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Subsidising Innovation over the Business Cycle*

Isabel Busom † and Jorge Vélez-Ospina ‡

June 26, 2020

Abstract

We investigate whether the impact of direct support for business investment in R&D and innovation varies over the business cycle. We study whether firms that obtain public support in a recession differ from firms that obtain it during expansions; whether the impact of support is smaller in recessions than in expansions, and whether effects vary with the treatment pattern. Using firm-level data from Spain during the period 2005 to 2014, we combine propensity score matching and difference-in-differences methods to estimate firms' response. We find that (i) while the impact of support on monetary investment in innovation is pro-cyclical, it is counter-cyclical in terms of the employee-time allocation to innovation activities; (ii) the additionality of a one-year treatment is smaller than that of a longer treatment. Direct public support may have thus prevented a decline of the firms' knowledge capital during the recession.

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

* *Acknowledgements*: We are indebted to Federica Di Giacomo, Pierre Mohnen, Pere Ortín, Bettina Peters, Amparo Sanchis and Agustí Segarra for their insightful comments to preliminary drafts of the paper. We thank three anonymous reviewers for their very helpful comments and suggestions, and to the editorial board of the SPRU working paper series. The authors acknowledge funding support from the Spanish Ministry of Economy and Competitiveness, project RTI2018-095799-B-I00 (Busom) and ECO2017-86305-C4-2-R (Velez-Ospina), as well as from Generalitat de Catalunya 2017SGR 207 (Busom) and FECYT.

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1 Introduction

The global economic and financial crisis that unleashed in 2008 had a globally negative impact on R&D and innovation. In the OECD member countries as a whole the growth rate of GDP fell by 3.5% in 2009, and business R&D investment dropped by 4.2%, while public expenditure -the sum of R&D expenditures by the government and higher education sectors- increased by 4.6% that same year (OECD-STI 2014). Over the period 1996-2012, gross expenditure in R&D has exhibited, at this aggregate level, a pro-cyclical behaviour. The correlation between the growth rates of GDP and of gross domestic R&D expenditure was positive, with a correlation coefficient of about +0.70. This mirrors mostly the behaviour of business intramural expenditure in R&D, since the correlation between the growth rates of GDP and of public R&D expenditure was negative across that same period, with a value of -0.34. This suggests a mildly counter-cyclical behaviour of public expenditure, which might have mitigated, in the aggregate, the potential threat to long-term growth derived from reduced business-financed R&D investment.[1]

A closer look at the data shows that investment in R&D took different paths in different countries both around 2008/9 and in the aftermath of the crisis. In many OECD countries, the rate of growth of business-financed R&D fell in 2008 and even more in 2009. Regarding public spending in R&D, a study by Pellens, Peters, Hud, Rammer, and Licht (2018) in a panel of twenty-six OECD countries over the period 1995-2015, finds that while on average public R&D behaved pro-cyclically in this period, in some countries it followed a counter-cyclical pattern. This disparate cross-country evolution is worrisome, as it may have implications for long term productivity growth and income level convergence (Veugelers 2016; Veugelers et al. 2017; Duval, Hong, and Timmer 2020; Ridder 2017). This prospect highlights the relevance of evaluating the ability of public support to induce more business effort in R&D and innovation over downturns. This involves investigating the stability of the additionality –multiplier effect- of direct public support. Higher additionality during recessions than in expansions would mean

[1]Correlations have been computed by the authors using OECD data from the Main Science and Technology Indicators, published in STI Outlook 2014, Chapter 1, Fig 1.4.

that reducing public support during the former would be more harmful to long-run growth. Conversely, small increases of public support during recessions would induce more private effort than in expansions. A counter-cyclical additionality effect might thus contribute to stabilize knowledge related activities in the private sector during the cycle, and hence justify a counter-cyclical public support policy.

Research on the effect of public support to R&D over time and across the business cycle is quite sparse. The studies that focus on the crisis years are Hud and Hussinger (2015), for German firms; Aristei, Sterlacchini, and Venturini (2017), for a sample of firms from five EU countries, and Cruz-Castro, Holl, Rama, and Sanz-Menéndez (2018) for Spanish firms. The results of the first two studies suggest that the additionality of R&D support has been pro-cyclical, while the third finds some evidence of the opposite in that it prevented recipients from abandoning innovation activities. The main limitation of these studies, however, is that the data used are, basically, cross-sectional or cover a very short period, thus conditioning the empirical methodology and scope of the analysis.

In this article, we contribute to expand and enrich existing empirical research by using firm-level panel data from Spain covering the period 2005 to 2014. Spain, one of the large members of the European Union, is a moderate innovator that experienced sharp public budget cuts after 2008. Up to 2007, business expenditure on R&D (BERD) was increasing at a high rate, converging to the euro-zone ratio of BERD with respect to GDP. The crisis broke this path, and only about eight years later business investment in R&D has started to grow again. At the same time, fiscal consolidation led to a reduction in public support to business-performed R&D. The percentage of BERD financed by the government reached a maximum of 17.9% in 2008, falling thereafter to about one-half this share by 2017.[2]

How damaging is the reduction of direct support to R&D? Our firm-level panel data allow us to address the following specific empirical questions: 1) Does firms' access to

[2]The evolution of GDP over the period 2006 to 2016 in Spain was similar to the average of the nineteen-euro zone countries, except that the recession period lasted longer, including years 2011 to 2013. Business R&D spending (BERD) followed a more negative path, experiencing a sharp decline during 2008 and 2009. The recovery started slowly after 2013. For further information, see CDTI Annual Report, 2016 and 2017.

support vary over the business cycle? 2) Does the impact of support remain constant in recessions and expansions? 3) Does public support affect two different measures of R&D activity -private R&D investment and R&D employment- similarly? And finally, 4) Are results sensitive to the length or frequency of participation, and how long do effects last? The first question intends to establish whether firms that benefit from public support in recessions differ from firms that benefit from it during expansions, as both firms and the public agency could change their behaviour over the cycle. The second question aims at determining whether the impact of public support is smaller in recessions than in expansions or otherwise. The third question intends to inquire beyond the standard expenditure effect of public support and look into the time allocation of employees to R&D activities. The last question explores some dynamic aspects of direct support, testing whether and how receiving support only once or more than once makes a difference in firms' response both in intensity and over time.

We employ a propensity score matching combined with difference-in-differences (conditional difference-in-differences, CDiD, J. Heckman, Ichimura, Smith, and Todd 1998), which allows us to address selection on both observables and unobservables associated with the allocation of R&D funding and firms' innovation decisions. We first compare firms' participation in public R&D across the phases of the business cycle. We define a treatment pattern here as the number of years a firm reports receiving a subsidy within a given period. We then identify several treatment patterns 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.

Our work expands and complements the analysis of direct support to business R&D during the crisis carried out by Hud and Hussinger (2015) and Aristei et al. (2017), as well as Cruz-Castro et al. (2018). The main findings are the following. First, the relationship between observed firm characteristics and the probability of obtaining support remains quite stable over the cycle. This precludes attributing impact differences to changes in the profile of recipients of subsidies. Second, the effect of public support 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 recession, 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 than pre-crisis. 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 recession. 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 –i.e., length or frequency of participation- the additionality effect 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 article is as follows. Section 2 provides an overview of research on the cyclical behaviour of R&D investment and the impact of R&D support during the last economic crisis. Section 3 describes the data. Section 4 describes the empirical strategy. Section 5 presents and discusses estimation results. Section 6 concludes.

2 R&D, business cycles and public support: evidence and hypotheses

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 on the specific case of the 2008 financial crisis. We then discuss the implications for direct support policies and their ex-post evaluation and highlight the research gaps that we intend to address here.

R&D investment over the business cycle.

Investment in intangibles and R&D investment in particular, is generally affected by financing constraints (Hall, Moncada-Paternò-Castello, Montresor, and Vezzani 2016). In addition, extensive firm-level empirical research provides strong evidence that business R&D investment is pro-cyclical on average, both at the aggregate and firm-level. This observed regularity would be the net outcome of two opposing mechanisms. On one hand, capital market imperfections and knowledge spillovers, jointly or separately, would drive the pro-cyclicality of business R&D investment as well as the introduction of product innovations. The former two factors would thus not only originate a well-known static market failure, but would also induce a dynamic misallocation of R&D investment over the cycle, with negative long-run consequences for productivity and growth. On the other hand, a competing and opposite hypothesis –known as the Schumpeterian view of recessions- is that the opportunity cost of productivity-enhancing investments (R&D), relative to standard physical capital investment, falls during recessions, thus providing an incentive to increase these activities, which would then exhibit a countercyclical behaviour. Each of these hypotheses may lead to different policy implications. The first would suggest that increasing public support in recessions would be beneficial for growth; if instead the second hypothesis prevailed, there would be no need for a countercyclical R&D support policy.

Contributions by Barlevy (2007); Aghion, Angeletos, Banerjee, and Manova (2010); Aghion, Askenazy, Berman, Cette, and Eymard (2012) and Fabrizio and Tsolmon (2014) illuminate this issue. Barlevy (2007) develops a theoretical model where knowledge spillovers, and the ensuing lack of appropriability, explain the pro-cyclical behaviour 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 the absence of financial constraints. Fabrizio and Tsolmon (2014) test Barlevy's hypothesis using a Compustat panel data set of 7,754 public US firms from 1975 to 2002. R&D investments and patented innovations turn out to be strongly pro-cyclical, especially in industries with weaker IP protection. Aghion et al. (2010) develop a model that shows that when capital markets are perfect the composition of investment –long term versus short term- is determined by their opportunity-cost, and the fraction of long-term investment over total investment is countercyclical. This prediction is reversed, however, when credit constraints are tight. They find empirical support for the model's predictions using a panel of 21 OECD countries. In Aghion et al. (2012), using a large French firm-level data set during the period 1993-2004, they find evidence that indeed R&D investment is countercyclical without credit constraints, becoming 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. In addition, for more credit-constrained firms, R&D investment drops during recessions but does not increase proportionally during upturns. The bottom line of these contributions is that capital market imperfections and lack of, or limited, appropriability will induce both a static and a dynamic market failure when it comes to investing in R&D. The question is then whether direct public support would reduce this failure.

Previous empirical evidence in the case of Spain shows similar results. 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 investment in intangibles, including R&D, to be pro-cyclical for financially constrained firms. These are typically young and small firms as well as firms in medium-high technological intensity industries. Beneito, Rochina-Barrachina, and Sanchis-Llopis (2015) obtain similar results when analysing a large sample of Spanish manufacturing firms during the period 1990–2006.

The 2008 recession

The 2008 crisis has prompted research on the behaviour of business R&D in different countries. Results show quite generally a pro-cyclical reaction, although there are some differences across firm size, R&D intensity, competitive environment and type of innovation. Cincera, Cozza, Tübke, and Voigt (2012) analyse 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. Firm size is also found to matter, in a non-linear way, with investment falling with size up to a certain level, and then increasing with size. Similarly, Paunov (2012) finds that the crisis led many Latin-American firms to stop innovation projects. Peters et al. (2014) use a large data set 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 EU member states to describe the behaviour of several R&D and innovation indicators over the business cycle.[3] They find 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 different reactions depending on the 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. Archibugi, Filippetti, and Frenz (2013), analyse data from the European Innobarometer Survey 2009, and conclude that while before the crisis, incumbent enterprises were expanding their innovation investment, while just after the crisis innovation investment was driven by a number of small enterprises and new entrants. Arvanitis and Woerter (2013) find some heterogeneity in the response of Swiss manufacturing firms to the crisis, depending on firm size, R&D intensity and (lack of) price competition. Giebel and Kraft (2015) study German manufacturing firms during the period 2004-2011, and find that innovative firms using external sources to finance investment reduce their capital expenditures during the financial crisis more than innovative but not dependent on external finance firms, or even than non-innovative firms.[4] Knudsen and Lien (2014) compare changes in investment in physical assets, R&D and human capital during recessions in a large sample of Norwegian firms, finding that R&D investment was more sensitive to credit shocks, while investment in physical assets was more sensitive to demand shocks. All this evidence points basically in the same direction.

Regarding Spain, two studies focus on the effects of the 2008 crisis on R&D and innovation investment. Garicano and Steinwender (2016) distinguish between two types of shocks: credit shocks and demand shocks, on two types of investments, depending on

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

[4]It is also interesting to note that not only R&D behaves on average pro-cyclically, but there is evidence that the adoption of new technologies also does (Anzoategui, Comin, Gertler, and Martinez 2019).

their short or long time to payoff. They find that, over the period 2003 to 2010, credit shocks reduce the value of long term investments of manufacturing firms more than demand shocks, and more than investments with a shorter time to payoff. That is, with credit shocks, firms would be concerned about surviving in the short term, foregoing uncertain expected profits in the long run. This would imply that the 2008 credit crunch affected more severely R&D investments. Finally, Salas-Fumás and Ortiz (2019), using Spanish CIS data over the period 2003 to 2014, find that firms' perceptions of the credit crunch, as well as the demand shock, contributed to a fall in the proportion of firms introducing innovations during the recession, and increased the proportion of firms abandoning ongoing innovation projects. We can thus conclude that the behaviour of firms during the 2008 crisis was quite similar across countries, even if it was not uniform across firms.

Additionality of direct public support and the business cycle.

All this body of evidence raises a policy question: would it be possible for a counter-cyclical direct public support to R&D to mitigate the dynamic failures predicted by the models described above? To the best of our knowledge, this question has not been thoroughly investigated.[5] The answer hinges on the sign and size of the additionality effect during recessions relative to expansions.[6] Only a small number of firm-level studies focus on the effects of public support during the financial crisis years: Hud and Hussinger

[5]Previous firm-level studies investigate whether direct public support –through grants and/or loans- crowds out private investment, or whether on the contrary it leverages private effort, that is, input additionality. Many use matching methods, such as propensity score, to estimate input and output treatment effects. The literature is quite extensive, but mostly focuses on static, immediate effects. For recent surveys on existing research see Becker 2015; Dimos and Pugh 2016; Zúñiga-Vicente, Alonso-Borrego, Forcadell, and Galán 2014)

[6]The magnitude and sign of public spending multipliers over the business cycle have been investigated mostly at the macroeconomic level. Whether the fiscal multiplier is pro-cyclical is a controversial issue. For example, Auerbach and Gorodnichenko (2012) find that in the US the average government spending multiplier is higher during recessions than during expansions. Canzoneri, Collard, Dellas, and Diba (2016) corroborate 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. Recently, Ramey and Zubairy (2018) obtain nuanced results. In view of these findings, we would expect the multiplier of direct support to R&D to vary over the cycle and possibly across countries, reflecting institutional features, industry composition and size distribution of firms.

(2015), Aristei et al. (2017)), and, in the case of Spain, Cruz-Castro et al. (2018). Hud and Hussinger (2015) use German SMEs firm-level data for 2006 to 2010 to estimate the overall treatment effect on the treated (ATT) of public support recipients. They find that it is positive, and therefore reject crowding out. They also investigate whether the ATT changes over time, regressing the estimated treatment effect on a set of time dummies, and find that the average treatment effect was significantly lower and even negative in 2009, when GDP fell in Germany, than in 2006. The estimated magnitudes suggest that in 2009 firms changed their investment choices producing a crowding-out effect (op. cit., pg 1852). Their research is limited, however, by the fact that their panel of firms is highly unbalanced, affecting the applicable empirical methodology. Aristei et al. (2017) estimate and 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, they do not find evidence of significant additionality in any of the five countries, including Germany, as in Hud and Hussinger (2015).[7] The main limitation is that the data used in their study are cross-sectional, and treatment effects for each year for a given country cannot be identified and thus compared across the cycle. Taken together these results suggest that the additionality of R&D support has been pro-cyclical. Cruz-Castro et al. (2018) use a panel of Spanish CIS firms in 2008 and in 2012 to analyse whether recipients of regional direct support to R&D were less likely to discontinue R&D activities in 2012 (during the crisis) than in 2008. They find that regional support allowed firms' R&D activities that would have been otherwise cutback. This is a form of positive additionality during the recession.

A final issue that has been relatively neglected in the literature are the dynamic effects of direct subsidies: effects may not be immediate; they can also be temporary or long-lasting. The evidence so far is disparate. 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-Castells (2013), find that in Spain one-shot subsidies

[7]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/.

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 timing of the effects of R&D subsidies granted in the period 2002 to 2007 to Finnish SMEs on labour productivity, employment and human capital up to five years after a subsidy is granted, find that effects are often significant one and two years after treatment. They study an expansionary period, so the open question is whether effects are similar during a recession.

Our research analyses in a comprehensive way the effects of public support during an expansion and during a recession, as well as the dynamic effects of this support on R&D investment and on the allocation of employee time to R&D activities. Furthermore, we take into account the duration or frequency of support, offering novel insights. The use of a large balanced panel of firms allows us to use empirical methods to deal with selection both on observable and on unobservable factors, and to estimate dynamic impacts over the cycle. In particular, we test the following hypotheses. Hypothesis 1: The strong financial component of the crisis would make innovating, credit-constrained firms more likely to apply for and obtain direct support. Hypothesis 2: The additionality effect of support on privately financed R&D investment is likely to be lower during recessions than in expansions because of reduced availability of both internal and external funds. Hypothesis 3: Access to public support is likely to allow innovators to hoard their skilled workers in times of crisis. Because it takes time to build skilled teams to perform R&D and innovation, and this human capital is likely to be firm-specific, supported firms are more likely to increase the time allocation of R&D activities (Bloom, Romer, Terry, and Van Reenen 2013). Thus, public support would have a positive additionality effect in the allocation of skilled employees to knowledge-generating activities, even if monetary investment does not increase significantly. Hypothesis 4: The effect of a one-shot subsidy is likely to be smaller than longer treatment patterns because the scope and nature of the innovation projects in the first case are likely to be limited.

3 Data

The Spanish government provides support to business R&D since the mid-80's through two types of programs: direct support –subsidies and loans– and indirect support through tax incentives. Regional governments and the European Union also provide direct support, but national funding is largely the most important source. Most direct national support is channelled 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, depending on the nature of projects. The policy has been overall quite stable in terms of programs and eligibility criteria, except for two changes that took place in 2008. That year some programs were reclassified in order to comply with EU regulations on state aids, and in addition, from then on the cost of physical assets (instruments and equipment) is no longer eligible for funding. These adjustments lead to a drop of CDTI's committed funds for direct support that year. Direct support had expanded significantly from 2002 to 2007, almost tripling in nominal terms and reaching €1311M in 2007.[8] It fell by about 24% in 2008, but increased almost to the 2007 level from 2009 to 2011, in an explicit government effort to help innovative firms weather the crisis. This effort could not be sustained, however, and from 2012 to 2014 the volume of direct funding oscillated between €780M and €843M. Regional government funding also experienced a significant contraction in this period (Cruz-Castro et al. 2018). There was, thus, an overall reduced supply of funds from 2012 on.

We use annual firm-level data from the Spanish Technological Innovation Panel (PITEC), produced by the National Statistical Institute (INE) and 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 barri-

[8]Spain also provides indirect support to R&D through tax incentives. Up to the crisis, the volume of grants and loans was higher than indirect support (Busom, Corchuelo, and Martínez-Ros (2017)). According to the OECD, however, this changed during the crisis years and beyond: the share of R&D tax incentives as a percentage of total support was about 25% in 2006, but it increased as direct support suffered severe cuts. See OECD, R&D Tax Incentive Indicators, http://oe.cd/rdtax, July 2017 and OECD STI Scoreboard 2017.

ers to innovation, along with sales volume, human capital and firm's age. In this study we essentially focus on SMEs (firms with less than 200 employees).[9] The bulk of firms in the economy are SMEs. They tend to be more sensitive than large firms to credit supply (Mach and Wolken, 2011; Artola and Genre, 2011; Schmitz, 2018). In addition, a major goal of public support programs is to engage SMEs in R&D and innovation activities. In the case of CDTI, between 73% to 87% of the projects approved were carried out by SMEs; their share in total CDTI funding oscillated between 63% and 76% in the period 2005 to 2015.

From the original PITEC unbalanced panel we obtain a balanced panel of 9,339 firms that includes all SMEs that stay in the sample for the whole 10 year period. This allows us to eliminate spurious differences induced by changes in the composition of the sample.[10] 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).[11] We impose three more filters. First, we drop firms that experienced a merger or takeover process, as well as drastic employment incidents. Second, we eliminate observations with extreme values or zero sales. Finally, we also exclude from the analysis primary and construction sectors. The final balanced panel includes 3,356 SMEs.[12] All monetary variables are expressed in constant values at 2010 prices.[13] The time span encompasses the expansion

[9]We decide to use 200 as the size threshold to be in correspondence to the sampling frame used by PITEC, which comprises four sub-samples: i) firms with 200 employees or more; ii) firms of any size with intramural R&D expenditures. The remaining sample is representative of firms with fewer than 200 but more than 10 employees: it includes firms reporting external but no intramural R&D expenditures, as well as firms with no innovation expenditure at all. We can also obtain a balanced panel of 1,169 large firms (62% of the unbalanced panel) and replicate the same analysis as for SMEs. An important limitation for the sample of large firms, however, is the difficulty to find a satisfactory sample of untreated counterfactuals to allow for reliable inference. We report very tentative results in section 5.4.

[10]One implication of this restriction is the possible survivorship bias. Unfortunately, we are unable to control for this potential source of bias. In particular, from the data we cannot distinguish a firm for which data are missing and a firm that closes down. In an attempt to assess whether this might affect our results we also carry out estimations using the unbalanced panel.

[11]This corresponds to 8,007 innovative firms.

[12]The balanced panel sample of SMEs represents 53% of firms in the unbalanced SMEs panel.

[13]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

period (2005-2008), the recession years (2009-2012) and the modest beginning of the recovery (2013-2014). Since there is some uncertainty about classifying the whole year 2013 as crisis or beginning of recovery year, we later check the robustness of results under the alternative classification.

Our empirical analysis will focus on the effect of total direct public support (loans and direct subsidies) from central and regional governments.[14] 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 both central and regional agencies, which may not always coincide.

We first focus on the analysis of SMEs, and refer to large firms in section 5.4. Table 1 shows that the number of SMEs investing in innovation in the balanced panel decreased steadily since 2005. Innovation expenditures are defined in the CIS as those that aim at developing and introducing innovations that are new to the firm or to the market. They include investment in R&D, which is quantitatively the most important of these expenditures. 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.

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the description and results of the empirical analysis should be interpreted with some caution. Tables A1.1 and A1.2 provide the definitions of the variables used and summary statistics respectively.

[14] In Spain, the main users and beneficiaries of R&D tax incentives are large firms. Busom, Corchuelo, and Martínez-Ros (2014) find that in the case of financially constrained manufacturing SMEs are more likely to turn to direct support. The database we use, PITEC, does not include information on the use of tax incentives, so we are unable to investigate how the crisis affected the use of tax incentives.

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.

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 to a project, 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. Table 2 shows that about 55% of firms in the balanced panel received public support at some point (this corresponds to 1,844 firms out of 3,362 firms in the total sample), 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 2: Frequency of participation over the years. SMEs

	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	1,844	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 both investment in 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.

4 Empirical Strategy

Several factors may induce a different response of firms to direct R&D support over the business cycle. One is that the nature of applicants may change because 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 might be more sensitive to a tightening than to an expansion of credit. SMEs especially may cut down long-term investments in recessions characterized by a credit squeeze faster and more intensely than they can increase them 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 treatment patterns and estimate the impact of public support before, during and after the crisis conditional on a given pattern.

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 μ_i allows firms who are homogenous in their observed characteristics to be heterogeneous in unobserved permanent features. The model is the following:

$$s_i^* = \alpha_{10}s_{i,t-1} + \beta_{10}x_{i,t-1} + \eta_i + u_{i,t} \tag{1}$$

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 1978's 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 is:

$$s_i^* = \alpha_{11} + \alpha_{10}s_{i,t-1} + \alpha_{21}s_{i0} + \beta_{10}x_{i,t-1} + \alpha_{31}\bar{z}_i + v_{i,t} \tag{3}$$

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 them. 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, the ratio of R&D researchers over employment, cooperation for innovation activities, continuous R&D performers 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. All variables are lagged one period. Finally, industry dummies are included to control for sector heterogeneity. All variables are defined in Table A1.1 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 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 labour 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.[15]

Direct support is received by firms at different points in time. Effects may last more than one period, and vary over time depending on the business cycle phase at the time when support is granted. Thinking in terms of the design of an ideal experiment, the key issue to obtain the counterfactual is defining the appropriate control group for treated firms at the time of treatment. 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.

[15]For a recent example of the use of matching methods to public suport to R&D and innovation from a static perspective, see Czarnitzki and Hussinger (2018).

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 $S_{i,t} = \{0, 1\}$[16]. 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

[16] 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.

naive comparison between supported and unsupported firms because it might be the 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.[17] 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 modelling 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)[18]. Using the matched sample already makes supported and control firms more similar than an unmatched sample of firms would be. In our case we use nearest neighbour matching. The estimation model is,

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

The model includes two main effects: first, it assumes that there is an individual

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

[18]This method has been implemented by many authors in other empirical areas: J. Heckman et al. (1998); Smith and Todd (2005)

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 term $D_{i,t}$, the same as in equation 6, where $(S_{i,t} \cdot d_t) = D_{i,t+\delta}$. A vector of firm time-varying covariates is represented by $X_{i,t}$. 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. 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.[19] 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; while $\tau > 0$ may imply either crowding-in or partial crowding out, because not knowing the amount of the subsidy we cannot identify the effect on net private investment. When the outcome is 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

We estimate a dynamic probit model for each of the three distinct phases of the cycle. The dependent variable takes the value one if the firm has received public funding, and zero otherwise. Table 4 shows the marginal effects, calculated at the average value. 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_{it-1}) in order to control for observed heterogeneity. Columns

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

2, 5, and 8 report results using Mundlak's specification, and columns 3, 6 and 9 show estimates of pooled probit models. 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 overestimate persistence, as expected.[20] 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: conditional on firm-level observed and unobserved heterogeneity, a firm participating in $t-1$ has a probability of receiving funding which is approximately 30 PP higher than that of unsubsidised firms before the crisis (2005-2008), while the same probability lowers to 27 PP (2009-2012) and 22 PP (2013-2015). We interpret this as an indicator that the probability to obtain support of 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 recession. 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, continuous R&D performers, cooperation, and domestic ownership remains positive and stable throughout the cycle. We also find that continuous R&D performers are more likely to participate

[20] 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.

throughout the cycle, and marginal effects are slightly higher during the crisis. Another interesting finding is that the sign of the innovation effort is the opposite of that of the corresponding time-averaged variable. In particular, the level of innovation effort is negatively correlated with the probability of participating. However, the time-average values of the level of innovation effort show a positive and significant impact on the probability of getting support. This result could be an indication that previous R&D effort decreases the likelihood of receiving support; however, in the long-run firms investing heavily in R&D have a larger probability of receiving funding. Finally, firms from high-tech services are more likely to participate during the recession and recovery.[21] From these results we conclude that there is no evidence that changes in the impact of support on firms' innovation investment could be attributed to changes in the joint outcome of firms' application decision and the public agency's selection rule. This concurs with Hud and Hussinger 2015's results for Germany.

[21]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. We report results of this robustness exercise in section 5.3, and provide the corresponding tables as Supplementary Material.

Table 4: Participation. Dynamic Probit Estimations (Marginal Effects)

	Period 1: 2005-2008			Period 2: 2009-2012			Period 3: 2013-2015[a]		
	Woold1	Woold2	Pool	Woold1	Woold2	Pool	Woold1	Woold2	Pool
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Public support ($t-1$)	0.120***	0.173***	0.296***	0.231***	0.237***	0.268***	0.212***	0.206***	0.225***
	(0.012)	(0.015)	(0.005)	(0.009)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Public support (t_0)	0.125***	0.102***		0.102***	0.067***		0.050***	0.048***	
	(0.011)	(0.013)		(0.013)	(0.006)		(0.006)	(0.006)	
Sales growth (log dif)	0.007	0.003	0.012	0.003	-0.003	0.003	0.008	0.004	0.008
	(0.010)	(0.011)	(0.012)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
External Funding ($t-1$)	0.017**	0.0214**	0.019**	0.008	-0.002	0.010	-0.002	0.005	0.000
	(0.007)	(0.009)	(0.007)	(0.006)	(0.008)	(0.006)	(0.006)	(0.009)	(0.006)
Demand Uncertainty ($t-1$)	0.000	0.001	0.002	0.007	0.007	0.005	-0.007	-0.004	-0.007
	(0.007)	(0.011)	(0.008)	(0.006)	(0.009)	(0.006)	(0.006)	(0.009)	(0.006)
Continuous R&D performer ($t-1$)	0.108***	0.064***	0.116***	0.110***	0.067***	0.109***	0.095***	0.054***	0.095***
	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
R&D employees ($t-1$)	0.076***	0.0285	0.081**	0.052**	0.010	0.052*	0.012	-0.017	0.022
	(0.028)	(0.029)	(0.030)	(0.023)	(0.023)	(0.023)	(0.020)	(0.020)	(0.020)
Higher education ($t-1$)	0.077***	0.0416**	0.088***	0.037***	0.020*	0.052***	0.036***	0.024**	0.048***
	(0.015)	(0.016)	(0.017)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
IP Protect ($t-1$)	-0.001	-0.006	-0.003	-0.002	-0.007	-0.004	0.003	0.000	0.002
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Cooperation ($t-1$)	0.057***	0.056***	0.071***	0.052***	0.045***	0.057***	0.037***	0.033***	0.040***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Size $x \leq 20$ ($t-1$)	-0.034***	-0.051***	-0.035**	-0.029***	-0.041***	-0.026**	-0.019*	-0.020**	-0.019
	(0.012)	(0.012)	(0.012)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Size $20 < x \leq 50$ ($t-1$)	-0.016	-0.026*	-0.014	-0.013	-0.022**	-0.009	-0.009	-0.009	-0.006
	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Size $50 < x \leq 100$ ($t-1$)	-0.009	-0.010	-0.006	0.003	-0.003	0.006	-0.001	0.000	0.001
	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)

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Table 4 – Continued

	Period 1: 2005-2008			Period 2: 2009-2012			Period 3: 2013-2015[a]		
	Woold1	Woold2	Pool	Woold1	Woold2	Pool	Woold1	Woold2	Pool
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Group ($t-1$)	-0.004	-0.010	-0.003	-0.002	-0.003	-0.001	0.004	-0.002	0.004
	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Foreign ($t-1$)	-0.031*	-0.036**	-0.040**	-0.055***	-0.054***	-0.059***	-0.042***	-0.041***	-0.044***
	(0.014)	(0.015)	(0.015)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Export ($t-1$)	0.004	-0.003	0.003	-0.001	-0.004	-0.003	-0.003	-0.008	-0.004
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)
Young	0.014*	0.011	0.017	0.009	0.008	0.013	-0.041	-0.043	-0.046
	(0.008)	(0.008)	(0.009)	(0.010)	(0.009)	(0.010)	(0.029)	(0.029)	(0.030)
High tech Manufac.	-0.012	-0.029	-0.015	-0.007	-0.021*	-0.006	-0.010	-0.019	-0.009
	(0.015)	(0.015)	(0.016)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Medium tech Manufac	0.005	-0.004	0.003	-0.003	-0.011	-0.005	0.000	-0.004	0.000
	(0.009)	(0.009)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
High-tech services	0.009	0.004	0.009	0.030***	0.021**	0.032**	0.002	-0.001	0.004
	(0.013)	(0.013)	(0.013)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Rest Services	-0.007	-0.001	-0.006	0.012	0.012	0.012	0.002	0.001	0.004
	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
UE support ($t-1$)	0.063***	0.060***	0.078***	0.074***	0.062***	0.084***	0.040***	0.033***	0.046***
	(0.016)	(0.017)	(0.018)	(0.014)	(0.013)	(0.013)	(0.011)	(0.010)	(0.010)
Innovation intensity ($t-1$)	0.006***	-0.013***	0.006**	0.002	-0.011***	0.003*	0.002	-0.008***	0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
M_Innovation intensity		0.043***			0.031***			0.021***	
		(0.002)			(0.002)			(0.002)	
M_External funding		-0.011			0.016			-0.010	
		(0.013)			(0.010)			(0.010)	
M_Demand Uncertainty		0.001			0.001			-0.001	
		(0.013)			(0.011)			(0.011)	
Log likelihood	-3261.115	-3112.0599	-3321.7829	-3861.909	-37206.206	-3943.527	-2302.0221	-2225.6514	-2339.3505

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Table 4 – Continued

	Period 1: 2005-2008			Period 2: 2009-2012			Period 3: 2013-2015[a]		
	Woold1	Woold2	Pool	Woold1	Woold2	Pool	Woold1	Woold2	Pool
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
lnsig2u	-0.678***	-1.559***		-3.092***	-11,788		-13,119	-12.92	
	(0.189)	(0.368)		(0.820)	(9.624)		(12.773)	(9.820)	
Sigma u	0.712***	0.458***		0.213***	0.003		0.001	0.002	
	(0.067)	(0.084)		(0.087)	(0.013)		(0.009)	(0.008)	
Rho	0.336***	0.174***		0.043	0.000		0.000	0.000	
	(0.042)	(0.053)		(0.034)	(0.000)		(0.000)	(0.000)	
Wald Chi2	1854.72***	2172.49***	3141.75***	3911.87***	4060.95***	4284.65***	2731.33***	2600.35***	2339.35***
N	9,620	9,620	9,620	12,826	12,826	12,826	9,616	9,616	9,616
Firms	3,207	3,207	3,207	3,207	3,207	3,207	3,207	3,207	3,207

Marginal effects at the average value; Standard errors calculated using delta method (in parentheses). In columns (1) and (2) the integration method is mvaghermite using eight quadrature points; Time dummies included in all specifications. M_ denotes the within mean of the corresponding variable, from year 1 to year T. Initial values differ for each period. Reference category for size is $100 < x \leq 200$.
[a]Note that 2015 has been included to carry out the estimation of this period. The accuracy of the results has been checked using 12 and 16 quadrature points. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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	0.256
Period 2: 2009-2012	0.374
Period 3: 2013-2015	0.368

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

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 in Table 4.[22] 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.

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 treatment patterns or histories. The basic idea of the treatment pattern is intuitive: a time window during which the firms may have received funding. We proceed as follows. First, we divide the 2005-2014 period into three sub-periods or time-windows, according to the evolution of GDP growth as shown in Figure ??: 2006-2008; 2009-2012 and 2013-14. We then 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. Next, we focus on four treatment patterns that last one and two years within each time window (see table 6 below). Finally, since we do not know the firm's participation history before 2005, we 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.[23]

[22] The probability is estimated as follows: $Prob(s_{i,t}|s_{i,t-1}, \eta_i, x_{i,t}) = prob(\frac{u_{i,t}}{\sigma_u} > \frac{-\alpha_{10}s_{i,t-1} - \eta_i - x_{i,t}\beta}{\sigma_u}) = \Phi(z_{i,t})$ where $z_{i,t} = -(\frac{-\alpha_{10}s_{i,t-1} - \eta_i - x_{i,t}\beta}{\sigma_u})$ as suggested by J. J. Heckman (1981)

[23] The size of the sample of large firms in the balanced panel allows us to estimate a dynamic random effects model for receiving direct support 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. Unlike SMEs, however, for large we do not find evidence that the probability of participation was correlated with lack of access to external funding. We report results in section 5.4.

We match firms treated at a given point in time with controls –firms that never participate- through the nearest neighbour 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 pattern and firms that never participate. For the crisis period the propensity score is estimated with data for 2008.[24] Table 6 shows the patterns studied, the number of treated firms in each pattern, and the number of potential controls.[25]

Table 6: Treatment patterns. SMEs

Treatment pattern	Treatment Condition	Number of treated Firms	Number of Controls
	Expansion		
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
	Recession		
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

Note: The sample includes firms that invest in innovation at least one year during the period in the balanced panel for the period 2005-2014. Note that treated firms in this table are not the same as those in Table 2, because firms that had received funding in 2005 were dropped.

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 pattern. Before matching there are significant differences between treated and non-treated firms, especially with respect to employees with higher education, firm age, support from UE and innovation intensity in $t-1$. After matching, differences are no longer significant, and the mean bias drops significantly. The quality of the match after discarding some observations is

[24] Yearly cross-sectional estimates of participation probabilities are available upon request.
[25] We cannot analyse all patterns because the number of treated firms is too small in some cases.

high. Overall, we can safely conclude that balancing is satisfactory.[26]

We next estimate the model specified in equation [7] for each of the treatment patterns on Table 6 and each of the two outcomes of interest.[27] We estimate four versions of this equation: 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 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).[28] Tables A1.2 and A1.3 in the Appendix report the estimated value of the treatment effect every year since participation for firms exhibiting each treatment pattern. 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 1 below displays estimated treatment effects for the treated over time when the outcome is the number of employees allocated to R&D activities in FTE (Table A1.3), by estimation method. It shows that while all methods produce similar estimates of effects of support in the period 2006-2008 when firms participate twice, DiD and DiD-weighted tend to overestimate effects relative to the other two methods when firms participate only once in the period. This suggests that adding matching or controls to DiD provide a more adequate control group. Effect estimates during the expansion exhibit an inverse U-shaped pattern for the next 3 to 4 years, drop to 0, and then have again a positive but weaker effect thereafter. During the recession DiD and DiD-weighted also seem to overestimate treatment effects. However, during the recession, estimated treatment effects are positive.

[26]The distribution of the propensity-score for treated and control firms before and after matching is figure A1.1

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

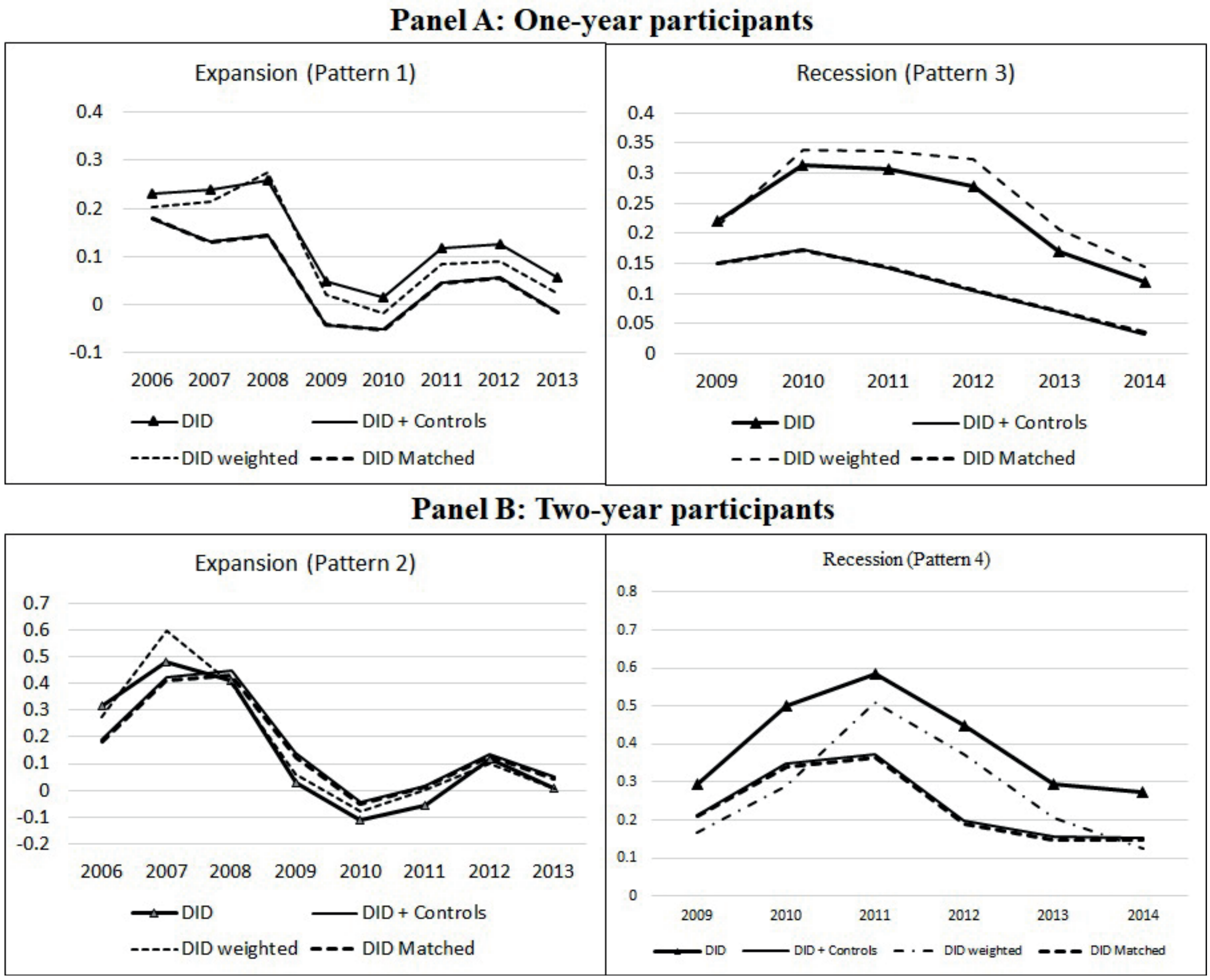
[28]Weighting observations by their inverse probability of treatment was proposed by Hirano and Imbens (2001). In this case firms that participate in the program are given weight of $1/p$ and those that did not are weighted by a factor equal to $1/(1-p)$, where p is the estimated probability of being 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.

Table 7: Difference in covariates before and after matching (t-statistic). SMEs

	Treatment pattern											
	(1) Expansion 1 year			(2) Expansion 2 years			(3) Recession 1 year			(4) Recession 2 years		
	Treated (N=119)	Control (N=1512)		Treated (N=40)	Control (N=1512)		Treated (N=117)	Control (N=1512)		Treated (N=62)	Control (N=1512)	
		UM	M		UM	M		UM	M		UM	M
Sales growth	0.63	0.64	0.67	0.68	0.64	0.68	0.43	0.41	0.39	0.37	0.41	0.44
O. External funding	0.33	0.25*	0.39	0.25	0.25	0.23	0.27	0.25	0.24	0.23	0.25	0.19
O. Demand Uncertainty	0.19	0.19	0.18	0.25	0.19	0.15	0.21	0.2	0.25	0.23	0.2	0.23
Continuous R&D performer	0.61	0.49**	0.58	0.75	0.49***	0.73	0.44	0.43	0.4	0.45	0.43	0.37
R&D employees	0.04	0.04	0.04	0.05	0.04	0.06	0.03	0.03	0.04	0.04	0.03	0.06
Higher education	0.25	0.23	0.24	0.35	0.23***	0.38	0.25	0.23	0.24	0.26	0.23	0.3
IP protect	0.37	0.33	0.34	0.35	0.33	0.43	0.32	0.25	0.31	0.26	0.25	0.18
Cooperation	0.32	0.22**	0.27	0.33	0.22	0.4	0.21	0.17	0.22	0.24	0.17	0.21
Size. x20	0.27	0.27	0.24	0.33	0.27	0.38	0.21	0.25	0.21	0.27	0.25	0.32
Size 20x50	0.32	0.33	0.34	0.38	0.33	0.35	0.33	0.33	0.35	0.37	0.33	0.39
Size 50x100	0.29	0.25	0.28	0.25	0.25	0.28	0.31	0.24*	0.24	0.18	0.24	0.11
Group membership	0.2	0.26	0.2	0.3	0.26	0.33	0.26	0.28	0.24	0.18	0.28*	0.15
Foreign Ownership	0.08	0.09	0.08	0.1	0.09	0.13	0.07	0.1	0.06	0.06	0.1	0.02
Export	0.77	0.71	0.86	0.65	0.71	0.7	0.79	0.71**	0.86	0.73	0.71	0.61
young	0.23	0.17*	0.24	0.38	0.17***	0.4	0.12	0.12	0.09	0.15	0.12	0.19
High tech Manufac.	0.08	0.04	0.04	0.08	0.04	0.08	0.05	0.04	0.03	0.1	0.04**	0.06
Medium tech Manufac.	0.27	0.27	0.37	0.35	0.27	0.28	0.25	0.27	0.25	0.35	0.27	0.32
High-tech services	0.1	0.09	0.12	0.1	0.09	0.15	0.09	0.09	0.06	0.06	0.09	0.08
Other Services	0.14	0.2	0.12	0.15	0.2	0.15	0.19	0.2	0.21	0.18	0.2	0.24
UE support	0.03	0.01*	0.03	0	0.01	0	0.02	0.01	0.01	0.02	0.01	0
Innovation intensity	7.36	6.83*	6.85	7.51	6.83	7.49	6.25	5.91	6.73	5.47	5.91	5.4
Mean Bias		9.7	8.1		16.3	8.6		7.3	7		11.8	10.1
LR Chi2		27.9	11.89		40.72***	9.97		17.64	13.05		22.46	8.66

Notes: UM= Unmatched sample; M=Matched sample; [a] none of the treated firms received EU support in 2005; Innovation intensity in logs; significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$; LR Chi2: Joint significance test. Note that all these covariates are used in the dynamic probit estimation shown in Table 4.

Figure 1: Evolution of estimated Average Treatment Effects on the treated (ATT) for different participation patterns: 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. Treatment patterns are as described in Table 4, and estimates are reported in Table A1.2

Our preferred estimates are those obtained with DiD combined with 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 A1.2 for detailed results for treatment patterns 1 and 3 respectively). In fact, we do not find significant effects during the recession. Although we can reject full crowding out for one-year participants before the crisis, we cannot reject it during the downturn, in line with the results found by Hud and Hussinger (2015). However, for firms that participate twice –we now compare treatment pattern 2 to treatment pattern 4- we find that treatment effects might have been significant and last longer during the recession years.[29]

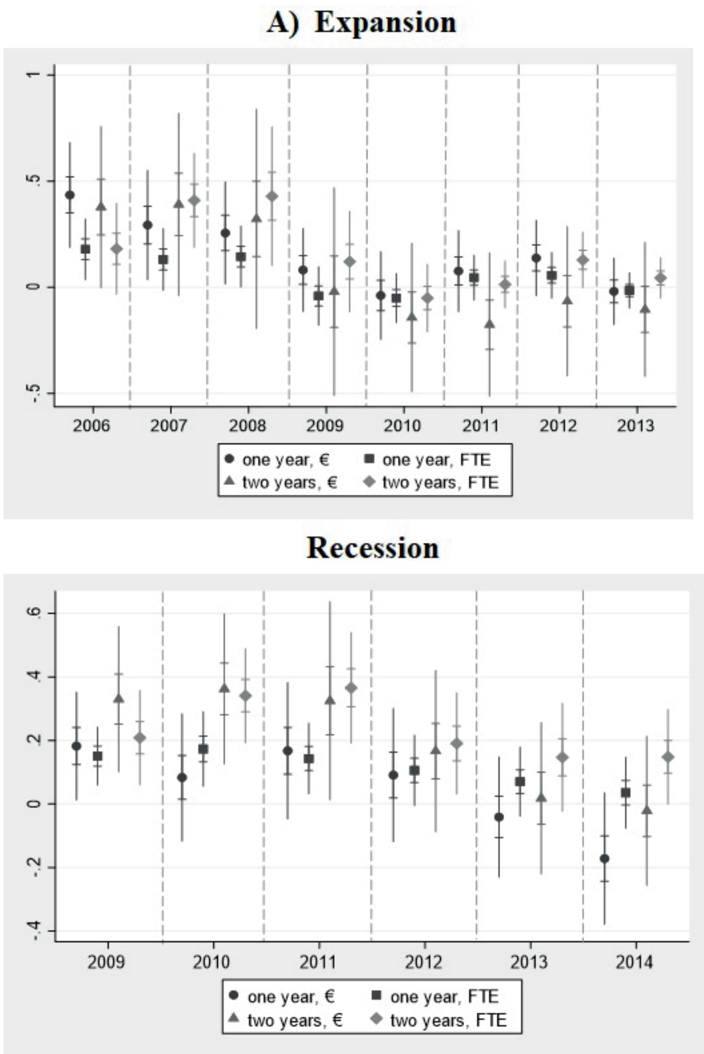
When we examine treatment effects on the allocation of human capital to innovation activities –R&D employees in full-time equivalent- we find that, according to the DiD+Matching estimation, treatment effects are somewhat higher and last longer during the recession years, suggesting a counter-cyclical behaviour whether firms participate one year or two years (see Table A1.2). Figure 2 illustrates the differences of estimated treatment effects during expansion and recession years for two outcomes (total innovation investment per employee and human resources allocated to innovation, in FTE) and two treatment patterns.

Our results 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 recession 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. 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 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.[30]

[29]Note that 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.

[30]It is possible that the firms that received public support during the recession were those firms willing to take the risk of acting counter-cyclical and increasing R&D. However, in absence of information on whether a firm applied for support, rather than just obtained support, we cannot investigate the impact the recession may have had on application behaviour. From annual CDTI reports, we just know that the total number of applications kept increasing from 2005 to 2013.

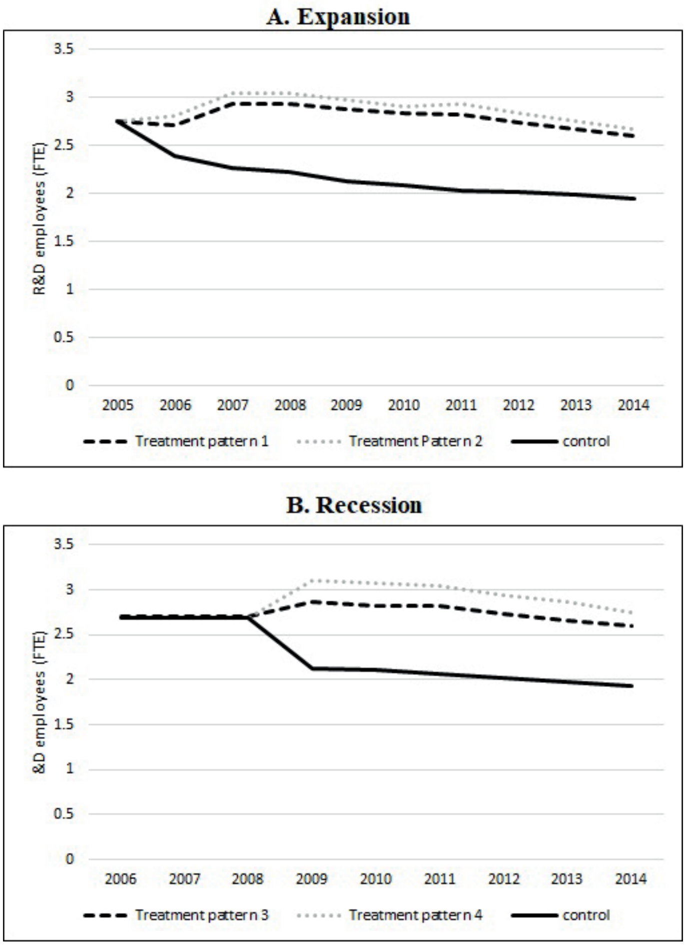
Figure 2: Estimated treatment effects before and during the crisis



Notes: Graph shows point estimates and capped spikes show confidence intervals from tables A1.2 (investment per employee) and A1.3 (R&D personnel in FTE) (column 4: DiD+Matching).

Figure 3, which is based on the last column of Table A1.4, shows the intensity of the yearly treatment effect of an average firm and compares it with the counterfactual of no treatment. These effects are obtained from the predicted number of R&D FTE employees for the different treatment patterns. Overall, differences in R&D person between treated and control firms are sizeable after the treatment. Three clear insights can be drawn. First, in the absence of the subsidy, the average firm allocates less employee time to R&D activities. For control firms, the level of R&D FTE employees started just above 2.5 FTE employees and remained below two FTE employees in years 9 and 10. Second, the effects of different patterns exhibit a similar trend across expansion and recession years. For the average treated firm, FTE employees start from just above 2.5 employees, and increase up to years 4 (panel A) and 2 (panel B). Treated firms' FTE then follows a downward trend stabilizing at the level of 2.5 employees on average. Finally, treatment effects of firms receiving subsidies for two years are slightly higher compared to firms participating only one year (the dotted grey line is always above the dark one).

Figure 3: Effects on different treatment patterns against the benchmark of no treatment.



Notes: R&D FTE employees on the vertical axis of each figure.

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. As Takalo, Tanayama, and Toivanen (2017) and Lach, Neeman, and Schankerman (2017)) note, the magnitude of the additionality estimate does not imply that the policy is welfare increasing.

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 and show.

5.3 Robustness

We address several issues regarding the robustness of our results. We analyse their sensitivity to using the unbalanced panel, the presence of anticipation effects, and the inclusion of 2013 in the definition of the crisis period. First, we have tested the effects of using the unbalanced panel; employing the same methods to estimate treatment effects, we obtain very similar results. Second, 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 $t+2$ (anticipation effects). 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 three 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. We do not find strong evidence of anticipation in terms of investment in innovation per employee, although for treatment pattern 3 the coefficient for year 2008 is significant at the 5% level. Finally, in the baseline estimations, year 2013 is considered to be the start of the recovery period. The Spanish Business Cycle Dating Committee, linked to the Spanish Economic Association characterizes the crisis in Spain as a double recession.[31] It sets the peak of economic activity in the second quarter of 2008, with a pause the fourth quarter of 2009 to the fourth quarter of 2010, and then a second recession with the trough in the second quarter of 2013. It is thus not obvious whether this year should be included in the crisis period or in the recovery period. To test the robustness of the analysis above, we re-estimate

[31] http://asesec.org/CFCweb/en/

the model with 2013 classified as crisis period, and find that the main results hold.[32]

5.4 Large firms: tentative results.

In an attempt to generalize our results to large firms, which are responsible for the majority of R&D expenditure in Spain (about 80% of the total business R&D), we build a balanced panel of about 1,169 large firms with more than 200 employees. About 66% of large firms 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 41% 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 (see Tables A2.1 to A2.3 in Appendix 2).

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 of correlation between the probability of participation and lack of access to external funding (see table A2.4 in Appendix 2).

When looking at treatment patterns over the cycle, we find that the number of firms experiencing the same participation pattern is too small to obtain reliable estimates of treatment effects for the same cases as for SMEs. Table 8 shows the number of treated and potential controls for the cases analogous to SMEs.

[32] All robustness estimation results are available as supplementary material.

Table 8: Treatment patterns. Large firms

Treatment pattern	Treatment Condition	Number of treated Firms	Number of Controls
	Expansion		
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
	Recession		
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 treatment patterns, we tentatively estimate treatment effects only for patterns 1 and 3. The estimated effects on both total innovation investment per worker and the employee time dedicated to R&D activities are not significantly different from zero both during the expansion and during the recession, except for firms participating one year during the expansion (treatment pattern 1). In the latter case, we find an immediate positive and significant treatment effect on the employee time dedicated to R&D activities in 2008 (tables A2.5 and A2.6 in Appendix 2). Results suggest that large firms are less responsive to public support than SMEs. These findings, however, are to be considered only extremely tentative given the available sample sizes.

6 Concluding Remarks

The global economic and financial crisis that unleashed in 2008 had a globally negative impact on business investment in R&D and innovation. In some countries public funding of R&D, whether carried out by the public or private sectors, also dropped because of fiscal consolidation. The risk of divergent productivity growth paths that this entails is bothersome. To assess the cost of decreasing public support to business R&D, we analyse whether its effects on firms' investment in innovation activities differs across expansions and recessions. The research questions we have focused on are: 1)

Does firms' access to support vary over the business cycle? 2) Does the impact of support remain constant over the cycle? 3) How does public support affect private R&D investment and R&D employment? 4) Are effects sensitive to the length or frequency of program participation, and how long do effects last? To the best of our knowledge, existing research is sparse and not as comprehensive as the analysis we carry out here.

With respect to the first question, 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 years. This means that differences in effects during expansions and recessions are unlikely to be induced by changes in the type of firms obtaining public support. Regarding the remaining questions, our richer data compared to previous studies produce more nuanced results. We find that the additionality effect varies depending on the firms' treatment pattern and with the type of outcome. Timing and length of participation matter, with longer treatment leading to higher additionality. We also find that while the impact of public support during the years 2005 to 2014 is pro-cyclical for investment in innovation in monetary terms, when looking at the time allocation to R&D activities the additionality effect is higher and longer during the recession. These results are robust for SMEs. Overall, they 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 –monetary investment in particular– are reduced. One limitation of our study is that we can only obtain very tentative results for large firms, because of the lack of a large enough control group of non-supported firms for each treatment pattern. A second limitation is that the database, PITEC, does not provide information on two important issues: whether a firm applied for support but was rejected, and whether the firm uses tax incentives to R&D. Since Spain is among the countries that provide R&D tax credits, the estimated effects of direct support may partly capture the effects of tax credits. However, given that in practice mostly large firms benefit from tax credits, we expect our results for SMEs not to be too biased.

Allowing for the necessary prudence in interpreting the policy implications of our findings, our results bring about some thoughts about public support to business R&D and innovation activities. As the OECD database on R&D tax incentives shows, many countries have increased their reliance on this instrument relative to direct support (Appelt, Galindo-Rueda, and Cabral 2019). Yet, the evidence on the comparative effectiveness of each form of support is scarce and controversial, in part because the design of tax incentives varies across countries, with different provisions for firm size and loss and tax liability status.[33] The performance of R&D tax incentives over the business cycle has not been studied, but it is likely that they are highly procyclical, to the extent that many firm's profits are. Work by Edgerton (2010) suggests that during recessions, when cash flows are low, tax incentives in general have the smallest impact on investment. This may well carry over to R&D tax incentives. Thus, if these hypotheses were to be confirmed, our results regarding the effectiveness of direct support during recessions provide an additional argument in favour of the use of this instrument.

A set of related issues remain to be explored regarding the effects of direct support. One of them is to focus specifically on treatment duration –spell length- and its effects on innovation outcomes such as the introduction of innovations that are new to the firm and of innovations that are new to the market, on the probability of starting and stopping of innovation projects, and on the type of projects undertaken. A better understanding of these effects and comparing them with those of R&D tax incentives may contribute to improving the efficiency of the policy mix.

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[33] See Appelt et al. (2019) for aggregate level comparative evidence, and Álvarez-Ayuso, Kao, and Romero-Jordán (2018) for firm-level evidence for Spain.

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Appendix 1

Table A1.1: Definition of Variables

Variable Name	**Variable 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
Continuous R&D performer	Binary; firm engages in R&D activities on a continuous basis.
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
Cooperation (t-1)	Binary; firm reports active cooperation for innovation activities with other firms or institutions.
R&D employees (t-1)	Percentage of R&D employees over the total workforce of the firm.
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
Size $200 < x \leqslant 400$	Binary; Firm Size $200 < x \leqslant 400$ employees
Size $400 < x \leqslant 700$	Binary; Firm Size $400 < x \leqslant 700$ employees
Size. $x > 700$	Binary; Firm Size $x > 700$ employees
Young	Firm is young (age < 10 years)
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.

Continued on next page

Table A1.1 – continued from previous page

Variable Name	Variable Definition
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 A1.2: SMEs. Treatment effects. Outcome: Ln(Total Innovation Investment per worker)

	DiD (Naive) (1)	DiD (Controls) (2)	DiD (Weighted) (3)	DiD (Common Support) (4)
Treatment pattern 1				
2006	0.311***	0.440***	0.250**	0.435***
	(0.101)	(0.126)	(0.122)	(0.126)
2007	0.192*	0.297**	0.231*	0.293**
	(0.108)	(0.131)	(0.130)	(0.131)
2008	0.158	0.259**	0.140	0.256**
	(0.115)	(0.123)	(0.138)	(0.123)
2009	-0.036	0.086	-0.082	0.081
	(0.092)	(0.100)	(0.099)	(0.100)
2010	-0.153	-0.032	-0.223**	-0.039
	(0.101)	(0.105)	(0.105)	(0.105)
2011	-0.045	0.079	-0.011	0.076
	(0.107)	(0.097)	(0.153)	(0.098)
2012	0.025	0.143	0.033	0.138
	(0.099)	(0.090)	(0.134)	(0.090)
2013	-0.130	-0.019	-0.164	-0.020
	(0.098)	(0.080)	(0.103)	(0.080)
observations	16,310	14,677	16,310	14,461
Treatment pattern 2				
2006	0.489***	0.419**	0.635***	0.378*
	(0.133)	(0.198)	(0.167)	(0.194)
2007	0.418**	0.408*	0.506**	0.391*
	(0.196)	(0.224)	(0.206)	(0.219)
2008	0.283**	0.354	0.227	0.322
	(0.134)	(0.267)	(0.147)	(0.264)
2009	-0.142	0.008	-0.219	-0.021
	(0.169)	(0.251)	(0.168)	(0.249)
2010	-0.235*	-0.143	-0.286**	-0.142
	(0.139)	(0.182)	(0.138)	(0.178)
2011	-0.297**	-0.194	-0.431***	-0.176
	(0.133)	(0.176)	(0.161)	(0.172)
2012	-0.155	-0.055	-0.410*	-0.066
	(0.184)	(0.179)	(0.213)	(0.179)
2013	-0.216	-0.097	-0.217	-0.105
	(0.180)	(0.160)	(0.139)	(0.161)
observations	15,520	13,966	15,390	10,845
Treatment pattern 3				
2009	0.236***	0.180**	0.223**	0.120
	(0.085)	(0.086)	(0.100)	(0.099)
2010	0.187*	0.082	0.121	0.063
	(0.100)	(0.102)	(0.119)	(0.108)
2011	0.276**	0.161	0.228**	0.144
	(0.112)	(0.110)	(0.111)	(0.127)
2012	0.220**	0.092	0.190*	0.118
	(0.109)	(0.107)	(0.109)	(0.128)

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Table A1.2 – continued from previous page

	DiD (Naive) (1)	DiD (Controls) (2)	DiD (Weighted) (3)	DiD (Common Support) (4)
2013	0.031	-0.045	0.010	-0.002
	(0.100)	(0.097)	(0.096)	(0.114)
2014	-0.093	-0.174*	-0.117	-0.182
	(0.107)	(0.106)	(0.107)	(0.132)
observations	16,290	14,659	16,290	14,533
Treatment pattern 4				
2009	0.400***	0.333***	0.181	0.330***
	(0.133)	(0.116)	(0.138)	(0.117)
2010	0.482***	0.372***	0.243	0.363***
	(0.133)	(0.120)	(0.182)	(0.121)
2011	0.480***	0.334**	0.362**	0.325**
	(0.159)	(0.159)	(0.155)	(0.159)
2012	0.372***	0.181	0.247*	0.167
	(0.142)	(0.130)	(0.130)	(0.130)
2013	0.148	0.031	0.087	0.018
	(0.143)	(0.121)	(0.145)	(0.122)
2014	0.101	-0.010	-0.043	-0.021
	(0.136)	(0.120)	(0.132)	(0.120)
observations	15,740	14,164	15,740	13,498
Fixed Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Notes: 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 A1.3: Treatment Effects. Outcome: Human Capital (R&D Employees in FTE)

	DiD (Naive) (1)	DiD (Controls) (2)	DiD (Weighted) (3)	DiD (Common Support) (4)
Treatment pattern 1				
2006	0.232***	0.177**	0.204***	0.179**
	(0.060)	(0.073)	(0.060)	(0.073)
2007	0.238***	0.131*	0.214***	0.131*
	(0.067)	(0.074)	(0.061)	(0.074)
2008	0.259***	0.144**	0.276***	0.144**
	(0.071)	(0.073)	(0.076)	(0.073)
2009	0.050	-0.041	0.022	-0.042
	(0.071)	(0.070)	(0.076)	(0.070)
2010	0.015	-0.050	-0.018	-0.051
	(0.064)	(0.059)	(0.057)	(0.059)
2011	0.118**	0.045	0.085	0.046
	(0.054)	(0.054)	(0.054)	(0.054)
2012	0.125**	0.057	0.089	0.057
	(0.057)	(0.055)	(0.059)	(0.055)
2013	0.056	-0.015	0.023	-0.015
	(0.054)	(0.042)	(0.054)	(0.042)
observations	16,189	14,576	16,189	14,360
Treatment pattern 2				
2006	0.315***	0.192*	0.275**	0.181*
	(0.099)	(0.108)	(0.112)	(0.109)
2007	0.479***	0.423***	0.597***	0.409***
	(0.103)	(0.112)	(0.104)	(0.113)
2008	0.413***	0.446***	0.399***	0.429**
	(0.104)	(0.166)	(0.132)	(0.167)
2009	0.030	0.138	0.062	0.121
	(0.091)	(0.119)	(0.111)	(0.121)
2010	-0.110	-0.042	-0.078	-0.051
	(0.084)	(0.079)	(0.078)	(0.081)
2011	-0.054	0.018	-0.000	0.013
	(0.077)	(0.054)	(0.083)	(0.056)
2012	0.116	0.133**	0.103	0.129*
	(0.082)	(0.065)	(0.068)	(0.067)
2013	0.010	0.051	0.004	0.044
	(0.071)	(0.048)	(0.079)	(0.049)
observations	15,410	13,874	15,287	10,770
Treatment pattern 3				
2009	0.220***	0.151***	0.213***	0.151***
	(0.052)	(0.047)	(0.056)	(0.047)
2010	0.313***	0.173***	0.338***	0.173***
	(0.062)	(0.060)	(0.067)	(0.060)
2011	0.306***	0.142**	0.336***	0.143**
	(0.066)	(0.057)	(0.068)	(0.057)
2012	0.277***	0.105*	0.324***	0.106*
	(0.067)	(0.056)	(0.069)	(0.056)
2013	0.170**	0.069	0.206***	0.071

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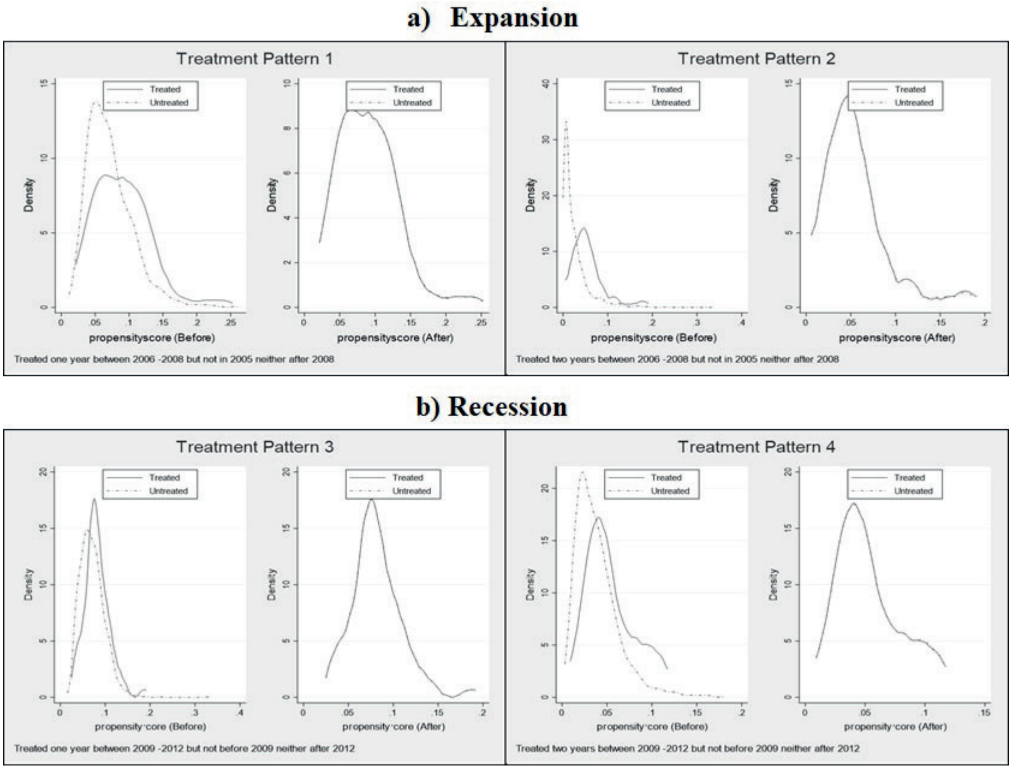
Table A1.3 – continued from previous page

	DiD (Naive) (1)	DiD (Controls) (2)	DiD (Weighted) (3)	DiD (Common Support) (4)
	(0.071)	(0.055)	(0.072)	(0.055)
2014	0.120	0.033	0.145*	0.035
	(0.078)	(0.057)	(0.081)	(0.057)
observations	16,168	14,557	16,168	14,432
Treatment pattern 4				
2009	0.296***	0.211***	0.166	0.209***
	(0.106)	(0.076)	(0.138)	(0.076)
2010	0.502***	0.347***	0.291**	0.341***
	(0.102)	(0.075)	(0.127)	(0.076)
2011	0.584***	0.373***	0.508***	0.366***
	(0.094)	(0.089)	(0.108)	(0.089)
2012	0.448***	0.199**	0.374***	0.191**
	(0.089)	(0.081)	(0.106)	(0.081)
2013	0.296***	0.155*	0.207*	0.147*
	(0.112)	(0.086)	(0.124)	(0.087)
2014	0.273***	0.154**	0.124	0.148*
	(0.102)	(0.076)	(0.117)	(0.076)
observations	15,620	14,064	15,620	13,403
Fixed Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Notes: Dependent variable: R&D employees (FTE). Standard errors in parentheses; standard errors are clustered at the firm level. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Figure A1.1: SMEs. Distribution of the Propensity Score Before and After Matching



Appendix 2: Large Firms

Table A2.1: 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 A2.2: Large Firms. Spells of Participation

	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 A2.3: 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 large 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 A2.4: Large Firms. Dynamic Probit Participation

	Period 1: 2005-2008			Period 2: 2009-2012			Period 3: 2013-2015		
	Woold1	Woold2	Pool	Woold1	Woold2	Pool	Woold1	Woold2	Pool
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Public support $(t-1)$	0.105***	0.139***	0.224***	0.186***	0.193***	0.215***	0.188***	0.187***	0.198***
	(0.020)	(0.024)	(0.007)	(0.013)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)
Public support (t_0)	0.084***	0.073***		0.073***	0.054***		0.032***	0.029***	
	(0.017)	(0.020)		(0.020)	(0.009)		(0.009)	(0.009)	
Sales growth (log dif)	-0.030**	-0.035**	-0.037*	0.015	0.013	0.014	0.009	0.007	0.010
	(0.015)	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)	(0.021)	(0.020)	(0.017)
External funding $(t-1)$	0.005	-0.009	0.006	-0.010	-0.029**	-0.009	0.010	0.002	0.012
	(0.011)	(0.018)	(0.012)	(0.009)	(0.014)	(0.010)	(0.009)	(0.014)	(0.009)
Demand Uncertainty $(t-1)$	0.028**	0.013	0.033**	0.002	-0.005	0.003	0.013	0.029**	0.015
	(0.011)	(0.017)	(0.013)	(0.010)	(0.014)	(0.010)	(0.009)	(0.015)	(0.010)
Continuous R&D performer $(t-1)$	0.118***	0.102***	0.133***	0.115***	0.092***	0.121***	0.083***	0.062***	0.0866***
	(0.012)	(0.013)	(0.013)	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)	(0.013)
R&D employees $(t-1)$	0.226*	0.155	0.238	0.235**	0.134	0.295**	0.135	0.081	0.169*
	(0.124)	(0.126)	(0.133)	(0.119)	(0.107)	(0.111)	(0.098)	(0.097)	(0.081)
Higher education $(t-1)$	-0.032	-0.048**	-0.027	0.030	0.016	0.036	0.027	0.014	0.032
	(0.022)	(0.023)	(0.023)	(0.019)	(0.019)	(0.019)	(0.018)	(0.019)	(0.020)
IP protect $(t-1)$	0.004	0.005	0.004	-0.007	-0.008	-0.006	-0.012	-0.014	-0.010
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Cooperation $(t-1)$	0.031***	0.029***	0.040***	0.027***	0.023***	0.028***	0.017*	0.017*	0.0191*
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Size $400 < x \leq 700$ $(t-1)$	-0.007	-0.009	-0.007	-0.024***	-0.025***	-0.027**	-0.007	-0.007	-0.008
	(0.010)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)
Size $x > 700$ $(t-1)$	0.000	-0.003	-0.001	-0.020**	-0.020**	-0.021*	0.006	0.006	0.005
	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Group $(t-1)$	-0.002	0.000	-0.002	0.006	0.004	0.009	0.005	0.002	0.003
	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)	(0.011)

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Table A2.4 – Continued

	Period 1: 2005-2008			Period 2: 2009-2012			Period 3: 2013-2015		
	Woold1	Woold2	Pool	Woold1	Woold2	Pool	Woold1	Woold2	Pool
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Foreign $(t-1)$	-0.029***	-0.029***	-0.041***	-0.051***	-0.048***	-0.060***	-0.023**	-0.021**	-0.0268**
	(0.010)	(0.011)	(0.011)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Export $(t-1)$	0.040	0.035***	0.048***	0.013	0.008	0.016	-0.005	-0.007	-0.002
	(0.012)	(0.013)	(0.013)	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
Young	0.026*	0.028*	0.026	0.017	0.009	0.015	0.022	0.020	0.026
	(0.014)	(0.014)	(0.014)	(0.019)	(0.019)	(0.019)	(0.037)	(0.035)	(0.044)
High tech Manufac.	0.010	0.000	0.013	-0.032**	-0.044***	-0.029	-0.037**	-0.039**	-0.0355*
	(0.018)	(0.018)	(0.019)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)
Medium tech Manufac	0.010	0.006	0.012	-0.003	-0.009	0.000	0.002	0.000	0.004
	(0.012)	(0.012)	(0.013)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)
High-tech services	0.061***	0.071***	0.066**	0.004	0.009	0.002	0.020	0.026	0.019
	(0.018)	(0.019)	(0.021)	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)	(0.018)
Rest Services	0.011	0.023*	0.010	-0.027**	-0.013	-0.031***	-0.037***	-0.030***	-0.0388**
	(0.013)	(0.014)	(0.014)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)
UE support (t-1)	0.034**	0.030*	0.053**	0.041***	0.031**	0.051***	0.037***	0.037***	0.0405***
	(0.017)	(0.018)	(0.019)	(0.015)	(0.014)	(0.013)	(0.013)	(0.013)	(0.012)
Innovation intensity (t-1)	0.001	-0.011***	0.000	0.001	-0.011***	0.001	0.000	-0.010***	0.000
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
M_Innovation intensity		0.022***			0.022***			0.016***	
		(0.004)			(0.004)			(0.003)	
M_External funding		0.035*			0.028*			0.016	
		(0.021)			(0.016)			(0.017)	
M_Demand Uncertainty		0.018			0.011			-0.023	
		(0.021)			(0.017)			(0.017)	
Log likelihood	-776.878	-755.827	-787.996	-985.79	-962.970	-1005.179	-605.776	-592.195	-611.865
lnsig2u	-0.841	-1.605		-3.126	-10.354		-13.950	-15.271	
	(0.477)	(0.869)		(1.732)	(12.358)		(23,718)	(149.26)	
Sigma u	0.657***	0.448		0.209*	0.006		0.001	0.000	

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Table A2.4 – Continued

	Period 1: 2005-2008			Period 2: 2009-2012			Period 3: 2013-2015		
	Woold1	Woold2	Pool	Woold1	Woold2	Pool	Woold1	Woold2	Pool
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	(0.157)	(0.194)		(0.181)	(0.035)		(0.011)	(0.036)	
Rho	0.301***	0.167		0.042*	0.000		0.000	0.000	
	(0.100)	(0.121)		(0.070)	(0.000)		(0.000)	(0.000)	
Wald Chi2	548.18***	628.15***	1089.21***	1261.53***	1554.90***	1465.33***	972.01***	932.21***	1031.71***
N	3,402	3,402	3,402	4,536	4,536	4,536	3,402	3,402	3,402
Firms	1,134	1,134	1,134	1,134	1,134	1,134	1,134	1,134	1,134

Marginal effects at the average value; Standard errors calculated using delta method (in parentheses). In columns (1) and (2) the integration method is mvaghermite using eight quadrature points; Time dummies included in all specifications. M_ denotes the within mean of the corresponding variable, from year 1 to year T. Initial values differ for each period. Reference category for size is $200 < x \leq 400$. The accuracy of the results has been checked using 12 and 16 quadrature points. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2.5: Large firms. Difference-in-difference estimations. Outcome: Ln(Total Innovation Investment per worker)

	DiD (Naive) (1)	DiD (Controls) (2)	DiD (Weighted) (3)	DiD (Common Support) (4)
Treatment pattern 1				
2006	-0.032	0.085	0.162	0.051
	(0.198)	(0.264)	(0.288)	(0.263)
2007	0.156	0.284	0.180	0.293
	(0.202)	(0.268)	(0.247)	(0.268)
2008	-0.002	0.130	-0.083	0.145
	(0.225)	(0.246)	(0.255)	(0.249)
2009	0.010	0.159	-0.215	0.189
	(0.204)	(0.215)	(0.211)	(0.217)
2010	0.166	0.213	0.104	0.253
	(0.167)	(0.222)	(0.196)	(0.224)
2011	0.146	0.227	0.046	0.240
	(0.173)	(0.217)	(0.174)	(0.223)
2012	-0.154	-0.028	-0.231	-0.039
	(0.164)	(0.172)	(0.188)	(0.178)
2013	-0.119	-0.042	-0.153	-0.036
	(0.166)	(0.169)	(0.173)	(0.177)
observations	7,390	6,651	7,390	5,130
Treatment pattern 3				
2009	0.400**	0.230	0.616**	0.264
	(0.172)	(0.160)	(0.272)	(0.166)
2010	0.150	-0.029	0.024	-0.037
	(0.229)	(0.236)	(0.510)	(0.235)
2011	0.350	0.181	0.165	0.177
	(0.220)	(0.242)	(0.496)	(0.241)
2012	0.374**	0.203	-0.005	0.184
	(0.185)	(0.204)	(0.438)	(0.210)
2013	0.309	0.152	0.403*	0.161
	(0.196)	(0.200)	(0.207)	(0.205)
2014	-0.056	-0.199	-0.506	-0.223
	(0.230)	(0.246)	(0.653)	(0.247)
observations	7,390	6,651	7,390	4,716
Fixed Effects	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Note: As in Table A1.2

Table A2.6: Large Firms. Treatment Effects. Outcome: R&D Employees (FTE)

	DiD (Naive) (1)	DiD (Controls) (2)	DiD (Weighted) (3)	DiD (Common Support) (4)
Treatment pattern 1				
2006	0.233	0.217	0.253	0.211
	(0.153)	(0.149)	(0.214)	(0.150)
2007	0.189	0.115	0.135	0.124
	(0.141)	(0.128)	(0.185)	(0.128)
2008	0.398***	0.308**	0.472**	0.289**
	(0.123)	(0.142)	(0.195)	(0.142)
2009	0.087	0.094	0.042	0.084
	(0.130)	(0.120)	(0.157)	(0.120)
2010	0.189	0.123	0.170	0.117
	(0.125)	(0.100)	(0.137)	(0.100)
2011	0.064	0.076	0.030	0.057
	(0.118)	(0.093)	(0.118)	(0.092)
2012	0.029	0.081	0.009	0.066
	(0.106)	(0.101)	(0.136)	(0.101)
2013	-0.010	-0.043	-0.070	-0.062
	(0.100)	(0.101)	(0.119)	(0.100)
observations	7,358	6,621	7,358	5,100
Treatment pattern 3				
2009	0.595***	0.257	0.757	0.245
	(0.171)	(0.176)	(0.487)	(0.178)
2010	0.515***	0.044	0.710*	0.034
	(0.177)	(0.133)	(0.420)	(0.133)
2011	0.418***	0.005	0.444	-0.003
	(0.155)	(0.157)	(0.362)	(0.158)
2012	0.344*	-0.033	0.379	-0.044
	(0.194)	(0.155)	(0.391)	(0.157)
2013	0.056	-0.245	0.027	-0.262
	(0.207)	(0.188)	(0.530)	(0.189)
2014	0.026	-0.286	0.107	-0.310
	(0.234)	(0.213)	(0.512)	(0.214)
observations	7,365	6,628	7,365	4,695
Fixed Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Note: As Table A1.3

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Suggested citation:
Isabel Busom and Jorge Vélez-Ospina (2020). Subsidising Innovation over the Business Cycle. SPRU Working Paper Series (SWPS), 2020-09: 1-59. ISSN 2057-6668. Available at: www.sussex.ac.uk/spru/swps2020-09

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