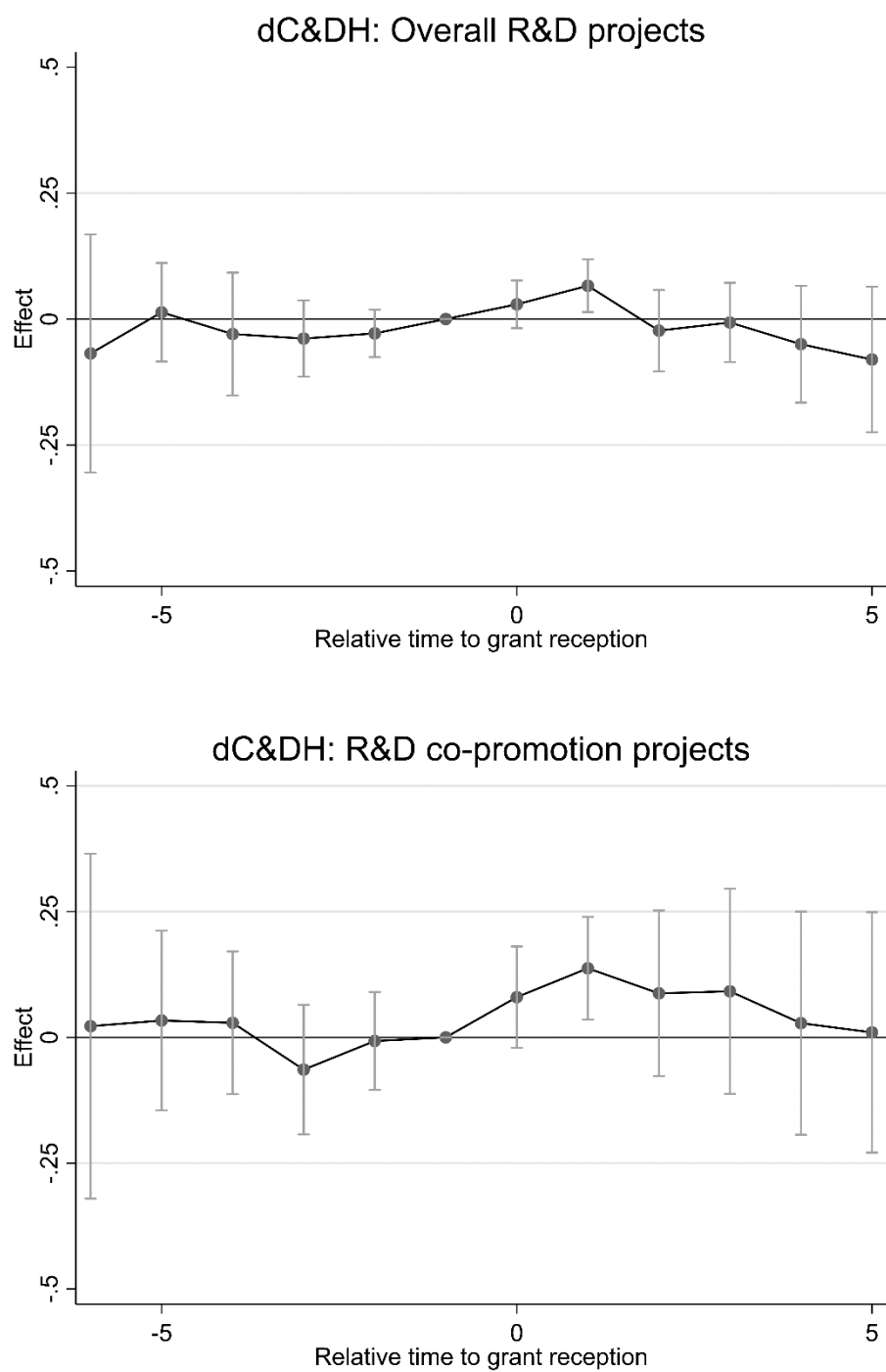
Figure 2: C&S estimates for Gross Value Added by R&D treatment typologies, all sizes

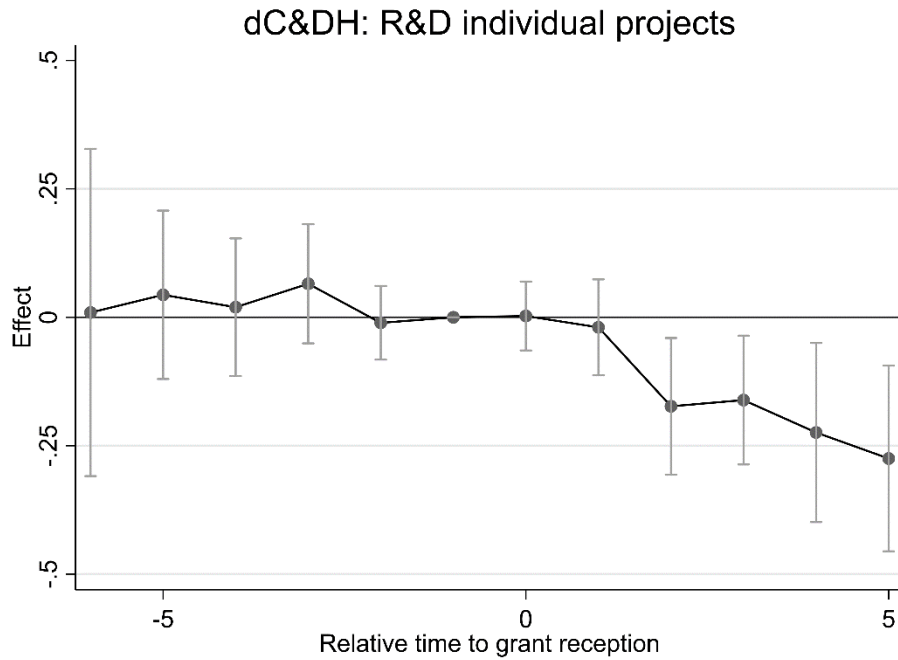




Notes. The estimates are performed by Callaway and Sant'Anna (2021). The models do not include additional controls. We report the 95% confidence interval.

Figure 3: dC&DH estimates for Gross Value Added by R&D treatment typologies, all sizes





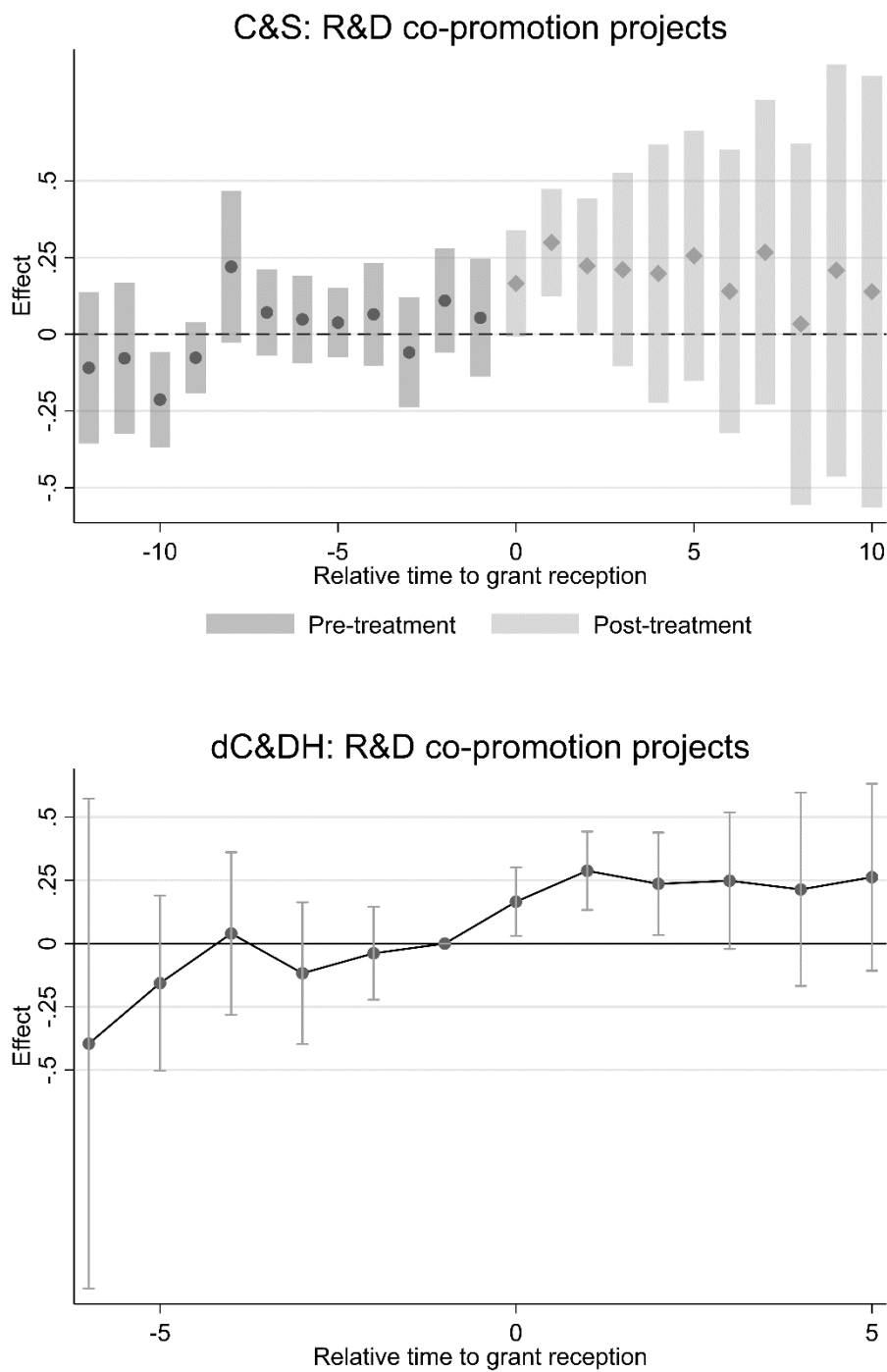
Notes. The estimates are performed by de Chaisemartin and D'Haultfoeuille (2020). The models do not include additional controls. We report the 95% confidence interval.

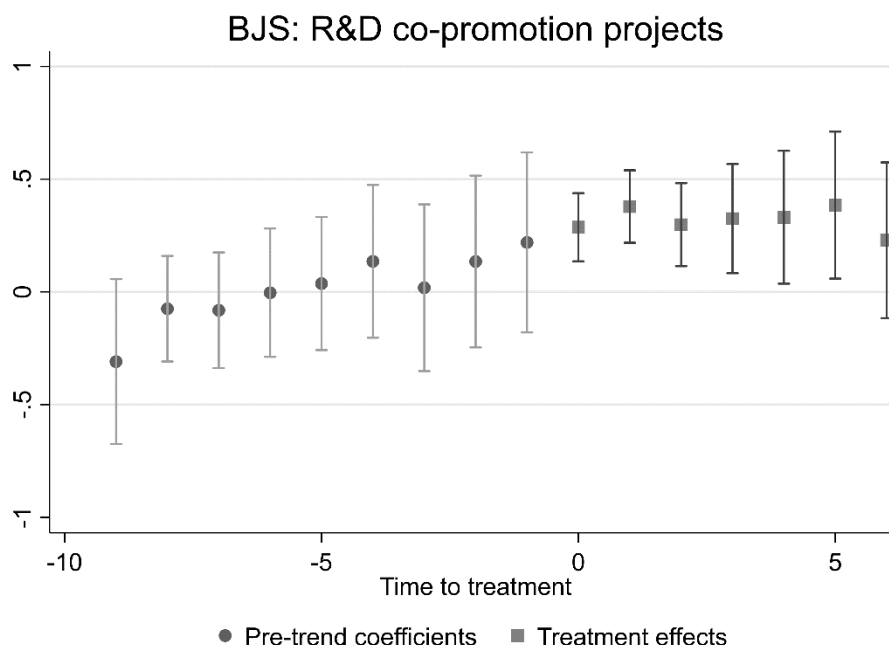
We now turn our attention to the role of firm size. Specifically focusing on co-promotion projects, our analysis, as depicted in Figure 4, suggests that public grants appear to yield a lasting positive impact for at least two periods for micro- and small-sized firms. The estimates provided by C&S, visible in the top panel of Figure 4, demonstrate a nearly 30% return after one year — approximately four times the estimate for the entire sample. Two periods later, this return diminishes to around 22%, still statistically significant at the five percent significance level. Assuming a 10% significance level, we discern an immediate effect of 16.6%. This result might be attributable to firms initiating their investments in the period between project approval and contract signing.

Corroborating these findings, the estimates by dC&DH, displayed in the middle panel, support the above conclusions. In both instances, the trend tests previously discussed do not dismiss the validity of these results, although this conclusion for C&S is only valid assuming one pre-treatment period. The estimates using the BJS method, as shown in the bottom panel of Figure 4, align with the results from C&S and dC&DH. Still, they indicate considerably higher effects that endure over a more extended period, revealing a permanent positive impact of public grants. Nonetheless, it is crucial to put these outcomes into perspective since they are predicated on stronger assumptions about pre-trends compared to those of C&S and dC&DH. However, these

robust findings do not apply to medium and large-sized firms – as demonstrated in Figure A.1 in the Appendix.

Figure 4: C&S, dC&DH and BJS estimates for Gross Value Added, R&D co-promotion projects, micro and small-sized firms





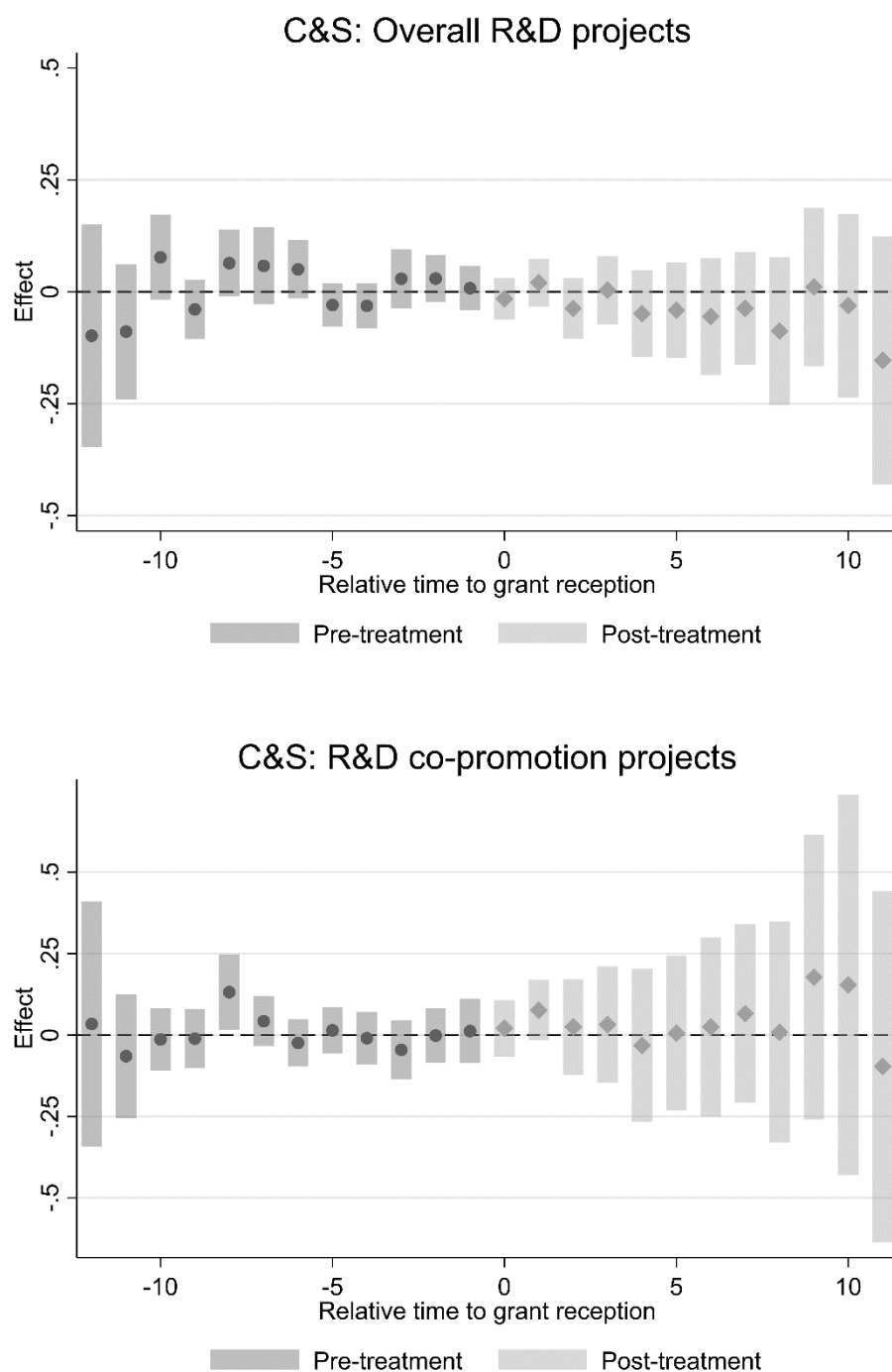
Notes. The estimates are performed by C&S, dC&DH and BJS. The models do not include additional controls. We report the 95% confidence interval.

Labour Productivity

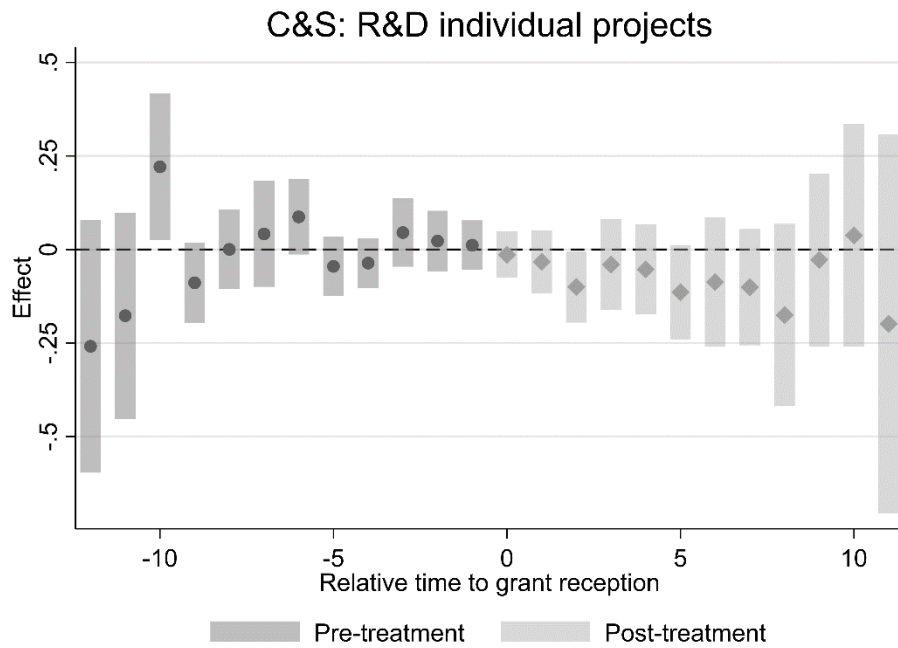
This section displays the results of our estimations on LP, following a similar methodology to that used for GVA – Figures 5 and 6 correspond to Figures 2 and 3, respectively. Contrary to our findings for GVA, considering all sizes firms, we do not observe a positive impact of R&D grants on LP, regardless of the type of R&D grant or estimator (C&S or dC&DH) used. However, when focusing on micro- and small-sized firms and on R&D co-promotion projects, we notice, as with GVA, a transitory positive effect of grants on LP that subsides after one year post-treatment (Figure 7). For the C&S estimation, seen in the top panel, the impact magnitude is approximately 18% (slightly above half of the effect observed for GVA), statistically significant at a 5% level. The returns under the dC&DH and BJS estimations are approximately 17%, aligning with our findings for GVA. Upon testing the validity of assumptions concerning pre-trends, we find these estimates are only valid when considering a limited number of pre-treatment periods. Figure A.2 in the Appendix presents the estimated results for medium- and large-sized firms, suggesting no significant robust impact of R&D co-promotion grants on LP. Our results indicate that, as observed with GVA, a positive

and significant effect is only discernible for micro- and small-sized firms benefiting from R&D co-promotion grants.²

Figure 5: C&S estimates for Labour Productivity by R&D treatment typologies

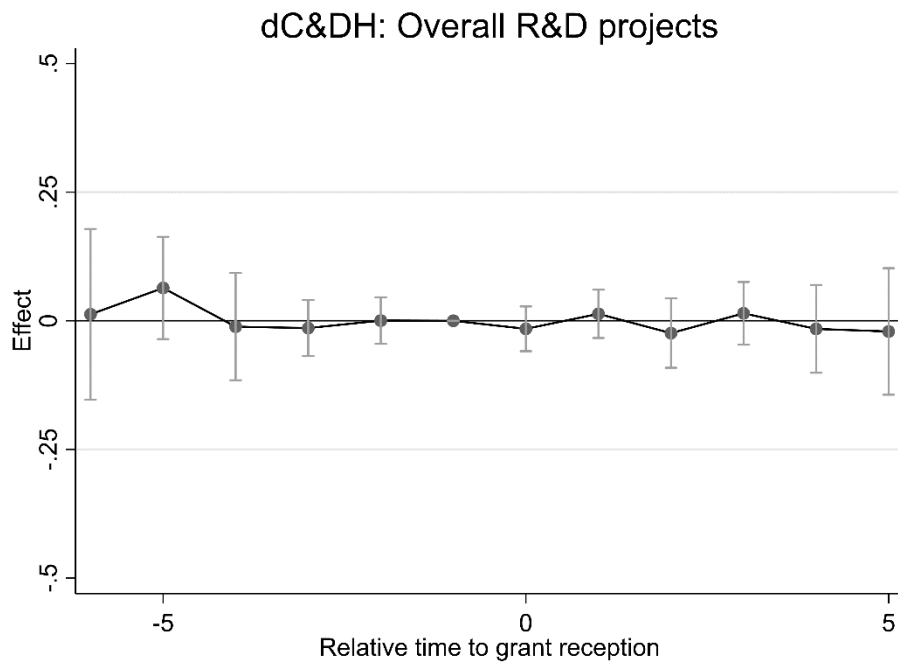


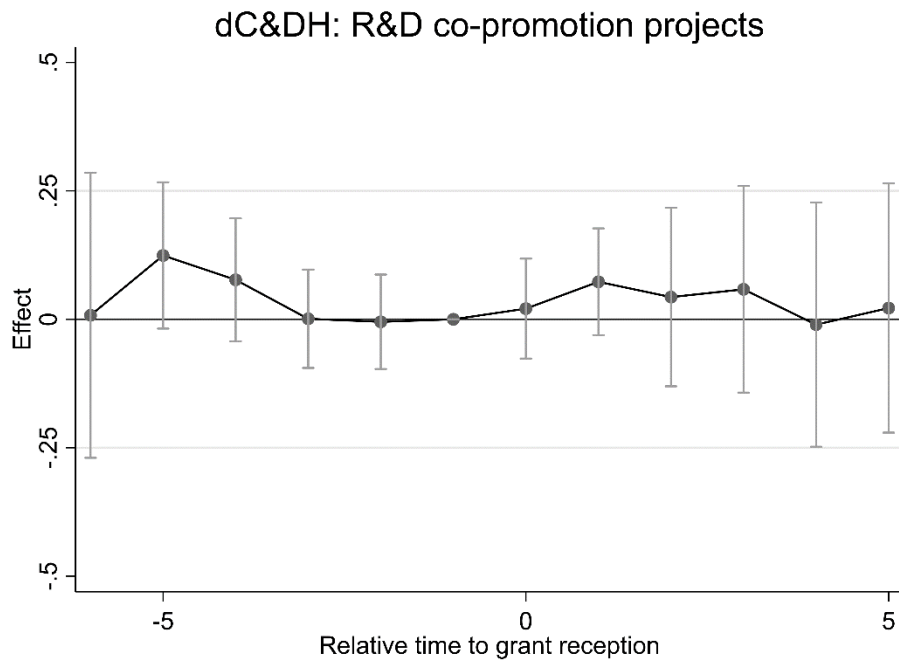
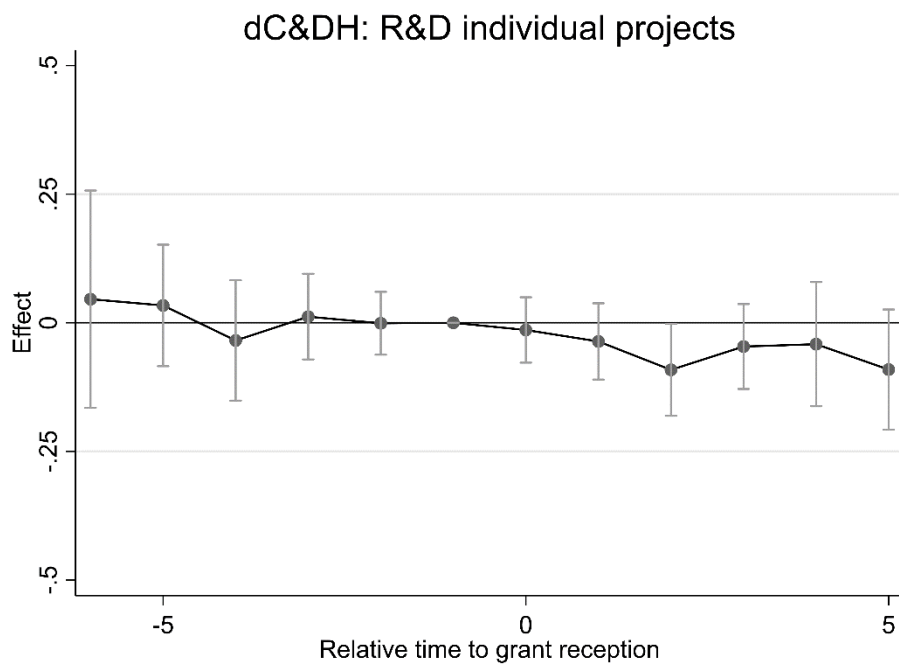
² Results for individual and R&D projects, stratified by firm size categories, are available upon request.



Notes. The estimates are performed by Callaway and Sant'Anna (2021). The models do not include additional controls. We report the 95% confidence interval.

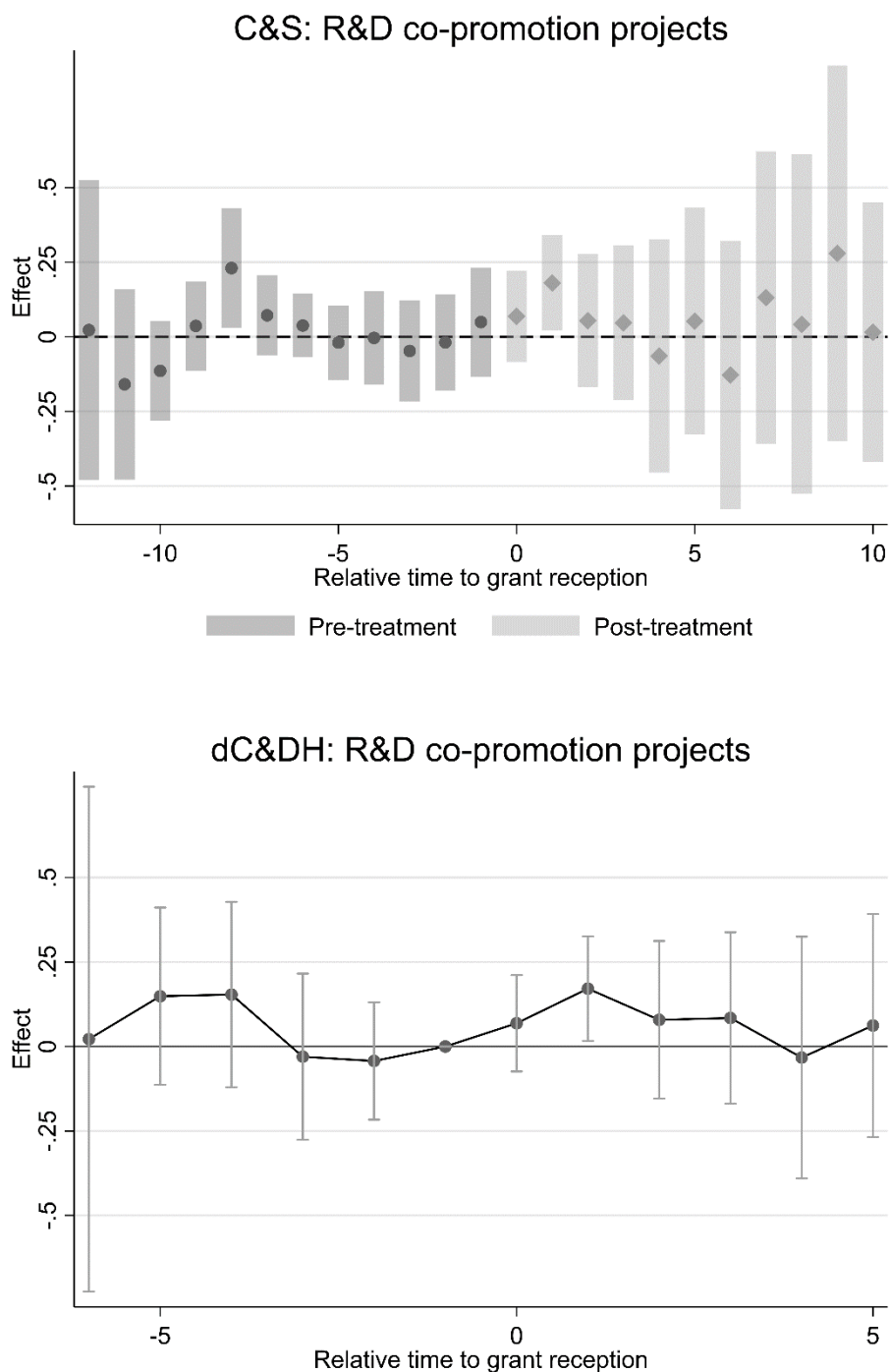
Figure 6: dC&CH estimator estimates for Labour Productivity by R&D treatment typologies

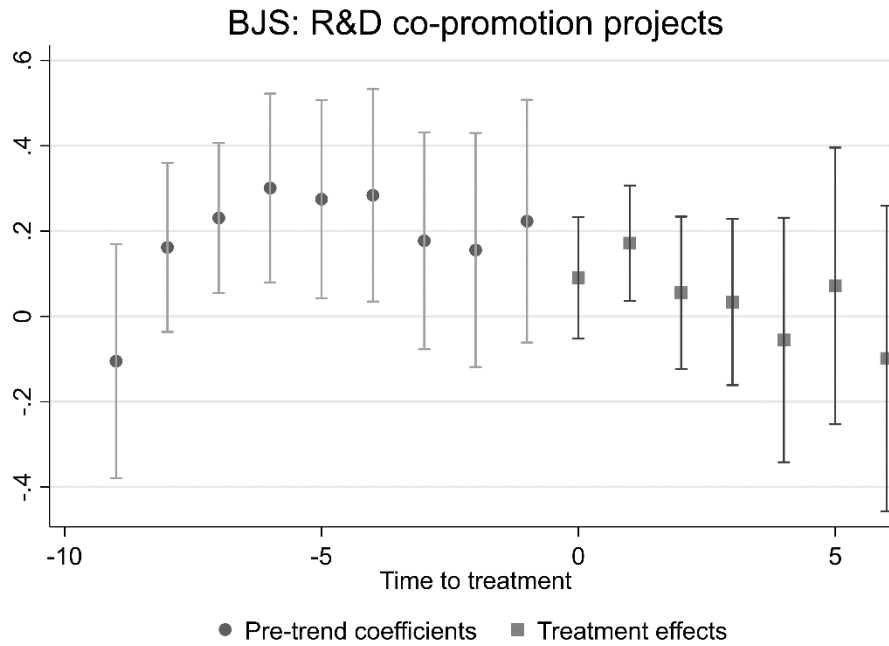




Notes. The estimates are performed by de Chaisemartin and D'Haultfoeuille (2020) (dC&DH). The models do not include additional controls. We report the 95% confidence interval.

Figure 7: C&S, dC&DH and BJS estimates for Labour Productivity, R&D co-promotion projects, micro- and small-sized firms



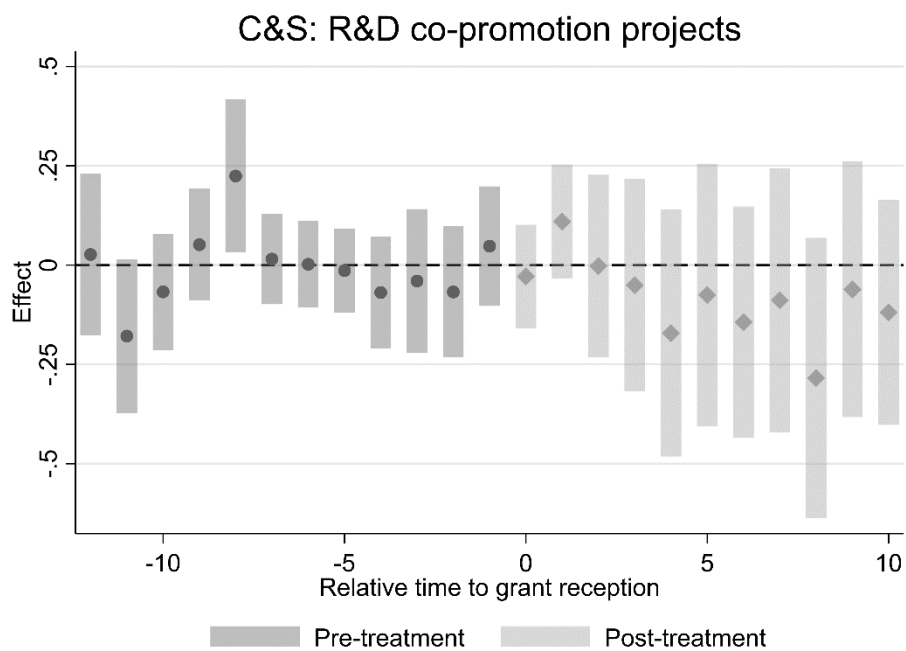
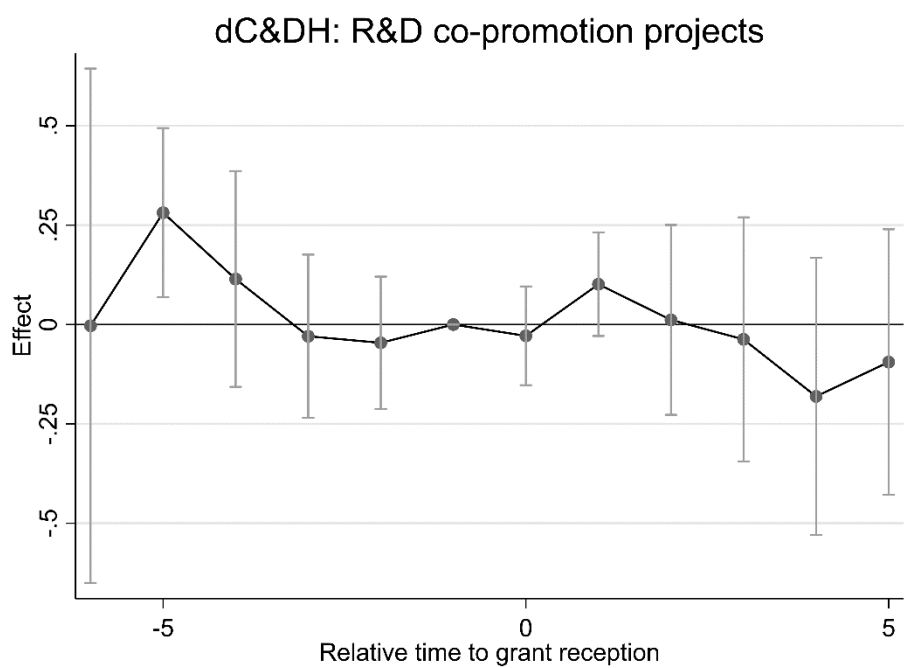


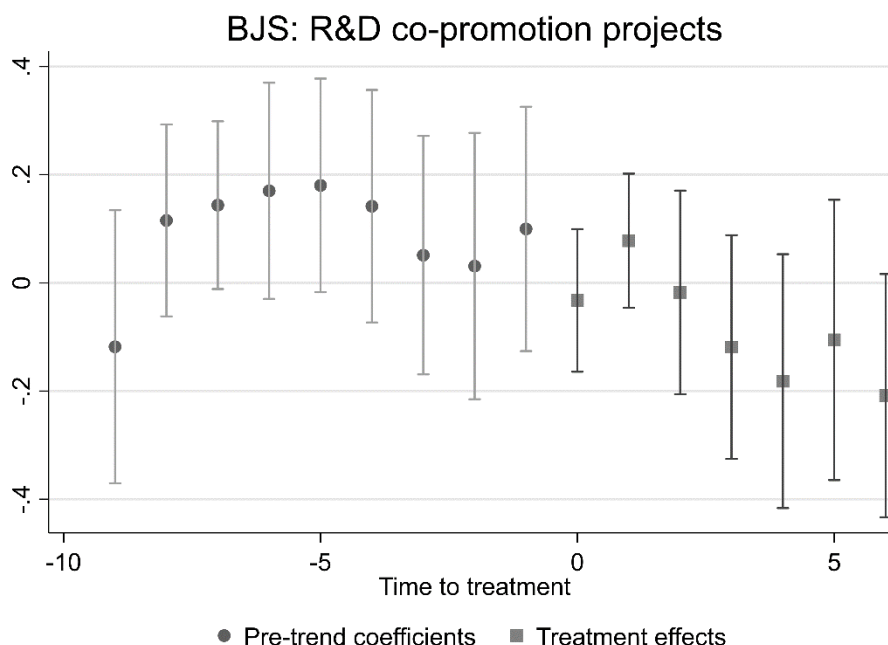
Notes. The estimates are performed by C&S, dC&DH, and BJS. The models do not include additional controls. We report the 95% confidence interval.

Total Factor Productivity

We do not find a statistically significant effect of R&D grants on TFP, except for the group of micro and small-sized firms engaged in R&D co-promotion projects – see Figure 8. However, our findings at a 5% significance level do not reveal a significant positive impact of R&D grants on TFP, a slight positive return of approximately 12.6% is observed at a 10% significance level under the C&S estimator. Nonetheless, given the specificity of this case, we consider that this result lacks the necessary robustness.

Figure 8: C&S, dC&DH and BJS estimates for Total Factor Productivity, R&D co-promotion projects, micro- and small-sized firms





Robustness checks

In order to check the robustness of our findings, we start by performing a sensitivity analysis computing robust inference according to Rambachan & Roth (2023) – see Figures A.3 and A.4 in the Appendix. Given the results presented above, we focus on just one year after treatment on the sample of micro- and small-sized firms for R&D co-promotion projects, both for GVA and LP. While for dC&DH estimator the robustness inference implies that there are no effects on GVA and LP, for the C&S estimator we find a statistically significant positive effect on GVA at the 5% level only when $\bar{M}$ is 0.5, which is highly restrictive – see Rambachan & Roth (2023) for a detailed discussion. The take-away of these results is that the effects of R&D grants on firms' productivity seem to be elusive.

Secondly, we re-estimated the models mentioned above, integrating additional control variables. As described in Section 4.1, these controls include firms' tangible and intangible assets, profitability, liquidity, and financial autonomy, as well as a series of dummies to account for the firm's industry. These estimates corroborate our previous results.³

³ Results are available upon request.

5. Concluding Remarks

There is a broad consensus regarding government agencies' investment in supporting R&D projects by private firms. Assessments of the outcomes of such public initiatives are contingent on analytical efforts that depend on the best data and methods available. So far, success in capturing the effects of publicly-funded R&D has been partial since information is limited and the full potential of the “causality revolution” in econometrics has not yet been realised. Our work aims at contributing to ameliorate this scarcity of systematic knowledge from an empirical and methodological perspective.

This study focuses on the impacts of R&D co-promotion projects funded by public subsidies on firms' performance, namely on gross value added and productivity, comparing the same effects with the impacts observed from R&D subsidized projects carried out individually. This investigation benefits from using a very rich dataset, comprising project and firm-level information, for the period 2007-2019, of the population of firms that has ever applied for an R&D project, be it individually or in co-promotion. That is to say, we provide comparisons that are rare among assessments of the same kind and draw from data for the population of candidates and firms financed for over ten years.

Our study suggests that R&D subsidies are effective but only for a specific group of firms and grants, namely micro- and small-sized firms and R&D projects in co-promotion. We observed a significant effect on gross value added of over 20% in the first year following the grant allocation. However, this effect only lasted for a maximum of two periods before disappearing. Similarly, for LP, a significant effect is observed one year after receiving the grant, estimated to be around 17-18%. However, no robust and statistically significant effect is found for TFP. The analysis of the dynamic effects shows that there is no lasting impact of the R&D grant on the firms' performance. Although our results indicate there may exist some positive effects of R&D grants, sensitivity analysis based on robust inference reveals that these effects may be elusive, indicating a need for further research.

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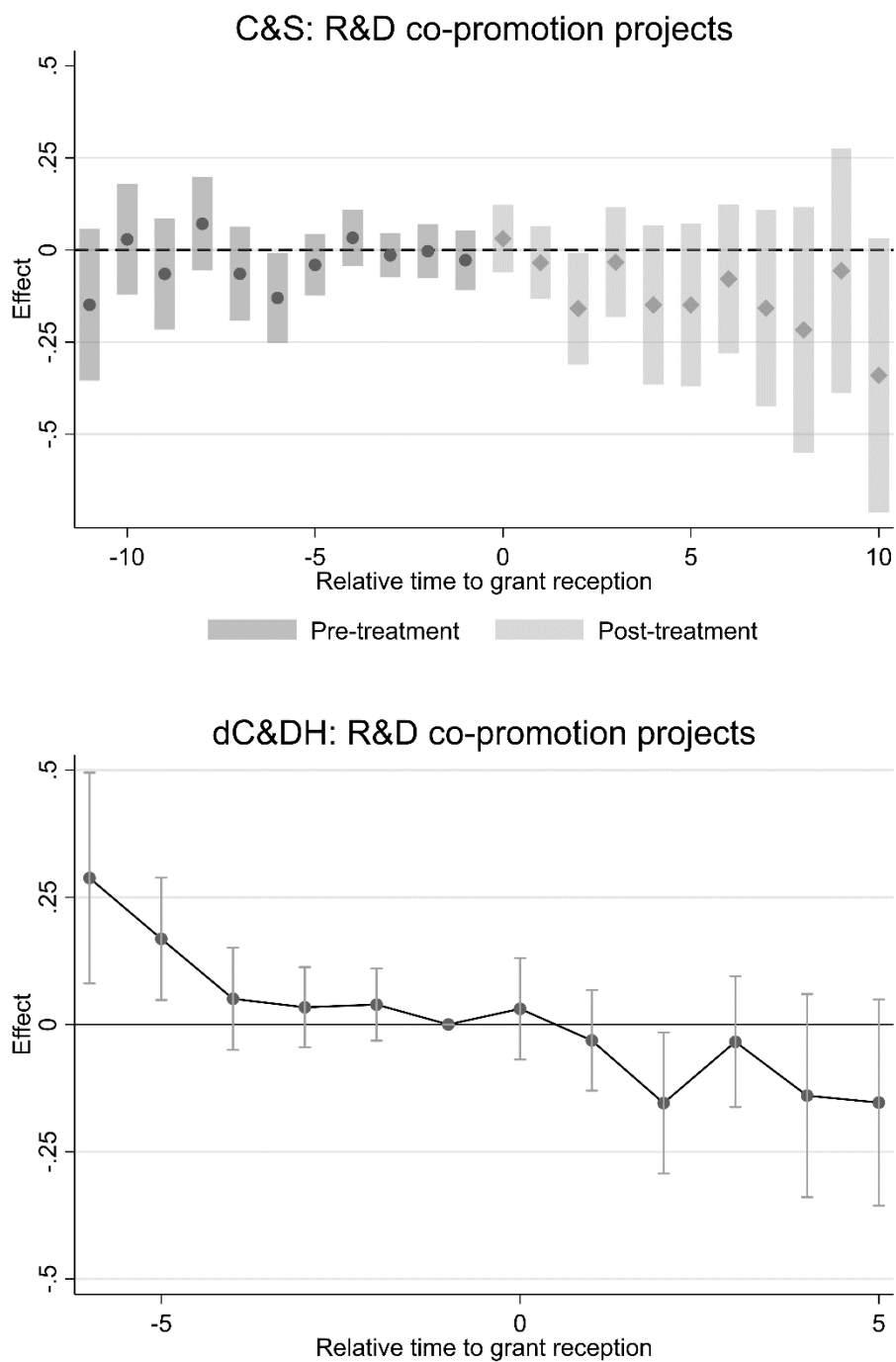
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Appendix

Figure A.1: C&S, dC&DH and BJS estimates for Gross Value Added, R&D co-promotion projects, medium and large-sized firms



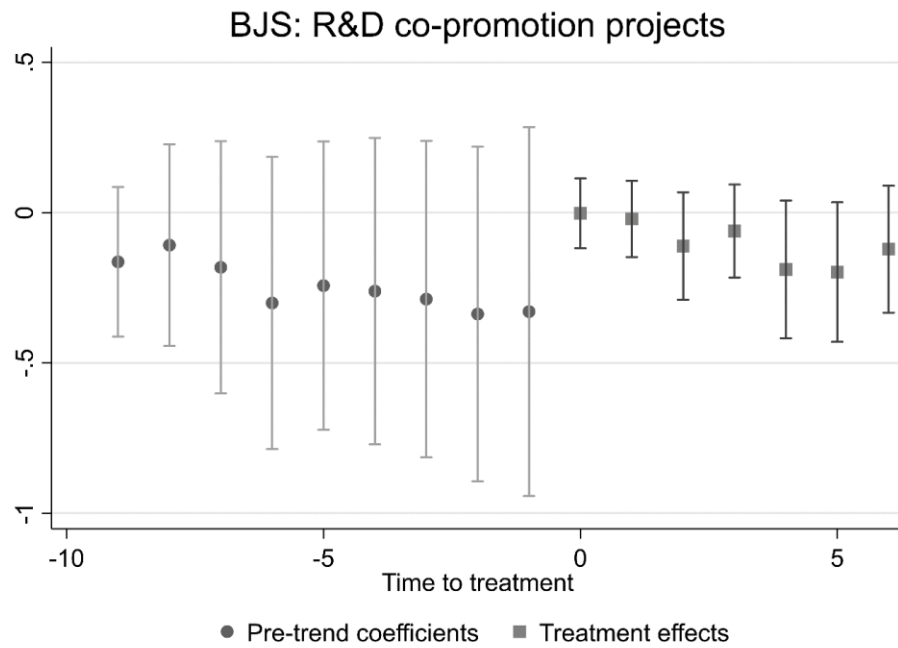
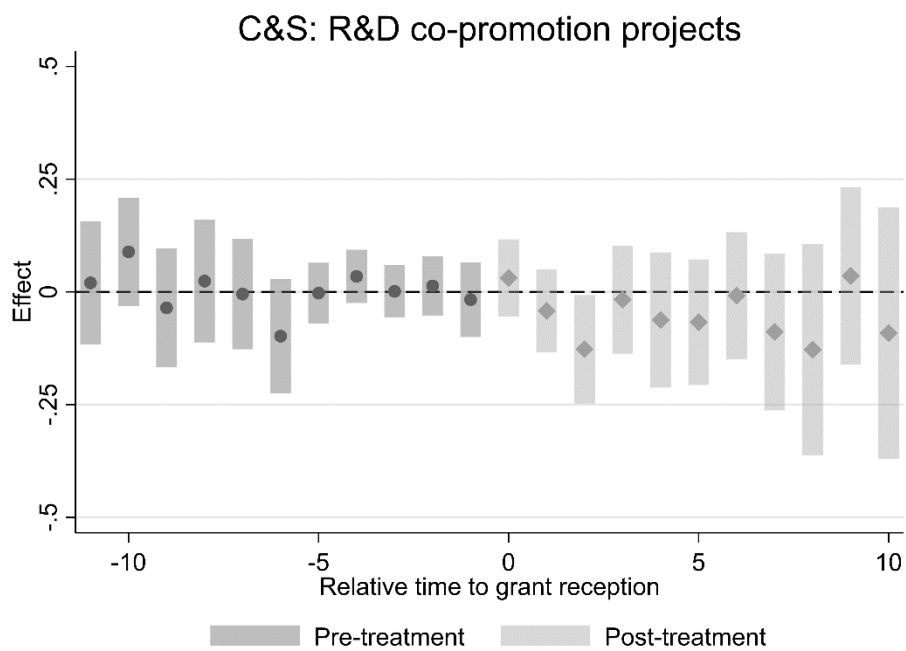


Figure A.2: C&S, dC&DH and BJS estimates for Labour Productivity, R&D co-promotion projects, medium and large-sized firms



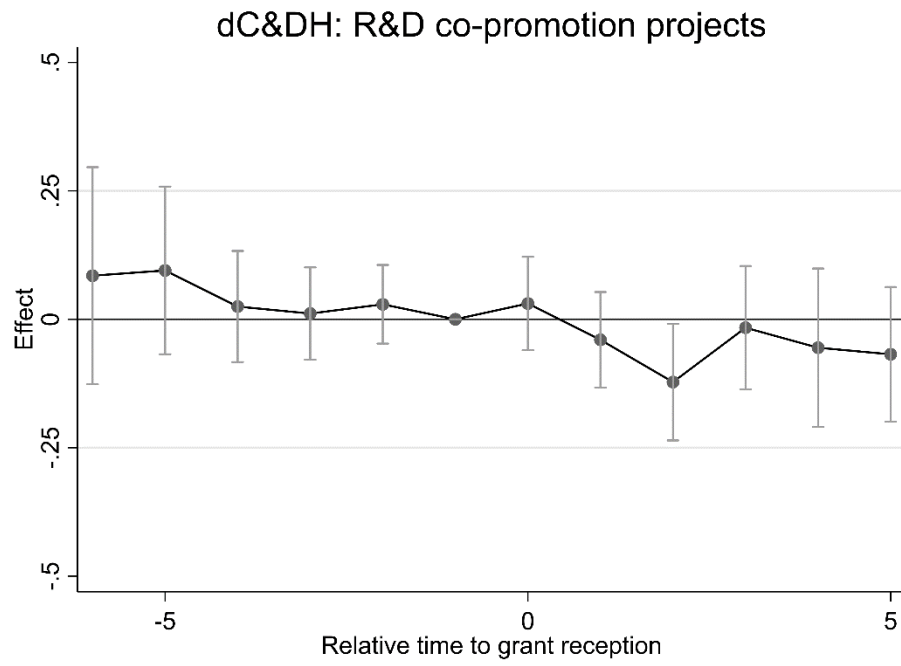
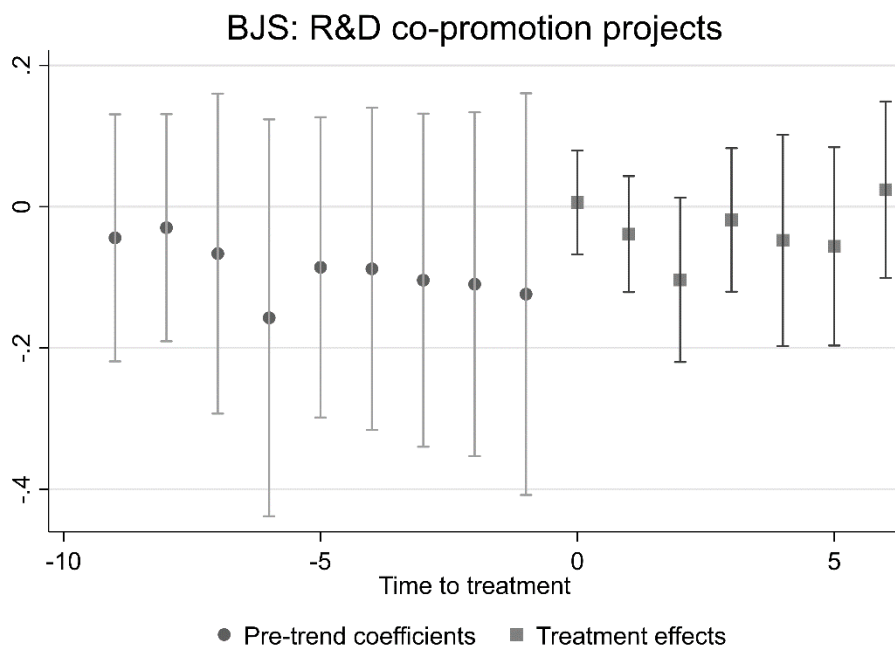


Figure A.3: R&R sensitivity analysis for the estimates by C&S and dC&DH on Micro-Small firms for GVA

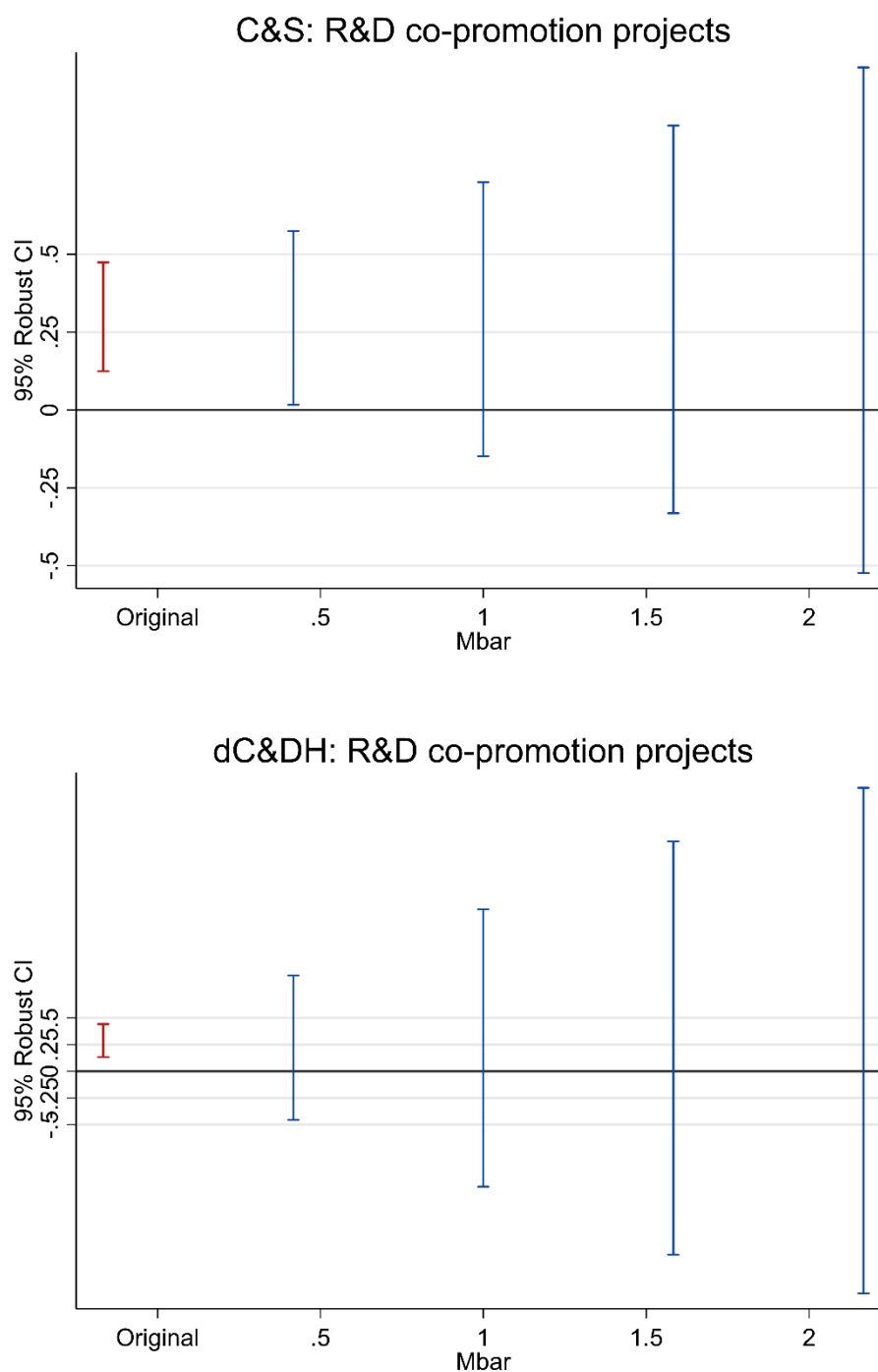


Figure A.4: R&R sensitivity analysis for the estimates by C&S and dC&DH on Micro-Small firms for Labour Productivity

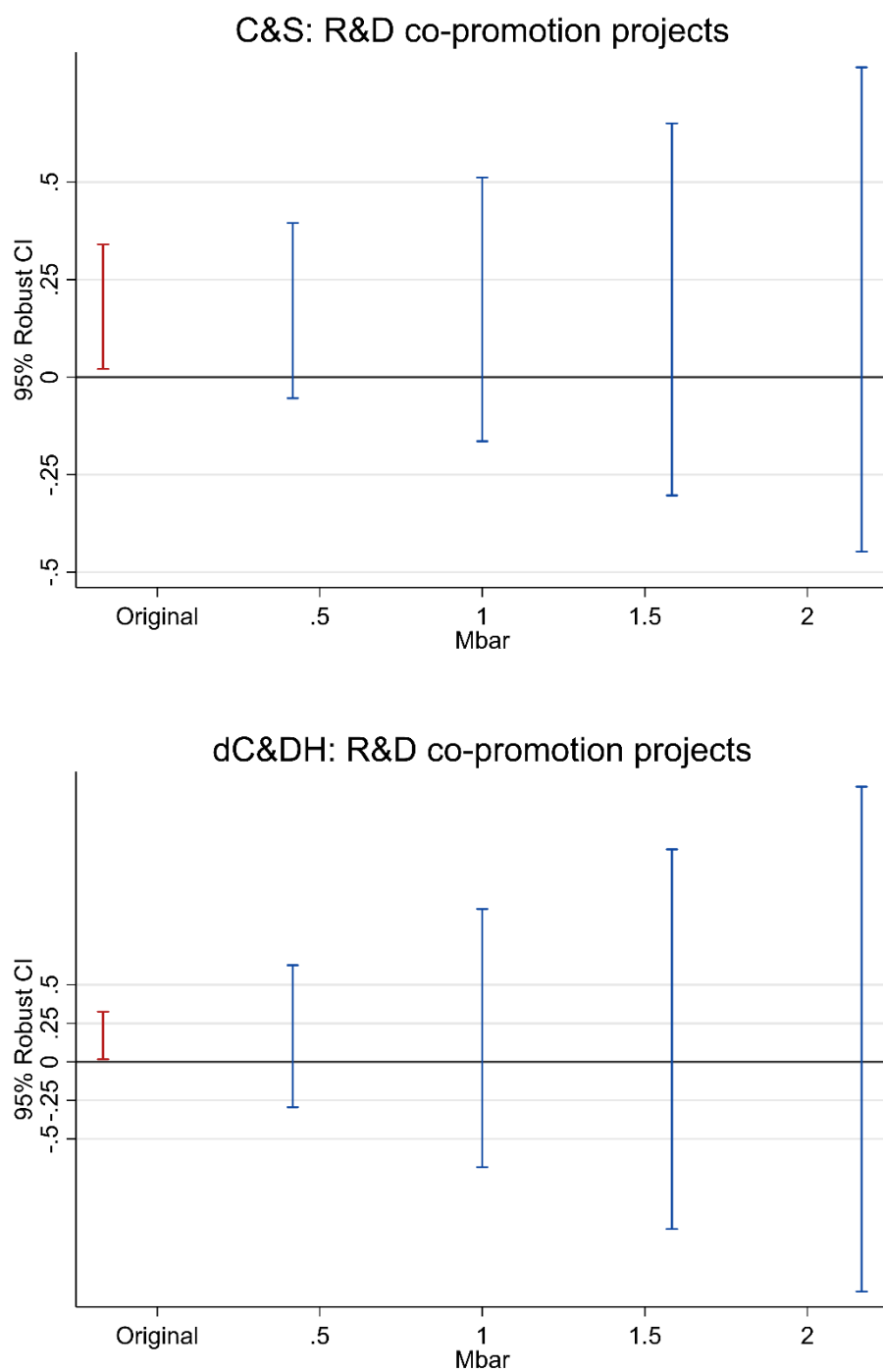


Table A.1: PSM-DiD impact evaluations of R&D subsidies

Ano	Authors (journal)	Type of project	Time window	Spatial unit	Sample	Control Group	Outcome Variable	Effect
2015	Karhunen & Huovari (<i>Small Business Economics</i>)	Individual support	2000-2012	Finland: SMEs that were granted an R&D subsidy over the period from 2002 to 2007	1221 firms	1874 matched firms from a pool of 32.590 non-funded firms	Labour Productivity Employment	- +
2018	Szűcs (<i>Research Policy</i>)	Co-promotion support	2005-2014	Europe: EC's extensive Seventh Framework Program	1975 funded firms	44 000 innovative non-funded firms	Employment Revenue Growth	+ +
2019	Bellucci, Pennacchio & Zazzaro (<i>Small Business Economics</i>)	Individual (I) and Co-promotion (C) support	2003-2012	Italy: SMEs receiving public grants	62 SMEs with co-promotion projects 176 SMEs with individual projects	6067 non-applicant SMEs that meet the eligibility criteria to being awarded funds	R&D Expenditure Employment R&D Intensity Profitability Sales	I C + + + + + + + + 0/+ 0
2019	Dai & Wang (<i>China Economic Review</i>)	Individual support	2006-2016	China: Effect of the high- and new-technology enterprise (HNTE) program	1816 certified firms	Non-certified firms	R&D Intensity Productivity	+ +
2019	Vanino, Roper & Becker (<i>Research Policy</i>)	Co-promotion support	2004-2016	UK: all publicly funded research projects supported by the UK Research Councils	10.000 firms	All population of non-treated UK firms	Employment Turnover	+ +
2022	Mulligan, Lenihan, Doran & Roper (<i>Research Policy</i>)	Co-promotion support	2007-2017	Ireland: Research centre collaborations with firms	75 firms who collaborated with research centres	886 firms which performed in-house R&D and had information in the BERD (Business Expenditure on Research and Development) survey	R&D Intensity	+

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