Innovation subsidies and the business cycle*

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Abstract

This paper investigates the impact of public support to business investment R&D over the different phases of the business cycle. It uses firm-level data for Spain during the period 2005 to 2014, thus covering an expansion, a recession and a recovery. Propensity score matching and differences in differences methods are combined to estimate the response of supported firms in each phase. Findings show that the profile of beneficiaries of public support did not change significantly over the cycle. Estimated effects depend on the stage of the cycle, the duration of support and the type of outcome indicator. The impact on total investment is positive during expansion years and null during the crisis years; when looking at firms' allocation of human resources to R&D, the multiplier effect is higher during the crisis years; finally effects last longer for longer spells. Direct support allowed participating firms to allocate more of their employees' time to R&D activities during the recession. This suggests that under some conditions the multiplier of public support to innovation may be higher during recessions.

Keywords— subsidies, innovation, R&D, policy evaluation, business cycle
JEL Classification— C14, C21, D22, L29, L53, H50, O25, O38

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1 Introduction

The global economic and financial crisis that unleashed in 2008 had a negative impact on R&D and innovation globally. In the OECD countries as a whole the growth rate of GDP fell by 3.5% in 2009, while business R&D investment dropped by 4.2% (OECD 2014). Investment in R&D has exhibited, at this highly aggregate level, a pro-cyclical behavior over the last twenty years, according to data published by the OECD. The growth rate of GDP and of gross domestic R&D investment have been positively correlated over the period 1996-2016, with a correlation coefficient of about +0.70. This mirrors mostly the behavior of business R&D, since the correlation between GDP and of public R&D expenditure growth rates has been negative across that same period, with an absolute value of 0.34, which is suggestive of a mildly counter-cyclical behavior on average.[1] The potential threat to long-term growth derived from reduced business R&D effort in downturns may thus have been partially mitigated by public investment.

A closer look at the data, however, shows that public investment in R&D took different paths in different countries around 2008/9. While increasing in Germany and Austria (OECD-STI 2014), they fell in France, Spain and Italy. Since then a declining trend is observed both sides of the Atlantic, resulting in a decreasing percentage of business R&D financed with public funds. This evolution is worrisome, as it may have implications both for long term growth and for income level convergence across countries, especially if cross-country differences in public R&D investment persist (Duval, Hong, and Timmer 2017; Ridder 2017; Veugelers 2016; Veugelers et al. 2017). In a recent study on the evolution of public R&D spending in a panel of twenty six OECD countries over the period 1995-2015, Pellens, Peters, Hud, Rammer, and Licht (2018) show that on average public R&D behaved pro-cyclically, but in some non-EU countries and European innovation leaders it followed a counter-cyclical pattern. Their analysis suggests that differences in this evolution responded to a good extent to each country public deficit and government debt level. Countries experiencing adverse conditions in

[1] These correlations have been computed by the authors using statistical data from the Main Science and Technology Indicators published by the OECD, mainly GERD, BERD and GOVERD series, accessed by the authors on August 16, 2018.

this respect can hardly be expected to significantly increase public R&D investment for some time. This prospect highlights the importance of evaluating the ability of public support to induce more private effort in R&D and innovation over the phases of the business cycle, and in particular during recessions. It involves testing the stability of the multiplier –or, what in the evaluation literature is known as the degree of additionality- of this form of public support. A higher multiplier during recessions would mean that reducing public support during this phase would be more harmful for long-run growth, and, conversely, small increases of public support would induce more private effort than in expansions and hence contribute to a steady flow of knowledge generation during the cycle.

In this paper we contribute to empirical research on the impact of public support to business R&D by addressing two questions: 1) Does firms' access to support vary over the cycle? 2) Does the impact of support remain constant over the cycle? The first question intends to determine whether firms that benefit from public support in recessions differ, in some observable characteristics, from firms that benefit from it during expansions. Both firms' and public agency behavior could affect participation and cause different impacts. The second question intends to determine whether the impact of public support is smaller in recessions than in expansions or otherwise. To that end we use firm-level panel data from Spain covering the period 2006 to 2014. Spain, one of the large members of the European Union, is classified as a moderate innovator and has experienced intense government budget cuts after 2008. We first compare firms' participation in public R&D across the three phases of the business cycle. We then identify several participation spells and estimate the response of participants over time compared to non-participants for two outcome variables: investment in innovation per employee and time allocation of employees to innovation activities.[2]

Our main findings are summarized as follows. First, we do not observe significant changes in the allocation of public support to firms over the cycle; this precludes attributing impact differences to changes in the profile of recipients of subsidies. Second,

[2] In this paper investment in innovation and investment in R&D will be synonymous, since in the sample used most firms that invest in innovation also invest in R&D

the effect of public depends on three factors: the stage of the cycle, the duration of support and the type of outcome indicator. For firms participating one year during the recesion, their innovation investment did not increase, in contrast to expansion years. This suggests that treatment effects were pro-cyclical for these firms. However, for firms that participate for two years during the recession we find that treatment effects have been significant and higher during these years. Finally, when looking at a different indicator, in particular firm's allocation of human resources within the firm, we find that the additionality effect is higher during the crisis. In particular, both for SMEs and large firms direct support seems to have allowed firms to allocate more of their employees' time to R&D and innovation activities. This suggests that under some conditions the multiplier of public support may be higher during recessions, thus magnifying the negative impact of budget cuts for this kind of policy.

The layout of the paper is the following. Section 2 provides an overview of existing research on the cyclical behavior of R&D investment and the impact of R&D support during the last economic crisis. Section 3 describes the data. Section 4 discusses the empirical strategy. Section 5 presents and discusses estimation results. Section 6 concludes.

2 R&D, business cycles and public support: Some background

In this section we review the main arguments and evidence about the behavior of R&D investment over the business cycle as well as recent research that focuses specifically on the 2008 financial crisis. We then discuss the implications for R&D policies and their ex-post evaluation, and bring forward some research gaps.

Extensive firm-level empirical research provides strong evidence that business R&D investment is pro-cyclical on average, both at aggregate and firm level. This evidence is consistent with the hypothesis that capital market imperfections and knowledge spillovers, jointly or separately, drive the pro-cyclicality of business R&D investment and the introduction of product innovations, outweighing the counter-cyclical effect that lower opportunity costs of R&D could potentially have during recessions. The former two factors would thus not only originate well-known a static market failure, but may be responsible for a dynamic misallocation of R&D investment over the cycle, with long-run consequences for productivity and growth. These negative effects could possibly be mitigated through a counter-cyclical R&D subsidy policy.

From the pertinent body of work we highlight several contributions. With the focus on spillovers, Barlevy (2007) develops a theoretical model where the presence of knowledge spillovers explains the pro-cyclical behavior of innovation even if the opportunity cost of innovations, relative to production, falls during recessions. The reason is that innovators, knowing that imitation will take place at some point, will prefer to concentrate their R&D and innovation in booms, when appropriable returns are higher. Thus during recessions there would be under-provision of R&D, even in absence of financial constraints. Fabrizio and Tsolmon (2014) explicitly test Barlevy's hypothesis using Compustat data to construct a panel data set of 7,754 public firms from 1975 to 2002. They find that R&D investments and patented innovations are strongly pro-cyclical and that innovation is more pro-cyclical in industries with weaker IP protection. Furthermore higher product obsolescence rate also contributes to pro-cyclicality of R&D.

Investment in intangibles, and R&D investment in particular, is generally affected by financing constraints, as documented in extensive research (Hall, Moncada-Paternò-Castello, Montresor, and Vezzani 2016). Aghion, Angeletos, Banerjee, and Manova (2010); Aghion, Askenazy, Berman, Cette, and Eymard (2012) among others, have studied the relationship between imperfect capital markets and the behavior of investment in R&D over the business cycle. Aghion et al. (2010) distinguish between short-term and long-term investments, where the latter contributes to productivity growth but involves a higher liquidity risk. The model predicts that when capital markets are perfect the composition of investment is determined by its opportunity-cost and the fraction of long-term investment is countercyclical. This prediction is reversed, however, when credit constraints are tight, as firms do not wish to take the risk of a liquidity shock if they engage in long-term investment during a recession. In Aghion et al. (2012) the authors test this prediction using a large French firm-level data set during the period 1993-2004. They find that R&D investment is countercyclical without credit constraints, but it becomes pro-cyclical as firms face tighter credit constraints in two types of sectors: those that depend on external finance, or that are characterized by a low degree of asset tangibility. They also find that in more credit-constrained firms, R&D investment drops during recessions but does not increase proportionally during upturns.

Similar patterns are found in other countries. In the case of Spain, López-García, Montero, and Moral-Benito (2013) test the pro-cyclicality hypothesis of private investment in R&D and other intangible assets relative to total investment with a large sample of Spanish firms during the period 1991 to 2010. They find that investment in intangibles, including R&D, is counter-cyclical except for financially constrained firms. These are typically young and small firms - with less than 50 employees- as well as firms in medium-high technological intensity industries. For these firms both R&D and knowledge acquisition through patents and licenses behave pro-cyclically. Beneito, Rochina-Barrachina, and Sanchis-Llopis (2015) results confirm the pro-cyclical behavior of R&D of Spanish manufacturing firms during the period 1990–2006. Finally, Garicano and Steinwender (2016) find that credit shocks reduce the value of long term investments of manufacturing firms more than demand shocks.

Recent research has focused specifically on the 2008 crisis, featuring a strong financial component relative to previous episodes, and the response of business R&D. Results show quite generally a pro-cyclical reaction. Cincera, Cozza, Tübke, and Voigt (2012) analyze the R&D survey of the top European R&D performers conducted in 2009 and find that R&D intensive firms were more likely to decrease R&D investment, while the association with firm size was U-shaped. Similarly, Paunov (2012) finds that the crisis led many Latin-American firms to stop innovation projects. Giebel and Kraft (2015) study German manufacturing firms and find that their investment was more negatively affected than non-innovators during the crisis. Peters et al. (2014) use data from several waves of the European Community Innovation Surveys (the first covering the years 1998-2000 and the last covering the period 2008-2010) for about 20 member states to describe the behavior of several R&D and innovation indicators over the business cycle.[3] Their results show that R&D investment follows mostly a pro-cyclical pattern, but that when it comes to the introduction of innovations in the market there are some different patterns by type of innovation. During recessions the introduction of products that are new to the firm but not to the market increases, while innovations new to the market bunch in booms; process innovations do not appear to be sensitive to the cycle. Arvanitis and Woerter (2013) find some heterogeneity in the response of Swiss manufacturing firms to the crisis with firm size, R&D intensity and (lack of) price competition contributing to explain these different responses. Finally, Anzoategui, Comin, Gertler, and Martinez (2016) investigate the adoption of new technologies over the cycle, finding that is also highly pro-cyclical, and that the speed at which new technologies are incorporated in production –technological diffusion- has declined after the financial crisis a result of the recession.

All this evidence raises a new question: would countercyclical public support to R&D be able to mitigate the dynamic failure predicted by the models described above? The answer hinges on the sign and size of the multiplier or additionality effect during recessions. To the best of our knowledge, this question has not been thoroughly investigated. Most existing firm-level studies test whether direct public support –through grants and/or loans- crowds out private investment, or whether on the contrary it leverages private effort, and estimate the magnitude of this impact, but they pre-date the 2008 crisis. Two firm-level studies focus on the financial crisis years: Hud and Hussinger (2015) and Aristei, Sterlacchini, and Venturini (2017). Hud and Hussinger (2015) use German SMEs firm-level data for 2006 to 2010. Using propensity score matching they estimate the treatment effect for each firm and year, and then regress estimates on a set of time dummies. They find that the average treatment effect was significantly lower in 2009, when GDP fell in Germany, than in 2006. The estimated magnitudes suggest that public funds might have been partially used for investments other than R&D in 2009. Their research is limited, however, by the fact that their panel of firms is highly unbalanced, affecting their methodological approach. Aristei et al. (2017) estimate and

[3] Their data includes about 414,474 firm-level observations from both manufacturing and service sectors.

compare the effect of public support in five European Union countries during the crisis period. Using firm-level data from each country, and restricting the treatment to direct support only, excluding tax incentives, they do not find evidence of additionality in any of the five countries, including Germany.[4] The main limitation is that the data used in their study are basically cross-sectional and treatment effects for each year for a given country cannot be identified. Nevertheless, and although weaker than Hud and Hussinger's, taken together these results suggest that the multiplier of R&D support has been pro-cyclical.

At the macroeconomic level whether the fiscal multiplier is pro-cyclical is a controversial issue. Auerbach and Gorodnichenko (2012) find that the average government spending multiplier is higher during recessions than during expansions; private investment in particular responds counter-cyclically to government spending. They also show that some country characteristics are correlated with the size of government spending multipliers: increases in the government debt ratio reduce the multiplier in recessions, while the degree of labor rigidity increase it. Research by Canzoneri, Collard, Dellas, and Diba (2016) corroborates that the magnitude of government spending multiplier is inversely correlated with the cycle. In contrast, Owyang, Ramey, and Zubairy (2013) find no evidence that in the United States multipliers are higher during periods of high unemployment; in Canada, however, multipliers are higher during periods of slack. Recently, Ramey and Zubairy (2018) obtain nuanced results: multipliers in the US would be uncorrelated with the business cycle except when interest rates are near zero. In view of these results we would expect the multiplier of direct support to R&D likely to vary over the cycle and across countries, reflecting institutional features, specific features of the macroeconomic environment, industry composition or firm size distribution.

A final issue to consider is that the studies reported show estimates of the short-run impact of R&D subsidies. Although very few studies explore the dynamic effects of direct subsidies, there is some evidence that effects may not be immediate; they can

[4] The data consist of nation-wide representative, cross-sectional samples of manufacturing firms from the EFIGE (European Firms in the Global Economy) survey conducted in 2010, with questions referring to the period 2007-2009. The countries included in their study are France, Germany, Italy, Spain and the UK. They all provide direct support, and all but Germany also provide tax incentives. For information about this data set, see http://bruegel.org/publications/datasets/efige/.

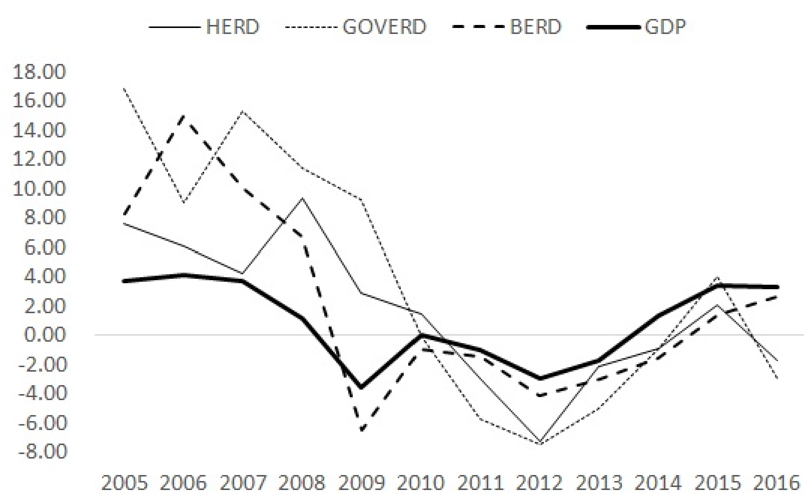
also be temporary or long-lasting. Colombo, Croce, and Guerini (2013), for instance, find that in Italy public support has a temporary effect on private R&D investment. In contrast, Arqué and Mohnen's (2013), find that in Spain one-shot subsidies cause a substantial increase in both the share of R&D performing firms and on average R&D expenditures over time. Einiö (2014) finds that R&D subsidies in Finland do not have an immediate impact on productivity, but they do in the long-term. Karhunen and Huovari (2015), who look at the effects of R&D subsidies granted in the period 2002 to 2007 on labor productivity, employment and human capital of Finnish SMEs up to five years after a subsidy is granted, find that effects are often significant one and two years after treatment.

Our research addresses both issues, the comparison of effects of public support during an expansion and during a recession, and the dynamic effects of this support. In contrast to Hud and Hussinger (2015) and Karhunen and Huovari (2015) we use a large balanced panel of firms, which allows us to use better empirical methods to deal with selection on unobservables and with dynamic issues. This is important because effects of support might not be immediate, but take some time, as discussed above. Furthermore, effects of public support might differ according to the duration or frequency of support. In addition, we compare the effects of support on two outcome variables: investment in innovation (which includes R&D investment) and time allocation to R&D activities.

3 Data

The evolution of GDP over the period 2006 to 2015 in Spain has been similar to the average of the nineteen-euro zone countries, except that the recession period has lasted longer, including years 2011 to 2013. Figure 1 shows that the growth rate of GDP began to fall in Spain in 2008 and continued to contract throughout 2009. Business R&D spending (BERD) followed a similar although more severe path, experiencing a sharp decline during 2008 and 2009. Both variables show an uncertain fluctuation over the period of 2009-2012, with the recovery starting after 2013. The government implemented at the onset of the crisis some policy initiatives to stimulate the economy and employment through innovation and R&D. In 2009 "Plan E" included EUR 490 million directly related to R&D and innovation, more than 16% of total budget. Furthermore, in November 2009 a new Law on Science, Technology, and Innovation was enacted, and the State Innovation Strategy (2010) set a budget of EUR 3.2 billion in 2010 (an increase of 48% from 2009) (OECD-STI 2014). These efforts were not sustained, however, and government spending in R&D (GOVERD) experienced a negative growth rate since 2010, remaining negative for the four following years. Finally, the evolution of R&D spending in Higher Education (HERD) has been similar to that of government spending. The share of business R&D investment financed by the government experienced a remarkable fall over this period. It reached its peak in 2008 at 17.9%, and declined steadily to 9.4% in 2015 (OECD: 2017).

Figure 1: Real growth rates of GDP and R&D spending by performer in Spain 2005-2016



Data sources are as follows. OECD Main Science and Technology Indicators for BERD, GOVERD and HERD growth rates. The OECD reports a time series break in 2008: beginning in 2008, the R&D questionnaire includes a specific category for on-site consultants undertaking R&D projects in the enterprise; as well as a specific category within the breakdown of current costs. The source for the GDP growth rate is Eurostat.

Since the mid-80's the government provides support to business R&D basically through two types of programs: direct support –through subsidies and loans– and tax incentives. Regional governments and the European Union also provide direct support, but national funding is by and large the most important source. Direct support is provided through a combination of reimbursable loans and non-reimbursable subsidies. Most is channeled to firms through a public agency, the Centro para el Desarrollo Tecnológico Industrial (CDTI). The agency can finance up to 75% of the cost of a project; up to 30% of the cost can be supported with a non-refundable subsidy. The policy has been overall quite stable, the main substantive change observed during the period we study being that since 2008 the cost of physical assets (instruments and equipment) is no longer eligible for funding. Up to the crisis years the volume of grants and loans was higher than support through R&D tax incentives (Busom, Corchuelo, and Martínez-Ros 2017), but this changed during the crisis and beyond: the share of R&D tax incentives as a percentage of total support was about 25% in 2006, but by 2015 it reached 51 %.[5]

We use annual firm level data from the Spanish Technological Innovation Panel (PITEC), produced by the National Statistical Institute (INE) and is based on the European Community Innovation Survey (CIS), during the period extending from 2005 to 2014. PITEC provides a broad range of information on innovation activities, including innovation and R&D expenditures, public funds obtained for R&D and perceived barriers to innovation, along with sales volume, human capital and firm's age. In this study we will separately analyze SMEs (firms with less than 200 employees) and large firms, as SME tend to be more sensitive to credit supply (Artola and Genre 2011; Mach and Wolken 2012 Schmitz, 2018).

From the original PITEC unbalanced panel we obtain a balanced panel that includes all firms that stay in the sample for the whole period (10 years); this allows us to eliminate spurious differences that could be generated by changes in the composition of the sample. We further limit the sample to firms that invested in innovation at least once in the period under study, the idea being to exclude firms that do not intend to innovate (i.e., those that report that they do not need to innovate at all). We impose three more filters. First, we drop firms that experienced a merger or takeover

[5] See OECD, R&D Tax Incentive Indicators, http://oe.cd/rdtax, July 2017 and OECD STI Scoreboard 2017.

process, as well as drastic employment incidents. Second, we eliminate observations with extreme values or zero sales. Finally, we also exclude from the analysis the primary and construction sectors. The final balanced panel includes 3,362 SMEs and 1,169 large firms.[6] All monetary variables are expressed in constant values at 2010 prices.[7] The time span encompasses the pre-crisis period (2005-2008), the crisis years (2009-2012) and the recovery (2013-2014).

PITEC does not include information on tax incentives; our empirical analysis, therefore, will focus on the effect of the direct public support (loans and direct subsidies) from the central government and regional authorities.[8] Both jurisdictions jointly represented 81% of direct support in 2015. The advantage of using this variable, reported in PITEC is its annual availability, while separate information by jurisdiction is available only for three year periods. The main disadvantage is that observed firm participation will reflect a combination of allocation criteria by central and regional agencies, which may not always coincide.

Innovation expenditures are defined in the CIS as those that aim at developing and introducing innovations new to the firm or to the market. Investment in R&D is quantitatively the most important of these expenditures. We first focus on the analysis of SMEs, and refer tp large firms in section 5.4. Table 1 shows that the number of firms investing in innovation and R&D in the balanced panel decreased steadily since 2005. The number of firms investing in R&D in our sample dropped by 28% over the period. The share of R&D performers receiving public support fell from 35% in 2005 to 28% in 2014. Furthermore the average rate of public funding among supported firms fell from about 40% in 2005 to 31% in 2014.

[6] The balanced panel sample of SMEs represents 53% of the unbalanced SMEs panel; 62% in the case of large firms.

[7] It should be noted that continuous variables in PITEC - the volume of sales, exports volume or total expenditure on innovation- undergo a process of anonymization, unlike qualitative or percentage variables. López (2011) compared estimates obtained with the original and anonymous data and concluded that the anonymization procedure does not generate significant biases. Nevertheless, both the description and results of the empirical analysis should be interpreted with some caution. Details on definitions of the variables used are reported in Table A1

[8] In Spain the main users and beneficiaries of R&D tax incentives are large firms. López-García et al. (2013) find that in the case of SMEs when firms are financially constrained are more likely to turn to direct support.

Firms can get support for up to three years in a single application, and can apply for and obtain support repeatedly. PITEC does not provide information on the duration of support, on rejected applications or on other features of funded projects; we only observe whether a firm declares having public support a given year. Tables 2 and 3 below show, respectively, the frequency of participation over the ten-year period and one lag transition probabilities of public funding. Tables 2 and 3 below show, respectively, the frequency of participation over the ten-year period and one lag transition probabilities of public funding. Table 2 shows that about 55% of firms in the balanced panel received public support at some point, and about 40% of participant firms did so for one or two years. One third of the firms participated for six years or more, suggesting that a substantial proportion of supported firms received R&D subsidies on a regular basis. It is not possible to know, as explained above, whether this is the outcome of firms in this group performing long-term projects lasting 3 or more years and applying for support every 3 years, or whether it is the outcome of success in repeated annual applications.

Table 1: Evolution of Innovation expenditures and direct support. SMEs.

(1)	Firms with innovation expenditures (2)	Firms doing R&D (3)	% doing RD over firms with innovation (4)	% receiving public funding* (5)	% receiving public funding** (6)	Mean Public funding/R&D *** (7)
2005	3,030	2,741	90.46	31.82	35.17	39.92
2006	2,901	2,537	87.45	31.13	35.59	35.44
2007	2,783	2,453	88.14	31.26	35.47	37.39
2008	2,702	2,387	88.34	32.16	36.41	37.51
2009	2,685	2,309	86.00	33.45	38.89	37.82
2010	2,612	2,232	85.45	31.28	36.60	36.40
2011	2,638	2,229	84.50	28.54	33.78	34.73
2012	2,515	2,169	86.24	25.57	29.65	32.21
2013	2,391	2,088	87.33	25.05	28.69	29.44
2014	2,239	1,968	87.90	24.39	27.74	31.07

Notes: *If innovation expenditures are positive; **if research and development expenditures (R&D) are positive. *** if the subsidy is positive. Sample: 3,362 SMEs that remain in the panel for 10 years and invested in innovation at least once during the period under study.

Table 2: Frequency of participation over the period

	Number of Firms	Percent
1 year	434	23.50%
2 years	300	16.27%
3 years	209	11.33%
4 years	172	9.33%
5 years	128	6.94%
6 years	126	6.83%
7 years	104	5.64%
8 years	109	5.91%
9 years	103	5.59%
10 years	159	8.62%
Total recipients	1,847	100.00%

Sample: Firms that stay for ten years in the panel and invest in innovation at least one year during the period.

Table 3 shows that, as found in other studies, both investment an innovation and receiving public support are highly persistent. About 71% of recipients of support in one year remained supported the following year, while 29% did not. Furthermore, 93% of non-supported firms in [t] maintained their status in [t+1]. We also find high persistence of investment in innovation effort: each year about 72% of firms that did not have innovation activities remained in the same situation the following year, while 28% engaged in innovation. In turn, 90% of firms that had innovation activities one year continued doing so in the following year. These facts are in line with those found in Peters (2009) and Busom et al. (2017).

Table 3: Transition probabilities of public support and of innovation effort

Status at t-1	Funding status at t		Innovation Status at t	
	No (%)	Yes (%)	No (%)	Yes (%)
No (%)	92.6	7.3	72.4	27.5
Yes (%)	29.1	70.9	10.3	89.6

Note: The sample includes firms that invest in innovation at least one year during the period in the balanced panel. Percentages are very similar when using the unbalanced panel.

In addition we observe that some firms will be supported only during the growth period, others during the recession others in both, and finally some may never participate.

This will be of critical importance in defining the empirical strategy.

4 Empirical Strategy

Several factors may induce a different average response of firms to direct R&D support over the business cycle. One is that the nature of applicants may change as a result of variation in firms' incentives to apply for support or to changes in policy priorities leading to changes in the selection rules in expansions and in recessions. This would be a compositional effect. A second factor may be that the nature of specific shocks affects firms' response to support. Firms' R&D related decisions may be more sensitive to a tightening than to an expansion of credit. SMEs specially may cut down long-term investments in recessions characterized by a credit squeeze faster and more intensely than they can increase it in expansions. In this case a given amount of public support may be more effective in helping SMEs maintain their R&D activities during recessions than in inducing firms to engage or expand their innovation activities during expansions.

What we do next is to check the stability of the determinants of firm participation in government support programs through the 2005-2014 period. We are interested in testing whether the evolution of the firms' sales and firm's perception about external funding constraints are correlated with program participation status. Controlling for this, we will then look at different firm participation spells and estimate the impact of public support before, during and after the crisis conditional on a given spell.

4.1 Access to public support over the cycle

We estimate a random effects dynamic probit participation model for each of the three distinct periods: Before the crisis (2005–2008), during the crisis (2009–2012) and after the crisis (2013–2014). As explained above we observe whether firms have obtained direct support in a given year, but do not know whether a non-participant is a rejected applicant. Estimates reflect the joint outcome of the firms' decisions to apply for it and the selection rule that the administration follows.

The observed discrete variable s_i is associated with a underlying latent variable s_i^*.

The probability of participating is assumed to be a function of the firm's participation state in the previous year, $s_{i,t-1}$; a set of lagged observable covariates $x_{i,t-1}$; an unobservable time-invariant firm-specific effect η_i; and of a time-varying idiosyncratic random error term $u_{i,t}$. The individual specific unobserved permanent component η_i allows firms who are homogeneous in their observed characteristics to be heterogeneous in unobserved permanent features. The model is the following:

$$s_i^* = \alpha_{10} s_{i,t-1} + x'_{i,t-1}\beta_{10} + \eta_i + u_{i,t} \tag{1}$$

Variables $x_{i,t-1}$ are assumed to be exogenous with respect to $u_{i,t}$, but may be endogenous with respect to unobserved individual effects η_i, as well as the initial conditions s_{i0}. To consistently estimate this model, Wooldridge (2005) proposed modelling the distribution of η_i conditional on the initial conditions s_{i0}, and all lagged values for each exogenous covariates $z_i = (z_{i1}, z_{i2}, \ldots, z_{iT})$. Alternatively, Mundlak's (1978) approach replaces lagged exogenous variables by their time average. In this case the individual effects model can be expressed as follows:

$$\eta_i = \alpha_{11} s_{i,t-1} + \alpha_{21} s_{i0} + \alpha_{31}\bar{z}_i + \epsilon_{i,t} \tag{2}$$

The final model can be written as:

$$s_i^* = \alpha_{11} + \alpha_{10} s_{i,t-1} + \alpha_{21} s_{i0} + x'_{i,t-1}\beta_{10} + \alpha_{31}\bar{z}_i + v_{i,t} \tag{3}$$

One of the novelties of our specification is that we test whether public support is correlated with firm's sales growth in the previous period and whether this correlation changes over the phases of the business cycle. We would expect companies suffering from sales contractions not to plan new, costly innovation projects and therefore would not apply to public support programs, as these do not fund 100% of a project cost. Innovative start-ups, for instance, are more likely to suffer from venture capital drought in recessions (Paik and Woo 2014). It is possible however that firms that have unsupported ongoing projects turn to public support when external and internal sources of funds deteriorate in order to be able to finish their projects. If the first effect dominates, we would expect the correlation between sales growth and the probability of participating to be positive.

We also test whether the correlation with perceived barriers to innovation –such as access to external funding and demand uncertainty- remains constant and significant over time. As control variables we will include firm size, age, export status, group membership, foreign ownership, the percentage of employees with higher education and use of intellectual property rights, in line with previous research. Moreover, as innovation expenditures are found to be persistent in the literature, previous innovation expenditures will be controlled for. Finally, industry dummies are included to control for sector heterogeneity. All variables are defined in Table A1 in the Appendix.

4.2 Impact of public funding on firms' investment in innovation over time

The study of dynamic effects of public policies is an important aspect of policy evaluation and also an area that often demands methodological developments. A longitudinal framework raises many challenges because of issues related to dynamic selection into participation, duration, timing and multiple program participation are to be faced. A case in point is the micro-level evaluation of labor market policies (Lechner 2015; Lechner and Wiehler 2013). In this literature a matching approach has been combined with differences-in-differences, a strategy that may be appropriate in our case as well, as we discuss next.

Direct support is received by firms at different points in time and its effects may both last more than one period and vary over time depending on the business cycle phase when support is granted. Thinking in terms of the design of an ideal experiment, the key issue is defining the appropriate control group for treated firms at the time of treatment in order to obtain the counterfactual. A non-treated firm should be used as a comparison unit for one treated at time t only if both have the same treatment history before the time of treatment and the untreated status does not change for some time. In addition, potential outcomes for firms that receive support twice in a program, should be allowed to differ from those that receive it just once. We therefore need to take into account participation experience at the time of treatment. Treatment effects should be estimated conditional on a given starting year when the firm is granted support and on when it leaves the funding scheme.

The experiment would require performing a random allocation of identical firms to treatment in different phases of the cycle, and compare the outcomes ($Y_{i,t}$) of treated and untreated firms over time. To set this experiment up, let $Y_{i,t}$ equal the (log) innovation outcome for the firm i at time t, and the subsidy treatment be a binary random variable $S_{i,t} = \{0, 1\}$[9]. We would observe two possible outcomes for each pair of firms, depending on the firm's participation state. It could be either $Y_{0i,t}$ or $Y_{1i,t}$. Besides, assuming that outcomes of treated and non-treated firms have the same trend before treatment:

$$E[Y_{0i,t}|t, S_{i,t}] = E[Y_{0i,t}|t] \tag{4}$$

Then the causal effect (τ) is obtained as follows:

$$E[Y_{1i,t}|t, S_{i,t}] - E[Y_{0i,t}|t] = \tau \tag{5}$$

To allow the treatment effect to vary over time, let $D_{I,t+\delta}$ be an interaction term between support status ($S_{i,t}$) and period d_t, where d_t is a time dummy that switches on for observations obtained after support is granted. Treatment effects in Equation [6] below could be estimated by a difference in difference model using longitudinal data.

$$Y_{i,t} = \alpha + \sum_{\delta=0}^{q} \tau_{+\delta} D_{i,t+\delta} + \epsilon_{i,t} \tag{6}$$

where $(S_{i,t} \cdot d_t) = D_{i,t+\delta}$ and $\epsilon_{i,t} = Y_{0i,t} - E[Y_{0i,t}|t, S_{i,t}]$.

The estimator $\tau_{+\delta}$ measures the average change in firm's innovation outcome between firms that obtained support in period $\tau + \delta$ and firms that did not in the same period. However, when assignment to treatment is not random, equation [6] entails a naive comparison between supported and unsupported firms because it might be the

[9] A continuous treatment variable could be also used; however information on the amount of support is often unavailable or of low quality, so in practice a binary treatment is employed.

case that companies that are already successful in conducting innovations are more likely to apply and obtain support; furthermore, participation status at t and future potential outcomes may be correlated. Thus, the assumption expressed in [4] would be violated if we do not control for the systematic differences among firms.

To correct for this bias in observational data, different econometric techniques have been proposed. One of the most widely used approaches is matching on observables.[10] Let's suppose a firm receives support in 2006 only, so from the pool of non-policy users (control group), we should search for a similar firm (based on observables) that remains untreated over the whole period and then estimate their difference in conditional outcomes over time. Unbiased estimation of the average treatment effect relies entirely, however, on the observed covariates (unconfoundedness assumption). Thus, wiping out any unobservable-to-analyst characteristic that may bias the estimation is highly recommended. Athey and Imbens (2017) suggest that methods that combine modeling of the conditional mean with matching or weighting based on the propensity-score produce quite robust estimators, and are recommended for effective causal estimation using observational data.

To overcome the drawbacks of using simple matching –mainly the existence of unobservable permanent differences- we use Conditional DiD: we apply the difference-in-differences approach to the sample of firms that satisfies the common support condition (defined as the overlap of the distribution of propensity score for supported and unsupported firms)[11]. Using the matched sample already makes supported and control firms more similar than an unmatched sample of firms would be. The estimation model is,

$$Y_{i,t} = \alpha_i + \lambda_t + \sum_{\delta=0}^{q} \tau_{+\delta} D_{i,t+\delta} + \sum_j X'_{i,t}\beta + \epsilon_{i,t} \tag{7}$$

The model includes two main effects. First, it assumes that there is an individual time-invariant heterogeneity component (α_i) which is unobserved, and a year effect, λ_t, which is modelled as a time-year dummy variable. Second, it includes an interaction

[10] Control-function, Instrumental variables and Selection-models are also used. Cerulli et al. (2015) discusses the advantages and drawbacks of each of these approaches.

[11] This method has been implemented for example by Heckman, Ichimura, Smith, and Todd (1998); Smith and Todd (2005)

term $D_{i,t}$, the same as in equation 6, where $(S_{i,t} \cdot d_t) = D_{i,t+\delta}$. $X_{i,t}$ is a vector of firm time varying covariates. Note that the sum on the right-hand side allows for q leads of participation $(\tau_{+1}, \tau_{+2}, \ldots, \tau_{+q})$.

We will assess the impact of public support over time on two different outcomes. The first is investment in innovation per employee; this allows testing for full crowding out. The second outcome the number of employees (researchers, technicians and auxiliary staff) dedicated to R&D in full time equivalent units (FTE). Both outcomes provide complementary information on the effects of subsidies, as firms might reallocate highly qualified workers between production and research tasks without changing innovation budgets.[12] Interpretation of τ depends on which dependent variable is used in estimating 7. When the measured outcome is total investment (private investment plus the subsidy) per employee, $\tau \leq 0$ implies full crowding out. If instead the outcome is investment net of the subsidy, or the employee time dedicated to R&D, then $\tau = 0$ implies that neither additionality nor crowding-out effect occur; $\tau < 0$ indicates that some crowding-out is at work, and $\tau > 0$ indicates crowding-in effects.

5 Results

5.1 Access to direct support over the cycle

Table 4 shows the results of estimating a dynamic probit model for the three distinct phases of the cycle. The dependent variable takes the value one if the firm has received public funding, and zero otherwise. Columns 1, 4, and 7 display the maximum likelihood estimates of specification 3, using the lag of public funding $(t-1)$, its initial value (funding at t_0), and different lagged explanatory variables $(X_{i,t-1})$ in order to control for observed heterogeneity. Columns 2, 5, 8 report results using Mundlak's specification, and columns 3, 6 and 9 show estimates of a pooled probit. Both dynamic estimators lead to similar and significant coefficient estimates for lagged public funding, which is a measure of true state dependence of participation, while pooled probit estimates

[12] The data source (PITEC) provides detailed information about R&D personnel in full-time equivalent (FTE), following the OECD guidelines.

overestimate persistence, as expected.[13] Firms that have previously participated in public funding programs have higher probability of doing so later. This result is close to findings by Busom et al. (2017), who used a similar model with a panel of Spanish manufacturing firms over the period 2001–2008. Estimates suggest that persistence is slightly increasing during the recession phase and immediately after. We interpret this as an indicator that the probability to obtain support by previous non-participants fell with the recession. The initial value of public funding is also significant, implying that there is an important correlation between unobserved heterogeneity and the initial condition.

We do not find evidence that the firm's sales growth is correlated with participation in any of the phases of the cycle. Interestingly, firms that reported facing difficulties to access external funding are more likely to participate during the expansion phase, but not during the crisis. A plausible explanation is that many firms delay innovation plans during recessions and do not even search for support. They plan to engage in innovation activities –especially R&D- during expansions, and seek public support then because even during expansions SMEs are likely to face limited access to external funds for R&D. It is also possible that during recession years all firms face financial constraints, so that this perception would not explain differences in participation. The correlation with other variables such as the firm's human capital, domestic ownership and size remain positive and stable throughout the cycle. We find some indication that young firms might have been more likely to participate during the expansion, but not during or after the recession. Finally, firms from high-tech services are more likely to participate during the recession and recovery.[14] From these results we conclude that any changes in the impact of support on firms' innovation investment should not be attributed to potential changes in the joint outcome of firms' application decision and the public agency's selection rule. This is very similar to Hud and Hussinger (2015)'s

[13] Recall that the duration of support is not known, and that about 49% firms are supported for more than 3 years. This is likely to lead to a high estimated coefficient.

[14] We have also estimated the same model for the unbalanced panel, with 18,664 observations and 6,623 firms. We find that most results are very similar, and that firms that are in the balanced panel are more likely to participate. The main difference we find is that sales growth is positively correlated with the probability of participating.

results for Germany.

Table 4: Participation. Dynamic Probit estimation

	Period 1: 2005-2008			Period 2: 2009-2012			Period 3: 2013-2014		
	Woold1	Woold2	Pool	Woold1	Woold2	Pool	Woold1	Woold2	Pool
Public funding $(t-1)$	0.940***	1.177***	1.592***	1.557***	1.529***	1.667***	1.690***	1.701***	1.770***
	(0.0750)	(0.0800)	(0.0359)	(0.0343)	(0.0353)	(0.0336)	(0.0537)	(0.0558)	(0.0530)
Public funding (t_0)	0.933***	0.644***		0.451***	0.434***		0.404***	0.404***	
	(0.101)	(0.0982)		(0.0329)	(0.0347)		(0.0500)	(0.0539)	
Sales growth	0.0836	0.0443	0.0879	0.0192	-0.0265	0.0187	0.0983	0.0193	0.0904
	(0.0722)	(0.0704)	(0.0623)	(0.0519)	(0.0537)	(0.0531)	(0.0780)	(0.0875)	(0.0755)
External funding $(t-1)$	0.123**	0.133*	0.0975**	0.0377	-0.00794	0.0523	0.00172	0.0829	0.0166
	(0.0472)	(0.0614)	(0.0364)	(0.0321)	(0.0510)	(0.0318)	(0.0489)	(0.0784)	(0.0486)
Demand Uncertainty $(t-1)$	0.0429	0.0634	0.0402	0.0511	0.0216	0.0376	-0.0111	0.0528	-0.0163
	(0.0520)	(0.0672)	(0.0405)	(0.0342)	(0.0529)	(0.0343)	(0.0539)	(0.0820)	(0.0531)
IP protect $(t-1)$	0.0623	-0.00434	0.0496	0.0657*	0.00438	0.0586	0.104	0.0362	0.0925
	(0.0454)	(0.0415)	(0.0347)	(0.0331)	(0.0342)	(0.0330)	(0.0539)	(0.0563)	(0.0542)
Higher education $(t-1)$	0.864***	0.334***	0.657***	0.307***	0.137	0.393***	0.253*	0.0350	0.341**
	(0.112)	(0.101)	(0.0817)	(0.0679)	(0.0714)	(0.0673)	(0.107)	(0.116)	(0.104)
Group $(t-1)$	-0.00330	-0.0156	0.00695	0.0219	-0.00103	0.0333	0.00637	-0.0452	0.00984
	(0.0565)	(0.0505)	(0.0418)	(0.0366)	(0.0381)	(0.0353)	(0.0546)	(0.0577)	(0.0535)
Foreign $(t-1)$	-0.231*	-0.242**	-0.217**	-0.294***	-0.297***	-0.328***	-0.372***	-0.372***	-0.383***
	(0.101)	(0.0911)	(0.0727)	(0.0669)	(0.0688)	(0.0652)	(0.107)	(0.111)	(0.101)
Export $(t-1)$	0.114*	0.0188	0.0783	0.0423	-0.00110	0.0293	0.0719	0.0268	0.0593
	(0.0563)	(0.0512)	(0.0418)	(0.0399)	(0.0420)	(0.0388)	(0.0650)	(0.0699)	(0.0626)
Size. $x \leq 20$	-0.404***	-0.470***	-0.300***	-0.298***	-0.376***	-0.284***	-0.351***	-0.349***	-0.354***
	(0.0869)	(0.0805)	(0.0612)	(0.0575)	(0.0601)	(0.0552)	(0.0885)	(0.0935)	(0.0854)
Size. $20 < x \leq 50$	-0.205**	-0.241***	-0.1424**	-0.142**	-0.201***	-0.125*	-0.166*	-0.175*	-0.152
	(0.0769)	(0.0695)	(0.0537)	(0.0518)	(0.0540)	(0.0491)	(0.0805)	(0.0842)	(0.0781)
Size. $50 < x \leq 1000$	-0.105	-0.0924	-0.0640	-0.0375	-0.0710	-0.0232	-0.0504	-0.0383	-0.0430
	(0.0766)	(0.0691)	(0.0549)	(0.0526)	(0.0548)	(0.0502)	(0.0812)	(0.0851)	(0.0767)
Age (Log)	-0.0719	-0.0643*	-0.0542*	-0.0518	-0.0438	-0.0714*	-0.0223	-0.0193	-0.0524
	(0.0369)	(0.0326)	(0.0270)	(0.0296)	(0.0307)	(0.0288)	(0.0532)	(0.0564)	(0.0512)
High tech Manufac.	0.00553	-0.187*	0.0207	0.0102	-0.139*	0.0163	-0.00515	-0.130	0.00412
	(0.108)	(0.0935)	(0.0781)	(0.0684)	(0.0703)	(0.0684)	(0.105)	(0.109)	(0.105)
Medium tech Manufac	0.0807	-0.0284	0.0420	-0.0107	-0.0858*	-0.0224	0.0444	-0.00824	0.0413
	(0.0628)	(0.0547)	(0.0441)	(0.0412)	(0.0427)	(0.0415)	(0.0641)	(0.0674)	(0.0641)
High-tech services	0.147	0.0396	0.0962	0.215***	0.118	0.214***	0.152	0.126	0.156
	(0.0898)	(0.0793)	(0.0640)	(0.0581)	(0.0607)	(0.0569)	(0.0906)	(0.0967)	(0.0878)
Rest Services	-0.0690	-0.00530	-0.0441	0.0287	0.0398	0.0235	0.0583	0.108	0.0587

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Table 4 – Continued

	Period 1: 2005-2008			Period 2: 2009-2012			Period 3: 2013-2014		
	Woold1	Woold2	Pool	Woold1	Woold2	Pool	Woold1	Woold2	Pool
	(0.0768)	(0.0688)	(0.0570)	(0.0508)	(0.0533)	(0.0503)	(0.0809)	(0.0872)	(0.0785)
UE support ($t-1$)	0.611***	0.449***	0.534***	0.576***	0.444***	0.636***	0.472***	0.336***	0.524***
	(0.117)	(0.109)	(0.0896)	(0.0779)	(0.0801)	(0.0721)	(0.0964)	(0.100)	(0.0935)
Innovation Effort ($t-1$)	0.103***	-0.0633***	0.0860***	0.0675***	-0.0566***	0.0703***	0.0575***	-0.0826***	0.0593***
	(0.0103)	(0.0134)	(0.00933)	(0.00602)	(0.00834)	(0.00680)	(0.00860)	(0.0121)	(0.00944)
M.Innovation Effort		0.327***			0.238***			0.240***	
		(0.0187)			(0.0112)			(0.0157)	
Innovation (t_0)		-0.162			-0.136*			0.0573	
		(0.113)			(0.0695)			(0.116)	
M.External funding		-0.0851			0.0697			-0.105	
		(0.0764)			(0.0615)			(0.0883)	
M.Demand Uncertainty		-0.0222			0.0524			-0.0620	
		(0.0834)			(0.0652)			(0.0941)	
Constant	-2.384***	-2.994***	-1.975***	-1.736***	-2.294***	-1.617***	-2.049***	-2.616***	-1.899***
	(0.176)	(0.205)	(0.131)	(0.128)	(0.148)	(0.125)	(0.190)	(0.264)	(0.185)
Log likelihood	-3597.4564	-3326.2692	-3657.16	-4274.7168	-4000.207	-4366.9469	-1756.7038	-1600.594	-1788.6593
lnsig2u	-0.649***	-1.592***		-12.43	-13.23		-14.84	-13.16	
	(0.183)	(0.373)		(10.84)	(10.71)		(16.20)	(11.95)	
Sigma u	0.723	0.451		0.002	0.001		0.002	0.001	
	(0.066)	(0.084)		(0.011)	(0.007)		(0.005)	(0.008)	
Rho	0.343	0.169		0.000	0.000		0.000	0.000	
	(0.041)	(0.505)		(0.000)	(0.000)		(0.000)	(0.000)	
Wald Chi2	1976.7***	2325.13***		4425.03***	4247.07***		2825.69***	1809.26***	
N	10,047	10,047	10,047	13,421	13,421	13,421	6,708	6,708	6,708
Firms	3,354	3,354	3,354	3,356	3,356	3,356	3,354	3,354	3,354

Standard errors in parentheses. In columns (1) and (2) the integration method is mvaghermite; Time dummies included in all specifications. M.Innovation Effort is the within mean of Innovation effort from year 1 to year T. M.External funding (t-1) and M.Demand Uncertainty ($t-1$) are the within mean of external funding and demand uncertainty respectively, from year 1 to year T. Initial values differ for each panel * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5 reports the estimated average probability of being supported in period t, given participation in $t-1$, based on the results in columns 2, 5 and 8. Persistence is found to be higher after the onset of the crisis, suggesting that a number of firms were repeatedly supported through this period. To summarize, the process of being granted support seem to be quite stable along the phases of the business cycle, as basically the same subset of variables are correlated with the likelihood of obtaining support over the three periods.

Table 5: Within-period estimated average probability of being supported in period t, given participation in t-1.

	Estimated magnitude of state dependence
Period 1: 2005-2008	0.278
Period 2: 2009-2012	0.398
Period 3: 2013-2014	0.392

Note: Based on the results given in Table 4, columns 2, 5 and 8.

5.2 Impact of direct support on firms' investment in innovation

To perform the experiment described in section 4 and estimate the average treatment effects on the treated we have to choose a valid control group. This involves taking into account the firm's timing of participation: firms that obtain grants during the initial expansion phase should be compared with firms that are not treated during the whole period; and firms that receive funding during the recession should be compared to (matched) firms untreated during the recession and that were not treated previously either, as treatment effects can last for longer than the treatment year. To this end, we construct the participation spells or histories. The basic idea of the participation spells is intuitive: a time window during which the firms may have received funding. The procedure is the following: 1) we divide the 2005-2014 period in three sub-periods or time-windows, according the evolution of GDP growth as shown in Figure 1 in section 3: 2006-2008; 2009-2012 and 2013-14; 2) we consider the timing of participation of each firm within each phase, that is whether a firm participates in all, two or one of the three periods; 3) we focus on four participation spells or patterns that last one and two years within each time window (see table 6 below); 4) since we do not know the firm's participation history before 2005, we will perform the analysis for the sample of firms that were not participating in 2005, that is we drop from the sample firms that were participating that year.

Table 6: Participation spells. SMEs

Participation Spells	Treatment Condition	Number of treated Firms	Number of Controls
	Before Crisis: 2005-2008		
1	Participated one year between 2006 and 2008 but not in 2005 nor after 2008.	119	1,512
2	Participated two years between 2006 and 2008 but not in 2005 nor after 2008.	40	1,512
	During Crisis: 2009-2012		
3	Participated one year between 2009 and 2012 but not before 2009 nor after 2012.	117	1,512
4	Participated two years between 2009 and 2012 but not before 2009 nor after 2012.	62	1,512

We match firms treated at a given point in time with controls –firms that never participate- through the nearest neighbor matching procedure. For the expansion period, 2006-8, we use the estimated probability of participating in 2006 (the propensity score) using covariate values for 2005. The sample includes firms that exhibit a particular participation spell and matched firms that never participate. For the crisis period the propensity score is estimated with data for 2008 with lagged covariates.[15] Table 6 shows the spells studied, the number of treated firms in each spell, and the number of potential controls.[16]

[15] Yearly cross-sectional estimates of participation probabilities are available upon request.

[16] We cannot analyze all spells because the number of treated firms is too small in some cases.

The purpose of matching on the propensity score is to obtain a sample of controls for treated firms such that the joint distribution of the set of covariates for treated and non-treated firms overlaps. Table 7 reports the t-test of equality of the means of the matching covariates used in the analysis for each participation spell. Before matching there are significant differences between treated and non-treated firms, especially with respect to employees with higher education, firm age, support from EU and innovation intensity in t-1. After matching, differences are no longer significant, and the mean bias drops significantly. The distribution of the propensity-score for treated and control firms before and after matching are displayed in Figure A1 in the Appendix. The quality of the match after discarding some observations is high. Overall, we can safely conclude that balancing is satisfactory.

Table 7: before and after matching (t-statistic)

Participation Patterns	Pre-crisis 1 year		Pre-Crisis 2 years		During crisis 1 year		During crisis 2 years	
Variables	UM	M	UM	M	UM	M	UM	M
Sales (growth)	-0.31	-0.14	0.40	0.50	0.38	-0.62	-0.60	-0.43
O. External funding	1.87*	0.29	0.00	0.54	0.63	-0.17	-0.39	0.51
O. Demand Uncertainty	0.15	0.52	0.99	2.36***	0.45	-0.41	0.57	0.51
IP protect	0.85	1.00	0.25	0.50	1.58	0.32	0.14	-0.94
Higher education	0.64	-0.19	3.12***	-1.19	0.94	-0.92	0.93	-0.82
Group membership	-1.43	0.17	0.55	-0.77	-0.59	-0.54	-1.80	0.67
Foreign Ownership	-0.33	0.48	0.14	-0.35	-1.02	-0.31	-0.86	0.00
Export	0.02	-0.15	-0.80	0.25	2.05**	-0.80	0.34	0.24
Size. $x \leq 20$	-0.17	1.34	0.80	-0.26	-1.16	-0.19	0.37	0.24
Size. $20 < x \leq 50$	0.91	-0.32	0.64	0.73	0.07	0.00	0.67	-0.22
Size. $50 < x \leq 100$	-0.18	-0.15	0.03	0.29	1.67*	0.00	-1.11	-1.60
Age	1.60	-0.90	-2.9***	-0.13	-0.58	-0.20	-0.89	0.16
High tech Manufac.	0.07	-0.45	0.95	-0.74	0.39	0.00	1.96**	-0.74
Medium tech Manufac.	0.25	0.22	1.19	0.77	-0.43	0.00	1.55	0.88
High-tech services	-1.51	0.20	0.13	0.39	0.00	-0.52	-0.78	-0.46
Other Services	1.77*	0.00	-0.78	-0.98	-0.31	-0.20	-0.43	0.58
UE support	1.78*	0.33	-0.59	n.u.	1.42	1.42	0.99	1.00
Innovation intensity	-0.31	-0.14	1.35	-0.60	0.95	-0.35	-0.94	0.53
Mean Bias	7.80	5.60	13.40	15.00	7.70	5.80	10.80	12.90
LR Chi2	17.41	7.17	25.61*	15.37	17.90	4.84	19.61	14.59

Notes: UM= Unmatched sample; M=Matched sample; [a]none of the treated firms received EU support in 2005; Age and Innovation intensity are in logs; significance levels: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$; LR Chi2: Joint significance test.

We next estimate the model specified in equation [7] for each of the spells on Table 6 and each of the two outcomes of interest.[17] Four versions of this equation will be estimated: i) a standard DID model without controls using the whole sample of treated and untreated firms; ii) a DID with the same sample including all the controls used in the propensity score matching (DiD+controls); iii) a weighted version of the DID, where observations are weighted according to the propensity score (DiD weighted), and iv) a DID model using only the sample of treated and matched controls (DiD Matched).[18] Tables A2 and A3 in the Appendix report the estimated value of the treatment effect every year since participation for firms exhibiting each spell. We find that treatment estimates vary depending on the estimation method. DiD and DiD with controls generally overestimate treatment effects compared to DiD-weighted or DiD-matched. Figure 2 illustrates differences in estimated treatment effects for the treated by estimation method when the outcome is the number of employees allocated to R&D activities in FTE (Table A3).

Our preferred estimates are those obtained with DiD+Matching. In the case of innovation investment per employee, we find that treatment effects of firms that participated once during the expansion phase are higher than treatment effects for firms that participated once during the recession (see Table A2 for detailed results for spells 1 and 3 respectively). In fact, during the recession no significant effects are found. Although we can reject full crowding out for one year participants before the crisis, we cannot reject it during the downturn, in line with results found by Hud and Hussinger (2015). This suggests that treatment effects were pro-cyclical. However, for firms that participate twice –we now compare participation spell 2 to participation spell 4- we find that treatment effects might have been significant and higher during the recession

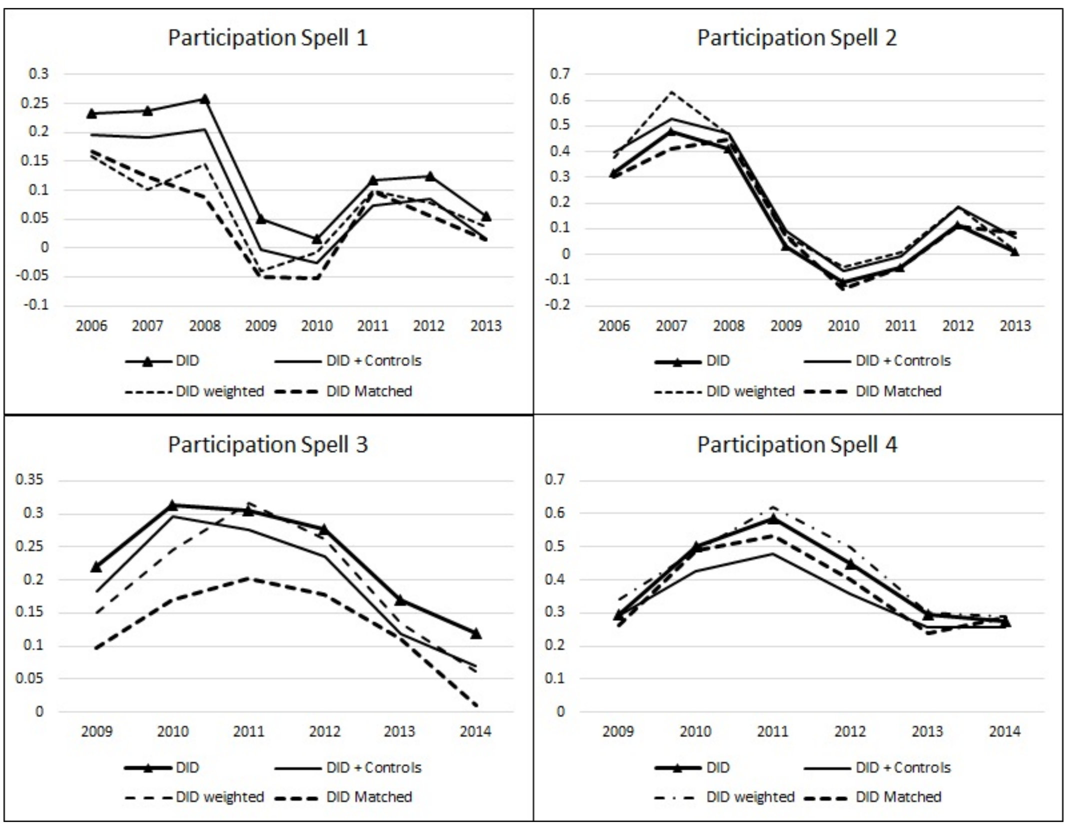
[17] We focus on total investment in innovation per employee and number of employees allocated to R&D activities. We decide not estimate the effect on net investment because the reported amount of subsidy received is very noisy.

[18] Weighting observations by their inverse probability of treatment was proposed by Hirano and Imbens (2001). In this case firms that participate in the program are given weight of $1/p$ and those that did not are weighted by a factor equal to $1/(1-p)$, where p is the estimated probability of being supported (the propensity score). That is, each firm is weighted with the inverse of the probability of the treatment. Intuitively, treated firms that resemble the controls are given more weight, and control cases that look like they should have got the treatment also get more weight.

years.[19]

When we examine treatment effects on the allocation of human capital to innovation activities –R&D employees in full time equivalent- we find that, according to the DiD+Matching estimation, treatment effects are somewhat higher and last longer during the recession years, suggesting a counter-cyclical behavior whether firms participate one year or two years (see Table A3). Figure 3 illustrates the differences of estimated treatment effects before and during the crisis years for two outcomes (total innovation investment per employee and human resources allocated to innovation, in FTE) and two participation spells.

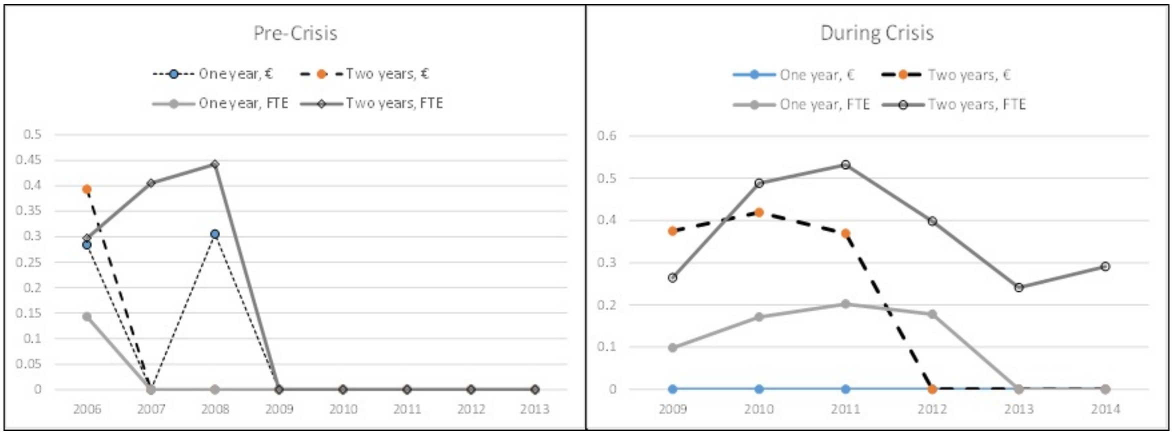
Figure 2: Estimated Average Treatment Effects on the treated (ATT) by estimation method. Outcome: R&D employees in FTE



Notes: The vertical axis measures the difference in average number of full time equivalent employees dedicated to R&D activities. Participation spells are as described in Table 4, and estimates are reported in Table A3.

[19] Spillovers from additional R&D activities induced by the policy flowing from treated firms to untreated firms with some delay could distort the true causal effect.

Figure 3: Estimated treatment effects before and during the crisis



Notes: Graphs show significant estimated coefficients from tables A2 and A3. Non-significant coefficients are set to 0.

Our results, summarized in Table 8 below, suggest two conclusions. First, effects of public support over the business cycle would depend on the duration of support, possibly reflecting different innovation project types. And second, while the effect of support on innovation investment is smaller –null- during the crisis years relative to expansion years, receiving support allowed firms to protect and expand their investment in R&D human capital relative to non-participants' investment.

Table 8: Multipliers over time by outcome

	Pre-Crisis		During Crisis	
	One Year	**Two-year**	**One Year**	**Two-year**
Innovation Investment/L, €	$\tau > 0$ (2 years)	$\tau > 0$ (2 years)	$\tau = 0$	$\tau > 0$ (3 years)
R&D employees, FTE	(1 year)	$\tau > 0$ (3 years)	$\tau > 0$ (4 years)	$\tau > 0$ (6 years)

Note: Duration of the estimated effect in parenthesis.

Clearly, public support does not seem to induce higher investment in innovation activities in recession years relative to expansion years for firms that participate only one-year. For these firms the multiplier effect of public support in monetary investment would be pro-cyclical. These firms, however, allocate more human resources to R&D during the recession, and for a longer period of time. Our interpretation is that during the crisis firms receiving public support during the recession reduced and reassigned the composition of innovation activities such that they could preserve their most valuable asset, human capital. For firms with more ambitious or lengthier innovation projects, as measured by a participation length of two years, the multiplier for both investment and employee time allocated to R&D is found to be counter-cyclical. The duration of the impact is longer as well.

On a cautionary note, we do not intend to imply, from these results, that allocating public subsidies to firms for one year is not a good policy. The magnitude of the multiplier, usually known as the extent of additionality in the innovation policy evaluation literature, does not imply that the policy is welfare increasing, as Takalo, Tanayama, and Toivanen (2017) and Lach, Neeman, and Schankerman (2017) have recently pointed out.

5.3 Robustness

We address two different issues regarding the robustness of our results. One is the potential sensitivity of results to changes in the sample. In this regard, we have used the same methods to estimate treatment effects with the unbalanced panel and obtain very similar results. The second concern relates to potential anticipation effects. Firms may react to a policy before its implementation, so that the outcome at t would be correlated with future program participation at $t+1$ or $t+2$. For instance, a firm wishing to obtain direct support might decide to improve its technological capabilities to increase its chances of obtaining a grant (Cerulli et al. 2015). To test for anticipatory effects, we follow Autor (2003) and extend equation 7, adding some leads for future participation in public innovation programs. This test also allows us to validate a fundamental assumption for any DID strategy, in which the outcome in treatment and control group would follow the same time trend in the absence of the treatment. We estimate the following equation:

$$Y_{i,t} = \alpha_i + \lambda_t + \sum_{\delta=1}^{q} \tau_{-\delta} D_{i,t-\delta} + \sum_{\delta=0}^{q} \tau_{+\delta} D_{i,t+\delta} + \sum_{j} X'_{i,t}\beta + \epsilon_{i,t} \tag{8}$$

If $\tau_{-\delta}$ is not statistically significant then pre-treatment trends between treated and non-treated can be considered as similar. However, it might be that a lag is significant, suggesting that a forward-looking feature of firm's decision-making process can be at work. Since we do not have but one pre-treatment year for firms in spell 1 and spell 2, we estimate the above model for firms that participate during the crisis years: spell 3 and 4. We find that no strong evidence of anticipation in terms of total or private investment in innovation per employee, although for spell 3 the coefficient for year 2008 is significant at the 10% level. In the case of spell 4, where we observe a drop in the allocation of employees to innovation prior to treatment years 2006 to 2008.

5.4 Large firms

We build a balanced panel of about 1,169 large firms with more than 200 employees from the same source, PITEC. About 66% of them were investing in innovation in 2005, and 49% in R&D. These percentages increased slightly up to 2009, and then dropped again to the levels of 2005 by 2014. Likewise, while in 2009 and 2010 public support reached about 40% of R&D performers, this percentage had declined to 32% by 2014. The average ratio of public support to total R&D was close to about 25% during the expansion and early recession years, but fell to 17% later. Most R&D performers received support for two years or more. Both innovation and participation status are highly persistent (A4 and A5 in the Appendix).

The size of the sample of firms in the balanced panel receiving direct support allows us to estimate a dynamic random effects model for each phase of the business cycle and compare estimates with those obtained for SMEs. Results are quite similar with respect to persistence of participation, which is higher during the recession. As before, this is consistent with the hypothesis that budget cuts lead to a sharp reduction in the probability that previously untreated firms would obtain support during the recession. Unlike SMEs, however, we do not find evidence that the probability of participation was correlated with lack of access to external funding (see table A7 in the Appendix).

When looking at participation spells over the cycle, we find that the number of firms experiencing the same participation spell is in many cases too small to obtain reliable estimates of treatment effects for the same cases as for SMEs. Table 9 shows the number of treated and potential controls for the cases analogous to SMEs.

Table 9: Participation spells. Large Firms

Participation Spells	**Treatment Condition**	**Number of treated Firms**	**Number of Con-trols**
	Before Crisis: 2005-2008		
1	Participated only one year between 2006 and 2008 but neither in 2005 nor after 2008.	35	704
2	Participated only two years between 2006 and 2008 but neither in 2005 nor after 2008.	8	704
	During Crisis: 2009-2012		
3	Participated only one year between 2009 and 2012 but neither before 2009 nor after 2012.	35	704
4	Participated only two years between 2009 and 2012 but neither before 2009 nor after 2012.	20	704

Because of the small number of observations for these participation spells, we estimate tentatively treatment effects only for spells 1 and 3. As before, we find that using DiD or DiD with controls leads to treatment estimates that are higher than estimated obtained with DiD combined with matching. The estimated effect on total innovation investment per worker is not significantly different from zero both during the expansion years and during the recession. For firms participating one year during the expansion phase (participation spell 1), we find a positive and significant treatment effect on the employee time dedicated to R&D activities in 2009, that is, an effect with at least one year of delay. For firms participating one year during the recession phase (participation spell 3), we obtain an immediate positive and significant effect; this effect does not seem to last after that year. These results, however, are to be considered only extremely tentative given sample size. They only suggest that large firms and SMEs respond differently to public support, as found in other research.

6 Concluding Remarks

We have studied whether the allocation of public support for business R&D changes over the business cycle during the recent crisis, and whether its effect on some indicators of firms' innovation effort changes over the phases of the cycle. We find that, in line with the results of Hud and Hussinger (2015) for Germany, the allocation of R&D subsidies in Spain did not change significantly during the crisis. Our results regarding the multiplier, however, differ to some extent. We find that the multiplier varies depending on the firms' participation spell and with the type of outcome. Timing and length of participation matter, with longer spells leading to a higher multiplier. We also find that while the impact of public support during the recession years is pro-cyclical for investment in innovation in monetary terms, when looking at the time allocation to R&D activities the multiplier is higher and longer during the recession. These results are robust for SMEs. Overall, these results suggest that an appropriate allocation of support to business R&D may mitigate the negative effect that recessions have on highly cyclical R&D investments through the reallocation of human capital to R&D activities, even if other innovation activities are reduced.

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Appendices

Table A1: Variable definition

Variables	**Definition**
Public support	Binary indicator of participating in public support programs from the Central or regional administrations.
Innovation Intensity	Log of innovation investment per employee in constant prices
R&D employees in FTE	Number of R&D employees (researchers, technicians and auxiliary staff) Full Time Equivalent (FTE).
Sales growth	Real growth rate of sales calculated as (Ln (sales) t - ln(sales) t - 1). Sales have been deflated with the GDP deflator, at 2010 prices.
External funding (t-1)	Binary: Firm declares that access to external funding is an important obstacle
Demand Uncertainty (t-1)	Binary; Firm declares that demand uncertainty is an important obstacle for innovating
IP protect (t-1)	Binary; Firm uses formal IP mechanisms
Higher education (t-1)	The share of employees with higher education
Group (t-1)	Binary; Firm belongs to a business group.
Foreign (t-1)	Binary; for multinational firms with participation of foreign capital greater than 50%
Export (t-1)	Binary; Firm has sold products and/or services in the international market (European and third party).
Size. $x \leqslant 20$	Binary; Firm Size $x \leqslant 20$ employees
Size $20 < x \leqslant 50$	Binary; Firm Size $20 < x \leqslant 50$ employees
Size $50 < x \leqslant 100$	Binary; Firm Size $50 < x \leqslant 100$ employees
Size $100 < x \leqslant 200$	Binary; Firm Size $100 < x \leqslant 200$ employees
Age (Log)	Years of the company since its creation (in logarithms).
High tech Manufac.	Binary; firm belongs to the Manufacturing sectors: pharmacy, IT products, electronic and optical products, aeronautical and space industries.
Medium Tech Manufac	Binary; firm belongs to the Manufacturing sectors: chemicals, mechanical and electrical equipment, other machinery, motor vehicles, naval construction.
Other Manufacturing	Binary; firm belongs to remaining manufacturing sectors: food, beverages and tobacco, textiles, clothing, leather and footwear, wood and cork, cardboard and paper, rubber and plastics, metal manufactures, other transport equipment, furniture, other manufacturing activities, graphic arts.
High Tech Services	Binary; firm belongs to the High Technology Services sectors: telecommunications, programming, consulting and other information activities, other information and communications services, R&D services.
Other Services	Binary; firm belongs to other Services sectors: repair and installation of machinery and equipment, commerce, transportation and storage, hotels and accommodation, financial and insurance activities, real estate activities, administrative activities and auxiliary services, education, sanitary activities and social services, artistic, recreational and entertainment activities, other services.
EU support	Binary indicator of participating in public support programs from the European Union.

Table A2: Treatment effects. Outcome: Ln(Total Innovation Effort per worker)

	DiD (Naive)	DiD (Controls)	DiD (Weighted)	DiD (Common Support)
Participation Spell 1				
2006	0.311***	0.438***	0.280**	0.284**
	(0.101)	(0.134)	(0.115)	(0.142)
2007	0.192*	0.326**	0.214*	0.220
	(0.108)	(0.141)	(0.115)	(0.149)
2008	0.158	0.283**	0.162	0.305**
	(0.115)	(0.136)	(0.123)	(0.150)
2009	-0.036	0.104	-0.053	0.076
	(0.092)	(0.111)	(0.092)	(0.125)
2010	-0.153	-0.022	-0.214**	-0.099
	(0.101)	(0.116)	(0.106)	(0.127)
2011	-0.045	0.087	-0.018	0.106
	(0.107)	(0.104)	(0.130)	(0.106)
2012	0.025	0.152	0.047	0.165
	(0.099)	(0.094)	(0.115)	(0.103)
2013	-0.130	0.001	-0.177	0.002
	(0.098)	(0.082)	(0.115)	(0.093)
Participation Spell 2				
2006	0.489***	0.538***	0.481***	0.393*
	(0.133)	(0.199)	(0.157)	(0.212)
2007	0.418**	0.484**	0.331*	0.335
	(0.196)	(0.228)	(0.185)	(0.246)
2008	0.283**	0.368	0.142	0.330
	(0.134)	(0.261)	(0.118)	(0.302)
2009	-0.142	-0.039	-0.324**	-0.198
	(0.169)	(0.256)	(0.152)	(0.308)
2010	-0.235*	-0.138	-0.338**	-0.292
	(0.139)	(0.187)	(0.135)	(0.195)
2011	-0.297**	-0.200	-0.319**	-0.269
	(0.133)	(0.177)	(0.135)	(0.195)
2012	-0.155	-0.039	-0.248	-0.165
	(0.184)	(0.193)	(0.229)	(0.202)
2013	-0.216	-0.103	-0.204	-0.127
	(0.180)	(0.168)	(0.186)	(0.190)
Participation Spell 3				
2009	0.236***	0.180**	0.210**	0.121
	(0.085)	(0.086)	(0.107)	(0.097)
2010	0.187*	0.161	0.106	0.118
	(0.100)	(0.107)	(0.127)	(0.113)
2011	0.276**	0.239**	0.216*	0.170
	(0.112)	(0.115)	(0.120)	(0.127)
2012	0.220**	0.179	0.195*	0.188
	(0.109)	(0.110)	(0.113)	(0.128)
2013	0.031	-0.016	0.011	0.035
	(0.100)	(0.102)	(0.094)	(0.118)
2014	-0.093	-0.164	-0.115	-0.177
	(0.107)	(0.108)	(0.107)	(0.135)

Continued on next page

Table A2 – continued from previous page

	DiD (Naive)	DiD (Controls)	DiD (Weighted)	DiD (Common Support)
Participation Spell 4				
2009	0.400***	0.349***	0.257	0.375***
	(0.133)	(0.127)	(0.176)	(0.132)
2010	0.482***	0.412***	0.420**	0.421**
	(0.133)	(0.135)	(0.164)	(0.172)
2011	0.480***	0.387**	0.399**	0.373*
	(0.159)	(0.171)	(0.203)	(0.213)
2012	0.372***	0.277*	0.384***	0.196
	(0.142)	(0.148)	(0.129)	(0.190)
2013	0.148	0.091	0.148	0.012
	(0.143)	(0.145)	(0.151)	(0.165)
2014	0.101	0.043	0.102	0.051
	(0.136)	(0.138)	(0.148)	(0.179)
Fixed Effects	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Dependent Variable: Ln (1 + Total innovation expenditures). Standard errors in parentheses; Standard errors are clustered at the firm level. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table A3: Treatment effects. Outcome: Human Capital (R&D employees in FTE)

	DiD (Naive)	DiD (Controls)	DiD (Weighted)	DiD (Common Support)
Participation Pattern 1				
2006	0.232***	0.197**	0.239***	0.143*
	(0.060)	(0.079)	(0.059)	(0.085)
2007	0.238***	0.191**	0.251***	0.149
	(0.067)	(0.084)	(0.061)	(0.091)
2008	0.259***	0.205**	0.306***	0.145
	(0.071)	(0.085)	(0.072)	(0.091)
2009	0.050	-0.005	0.040	-0.054
	(0.071)	(0.082)	(0.073)	(0.091)
2010	0.015	-0.025	-0.001	-0.069
	(0.064)	(0.075)	(0.057)	(0.081)
2011	0.118**	0.074	0.107**	0.051
	(0.054)	(0.061)	(0.055)	(0.068)
2012	0.125**	0.086	0.135**	0.074
	(0.057)	(0.062)	(0.057)	(0.068)
2013	0.056	0.017	0.050	0.020
	(0.054)	(0.048)	(0.054)	(0.054)
Participation Pattern 2				
2006	0.315***	0.396***	0.376***	0.297*
	(0.099)	(0.140)	(0.109)	(0.157)
2007	0.479***	0.529***	0.633***	0.405**
	(0.103)	(0.142)	(0.123)	(0.159)
2008	0.413***	0.473**	0.466***	0.442**
	(0.104)	(0.190)	(0.118)	(0.205)
2009	0.030	0.089	0.073	0.067
	(0.091)	(0.146)	(0.106)	(0.171)
2010	-0.110	-0.060	-0.047	-0.141
	(0.084)	(0.115)	(0.083)	(0.132)
2011	-0.054	-0.005	0.008	-0.053
	(0.077)	(0.100)	(0.078)	(0.114)
2012	0.116	0.184*	0.184*	0.110
	(0.082)	(0.097)	(0.102)	(0.101)
2013	0.010	0.069	0.014	0.085
	(0.071)	(0.064)	(0.076)	(0.073)
Participation Pattern 3				
2009	0.220***	0.182***	0.209***	0.098**
	(0.052)	(0.051)	(0.060)	(0.047)
2010	0.313***	0.297***	0.338***	0.171**
	(0.062)	(0.068)	(0.068)	(0.072)
2011	0.306***	0.274***	0.340***	0.201***
	(0.066)	(0.067)	(0.070)	(0.075)
2012	0.277***	0.237***	0.324***	0.178**
	(0.067)	(0.071)	(0.070)	(0.076)
2013	0.170**	0.119*	0.204***	0.112
	(0.071)	(0.069)	(0.072)	(0.082)
2014	0.120	0.071	0.146*	0.012
	(0.078)	(0.076)	(0.080)	(0.092)

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Table A3 – continued from previous page

	DiD (Naive)	DiD (Controls)	DiD (Weighted)	DiD (Common Support)
Participation Pattern 4				
2009	0.296***	0.297***	0.343***	0.264***
	(0.106)	(0.101)	(0.129)	(0.084)
2010	0.502***	0.430***	0.485***	0.488***
	(0.102)	(0.104)	(0.124)	(0.110)
2011	0.584***	0.476***	0.619***	0.532***
	(0.094)	(0.115)	(0.119)	(0.127)
2012	0.448***	0.355***	0.497***	0.398***
	(0.089)	(0.104)	(0.095)	(0.128)
2013	0.296***	0.262**	0.303**	0.241*
	(0.112)	(0.112)	(0.122)	(0.124)
2014	0.273***	0.258***	0.289***	0.291**
	(0.102)	(0.099)	(0.109)	(0.128)
Fixed Effects	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Notes: Standard errors in parentheses; standard errors are clustered at the firm level. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Figure A1: SMEs. Distribution of the Propensity Score before and after matching

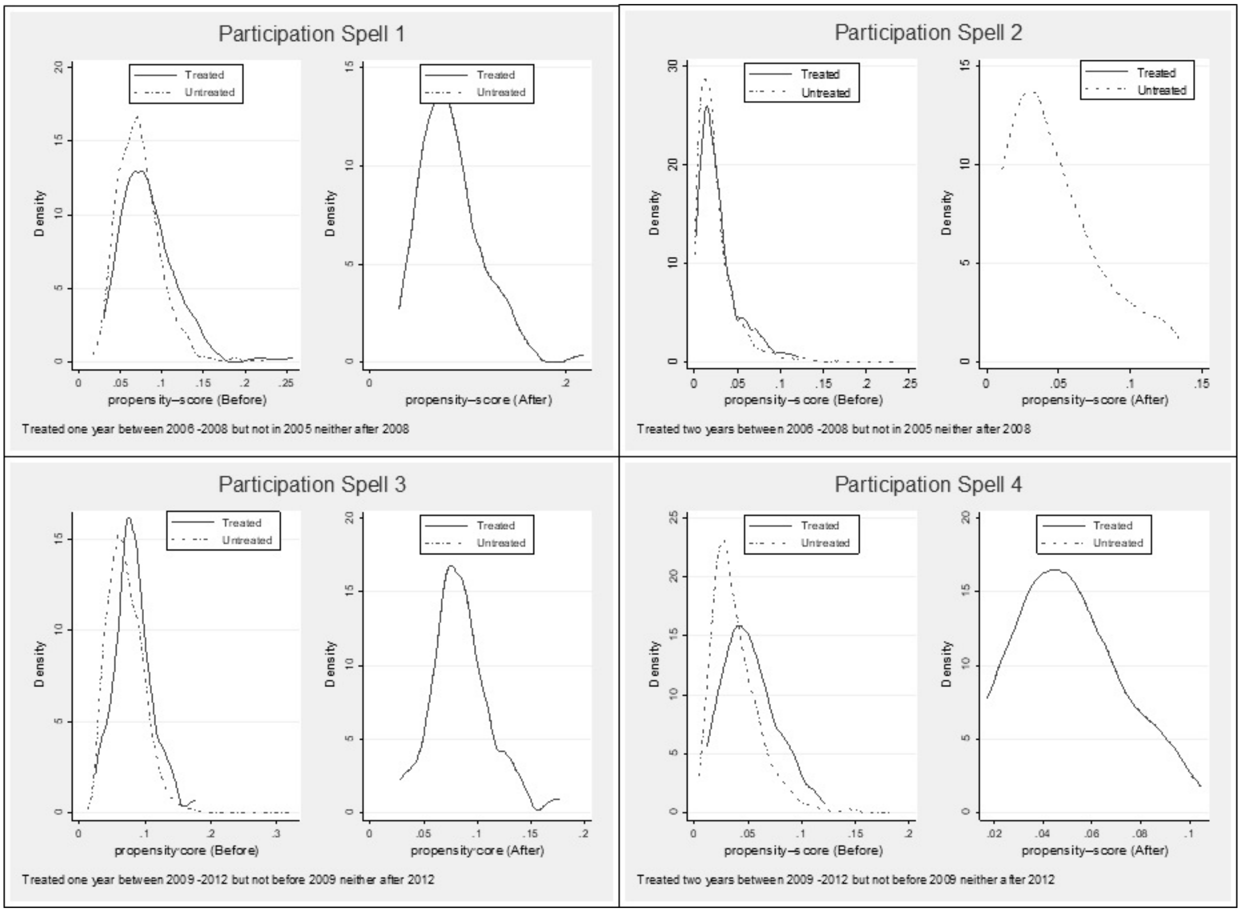

Table A4: Large Firms. Innovation expenditures and public funding.

(1)	Firms with innovation expenditures (2)	Firms doing R&D (3)	% doing RD over firms with innovation (4)	% receiving public funding* (5)	% receiving public funding** (6)	Mean Public funding/R&D *** (7)
2005	771	575	74.58	26.33	35.30	25.62
2006	780	577	73.97	30.13	40.73	25.36
2007	797	587	73.65	28.98	39.35	24.67
2008	816	601	73.65	30.76	41.76	27.93
2009	838	602	71.84	29.83	41.53	27.40
2010	809	596	73.67	29.91	40.60	25.59
2011	811	589	72.63	29.35	40.41	21.95
2012	799	586	73.34	25.53	34.81	19.42
2013	782	593	75.83	24.04	31.70	19.02
2014	774	589	76.10	24.68	32.43	17.03

Notes: *If innovation expenditures are positive; **if research and development expenditures (R&D) are positive. *** if the subsidy is positive. Sample: Balanced panel of 1,169 firms that remain in the panel for 10 years and that invested in innovation at least once in the period under study.

Table A5: Large Firms. Spells of participation over the 10-year period.

	Number of Firms	Percent
1 year	98	21.1%
2 years	70	15.1%
3 years	39	8.4%
4 years	42	9.0%
5 years	31	6.7%
6 years	24	5.2%
7 years	36	7.7%
8 years	34	7.3%
9 years	23	4.9%
10 years	68	14.6%
Total recipients	465	100.00%

Sample: Firms that stay for ten years in the panel and invest in innovation at least one year during the period.

Table A6: Large firms. Transition probabilities of public support and of innovation effort

Status at t-1	Funding status at t		Innovation Status at t	
	No (%)	Yes (%)	No (%)	Yes (%)
No (%)	94.48	5.52	76.85	23.15
Yes (%)	23.77	76.23	10.55	89.45

Note: The sample includes firms that invest in innovation at least one year during the period in the balanced panel. Percentages are very similar when using the unbalanced panel.

Table A7: Large firms. Dynamic Probit participation

	Period 1: 2005-2008			Period 2: 2009-2012			Period 3: 2013-2014		
	Woold1	Woold2	Pool	Woold1	Woold2	Pool	Woold1	Woold2	Pool
Public Funding $(t-1)$	1.332***	1.415***	1.869***	1.734***	1.717***	1.860***	2.024***	2.045***	2.116***
	(0.175)	(0.175)	(0.0744)	(0.0667)	(0.0681)	(0.0641)	(0.104)	(0.106)	(0.0998)
Public Funding (t_0)	0.839**	0.738**		0.529***	0.522***		0.472***	0.511***	
	(0.256)	(0.250)		(0.0715)	(0.0754)		(0.107)	(0.114)	
Sales growth (log dif)	-0.286	-0.295	-0.252*	0.131	0.106	0.111	-0.0638	-0.0747	-0.0407
	(0.150)	(0.152)	(0.116)	(0.132)	(0.134)	(0.127)	(0.187)	(0.195)	(0.269)
External Funding $(t-1)$	0.162	-0.0509	0.142	-0.0368	-0.236*	-0.0137	0.193	0.162	0.216*
	(0.107)	(0.164)	(0.0873)	(0.0726)	(0.114)	(0.0735)	(0.104)	(0.170)	(0.0994)
Demand Uncertainty $(t-1)$	0.269*	0.0432	0.242*	0.0968	0.0518	0.110	0.120	0.257	0.149
	(0.111)	(0.155)	(0.0979)	(0.0761)	(0.115)	(0.0757)	(0.109)	(0.179)	(0.113)
IP Protect $(t-1)$	0.162	0.137	0.141*	0.0569	0.0159	0.0637	0.0152	-0.0616	0.0467
	(0.0856)	(0.0829)	(0.0681)	(0.0646)	(0.0661)	(0.0630)	(0.101)	(0.104)	(0.0936)
Higher education $(t-1)$	0.0811	-0.184	0.137	0.386**	0.248	0.455**	0.364	0.170	0.475*
	(0.204)	(0.208)	(0.158)	(0.147)	(0.154)	(0.139)	(0.219)	(0.235)	(0.211)
Group $(t-1)$	-0.0739	-0.0694	-0.0689	0.0158	-0.0220	0.0343	0.138	0.132	0.111
	(0.102)	(0.101)	(0.0833)	(0.0817)	(0.0852)	(0.0799)	(0.144)	(0.150)	(0.121)
Foreign $(t-1)$	-0.344***	-0.291**	-0.335***	-0.358***	-0.345***	-0.418***	-0.242*	-0.253*	-0.287**
	(0.103)	(0.0985)	(0.0819)	(0.0750)	(0.0774)	(0.0718)	(0.110)	(0.114)	(0.107)
Export $(t-1)$	0.525***	0.375**	0.465***	0.165	0.103	0.192*	-0.0438	-0.142	0.00672
	(0.124)	(0.121)	(0.0975)	(0.0884)	(0.0929)	(0.0859)	(0.140)	(0.149)	(0.126)
Size $200 < x \leq 400$	-0.216*	-0.234*	-0.192*	-0.264***	-0.277***	-0.287***	0.114	0.0682	0.0804
	(0.102)	(0.101)	(0.0783)	(0.0726)	(0.0753)	(0.0701)	(0.116)	(0.120)	(0.111)
Size $400 < x \leq 700$	-0.133	-0.154	-0.124	-0.201*	-0.212**	-0.213**	0.0795	0.0701	0.0434
	(0.104)	(0.103)	(0.0827)	(0.0786)	(0.0812)	(0.0767)	(0.125)	(0.130)	(0.116)
Age	-0.0295	-0.0456	-0.0147	-0.0293	-0.0270	-0.0134	0.0761	0.0804	0.0805
	(0.0531)	(0.0512)	(0.0446)	(0.0461)	(0.0470)	(0.0460)	(0.0799)	(0.0815)	(0.0805)
High-tech Manufac.	0.169	-0.0233	0.131	-0.288*	-0.465***	-0.243*	-0.438*	-0.456*	-0.402*
	(0.176)	(0.166)	(0.142)	(0.127)	(0.129)	(0.124)	(0.198)	(0.203)	(0.179)
Medium-tech Manufac.	0.228	0.146	0.189*	-0.0200	-0.0913	0.00577	0.173	0.143	0.190
	(0.120)	(0.113)	(0.0943)	(0.0853)	(0.0871)	(0.0834)	(0.128)	(0.132)	(0.122)
High-tech Services	0.398*	0.519**	0.317*	-0.0947	-0.0408	-0.0858	0.223	0.312	0.202
	(0.182)	(0.184)	(0.148)	(0.133)	(0.139)	(0.123)	(0.192)	(0.205)	(0.195)
Rest Services	-0.137	0.0613	-0.129	-0.347***	-0.191	-0.388***	-0.316*	-0.222	-0.344*
	(0.122)	(0.121)	(0.101)	(0.0922)	(0.0975)	(0.0903)	(0.148)	(0.156)	(0.138)
EU support $(t-1)$	0.623***	0.445**	0.630***	0.470***	0.329**	0.580***	0.449**	0.420*	0.494***

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Table A7 – Continued

	Period 1: 2005-2008			Period 2: 2009-2012			Period 3: 2013-2014		
	Woold1	Woold2	Pool	Woold1	Woold2	Pool	Woold1	Woold2	Pool
	(0.170)	(0.166)	(0.143)	(0.116)	(0.118)	(0.104)	(0.163)	(0.166)	(0.146)
Innovation Effort $(t-1)$	0.0944***	-0.0585*	0.0809***	0.0950***	-0.0510*	0.1000***	0.0750***	-0.0833**	0.0795***
	(0.0174)	(0.0260)	(0.0134)	(0.0136)	(0.0212)	(0.0141)	(0.0196)	(0.0304)	(0.0195)
M.Innovation effort		0.278***			0.244***			0.238***	
		(0.0359)			(0.0265)			(0.0365)	
Innovation (t_0)		-0.249			-0.148			-0.133	
		(0.157)			(0.0894)			(0.135)	
M.External funding $(t-1)$		0.218			0.275*			0.118	
		(0.189)			(0.135)			(0.192)	
M.Demand Uncertainty $(t-1)$		0.419*			0.0858			-0.202	
		(0.197)			(0.138)			(0.206)	
_cons	-2.342***	-2.798***	-2.070***	-1.849***	-2.338***	-1.889***	-2.748***	-3.103***	-2.726***
	(0.290)	(0.326)	(0.207)	(0.217)	(0.236)	(0.223)	(0.388)	(0.416)	(0.372)
lnsig2u									
_cons	-1.232*	-1.730		-11.49	-12.57		-13.79	-14.27	
	(0.623)	(0.922)		(11.09)	(19.23)		(32.09)	(17.71)	
Log likelihood	-886.21946	-834.7115	-896.26319	-1111.3071	-1058.8653	-1138.1354	-458.17352	-432.96091	-467.73488
lnsig2u	-1.2323***	-1.7303***		-11.4886	-12.57184		-13.794	-14.167	
	(0.623)	(0.922)		(11.087)	(19.2318)		(32.094)	(17.706)	
Sigma u	0.5400	0.421		0.003	0.002		0.001	0.001	
	(0.1681)	(0.194)		(0.018)	(0.0179)		(0.0162)	(0.0162)	
Rho	0.2257	0.150		0.000	0.000		0.000	0.000	
	(0.109)	(0.118)		(0.000)	(0.000)		(0.000)	(0.000)	
Wald Chi2	735.28***	726.71***	1,181.96***	1543.02***	1438.62***	1,662.18***	726.60***	664.40***	753.02***
N	3,501	3,501	3,501	4,675	4,675	4,675	2,338	2,338	2,338
Firms	1,168	1,168	1,168	1,169	1,169	1,169	1,168	1,169	1,169

Standard errors in parentheses. In columns (1) and (2) the integration method is mvaghermite; Time dummies included in all specifications. M.Innovation Effort is the within mean of Innovation effort from year 1 to year T. M.External funding (t-1) and M.Demand Uncertainty $(t-1)$ are the within mean of external funding and demand uncertainty respectively, from year 1 to year T. Initial values differ for each panel * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A8: Large firms. Difference-in-difference estimations. Ln(Total Innovation Effort per worker)

	DiD (Naive)	DiD (Controls)	DiD (Weighted)	DiD (Common Support)
Participation Spell 1				
2006	0.032	0.204	0.250	0.112
	(0.193)	(0.240)	(0.251)	(0.287)
2007	0.168	0.364	0.215	0.222
	(0.204)	(0.247)	(0.223)	(0.301)
2008	0.058	0.246	-0.023	0.246
	(0.221)	(0.231)	(0.203)	(0.256)
2009	0.077	0.274	-0.165	0.160
	(0.201)	(0.212)	(0.174)	(0.252)
2010	0.232	0.336*	0.145	0.294
	(0.162)	(0.199)	(0.166)	(0.248)
2011	0.230	0.346*	0.156	0.254
	(0.165)	(0.199)	(0.150)	(0.250)
2012	-0.132	-0.007	-0.154	-0.145
	(0.143)	(0.156)	(0.167)	(0.197)
2013	-0.085	0.022	-0.174	0.054
	(0.153)	(0.156)	(0.212)	(0.201)
Participation Spell 3				
2009	0.368**	0.301*	0.549**	0.158
	(0.178)	(0.173)	(0.271)	(0.228)
2010	0.141	0.103	0.356	0.036
	(0.217)	(0.213)	(0.497)	(0.207)
2011	0.369	0.305	0.538*	0.037
	(0.203)	(0.200)	(0.280)	(0.231)
2012	0.351**	0.284	0.153	0.054
	(0.162)	(0.194)	(0.200)	(0.241)
2013	0.302	0.241	0.317	0.078
	(0.187)	(0.183)	(0.219)	(0.224)
2014	-0.106	-0.128	-0.127	-0.293
	(0.194)	(0.197)	(0.290)	(0.232)
Fixed Effects	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Standard errors in parentheses; standard errors are clustered at the firm level. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. 1) Dependent Variable: Ln (1 + Total innovation expenditures).

Table A9: Large firms. Difference-in-difference estimations. R&D employees FTE

	DiD (Naive)	DiD (Controls)	DiD (Weighted)	DiD (Common Support)
Participation Pattern 1				
2006	0.285*	0.349*	0.329	0.124

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Table A9 – continued from previous page

	DiD (Naive)	DiD (Controls)	DiD (Weighted)	DiD (Common Support)
	(0.169)	(0.205)	(0.236)	(0.231)
2007	0.232	0.325*	0.084	0.235
	(0.159)	(0.188)	(0.144)	(0.237)
2008	0.461***	0.555***	0.438***	0.487***
	(0.130)	(0.152)	(0.167)	(0.186)
2009	0.167	0.281	0.006	0.217
	(0.144)	(0.172)	(0.126)	(0.215)
2010	0.280**	0.348**	0.139	0.298
	(0.138)	(0.167)	(0.109)	(0.205)
2011	0.150	0.227	0.019	0.139
	(0.123)	(0.140)	(0.091)	(0.172)
2012	0.114	0.202	0.011	0.175
	(0.111)	(0.131)	(0.114)	(0.165)
2013	0.077	0.146	-0.053	0.123
	(0.102)	(0.118)	(0.096)	(0.150)
Participation Pattern 3				
2009	0.601***	0.517***	0.952**	0.459**
	(0.164)	(0.161)	(0.397)	(0.186)
2010	0.508***	0.467***	0.893**	0.348**
	(0.160)	(0.154)	(0.401)	(0.166)
2011	0.394***	0.331***	0.634**	0.265**
	(0.129)	(0.119)	(0.275)	(0.120)
2012	0.318**	0.268	0.504	0.124
	(0.158)	(0.170)	(0.322)	(0.211)
2013	0.040	-0.029	0.255	-0.243
	(0.172)	(0.178)	(0.408)	(0.195)
2014	-0.008	-0.054	0.292	-0.206
	(0.191)	(0.184)	(0.393)	(0.206)
Fixed Effects	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Standard errors in parentheses; standard errors are clustered at the firm level. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. 1) Dependent Variable: R&D employees in FTE.

Supplementary Materials

Supplementary materials are available in the following repository: https://github.com/velezjorgea/Paper-Innovation-Subsidies-