Three Empirical Essays on R&D subsidies and Innovation in Firms

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Summary

This thesis consists of three essays organized in three chapters. Their common thread is that they all aim at deepening our understanding of how direct support to innovation in firms through subsidies works in different countries, across industries or over time. Implementing effective innovation policies is not an easy task, even though theoretical arguments and empirical evidence support public intervention in this regard. Policy makers have imperfect information about which innovation projects are deterred, and to what extent, as a consequence of knowledge spillovers or of firms' financial constraints, and about whether the social benefits of supporting them would exceed social costs and when. Ex-post policy evaluation becomes then an important tool help check the effects of a policy given the institutional and business environment. It can also provide useful information to revise it. These three essays contribute fresh empirical evidence on the allocation of public support to firms and on its impact on innovation and/or productivity in an emerging country (Chapter 2) and on dynamic aspects of innovation support in a high income country (Chapters 3 and 4). They all use firm-level data from business innovation surveys conducted by the respective statistical offices.

Chapter 2 examines the relationship between innovation subsidies, innovation effort and productivity in Colombia. It extends the recursive model developed by Crepon-Duguet-Mairesse (CDM) at the first and at the last stage of the model. In order to explicitly model access to innovation subsidies it adds a corresponding equation as the first step of the model. It takes into account, in the last step, the potentially heterogeneous impact of innovation on productivity. The main findings are: (i) while in manufacturing and traditional services the allocation of public support is correlated with firms' perceived financing constraints, in knowledge-intensive services regulations may affect firms' incentives to apply for and obtain support; (ii) public support is positively and significantly correlated with investing in innovation in all three types of industries, although the correlation is higher in manufacturing; (iii) the

labor productivity of firms at the lower tail of the productivity distribution seems to respond more to innovation than firms at the upper tail in all industries. Since, as a middle-income country, there would be room for innovating through imitation and adoption of knowledge, these results suggest that factors that affect innovation incentives other than the appropriability of knowledge are a bottleneck for firms' innovativeness. Human capital, trade restrictions and regulations may be among them.

Chapter 3 investigates the impact of direct support for innovation over the business cycle in Spain. It examines whether firms that benefit from public support in recessions differ from firms that benefit from it during expansions, whether the impact of public support is smaller in recessions than in expansions or otherwise, and whether these effects vary with the length of the subsidy spell, where spell is defined as the number of years a firm reports receiving a subsidy within a given period. The main findings are: (i) the timing and length of participation in the program matter, with longer spells leading to higher additionality; (ii) while the impact of public support during the recession years is pro-cyclical for investment in innovation in monetary terms, when looking at the employee-time allocation to R&D activities the additionality is higher and longer during the recession. These results suggest that public support allows firms to assign employee time to innovation activities that would not be performed without support. That is, public support has prevented the reduction of knowledge capital during the big recession.

Chapter 4 explores the determinants of persistence in the use of R&D subsidies in Spain and analyzes the extent to which continuous engagement in R&D subsidization affects the success of investment effort and the firms' decision to stop innovation projects. Results are the following: (i) firms receiving public funding for R&D activities accumulate knowledge and experience that would increase the chances of getting support in future applications; (ii) continuous R&D performers have a positive likelihood of reducing the hazard of ending an R&D subsidy spell; (iii) new-to-market product innovation is triggered by small firms participating continuously into the R&D subsidization program, in all industries as a whole but especially in knowledge intensive services and medium-low-tech manufacturing; and (iv) survival in R&D subsidization also reduces the likelihood of abandoning R&D projects at either the concept stage or mature stages.

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Chapter 1

Introduction

1.1 Overview

Implementing effective innovation policies is not an easy task, even though theoretical arguments and empirical evidence support public intervention in this regard. Policy makers have imperfect information about which innovation projects are deterred, and to what extent, as a consequence of knowledge spillovers, of firms' financial constraints or of failures in complementary markets. Ex-ante evaluation of whether the social benefits of supporting a particular project would exceed social costs is difficult, as is anticipating the timing of outcomes and whether the policy impact will be permanent or temporary. Ex-post policy evaluation becomes then an important tool help check the effects of a policy given the institutional and business environment. It can also provide useful information to revise it.

These three essays contribute fresh empirical evidence on the allocation of public support to firms and on its impact on innovation investment, outcomes and/or productivity. Chapter 2 analyzes the case of an emerging country, Colombia, in a cross-sectional setting. It expands the well-known Crepon-Duguet-Mairesse framework by integrating the allocation of public subsidies to innovation as an additional equation into the model. It also allows for variation in the association between innovation and productivity, and for variation across industries, given the large heterogeneity observed in these dimensions. Chapters 3 and 4 focus on dynamic aspects of the allocation of direct support to R&D and innovation in a high-income country, Spain. In this case, because longitudinal data are available, the focus is, respectively, on the impact of public subsidies on firms' innovation activities across the business cycle, and on the impact of the length of participation on innovation outcomes.

All three chapters use firm-level data from firm-level innovation surveys conducted by the respective statistical offices. Inspired in the European Community Innovation Survey, which in turn is based on the OECD Oslo Manual, these surveys provide quantitative and qualitative information on innovation activities, types and outcomes in firms in all industries. Access by researchers to firm-level data has promoted extensive empirical research on innovation at the firm level. Because questionnaires contain share some common questions, they also have enabled to some extent comparative, cross-country studies.

Current innovation surveys, however, suffer from some limitations. Mairesse and Mohnen (2010) point out some of them. Ease of access to microdata by researchers is not uniform across countries; survey periodicity varies, so that longitudinal data sets are not always available to researchers; relevant information about the firm (human capital, management practices, capital intensity, performance indicators) or its context (firm's position in the market, degree of competition, strength of regulatory constraints, labor market factors) is not collected; sampling procedures are not uniform; merging innovation survey data with other firm-level surveys is often not possible. These limitations add to the measurement issues regarding the definition of innovation, innovation types, inputs and outcomes. In these surveys, for example, answers to many questions reflect subjective perceptions of the respondents, which may lead to over-reporting innovations, especially of organizational or marketing types. Limitations are identified, among others, in Cirera and Muzi (2016) concerning innovation in developing countries; in a report published by the National Academies of Sciences, Medicine, et al. (2017), *Advancing Concepts and Models for Measuring Innovation: Proceedings of a Workshop*, and at the Blue Sky Forum organized by the OECD every ten years.

Particularly relevant for policy evaluation is the lack of information on the ease of imitation as a deterrent of potential innovation projects; on objective indicators of financial constraints to complement subjective perceptions, and on some specifics of public support, such as distinguishing between applying and obtaining, and duration of support when obtained. All three essays are affected by some of these limitations, conditioning the questions that can be addressed, the type of empirical analysis that can be performed, the interpretation of the results, and thus the discussion of their policy implications. The content of each chapter is summarized next.

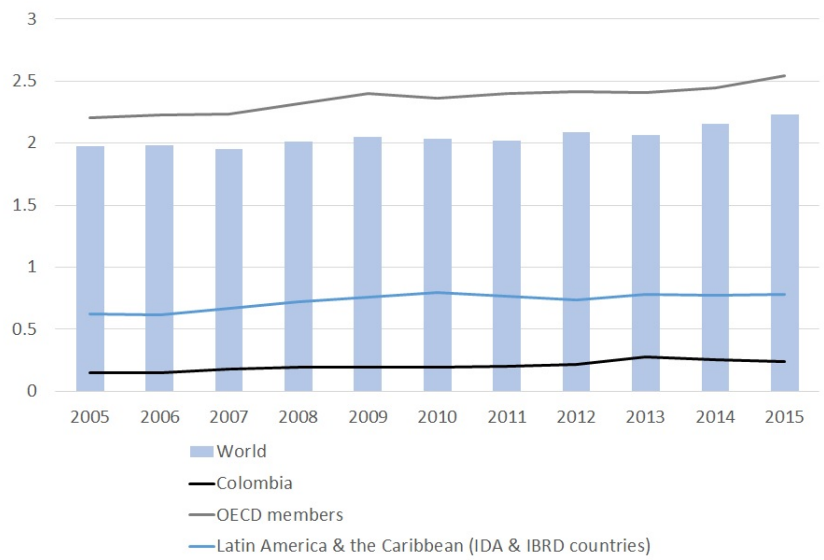
1.2 Chapter 2. Innovation, Public Support, and Productivity: A Cross-Industry Comparison

Innovation is an extremely important concern in Latin American countries. As a recent World Bank report by Cirera and Maloney (2017) highlights, innovation –in its wider sense, which includes from frontier R&D to generate new-to-the-world products to adoption of technologies, managerial and organizational practices– is critical for productivity growth and hence for accelerating development and reducing poverty. Even though potential returns to innovation are very large in developing countries, they invest much less in innovation than advanced countries (Goñi and

Maloney 2017). Cirera and Maloney (2017) refer to this as the *Innovation Paradox*. They identify three determinants of innovation performance, one of them being the government capability to implement effective innovation policies. Market and government failures may be more widespread in these countries, so that implementing an effective policy mix may be harder when the scope of these failures is high, complementary factors are missing and institutions are weak. Identifying the barriers for an effective innovation policy is therefore of paramount importance, especially given that these barriers often arise from several parts of the economic system. Consequently, an exclusive focus on R&D may not be appropriate, as Cirera and Maloney (2017) point out. Among others, managerial capabilities need to be developed as well (Bruhn, Karlan, and Schoar 2018).

Colombia even lags behind other Latin-American economies regarding innovation and productivity. Over the last decade, R&D investment has reached about 0.2% of the GDP, which compared to the average of the region (0.7%), is relatively low (see Figure 1.1).

Figure 1.1: Research and Development Expenditure (as % of GDP)



Note: Data extracted from the World Bank. Last update 14-Nov-2018.

Colombia has implemented specific policies to foster innovation in the business sector. Direct support through subsidies and loans, and tax deductions for R&D and technological development projects are available to firms. There is nonetheless little empirical evidence on the profile of beneficiaries from this support, on the correlation between the allocation of support and actual or perceived barriers to innovation, and on the final impact on productivity. These are important matters to consider in order to evaluate the effectiveness and potential shortcomings of policies intended to foster innovation.

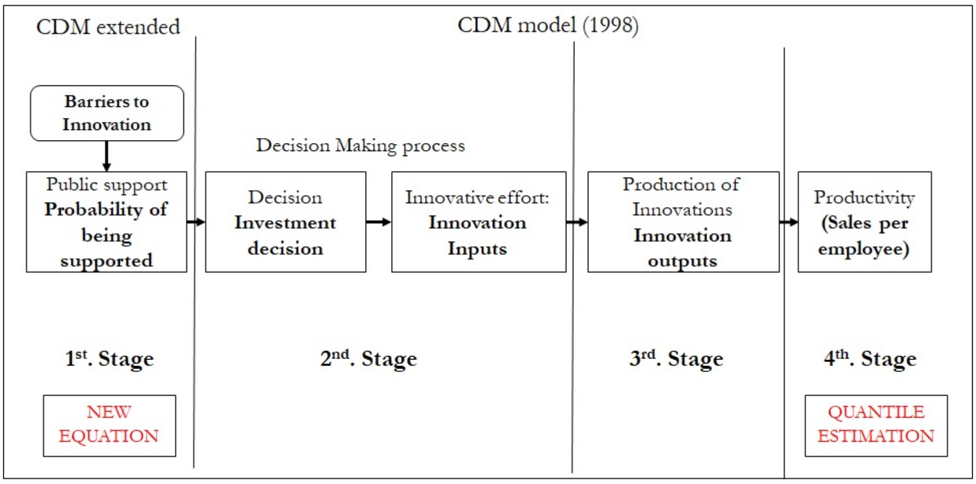
Several issues have to be taken explicitly into account when analyzing direct support –loans or grants- to firms in particular: i) allocation of support is not random, but a result of a firm's decision to apply for it and the public agency to award it; perceived barriers to innovation may affect the resulting allocation; ii) returns to innovation may differ significantly across the firms' productivity distribution, and iii) allocation of support and returns to innovation might differ across manufacturing and service industries.

This chapter addresses these three issues extending earlier work. Although public support has been used as an explanatory variable in the CDM framework, as in Griffith, Huergo, Mairesse, and Peters (2006), to the best of our knowledge only Czarnitzki and Delanote (2017), who use Belgian data, account for its endogeneity by instrumenting it. They do not analyze the allocation process, however. Regarding returns to innovation, some previous studies find that the returns to innovation vary with firms' productivity (Bartelsman, Dobbelaere, and Peters 2014; Segarra and Teruel 2011) although in opposite directions in different countries. If private returns to innovation -as measured by their contribution to labor productivity- are higher for more productive firms, then direct public support for innovation should focus on the subset of productive firms that underinvest in innovation. If returns to innovation are the same on average for all firms at any productivity level, then there would be no need for a targeted support policy.

A cross-industry comparison is emphasized in this essay because services account for about 60% of GDP in Colombia. Services have some differential traits with respect to manufacturing industries, and these traits may shape incentives to innovate. Service industries often produce intangible products (e.g., information, consulting services); the quality and value to the user are not revealed until consumption; consequently, uncertainty may be higher. Service and manufacturing industries differ as well in terms of market features such as the degree of competition and regulation. Restrictions to FDI, barriers to entry and conduct regulation could significantly affect some activities within the service industry (think of telecommunications, financial services or education) compared to manufacturing. Third, the ability to generate innovations through R&D is very heterogeneous across different industries, with adoption of technologies (ICTs) being more important in some (Paunov and Rollo 2016; Segarra-Blasco 2010).

To address these issues the basic Crèpon-Duguet-Mairesse model, designed to test the links between R&D, innovation and productivity at the firm level, is extended in two ways: first, an equation describing the allocation of direct support is added as the first step of the model; second, the productivity equation in the last step is estimated using quantile regression methods to allow for potentially heterogeneous returns to innovation. Figure 1.2 represents the four stages of the extended model.

Figure 1.2: An Extended version of the CDM (1998)



The data set for this chapter is drawn on two firm-level datasets gathered by the Colombian National Statistics Department (DANE): the Survey of Innovation and Technological Development in Services, EDITS-III (2010-2011) and the Survey of Innovation and Technological Development in Manufacturing, EDIT (2009-2010).[1] The sample consists of 905 manufacturing firms, 954 firms in knowledge-intensive business services (KIS), and 1,419 firms in remaining service activities. The sampling procedure differs across manufacturing and services, so the sample is not equally representative in both cases. In manufacturing firms with 10 or more employees are sampled; in KIS, firms with 20 or more employees, except for banking activities, where all the census is sampled. In traditional services firms with at least 20 employees in utilities, education and health and entertainment, film and TV are sampled, while in the wholesale and retail trade only firms with at least 50 employees, and in hospitality at least 40, are sampled. This has to be taken into account in all cross-industry comparisons, as the sample for traditional services will be biased towards larger firms.

Because these are basically cross-sectional data, the aim is to uncover regularities and correlations that may be informative from a policy perspective, without claiming to establish causal relations. Simultaneity issues cannot be properly addressed. A case in point is the potential endogeneity of perceived barriers to innovate, in particular of financial constraints. Innovation surveys do not provide factual or

[1] DANE is the acronym for Departamento Administrativo Nacional de Estadística. See the website: www.dane.gov.co. EDIT is the acronym for Encuesta de Desarrollo e Innovación Tecnológica.

objective information (i.e., a firm's credit rating). In our case, we test for exogeneity using as instruments the log of firm size and lagged sales per worker and do not reject the null.

Significant differences across manufacturing and certain service industries are found. The first concerns the allocation of public support for innovation. Firms that face financing constraints are more likely to benefit from public support in manufacturing and in traditional services. In knowledge-intensive services (KIS), however, firms that perceive regulations to be a hurdle for innovation are more likely to have public support. Controlling for previous innovation effort, engaging in innovation activities is positively correlated with public support, especially in manufacturing and KIS.

Regarding the link between innovation and productivity, in all service industries, including KIS, introducing all types of innovations increases productivity of firms below the median of the productivity distribution, but not of those above it. Within manufacturing innovation results in higher productivity in all quantiles of the distribution, but again slightly more in lower quantiles. At the same time, returns to human capital are significant and increasing with productivity in all industries, suggesting that investing in human capital is private and socially profitable across the board.[2]

With respect to policy implications, this empirical analysis suggests that improving the financial system to make it easier for innovators to obtain private funding could help promote innovation in manufacturing or traditional services. This might not be sufficient for KIS, where access to public funding for innovation is correlated with the perception that regulations are an obstacle to innovate. Some regulations may dampen the returns to innovation in this sector, and innovation support might be a way to offset this effect. The World Bank's Enterprise Survey for Colombia reports some indicators of potential bottlenecks for 2017/18. Out of 993 surveyed firms, 24% identify customs and trade regulations as a major constraint; the number of days to clear import from customs or to obtain an import license is high (almost 18 and 30 days respectively); as are the number of days to obtain a construction-related permit or an operating license.[3] Further analysis to identify the type of regulations that might hinder innovation activities in KIS in Colombia is needed. This suggests that there may be complementarities between innovation policy and other policies (Goñi and Maloney 2017; Mohnen and Röller 2005). Recent work by Arque-Castells (2018) also provides empirical insights on these complementarities across 28 EU countries.

[2] This chapter, started in 2014 and finished in 2016, has been published with the title "Innovation, Public Support, and Productivity in Colombia. A Cross-industry Comparison" in *World Development, 99 (2017)*, pp.75-94.

[3] See The World Bank Group, Enterprise Surveys: https://bit.ly/2ZKpJkf

As stated above, the data used in this chapter are basically cross-sectional. Although the availability and use of some lagged variables may help somewhat in reducing simultaneity and endogeneity issues, this does not eliminate them necessarily. To better control for unobserved factors, longitudinal data would be preferred. Since the Colombian Statistical Office (DANE) is running these surveys periodically, this opens the door to a replication exercise (for other years) as well as to using a more appropriate econometric framework to unveil the causal relationship between public support for innovation and its dynamic effects on productivity, in line with Raymond, Mairesse, Mohnen, and Palm (2015). Besides, a longitudinal perspective should be looking at what barriers affect the different components of R&D, distinguishing between exploratory (i.e research) and exploitative (i.e., development) activities. A second avenue for further research would focus on the relationship between innovating and exporting, as in Peters, Roberts, and Vuong (2018), who show that trade related regulations, such as export or import tariffs, may affect returns to innovation and R&D. A deeper understanding of both the self-selection into exporting and innovating in Colombia could be an issue of policy interest as well.

Finally, in many emerging and developing countries, including Colombia, a dual-economy system exists, that is, formal and informal economic activities. A line of work is exploring how innovation and the allocation of public support are affected by informality or by corruption. This is an important issue for future research.[4]

1.3 Chapter 3: Subsidizing Innovation over the Business Cycle

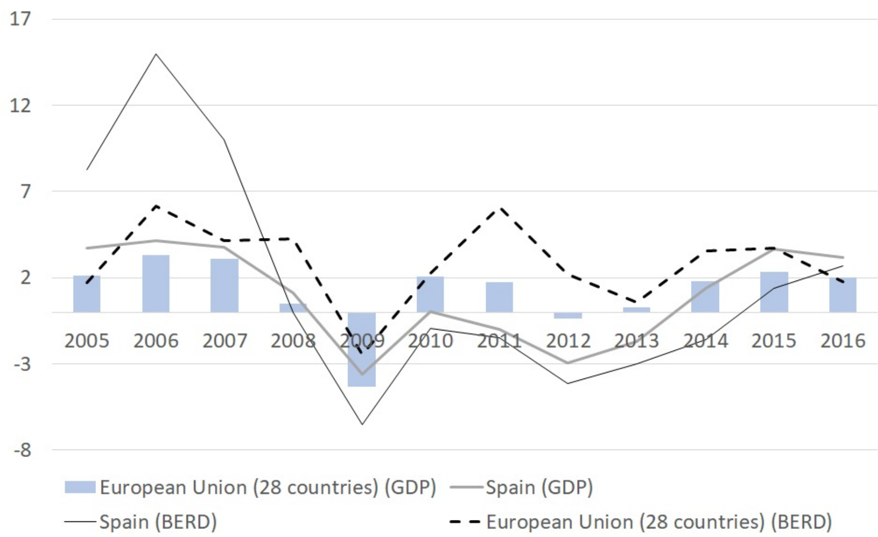
This chapter investigates the impact of public support to business investment in R&D over the different phases of the business cycle. It addresses the following questions: (i) Does firms' access to support vary over the business cycle? (ii) Does the impact of support remain constant over the cycle? (iii) How does support affect monetary (R&D investment) and non-monetary (R&D employment) decisions? The first question intends to determine 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 behavior over the cycle. For instance, financially constrained firms might apply for support during expansions, but abstain from doing so during recessions. The second question intends to determine whether the impact of public support is smaller in recessions than in expansions or otherwise.

[4] Fu, Mohnen, and Zanello (2018) is one of the few papers that analyzes the relationship between innovation and productivity using a CDM framework and capturing the effects for formal and informal firms.

The third question intends to inquire beyond the standard monetary effect of public support and look into the time allocation of employees to R&D activities. Firm-level panel data from Spain covering the period 2006 to 2014 are used to investigate these questions.

This research is related to studies on firms' R&D and innovation investment choices during the recent crisis and to studies evaluating the impact of public support on these decisions. Earlier studies have shown that business R&D investment is pro-cyclical on average, both at the aggregate and firm level (Aghion, Angeletos, Banerjee, and Manova 2010; Aghion, Askenazy, Berman, Cette, and Eymard 2012; Beneito, Rochina-Barrachina, and Sanchis-Llopis 2015; Cincera, Cozza, Tübke, and Voigt 2012; Fabrizio and Tsolmon 2014). Figure 1.3 unveils a significant positive correlation between GDP growth and business R&D investment growth at the aggregate European Union level. In 2009 business R&D investment (BERD) in the EU-28 area dropped by 2.5% while GDP decreased by 3.5. Spain followed a similar but more severe path.

Figure 1.3: Growth rate of GDP and Business R&D Investment (BERD)



Note: Data extracted from the OECD Main Science and Technology Indicators for BERD, GDP growth rates.

Empirical research suggests that procyclicality is mainly driven by the joint or separate action of market imperfections and knowledge spillovers, generating not only a static market failure but also inducing a dynamic misallocation of R&D investment over the cycle. A question then arises: would a countercyclical policy providing public support to R&D be able to mitigate the dynamic failure predicted by previous models? The answer hinges on the sign and size of the multiplier or additionality effect during recessions.

Only two firm-level studies focus on the effect of public support to R&D during the financial crisis years: Hud and Hussinger (2015) and Aristei, Sterlacchini, and Venturini (2017). Hud and Hussinger (2015) use German SMEs firm-level data from the period 2006 to 2010. They find that public subsidies have an overall positive effect on firms' private R&D investment, but they also find some evidence of a small and temporary crowding out effect in 2009. By 2010 the estimated additionality effect becomes positive again, but is smaller than during the pre-crisis years. A closer analysis of firms that received R&D subsidies before, during and after the crisis indicates that SMEs firms changed their investment behavior during the crisis year, allocating funds that would have been spent on R&D to other business areas. These findings suggest a negative or pro-cyclical multiplier of R&D subsidies. Aristei et al. (2017) compare the effect of public support in five EU countries during the crisis period and do not find evidence of additionality in any. It would then seem that public support would be less effective during recessions. The data used in both studies face some limitations though, as they do not use a long enough firm-level panel.

This chapter extends previous work by the cited authors in several directions owing to the availability of firm-level panel data, in particular data from the Spanish Innovation Panel (PITEC) for the period 2005 and 2014. The empirical strategy consists of both analyzing the allocation of public support and its determinants over time as well as estimating the impact or the degree of additionality of R&D subsidies on investment in innovation per employee and also on the employee time allocation to R&D activities. Estimates are obtained for several participation spells within three distinct periods: before the crisis (2005-2008), during the crisis (2009-2012), and after the crisis (2013-2014). A spell is defined here as the number of years a firm reports receiving a subsidy within a given period. A semi-parametric local linear matching approach (the propensity score) combined with difference-in-differences (conditional difference-in-differences, CDID, Heckman, Ichimura, Smith, and Todd 1998) allows addressing selection on both observables (through matching) and unobservables (by differencing) associated with subsidization of R&D. This approach intends to mimic an experimental setting as closely as possible. That is, subsidy recipients (treated firms) are matched to a sample of non-recipients (control firms) that are closely similar to the treated in observed dimensions before treatment. The treatment effect is then estimated by differences in differences. This may lead to relatively small sample sizes and associated problems, such as low statistical power, so there is a trade-off. Finally, the richness of the data allows to take into account that the effects of support take some time to unfold, that firms receive direct support at different points in time and that its effects may last more than one period.

Findings are the following. First, the allocation of R&D subsidies in Spain did not change significantly during the crisis. Second, the multiplier varies depending on the firms' participation spell and with the type of outcome –monetary or non-monetary- considered. Third, timing and length of participation matter, with longer spells leading to a higher multiplier. While the impact of public support during the recession years is found to be pro-cyclical for investment in innovation in monetary terms, when looking at the time allocation to R&D activities the multiplier is higher and longer during the recession. These results are robust for SMEs. Overall, they suggest that direct support to business R&D may mitigate the negative effect that recessions have on highly cyclical R&D investments through the reallocation of more human capital to R&D activities, even if monetary investment does not increase. That is, public support allows firms to assign employee time to innovation activities that would not be performed without support. Public support may have prevented the reduction of knowledge capital during the big recession by subsidy recipients.

Several mechanisms could explain why firms may hoard their skilled workers in times of crisis. First, according to Bloom, Romer, Terry, and Van Reenen (2013), the presence of "trapped factors" or fixed inputs may lead to a higher innovation activity when a firm faces a negative shock. The opportunity cost of inputs used to design and produce new goods would fall, and skilled employees might be trapped because they have human capital that is specific to the firm. Second, the type of labor contracts may also play a role in the decision to keep skilled employees in order to preserve the absorptive capacity of the firm. This would be consistent with Lopez-Garcia and Montero (2012), who find that for the case of Spain, the share of temporary employees within the firm is negatively associated with the firm's probability of innovating.

A natural extension of this line of research would consist in including more post-crisis years as data from the PITEC surveys become available. This would allow analyzing whether innovation investment, allocation of employees and innovation outcomes have changed relative to the pre-crisis period.

Some areas of further research could look further into the effects of the subsidy multiplier over the business cycle. For instance, research questions that could be asked include analyzing separately the subsidy multiplier on the exploratory (i.e., research) and exploitative (i.e., development) components of R&D. Moreover, there is room for further progress in determining the changes in the firm's R&D personnel structure that could also happen in the face of a crisis.

1.4 Chapter 4: Duration Dependence in R&D Subsidization and Firm's Innovative Behavior

The main aim of Chapter 4 is to investigate the degree of persistence in the use of R&D subsidies and its potential impact on firms' innovation outcomes. Three questions are addressed: (i) what are the drivers of a firm's persistent use of R&D subsidies?; (ii) what is the effect of continuous use of R&D subsidies on firm's introduction of product and process innovations ?; (iii) to what extent continuous engagement in R&D subsidization prevents a firm from stopping innovation projects? This chapter examines the relationship between firm-specific characteristics, and the continued use of public support measured by R&D subsidy spells at the firm level and tests whether continuity in the use of R&D subsidies leads to better innovation outcomes. A spell is defined here as a period of uninterrupted use of R&D subsidies by the firm.

Examining the role of firms' subsidy history is an aspect that has received some attention over the last years. Hussinger (2008) and Aschhoff (2009) provide evidence that subsidy history matters for both the allocation of support and its potential effects on innovation. Most recent work on this regard has found true state dependence of participation in both R&D subsidization and R&D tax incentives, meaning that successful applicants in past applications would be more likely to get funding in subsequent years (Busom, Corchuelo, and Martínez-Ros 2017). However, much less attention has been paid to examine the drivers of persistence in subsidy use and its potential effect on firms' innovation results. Aschhoff (2009), has addressed this issue to a certain extent, finding that frequent recipients of R&D grants have higher chances of increasing their R&D inputs and outputs. However, in her case data is cross-sectional, limiting her methodological approach.

The study of the effectiveness of different policy instruments used by governments and public agencies -subsidies, loans, tax deductions, and so forth- to provide incentives to increase private R&D and innovation investment has been the focus of evaluation research for some time (see Zúñiga-Vicente, Alonso-Borrego, Forcadell, and Galán 2014 for a survey). The most recent evidence is provided by Czarnitzki and Hussinger (2018), who analyze the link between public funding and R&D input and output in Germany. In general, empirical studies show that R&D subsidies have the potential for encouraging firms to engage in R&D and to invest more intensely (in the case of Spain, see Arqué-Castells 2013; Arqué-Castells and Mohnen 2015).

Most studies use a static, treatment-effects approach because panel data are seldom available. They thus offer only limited insights into the extent of continuity of participation in R&D subsidy programs, on its drivers and on its potential effects on the innovation behavior at the firm level. There is a lack, however, of empirical evidence focusing on the analysis of the effect of persistence in the use of R&D subsidies on innovation results. Absent crowding out effects, we might reasonably expect that persistence in benefiting from R&D subsidies will induce firms to achieve higher innovation results as well as providing them with higher chances to continue performing their innovation projects. This means that a higher number of consecutive years using the policy would also be an input for increasing the rate of innovation success.

This chapter contributes to previous literature in several ways. First, persistent use of R&D subsidies is modeled as the number of successive years in which a firm gets R&D funding (R&D subsidy spells) instead of analyzing whether firms that receive support in period t they get funding in time $t+1$. For this purpose, discrete-time duration models are used to measure the degree of persistence in the use of R&D subsidies. Second, the effect of continuous use of R&D subsidies on innovation outcomes is analyzed by modeling a standard innovation production function which relates innovation outcomes to innovation inputs such as R&D, skills and other firm-level characteristics and introducing the degree of persistence into the model. Appropriate non-linear dynamic probit and panel data models are estimated to uncover these relationships.

The third aspect this chapter investigates is the interruption of innovation effort. Some evidence has shown that when firms receive public support for innovation, economic outcomes beyond productivity, such as firm survival and employment improve (BEIS 2014; Cerulli and Potì 2012; Czarnitzki and Delanote 2017; Hottenrott and Lopes-Bento 2014). In recent years, there has also been an increasing amount of literature on understanding the mechanisms underlying the decision of quitting innovation projects (Mohnen, Palm, Van Der Loeff, and Tiwari 2008 for the Netherlands; Radas and Bozic 2012 for the case of Croatian firms; Garcia-Vega and Lopez 2010 and García-Quevedo, Segarra-Blasco, and Teruel 2018 for the Spanish case). All these studies however overlook the fact that public funding can reduce the potential risk of stopping innovation projects.

Our results suggest the following: (i) firms receiving public funding for R&D activities accumulate knowledge and experience that increase the chances of getting support in future applications; (ii) continuous R&D performers have a positive likelihood of reducing the hazard of ending an R&D subsidy spell. This holds across both manufacturing and services industries, of different technological intensity; (iii) new-to-market product innovation is triggered by SMEs participating continuously into the R&D subsidization program, in all industries as a whole but especially in knowledge-intensive services and medium-low-tech manufacturing and (iv) survival in R&D subsidization also reduces the likelihood of abandoning R&D projects at either the concept stage or mature stages, especially in high-tech manufacturing.

The findings in this study are subject to some limitations. First, the lack of information on the duration of a subsidy award from a single application could lead to an overestimation of persistence in project subsidization. Second, it is not possible to identify subsidy application costs and how they might change over time because of lack of information on all applications, including those that have been rejected. Third, when analyzing the decision to stop innovation projects we could not control for the number of projects a firm is conducting, information that could help identify the firm's capacity to deal with different project portfolios.

With these considerations in mind, these findings may provide some insights into innovation policies. When designing programs policymakers could take into account that firm participation is to a good extent a self-sustained process, in part maybe because application costs fall, in part because once a firm engages in R&D the cost of producing new ideas and further innovations falls or a combination of both. Identifying the factors that determine application costs could be useful, especially if the policy aims at encouraging the spread of socially beneficial innovation activities across firms. The finding that new-to-market product innovation is triggered by SMEs participating continuously into the R&D subsidization program suggests that the agency's selection of projects is successful in identifying truly innovation projects. The social benefits of occasional participation would not be obvious.

A number of issues would deserve further research. One is investigating how persistence in R&D subsidization is reinforced by persistence in performing R&D activities, that is, what mechanisms are driving the reinforcement process. The second would involve estimating the social returns of innovation subsidies in Spain, in line with work by Takalo, Tanayama, and Toivanen (2013) for Finland and Koehler (2018) for Germany.

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Chapter 2

Innovation, Public Support and Productivity in Colombia. A Cross-Industry Comparison*

2.1 Introduction

In this essay we contribute new evidence on the relationship between public support, innovation and productivity at the firm level in Colombia by investigating several unexplored issues. First we identify and compare the profile of firms that have access to public support for innovation in manufacturing and service industries separately; second, we examine whether the association between the introduction of innovations and productivity varies across the productivity distribution; third, we distinguish between technological and non-technological innovation, since the latter may be especially relevant in the service industries relative to manufacturing.

Colombia has experienced a steady growth of GDP per capita during the last decade. According to a recent report by the OECD, the commodity boom and macroeconomic reforms have been driving this performance; but productivity remains low (OECD 2015a). Developing an environment that increases the opportunities for and returns to innovation in all sectors can make a difference and complement other policies designed to stimulate sustained productivity growth, such as

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improving the regulatory framework, the financial system and the quality of education (Goñi and Maloney 2017; Nguyen and Jaramillo 2014).

Comparative empirical research carried out for several Latin-American and Caribbean countries (LAC) shows that both technological and non-technological innovation increase labor productivity in manufacturing industries (Casaburi et al. 2016; Crespi and Zuniga 2012). In 2013, however, manufacturing accounted for about 11% of GDP in Colombia, while the share of services was close to 60% and on average contributed 2.8 percentage points to GDP growth during the period 2005-2013 (OECD 2015b). The evolution of productivity in the service industries will therefore have a significant impact on aggregate productivity and growth. The ability to innovate in these industries can be expected to play a major role in this evolution, not only because of their weight but also because the role that some, like consulting services, play on the productivity of many other firms, especially on small and medium ones, through improving managerial capital (Bruhn, Karlan, and Schoar 2013).

Business investment in R&D in Colombia is low: it accounts for about 30% of all R&D investment, below the average rate of 40% in Latin America, which is in turn well below the 65-75% business share in advanced countries (OECD 2014). Yet, the degree of business sector involvement in R&D and more generally in innovation is important not only for developed countries but also for countries that are or intend to be on a catching up path. Extant evidence shows that countries and firms can benefit from others' knowledge and innovations provided that they develop absorptive (technology transfer) capabilities. Investing in innovation activities, especially in R&D, enables this process (Griffith, Redding, and Reenen 2004; Li 2011).

Colombia has implemented specific policies to promote innovation in the business sector: in particular, tax deductions for R&D and technological development projects, and direct support through subsidies and loans, are available to firms. Little is known, however, about who benefits from this support, how its allocation correlates with actual or perceived barriers to innovation and to innovation effort, and whether the returns to innovation differ significantly across the firms' productivity distribution.

To investigate these issues we use two firm-level datasets gathered by the Colombian National Statistics Department (DANE): the Survey of Innovation and Technological Development in Services, EDITS-III (2010-2011) and the Survey of Innovation and Technological Development in Manufacturing, EDIT (2009-2010). Because these are basically cross sectional data, we mainly aim at uncovering regularities and correlations that may be informative from a policy perspective, but cannot claim to establish causal relations.

The following results stand out. Regarding access to public support, we find some differences across sectors: in manufacturing and traditional service industries the probability to obtain direct public support is higher for firms that face high financing constraints. In knowledge intensive services (KIS), in contrast, this type of constraint is not found to be significantly associated with public support; instead, firms reporting that complying with regulations is an important barrier for innovating are more likely to obtain it. If regulations respond to efficiency criteria, this would suggest that public funds complement other policies. But if regulations create inefficiencies instead of addressing them, then public support may just be a means of partially offsetting their negative effects. We also find that in all industries firms that invest in R&D are more likely to obtain support, implying that knowledge generation, rather than pure imitation, is encouraged.

Regarding returns to innovation, we find that in manufacturing industries introducing innovations (product, process or non-technological) increases productivity at all levels of the productivity distribution. In contrast, in service industries including KIS, the introduction of all types of innovations increases productivity of firms below the median of the productivity distribution more than the productivity of those above. This suggests that less productive firms would benefit relatively more from introducing innovations, and that reducing barriers to innovation in the least productive firms would narrow down the productivity dispersion as well as increase the mean significantly.

The outline of the chapter is the following: in section 2.2 we address some conceptual issues, discuss closely related previous work and explain how we extend it; section 2.3 contains a description of the data we use from the Colombian firm-level innovation surveys; in section 2.4 we lay out the empirical framework and the hypotheses that will be tested; section 2.5 discusses results, and in section 2.6 we summarize our findings and draw some implications for policy and further research.

2.2 Previous Work, Conceptual Issues and Open Questions

Access to data from innovation surveys conducted by national statistical offices in an increasing number of countries has enabled the expansion of empirical research on the determinants of investment in innovation and on the private and social returns to these investments. The development by Crepon, Duguet, and Mairessec (1998) of an empirical framework to investigate simultaneously, at the firm level, the chain of links between the decisions to invest in innovation, the production of technological innovations, and their effect on productivity has contributed to a great extent to this progress. This empirical framework -known as the CDM model- consists basically of a system of four recursive equations where the first two model the decision to invest in R&D and investment effort, conditional on deciding to invest at all; the third models innovation output as a function of R&D investment, and finally innovation output enters the productivity equation.[1].

Cross-country comparative studies based on firm level data for manufacturing industries in developed countries have uncovered some regularities that hold across their diverse institutional and economic environments. For example, in European countries, the probability of engaging in R&D is generally associated with exposure to international competition, firm size and access to public funding; R&D investment intensity is highly correlated with introducing product and process innovations, and product innovation in turn is positively correlated with labor productivity (Aw, Roberts, and Xu 2011; B. H. Hall, Mairesse, and Mohnen 2010).[2] Similar patterns are observed in manufacturing industries in emerging countries (Jefferson, Huamao, Xiaojing, and Xiaoyun 2006).

To what extent do these regularities hold in the service industries, which account for a large share of GDP in developed countries as well as in many developing countries? Services include a large and very heterogeneous set of activities that differ from manufacturing in several respects. First, many produce mostly intangible outputs, which often present more measurement difficulties than tangibles. In addition, intangibility of many services means that they may be affected, to a greater extent than manufacturing industries, by issues derived from asymmetric information regarding service quality and properties. Some services consist precisely on the provision of information -consulting services, health, education, research, financial services-, and information goods have some distinctive traits. One of them is that their quality and value to the user or consumer may be uncertain until it is consumed; this may provide more room for problems such as adverse selection and moral hazard, which are consequences of the asymmetric information situation between the two parts of a transaction. It is well known that asymmetric information can generate market failures in financial, insurance and health services. These market failures are likely to affect costs and rewards of innovating. For instance, they can raise the cost of capital for corporations, reducing investment in general (Choi, Jin, and Yan 2013).

A second difference between manufacturing and service industries is that competitive pressure varies across activities: only some services are internationally traded, in contrast to manufacturing goods. Even when technically feasible, trade in services may be further restricted through regulations. In this regard, the OECD computes

[1] For a recent extension that introduces dynamics into the model see Raymond, Mairesse, Mohnen, and Palm (2015)

[2] Aw et al. (2011) provide further evidence on the dynamic links between decisions to invest in R&D, exporting and productivity, using plant-level data for the Taiwanese electronics industry.

a Services Trade Restrictiveness Index (STRI) for 42 countries and reports that in the case of Colombia this index is below the average in 18 out of 22 sectors, with legal, architecture, engineering and road transport among the lowest. However, telecommunications, insurance and broadcasting are at or above the mean, which means that trade-related regulations in these activities could be further improved.[3] Openness to trade is usually positively correlated with innovation, both in manufacturing and services (Zahler, Iacovone, and Mattoo 2014). More broadly, trade and institutional quality are found to be correlated with productivity growth, one of the channels being their impact on international knowledge diffusion (Coe, Helpman, and Hoffmaister 2009).

Third, and related to the previous point, additional government regulations such as restrictions to FDI, barriers to entry and conduct regulations affect many services (telecommunications, professional and financial services, utilities, health services, education). These regulations may influence firms' incentives to innovate or to adopt innovations, and ultimately affect productivity growth. Both sector specific and broader studies contribute evidence in this respect. Gruber and Koutroumpis (2013), use data on the adoption of broadband services in a panel of 167 countries and assess the effects of different regulatory frameworks on adoption of innovations; Andrews and Cingano (2014) provide broad evidence on the relation between policy frictions and productivity. Van der Marel, Kren, and Iootty (2016) assess the effect of services regulation on productivity using a large data set at the firm level in European Union member countries. They use services policy indicators across countries and several TFP measures at the micro-level to track down this relationship. Furthermore, they separate an overall index of regulations into restrictions that refer only to entry barriers and restrictions that concern the operations of the firm -conduct regulations-. Their results suggest that reducing these restrictions would increase the productivity performance of firms operating in both services and manufacturing industries; that lowering regulations on the operations of the firms would have an impact on firm-level TFP in all countries, and that institutionally weak countries - meaning weak or unqualified regulatory bodies, and low level of trust- are more likely to suffer significantly more from restrictive regulations.

In manufacturing industries most innovations are based on the ability to generate new knowledge by engaging in costly research and development activities. Their outcome -knowledge- may be subject to spillovers that reduce private returns and therefore the incentives to carry them out. In services, however, innovation sources may be more diverse: some may be based on ideas that involve the adoption of ICTs, or on organizational or marketing changes that are less likely to involve significant

[3] The OECD also notes that Colombia maintains some restrictions for foreigners as well as preferential treatment for Colombian inputs in the public procurement market (OECD 2015a).

idea development costs relative to size of knowledge spillovers. Returns to innovation might, therefore, be less affected by this potential source of market failures in some services, although knowledge-intensive business services, on the contrary, might be more affected. We next discuss these as well as some measurement issues.

2.2.1 Measurement of Productivity and Innovation in Manufacturing and Service Activities

The measurement of output, productivity and innovation in services has been a challenge for statistical agencies responsible for quantifying and characterizing economic activities. In particular, the measurement of average capital and labor productivity and of multifactor productivity in market and non-market services, has been addressed by economic researchers for some time. In his introduction to a volume collecting the contributions to a conference organized in 1990, Griliches (1992) wrote: "the possibility that difficulties in measuring output and prices in services may have resulted in a mismeasurement of productivity growth in these sectors, a mismeasurement that accounts for some or even much of the observed contrast with the productivity experience of commodities".[4] The volume edited by Skinner, Staiger, Berndt, and Hulten (2007) provides an account of contributions to measurement since Griliches. In one of the chapters, Bosworth and Tripplet describe some of the advances and use currently available data and methods to compute productivity. They find that, in the USA in particular, labor productivity growth in the 1995-2001 period was higher in the service industries than in goods industries; within-industry heterogeneity though was also high, both within manufacturing and within service industries. Evidence shows that dealing with measurement issues has implications for establishing economic facts and analysis: widespread beliefs that services are characterized by low productivity or low capital intensity are not confirmed when better data are collected. Data improvements are thus key for characterizing similarities and differences both within and across economic activities and to testing hypothesis about productivity and the role of innovation in these activities.

Gallouj and Djellal (2011) note that OECD manuals providing guidelines for the measurement of innovation and knowledge activities have evolved in order to reflect the changes that have taken place over time with respect to what and how innovation is performed in all economic sectors, including services.[5] Thus, while

[4] Griliches collaborated with government economists and statisticians in statistical agencies to improve measurement of output and prices of all economic activities, and inspired other scholars to do so.

[5] The Frascati Manual, first published in 1962, has been revised several times to keep up with new measurement needs as the scope of knowledge and innovation has been expanding; in 2015 the seventh revision has been published. The OECD's Oslo Manual, first published in 1992, was last revised in 2005. The main novelty of the last revision was precisely the specific attention paid to capturing non-technological innovation -marketing and organizational-, linkages between different

measurement issues certainly call for further work, the quality and scope of indicators of innovation inputs and outputs in all industries, including services, have been improving over time, allowing for a better description of facts and analysis. Recent national innovation surveys show that in most countries a majority of firms introduces technological and non-technological innovations simultaneously, and a smaller share introduce only marketing or organizational innovations, or only product or process innovations (see OECD 2015c, p. 162-163). We also observe that in service industries a higher percentage of firms introduce only non-technological innovations than in manufacturing industries, but still the percentage introducing all types of innovations simultaneously is generally higher in both industries.

What about cross industry differences in how innovations are developed? Innovations are the outcome of implementing new ideas connected with the production and delivery of goods and services. In some but not all cases finding and implementing new ideas may require a significant effort. When this work is systematic, creative, uncertain, reproducible and novel, it is called R&D in the OECD's Frascati Manual: "Research and experimental development comprise creative and systematic work undertaken in order to increase the stock of knowledge – including knowledge of humankind, culture and society – and to devise new applications of available knowledge" (OECD 2015a, p. 44). R&D is thus one input for innovation, but possibly not necessary nor sufficient to obtain some types of innovations: certain marketing and organizational innovations can be invented and implemented without investing in R&D. To the extent that these types of innovation are more frequent in service than in manufacturing industries, we would expect R&D activities to be less used in the former, as observed so far. This may change in the near future, however, as recent developments in the scientific fields of psychology, neurosciences and behavioral economics suggest that R&D activities are likely to play an increasing role in generating these type of innovations across all industries, and maybe especially in services.

Innovative activities are very heterogeneous across service industries with respect to the costs and methods of innovating. Innovation, in many instances and in all industries, does not necessarily rely on systematic activities to obtain scientific and technical knowledge, but on informal human ingenuity, interactions with suppliers and customers, new combinations of other innovations. Some examples illustrate the diversity of innovation in services, as well as how its sources and process may change over time. Google, a firm specialized in Internet-related services and products, has a wide portfolio of research projects, investing about 13% of its revenues on R&D

innovation types and innovation in services. Furthermore, the concept of innovation activities includes not only R&D investment, but also development and support activities, such as market preparation, acquisition of external knowledge or capital goods, and training.

and covering a wide range of fields, from computer science to education innovation. In the food services, culinary chefs are involved in research with food scientists to explore new ways of cooking -think of molecular gastronomy, for instance-. Administrative and support services are likely to rely on innovation through suppliers' R&D: robots for office and building cleaning are an example. Organizational and marketing innovations may or may not rely on R&D. Some illustrative examples come to mind. Bicycle sharing systems in large cities (bicing) are land transportation innovations that do not necessarily require significant R&D.[6] In contrast, innovation in education or organizational change in private and public organizations may benefit from applied research and experiments in the behavioral and psychological sciences (Beshears and Gino 2014).

Following the latest revision of the OECD Frascati Manual and the ISIC classification of activities (Revision 4), recent work by Galindo-Rueda and Verger (2016) provides an updated classification of all economic activities, including a wide range of services, according to their R&D intensity. Industries are classified into five groups: high, medium-high, medium, medium-low, and low R&D intensity. They find that two service activities, namely scientific research and development and software publishing are classified as high R&D intensity industries, while IT and other information services are ranked as medium-high R&D intensity. No services would be classified as medium R&D intensity activities; while several manufacturing industries would be included in this category: rubber and plastic products, building of ships, basic metals, among others. Professional and technical services (except scientific R&D), telecommunications services and publishing of books and periodicals are classified as medium-low R&D intensity activities. The class of low R&D intensity industries includes remaining services -financial and insurance, utilities, audiovisual and broadcasting, wholesale and retail trade, arts, transportation and storage, real estate and accommodation and food service activities. It thus appears that service activities are quite polarized in terms of R&D intensity, unlike manufacturing activities, where R&D intensity varies gradually. This does not mean, as the examples discussed above illustrate, that low R&D intensity industries cannot be innovative. It means that the cost of innovating is unlikely to be high relative to appropiable -private- benefits, or that technical risk is likely to be low. The threat of imitation may be less likely to deter a firm from innovating, as lead advantage can give the firm a high enough payoff.

[6] "Bicing" consists of a network of stations to lend and return bicycles in large cities. Many stations are located next to public transport stops; each bike serves several users per day. This system is often implemented through public-private partnerships, and IT has enabled its recent success. Previous attempts to introduce this service failed mostly because of the difficulties to control for theft and vandalism. Some examples where this innovation has been successfully implemented are Barcelona, Melbourne, Paris, Stockholm and Wuhan among others.

2.2.2 Evidence

How do differences described above between manufacturing and service industries affect incentives to innovate in each industry? Does the impact that innovations have on productivity differ as well? Studies for developed countries find that similarities are substantial, especially for some types of services. Work by Lööf and Heshmati (2006) for Sweden, Arvanitis (2008) for Switzerland and Musolesi and Huiban (2010) for France shows that investment in internal or external R&D and introduction of innovations in services are significantly correlated, and that innovations affect productivity, as in manufacturing.[7] Studies that focus on services, such as Segarra-Blasco (2010) for Catalan firms, and Peters, Riley, Siedschlag, Vahter, and McQuinn (2014) three European countries (United Kingdom, Germany and Ireland), corroborate the positive relationship between innovation and productivity in services.[8] With respect to public support, in addition, Musolesi and Huiban (2010) find that firms in KIS that receive public support are more likely to introduce technological innovations, although not other types of innovation.[9]

Do determinants and consequences of innovation in manufacturing and services in Latin America, and in Colombia in particular, follow similar patterns as in developed countries? Several studies have investigated this question for manufacturing industries.[10] Raffo, Lhuillery, and Miotti (2008) and Crespi and Zuniga (2012) use the CDM framework to perform comparative cross-country studies for manufacturing industries in LAC.[11] Although their respective empirical specifications differ, they all find that the probability of investing in innovation activities (Raffo et al. 2008) or in R&D (Crespi and Zuniga 2012) increases with firm size; that the probability of introducing product or process innovations depends on the magnitude of this investment, and that productivity (usually proxied by sales per employee) is higher for firms that introduce innovations in almost all LACs investigated. Crespi

[7] Musolesi and Huiban (2010) focus on KIS services. They find that R&D activities and the acquisition of equipment, licenses or software are a significant determinant of the decision to produce technological innovations, but not non-technological ones. All innovations have a strong and positive effect on productivity, measured by added value of the employee.

[8] As to the incentives to invest in innovation, Segarra-Blasco (2010) and Peters et al. (2014) find that firm size and participation in international markets are positively correlated to the probability of investing in innovation, much like manufacturing firms.

[9] The relationship between firm size, foreign ownership and investment in innovation activities in services and type of innovation -process vs. product; technological vs. non-technological- varies across these countries, possibly reflecting institutional differences.

[10] Alvarez, Bravo-Ortega, and Zahler (2015) use the CDM framework to compare the links between innovation and productivity in manufacturing and service firms in Chile, finding many similarities.

[11] Raffo et al. (2008) estimate the same CDM model for France, Spain, Switzerland, Argentina, Brazil and Mexico. Crespi and Zuniga (2012) focus on six LACs, including Colombia. For an empirical analysis of individual LAC countries, see for example Miguel Benavente (2006) for Chile; Chudnovsky, López, and Pupato (2006) for Argentina; Tello (2015) for Peru, Aboal and Garda (2016) for Uruguay, and Rodriguez Moreno and Barrachina Maria (2015) for Ecuador.

and Zuniga (2012) conclude that promoting innovation can indeed be an effective way to increase productivity in LACs, and that the main policy concern should be removing the obstacles that deter manufacturing firms from investing in innovation.

Many governments in LACs have implemented programs to foster innovation in the private sector. Like in OECD countries, some provide direct support through matching grants, non-refundable grants and credit lines to firms that have innovation projects. Alvarez et al. (2015) for Chile, and Gallego, Gutiérrez, and Taborda (2015) for Colombia, use the CDM model to compare innovation effort and outcomes in manufacturing and service industries taking into account public support. Gallego et al. (2015) assume that public funding is not related to the discrete decision to invest in innovative activities, but only to innovation intensity.[12] They find public support to be the most important variable associated with innovation intensity in KIS but not in traditional services, and that innovation effort in turn is correlated with labor productivity in all industries. These findings suggest that access to finance by potentially innovative firms might be a significant barrier for increasing the mass of innovating firms in some industries in Colombia and other LAC, but they do not pursue this specific question further.[13]

Recently Crespi, Garone, Maffioli, and Melendez (2015) evaluate the impact of some programs from the Colombian Innovation Agency (COLCIENCIAS) on the productivity of manufacturing industries over the period 1998-2007.[14] Their results support the conclusion that these programs have a positive effect on the introduction of new products and on labor productivity in the long term. They do not investigate, however, whether receiving public support is correlated with innovation barriers that firms perceive to be important. From a policy perspective it is essential to know whether public support addresses in practice common sources of underinvestment in innovation (Busom, Corchuelo, and Martínez-Ros 2014). Even if support programs have positive effects on some measures of performance, this does not prove that these programs reach firms that face financing or other market failures that often affect innovation.

Evidence that Colombian manufacturing firms face constraints in accessing to credit, although not specifically for innovation activities, is provided by Eslava, Maffioli, and Meléndez (2014), who show that public untargeted lending programs ease these constraints -especially long term lending-, allowing firms that benefit

[12] Gallego et al. (2015) use EDIT 2007-8 for manufacturing, and EDIT 2008-9 for services. Their sample of service firms has a smaller number of observations (562 firms) than ours.

[13] In addition they assume that receiving public support is uncorrelated with unobserved variables in the innovation investment decisions.

[14] Research to evaluate the effectiveness of this type of programs has been expanding. B. Hall and Maffioli (2008) provide a review of existing evidence for some LAC.

from them to grow and invest.[15] These observations lead us to expand the CDM model including an additional equation in order to test whether public funds reach financially or otherwise constrained firms willing to innovate, and whether observed support allocation patterns differ across industries.

Another issue that has not been investigated in depth is whether private returns to introduction of innovations vary significantly across firms. Firm level productivity is known to be highly heterogeneous within industries in a given country, reflecting differences in managerial talent, labor quality, R&D or export status as well as factors external to the firm such as a poor regulatory environment (Syverson 2011). Most research on the relationship between these variables and productivity measures is based on estimates at the conditional mean of the productivity distribution. These estimates, however, may not reflect accurately the link along the whole productivity distribution. Quantile regression methods may be more appropriate when the distribution of the outcome departs from normality. Work by Yasar, Nelson, and Rejesus (2006) and Powell and Wagner (2014) shows that the relationship between export status and productivity varies across manufacturing firms' productivity levels in Turkey and Germany, respectively. It turns out that in Turkey the productivity effects of exports are larger at the upper tail of the distribution, while in Germany evidence suggests the opposite result.

Most empirical studies on the returns to innovation or to R&D are based too on estimates of the innovation (or R&D) premium at the conditional mean of the productivity distribution. Whether returns to innovation vary across the distribution has been studied in a small number of cases. Some examples are Coad and Rao (2008), who find that innovation is important for some fast-growth firms in the US; Segarra and Teruel (2011), in contrast, find that internal R&D investment in Catalonia has a highest impact on the productivity of firms in the lowest quantile rather than on those in the highest quantile. Similarly, Damijan, Kostevc., and Rojec (2012) also find that manufacturing firms with below average productivity benefit more from innovation than other firms in Slovenia.[16] Finally, Bartelsman, Dobbelaere, and Peters (2015) find that returns to product innovation are higher for more productive firms in most industries -manufacturing and services- in Germany and the Netherlands, while returns to process innovations seem to be negative in service industries. This result would suggest that public support to innovation should not

[15] Eslava et al. (2014) use a large sample of loan beneficiaries and firm-level data from the Annual Manufacturing Survey over the period 2004-2009. They use propensity score (PS) estimates to match beneficiaries and non-beneficiaries and obtain impact estimates; the specification for the PS is not shown, and we cannot compare it with our estimates. Daude and Pascal (2015) provide evidence that the efficiency of the Colombian banking system could be improved.

[16] Segarra and Teruel (2011) use a sample of Catalan manufacturing and KIS firms; Damijan et al. (2012) use data from Slovenian firms; in both cases the data sources are the respective Community Innovation Surveys (CIS).

be assigned to process innovations in service industries unless significantly positive knowledge spillovers are involved.

The link between productivity and innovation activities in Colombian firms may exhibit a high degree of heterogeneity as well, especially in service industries. According to a study by Busso, Madrigal, and Pagés (2013), total factor productivity at the firm level shows a high dispersion in several LAC relative to the US, particularly in Colombia. This would have implications for innovation policy: if private returns to innovation -as measured by their contribution to labor productivity- are higher for more productive firms, then direct public support for innovation should focus on the subset of productive firms that face innovation barriers. If returns to innovation are the same on average for all firms at any productivity level, then there would be no need for a targeted support policy. But if instead the innovation premium is higher for firms in the lower tail of the productivity distribution, public effort should address the factors that deter innovation in these low productivity firms.

2.3 Data and Variables

The Colombian National Statistics Department (DANE) conducts two innovation surveys, one for manufacturing firms (EDIT), and another for service firms (EDITS), following the OECD Oslo and Bogota Manual guidelines.[17] For manufacturing the sample includes establishments with 10 or more employees or with an annual production greater than USD $68,700 according to the directory of firms from the Annual Manufacturing Survey (ASM). For the service sector survey (EDITS), sample inclusion parameters vary across activities according to the one digit level ISIC classification: while all firms in financial intermediation are sampled, in other service activities only those with more than 20 employees -or more than 50 in some cases- or a given level of sales are included (see Table 2.A1 in the Appendix). The sample does not intend to represent the whole universe of firms in service industries.

We use the 2010-2011 wave for the services sector (EDITS 2010-2011), and the 2009-2010 wave for manufacturing (EDIT 2009-2010). Our working sample consists of 905 manufacturing firms, 954 firms in knowledge intensive business services (KIS), and 1,419 firms in remaining service activities, which we will refer to as traditional.[18] Table 2.1 shows the composition of the sample by industry and firm size.

[17] The Colombian statistical office (DANE) pays special attention to the specific features of service activities relative to manufacturing and takes into account the reflections made by Gallouj and Djellal (2011) and others in this respect when designing the innovation survey. See DANE (2016).

[18] Traditional services include wholesale and retail trade, hotels and restaurants, health and social services, other social and personal services, as well as utilities, while KIS includes business services; financial intermediation and transport, storage and communications. See Table 2.A1 for more details on sample composition.

Table 2.1: Sample Composition by Firm Size

Number of employees	All Services	KIS	Traditional	Manufacturing
$\leq$ 50	53.60%	60.50%	48.90%	47.00%
51-150	16.00%	14.40%	17.10%	19.40%
>150	30.40%	25.20%	34.00%	33.60%
Total	100%	100%	100%	100%

Innovation surveys collect information on firm features (size, human capital, exporting status), on their innovation activities and output, including the firms' perceptions concerning the importance of some barriers to innovation, and whether the firm has benefited from public funds to innovate. Some of the survey questions refer to the two year period, and others to the survey year and/or the year before. Innovation activities include internal and external R&D, investment in physical capital or ICTs to produce new goods or services, marketing and design expenditures for innovations, technology transfer payments, and specialized training.

In our sample about 28% of firms in KIS, 30% in traditional services and 31% in manufacturing report having invested in some innovation activity within the survey period. Table 2.2 provides a description of the main innovation related activities. Table 2.A2 in the Appendix provides the definition of each variable. In service industries including KIS the percentage of firms that engage in R&D is about half of those that invest in innovation activities, while in manufacturing the percentage is higher, especially across firms with more than 50 employees. This is consistent with the usually higher importance of introducing innovations by adopting ICTs in services.

Process and organizational innovations are more frequent, on average, than product or marketing innovations, but they are all highly correlated. The pairwise tetrachoric correlation across innovation types is very high: 0.85 between product and process innovations in KIS, 0.78 in traditional services and 0.80 in manufacturing; the correlation between process and organizational innovations shows similar values. This suggests that firms that introduce one type of innovation are very likely to introduce another as well, possibly because of complementarities among them (Ballot, Fakhfakh, Galia, and Salter 2014). As a matter of fact, this pattern is found in other countries as well. According to the OECD STI Scoreboard 2015, in Sweden about 27% of innovative service firms introduce only one type of innovation; in Turkey the percentage is 27% as well, and in Spain it is 20%. The Scoreboard also provides information for Colombia: for years 2012-13, only 26 percent of firms introduced only one type of innovation. Furthermore, the picture is not very different in manufacturing industries: the percentage of firms introducing only one type of innovation was 29%, 26% and 21% respectively for the first three countries. In Colombia, with 18%, it was even lower.

In our sample we observe some differences across types of innovation: introduction of process innovations is somewhat more extensive than other types of innovations in all industries, especially in KIS, while product innovations are more common in large manufacturing firms (see Table 2.2). Organizational innovations are slightly more widespread in KIS, but we do not observe significant differences across industries in the introduction of marketing innovations. As observed elsewhere, the percentage of firms that introduce any innovation increases with firm size in all industries.

The distribution of the log of sales per employee, which we will use as a proxy for labor productivity, exhibits some differences across industries and firm size. Dispersion is larger in service industries than in manufacturing, pointing to a greater heterogeneity among the former. In our sample, service firms at the 90th percentile of productivity are about 50 times -four times in the log scale- more productive than firms at the 10th percentile, both in KIS and in traditional services. In manufacturing the ratio is about 22 to 1. In addition, the distribution of the log of labor productivity is skewed to the right, especially in the case of traditional services. Extreme values are frequently observed in all industries, with a value for kurtosis of about 5, exceeding in two units that of the standard normal distribution. These differences are consistent with findings by Busso et al. (2013), who explore whether distortions in input and output markets in LAC contribute to explaining these differences in productivity. They find that resource misallocation is higher in services than in manufacturing, for countries where data for service industries are available. Variation in technologies and processes, in the distribution of human capital and management quality might contribute as well to explain these differences.[19] Finally, we observe in our sample that in service industries, both traditional and KIS, average productivity falls with size, in contrast to manufacturing, where productivity is higher in larger firms.

A range of public programs provide support for business innovation in Colombia. Some supply grants that co-finance R&D and innovation projects at a rate below the full cost of a project (FOMIPYME, SENA, COLCIENCIAS).[20] According to the Colombian statistical office, DANE, about 60% of all public funds were provided

[19] Lemos and Scur (2015) provide a description of the distribution of management practices at firm-level in Colombia and other countries. They find that the average score of management practices in Colombia is below the expected value given its development level, and that the distribution of scores shows a long and thick tail of underperforming firms.

[20] FOMIPYME is the acronym for the program Linea de innovacion, desarrollo y transferencia tecnologica; and SENA for the Programa Innovacion y Desarrollo Tecnologico-Ley 344/96. COLCIENCIAS has a cooperation program, Universidad CIA-CDT-Empresa, and a risk sharing program, Riesgo tecnológico compartido Empresa.

through co-financing in 2010 (75% in 2011) in the case of services. Other programs (Bancoldex, and Bancoldex-Colciencias) provide loans (credit lines) to finance the whole cost of R&D and innovation projects. These refundable loans represent a very small share of public funds allocated to services (5% in 2011). In manufacturing, in contrast, most support (65% in 2009, and 42% in 2010) is provided through loans, while the share of co-financing is 15% and 20% each of these years. Finally departmental and local funds for science and technology projects are available as well (39% of total public funds in 2010 in the case of services, and a similar share for manufacturing).[21] In our sample, on average 4% of firms in the services industries and 8% those in manufacturing report having benefited from direct support during the survey period, although figures are smaller for small firms and increase with size.[22] Grazzi and Pietrobelli (2016) report similar percentages for Latin-American firms. We do not have disaggregate information by program; we only know whether a firm received any type of public support for innovation projects.

[21] See DANE (2016).

[22] Colombia also provides some tax incentives: tax deductions from the corporate tax to firms that invest in R&D and income tax exemptions for software developers and others. We did not have access to information collected in EDIT on the use of tax incentives by firms in our sample. According to Mercer-Blackman (2008), however, very few firms use these incentives.

Table 2.2: Investment in Innovation, Public Support and Innovation Output.

By industry and firm size
Percentage of firms

	All services				KIS				Traditional Services				Manufacturing			
	Total	≤50	51-150	>150	Total	≤50	51-150	>150	Total	≤50	51-150	150	Total	≤50	51-150	>150
With Innovation Expenditures	28.69	18.17	35.78	43.49	26.94	17.33	41.6	41.67	26.67	18.39	31.36	44.94	30.83	18.35	35.23	45.72
Engage in R&D activities	13.11	6.61	11.84	25.21	14.04	7.45	18.24	27.5	12.47	5.91	8.23	24.07	21.44	7.05	22.73	40.79
Obtain Public Support	4.51	2.83	6.58	6.37	3.88	2.95	6.57	4.58	4.93	2.73	6.58	7.26	8.29	4.24	7.95	14.14
Introduce product innovations	16.31	9.99	20.99	25.48	16.24	8.35	21.25	29.96	16.67	11.64	19.1	22.7	21.21	10.11	19.31	37.82
Introduce process innovations	22.67	13.92	26.32	36.15	22.64	13.69	31.39	39.17	22.69	14.12	23.46	34.65	24.41	14.11	25.57	38.16
Introduce organizational innovations	21.99	12.74	26.05	36.15	21.59	12.65	31.38	37.5	22.27	12.82	23.05	35.47	22.43	12.94	25.00	34.21
Introduce marketing innovations	15.54	10.22	15.53	24.93	14.26	9.53	14.6	25.41	16.42	10.81	16.05	24.69	16.80	10.35	17.04	25.66
Introduce any innovation	34.13	22.66	40.79	50.83	31.97	20.97	43.8	51.67	35.58	24.06	39.09	50.41	37.57	23.52	39.77	55.92
Use formal IP protection	2.02	1.33	2.37	3.05	2.00	1.04	2.19	4.16	2.04	1.58	2.47	2.49	4.86	1.18	6.82	8.88
Log Sales per Employee (mean)	10.58	10.83	10.51	10.25	10.75	10.94	10.67	10.36	10.48	10.74	10.43	10.20	10.25	10.04	10.54	10.40

Authors' computations with the sample described in Table 2.A1.

Table 2.3: Innovation Barriers and other Firm Features

By industry and firm size

Percentage of firms

	KIS				Traditional				Manufacturing				All services			
	Total	≤50	51-150	>150	Total	≤50	51-150	>150	Total	≤50	51-150	150	Total	≤50	51-150	>150
A. Innovation Barriers																
Financing Constraints: Internal	21.49	24.96	21.17	13.33	24.31	28.38	21.81	19.71	33.92	40.94	36.93	22.37	24.31	26.82	21.58	17.59
Financing Constraints: External	20.65	24.78	18.98	11.67	20.22	24.93	15.23	15.98	25.63	31.53	24.43	18.09	20.39	24.86	16.57	14.54
Internal or External	27.88	32.41	27.00	15.50	30.01	35.01	26.75	24.69	39.67	47.05	43.18	27.3	29.20	33.83	26.84	22.29
Demand Risk	19.81	21.84	16.06	17.08	21.28	23.91	20.99	17.63	27.62	30.35	29.54	22.70	20.69	22.97	19.21	17.45
Lack of qualified personnel	18.55	19.06	18.98	17.08	20.51	19.74	22.63	20.54	25.08	31.06	26.14	16.12	19.71	19.43	21.32	19.39
Regulation	9.96	9.53	5.84	13.33	11.28	12.68	10.70	9.54	10.28	10.82	10.79	9.21	10.74	11.25	8.95	10.8
B. Sources of information																
Suppliers	22.06	18.44	20.55	26.67	24.57	21.08	30.97	24.54	21.91	19.35	18.29	25.13	23.64	20.00	26.88	25.25
Customers	26.64	26.95	28.77	25.19	23.72	24.02	19.47	25.27	26.70	21.77	29.27	28.8	24.81	25.22	23.12	25.24
Universities	6.02	5.67	4.11	7.41	8.31	6.37	7.08	10.25	6.04	0.00	4.87	10.47	7.45	6.09	5.91	9.31
Government	2.58	2.12	5.48	1.48	4.41	5.39	4.42	3.66	2.77	0.81	2.44	4.19	3.72	4.06	4.84	2.94
C. Firm characteristics																
Foreign ownership	2.94	1.03	3.65	7.08	2.67	0.86	4.11	4.35	4.75	1.29	1.64	5.19	2.78	1.18	2.36	5.82
Exporter	7.65	4.68	7.3	15.00	9.79	9.37	8.64	11.00	34.14	12.47	38.07	62.17	8.93	7.24	8.16	12.32
D. Skills																
Skills Low	7.65	11.09	0.73	3.33	4.09	7.64	1.23	0.41	2.76	5.41	1.14	0.00	5.52	9.21	1.05	1.39
Skills Medium	43.50	37.09	51.09	54.58	59.20	53.17	67.49	63.69	77.79	73.41	81.25	81.91	52.89	45.87	61.58	60.66
Skills High	48.85	51.82	48.18	42.08	36.72	39.19	31.28	35.89	19.45	21.18	17.61	18.09	41.59	44.93	37.37	37.95

Table 2.3 describes some other relevant features of firms in the sample that may correlate with their ability to obtain public support and to innovate. First, a high percentage of firms report that financing constraints are a very important barrier for their innovation plans, especially for firms with less than 50 employees, and for a higher percentage of firms in manufacturing than in service industries. Foreign ownership is more prevalent as firm size increases, both in manufacturing and services. Exporting, an activity also correlated with firm size, is more common among manufacturing than among service firms, as expected. Market sources of information -from customers or from suppliers- are of much higher importance to firms than institutional sources -universities or government centers-. Finally, it is interesting to note the differences in the distribution of human capital across firm size and industry in the sample: in service industries we find a higher proportion of firms that have a high level of human capital than in manufacturing, across all firm size intervals.[23]

2.4 Empirical Modeling

2.4.1 An Extended CDM Framework

We introduce several novelties to the recursive, static CDM framework. First, we add a first stage that accounts for access to public funding for innovation activities. Obtaining public support is not the outcome of a random process, but rather the consequence of a firm's decision to apply for it and the public agency's to award it. It is thus likely to be correlated with unobservables in other innovation decisions, leading to potentially important endogeneity bias in subsequent equations. The discrete decision to invest in innovative activities and the intensity of innovation effort follow, where the estimated probability of obtaining public support is included in both equations as independent variable. Predicted innovation effort becomes an input into the likelihood of introducing several types of innovations. Finally we estimate labor productivity as a function of each (predicted) type of innovation separately, allowing for a potentially different correlation between innovation type and productivity across the distribution of productivity. Our system consists of five equations that we explain next, while we discuss our hypotheses on regressors as well as the potential endogeneity issues that arise in section 2.4.2.

The first equation describes access to public support for business innovation. S_i, is observed as a binary variable, indicating whether a firm has received public

[23] This possibly reflects the different criteria used for sampling firms for the manufacturing and service surveys by DANE.

resources from sources explained in section 2.3 to carry out scientific, technological and innovative activities:

$$S_i^* = \begin{cases} 1 & \text{if } S_i^* = \Sigma x_{0i}\beta_0 + \varepsilon_{0i} > c \\ 0 & \text{if } S_i^* = \Sigma x_{0i}\beta_0 + \varepsilon_{0i} \leq c \end{cases} \tag{2.1}$$

We will estimate the probability of having obtained public support, $Pr[S_i = 1] = Pr[(\Sigma X_{0i}\beta_0 + \varepsilon_{0i} > c]$ through a probit model using the whole sample of firms, as all of them may be potentially eligible for support. Note that we do not observe whether the firm has applied for it and has been rejected. The observed variable thus indicates success at applying and obtaining, reflecting both incentives of firms to apply and the public agency preferences. This equation should be interpreted as a reduced form.

Investment in innovation activities is split as usual in two decisions: whether to invest or not (g_i), and the magnitude of investment (r_i) in innovation activities, where the latter is observed only if the firm has decided to invest a positive amount.[24] These decisions may be correlated with receiving public support, (S_i), as well as with additional variables (x_1) and (x_2) respectively:

$$g_i = \begin{cases} 1 & \text{if } g_{0,i}^* = fS_i^* + \Sigma x_{1i}\beta_1 + \varepsilon_{1i} > \tau \\ 0 & \text{if } g_{0,i}^* = fS_i^* + \Sigma x_{1i}\beta_0 + \varepsilon_{1i} \leq \tau \end{cases} \tag{2.2}$$

$$r_i = \begin{cases} r_i^* = mS_i^* + \Sigma x_{1i}\beta_1 + \varepsilon_{2i} & \text{if } g_i = 1 \\ 0 & \text{if } g_1 = 0 \end{cases} \tag{2.3}$$

Both equations are jointly estimated through a generalized Tobit model. The error terms are assumed to have a bivariate normal distribution. The introduction of innovations is observed as a binary variable which is a function of the predicted latent innovation effort and a set of other variables x_3:

$$I_i = \begin{cases} 1 & if : I_i^* = \alpha_I r_i^* + \Sigma x_{3i}\beta_1 + \varepsilon_{3i} > 0 \\ 0 & \text{if } I_i^* = \alpha_I r_i^* + \Sigma x_{3i}\beta_1 + \varepsilon_{3i} \leq 0 \end{cases} \tag{2.4}$$

Equation [2.4] will apply to four possible types of innovation: product, process, marketing and organizational. Each is estimated through a separate probit model, providing four estimated probabilities. These four equations are like a seemingly unrelated system: they have the same independent variables, and feedback effects across dependent variables are assumed away. In this sense they are reduced forms. To explicitly study the extent of pair-wise complementarity between all four types of innovation requires correcting for time-invariant individual effects so as not to attribute the complementarity to individual time invariant characteristics (Mohnen

[24] These two dependent variables refer to total investment in innovation activities, including R&D.

and Hall 2013). Our data do not allow us to control for unobservables, so we do not pursue this issue here.

Finally, labor productivity, y_i, measured as the logarithm of sales per employee, is assumed to depend on the introduction of innovations and a set of other variables x_4:

$$y_i = \alpha_0 + \alpha_I I_i + \beta_4 + X_{4i} + \epsilon_{4,i} \tag{2.5}$$

This equation is estimated replacing the innovation indicator I, by the estimated probability in [2.4], one at a time, and using both 2SLS and quantile regression methods.[25] Quantile regression allows the impact of regressors to vary along the distribution of labor productivity, which may be of importance in very heterogeneous industries such as services. Given $q \in (0, 1)$ and labor productivity (y_i), the qth quantile is

$$Q(q) = \inf\{y_i : F(y_i) \leq q\} \tag{2.6}$$

where F is the distribution function of y_i. Assuming that the quantile q of the conditional distribution of productivity (sales per worker, y_i) is linear in x_i, the conditional quantile regression model is defined by equation [2.7]:

$$Q_\theta(y_i \mid X_i) = Q_{y_{i,q}} = \beta_{1q} Prob[\alpha_I r_i^* + \Sigma x_{3i}\beta_1 + \varepsilon_{3i}] + \beta_{4q} x_{4i}\beta_4 + \mu_{i,q} \tag{2.7}$$

Coefficients measure the variation in productivity when a given characteristic changes, assuming that the conditional quantile of the firm remains the same. These coefficients may differ across quantiles.

2.4.2 Empirical Specification

In the first equation our main interest is to test whether perceived barriers to innovate are correlated with benefiting from public support. We focus in particular in two sources of barriers that could induce firms to apply for support programs: financing constraints -whether external or internal- and difficulties derived from complying with regulations.[26] Both can be modified by policy decisions, while other barriers such as demand uncertainty or access to highly skilled labor are harder to act upon through specific innovation policies.

Financing constraints are likely to be endogenous: innovators are more likely to be aware of financing constraints than non-innovators. This would explain why previous studies often find a positive correlation between the perception of financing

[25] See Koenker and Hallock (2001).

[26] Internal and external financing constraints are highly correlated, so a single indicator is defined (see Table 2.A2).

constraints and the likelihood of investing in innovation (Hajivassiliou and Savignac 2008, among others). To address this issue, we do not have access to an operational longitudinal panel data base, and cannot use lagged values of financing constraints. Therefore we instrument financing constraints and test for the validity of the assumption of exogeneity in the equation for public support. We use the Smith and Blundell (1986) test and the Rivers and Vuong (1988) test; both involve a two-step procedure. We also restrict the sample to firms that have invested in innovation activities or have introduced some type of innovation, whether technological or non-technological. As in Mancusi and Vezzulli (2014), the idea is to exclude firms that do not innovate not because they find barriers, but because they do not believe they need to.[27]

We include firms' perception of regulations as a barrier for innovation in this equation. Our argument is the following. Governments may implement policies that have opposite effects in terms of global efficiency: some policies reduce efficiency while other may enhance it. Innovation policy might be used to some extent, and among other goals, to offset the negative effects of efficiency reducing regulations by providing support for innovation in these sectors. Other regulations may be efficiency enhancing, such as those aiming at reducing environmental externalities, establishing safety standards and quality certifications. Governments might then use innovation policy to foster the development or adoption of technologies that enable firms to comply with these regulations. In these cases regulation and innovation policies would be complementary, while in the first case they would be conflicting from an efficiency perspective. Both types of regulated sectors might be targeted for public support for innovating. With the information we have from EDIT we cannot distinguish between efficient and inefficient regulations, but we can nevertheless test whether there is an association between regulation and allocation of public support.[28]

Low appropriability of returns generated by innovations is one of the standard arguments for market underprovision of innovations, and hence backing public support. Some innovation surveys ask firms whether the risk of imitation is substantial; others do not, in which case researchers use as a proxy some measure of patenting activity by the firm or in the industry. This measure has obvious limitations, as it proxies both the firm's stock of knowledge and its willingness -or perceived need- to protect inventions. In our specification we use a similar proxy, mostly for comparability, but the Colombian survey also allows us to use a direct measure of the

[27] The number of excluded firms is 100 in traditional services, 50 in KIS and 73 in manufacturing.

[28] Aboal et al. (2015) estimate that in LAC countries as a whole allocative efficiency contributes positively to productivity in almost all manufacturing industries, its contribution is negative in construction and several service industries, suggesting mobility barriers. Blind, Petersen, and Riillo (2017) show how regulatory capture may affect innovation costs.

ease of imitation. Both variables turn out not to be significantly correlated in our sample, hinting that they measure different phenomena.

Note that we observe whether firms obtain public funds, but not whether a firm applied for but was denied support. Estimated coefficients will then capture the net correlation between having public support and firm characteristics. We control for some features that are usually found to be associated with a firm being more inclined to innovate. These are firm size, being an exporter and the firm's productivity relative to the industry mean, the last two variables lagged one period. We do not expect ex-ante major qualitative differences across manufacturing and service industries, except that for the former exporter status is likely to be more significant, while regulations may be more relevant for services, as explained above.

Equation [2.2], the probability that a firm will invest in innovation, and equation [2.3], investment intensity, both include as independent variable the predicted probability of receiving public support. By providing funding, public support can help firms engage in innovation projects, increase the breadth of existing projects and/or allow firms to keep engaged in innovation (Arqué-Castells and Mohnen 2015). We assume that the predicted probability of obtaining public support captures the strength of financing constraints faced by firms: if constrained firms with good projects are more likely to apply for and obtain public support, and we assume that the public agency is able to discriminate across applicants, then this barrier would not have a further, direct relationship with investment decisions. This strategy is also followed by Gallego et al. (2015) and Casaburi et al. (2016), who use public support but not financing constraints in their specifications of the discrete and continuous investment decisions.

In addition, we assume that the binary decision to invest in innovation activities may be correlated with the firm's human capital, its previous innovation effort -capturing the degree of persistence of these activities-, relative productivity -more productive firms may obtain higher returns from innovating, as found by Aw et al. (2011)-, demand uncertainty and firm size. Investment intensity (innovation expenditures per employee) is assumed to be potentially correlated with the importance the firm gives to different sources of information, basically from market sources -suppliers and/or customers- and from research institutions -universities and public or private centers-, but not directly by firm size, as in Crespi and Zuniga (2012), Alvarez et al. (2015) and Casaburi et al. (2016).[29] We include foreign ownership and being an exporter in both equations, as the first may be a channel of international knowledge transfer, and the second may motivate innovation through the pressure of international competition.

[29] In addition to firm size, formal IP protection is also taken as exclusion restriction. Table 2.A3 describes the exclusion restrictions in the specified extended CDM model.

An innovation production function, equation [2.4], will be estimated for each type of innovation, that is, we estimate in fact four probit equations, where the same specification is used for all. Feedback effects across dependent variables are assumed away. In this sense they are reduced forms. We assume that in addition to predicted innovation expenditure per employee, the following inputs are correlated with introducing innovations: human capital (% employees with higher education, in three intervals), and market and institutional sources of information. We also assume that public support does not directly affect the introduction of innovations beyond the indirect effect through innovation investment. In addition we control for exporting status, foreign ownership and firm size, as in Crespi and Zuniga (2012).

Finally, labor productivity (equation [2.5]) is assumed to be correlated with the predicted probability of introducing innovations -one type at a time, in order to avoid a multicollinearity -, as well as with the firm's human capital, foreign ownership and exporting status, all lagged one period.[30] We will present and compare 2SLS and quantile regression estimates, showing the .15, .25, .50, .75 and .90 quantiles of the conditional productivity distribution. All equations include industry fixed effects.

2.5 Results

Access to Public Support

Table 2.4 reports our estimation results as well as the outcome of the exogeneity tests we conduct for financing constraints. We find that obtaining public support is significantly and positively correlated with perceived financing constraints for firms in manufacturing and in traditional services, but not in KIS.[31] In contrast, we find that in KIS firms that perceive regulations to be an important barrier to innovate are more likely to obtain public support. This highlights the distinct role of regulations in services: if they respond to efficiency criteria -environmental regulations, for instance-, this correlation would suggest that public funds for innovation complement other policies. But if regulations are not efficiency enhancing, but create inefficiencies instead, then public support to innovation may just be a means to partially offset the negative effects of the former, in which case the best approach would be to revise these regulations in the first place. It is unfortunate that innovation surveys do not draw more specific information on the kind of regulations affecting firms in different industries, since implications for policy may be rich and diverse. Anti-competitive service regulation may have direct effects in services by reducing

[30] Unfortunately the EDIT surveys do not provide information on the firm's physical capital or investment.

[31] Busom, Corchuelo, and Martínez-Ros (2015) also find that in Spain obtaining direct public support is uncorrelated with financing constraints in services, although they do not separate KIS from other services.

incentives to innovate, but also reduce innovation and productivity in downstream service-intensive industries, including manufacturing. Several studies provide evidence supporting this hypothesis. Barone and Cingano (2011) using OECD indicators accounting for barriers to entry, integration between competitive activities and natural monopolies, and restrictions on prices, fees or form of business, find that lower service regulation has positive effects on value added and productivity growth. Cette, Lopez, and Mairesse (2017) estimate a three equation model that includes a production function with R&D and ICT capital, and two factor demand functions for R&D and ICT capital where the role of upstream regulations is tested; they find that regulatory burden reduces R&D capital in downstream industries.[32] Querbach, Arndt, et al. (2017), in their report on regulatory policy in Latin America, conclude that in the case of Colombia the regulatory landscape is still fragmented and would benefit from using a regulatory impact assessment as well as from systematic ex post evaluations of regulations. The evidence just described as well as our finding suggest that regulatory reforms could spur innovation effort and complement other innovation policy initiatives.

We also find that ease of imitation is uncorrelated with having public support, which may reflect that this is not an important motivation for firms to apply for support, or for the agency to grant it; we cannot discriminate between these two mechanisms with the available information. Previous experience in R&D is positively correlated with access to public support in all industries, while using some type of formal intellectual property protection is highly significant only for KIS. Regarding the importance of firm size in accessing public support, we find that in traditional services larger firms have a higher probability of benefiting from support, but not in manufacturing or KIS. Exporter status, foreign ownership and relative productivity of the firm do not appear to be significantly associated to receiving public support in any industry.

Overall, our results regarding the allocation process suggests that on average: i) innovators in all industries face binding financing constraints and resort to public support mechanisms; ii) there is no evidence that imitation is a binding barrier; iii) regulations and intellectual property issues are relevant for KIS, and iv) most productive firms are not more likely to obtain support, either because they do not self-select into applying for it, or because public agencies on average do not discriminate across the productivity distribution of firms.

[32] See also Franco, Pieri, and Venturini (2016).

Table 2.4: Access to Public Support

	Traditional Services	KIS	Manufacturing
Financial Constraints	0.0441**	0.0160	0.0612**
	(0.0139)	(0.0159)	(0.0220)
Regulations	0.0252*	0.0494**	0.0256
	(0.0162)	(0.0178)	(0.0220)
Formal IP protection	0.0180	0.0755**	0.0368
	(0.0397)	(0.0360)	(0.0358)
Ease of Imitation	-0.0212	0.00584	-0.0228
	(0.0176)	(0.0190)	(0.0248)
Regular R&D	0.0887***	0.0594**	0.0987***
	(0.0210)	(0.0274)	(0.0253)
Exporter (t-1)	0.0134	0.0159	0.0290
	(0.0216)	(0.0262)	(0.0230)
Foreign ownership	-0.0419	ψ	0.00517
	(0.0385)		(0.0402)
Relative productivity (t-1)	0.0282	-0.0227	0.0938
	(0.0308)	(0.0236)	(0.0678)
50<size<150	0.0562**	0.0205	0.0198
	(0.0187)	(0.0211)	(0.0299)
Size >150	0.0441**	0.00442	0.0225
	(0.0189)	(0.0202)	(0.0318)
Observations	1319	849	832
LR Chi2	77.97***	45.75***	58.19***
Log Likelihood	-274.04	-150.20	-232.02
Pseudo R^2	0.1079	0.1321	0.114
Smith-Blundell[a] χ^2	1.88	1.25	0.16
Pvalue	0.17	0.26	0.69
Rivers-Vuong[b] z-statistic	1.72	1.13	0.29
Pvalue	0.09	0.26	0.77

Notes: Each column shows estimated average marginal effects. Estimation method: Probit. Robust standard errors in parentheses. Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. $^{\psi}$This variable is dropped from this equation because it predicts failure perfectly. [a] [b] Tests for endogeneity, where the suspected endogenous variable is financial constraints. The instruments used are the log of firm size and the lag of sales per worker (Hadlock and Pierce 2010). Under the null hypothesis the variable is exogenous.

Investing in Innovation

Table 2.5 reports estimates for the discrete decision to undertake innovation activities (columns 1, 3 and 5), and for the continuous, censored intensity of innovation expenditures (columns 2, 4 and 6). Regarding the discrete decision, we find that lagged innovation intensity is significantly associated with the probability of deciding to invest in innovation the following year in all three industries, suggesting that there is persistence in innovation activities, as highlighted in studies for other countries (Peters 2009). Controlling for previous innovation effort, engaging in innovation activities is highly and positively correlated with public support, especially in manufacturing and KIS. This suggests that receiving public support may increase the extensive margin of innovative firms, as found in Arqué-Castells and Mohnen (2015).[33] The likelihood of carrying out innovation activities increases with firm size in all three industries, as in Gallego et al. (2015), hinting that fixed and sunk costs of innovation are present in all industries. A higher level of human capital is associated with the likelihood of engaging in innovation in manufacturing firms, but we do not find it significant for services.

Conditional on deciding to invest in innovation, innovation expenditures per employee are positively correlated with obtaining public support in KIS, but not in manufacturing or in traditional services. This result differs from Gallego et al. (2015), who find that in manufacturing direct support is positively correlated with innovation expenditures.[34] This would be consistent with the fact that innovation often involves fixed costs, so public support would mostly affect the extensive rather than the intensive margin. An interesting difference between manufacturing and service firms concerns the role of foreign ownership, which is positively correlated with investment in innovative activities in manufacturing but not in KIS, even if in our sample the percentage of foreign owned firms among those with more than 50 employees in KIS is higher than in manufacturing. Differences in capital intensity and the nature of innovation across both industries might explain this result.

[33] Our data do not allow us to perform a full evaluation exercise of public programs. Crespi et al. (2015) have evaluated the effect of programs administered by the Colombian Innovation Agency (Colciencias) using longitudinal firm-level data. This allows them to use a fixed effects identification strategy to control for selection bias. Improving or extending their work would require to have access to additional data. Our results, however, add to theirs in that ours explicitly point to the channel through which public programs contribute to increasing productivity: relaxing financing constraints for innovation activities, and regulation related hurdles.

[34] See their results in Table 4 of their article, on page 622. Our results and theirs are not strictly comparable because of differences in sample size and composition (our sample of service firms is larger and less biased than theirs towards large firms) and empirical specifications.

Table 2.5: Probability of Investing in Innovation and Innovation Expenditure per Employee

	Traditional Services		KIS		Manufacturing	
	Decision	Intensity	Decision	Intensity	Decision	Intensity
	(1)	(2)	(3)	(4)	(5)	(6)
Pr(support)	0.533**	1.062	0.786**	3.393**	1.290***	0.936
	(0.252)	(1.333)	(0.377)	(1.637)	(0.326)	(1.235)
Innovation intensity (t-1)	0.104***	0.620***	0.117***	0.571***	0.107***	0.469***
	(0.00626)	(0.0487)	(0.00879)	(0.0654)	(0.00782)	(0.0545)
Exporter (t-1)	-0.00874	0.0183	-0.0342	-0.424	-0.0327	-0.552*
	(0.0499)	(0.337)	(0.0703)	(0.448)	(0.0490)	(0.253)
Foreign ownership	0.139*	0.390	-0.0401	-0.00196	0.0811*	0.875**
	(0.085)	(0.491)	(0.100)	(0.621)	(0.0885)	(0.445)
Information: market		0.0185		0.146		0.284
		(0.190)		(0.267)		(0.246)
Informations: institutions		-0.206		-0.262		0.178
		(0.215)		(0.315)		(0.267)
Skills Medium (t-1)	-0.167	-0.514	0.0671	-0.645	0.462*	1.635
	(0.109)	(0.616)	(0.119)	(0.678)	(0.243)	(1.727)
Skills High (t-1)	-0.189	-0.644	0.0420	-0.358	0.426*	2.174
	(0.105)	(0.630)	(0.110)	(0.681)	(0.234)	(1.737)
Formal IP protection	0.164*		-0.0412		-0.00597	
	(0.0958)		(0.138)		(0.0914)	
Demand Risk	0.0644**		-0.0328		-0.0127	
	(0.0265)		(0.0356)		(0.0373)	
Relative productivity	0.0387		-0.205		-0.364*	
	(0.0868)		(0.105)		(0.180)	
Size	0.0607***		0.0771***		0.0582**	
	(0.0105)		(0.0126)		(0.0204)	
Constant		2.487**		2.784***		1.085
		(0.764)		(0.916)		(1.775)
Industry fixed effects (1-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,319		876		832	
Censored Observations	904		625		559	
Uncensored Observations	415		251		273	
Wald test of independence ($\rho = 0$)	39.47***		31.62***		12.59***	

Notes: Each column shows the estimated marginal effects. *Pred* indicates that the variable is predicted. Method: Heckit Maximum likelihood. Standard Errors Obtained by Bootstrapping (50 replicates) in parentheses. Significance Levels: ***p<0.01, **p<0.05, *p<0.1 .

Introducing different types of Innovations

Estimated investment intensity is highly correlated with the probability of introducing each of the four types of innovations, as shown in Table 2.6. This is not a surprising result given that most firms introduce combinations of the different types at the same time. A one-percent increase in investment intensity raises the probability of introducing product innovations by 3 percentage points (pp.) in traditional services and KIS, and by about 7 pp. in manufacturing. Magnitudes are similar for product, organizational and marketing innovations in service industries, while this elasticity is slightly lower than product and process innovations in manufacturing. Alertness to market information is positively correlated with introducing all types of innovations across industries, as we would expect. Information from research institutions is less important but still significant for all but process innovations.

Is foreign direct investment associated with the introduction of innovations in Colombia? Some studies for developed countries have found that the answer varies across industries and countries. While Peters et al. (2014) do not find evidence of a significant relationship in services in the UK or in Germany, in the case of Ireland it is positive, suggesting that distance to the productivity frontier may play a role. In our case, we find a weak, negative correlation with product innovation in Colombian traditional services, as in Gallego et al. (2015) and with marketing innovation in manufacturing, but otherwise FDI seems unrelated to the introduction of innovations.

Our estimations show that employees' skills are highly correlated with the probability of introducing all sorts of innovation in manufacturing firms, and with product innovations in traditional services. Even if they appear not to be correlated with the intensity of innovation investment in the previous stage, the actual introduction of innovations is correlated with the firm's human capital, corroborating their complementarity. Surprisingly skills are not significant for KIS, although this might be attributed to the fact that very few firms in these industries do not have qualified employees. Finally, estimates confirm that large firms are more likely to introduce all kinds of innovation in services (both traditional and KIS), in line with previous studies (Mairesse and Robin 2009; Musolesi and Huiban 2010; Peters et al. 2014).

Table 2.6: Marginal Effects: Introduction of Innovations

	Product			Process			Marketing			Organizational		
	Traditional	KIS	Manuf	Traditional	KIS	Manuf	Traditional	KIS	Manuf	Traditional	KIS	Manuf
Innovation Intensity^{pred}	0.0392***	0.0334***	0.0714***	0.0535***	0.0446***	0.0793***	0.0379***	0.0232***	0.0482***	0.0385***	0.0306***	0.0572***
	(0.0049)	(0.0061)	(0.0073)	(0.0051)	(0.0071)	(0.007)	(0.005)	(0.007)	(0.008)	(0.0054)	(0.007)	(0.008)
Information: market	0.165***	0.165***	0.130***	0.213***	0.209***	0.186***	0.173***	0.171***	0.149***	0.229***	0.234***	0.195***
	(0.0192)	(0.0237)	(0.0274)	(0.0191)	(0.0257)	(0.0256)	(0.0179)	(0.0268)	(0.0281)	(0.0181)	(0.0237)	(0.0285)
Information: institutions	0.0813**	0.0706*	0.0626	0.0280	0.0623	0.0418	0.100***	0.0733*	0.0964**	0.118***	0.0925*	0.0689
	(0.0266)	(0.0325)	(0.0356)	(0.0306)	(0.0416)	(0.0368)	(0.0246)	(0.0338)	(0.0311)	(0.0288)	(0.0393)	(0.0388)
Exporter (t-1)	-0.0110	0.0166	0.0515*	-0.00752	0.0268	0.0278	-0.0252	0.0435	-0.00247	-0.0222	-0.0207	0.0233
	(0.0303)	(0.0346)	(0.0252)	(0.0329)	(0.0423)	(0.0287)	(0.0282)	(0.0370)	(0.0270)	(0.0309)	(0.0439)	(0.0281)
Foreign ownership	-0.130*	-0.0268	-0.0100	-0.0356	-0.0381	-0.0759	-0.0711	0.0834	-0.126*	-0.0880	-0.0839	-0.0383
	(0.0615)	(0.0489)	(0.0416)	(0.0558)	(0.0612)	(0.0510)	(0.0497)	(0.0516)	(0.0636)	(0.0631)	(0.0560)	(0.0600)
Formal IP protection	0.114*	0.0250	0.0577	0.0373	0.0601	0.0452	0.103*	0.0121	0.119**	0.0556	0.00172	0.145**
	(0.0511)	(0.0547)	(0.0459)	(0.0500)	(0.0751)	(0.0523)	(0.0436)	(0.0572)	(0.0420)	(0.0508)	(0.0688)	(0.0487)
Skills Medium (t-1)	0.882***	0.00526	0.511***	-0.0287	0.000167	0.677***	-0.0894*	-0.0469	0.614***	-0.0109	0.0628	0.767***
	(0.0608)	(0.0362)	(0.0506)	(0.0589)	(0.0401)	(0.0542)	(0.0431)	(0.0387)	(0.0490)	(0.0638)	(0.0413)	(0.0551)
Skills High (t-1)	0.893***	-0.0125	0.487***	-0.0561	-0.0180	0.632***	-0.0989*	-0.0746	0.557***	-0.00851	0.0269	0.761***
	(0.0612)	(0.0357)	(0.0569)	(0.0604)	(0.0403)	(0.0616)	(0.0443)	(0.0381)	(0.0542)	(0.0644)	(0.0409)	(0.0599)
Size	0.00913*	0.0245***	0.0197*	0.0315***	0.0240***	0.00625	0.0216***	0.0120*	0.00613	0.0323***	0.0273***	0.00597
	(0.0045)	(0.0047)	(0.0078)	(0.0049)	(0.0054)	(0.0088)	(0.0045)	(0.0052)	(0.0086)	(0.0049)	(0.0049)	(0.0085)

Industry fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Observations	1,319	876	832	1,319	876	832	1,319	876	832	1,319	876	832
Wald χ^2	672.89***	289.34***	1887***	410.81***	263.15***	2010***	331.41***	186.14***	2785***	382.62***	293.65***	3453***
Pseudo R^2	0.2923	0.380	0.387	0.328	0.372	0.395	0.338	0.270	0.304	0.331	0.378	0.317

Notes: ^{pred} denotes predicted innovation expenditure per employee. Bootstrapped standard errors in parenthesis. Significance Levels: ***p<0.01, . **p<0.05, *p<0.1

Labor Productivity

Quantile regression estimates for each type of innovation, along with standard 2SLS estimates, are reported in Tables 2.7 to 2.12. We find that in manufacturing industries product, process, marketing and organizational innovations are positively correlated with productivity. Two stage least squares (2SLS) provide coefficient estimates at the mean that are slightly higher for marketing and organizational innovations than for process innovations. However 2SLS estimates hide some heterogeneity across the productivity distribution: firms at the lower tail would benefit substantially more from innovating than more productive firms, although they all do. Our results differ from those found by Casaburi et al. (2016), who look at the effect of product and process innovations on labor productivity in the manufacturing sector. Using data from The World Bank Entreprise Surveys for 17 Latin American countries, they find that firms at the bottom of the distribution obtain lower returns from innovating than firms at the upper levels. Policy implications from our respective findings would thus differ; but heterogeneity across LACs in manufacturing should be investigated further before drawing any recommendations.

The picture that emerges for service industries in Colombia is different if we rely on 2SLS estimates: in both KIS and in traditional services the introduction of innovations, whether it is product, process or non-technological, appears to be unrelated to productivity. However, a closer look through quantile regression shows that in KIS product and marketing innovations increase significantly the productivity of firms in the 0.25th quantile, but not of those above it.[35] Therefore, removing barriers to innovation in low productivity firms would yield high returns. These barriers might stem from a variety of factors, including lack of competition, inefficient regulation and financing constraints. We do not find evidence that process and organizational innovations are correlated with labor productivity. Human capital, however, is always significant and higher for firms with higher productivity.

In traditional service firms the introduction of all types of innovations increases the productivity of firms at or below the median of the productivity distribution. The effect is strongest for product and marketing innovations, especially for firms at or below the median. 2SLS coefficients would underestimate again the impact of introducing innovations in services.

Also highly relevant from a policy perspective is our finding that increasing the firms' human capital would boost the productivity of firms both in services and in manufacturing, and relatively more that of firms at the top half of the distribution. Casaburi et al. (2016) also find a similar pattern for manufacturing firms in their study, and our coefficient estimates are quite similar to theirs. This suggests that

[35] The hypothesis of equality of coefficients is rejected.

limited availability of human capital is a wide-ranging hurdle for productivity growth in Colombia, where the number of engineering graduates per million inhabitants is low relative to other countries (Lederman, Messina, Pienknagura, and Rigolini 2013). Finer measures of human capital, such as indicators of managerial skills, would provide better insights into the bottlenecks for productivity growth, as Bartz, Mohnen, and Schweiger (2016) find for Eastern European countries. Finally, foreign ownership is on average positively correlated with productivity in most quantiles for all industries.

Table 2.7: Traditional Services: Product and Process Innovation and Productivity

	Product						Process					
	2SLS	Q=0.15	Q=0.25	Q=0.50	Q=0.75	Q=0.90	2SLS	Q=0.15	Q=0.25	Q=0.50	Q=0.75	Q=0.90
Innovation$^{\text{pred}}$	0.286	0.887***	0.643***	0.299***	0.114	0.00873	0.134	0.338	0.349***	0.212**	-0.0694	0.00612
	(0.162)	(0.274)	(0.138)	(0.0978)	(0.137)	(0.339)	(0.143)	(0.286)	(0.132)	(0.089)	(0.138)	(0.236)
Exporter $(t-1)$	0.679***	0.379	0.540***	0.540***	0.819***	1.136***	0.683***	0.291	0.614***	0.565***	0.832***	1.136***
	(0.143)	(0.264)	(0.204)	(0.114)	(0.232)	(0.355)	(0.146)	(0.393)	(0.187)	(0.13)	(0.249)	(0.394)
Foreign Ownership	0.686*	0.468	0.673*	0.696***	0.642*	0.843	0.655*	0.341	0.655*	0.658***	0.627**	0.843
	(0.291	(0.382)	(0.348)	(0.167)	(0.344)	(0.606)	(0.259)	(0.372)	(0.389)	(0.177)	(0.257)	(0.72)
Skills $(t-1)$	0.429***	0.428***	0.319***	0.324***	0.395***	0.581***	0.436***	0.524***	0.333***	0.356***	0.404***	0.584**
	(0.102)	(0.13)	(0.121)	(0.0851)	(0.0603)	(0.179)	(0.098)	(0.139)	(0.0598)	(0.0823)	(0.126)	(0.241)
Constant	11.96***	10.41***	10.82***	11.65***	12.72***	14.65***	11.96***	10.38***	10.79***	11.60***	12.71***	14.64***
	(0.18)	(0.258)	(0.177)	(0.2)	(0.245)	(0.841)	(0.218)	(0.262)	(0.092)	(0.24)	(0.263)	(0.931)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R(squared)	0.332	0.118	0.14	0.222	0.283	0.271	0.332	0.114	0.137	0.222	0.282	0.271

Notes: $^{\text{pred}}$ denotes predicted probability of introducing an innovation. Bootstrapped standard errors in parentheses. Pseudo R2 report . a measure of fit for quartiles. Significance Levels: ***p<0.01, **p<0.05, *p<0.1

Table 2.8: Traditional Services: Marketing and Organizational Innovation and Productivity

	Marketing						Organizational					
	2SLS	Q=0.15	Q=0.25	Q=0.50	Q=0.75	Q=0.90	2SLS	Q=0.15	Q=0.25	Q=0.50	Q=0.75	Q=0.90
Innovation^{pred}	0.255	0.799**	0.595***	0.263**	0.0987	-0.00791	0.046	0.312	0.326***	0.154	0.0619	-0.154
	(0.185)	(0.323)	(0.145)	(0.106)	(0.144)	(0.271)	(0.153)	(0.241)	(0.115)	(0.0978)	(0.121)	(0.261)
Exporter $(t-1)$	0.679***	0.372	0.545**	0.536***	0.842***	1.136*	0.689***	0.283	0.613**	0.557***	0.807***	1.083**
	(0.175)	(0.27)	(0.214)	(0.164)	(0.292)	(0.622)	(0.158)	(0.382)	(0.25)	(0.144)	(0.257)	(0.466)
Foreign Ownership	0.662*	0.367	0.667**	0.661***	0.830***	0.843	0.669*	0.417	0.658*	0.678**	0.626*	0.782
	(0.269)	(0.478)	(0.278)	(0.218)	(0.181)	(0.672)	(0.27)	(0.366)	(0.352)	(0.263)	(0.359)	(0.805)
Skills $(t-1)$	0.435***	0.455***	0.324***	0.352***	0.405***	0.581***	0.434***	0.538***	0.335***	0.351***	0.407***	0.541***
	(0.0855)	(0.141)	(0.0842)	(0.069)	(0.0769)	(0.163)	(0.0867)	(0.125)	(0.0977)	(0.0885)	(0.123)	(0.206)
Constant	11.97***	10.47***	10.83***	11.62***	12.72***	14.65***	11.99***	10.39***	10.81***	11.61***	12.71***	14.70***
	(0.189)	(0.269)	(0.188)	(0.263)	(0.38)	(0.866)	(0.228)	(0.231)	(0.134)	(0.231)	(0.264)	(1.038)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R(squared)	0.332	0.118	0.14	0.222	0.283	0.271	0.332	0.113	0.137	0.221	0.282	0.271

Notes: As in table 2.7 .

Table 2.9: KIS: Product and Process Innovation and Productivity

	Product						Process					
	2SLS	Q=0.15	Q=0.25	Q=0.50	Q=0.75	Q=0.90	2SLS	Q=0.15	Q=0.25	Q=0.50	Q=0.75	Q=0.90
Innovation^{pred}	0.0778	0.355	0.455**	0.0534	-0.0857	-0.0899	0.00582	0.26	0.24	0.0233	-0.106	-0.117
	(0.225)	(0.343)	(0.206)	(0.201)	(0.318)	(0.306)	(0.187)	(0.248)	(0.149)	(0.184)	(0.298)	(0.338)
Exporter $(t-1)$	0.396*	0.0981	0.244	0.576**	0.28	1.097**	0.401*	0.143	0.208	0.576**	0.268	1.098*
	(0.202)	(0.338)	(0.317)	(0.25)	(0.25)	(0.553)	(0.192)	(0.28)	(0.305)	(0.238)	(0.287)	(0.616)
Foreign Ownership	0.514**	0.746**	0.589*	0.297	0.673	0.178	0.525*	0.752***	0.575***	0.304	0.689*	0.201
	(0.171)	(0.321)	(0.34)	(0.348)	(0.486)	(0.309)	(0.223)	(0.223)	(0.194)	(0.313)	(0.38)	(0.325)
Skills $(t-1)$	0.687***	0.632***	0.546***	0.487***	0.950***	0.870***	0.687***	0.619***	0.585***	0.492***	0.952***	0.872***
	(0.121)	(0.103)	(0.124)	(0.0893)	(0.169)	(0.272)	(0.108)	(0.136)	(0.14)	(0.125)	(0.162)	(0.13)
Constant	10.18***	8.914***	9.514***	10.21***	10.86***	11.83***	10.20***	8.910***	9.524***	10.20***	10.86***	11.83***
	(0.101)	(0.16)	(0.113)	(0.0831)	(0.136)	(0.207)	(0.0817)	(0.141)	(0.119)	(0.0978)	(0.131)	(0.232)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R(squared)	0.178	0.085	0.078	0.095	0.111	0.125	0.178	0.085	0.077	0.095	0.111	0.126

Notes: As in table 2.7 .

Table 2.10: KIS: Marketing and Organizational Innovation and Productivity

	Marketing						Organizational					
	2SLS	Q=0.15	Q=0.25	Q=0.50	Q=0.75	Q=0.90	2SLS	Q=0.15	Q=0.25	Q=0.50	Q=0.75	Q=0.90
Innovation^{pred}	0.159	0.950**	0.484**	0.12	-0.106	-0.109	-0.0401	0.203	0.172	0.000807	-0.13	-0.263
	(0.239)	(0.413)	(0.231)	(0.291)	(0.399)	(0.444)	(0.161)	(0.29)	(0.193)	(0.187)	(0.282)	(0.276)
Exporter $(t-1)$	0.39	-0.14	0.215	0.574**	0.285	1.099	0.402**	0.114	0.204	0.576***	0.267	1.038*
	(0.23)	(0.306)	(0.264)	(0.238)	(0.32)	(0.67)	(0.148)	(0.295)	(0.276)	(0.192)	(0.216)	(0.534)
Foreign Ownership	0.481	0.498*	0.497**	0.278	0.688*	0.195	0.530*	0.834***	0.614*	0.316	0.711*	0.181
	(0.259)	(0.28)	(0.242)	(0.335)	(0.371)	(0.395)	(0.23)	(0.312)	(0.366)	(0.495)	(0.38)	(0.242)
Skills $(t-1)$	0.688***	0.703***	0.595***	0.488***	0.947***	0.867***	0.687***	0.635***	0.601***	0.504***	0.956***	0.872***
	(0.119)	(0.154)	(0.136)	(0.116)	(0.152)	(0.202)	(0.115)	(0.151)	(0.143)	(0.0938)	(0.206)	(0.283)
Constant	10.18***	8.784***	9.518***	10.20***	10.86***	11.83***	10.21***	8.934***	9.528***	10.20***	10.87***	11.89***
	(0.104)	(0.154)	(0.126)	(0.0888)	(0.118)	(0.273)	(0.116)	(0.145)	(0.136)	(0.0958)	(0.134)	(0.218)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R(squared)	0.178	0.086	0.078	0.095	0.111	0.125	0.178	0.084	0.077	0.095	0.111	0.126

Notes: As in table 2.7 .

Table 2.11: Manufacturing: Product and Process Innovation and Productivity

	Product						Process					
	2SLS	Q=0.15	Q=0.25	Q=0.50	Q=0.75	Q=0.90	2SLS	Q=0.15	Q=0.25	Q=0.50	Q=0.75	Q=0.90
Innovation^{pred}	0.777***	1.087***	0.750***	0.855***	0.672***	0.656***	0.704***	0.984***	0.692***	0.584***	0.588***	0.601***
	(0.173)	(0.342)	(0.174)	(0.208)	(0.113)	(0.213)	(0.18)	(0.203)	(0.143	(0.112)	(0.127)	(0.205)
Exporter $(t-1)$	0.679***	0.446***	0.582***	0.794***	0.857***	0.672***	0.719***	0.495***	0.613***	0.848***	0.888***	0.726***
	(0.0835)	(0.15)	(0.131)	(0.106)	(0.0778)	(0.126)	(0.0857)	(0.188)	(0.104)	(0.083)	(0.0664)	(0.127)
Foreign Ownership	0.669***	0.567*	0.411	0.619**	0.850***	0.54	0.734***	0.671**	0.443	0.823***	0.958***	0.625
	(0.165)	(0.3)	(0.276)	(0.256)	(0.19)	(0.474)	(0.205)	(0.292)	(0.313)	(0.273)	(0.216)	(0.547)
Skills $(t-1)$	0.452***	0.396***	0.267**	0.347***	0.548***	0.599***	0.456***	0.391***	0.283**	0.336***	0.542***	0.630***
	(0.0928)	(0.109)	(0.105)	(0.0819)	(0.0806)	(0.149)	(0.0839)	(0.14)	(0.125)	(0.0916)	(0.105)	(0.154)
Constant	9.695***	8.738***	9.220***	9.707***	10.24***	10.96***	9.669***	8.703***	9.206***	9.702***	10.24***	10.92***
	(0.0562)	(0.139)	(0.054)	(0.0391)	(0.0674)	(0.13)	(0.0569)	(0.122)	(0.0479)	(0.0266)	(0.0707)	(0.14)
Industry fixed effects	-	-	-	-	-	-	-	-	-	-	-	-
R(squared)	0.192	0.056	0.077	0.136	0.175	0.138	0.192	0.057	0.077	0.135	0.173	0.137

Notes: As in table 2.7 .

Table 2.12: Manufacturing: Marketing and Organizational Innovation and Productivity

	Marketing						Organizational					
	2SLS	Q=0.15	Q=0.25	Q=0.50	Q=0.75	Q=0.90	2SLS	Q=0.15	Q=0.25	Q=0.50	Q=0.75	Q=0.90
Innovation^{pred}	0.936***	1.175***	0.779***	0.876***	0.821***	0.753*	0.796***	1.107***	0.751***	0.751***	0.674***	0.666**
	(0.184)	(0.359)	(0.186)	(0.226)	(0.125)	(0.403)	(0.196)	(0.276)	(0.146)	(0.204)	(0.118)	(0.321)
Exporter $(t-1)$	0.727***	0.611***	0.676***	0.868***	0.919***	0.732***	0.712***	0.512***	0.660***	0.830***	0.890***	0.692***
	(0.105)	(0.157)	(0.114)	(0.0942)	(0.0764)	(0.172)	(0.0813)	(0.181)	(0.0841)	(0.0933)	(0.0814)	(0.142)
Foreign Ownership	0.787***)	0.401	0.398	0.547*	0.986***	0.827	0.709***	0.277	0.272	0.392	0.959***	0.845
	(0.175)	(0.504)	(0.35)	(0.322)	(0.298)	(0.61)	(0.191)	(0.375)	(0.282)	(0.292)	(0.315)	(0.575)
Skills $(t-1)$	0.478***	0.408***	0.337***	0.364***	0.593***	0.689***	0.448***	0.349***	0.252***	0.329***	0.553***	0.657***
	(0.0881)	(0.15)	(0.112)	(0.116)	(0.0875)	(0.199)	(0.0913)	(0.131)	(0.0897)	(0.119)	(0.122)	(0.21)
Constant	9.673***	8.724***	9.224***	9.698***	10.21***	10.96***	9.668***	8.716***	9.216***	9.697***	10.23***	10.95***
	(0.0516)	(0.13)	(0.0417)	(0.0289)	(0.0431)	(0.147)	(0.0653)	(0.116)	(0.0647)	(0.0439)	(0.075)	(0.157)
Industry fixed effects	-	-	-	-	-	-	-	-	-	-	-	-
R(squared)	0.192	0.049	0.072	0.13	0.171	0.135	0.192	0.049	0.073	0.13	0.17	0.135

Notes: As in table 2.7 .

2.6 Concluding Remarks

In this study we investigate two previously unexplored issues for manufacturing and service firms in Colombia: the existence of an association between perceived barriers to innovation and the allocation of public support for innovation, and the potential heterogeneity of returns to different types of innovation across the productivity distribution in each industry. We do it by extending the Crèpon-Duguet-Mairesse framework that relates innovation investment decisions, outcomes and productivity at the firm level by including an equation for the allocation of direct support and by using quantile regression methods to allow for potentially heterogeneous returns to innovation.

We find significant differences across manufacturing and service industries in several respects. The first concerns the allocation of public support for innovation. Firms that face financing constraints are more likely to benefit from public support in manufacturing and in traditional services. In knowledge intensive services (KIS), however, firms that perceive regulations to be a hurdle for innovation are more likely to have public support. This suggests that improving the financial system so that it becomes easier for innovators to obtain private funding could help promoting innovation in manufacturing or traditional services, but it might not be sufficient for KIS unless the efficiency effects of some regulations are evaluated and regulations revised accordingly.

Regarding the link between innovation and productivity, we find that in all service industries, including KIS, the introduction of all types of innovations increases productivity of firms below the median of the productivity distribution, but not of those above it. Within manufacturing innovation would result in higher productivity in all quantiles of the distribution, but again slightly more in lower quantiles. At the same time, returns to human capital are significant and increasing with productivity in all industries, suggesting that investing in human capital is private and socially profitable across the board. Our work thus contributes to the recent strand of research that examines the heterogeneous constraints and performance of firms, especially in developing and emerging countries (Paunov and Rollo 2016).

In terms of policy implications, our results suggest that public action toward factors that hinder innovation by low productivity firms in the service industries -human capital and some regulations- could significantly contribute to increasing productivity and reducing the range of its dispersion by decreasing the weight of the lower tail. Regarding human capital, the provision of consultancy services to enhance managerial capital could be an important and promising course of action, as found in Bruhn et al. (2013) for Mexico. However, entrepreneurs and SMEs may experiment several constraints at the same time, with varying intensity, so a mix of interventions might be necessary, after first identifying more precisely the nature of these constraints. For instance, more specific information on the kind of regulations affecting knowledge intensive firms -whether they are labor or product market related, or to environment, safety and standards- would allow a better identification of sector specific barriers to innovation. Using existing innovation surveys to introduce -at least in one wave- a set of questions to obtain a more accurate diagnose on which to base policy initiatives could be a fruitful avenue for action, as well as a starting point for the design of policy field experiments.

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Appendix

Table 2.A1: Sample Composition

CIIU Revision 3 A.C.	Division	Activities	Inclusion Parameters	Number of firms
		KIS		954
K: Real estate, renting and business activities	72, 73	Computing and R&D services	>20 employees	406
I: Transport, storage, communications	60.2, 60.4, 62, 64.1, 64.2	Transportation, post, and telecommunications	>20 employees	354
J: Financial intermediation	65.11, 65.12, 66, 67	Banking activities	CENSUS	194
		Traditional Services		1,419
E: Electricity, gas and water supply	40, 41	Electricity, gas and water supply	>20 employees	118
G: Wholesale and retail trade; reparation of equipment	50, 51, 52	Wholesale and retail trade; reparation of equipment	>50 employees; or sales >COP$5,000	794
H: Hotels and restaurants	55.1, 55.2	Hotels and restaurants	>40 employees; or sales >COP$3,000	185
M, N: Education, health and social services	80, 85	Education (private)	>20 employees; or sales >COP$1,000	189
O: Other community and social and personal services	90-92.1	Entertainment, film, TV industries	>20 employees; or sales >COP$1,000	133
		Manufacturing		
D	15-37	Manufacturing	>10 employees	905
		TOTAL		3,278

Notes: a Health services include only hospitals. Source: Survey of Innovation and Technological Development in Services EDITS-III (2010-2011) and Manufacturing EDIT IV (2009-2010). Sales are in million Colombian pesos (COP) of 2009.

Table 2.A2: Definition of Variables

Variable Name	**Variable Definition**	**Period of Time**
Productivity	Sales per employee (in logs)	t, $t-1$
Relative Productivity	A measure of productivity distance between firm i and the mean of its industry. Each firm's labor productivity in t-1 is divided by the average productivity of its industry.	t, $t-1$
Investment Intensity	Total Innovation expenditures per employee (in logs)	t, $t-1$
Process Innovation	Binary; 1 if the firm reports having introduced new or significantly improved production processes	p
Product Innovation	Binary; 1 if the firm reports having introduced new or significantly improved products	p
Marketing Innovation	Binary; 1 if the firm reports having introduced marketing innovations	p
Organizational innovation	Binary; 1 if the firm reports having introduced organizational innovations	p
Foreign ownership	Binary; 1 if foreign owners have at least 40% of the ownership in the firm.	p
Exporter	Binary; 1 if the firm has positive exports	t, $t-1$
R&D	Binary; 1 if the firm engaged in R&D activities in year t	t, $t-1$
Regular R&D	Binary; 1 if firm engaged in R&D every year	t, $t-1$
Public Support	Binary; 1 if the firm received local or regional funding for innovation projects	p
Innovation Barriers		
Financing constraints	Binary; 1 if the firm reported lack of funds, whether internal or external, as a barrier of high importance	p
Ease of imitation	Binary; 1 if the firm reported ease of imitation by third parties to be an important barrier to innovate	p
Demand risk	Binary; 1 if the firm considered demand uncertainty for innovations to be a barrier of high importance	p
Lack of qualified personnel	Binary; 1 if the firm reported lack of qualified personnel to be a barrier of high importance	p
Regulation	Binary; 1 if the firm reported regulations as barrier to be of high importance to innovation	p
Formal IP Protection	Binary; 1 if the firm uses registration of design patterns, trademarks or copyright to protect inventions or innovations	p
Information: Market	Binary; 1 if information from suppliers or from customers was of high importance for the firm	p
Information: Institutions	Binary; 1 if information from universities or other higher education, government or private nonprofit institutes was of high importance for the firm	p
Skills Low	Binary; 1 if the firm has no employees with higher education degree	t, $t-1$
Skills Medium	Binary; 1 if the firm has a positive share of employees with higher education but below 40%.	t, $t-1$
Skills High	Binary; 1 if the firm has more than 40% of employees with higher education	t, $t-1$

Continued on next page

Table 2.A2 – continued from previous page

Variable Name	Variable Definition	Period of Time
Skills	Percentage of employees holding higher education degrees	t, $t-1$
Firm size	Natural log of the number of employees	t, $t-1$
Industry dummies	Dummy variables are defined for each industry: five for traditional services, three for KIS (see Table 2.A1).	p

Note: p means that the corresponding survey question refers to the whole two-year period; t, t-1 means that the variable is available for each year.

Table 2.A3: Identification Strategy

Variables	First Stage	Second Stage		Third Stage	Fourth Stage
	Access to public support	Innova. Decision	Innova. Intensity	Introduction of innovations	Productivity (Sales/L)
Pr(Support)		x	x		
Innovation intensity (t-1)		x	x		
Pr(Innovation Intensity)				x	
Pr(Innovation)					x
Financial Constrains (t-1)	x				
Regulations (t-1)	x				
Formal IP protection (t-1)	x	x		x	
Ease of imitation (t-1)	x				
Regular R&D	x				
Exporter (t-1)	x	x	x	x	x
Foreign Ownership	x	x	x	x	x
Relative Productivity (t-1)	x	x			
50<size<150 (t-1)	x				
Size >150 (t-1)	x				
Log size (t-1)		x		x	
Information: market (t-1)			x	x	
Information: institutions (t-1)			x	x	
Skills Medium (t-1)		x	x	x	
Skills High (t-1)		x	x	x	
Skills (% higher education) (t-1)					x
Demand Risk (t-1)		x			
Industry FE	x	x	x	x	x

Chapter 3

Subsidizing Innovation over the Business Cycle[*]

3.1 Introduction

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

A closer look at the data shows that public investment in R&D took different paths in different countries around 2008/9. While increasing in Germany and Austria, they fell in France, Spain and Italy (OECD-STI 2014). In the US the real growth rate of Federal government R&D was positive until 2011, but turned negative in subsequent years; nonfederal government growth rates were negative since 2011 (Foundation 2018). Since then a declining trend is observed both sides of the

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

Atlantic, resulting in a decreasing percentage of business R&D financed with public funds. This evolution is worrisome, as it may have implications both for long term growth and for income level convergence across countries, especially if cross-country differences in public R&D investment persist (Duval, Hong, and Timmer 2017; Ridder 2017; Veugelers 2016; Veugelers et al. 2017). In a recent study on the evolution of public R&D spending in a panel of twenty six OECD countries over the period 1995-2015, Pellens, Peters, Hud, Rammer, and Licht (2018) show that on average public R&D behaved pro-cyclically, but in some non-EU countries and European innovation leaders it followed a counter-cyclical pattern. Their analysis suggests that differences in this evolution responded to a good extent to each country public deficit and government debt level. Countries experiencing adverse conditions in this respect can hardly be expected to significantly increase public R&D investment for some time. This prospect highlights the importance of evaluating the ability of public support to induce more private effort in R&D and innovation over the phases of the business cycle, in particular during recessions. It involves testing the stability of the multiplier –or, what in the evaluation literature is known as the degree of additionality- of this form of public support. A higher multiplier during recessions would mean that reducing public support during this phase would be more harmful for long-run growth, and, conversely, small increases of public support would induce more private effort than in expansions and hence contribute to a steady flow of knowledge generation during the cycle.

In this essay we contribute to empirical research on the impact of public support to private R&D by addressing the following questions: 1) Does firms' access to support vary over the business cycle? 2) Does the impact of support remain constant over the cycle? 3) Does public support affect private both R&D investment and R&D employment? The first question intends to determine 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 behavior over the cycle. For instance, financially constrained firms might apply for support during expansions, but abstain from doing so during recessions. The second question intends to determine whether the impact of public support is smaller in recessions than in expansions or otherwise. Given previous evidence showing the pro-cyclicality of private R&D investment, we would not expect higher additionality of public support during a downturn, especially in the face of a wide financial crisis and higher uncertainty. The third question intends to inquire beyond the standard monetary effect of public support and look into the time allocation of employees to R&D activities. Several mechanisms could explain why firms may hoard their skilled workers in times of crisis. First, according to Bloom, Romer, Terry, and Van Reenen

(2013), the presence of "trapped factors" or fixed inputs may lead to higher innovation activity when a firm faces a negative shock. The opportunity cost of inputs used to design and produce new goods would fall, and skilled employees might be trapped because they have human capital that is specific to the firm. Secondly, the type of labor contracts may also play a role in the decision to keep skilled employees in order to preserve the absorptive capacity of the firm. This would be consistent with López-García, Montero, and Moral-Benito (2013), who find that for the case of Spain, the share of temporary employees within the firm is negatively associated with the firm's probability of innovating. Finally, public support may have other effect, such as preventing firms from abandoning projects during a downturn. This last point will be investigated in the next chapter.

To address these questions, we use firm-level panel data from Spain covering the period 2006 to 2014. Spain, one of the large members of the European Union, is classified as a moderate innovator and has experienced sharp public budget cuts after 2008. We first compare firms' participation in public R&D across the three phases of the business cycle. We define a participation spell here as the number of years a firm reports receiving a subsidy within a given period. We then identify several participation spells and estimate the response of participants over time compared to non-participants for two outcome variables: investment in innovation per employee and time allocation of employees to innovation activities.[2]

Our main findings are summarized as follows. First, we do not observe significant changes in the allocation of public support to firms over the cycle; this precludes attributing impact differences to changes in the profile of recipients of subsidies. Second, 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. Finally, when looking at a different indicator, in particular firm's allocation of human resources within the firm, we find that the additionality effect is higher during the crisis. In particular, both for SMEs and large firms direct support seems to have allowed firms to allocate more of their employees' time to R&D and innovation activities. This suggests that under some conditions the multiplier of public support may be higher during recessions, thus magnifying the negative impact of budget cuts for this kind of policy.

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

The layout of this chapter is the following. Section 3.2 provides an overview of research on the cyclical behavior of R&D investment and the impact of R&D support during the last economic crisis. Section 3.3 describes the data. Section 3.4 describes the empirical strategy. Section 3.5 presents and discusses estimation results. Section 3.6 concludes.

3.2 R&D, Business Cycles and Public Support: Some background

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

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

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

Extensive research documents that investment in intangibles, and R&D investment in particular, is generally affected by financing constraints (Hall, Moncada-Paternò-Castello, Montresor, and Vezzani 2016). Aghion, Angeletos, Banerjee, and

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

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

Recent research has focused specifically on the 2008 crisis, featuring a strong financial component relative to previous episodes, and the response of business R&D. Results show quite generally a pro-cyclical reaction. Cincera, Cozza, Tübke, and Voigt (2012) analyze the R&D survey of the top European R&D performers conducted in 2009 and find that R&D intensive firms were more likely to decrease R&D investment, while the association with firm size was U-shaped. Similarly, Paunov (2012) finds that the crisis led many Latin-American firms to stop innovation projects. Giebel and Kraft (2015) study German manufacturing firms and find that their investment was more negatively affected than non-innovators during the crisis. Peters et al. (2014) use data from several waves of the European Community Innovation Surveys (the first covering the years 1998-2000 and the last covering the period 2008-2010) for about 20 member states to describe the behavior of several

R&D and innovation indicators over the business cycle.[3] Their results show that R&D investment follows mostly a pro-cyclical pattern, but that when it comes to the introduction of innovations in the market there are some different patterns by type of innovation. During recessions the introduction of products that are new to the firm but not to the market increases, while innovations new to the market bunch in booms; process innovations do not appear to be sensitive to the cycle. Arvanitis and Woerter (2013) find some heterogeneity in the response of Swiss manufacturing firms to the crisis with firm size, R&D intensity and (lack of) price competition contributing to explain these different responses. Finally, Anzoategui, Comin, Gertler, and Martinez (2016) investigate the adoption of new technologies over the cycle, finding it to be highly pro-cyclical. They also find that the speed at which new technologies are incorporated in production –technological diffusion– has declined after the financial crisis.

All this evidence raises a new question: would countercyclical public support to R&D be able to mitigate the dynamic failure predicted by the models described above? The answer hinges on the sign and size of the multiplier or additionality effect during recessions. To the best of our knowledge, this question has not been thoroughly investigated. Most firm-level studies test whether direct public support –through grants and/or loans- crowds out private investment, or whether on the contrary it leverages private effort, and estimate the magnitude of this impact, but they pre-date the 2008 crisis. Only two firm-level studies focus on the financial crisis years: Hud and Hussinger (2015) and Aristei, Sterlacchini, and Venturini (2017). Hud and Hussinger (2015) use German SMEs firm-level data for 2006 to 2010. Using propensity score matching they estimate the overall treatment effect on the treated (ATT), matching by location in East Germany and year of observation. 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. They 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 their methodological approach. 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, excluding tax incentives, they do not find evidence of additionality in any of

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

the five countries, including Germany.[4] The main limitation is that the data used in their study are basically cross-sectional and treatment effects for each year for a given country cannot be identified. Nevertheless, and although weaker than Hud and Hussinger's, taken together these results suggest that the multiplier of R&D support has been pro-cyclical.

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

A final issue to consider is that the studies reported above show estimates of the short-run impact of R&D subsidies. Although very few of them explore the dynamic effects of direct subsidies, there is some evidence that these effects may not be immediate; they can also be temporary or long-lasting. Colombo, Croce, and Guerini (2013), for instance, find that in Italy public support has a temporary effect on private R&D investment. In contrast, Arqué and Mohnen's (2013), find that in Spain one-shot subsidies cause a substantial increase in both the share of R&D performing firms and on average R&D expenditures over time. Einiö (2014) finds that R&D subsidies in Finland do not have an immediate impact on productivity, but they do in the long-term. Karhunen and Huovari (2015), who look at the effects of R&D subsidies granted in the period 2002 to 2007 on labor productivity,

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

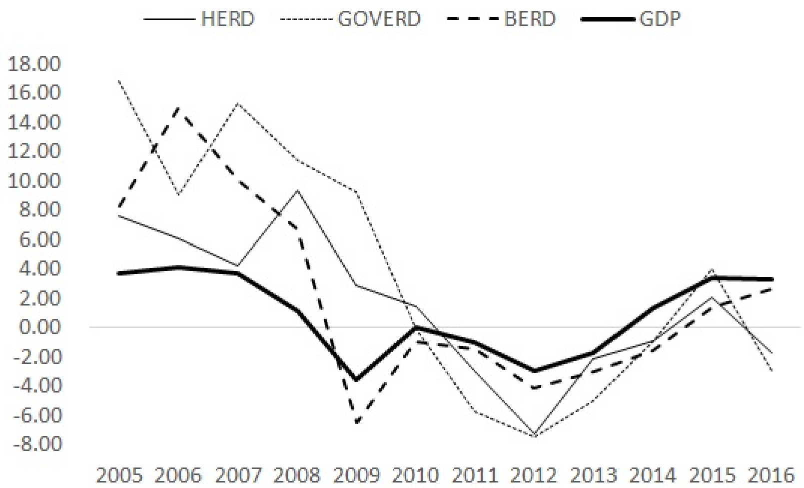
employment and human capital of Finnish SMEs up to five years after a subsidy is granted, find that effects are often significant one and two years after treatment.

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

3.3 Data

The evolution of GDP over the period 2006 to 2015 in Spain has been similar to the average of the nineteen-euro zone countries, except that the recession period has lasted longer, including years 2011 to 2013. Figure 3.1 shows that the growth rate of GDP began to fall in Spain in 2008 and continued to contract throughout 2009. Business R&D spending (BERD) followed a similar although more severe path, experiencing a sharp decline during 2008 and 2009. Both variables show an uncertain fluctuation over the period of 2009-2012, with the recovery starting noticeably after 2013. The government implemented at the onset of the crisis some policy initiatives to stimulate the economy and employment through innovation and R&D. One of them was the 2009 "Plan E" included EUR 490 million directly related to R&D and innovation, a share more than 16% of total budget. Furthermore, in November 2009 a new Law on Science, Technology, and Innovation was enacted, and the State Innovation Strategy (2010) set a budget of EUR 3.2 billion in 2010 (an increase of 48% from 2009) (OECD-STI 2014). These efforts were not sustained, however, and government spending in R&D (GOVERD) experienced a negative growth rate since 2010, remaining negative for the four following years. Finally, the evolution of R&D spending in Higher Education (HERD) has been similar to that of government spending. The share of business R&D investment financed by the government experienced a remarkable fall over this period. It reached its peak in 2008 at 17.9%, and declined steadily to 9.4% in 2015 (OECD: 2017).

Figure 3.1: Real Growth Rates of GDP and R&D Spending by Performer in Spain 2005-2016



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

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

We use annual firm level data from the Spanish Technological Innovation Panel (PITEC), produced by the National Statistical Institute (INE) and is based on the European Community Innovation Survey (CIS), during the period extending

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

from 2005 to 2014. PITEC provides a broad range of information on innovation activities, including innovation and R&D expenditures, public funds obtained for R&D and perceived barriers to innovation, along with sales volume, human capital and firm's age. In this study we will separately analyze SMEs (firms with less than 200 employees) and large firms, as SME tend to be more sensitive to credit supply (Artola and Genre 2011; Mach and Wolken 2012; Schmitz 2016).

From the original PITEC unbalanced panel we obtain a balanced panel that includes all firms that stay in the sample for the whole period (10 years); this allows us to eliminate spurious differences that could be generated by changes in the composition of the sample. We further limit the sample to firms that invested in innovation at least once in the period under study, the idea being to exclude firms that do not intend to innovate (i.e., those that report that they do not need to innovate at all). We impose three more filters. First, we drop firms that experienced a merger or takeover process, as well as drastic employment incidents. Second, we eliminate observations with extreme values or zero sales. Finally, we also exclude from the analysis the primary and construction sectors. The final balanced panel includes 3,356 SMEs and 1,169 large firms.[6] All monetary variables are expressed in constant values at 2010 prices.[7] The time span encompasses the pre-crisis period (2005-2008), the crisis years (2009-2012) and the recovery (2013-2014). 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.

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

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

[7] It should be noted that continuous variables in PITEC - the volume of sales, exports volume or total expenditure on innovation- undergo a process of anonymization, unlike qualitative or percentage variables. López (2011) compared estimates obtained with the original and anonymous data and concluded that the anonymization procedure does not generate significant biases. Nevertheless, both the description and results of the empirical analysis should be interpreted with some caution. Details on definitions of the variables used are reported in Table 3.A1

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

Innovation expenditures are defined in the CIS as those that aim at developing and introducing innovations new to the firm or to the market. Investment in R&D is quantitatively the most important of these expenditures. We first focus on the analysis of SMEs, and refer to large firms in section 3.5.4. Table 3.1 shows that the number of firms investing in innovation and R&D in the balanced panel decreased steadily since 2005. The number of firms investing in R&D in our sample dropped by 28% over the period. The share of R&D performers receiving public support fell from 35% in 2005 to 28% in 2014. Furthermore the average rate of public funding among supported firms fell from about 40% in 2005 to 31% in 2014.

Firms can get support for up to three years in a single application, and can apply for and obtain support repeatedly. PITEC does not provide information on the duration of support, on rejected applications or on other features of funded projects; we only observe whether a firm declares having public support a given year. Tables 3.2 and 3.3 below show, respectively, the frequency of participation over the ten-year period and one lag transition probabilities of public funding. Table 3.2 shows that about 55% of firms in the balanced panel received public support at some point, and about 40% of participant firms did so for one or two years. One third of the firms participated for six years or more, suggesting that a substantial proportion of supported firms received R&D subsidies on a regular basis. It is not possible to know, as explained above, whether this is the outcome of firms in this group performing long-term projects lasting 3 or more years and applying for support every 3 years, or whether it is the outcome of success in repeated annual applications.

Table 3.1: Evolution of Innovation Expenditures and Direct Support. SMEs.

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

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

Table 3.2: Frequency of Participation over the Period

	Number of Firms	Percent
1 year	434	23.50%
2 years	300	16.27%
3 years	209	11.33%
4 years	172	9.33%
5 years	128	6.94%
6 years	126	6.83%
7 years	104	5.64%
8 years	109	5.91%
9 years	103	5.59%
10 years	159	8.62%
Total recipients	1,844	100.00%

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

Table 3.3 shows that both investment an innovation and receiving public support are highly persistent. About 71% of recipients of support in one year remained supported the following year, while 29% did not. Furthermore, 93% of non-supported firms in [t] maintained their status in [t+1]. We also find high persistence of investment in innovation effort: each year about 72% of firms that did not have innovation activities remained in the same situation the following year, while 28% engaged in innovation. In turn, 90% of firms that had innovation activities one year continued doing so in the following year. These facts are in line with those found in Peters (2009) and Busom et al. (2017).

Table 3.3: Transition Probabilities of Public Support and of Innovation Effort

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

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

In addition we observe that some firms will be supported only during the growth period, others during the recession others in both, and finally some may never participate. This will be of critical importance in defining the empirical strategy.

3.4 Empirical Strategy

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

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

3.4.1 Access to Public Support over the Cycle

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

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

$$s_i^* = \alpha_{10} s_{i,t-1} + x'_{i,t-1}\beta_{10} + \eta_i + u_{i,t} \tag{3.1}$$

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 modeling the distribution of η_i conditional on the initial conditions s_{i0}, and all lagged values for each exogenous covariates $z_i = (z_{i1}, z_{i2}, \dots, z_{iT})$. Alternatively, Mundlak's (1978) approach replaces lagged exogenous variables by their time average. In this case the individual effects model can be expressed as follows:

$$\eta_i = \alpha_{11} s_{i,t-1} + \alpha_{21} s_{i0} + \alpha_{31} \bar{z}_i + \epsilon_{i,t} \tag{3.2}$$

The final model can be written as:

$$s_i^* = \alpha_{11} + \alpha_{10} s_{i,t-1} + \alpha_{21} s_{i0} + x'_{i,t-1} \beta_{10} + \alpha_{31} \bar{z}_i + v_{i,t} \tag{3.3}$$

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

We also test whether the correlation with perceived barriers to innovation –such as access to external funding and demand uncertainty- remains constant and significant over time. As control variables we will include firm size, age, export status, group membership, foreign ownership, the percentage of employees with higher education, 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. All variables are lagged one period. Moreover, as innovation expenditures are found to be persistent in the literature, previous innovation expenditures will be controlled for. Finally, industry dummies are included to control for sector heterogeneity. Variables are defined in Table 3.A1 in the Appendix.

3.4.2 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 labor market policies (Lechner 2015; Lechner and Wiehler 2013). In this literature a matching approach has been combined with differences-in-differences, a strategy that may be appropriate in our case as well, as we discuss next.

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

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

$$E[Y_{0i,t}|t, S_{i,t}] = E[Y_{0i,t}|t] \tag{3.4}$$

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

$$E[Y_{1i,t}|t, S_{i,t}] - E[Y_{0i,t}|t] = \tau \tag{3.5}$$

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 [3.6] below could be estimated by a difference in difference model using longitudinal data.

$$Y_{i,t} = \alpha + \sum_{\delta=0}^{q} \tau_{+\delta} D_{i,t+\delta} + \epsilon_{i,t} \tag{3.6}$$

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

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

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 [3.6] entails a 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 [3.4] would be violated if we do not control for the systematic differences among firms.

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

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

$$Y_{i,t} = \alpha_i + \lambda_t + \sum_{\delta=0}^{q} \tau_{+\delta} D_{i,t+\delta} + \sum_{j} X'_{i,t}\beta + \epsilon_{i,t} \tag{3.7}$$

The model includes two main effects. First, it assumes that there is an individual time-invariant heterogeneity component (α_i) which is unobserved, and a year effect, λ_t, which is modeled as a time-year dummy variable. Second, it includes an interaction term $D_{i,t}$, the same as in equation [3.6], where $(S_{i,t} \cdot d_t) = D_{i,t+\delta}$. $X_{i,t}$ is

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

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

a vector of firm time varying covariates. Note that the sum on the right-hand side allows for q leads of participation $(\tau_{+1}, \tau_{+2}, \ldots, \tau_{+q})$.

We will assess the impact of public support over time on two different outcomes. The first is investment in innovation per employee; this allows testing for full crowding out. The second outcome the number of employees (researchers, technicians and auxiliary staff) dedicated to R&D in full time equivalent units (FTE). Both outcomes provide complementary information on the effects of subsidies, as firms might reallocate highly qualified workers between production and research tasks without changing innovation budgets.[12] Interpretation of τ depends on which dependent variable is used in estimating [3.7]. When the measured outcome is total investment (private investment plus the subsidy) per employee, $\tau \leq 0$ implies full crowding out. If instead the outcome is investment net of the subsidy, or the employee time dedicated to R&D, then $\tau = 0$ implies that neither additionality nor crowding-out effect occur; $\tau < 0$ indicates that some crowding-out is at work, and $\tau > 0$ indicates crowding-in effects.

3.5 Results

3.5.1 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 3.4 shows the marginal effects, calculated at the average value. Columns 1, 4, and 7 display the maximum likelihood estimates of specification [3.3], using the lag of public funding $(t-1)$, its initial value (funding at t_0), and different lagged explanatory variables $(X_{i,t-1})$ in order to control for observed heterogeneity. Columns 2, 5, and 8 report results using Mundlak's specification, and columns 3, 6 and 9 show estimates of a pooled probit. Both dynamic estimators lead to similar and significant coefficient estimates for lagged public funding, which is a measure of true state dependence of participation, while pooled probit estimates overestimate persistence, as expected.[13] Firms that have previously participated in public funding programs have higher probability of doing so later. This result is close to findings by Busom et al. (2017), who used a similar model with a panel of Spanish manufacturing firms over the period 2001–2008. Estimates suggest that persistence is slightly increasing during the recession phase and immediately after.

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

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

We interpret this as an indicator that the probability to obtain support by previous non-participants fell with the recession. The initial value of public funding is also significant, implying that there is an important correlation between unobserved heterogeneity and the initial condition.

We do not find evidence that the firm's sales growth is correlated with participation in any of the phases of the cycle. Interestingly, firms that reported facing difficulties to access external funding are more likely to participate during the expansion phase, but not during the crisis. A plausible explanation is that many firms delay innovation plans during recessions and do not even search for support. They plan to engage in innovation activities –especially R&D- during expansions, and seek public support then because even during expansions SMEs are likely to face limited access to external funds for R&D. It is also possible that during recession years all firms face financial constraints, so that this perception would not explain differences in participation. The correlation with other variables such as the firm's human capital, continuous R&D performers, cooperation, and domestic ownership remains positive and stable throughout the cycle.[14] We also find that continuous R&D performers are more likely to participate 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. 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.

[14] We have also checked for the non-linearity of firm size, but results do not confirm such effect.

Table 3.4: 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 $x \leq 20$	-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 $20 < x \leq 50$	-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 $50 < x \leq 100$	-0.009	-0.010	-0.006	0.003	-0.003	0.006	-0.001	0.000	0.001

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Table 3.4 – 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)
	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
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)	

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Table 3.4 – 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)
Log likelihood	-3261.115	-3112.0599	-3321.7829	-3861.909	-37206.206	-3943.527	-2302.0221	-2225.6514	-2339.3505
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 3.5: 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 3.4, columns 2, 5 and 8.

Table 3.5 reports the estimated average probability of being supported in period t, given participation in $t-1$, based on the results in columns 2, 5 and 8. Persistence is found to be higher after the onset of the crisis, suggesting that a number of firms were repeatedly supported through this period. To summarize, the process of being granted support seem to be quite stable along the phases of the business cycle, as basically the same subset of variables are correlated with the likelihood of obtaining support over the three periods.

3.5.2 Impact of Direct Support on Firms' Investment in Innovation

To perform the experiment described in section 3.4 and estimate the average treatment effects on the treated we have to choose a valid control group. This involves taking into account the firm's timing of participation: firms that obtain grants during the initial expansion phase should be compared with firms that are not treated during the whole period; and firms that receive funding during the recession should be compared to (matched) firms untreated during the recession and that were not treated previously either, as treatment effects can last for longer than the treatment year. To this end, we construct the participation spells or histories. The basic idea of the participation spells is intuitive: a time window during which the firms may have received funding. We proceed as follows: 1) we divide the 2005-2014 period in three sub-periods or time-windows, according the evolution of GDP growth as shown in Figure 3.1 in section 3.3: 2006-2008; 2009-2012 and 2013-14; 2) we consider the timing of participation of each firm within each phase, that is, whether a firm participates in all, two or one of the three periods; 3) we focus on four participation spells or patterns that last one and two years within each time window (see table 3.6 below); 4) since we do not know the firm's participation history before 2005, we will perform the analysis for the sample of firms that were not participating in 2005, that is we drop from the sample firms that were participating that year.

We match firms treated at a given point in time with controls –firms that never participate- through the nearest neighbor matching procedure. For the expansion period, 2006-8, we use the estimated probability of participating in 2006 (the propensity score) using covariate values for 2005. The sample includes firms that exhibit a particular participation spell and matched firms that never participate. For the crisis period the propensity score is estimated with data for 2008 with lagged covariates.[15] Table 3.6 shows the spells studied, the number of treated firms in each spell, and the number of potential controls.[16]

[15] Yearly cross-sectional estimates of participation probabilities are available upon request.
[16] We cannot analyze all spells because the number of treated firms is too small in some cases.

Table 3.6: Participation Spells. SMEs

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

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 3.7 reports the t-test of equality of the means of the matching covariates used in the analysis for each participation spell. Before matching there are significant differences between treated and non-treated firms, especially with respect to employees with higher education, firm age, support from EU and innovation intensity in $t-1$. After matching, differences are no longer significant, and the mean bias drops significantly. The distribution of the propensity-score for treated and control firms before and after matching are displayed in Figure 3.A1 in the Appendix. The quality of the match after discarding some observations is high. Overall, we can safely conclude that balancing is satisfactory.

We next estimate the model specified in equation [3.7] for each of the spells on Table 3.6 and each of the two outcomes of interest.[17] Four versions of this equation will be estimated: i) a standard DiD model without controls using the whole sample of treated and untreated firms; ii) a DiD with the same sample including all the controls used in the propensity score matching (DiD+controls); iii) a weighted version of the DiD, where observations are weighted according to the propensity score (DiD weighted), and iv) a DiD model using only the sample of treated and matched controls (DiD Matched).[18] Tables 3.A2 and 3.A3 in the Appendix report the estimated

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

[18] Weighting observations by their inverse probability of treatment was proposed by Hirano and Imbens (2001). In this case firms that participate in the program are given weight of $1/p$ and

value of the treatment effect every year since participation for firms exhibiting each spell. We find that treatment estimates vary depending on the estimation method. DiD and DiD with controls generally overestimate treatment effects compared to DiD-weighted or DiD-matched. Figure 3.2 illustrates differences in estimated treatment effects for the treated by estimation method when the outcome is the number of employees allocated to R&D activities in FTE (Table 3.A3).

Table 3.7: Before and After Matching (t-statistic)

Participation Patterns	Pre-crisis 1 year		Pre-Crisis 2 years		During crisis 1 year		During crisis 2 years	
Variables	UM	M	UM	M	UM	M	UM	M
Sales growth	-0.31	-0.68	0.4	0.00	0.38	0.53	-0.6	-0.73
O. External funding	1.87**	-1.08	0.00	0.26	0.63	0.6	-0.39	0.44
O. Demand Uncertainty	0.15	0.33	0.99	1.11	0.45	-0.62	0.57	0.00
Continuous R&D performer	2.32**	0.39	3.2	0.25	0.24	0.66	0.29	0.91
R&D employees	0.53	0.5	0.99	-0.5	0.33	-0.58	0.53	-0.83
Higher education	0.64	0.3	3.12***	-0.47	0.94	0.47	0.93	-0.83
IP protect	0.85	0.54	0.25	-0.68	1.58	0.14	0.14	1.08
Cooperation	2.35**	0.85	1.49	-0.69	0.91	-0.32	1.42	0.43
Size. $x \leq 20$	0.02	0.44	0.8	-0.46	-1.16	0.00	0.37	-0.58
Size $20 < x \leq 50$	-0.17	-0.41	0.64	0.23	0.07	-0.27	0.67	-0.18
Size $50 < x \leq 100$	0.91	0.14	0.03	-0.25	1.67*	1.17	-1.11	1.02
Group membership	-1.43	0.00	0.55	-0.24	-0.59	0.3	-1.8	0.48
Foreign Ownership	-0.33	0.00	0.14	-0.35	-1.02	0.27	-0.86	1.37
Export	1.5	-1.67*	-0.8	-0.47	2.05**	-1.39	0.34	1.34
young	1.68*	-0.3	3.46***	-0.23	0.11	0.63	0.69	-0.71
High tech Manufac.	1.6	1.1	0.95	0.00	0.39	1.02	1.96**	0.66
Medium tech Manufac.	0.07	-1.67*	1.19	0.72	-0.43	0.00	1.55	0.38
High-tech services	0.25	-0.41	0.13	-0.67	0.00	0.98	-0.78	-0.34
Other Services	-1.51	0.58	-0.78	0.00	-0.31	-0.33	-0.43	-0.88
UE support	1.77**	-0.38	-0.59	[a]	1.42	0.58	0.99	1.00
Innovation intensity	1.78**	1.29	1.35	0.03	0.95	-1.11	-0.94	0.09
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: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; LR Chi2: Joint significance test.

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 3.A2 for detailed results for spells 1 and 3 respectively). In fact, during the recession no

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.

significant effects are found. Although we can reject full crowding out for one year participants before the crisis, we cannot reject it during the downturn, in line with results found by Hud and Hussinger (2015). This suggests that treatment effects were pro-cyclical. However, for firms that participate twice –we now compare participation spell 2 to participation spell 4- we find that treatment effects might have been significant and last longer during the recession years.[19]

When we examine treatment effects on the allocation of human capital to innovation activities –R&D employees in full time equivalent- we find that, according to the DiD+Matching estimation, treatment effects are somewhat higher and last longer during the recession years, suggesting a counter-cyclical behavior whether firms participate one year or two years (see Table 3.A3). Figure 3.3 illustrates the differences of estimated treatment effects before and during the crisis years for two outcomes (total innovation investment per employee and human resources allocated to innovation, in FTE) and two participation spells.

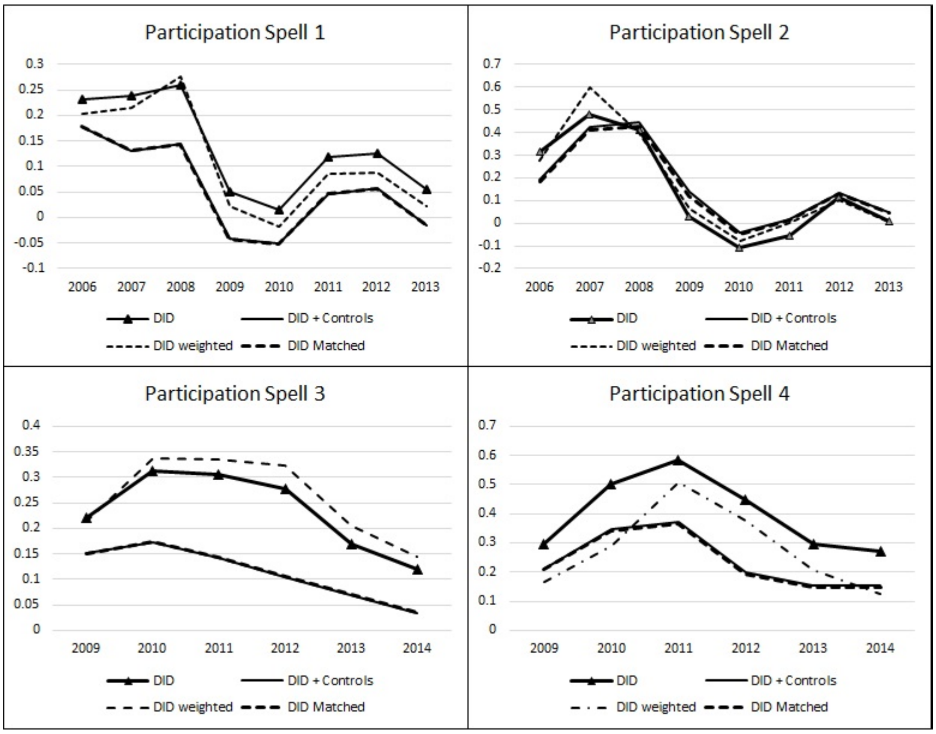
Our results, summarized in Table 3.8 below, suggest two conclusions. First, effects of public support over the business cycle would depend on the duration of support, possibly reflecting different innovation project types. And second, while the effect of support on innovation investment is smaller –null- during the crisis years relative to expansion years, receiving support allowed firms to protect and expand their investment in R&D human capital relative to non-participants' investment.

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

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

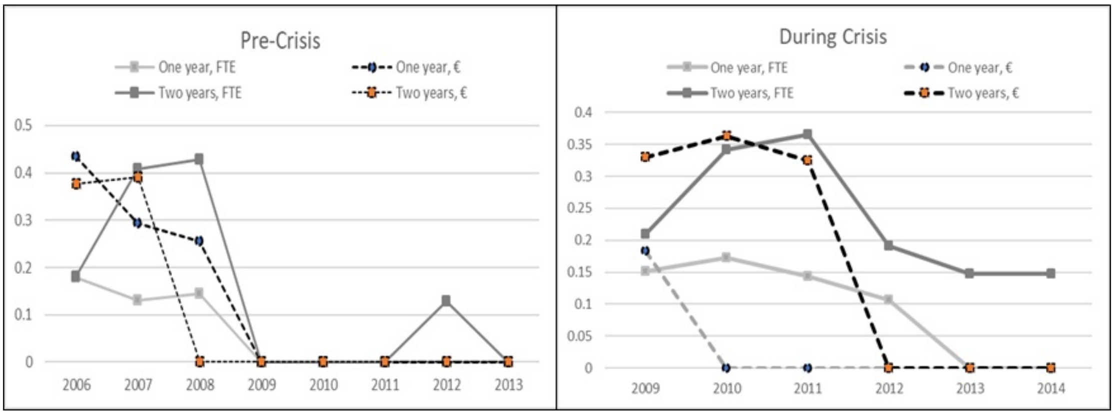
[19] Spillovers from additional R&D activities induced by the policy flowing from treated firms to untreated firms with some delay could distort the true causal effect.

Figure 3.2: Estimated Average Treatment Effects on the Treated (ATT) by Estimation Method. Outcome: R&D Employees in FTE



Notes: The vertical axis measures the difference in average number of full time equivalent employees dedicated to R&D activities. Participation spells are as described in Table 3.6, and estimates are reported in Table 3.A3.

Figure 3.3: Estimated Treatment Effects Before and During the Crisis



Notes: Graphs show significant estimated coefficients from tables 3.A2 and 3.A3. Non-significant coefficients are set to 0.

Table 3.8: Multipliers over time by Outcome

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

Note: Duration of the estimated effect in parenthesis.

3.5.3 Robustness

We address two different issues regarding the robustness of our results. We analyze their sensitivity to using the unbalanced panel, the presence of anticipation effects, and the inclusion of 2013 in the definition of the crisis period.

Unbalanced panel. A first issue is the potential sensitivity of results to changes in the sample. In this regard, we have used the same methods to estimate treatment effects with the unbalanced panel and obtain very similar results. We include descriptive statistics for the unbalanced and balanced panel in Table 3.A5; estimation results are in Tables 3.A6 to 3.A8.

Anticipation effects. Firms may react to a policy before its implementation, so that the outcome at t would be correlated with future program participation at $t+1$ or $t+2$. For instance, a firm wishing to obtain direct support might decide to improve its technological capabilities to increase its chances of obtaining a grant (Cerulli et al. 2015). To test for anticipatory effects, we follow Autor (2003) and extend equation [3.7], adding some leads for future participation in public innovation programs. This test also allows us to validate a fundamental assumption for any DiD strategy, in which the outcome in treatment and control group would follow the same time trend in the absence of the treatment. We estimate the following equation:

$$Y_{i,t} = \alpha_i + \lambda_t + \sum_{\delta=1}^{q} \tau_{-\delta} D_{i,t-\delta} + \sum_{\delta=0}^{q} \tau_{+\delta} D_{i,t+\delta} + \sum_{j} X'_{i,t}\beta + \epsilon_{i,t} \tag{3.8}$$

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

4, where we observe a drop in the allocation of employees to innovation prior to treatment years 2006 to 2008.

Definition of the crisis period. In the baseline estimations, 2013 is considered to be the start of the recovery period. The Spanish Business Cycle Dating Committee, linked to the Spanish Economic Association (http://asesec.org/CFCweb/en/) characterizes the crisis in Spain as a double recession. 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 the model with 2013 classified as crisis period. The main results still hold as shown in Table 3.A4.

3.5.4 Large Firms

We build a balanced panel of about 1,169 large firms with more than 200 employees from the same source, PITEC. About 66% of them were investing in innovation in 2005, and 49% in R&D. These percentages increased slightly up to 2009, and then dropped again to the levels of 2005 by 2014. Likewise, while in 2009 and 2010 public support reached about 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 3.A9 to 3.A11 in the Appendix 3).

The size of the sample of firms in the balanced panel receiving direct support allows us to estimate a dynamic random effects model for each phase of the business cycle and compare estimates with those obtained for SMEs. Results are quite similar with respect to persistence of participation, which is higher during the recession. As before, this is consistent with the hypothesis that budget cuts lead to a sharp reduction in the probability that previously untreated firms would obtain support during the recession. Unlike SMEs, however, we do not find evidence that the probability of participation was correlated with lack of access to external funding (see table 3.A12 in the Appendix).

When looking at participation spells over the cycle, we find that the number of firms experiencing the same participation spell is in many cases too small to obtain reliable estimates of treatment effects for the same cases as for SMEs. Table 3.9 shows the number of treated and potential controls for the cases analogous to SMEs.

Table 3.9: Participation Spells. Large firms

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

Because of the small number of observations for these participation spells, we estimate tentatively treatment effects only for spells 1 and 3 (see Tables 3.A13 and 3.A14). 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 years and during the recession except for firms participating one year during the expansion phase (spell 1) where we find a positive and significant treatment effect on the employee time dedicated to R&D activities in 2008. These results, however, are to be considered only extremely tentative given sample size. They only suggest that large firms and SMEs respond differently to public support, as found in other research.

3.6 Concluding Remarks

We analyze the behavior and effects of public support to business R&D and innovation investment over the phases of the business cycle. The research questions we intend to answer are: 1) Does firms' access to support vary over the business cycle? 2) Does the impact of support remain constant over the cycle? 3) Does public support affect private both R&D investment and R&D employment?

With respect to the first question, we find that, in line with the results of Hud and Hud and Hussinger (2015)) for Germany, the allocation of R&D subsidies in Spain did not change significantly during the crisis years. Regarding the second question, our richer data compared to previous studies produce more nuanced results. We find that the multiplier varies depending on the firms' participation spell and with the type of outcome. Timing and length of participation matter, with longer spells leading to a higher multiplier. With respect to the third question, we find that while the impact of public support during the recession years is pro-cyclical for investment in innovation in monetary terms, when looking at the time allocation to R&D activities the multiplier is higher and longer during the recession. These results are robust for SMEs. Overall, 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.

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Appendix 1

Table 3.A1: 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.
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.

Continued on next page

Table 3.A1 – continued from previous page

Variable Name	**Variable Definition**
EU support	Binary indicator of participating in public support programs from the European Union.

Table 3.A2: Treatment Effects. Outcome: Ln(Total Innovation Effort per worker)

	DiD (Naive) (1)	DiD (Controls) (2)	DiD (Weighted) (3)	DiD (Common Support) (4)
Participation Spell 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)
Participation Spell 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)
Participation Spell 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

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Table 3.A2 – continued from previous page

	DiD (Naive) (1)	DiD (Controls) (2)	DiD (Weighted) (3)	DiD (Common Support) (4)
	(0.109)	(0.107)	(0.109)	(0.128)
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)
Participation Spell 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)
Fixed Effects	Yes	Yes	Yes	Yes
Year Dummies	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 3.A3: Treatment Effects. Outcome: Human Capital (R&D Employees in FTE)

	DiD (Naive) (1)	DiD (Controls) (2)	DiD (Weighted) (3)	DiD (Common Support) (4)
Participation Spell 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)
Participation Spell 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)
Participation Spell 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
	(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)
Participation Spell 4				

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Table 3.A3 – continued from previous page

	DiD (Naive) (1)	DiD (Controls) (2)	DiD (Weighted) (3)	DiD (Common Support) (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)
Fixed Effects	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

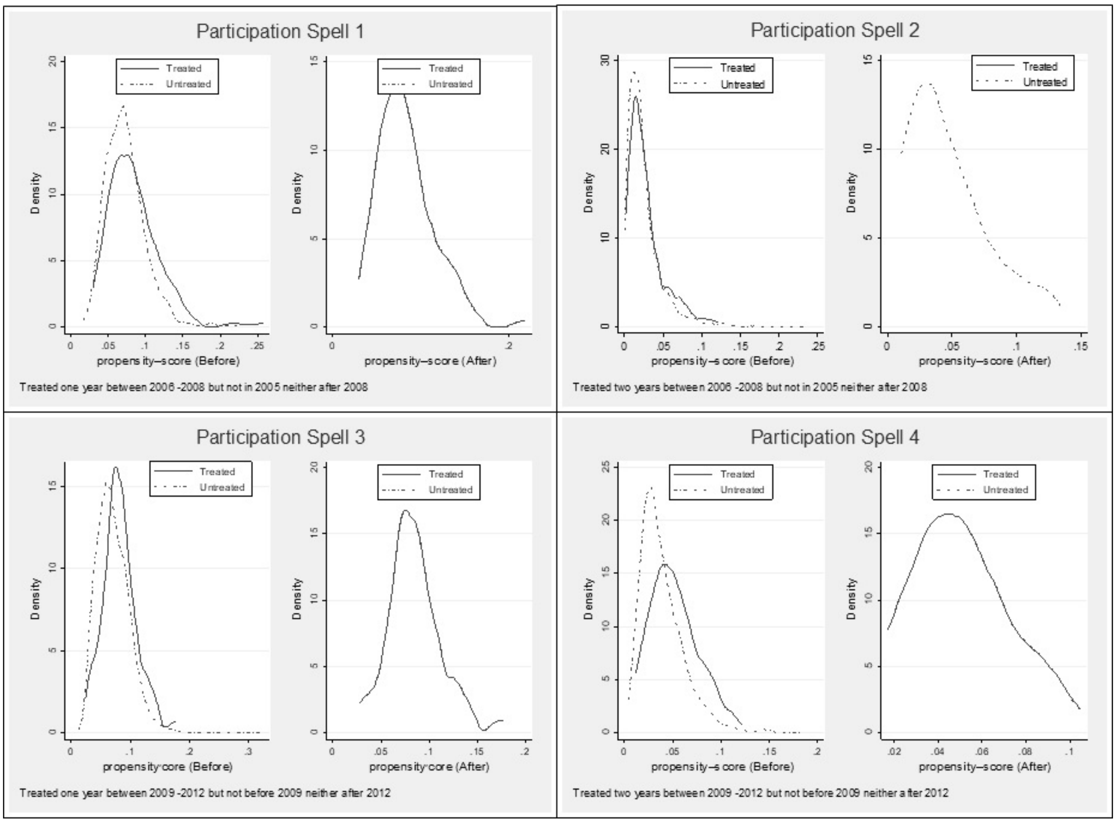
Notes: Dependent variable: R&D employees (FTE). Standard errors in parentheses; standard errors are clustered at the firm level. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 3.A4: Robustness check: Definition of the Crisis Period

	Ln(Total Innovation Effort per worker)		Human Capital (R&D) employees FTE	
	2013 classified as recovery	2013 classified as crisis	2013 classified as recovery	2013 classified as crisis
Participation Spell 3	(1)	(2)	(3)	(4)
2009	0.120	0.156	0.151***	0.164***
	(0.099)	(0.089)	(0.047)	(0.044)
2010	0.063	0.073	0.173***	0.152***
	(0.108)	(0.100)	(0.060)	(0.056)
2011	0.144	0.132	0.143**	0.159***
	(0.127)	(0.122)	(0.057)	(0.053)
2012	0.118	0.155	0.106*	0.109**
	(0.128)	(0.118)	(0.056)	(0.052)
2013	-0.002	0.066	0.071	0.115**
	(0.114)	(0.108)	(0.055)	(0.053)
2014	-0.182	-0.151	0.035	0.039
	(0.132)	(0.118)	(0.057)	(0.054)
Participation Spell 4				
2009	0.330***	0.274***	0.209***	0.152**
	(0.117)	(0.103)	(0.076)	(0.073)
2010	0.363***	0.267***	0.341***	0.286***
	(0.121)	(0.102)	(0.076)	(0.065)
2011	0.325**	0.232*	0.366***	0.365***
	(0.159)	(0.126)	(0.089)	(0.072)
2012	0.167	0.063	0.191**	0.175**
	(0.130)	(0.119)	(0.081)	(0.078)
2013	0.018	-0.015	0.147*	0.164**
	(0.122)	(0.105)	(0.087)	(0.074)
2014	-0.021	0.002	0.148*	0.135*
	(0.120)	(0.105)	(0.076)	(0.075)
Fixed Effects	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses; standard errors are clustered at the firm level. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. The number of treated firms for spells 3 and 4 is 135 and 77 firms respectively when 2013 is classified as crisis period.

Figure 3.A1: SMEs. Distribution of the Propensity Score Before and After Matching



Appendix 2: Unbalanced Panel

Table 3.A5: Descriptive Statistics: Balanced and Unbalance Panel

	2005-2008		2009-2012		2013-2015	
Variables	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Public Support	0.27	0.24	0.23	0.18	0.16	0.14
	(0.442)	(0.429)	(0.422)	(0.386)	(0.369)	(0.350)
Sales growth (log-dif)	0.04	-0.02	-0.04	-0.12	0.01	-0.05
	(0.265)	(0.449)	(0.290)	(0.487)	(0.292)	(0.479)
External funding	0.29	0.33	0.38	0.41	0.35	0.36
	(0.455)	(0.468)	(0.486)	(0.491)	(0.475)	(0.479)
Demand Uncertainty	0.22	0.23	0.28	0.28	0.24	0.23
	(0.415)	(0.418)	(0.449)	(0.451)	(0.425)	(0.423)
Continuous R&D performer	0.59	0.51	0.53	0.40	0.48	0.41
	(0.492)	(0.500)	(0.499)	(0.490)	(0.500)	(0.492)
R&D employees	0.07	0.07	0.07	0.06	0.06	0.06
	(0.137)	(0.147)	(0.141)	(0.158)	(0.146)	(0.143)
Higher education	0.31	0.31	0.31	0.31	0.34	0.34
	(0.287)	(0.301)	(0.286)	(0.301)	(0.291)	(0.304)
IP protect	0.33	0.30	0.27	0.23	0.20	0.18
	(0.469)	(0.460)	(0.444)	(0.419)	(0.403)	(0.388)
Cooperation	0.34	0.31	0.33	0.28	0.32	0.29
	(0.474)	(0.462)	(0.471)	(0.448)	(0.466)	(0.454)
Size. $x \leq 20$	0.29	0.36	0.30	0.38	0.31	0.34
	(0.453)	(0.481)	(0.456)	(0.486)	(0.463)	(0.475)
Size $20 < x \leq 50$	0.33	0.31	0.33	0.29	0.32	0.28
	(0.472)	(0.461)	(0.472)	(0.454)	(0.465)	(0.447)
Size $50 < x \leq 100$	0.23	0.19	0.24	0.18	0.25	0.21
	(0.424)	(0.391)	(0.425)	(0.380)	(0.431)	(0.407)
Group	0.27	0.27	0.31	0.31	0.34	0.36
	(0.443)	(0.441)	(0.461)	(0.463)	(0.472)	(0.481)
Foreign	0.07	0.06	0.08	0.08	0.09	0.10
	(0.257)	(0.245)	(0.274)	(0.271)	(0.284)	(0.294)
Export	0.71	0.63	0.75	0.67	0.78	0.74
	(0.454)	(0.482)	(0.435)	(0.469)	(0.412)	(0.437)
Young	0.22	0.25	0.08	0.10	0.01	0.01
	(0.417)	(0.432)	(0.277)	(0.306)	(0.0936)	(0.118)
High tech Manufac.	0.05	0.05	0.05	0.05	0.06	0.05
	(0.222)	(0.220)	(0.226)	(0.216)	(0.230)	(0.222)
Medium tech Manufac.	0.25	0.21	0.25	0.21	0.25	0.22
	(0.432)	(0.407)	(0.434)	(0.410)	(0.433)	(0.417)
High-tech services	0.15	0.15	0.14	0.14	0.14	0.14
	(0.354)	(0.362)	(0.350)	(0.351)	(0.347)	(0.347)
Rest Services	0.20	0.24	0.21	0.25	0.21	0.25
	(0.403)	(0.428)	(0.404)	(0.434)	(0.406)	(0.435)
UE support	0.04	0.03	0.04	0.04	0.06	0.05
	(0.189)	(0.178)	(0.206)	(0.187)	(0.230)	(0.220)
Innovation intensity (log)	7.28	6.78	6.66	5.20	5.78	5.03
	(3.320)	(3.725)	(3.757)	(4.341)	(4.150)	(4.349)
N	12,828	27,808	12,828	25,08 0	9,621	14,286

Notes: mean coefficients; sd in parentheses.

Table 3.A6: Participation. Dynamic Probit Estimation: Unbalanced Panel (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 $(t-1)$	0.125***	0.186***	0.273***	0.179***	0.188***	0.214***	0.189***	0.183***	0.201***
	(0.008)	(0.010)	(0.004)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Public support (t_0)	0.105***	0.079***		0.056***	0.049***		0.045***	0.042***	
	(0.008)	(0.009)		(0.004)	(0.004)		(0.004)	(0.004)	
Sales growth (log dif)	0.013**	0.012**	0.018**	0.011***	0.006	0.012**	0.015**	0.011	0.013*
	(0.004)	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)	(0.007)	(0.007)	(0.006)
External Funding $(t-1)$	0.006	0.004	0.006	0.005	-0.003	0.006	-0.004	-0.002	-0.003
	(0.004)	(0.006)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.007)	(0.004)
Demand Uncertainty $(t-1)$	0	0.003	0.001	0.005	0.005	0.004	-0.005	-0.008	-0.004
	(0.005)	(0.007)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.007)	(0.005)
Continuous R&D performer $(t-1)$	0.117***	0.069***	0.127***	0.099***	0.054***	0.099***	0.086***	0.047***	0.086***
	(0.005	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)
R&D employees $(t-1)$	0.053*	0.02	0.055**	0.030**	-0.004	0.029*	0.004	-0.017	0.009
	(0.016)	(0.017)	(0.017)	(0.014)	(0.013)	(0.014)	(0.013)	(0.015)	(0.009)
Higher education $(t-1)$	0.077***	0.049***	0.088***	0.032***	0.017**	0.041***	0.022***	0.011	0.031***
	(0.009)	(0.010)	(0.010)	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)
IP protect $(t-1)$	-0.005	-0.008*	-0.005	0.005	0.000	0.004	0.002	-0.001	0.002
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Cooperation $(t-1)$	0.045***	0.043***	0.056***	0.038***	0.033***	0.043***	0.030***	0.026***	0.034***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
Size $x \leq 20$	-0.043***	-0.049***	-0.043***	-0.036***	-0.035***	-0.035***	-0.020***	-0.022**	-0.020**
	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Size $20 < x \leq 50$	-0.023***	-0.027***	-0.022**	-0.014**	-0.015***	-0.013*	-0.009	-0.01	-0.007
	(0.007)	(0.007)	(0.007)	(0.006)	(0.005)	(0.005)	(0.007)	(0.006)	(0.007)
Size $50 < x \leq 100$	-0.016**	-0.016**	-0.015	0.001	-0.001	0.001	-0.004	-0.006	-0.003

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Table 3.A6 – 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)
	(0.007)	(0.007)	(0.008)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Group $(t-1)$	-0.009	-0.012**	-0.008	-0.004	-0.006	-0.003	-0.001	-0.006	-0.001
	(0.005)	(0.005)	(0.006)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Foreign $(t-1)$	-0.033***	-0.033 ***	-0.037***	-0.031***	-0.031***	-0.035***	-0.034***	-0.032***	-0.036***
	(0.010)	(0.010)	(0.010)	(0.008)	(0.007)	(0.008)	(0.009)	(0.009)	(0.009)
Export $(t-1)$	0.005	-0.002	0.004	-0.001	-0.005	-0.003	-0.003	-0.007	-0.004
	(0. 005)	-0.005	-0.005	-0.004	-0.004	-0.004	-0.006	-0.006	-0.006
Young	0.014***	0.012**	0.015**	0.002	0.001	0.005	-0.018	-0.019	-0.019
	(0. 005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)
High tech Manufac.	-0.003	-0.017*	-0.007	-0.007	-0.019**	-0.006	-0.011	-0.020**	-0.01
	(0.010)	(0.010)	(0.010)	(0.008)	(0.007)	(0.008)	(0.009)	(0.009)	(0.009)
Medium tech Manufac	0.006	-0.003	0.004	-0.006	-0.013***	-0.007	0.000	-0.005	0.000
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
High-tech services	0.011	0.004	0.011	0.017***	0.01	0.018**	0.005	0.002	0.008
	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)
Rest Services	-0.006	-0.001	-0.006	0.007	0.007	0.007	0.004	0.003	0.005
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
UE support $(t-1)$	0.058***	0.053***	0.071***	0.058***	0.048***	0.066***	0.033***	0.026***	0.040***
	(0.011)	(0.011)	(0.012)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Innovation intensity $(t-1)$	0.004***	-0.011***	0.004**	0.004***	-0.007***	0.004***	0.003***	-0.008***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
M_Innovation intensity		0.034***			0.024***			0.020***	
		(0.001)			(0.001)			(0.001)	
M_External funding		0.002			0.013**			-0.002	
		(0.008)			(0.006)			(0.008)	
M_Demand Uncertainty		-0.004			0.002			0.008	

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Table 3.A6 – 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)
		(0.009)			(0.007)			(0.008)	
Log likelihood	-6221.4082	-5880.8615	-6315.585	-5801.858	-5499.1382	-5910.973	-2920.0129	-2800.295	-2969.772
lnsig2u	-0.860***	-2.273***		-2.642***	-12.247		-13.993	-12.878	
	(0.151)	(0.470)		(0.419)	(8.663)		(11.468)	(7.774)	
Sigma_u	0.651***	0.321***		0.270***	0.002		0.001	0.001	
	(0.049)	(0.075)		(0.056)	(0.009)		(0.005)	(0.006)	
rho	0.298***	0.093***		0.066***	0.000		0.000	0.000	
	(0.032)	(0.039)		(0.026)	(0.000)		(0.000)	(0.000)	
Wald Chi2	3757.54***	4580.80***	6107.49***	6204.96***	6626.34***	7383.77***	3695.48***	3450.44***	3814.62***
N	19,913	19,912	19,913	24,007	24,007	12,826	13,756	13,756	13,756
Firms	7,233	7,232	7,232	6,846	6,846	6,846	5,750	5,750	5,750

Notes: As in Table 3.4

Table 3.A7: Treatment Effects. Outcome: Ln(Total Innovation Effort per worker): Unbalanced panel

	DiD (Naive) (1)	DiD (Controls) (2)	DiD (Weighted) (3)	DiD (Common Support) (4)
Participation Spell 1				
2006	0.302***	0.418***	0.179	0.434***
	(0.100)	(0.123)	(0.148)	(0.124)
2007	0.198*	0.267**	0.267*	0.273**
	(0.104)	(0.128)	(0.160)	(0.128)
2008	0.134	0.233**	0.233	0.251**
	(0.108)	(0.119)	(0.175)	(0.121)
2009	-0.022	0.084	-0.078	0.099
	(0.085)	(0.095)	(0.104)	(0.098)
2010	-0.117	-0.028	-0.164	0.008
	(0.098)	(0.104)	(0.114)	(0.103)
2011	0.011	0.115	0.027	0.109
	(0.102)	(0.094)	(0.180)	(0.097)
2012	0.022	0.117	0.005	0.147*
	(0.093)	(0.085)	(0.146)	(0.087)
2013	-0.090	0.001	-0.181	-0.012
	(0.093)	(0.075)	(0.123)	(0.077)
Participation Spell 2				
2006	0.473***	0.397**	0.526***	0.403**
	(0.129)	(0.195)	(0.179)	(0.192)
2007	0.434**	0.419*	0.525***	0.419*
	(0.191)	(0.221)	(0.186)	(0.218)
2008	0.288**	0.341	0.164	0.344
	(0.131)	(0.263)	(0.156)	(0.262)
2009	-0.108	0.015	-0.221	0.022
	(0.164)	(0.247)	(0.190)	(0.247)
2010	-0.180	-0.102	-0.302*	-0.096
	(0.134)	(0.176)	(0.166)	(0.174)
2011	-0.237*	-0.138	-0.526***	-0.129
	(0.131)	(0.173)	(0.198)	(0.171)
2012	-0.167	-0.078	-0.631**	-0.071
	(0.179)	(0.174)	(0.259)	(0.175)
2013	-0.170	-0.064	-0.305**	-0.068
	(0.176)	(0.158)	(0.149)	(0.159)
Participation Spell 3				
2009	0.276***	0.207**	0.245**	0.204**
	(0.081)	(0.081)	(0.101)	(0.081)
2010	0.267***	0.131	0.202*	0.126
	(0.094)	(0.098)	(0.116)	(0.098)
2011	0.345***	0.207**	0.339***	0.200*
	(0.104)	(0.105)	(0.121)	(0.105)
2012	0.226**	0.108	0.123	0.112
	(0.105)	(0.101)	(0.137)	(0.102)
2013	0.064	0.003	-0.005	-0.005
	(0.093)	(0.091)	(0.090)	(0.091)
2014	-0.073	-0.144	-0.058	-0.154
	(0.102)	(0.100)	(0.098)	(0.101)
Participation Spell 4				

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Table 3.A7 – continued from previous page

	DiD (Naive) (1)	DiD (Controls) (2)	DiD (Weighted) (3)	DiD (Common Support) (4)
2009	0.426***	0.354***	0.161	0.344***
	(0.130)	(0.114)	(0.139)	(0.114)
2010	0.544***	0.423***	0.281	0.406***
	(0.129)	(0.116)	(0.173)	(0.117)
2011	0.523***	0.391**	0.400**	0.370**
	(0.155)	(0.156)	(0.164)	(0.156)
2012	0.379***	0.199	0.275**	0.187
	(0.139)	(0.128)	(0.139)	(0.128)
2013	0.165	0.067	0.067	0.046
	(0.140)	(0.118)	(0.143)	(0.118)
2014	0.114	0.022	-0.010	0.004
	(0.133)	(0.116)	(0.135)	(0.116)
Fixed Effects	Yes	Yes	Yes	Yes
Year Dummies	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 3.A8: Treatment Effects. Outcome: Human Capital (R&D Employees in FTE): Unbalanced panel

	DiD (Naive) (1)	DiD (Controls) (2)	DiD (Weighted) (3)	DiD (Common Support) (4)
Participation Spell 1				
2006	0.216***	0.141**	0.190***	0.155**
	(0.057)	(0.071)	(0.060)	(0.071)
2007	0.244***	0.093	0.249***	0.103
	(0.065)	(0.073)	(0.063)	(0.073)
2008	0.277***	0.118*	0.391***	0.139*
	(0.068)	(0.071)	(0.087)	(0.072)
2009	0.102	-0.047	0.114*	-0.033
	(0.066)	(0.068)	(0.068)	(0.069)
2010	0.072	-0.056	0.081	-0.043
	(0.060)	(0.056)	(0.055)	(0.057)
2011	0.197***	0.046	0.195***	0.051
	(0.051)	(0.051)	(0.061)	(0.053)
2012	0.188***	0.044	0.201***	0.063
	(0.053)	(0.052)	(0.072)	(0.053)
2013	0.118**	-0.017	0.116**	-0.006
	(0.051)	(0.040)	(0.058)	(0.041)
Participation Spell 2				
2006	0.313***	0.141	0.274**	0.140
	(0.097)	(0.104)	(0.111)	(0.105)
2007	0.496***	0.396***	0.590***	0.392***
	(0.101)	(0.112)	(0.098)	(0.112)
2008	0.470***	0.452***	0.416***	0.450***
	(0.105)	(0.167)	(0.160)	(0.168)
2009	0.130	0.166	0.159	0.163
	(0.095)	(0.120)	(0.117)	(0.120)
2010	-0.017	-0.034	0.029	-0.031
	(0.084)	(0.074)	(0.088)	(0.075)
2011	0.060	0.043	0.125	0.043
	(0.085)	(0.053)	(0.101)	(0.055)
2012	0.215**	0.129**	0.198**	0.135**
	(0.085)	(0.062)	(0.087)	(0.062)
2013	0.118	0.071	0.117	0.073
	(0.081)	(0.048)	(0.100)	(0.049)
Participation Spell 3				
2009	0.288***	0.180***	0.256***	0.179***
	(0.054)	(0.048)	(0.060)	(0.048)
2010	0.405***	0.196***	0.468***	0.197***
	(0.061)	(0.059)	(0.082)	(0.059)
2011	0.418***	0.166***	0.518***	0.169***
	(0.068)	(0.056)	(0.080)	(0.056)
2012	0.334***	0.102*	0.391***	0.104*
	(0.069)	(0.055)	(0.072)	(0.055)
2013	0.204***	0.072	0.221***	0.069
	(0.070)	(0.053)	(0.070)	(0.053)
2014	0.154**	0.039	0.196**	0.034
	(0.078)	(0.058)	(0.078)	(0.058)
Participation Spell 4				

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Table 3.A8 – continued from previous page

	DiD (Naive) (1)	DiD (Controls) (2)	DiD (Weighted) (3)	DiD (Common Support) (4)
2009	0.385***	0.247***	0.265*	0.242***
	(0.105)	(0.073)	(0.138)	(0.073)
2010	0.600***	0.385***	0.434***	0.378***
	(0.102)	(0.075)	(0.132)	(0.075)
2011	0.684***	0.413***	0.692***	0.407***
	(0.094)	(0.088)	(0.114)	(0.088)
2012	0.527***	0.221***	0.531***	0.214***
	(0.088)	(0.079)	(0.110)	(0.079)
2013	0.353***	0.186**	0.319**	0.173**
	(0.110)	(0.085)	(0.125)	(0.085)
2014	0.318***	0.173**	0.224*	0.158**
	(0.101)	(0.075)	(0.117)	(0.075)
Fixed Effects	Yes	Yes	Yes	Yes
Year Dummies	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. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Appendix 3: Large Firms

Table 3.A9: Large Firms. Innovation Expenditures and Public Funding.

	Firms with innovation expenditures	Firms doing R&D	% doing RD over firms with innovation	% receiving public funding*	% receiving public funding**	Mean Public funding/R&D ***
(1)	(2)	(3)	(4)	(5)	(6)	(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 3.A10: 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 3.A11: 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 3.A12: 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 $400 < x \leq 700$	-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 $x > 700$	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

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Table 3.A12 – 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)
	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)	(0.011)
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	

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Table 3.A12 – 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)
	(0.477)	(0.869)		(1.732)	(12.358)		(23,718)	(149.26)	
Sigma u	0.657***	0.448		0.209*	0.006		0.001	0.000	
	(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 3.A13: Large Firms. Treatment Effects. Outcome: Ln(Total Innovation Effort per worker)

	DiD (Naive) (1)	DiD (Controls) (2)	DiD (Weighted) (3)	DiD (Common Support) (4)
Participation Spell 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)
Participation Spell 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)
Fixed Effects	Yes	Yes	Yes	Yes
Year Dummies	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 3.A14: Large Firms. Treatment Effects. Outcome: R&D Employees (FTE)

	DiD (Naive) (1)	DiD (Controls) (2)	DiD (Weighted) (3)	DiD (Common Support) (4)
Participation Spell 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)
Participation Spell 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)
Fixed Effects	Yes	Yes	Yes	Yes
Year Dummies	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. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Supplementary Materials

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

Chapter 4

Duration Dependence in R&D Subsidization and Firm's Innovative Behavior*

4.1 Introduction

Several sources of market failures that lead to a suboptimal provision of R&D investment justify the governments' promotion of research and innovation activities, both public and private. Using different policy instruments, the primary goal of policymakers is to achieve a level of R&D investment which is socially optimal. In particular, the intended effects not only may depend on the use of the policy but also on the continuity or persistence of its use.

Broadly speaking, sustained exposure to an innovation policy instrument may change the conditions under which both agencies allocate resources to firms and firms undertake innovation projects. On the one hand, public agencies could accumulate knowledge about the nature of the users of the policy (accumulation of "know-who"), and that could change the agencies' explicit or implicit screening rules. From the firm's perspective, on the other hand, having participated in R&D subsidy programs in the past may change expectations with respect to the potential profits generated from funded innovation projects as compared to other firms without such experience (Blanes and Busom 2004).

The study of the role of firms' subsidy history has been the focus of empirical research for some time. For instance, Hussinger (2008) and Aschhoff (2009) provide some evidence that subsidy history matters when trying to analyze the allocation of public support and its potential impacts. Some current research has indeed found that firms' participation in R&D stimulating policies is persistent over time (Aschhoff 2010; Busom, Corchuelo, and Martínez-Ros 2017). That means successful

* I greatly appreciated the insights from a conversation I had with Elisa Calza (UNU-MERIT) in the early stages of this essay.

applicants in past applications would be more likely to get funding in subsequent years. However, much less attention has been paid to examine the drivers of persistence in use and its potential effect on firms' innovation results. Aschhoff (2009) provides one of the first attempts to analyze this issue, finding that frequent recipients of R&D support have larger probabilities of increasing their R&D inputs and outputs. However, her results are quite limited by the nature of the data- in her case data are cross-sectional.

In addition, existing studies offer interesting but limited insights into the potential effect of R&D subsidization persistence on firms' innovation behavior. Several attempts have been made to study the effectiveness (or what is called additionality) of different instruments used by governments and public agencies -subsidies, loans, tax deductions, and so forth, to reduce the financial cost of R&D projects (Czarnitzki and Hussinger 2018; Zúñiga-Vicente, Alonso-Borrego, Forcadell, and Galán 2014). Almost all empirical studies find that R&D subsidies have the potential for encouraging firms to engage in R&D and to invest more intensely (Arqué-Castells 2013; Arqué-Castells and Mohnen 2015. These studies do not investigate when a firm stops participating in the program.

The essay tries to tackle three questions. The first is what are the drivers of persistence in the use of R&D subsidies? In other words, we examine the relationship between the firm-specific characteristics and the continuous use of public support measured by R&D subsidy spells at the firm level.[1] The bottom line of this is to find to what extent continuous engagement in the innovation policy is explained by firm heterogeneity (think, for instance, of firms of different size) or what characteristics drive its mechanism.

Second, the essay aims to analyze if persistence in the use of R&D subsidies can potentially affect the desired innovation outcomes. That is, does continuity in the use of R&D subsidies lead to more or better innovation outcomes? The effectiveness of direct subsidies may not be immediate; it may also depend on the passage of time, unfolding short-term or long-term effects (Arqué-Castells and Mohnen 2015; Colombo, Croce, and Guerini 2013). The previous chapter in this thesis finds evidence that the effect of R&D subsidies lasts longer for firms with more prolonged use of the policy, at least in terms of input additionality. It is thus natural to analyze the impact of the duration of program participation on innovation outcomes.

The third question is to what extent continuous engagement in R&D subsidization is related to the firm's decision to stop innovation projects? There has been an increasing amount of literature on understanding the contextual mechanisms underlying the process at which firms terminate innovation projects (Mohnen, Palm,

[1] A spell is defined here as the number of consecutive years the firm benefits from R&D subsidies. Note that definition is somewhat different from that used in chapter 3.

Van Der Loeff, and Tiwari (2008) for the Netherlands; Radas and Bozic (2012) for the case of Croatian firms; Garcia-Vega and Lopez (2010) and more recently García-Quevedo, Segarra-Blasco, and Teruel (2018) for the Spanish case). Overall, the literature shows that there is a strong association between the occurrence of hampering factors and the smooth realization of innovation projects. However, there is little empirical evidence regarding the role of public funding for innovation as a mechanism to mitigate the potential risks of stopping innovation projects. We believe that continuous engagement in R&D subsidies would lead to a lower probability of discontinuing or stopping innovation projects.

This study contributes to previous literature in several ways. First, persistent use of R&D subsidies is modeled as the number of successive years in which a firm gets R&D funding (R&D subsidy spells) instead of analyzing whether firms that receive support in period t, get funding in time $t+1$. For this purpose, discrete-time duration models are used to measure the degree of persistence in the use of R&D subsidies. Second, the effect of continuous use of R&D subsidies on innovation outcomes is analyzed by modeling a standard innovation production function which relates innovation outcomes to innovation inputs such as R&D, skills and other firm-level characteristics and introducing persistence into the model. This approach has the advantage of handling the possibility of endogeneity of subsidies in the innovation production function. To capture the impact of R&D persistence on innovation performance, we estimate non-linear dynamic models for three target variables: the introduction of technological innovations, and the turnover of new-to-firm innovation and the turnover of new-to-market innovation, to capture incremental and radical innovation respectively. Third, the effect of continuous use of R&D subsidies on the probability of stopping innovation projects at either the conception stage or the implementation stage or both is obtained by estimating bivariate dynamic probit models. Finally, the degree of persistence and the impact that continuous engagement in the policy may have on innovation is analyzed separately for SMEs and for large firms and for different industries.

We summarized our main findings as follows. First, we find that firms' continuous engagement into R&D subsidies is a self-sustained process which is in part fueled by the accumulation of experience in getting funding. This holds across industries, whether manufacturing or services, of different technological intensity. Second, continuous R&D performers have a positive likelihood of reducing the hazard of ending an R&D subsidy spell, in all industries except for high-tech manufacturing. Third, new-to-market product innovation is triggered by SMEs participating continuously into the R&D subsidization program, in all industries as a whole but especially in knowledge intensive services and medium-low-tech manufacturing. Fourth, R&D

subsidy persistence also reduces the likelihood of abandoning R&D projects at either the concept stage or mature stages, especially in high-tech manufacturing.

Bearing in mind that this study is subject to some limitations because of the lack of information on the duration of a subsidy award, all applications including rejected applicants and the number of projects a firm is undertaking, our findings may still offer some insights for innovation policies. First, the design of R&D stimulating policies could consider that participation is to a good extent a self-sustained process that could be explained by either application cost drop or a reduction in the cost of producing new ideas and further innovations or a combination of both. Thus, when encouraging the spread of socially beneficial innovation activities across firms, policymakers may need to identify the factors that determine application costs. Second, the finding that new-to-market product innovation is positively associated with SMEs taking part continuously into the R&D subsidization program may suggest that the public agency is successful in selecting genuinely innovative projects of SMEs. The social benefits of occasional participation would not be obvious. Finally, having found that sustained participation allows firms to undertake innovation projects that would be otherwise abandoned may be a desirable outcome if the project embodies a good idea such that social expected benefits outweigh costs. But, the continuation of a project may not be desirable otherwise.

The chapter has the following structure. In section 4.2 we provide some previous evidence. Section 4.3 briefly describes the data and the empirical methodology. Section 4.4 presents and discusses the estimation results. Finally, in Section 4.5 we conclude.

4.2 Previous Evidence

4.2.1 R&D Subsidization Persistence

The degree of R&D subsidization persistence can be defined as the potential effect of past subsidy participation on present subsidy access. In general, firms may have several characteristics or factors that can lead to repeated behavior (Geroski, Reenen, and Walters 1997). These characteristics could persist over time, inducing persistence in use of the R&D subsidies. On the one hand, these characteristics can be observable, such as the firm size or firm innovation profile, or unobservable such as managerial abilities or the preferences of the granting institutions.

Several reasons could explain real true dependence in the case of R&D subsidies. First, successful applicants in period t-1 would be more likely to get funding in subsequent years. This behavior is based on the hypothesis of "success-breeds-success," in which firms tend to replicate decisions and routines that are associated with positive outcomes such as getting public funding in previous applications. This implies that firms' behavior does not change dramatically over time which in turn it can be expressed as a result of path dependency (Arqué-Castells 2013).

Second, the presence of substantial sunk costs can be a motive for not applying for funding. They are determined by the complexity of the projects submitted. Planning and presenting R&D projects involve costs that may not be recoverable. Firms need to incur start-up costs for structuring and tailoring proposals (for instance, costs related to pre-market research, collecting information on new technologies, standards and technical information, searching for partners, etc). These costs can be considered, at least partly, as sunk costs and entail barriers to entry into and exit from R&D subsidy programs.

Third, subsidization persistence can also be driven by the targeting criteria and priorities of granting agencies. Public granting agencies may be keener to target firms towards specific regions, sectors, technologies (e.g., firms with digital content, or firms that apply green farming practices).[2] Moreover, public agencies might also prioritize firms of particular importance (e.g., smaller firms, young innovative firms, start-ups, high growth firms).

Fourth, subsidy experience can be considered as a learning process for two reasons: in terms of learning of innovation itself and regarding applying and getting support. Regarding the learning of innovation itself, by applying for funding and implementing innovation projects firms acquire a set of knowledge and capabilities that allow them to have more experience at innovating which is partly built because of the previous experience of getting public support. Moreover, having submitted applications, firms will gain experience at gauging which projects will be more suitable for funding. Such experience will lower the transaction cost of submitting new proposals (as the marginal cost of submitting could be lower) (Aschhoff 2010). Besides, the presence of information asymmetries, in which not all potential candidates for funding are aware of the availability of funding opportunities, increases the probability of experienced applicants of obtaining support since they may be more aware of the existent funding opportunities.

Finally, the experience gained through the process of submitting applications for funding brings information concerning the reputation of the firm, serving as a potential screening mechanism to possible financial agencies (public or private), as well as enhancing their ability to vet the innovativeness of the firm (Lerner 2002; Takalo and Tanayama 2010). Thus, the informational value of obtaining funding may also induce state dependence in R&D subsidization. Accessing public funding can also trigger a reputation effect which could also reinforce the chances of getting subsidies in future applications (Antonelli and Crespi 2013).[3]

[2] Blanes and Busom (2004) show that awards differ across high-tech and low-tech industries.

[3] This effect is usually referred as Merthon's Matthew effect (Merton 1968) in which for the

4.2.2 R&D Subsidization and Innovation Results

Theoretically, public subsidies for private R&D may reduce the cost of capital and increase the expected returns to investments, giving incentives for firms to expand their R&D investment (David, Hall, and Toole 2000; Howe and McFetridge 1976). Moreover, thanks to R&D stimulating policy, a firm will increase its experience in undertaking R&D activities, translating such experience into product innovations (Beneito, Rochina-Barrachina, and Sanchis 2014, 2015).

The study of the effectiveness of different policy instruments used by governments and public agencies -subsidies, loans, tax deductions, and so forth- to provide incentives to increase private R&D and innovation investment has been the focus of evaluation research for some time (see Zúñiga-Vicente et al. 2014 for the most recent survey). The most recent evidence is provided by Czarnitzki and Hussinger (2018), who analyze the link between public funding and R&D input and the relationship between additionally induced R&D input and technological performance in Germany. In general, empirical studies show that R&D subsidies have the potential for encouraging firms to engage in R&D and to invest more intensely (in the case of Spain, see Arqué-Castells 2013; Arqué-Castells and Mohnen 2015).

Some evidence has shown that when firms receive public support for innovation, economic outcomes beyond productivity, such as firm survival and employment improve (Beck, Lopes-Bento, and Schenker-Wicki 2016; BEIS 2014; Bérubé and Mohnen 2009; Cerulli and Potì 2012b; Czarnitzki and Delanote 2015, 2017; Foreman-Peck 2013; Hottenrott and Lopes-Bento 2014). In general, publicly induced R&D triggers significant output effects, but results confirm that the potential treatment effect of R&D subsidies on innovation outcomes may be heterogeneous. For instance, Hottenrott and Lopes-Bento (2014), estimating the treatment effect obtained from a matching estimator, find that R&D subsidies have a positive impact on new-to-market product innovations for SMEs but not for large firms. In another study, Czarnitzki and Delanote (2015) also perform a semi-parametric estimation, finding that treatment effects are higher for high-tech firms.

Despite such a large body of evidence on the effectiveness of innovation subsidies, there is a lack of empirical evidence studying the effect of persistence in the use of R&D subsidies on innovation results. Absent crowding out effects, we might reasonably expect that persistence in benefiting from R&D subsidies will induce firms to achieve more or better innovation results as well as providing them with

context of scientific research, funding is allocated to authors because of sheer reputation. In Sociology, this effect is described by the adage "the rich get richer and the poor get poorer." For the process of public funding for innovation, there are two sources of persistence explaining this effect. First, public agencies do not have the necessary information set to optimally allocate funding, so that their decisions are based on firm's prior assessments. Second, funds can be allocated to widely known firms with the aim of improving agency's reputation (Antonelli and Crespi 2013).

higher chances to continue performing their innovation projects. This means that a higher number of consecutive years using the policy would also be an input for increasing the rate of innovation success.

In recent years, there has also been an increasing amount of literature on understanding the mechanisms underlying the decision of quitting innovation projects (Canepa and Stoneman 2007 for the UK; Mohnen et al. 2008 for the Netherlands; Radas and Bozic 2012 for the case of Croatian firms; Garcia-Vega and Lopez 2010 and García-Quevedo et al. 2018 for the Spanish case). can occur for a number of reasons: (i) poor access to critical resources (experts or financial constraints), or (ii) the firm learns that the idea is not good, either technically or commercially.

The evidence shows that there is a strong association between the occurrence of hampering factors and the smooth realization of innovation projects (Canepa and Stoneman 2007; Galia and Legros 2004; Mohnen et al. 2008; Radas and Bozic 2012). On the one hand, given the intrinsic uncertainty in the course of innovation, financing mechanisms are believed to play an important role. In this respect, using a sample of Dutch firms Mohnen et al. (2008) measure the impact of the obstacles on four decisions: abandoning, prematurely stopping, severely slowing down, or not starting a project. According to their results, financial limitations significantly slow down the development of a project and affect premature suspension. Abandoning innovation projects is also explained by factors such as the shortage of qualified human resources and the lack of competition (Hewitt-Dundas 2006).

In Spain, two empirical studies analyze the determinants of the abandonment of innovation projects of Spanish companies. García-Vega and López (2010) and more recently García-Quevedo et al. (2018).[4] García-Vega and López (2010) study the relative importance of various types of obstacles to innovation. Distinguishing between SMEs and large companies, their results indicate that during an expansion phase market factors - such as operating in a market dominated by an incumbent firm or by a higher uncertainty of demand - are more important than financial factors in affecting the likelihood of abandoning an innovation project. Considering financial obstacles, the lack of external funding increases the probability of abandonment for large companies. For both large firms and SMEs, the uncertainty of demand is a factor that significantly affects the likelihood of abandonment.

García-Quevedo et al. (2018) extend the previous study in two ways, by using a more extended period, from 2004 to 2014, and by distinguishing between two types of innovation stopping: one that occurs in the design phase of a project, and

[4] Extending the empirical evidence, D'Este, Marzucchi, and Rentocchini (2017) study the exploratory component of R&D activity regarding the probability of stopping innovation projects. In another study, D'Este, Amara, and Olmos-Peñuela (2016) examine the interdependence between product innovation, the degree of innovation novelty and the abandonment of innovation projects. Their results indicate that innovation and abandonment are closely linked.

the other that materializes once it has been initiated. They find that market and knowledge related obstacles significantly increase the likelihood of abandonment in both cases. On the contrary, access to external financing has a negative effect on continuity in the conception phase, but not once a project has started. In line with other studies, they find that firms with higher R&D intensity and presence in international markets have a larger probability of abandonment. Finally, stopping innovation projects is more likely to occur in large firms.

When looking at the effect of public support to innovation, García-Vega and López (2010) find that the probability of abandonment is lower for companies that receive public support. This difference in the probability of abandoning an innovation project may be because of a combination of two factors. First, public support provides the funding that allows a project to be finalized, which otherwise the company might not have if it had to rely on own or external private financing. Secondly, it is also possible that firms with funded projects have different characteristics from those that do not receive public funding, characteristics that ultimately affect both their persistence in subsidy participation and the ability to complete an innovation project, not all of which would be observable. These unobservable factors may be related to idiosyncratic features of firms (human and organizational capital, or other intangibles); or to the expected private and social returns of each project.

We should also take into consideration that, to the extent that an innovation project has an exploratory component, it may be optimal to stop a research activity when a firm learns that it is a bad idea, as Ganglmair, Simcoe, and Tarantino (2018) show in the specific context of standards development within the Internet Engineering Task Force. They develop a model of the decision to continue or to abandon a research proposal and conduct a counterfactual policy experiment with R&D subsidies and with prizes. They find that subsidies, while increasing research output may lead to spending resources on bad ideas.

4.3 Data and Empirical Strategy

4.3.1 A brief Overview of the Data

This essay analyses a sample of Spanish firms drawn from The Spanish Technological innovation panel (PITEC). This survey has been conducted since 2003 by the *Fundación Española para la Ciencia y la Tecnología* under the sponsorship of the Spanish Statistical Office (INE). PITEC contains information on about 12,000 firms during 2005-2015. The database is based on the Community Innovation Survey (CIS) and is carried out yearly following the guidelines of the Oslo Manual (OECD 2005).

PITEC provides a broad range of information on firm characteristics and their innovation activities.[5] It also contains information about public support from the central government and regional authorities, which will be used for the purpose of this essay. Both jurisdictions represented 81% of direct support in 2015.[6] In the following empirical analysis the policy variable will include both sources of direct support. One advantage of using this variable is its annual availability; on the other hand, interpretation of results will have to be cautious in the sense that the selection criteria of central and local agencies might be different. It is worth clarifying that the econometric exercise uses information from R&D subsidies as PITEC does not provide information on tax incentives. Busom, Corchuelo, and Martínez-Ros (2014), studying the association between financing constraints and appropriability condition with R&D subsidies and tax credits, find that there are not cross-dependencies (i.e., they are not substitutes), and R&D subsidies are mostly used by SMEs when financially constrained. Moreover, the persistence in use between the R&D tax credit and R&D subsidies could differ as the former is more exclusively dependent upon firms' profits and not on public agency preferences.

The data description and empirical analysis are reported for SMEs and Large firms separately because of the potential heterogeneity between firms of different sizes (Fort, Haltiwanger, Jarmin, and Miranda 2013). It is also possible that the size of the firm also conditions the level of innovation. In particular, access to external financing tends to be more difficult for SMEs, with no reputation or credit history, and therefore they are more reliant on internal sources of funding.[7]

We restrict the sample to firms that had invested in innovation projects at least once in the period under study. The idea is to exclude those firms that are not trying to innovate and (i.e., those that report that they do not need to innovate at all), as in Czarnitzki and Demeulemeester (2016), Savignac (2008) and Blanchard, Huiban, Musolesi, and Sevestre (2012). To eliminate all fluctuations among firms, three more filters are carried out: first, we drop firms that experienced merger or takeover processes, and drastic employment incidents[8]; companies on a merger or acquisition

[5] PITEC has some firm-specific information, such as years of operation, if the firm belongs to a group and their export status. Using PITEC is also possible to identify the technology level of the sector in which the firm operates, following the NACE 2-digit classification.

[6] R&D subsidies in Spain are allocated by The Center for Industrial Technological Development (CDTI) aimed at giving support to private firms based on technical and market merit.

[7] Another reason that explains why we split the sample is the difference in the sampling method for both type of firms. The sample of large companies is considered representative of the population of companies of this size, including innovative and non-innovative companies. In the case of companies with 200 or fewer employees, the sample includes those that have internal or external R&D activities, to which a sample of companies without innovation expenditures has been added.

[8] PITEC provides an indicator that accounts for the reasons that justify an abnormal rate of change in employment such as a company belonging to sectors that have a period of seasonal strength; an absorbing company; changes of the reference unit (company to group, group to company).

process; employment regulation or liquidation phase; second, we eliminate observations with anomalies, such as extreme values and null sales.[9] Finally, the primary and construction sectors are also excluded from the analysis. The remaining sample comprises 1,549 SMEs and 406 large firms.

Table 4.1 reports information on the transition probabilities of public support status for the sample of firms that invest in innovation at least once during the period analyzed. The data shows that about 72% of SMEs that receive support in the period (t) continue in the same status in the subsequent ($t+1$). Moreover, 92% of SMEs that do not receive support in period (t) remain in the same status in the subsequent period, whereas 8% change their status. The transition probabilities for large firms are slightly similar. However, large firms that receive support at t have a higher probability of remaining in the same status at $t+1$ as compared to their SMEs counterparts (79% vs. 72%). Both large and SMEs are more persistent in not receiving funding (92% and 94%, respectively).

Table 4.1: Transition Probabilities of Public Support

Status at t-1	Funding status at t	
	No (%)	Yes (%)
SMEs		
No (%)	92.01	7.98
Yes (%)	28.37	71.63
Large firms		
No (%)	93.87	6.13
Yes (%)	21.36	78.64

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.

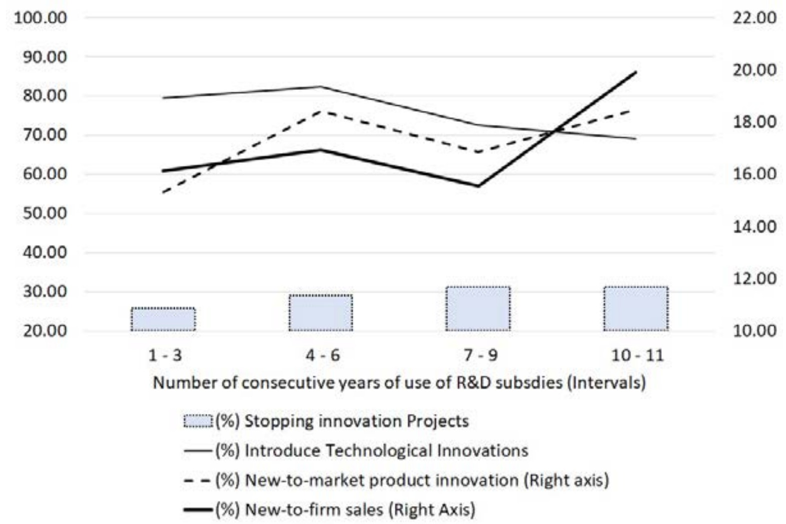
Figure 4.1 (for SMEs) and Figure 4.2 (for large firms) show the relationship between the level of R&D subsidization length (i.e., the number of consecutive years in which firms have been subsidized) and some output indicators including the average proportion of firms abandoning innovation projects. Data show that firms having longer spells of R&D subsidization have higher turnover from innovation.

Looking more closely at the trends, the average percentage of SMEs introducing products new to the market increases steadily from 15.33% in years 1 to 3 to 18.41% in years 4-6 then remaining the same for a period of three years and increasing again from the 7th and 9th year reaching a high of 20% in years 10-11 (20%) where the

[9] As anomalies we consider the observations of sales and employment with growth or decline by more than 250%.

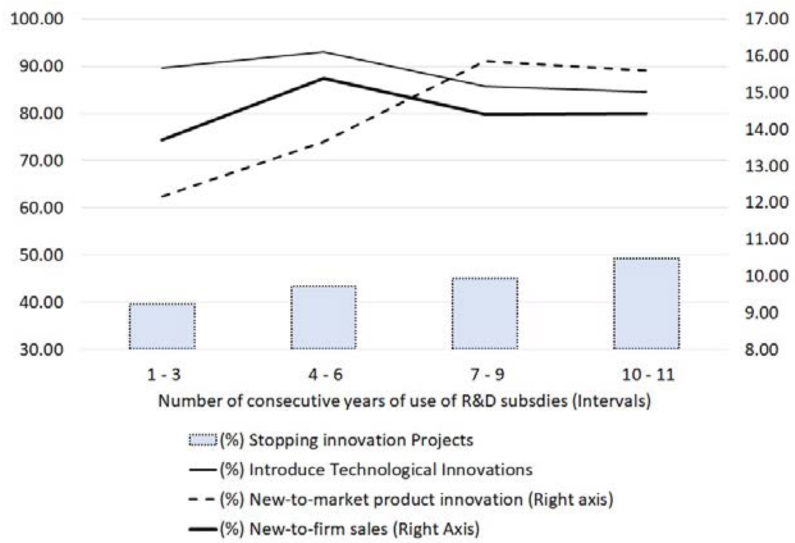
lengthiest experienced in the R&D subsidization scheme is reached. Large firms follow a similar pattern, although the increase is sharper from years 4-6. The figures for SMEs are slightly higher in comparison with other countries in the EU. According to the OECD STI Scoreboard 2017, the percentage of firms introducing radical innovations in European countries is about 13%.[10]

Figure 4.1: Public Support Persistence and Firm Innovation: SMEs



Notes: The sample includes firms that invest in innovation at least one year during the period in the balanced panel.

Figure 4.2: Public Support Persistence and Firm Innovation: Large firms



Notes: As in Figure 4.1

[10] Percentage calculated by the authors using the OECD STI Scoreboard 2017: http://www.oecd.org/sti/inno/inno-stats.htm

The rate of stopping innovation projects is reasonably stable across spells of continuous use of R&D subsidies for both SMEs and large firms. For SMEs, the percentage of abandoning hovered between a minimum of 25% and a maximum of 30%. For large firms, the average is 39%. Finally, the proportion of firms introducing technological innovations is quite stable over different participation spells for both SMEs and large firms.

4.3.2 Empirical Strategy

We initially investigate the determinants of R&D subsidy spells ending, with the expectation that spell duration is longer for firms with higher innovative effort.

Even though firms can get support for up to three years in a single application, we treat the duration of an R&D subsidy as a discrete variable since firms can apply for and obtain support repeatedly (on an annual basis).[11] In particular, the model we estimate is a duration dependence model, in which the dependent variable is the discrete time hazard rate for firm i in the time interval j to leave the subsidy scheme (subsidized or non-subsidized) h_{ij}. The idea behind this is to follow firms over time and observe at which point they no longer participate in the public support program. The model is specified following Prentice and Gloeckler (1978) as equation [4.1] below:

$$h_{ij}(X_{ij}) = 1 - exp(-exp(X'_{1it}\beta + \theta(t))) \tag{4.1}$$

where $\theta(t)$ is the baseline hazard that defines the extent to which the duration of subsidy spells affects the hazard rate. If the coefficient that accompanies θ is negative, then negative duration dependence is at work, meaning that as the time passes the lower is the risk of spell ending. X_{1it} contains a set of covariates (time-varying or fixed), including various firm's characteristics and innovation-related factors, β is the vector of regression coefficients we want to estimate. If $\beta > 0$, then increases in the value of the variable are associated with a larger hazard rate and shorter spells, other things being equal, and vice versa. From a dynamic point of view, β quantifies the influence of different factors on the likelihood of persistence in a specific event (Van den Berg 2001).

We add $u \sim N(0, \sigma_u^2)$ which allows for unobserved heterogeneity (also called "frailty") between individuals due to time-invariant omitted variables or measurement errors in regressors. It is convenient to specify a distribution of u to integrate out the unobserved effect. Hence, we will incorporate unobserved heterogeneity

[11] This case can also be interpreted as a "truly discrete", because the R&D subsidy spell ending can only happen at discrete values of time (e.g. length of time that at firm can participate in the policy is the project duration, change can only happen at the end of the project implementation (Allison 1982)).

checking its closed form expression. For that aim, we will treat u parametrically and non-parametrically.[12]

Taking logs in equation [4.1] and adding u into that expression, we obtain the following expression:

$$log(h_{ij}(X_{ij})) = \theta(t) + X'_{1it}\beta + u \tag{4.2}$$

Using the predicted log hazard rate $\hat{h}_{ij}$ from [4.2], one can estimate the level of persistence (survival rate):

$$\hat{S}_{ij} = \prod_{i=1}^{t}(1 - \hat{h}_{ij}) \tag{4.3}$$

Taking $\hat{S}_{ij}$, we model a standard innovation production function which relates innovation outcomes (I_{it}) to innovation inputs such as R&D, skills and other firm-level characteristics (Crépon, Duguet, and Mairessec 1998; Leiponen 2012; Leiponen and Byma 2009). However, our main interest is to link innovation results with the firm survival in the R&D subsidy program ($\hat{S}$). So that the firm's innovation strategy may benefit from participating continuously into the policy. This approach has the advantage of handling possible endogeneity between R&D subsidies and the production of innovations (Czarnitzki and Delanote 2017). Hence, we can put forward the following specification:

$$I_{it} = \gamma I_{i,t-1} + \alpha\hat{S} + X'_{2it}\beta + \eta_i + v_{it} \tag{4.4}$$

The I_{it-1} is the lagged innovation outcome and γ is the state dependence parameter; X_{2it} is a matrix of explanatory variables η_i is the idiosyncratic individual and time invariant firm's fixed effect and v_{it} is the usual error term. Both η_i and v_{it} are assumed to be normally distributed and independent of X_{2it} and v_{it} is not serially correlated.

Since innovation outcomes are found to be highly persistent as referred in different empirical applications (see Bas and Scellato 2014; Tavassoli and Karlsson 2015), we will use a dynamic specification in [4.4], meaning that having successful innovations in the previous period increases the probability of innovating in the current period.[13]

In a third stage, we explore the effect of R&D subsidy spells dependence on the abandoning of innovation projects. Using the predicted survival rate $\hat{S}$ (as in

[12] We will check if u follows a Gamma or Gaussian distribution. Besides, following Heckman and Singer (1984) we also treat u non-parametrically, characterizing it by using probability mass points in the unobserved heterogeneity distribution.

[13] In addition, the variables used would condition the estimation method. We will employ probit models for binary indicators and tobit models for the turnovers.

[4.4]), we estimate a dynamic probit equation to model the probability of a firm i of stopping innovation projects at either conception stage, or implementation stage, or both. Assuming that $Stop^*_{i,t}$ represents a latent indicator, the model is presented in equation [4.5] below:

$$Stop^*_{i,t} = Stop_{i,t-1}\alpha_{1i} + \hat{S}\delta_1 + X'_{3it-1}\beta + \varepsilon_{1i,t} \tag{4.5}$$

The observed model is:

$$Stop_{i,t} = \begin{cases} 1, & \text{if } (Stop^*_{i,t} > 0) \\ 0, & \text{otherwise} \end{cases} \tag{4.6}$$

where $Stop_{i,t}$ is a binary variable that represents the condition of stopping innovation projects for the firm i, and takes the value of 1 if any of the innovation activities or R&D projects are discarded in the conception phase or once the activity or project start or both at all, and 0 otherwise. $Stop_{it-1}$ is the corresponding one-year lag of the stopping condition of the firm. Our main regressor is $\hat{S}$. We expect that R&D subsidy persistence may have a positive, negative or not impact on the likelihood of stopping innovation projects ($\delta \gtreqless 0$).

4.3.3 Empirical Specification

If R&D subsidies obtained by a firm up to date t affects the probability that yet more public funding will be obtained at $t+1$, then spell length depends on what happens just prior to and/during the spell. We, therefore, expect that the length of R&D subsidies would be the outcome of both the firm's preference to apply for funding and the granting agencies' decision criteria. So that the vector X_{1it} in Equation [4.2] contains a set of control variables that reflect the innovative profile of the firms and their characteristics (Hottenrott and Lopes-Bento 2014; Huergo and Jaumandreu 2004; Mohnen et al. 2008).

As far as the innovative profile of the firm is concerned, we expect that the continuous use of the R&D subsidies would be correlated positively with the firm experience in undertaking R&D project (lower probability of spell ending). We control for regularity in R&D performance by including a dummy that indicates if the firm has performed R&D continuously. We would expect that regular R&D performers would have a higher chance to remain in a subsidy spell as public support programs may reach on average stable R&D performers who exhibit higher experience at undertaking innovation projects as found in Busom et al. (2017).

Continuous participation may also be explained by the firm performance in the innovative process, reflecting the firm's innovative intensity and technological and commercial success (Huergo and Moreno 2017). We include two binary variables: one for the generation of product and process innovations (technological innovations) and the other one for indicating whether the firm uses formal IP mechanisms or not. Also, the share of employees who hold higher education degrees and the ratio of R&D employees over the total number of employees in the firm are included, reflecting both the level of human capital involved in innovation projects and the level of sunk cost attached to R&D projects (Akcigit, Hanley, and Serrano-Velarde 2013; Cohen and Klepper 1996). Finally, we use a dummy that identifies if the firm has signed cooperation agreements with third parties for the promotion of innovation activities.

In the second set of control variables, we include some firm-level factors that capture the factors that can deter innovations, firm capabilities, and skills. First, the probability of R&D subsidy spell ending is not only assumed to be correlated with financial barriers but also with perceived knowledge and market barriers. Knowledge barriers refer to problems such as the availability of skilled personnel, information on technology and market, while market barriers reflect the perceptions about markets dominated by incumbents and characterized by uncertain demand.[14] Our expectation of the effect of each of the variables related to barriers to innovation on the probability of subsidy spell ending is that the latter may increase, decrease or remain unchanged to the extent that firms encounter barriers to innovation at different stages of their innovation process. Firms deterred from engaging in innovation activities would have different reasons to apply for public funding compared to those whose barriers are revealed throughout the innovation process. In particular, persistence in R&D subsidization could decrease if the cost of continuing R&D is higher than the cost of entry into R&D. As a reflection of this, it is expected that small firms when financially constrained may tend to end subsidization spells speedily.

Second, we also control for the variability in sales (sales growth) to account for the fluctuations of the market and a dummy variable indicating whether the firm invests in fixed capital (as a proxy for demand expectations and capital growth). Furthermore, we include a battery of variables reflecting the firm-specific characteristics that may affect the probability of R&D subsidy spell ending such as the size of the firm, age, and dummies that define if the firm belongs to a group of firms, is foreign owned, sell goods to international markets and receive funding from the European Union. All variables are lagged one period. Industry-specific and time effects are also used. Definitions of variables are in Table 4.A1.

We will estimate equation [4.4] for three different outcome variables: A binary variable that describes technological innovation (the introduction of new goods and services, new processes), the turnover due to New-to-market and the turnover due

[14] The barriers-related variables are defined as binary variables that take on the value of 1 if the firm considers the degree of importance of the barrier to be high or medium. The variable takes on the value of 0 if the firm considers the barrier of low importance or not relevant at all. This definition follows Hölzl and Janger (2014); Antonioli, Marzucchi, and Savona (2017) and García-Quevedo et al. (2018).

to New-to-firm innovations. These outcomes are selected for two reasons: first, turnovers from New-to-market and New-to-firm innovation help understand the degree of novelty of innovations. According to OECD (2018), new-to-market innovation represents a higher threshold for innovation than a new-to-firm innovation in terms of novelty, so that it could be considered as an innovation that is far from the market and consequently riskier and more radical. Second, turnovers achieve a wider coverage of the possible effects of innovation policy than other more traditional indicators (Foreman-Peck 2013).[15]

The set of firm-level control variables X_{3it} and X_{4it} in the fourth and fifth equations includes the outcomes that reflect the innovation process. First, the log of R&D expenditures is included as customary in the literature. Second, we control for variables capturing the strength of human capital such as the proportion of R&D employees in the firms and the proportion of workers holding higher education degrees. We also include in our analysis a set of control variables that are linked to the innovation activity such as binaries for export, intellectual property rights, a measure of the extent of firm's cooperation for innovation activities and two proxy variables for the importance that the firm gives to the different sources of information: breadth and depth of knowledge. The former is based on the number of sources of information used by the firm.[16] The latter reflects the number of information sources rated as highly significant. It is expected that the firm might improve the probability of gaining knowledge translating it into a larger likelihood of introducing innovations (Cassiman and Veugelers 2002; Leiponen and Helfat 2010; Roper, Du, and Love 2008).

All explanatory variables in models [4.4] and [4.5] refer to the period $t-2$. We choose this dating to reduce potential endogeneity problem between the right-hand side variables and potential changes in the dependent variables which in all cases refer to a three-year period. The only exception to this dating regards the dummies for sector, group, young and foreign ownership as they are highly persistent over time.

Also, while following the same structure as Model [4.4], in Model [4.5] we assume that the decision to undertake innovation activities and the presence of financial constraints are also likely to be simultaneously determined.[17] Thus, it is assumed

[15] Foreman-Peck (2013), shows that using turnovers is more appropriate when evaluating the extent to which a policy boost innovation and well-being.

[16] PITEC provides information on the following sources of information: suppliers, clients, competitors, private R&D institutions, universities, public research organizations, technology centers, conferences, scientific reviews and professional associations.

[17] Firms that are innovative may declare themselves as subject to financial limitations and vice versa. For these reasons, when making the empirical modeling, it is necessary to take into consideration the potential endogeneity of the variable proxying for the barriers to innovation related to financial constraints.

that the presence of financial constraints simultaneously determines the likelihood of abandonment (equation [4.5]). The existence of financial barriers could increase the chance of stopping innovative projects, and once innovation slows down, financial difficulties are likely to get worse. In this respect, Savignac (2008) and Blanchard et al. (2012) propose an econometric methodology where financial obstacles affect the probability that companies would complete their innovation projects. So that we implement a system of simultaneous equation for the probability of stopping innovations using an equation for facing financial constraints, where the dependent variable indicates if the firm is hampered by financial constraints or not (FC^*_{it}) (Equation [4.7]). The simultaneous estimation allows to consider the correlations between the likelihood of stopping innovation projects and the probability of facing financial barriers while providing a correlation parameter that yields information about the co-variance structure of the error terms.

$$FC^*_{it} = AvFC_{it}\theta_2 + \hat{S}\delta_2 + X'_{4it}\beta + \mu_{i2} + \varepsilon_{2it} \tag{4.7}$$

This reduced form solves for the endogenous variable $FC_{i,t}$ (if at all possible) by assuming that at least one of the covariates on equation [4.7] is uncorrelated with the potential outcome $Stop^*_{it}$ other than through the FC^*_{it} variable. Thus, we can recover the causal effect of FCi, t on $Stop^*_{it}$ over the whole distribution of $Stop^*_{it}$. The average of perceived financial constraints at the sectoral level is used ($AvFC_{it}$) as exclusion restriction. This variable is obtained as the yearly average perceived internal and financial constraint at sector 2-digit level excluding the value stated by the firm i from the average. The average serves as a proxy of the perceived financial constraints that firms in the same sector may be facing, which is believed to be a good predictor of the financial barriers faced by individual firms, even after controlling for other sector- and technology-related characteristics. Restricting the instrument to sector-level information allows to drive out the correlation between financial constraints and individual firm characteristics, such as the strategic decisions of the managers. Equation [4.7] also controls for the rate of R&D subsidy persistence ($\hat{S}$).

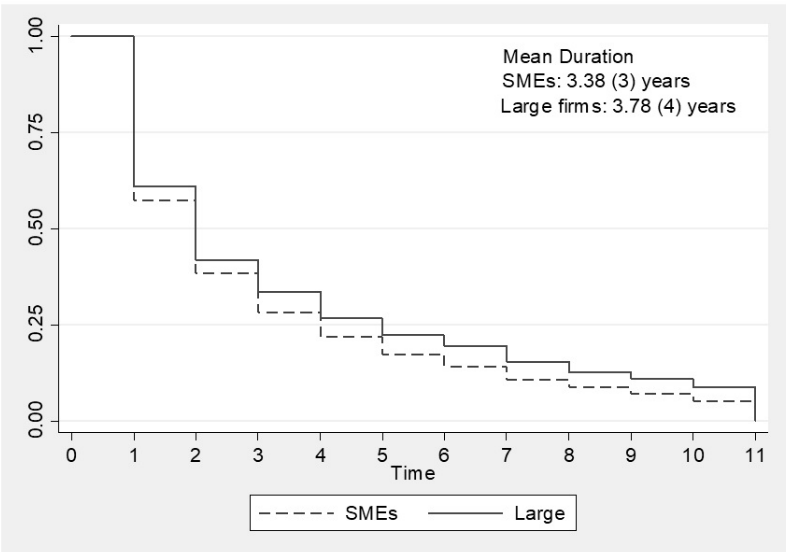
Finally, following Rabe-Hesketh and Skrondal (2013) we estimate [4.4] and [4.5] including the lagged value of the respective outcome variable and its initial value in the spirit of Wooldridge (2005). We also add the within-means of the explanatory variables for all years excluding the first one. This procedure helps deal with the potential correlation between the individual firm's unobserved heterogeneity and time-varying variables.

4.4 Results

4.4.1 R&D Subsidy Participation Dependence and its drivers

To estimate equation [2] we need to define the R&D subsidy spell (i.e., the number of uninterrupted years a firm receives a subsidy). We estimate equation [2] for the sample of firms that received R&D subsidies in any of the years considered. However, since the survival analysis of R&D subsidies is based on spells, it suffers from left and right censoring, meaning that certain spells start before and finish after the period of study. Table 4.A2 reports the sample distribution considering the number and types of R&D subsidy spells. In this regard, we account for all left-censoring adding a dummy variable for left-censored spells and retain completed and right-censored observations under the assumption that censoring is not informative so that the R&D spell length includes all firms who are censored in interval ending in t. The final sample for the estimation model has 7,195 R&D subsidy spells (SMEs) and 2,181 spells for large firms, corresponding to 1,549 SMEs and 406 large firms. Out of the total number of SMEs (large firms), 60.10% (64.53%) experience only one R&D subsidy spell; 29.63% (27.09%) encounter 2 spells, 9.04% (7.64%) and 1.23% (0.74%) experience three and four spells respectively.

Figure 4.3: Kaplan-Meier Survival Estimates for Participation in the R&D subsidy



Note: Sample of firms that invested in innovation at least once and obtained public support.

Figure 4.3 plots a description of the Kaplan-Meir survival estimates. The decreasing slope of the figure suggest that the probability of survival decreases as long as the duration of the spell increases. Besides, persistence in R&D subsidization is low in the initial stages as the survival function decreases quickly from 1st year to 2nd year. However, after years 4th and 5th survival rates are quite constant. Furthermore, large firms have higher median survival participation than SMEs (4yrs. vs. 3yrs). This result is also reflected in the survival probabilities depicted for R&D subsidy spells in SMEs and large firms as the steepness of the curve is higher for SMEs as compared to large firms. Table 4.A3 in the appendix reports the estimates of the survival function. For an SME the probability of remaining five years in the subsidy spell is 17% whereas the same probability is 22% for R&D subsidy spells in the sample of large firms.

Table 4.2 reports the results for the hazard function considering both SMEs and large firms. Estimations are performed by maximum likelihood. We consider four different estimation methods all of them reported as robustness checks: (i) a complementary log-logistic form for the hazard (*Cloglog*) model that assumes a Gaussian distribution for the unobserved heterogeneity (Columns 1 and 5). (ii) a *Cloglog* model that assumes a Gamma distribution (columns 2 and 6); (iii) a *Cloglog* model with "mass points" which treats unobserved heterogeneity non-parametrically (columns 3 and 7).[18] (iv) a standard Random Effects probit model (columns 4 and 8). Coefficients shown are marginal effects.

Following Máñez, Rochina-Barrachina, Sanchis-Llopis, and Sanchis-Llopis (2015) and Triguero, Córcoles, and Cuerva (2014), we control for left-censored subsidy spells in all specifications using a dummy which identifies all spells whose starting date is unobserved. Results for this variable show negative and significant coefficients, suggesting that left-censored spells may have a longer spell duration.[19]

When estimating the hazard function [4.3] and testing unobserved heterogeneity non-parametrically, we fail to reject the null hypothesis (see the bottom of Table 4.2). Thus, we consider the random-effects complementary log-log model, which assumes a normal distribution for the unobserved heterogeneity, as the most reliable empirical specification for our data. Note that all estimation methods give quite similar results.[20]

In relation to subsidization experience (state dependence or θ in our specification), we find that both SMEs and large firms experience a pattern of negative

[18] The essence of this estimation is to avoid arbitrary assumptions on functional form duration baseline and unobserved heterogeneity (Heckman and Singer 1984). The mass points and associated probabilities for each firm are unknown. This estimation method treats unobserved heterogeneity non-parametrically.

[19] When disregarding left censoring from the estimations, coefficients overestimate persistence. However, we reckon that this approach just mitigates rather than correct the upward bias due to left-censoring.

[20] Logit estimates are effects on log-odds scale.

duration dependence. This is shown by the negative and significant estimated coefficient for this variable, suggesting that the probability of subsidy spell termination decreases as the firm accumulates experience in the subsidization program (i.e. the longer the R&D subsidy spell length, the lower the risk of spell ending).[21] This result confirms our expectation: successful applicants in period $t-1$ would be more likely to get funding in subsequent years as they may have gained experience and knowledge from the support program and tend to replicate successful behavior. This finding supports previous research on R&D subsidy persistence in which a firm receiving public support in period t is posititively and significantly affected by its subsidy history (Antonelli and Crespi 2013; Aschhoff 2010; Busom et al. 2017)

The experience gained with the passage of survival time is also funneled through the accumulation of innovation efforts and knowledge. Results show that for both SMEs and large firms the probability of terminating an R&D subsidy spell is notably lower for continuous R&D performers (as shown by the negative and significant coefficient for this variable). The existent evidence suggests that firms already conducting R&D are more likely to apply for funding and obtain a higher probability of funding, increasing the chances of persistence (Blanes and Busom 2004; Busom et al. 2017). In conjunction with this, firms having a greater share of employees holding higher education as well as with a higher ratio of R&D employees reduce the risk of spell ending. This result is expected as firms with more qualified personnel are more capable of assimilating and integrating new knowledge and consequently more likely to apply and obtain public support. Although only related to participation in the R&D policies, previous evidence shows that the availability of human capital explains participation in R&D programmes (Antonelli and Crespi 2013; Busom et al. 2017).

We also find evidence that firms that have had in the past cooperation agreements for technological activities have a lower the hazard of spell ending, for both small and large firms. Successful innovation depends on the capacity of the firms to integrate new knowledge. Part of this knowledge is obtained from external sources from which firms can also share the cost and risk of innovation (Cassiman and Veugelers 2002; Franco and Gussoni 2014). This can be because of public agencies' preference to grant R&D subsidies for firms that use R&D collaborative agreements as shown by Czarnitzki, Ebersberger, and Fier (2007); Huergo and Trenado (2010) and Afcha and García-Quevedo (2016).

Table 4.2 also shows that standard measures of barriers to innovation are not found to be significant. Even though financially constrained SMEs will turn to use

[21] It is important to bear in mind the possible overestimation of persistence due to the fact that projects may be funded for one to three years. PITEC does not provide information, however, on project duration.

R&D subsidies more frequently as shown by Busom and Corchuelo (2014), financing constraints could carry more weight in the first stages of project implementation. García-Quevedo et al. (2018) show that firms are sensitive to internal and external financial constraints during the implementation of innovation projects, increasing the likelihood of stopping projects as well as lowering the propensity to seek and obtain state support for innovation.

Among the characteristics of the firm, we find the following results. First, a negative relationship between firm size and the probability of subsidy spell ending: The larger the size, the lower the hazard of spell ending (as shown by the negative coefficient of log size). Second, we observe that being a young firm reduces the probability of leaving the subsidy program. These results support the idea that one of the policy priorities is targeting young innovative SMEs, increasing the chances for them to use the policy measure continuously. These results are in correspondence with previous findings Busom et al. (2017) and Busom et al. (2014) who find that SMEs and young firms are more likely to participate in R&D stimulating programs (subsidies and tax-credits). Third, access to EU funding has a negative and significant effect on the likelihood of interrupting a spell of R&D subsidization. The latter result could be the reflection of firms accumulated expertise in knowledge about the funding system and its opportunities (Aschhoff 2009). Four, firms who are foreign owned have higher hazard rates, suggesting that R&D subsidies are oriented towards domestic firms. Finally, sales growth and being an exporter are not found to be significant.

Table 4.2: ML Estimates for Discrete Time Proportional Hazard models: R&D Subsidy Spells

	SMEs				Large Firms			
	(1) Clolog (Normal)	(2) Clolog (Gamma)	(3) Clolog (Mass points)	(4) Probit (RE)	(5) Clolog (Normal)	(6) Clolog (Gamma)	(7) Clolog (Mass points)	(8) Probit (RE)
(θ) Persistence (log)	-0.252***	-0.252***	-0.252***	-0.224***	-0.254***	-0.255***	-0.141	-0.251***
	(0.037)	(0.037)	(0.037)	(0.030)	(0.070)	(0.070)	(0.094)	(0.057)
R&D expenditures (log) $(t-1)$	0.004	0.004	0.004	-0.001	-0.018	-0.018	-0.019	-0.014
	(0.008)	(0.008)	(0.008)	(0.007)	(0.015)	(0.015)	(0.017)	(0.013)
Continuous R&D performer	-0.273***	-0.273***	-0.273***	-0.212***	-0.375**	-0.375**	-0.357	-0.309**
	(0.062)	(0.062)	(0.062)	(0.051)	(0.164)	(0.165)	(0.228)	(0.137)
Technological innovation $(t-1)$	-0.001	-0.001	-0.001	0.004	-0.180	-0.180	-0.145	-0.138
	(0.069)	(0.069)	(0.069)	(0.056)	(0.149)	(0.149)	(.)	(0.125)
R&D employees $(t-1)$	-0.594***	-0.594***	-0.594***	-0.444***	-0.902	-0.903	-0.929	-0.512
	(0.184)	(0.184)	(0.184)	(0.128)	(0.657)	(0.657)	(1.351)	(0.419)
Higher education $(t-1)$	-0.314***	-0.314***	-0.314***	-0.290***	-0.098	-0.098	-0.162	-0.049
	(0.108)	(0.109)	(0.108)	(0.083)	(0.216)	(0.216)	(.)	(0.165)
IP protect $(t-1)$	0.089*	0.089*	0.089*	0.057	-0.084	-0.084	-0.094	-0.059
	(0.049)	(0.049)	(0.049)	(0.037)	(0.095)	(0.095)	(0.105)	(0.070)
Cooperation $(t-1)$	-0.265***	-0.265***	-0.265***	-0.206***	-0.332***	-0.332***	-0.338***	-0.241***
	(0.049)	(0.049)	(0.049)	(0.038)	(0.104)	(0.103)	(0.085)	(0.078)
Size (log) $(t-1)$	-0.186***	-0.186***	-0.186***	-0.147***	-0.039	-0.039	-0.050***	-0.017
	(0.034)	(0.034)	(0.034)	(0.026)	(0.052)	(0.051)	(0.005)	(0.039)
Young	-0.207**	-0.207**	-0.207**	-0.108*	-0.323	-0.323	-0.408	-0.195
	(0.081)	(0.081)	(0.081)	(0.056)	(0.228)	(0.228)	(0.251)	(0.157)
Sales growth	-0.088	-0.088	-0.088	-0.076	-0.326*	-0.326*	-0.335	-0.226
	(0.077)	(0.077)	(0.077)	(0.055)	(0.172)	(0.172)	(.)	(0.138)
Fixed investment $(t-1)$	-0.208***	-0.208***	-0.208***	-0.171***	0.188	0.188	0.186	0.144
	(0.063)	(0.063)	(0.063)	(0.052)	(0.187)	(0.183)	(.)	(0.145)
Financial Constraints $(t-1)$	0.065	0.065	0.065	0.045	0.028	0.028	0.016	0.001
	(0.047)	(0.047)	(0.047)	(0.036)	(0.096)	(0.096)	(.)	(0.072)
Mkt Barriers: Dominated $(t-1)$	-0.056	-0.056	-0.056	-0.043	0.041	0.041	0.067	0.027
	(0.058)	(0.058)	(0.058)	(0.044)	(0.126)	(0.126)	(0.188)	(0.094)
Mkt Barriers: Uncertainty $(t-1)$	0.037	0.037	0.037	0.031	-0.003	-0.003	0.007	0.013
	(0.055)	(0.055)	(0.055)	(0.042)	(0.114)	(0.114)	(0.122)	(0.084)

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Table 4.2 – Continued

	SMEs				Large Firms			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Clolog	Clolog	Clolog	Probit	Clolog	Clolog	Clolog	Probit
	(Normal)	(Gamma)	(Mass points)	(RE)	(Normal)	(Gamma)	(Mass points)	(RE)
Group $(t-1)$	-0.001	-0.001	-0.001	-0.005	-0.062	-0.062	-0.008	-0.029
	(0.054)	(0.054)	(0.054)	(0.041)	(0.129)	(0.131)	(.)	(0.095)
Foreign	0.249**	0.249**	0.249**	0.193**	0.303***	0.303***	0.294	0.249***
	(0.109)	(0.109)	(0.109)	(0.088)	(0.115)	(0.115)	(.)	(0.087)
Exporter $(t-1)$	0.065	0.065	0.065	0.050	-0.139	-0.139	-0.181***	-0.106
	(0.063)	(0.063)	(0.063)	(0.048)	(0.148)	(0.148)	(0.027)	(0.116)
High tech. Manuf	-0.008	-0.008	-0.008	0.011	0.147	0.147	0.141	0.077
	(0.098)	(0.098)	(0.098)	(0.078)	(0.175)	(0.174)	(0.197)	(0.130)
Medium tech Manuf	-0.066	-0.066	-0.066	-0.061	-0.011	-0.011	-0.016	-0.034
	(0.062)	(0.062)	(0.062)	(0.050)	(0.119)	(0.119)	(0.137)	(0.089)
High. tech. Services	-0.187**	-0.187**	-0.187**	-0.147**	-0.047	-0.047	-0.094	-0.086
	(0.087)	(0.087)	(0.087)	(0.066)	(0.191)	(0.191)	(0.209)	(0.141)
Rest of services	-0.141*	-0.141*	-0.141*	-0.109*	0.176	0.176	0.204	0.121
	(0.080)	(0.080)	(0.080)	(0.062)	(0.146)	(0.145)	(0.136)	(0.113)
UE funding $(t-1)$	-0.228***	-0.228***	-0.228***	-0.193***	-0.432***	-0.432***	-0.436***	-0.343***
	(0.083)	(0.083)	(0.083)	(0.060)	(0.134)	(0.134)	(0.140)	(0.096)
Left censoring	-0.348***	-0.348***	-0.348***	-0.258***	-0.334***	-0.334***	-0.384	-0.247***
	(0.050)	(0.050)	(0.050)	(0.040)	(0.105)	(0.105)	(0.398)	(0.078)
Constant	2.013***	2.013***	2.013***	2.137***	1.874***	1.874***	1.792***	1.871***
	(0.158)	(0.158)	(0.162)	(0.133)	(0.420)	(0.417)	(0.035)	(0.323)
Log likelihood	-3501	-3501	-3501	-3464	-985.67	-987.093	-986.399	-972.085
σ_u	0.001				0.002			
Test for heterogeneity	No	Yes	Yes	No	No	Yes	Yes	No
χ^2 test		-0.001				0.000		
m2 Constant			-0.000				1.852	
m2 p-value			(0.207)				(.)	
AIC	7070.353	7070.353	7070.353	6996.171	2042.187	2042.187	2024.797	2012.171
BIC	7300.325	7300.326	7300.325	7226.143	2232.635	2232.635	2170.434	2202.618
N	6,399	6,399	6,399	6,399	2,001	2,001	2,001	2,001

All estimations were run with bootstrapped errors. All models include year dummies. aParameter rho represents the fraction of variance due to unobserved heterogeneity. The reported χ^2 test for the presence of unobserved heterogeneity. $m2$ represents the second mass points. If $m2$ is significant, there is unobserved heterogeneity. (.) not reported because of converge problems
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.4.2 R&D Subsidy Spells Dependence and Firm Innovative Behavior

We now address the question, "what impact does continuous engagement in R&D public funding have on outcomes for firms that receive support?" In particular, we are interested in understanding the impact on firm outcomes, measured by the introduction of product and process innovations (technological innovation), but also recognizing that an additional impact may be that firms achieve more innovations in the market. However, results may differ depending on the type of projects undertaken by the firm as well as the type of projects favored by the public agency. Firms and public agencies can either opt for projects that involve a more radical and risky nature or a more incremental innovation. In other words, it is difficult to predict potential effects, especially when innovation results may differ over time, being riskier innovations more visible in the long-term.

Table 4.3 reports, in columns 1, 4, and 7, the coefficients from a random effect probit model that estimates the probability of introducing technological innovations. Remaining columns report random-effects Tobit regressions with right censoring, from which the dependent variables are the proportion of sales due to innovations for the market or the firm (or turnovers). Remember that we use the estimates from table 2 (cloglog model with normal distribution) to derive logistic predicted hazard rates for each firm given the values of the covariates and the value of the time interval (j) to leave the subsidy scheme in the relevant spell year. Using the predictions of the hazard rate we obtain the within sample prediction of the predicted survival rate $\hat{S}$ by each firm as expressed in equation [4.3].

We can see that in all the models presented; innovation outcomes are highly persistent as shown by the lagged variable for innovation outcomes. Also, the initial values show positive and significant effects. This finding is in agreement with previous evidence that accounts for the degree of persistence in innovation and R&D (Bas and Scellato 2014; Peters 2009; Tavassoli and Karlsson 2015).

When examining the relationship between R&D subsidy survival and innovation outcomes, the coefficients obtained are in line with the hypothesis that continuous participation in the policy may increase innovation results. This result is in line with Aschhoff's (2009) which shows that R&D stimulating measures help firms generate products and services new to the market.

Despite the presence of some common features, we observe differences in behavior between both groups of companies: in the case of SMEs, the predicted survival rate increases the likelihood of introducing technological innovations and the turnover from new-to-market. Large firms, unlike SMEs, do not seem to derive positive returns to R&D subsidy persistence. The findings observed in this study mirror those of the previous studies that have examined the effect of R&D policy on innovation performance. For a sample of Swiss firms, Beck et al. (2016) find that the publicly induced part of the R&D investment has a positive and statistically significant on radical innovation.

Table 4.3: Innovation Outputs

	SMEs			Large Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
	Tech Innnovation	Turnover market	Turnover firm	Tech Innnovation	Turnover market	Turnover firm
$\hat{S}$ (Survival Predicted)	0.788***	3.682**	1.418	0.521	3.860	-3.298
	(0.162)	(1.649)	(1.644)	(0.434)	(2.151)	(2.241)
Innovation output (first lag)	1.953***	0.448***	0.471***	2.041***	0.528***	0.554***
	(0.089)	(0.019)	(0.018)	(0.268)	(0.034)	(0.032)
R&D expenditures (log) $(t-2)$	-0.016	0.654	-0.427	0.135	-2.039**	1.214
	(0.057)	(0.626)	(0.616)	(0.151)	(0.830)	(0.876)
R&D employees $(t-2)$	0.039	4.302*	-1.555	-0.973	11.696***	5.279
	(0.223)	(2.517)	(2.561)	(0.713)	(4.309)	(4.253)
Higher education $(t-2)$	0.062	3.554	-4.040*	-0.291	-2.114	6.410*
	(0.230)	(2.490)	(2.449)	(0.586)	(3.227)	(3.408)
IP protect $(t-2)$	0.176**	1.710**	0.185	0.060	-2.285**	-0.317
	(0.071)	(0.755)	(0.756)	(0.209)	(1.060)	(1.075)
Cooperation $(t-2)$	0.076	0.189	-1.362*	0.548***	1.846	0.635
	(0.068)	(0.794)	(0.803)	(0.201)	(1.209)	(1.227)
Depth 0-10	-0.009	-0.162	0.065	0.019	-0.091	0.151
	(0.018)	(0.197)	(0.200)	(0.050)	(0.255)	(0.251)
Breadth 0-10	0.057***	0.292*	0.456***	0.045	0.129	0.281
	(0.012)	(0.155)	(0.155)	(0.039)	(0.236)	(0.240)
Size (log) $(t-2)$	0.142	0.357	-0.682	-0.474	-1.540	1.237
	(0.164)	(1.709)	(1.677)	(0.433)	(2.337)	(2.467)
Young	0.084	1.548	-0.918	0.516	2.478	2.223
	(0.112)	(1.201)	(1.201)	(0.476)	(2.575)	(2.604)
Sales growth	-0.030	1.583	-0.425	-0.261	1.178	1.540
	(0.101)	(1.093)	(1.073)	(0.374)	(1.807)	(1.914)
Group $(t-2)$	0.031	1.243	2.430***	-0.171	1.185	-2.790*
	(0.080)	(0.897)	(0.932)	(0.297)	(1.492)	(1.483)
Foreign	-0.000	-2.873	-3.139	0.575*	1.180	2.214
	(0.181)	(1.964)	(2.014)	(0.316)	(1.391)	(1.357)
Exporter $(t-2)$	-0.044	-1.063	0.151	-0.328	-0.763	-0.887
	(0.082)	(0.955)	(0.973)	(0.372)	(1.806)	(1.819)
Initial value (t_0)	0.052	0.076***	0.027	0.393	0.090***	0.038
	(0.112)	(0.017)	(0.017)	(0.415)	(0.030)	(0.023)
Time averages						
M.Size	0.066	-0.553	0.127	0.534	4.057*	-2.454
	(0.163)	(1.741)	(1.716)	(0.467)	(2.444)	(2.559)
M.age	-0.017	0.213	-0.184	0.406**	0.142	1.204
	(0.074)	(0.874)	(0.907)	(0.191)	(0.887)	(0.864)
M.R&D	0.048	0.888	1.310*	-0.198	2.131**	-1.305
	(0.066)	(0.764)	(0.775)	(0.182)	(0.953)	(0.983)
M.Higher education	-0.106	-4.357	6.897**	-0.288	4.479	-7.527*

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Table 4.3 – Continued

	SMEs			Large Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
	Tech Innnovation	Turnover market	Turnover firm	Tech Innnovation	Turnover market	Turnover firm
	(0.279)	(3.198)	(3.240)	(0.795)	(4.436)	(4.487)
Constant	-1.994***	-13.714**	-0.808	-2.462*	-4.418	3.867
	(0.508)	(5.945)	(6.198)	(1.458)	(6.545)	(6.332)
lnsig2u	-2.163***			-1.095		
	(0.528)			(0.746)		
sigma_u		7.360***	8.626***		3.789***	1.794
		(0.640)	(0.590)		(1.106)	(2.290)
sigma_e		21.540***	21.014***		17.656***	18.793***
		(0.266)	(0.258)		(0.370)	(0.401)
Rho	0.1032***	0.104***	0.144	0.251	0.044*	0.009
	(0.048)	(0.0173)	(0.018)	(0.140)	(0.025)	(0.0231)
N	4,848	4,848	4,848	1,594	1,594	1,594
Firms	1,095	1,095	1,095	305	305	305
Uncensored observations		4,641	4,596		1,567	1,541
Censored observations		207	252		27	53

Notes: Standard errors in parentheses; Standard errors are clustered at the firm level. Columns 1, 4, and 7 report estimates from a random effect probit model. Remaining columns report random-effects Tobit regressions with right censoring. Significance levels: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$; All models include year and industry dummies.

The correlation with other variables shows the following: First, considering new to market innovation, which has a higher degree of novelty compared to new-to-firm innovation, it is found to be positively and significantly associated with human capital (as expressed by the ratio of R&D researchers over employment). This innovation outcome also correlates positively and significantly with intellectual property right protection. Second, all outcomes are positively correlated with the importance that the firm gives to the different sources of information, especially for SMEs.

Finally, we implement a robustness check: instead of using a continuous variable for the turnovers, two binary variables, which reflect the degree of novelty from market and firm innovations, are introduced (see Table 4.A4 in the appendix). Results suggest that the estimates are not sensitive to the definition of the dependent variables.

4.4.3 R&D Subsidy Spell Dependence and the Decision to Stop Innovation Activities

We turn next to the analysis of the abandonment of innovation projects (Equation [4.5]). Table 4.4 displays the marginal effects of the bivariate dynamic probit models for SMEs and large companies respectively.[22] The dependent variable takes the

[22] The corresponding biprobit coefficients are reported in the Appendix in Table 4.A5.

value of one if the firm has abandoned innovation projects and zero otherwise. Each column reports the results for each stopping condition (implementation, conception or overall). Columns (1) to (3) display the estimation of the model for SMEs. Columns (4) to (6) report the estimation results for large firms.

The third question in this study sought to determine the extent to which R&D subsidy persistence offset firms' likelihood of stopping innovation projects. We find clear evidence of the impact of R&D subsidy persistence on firm's abandoning decision- the coefficients obtained are in line with the hypothesis that continuous use of the R&D subsidies reduces the likelihood of abandoning innovation projects. For both firms, SMEs and large the effect is negative and significant, showing that firms with continuous use of the policy could to a certain extent neutralize the risk of abandoning projects in the course of innovation.

However, some important nuances should be mentioned. First, large firms derive greater effects than SMEs. This may be a result of heterogeneities in firm innovation performance and firm size, suggesting that large firms rather than small firms might have been the more innovative (Tether 1998). Hence large firms are more likely to reduce the likelihood of slowing down since they could be more likely to get funding from public agencies (Cerulli and Potì 2012a). Second, our results show that the firm's response to public support is not neutral to the development stage of the innovation project. Marginal effects of public support on the implementation stage are slightly higher than those on the conception phase. For large firms, R&D subsidy survival does not render significance on the initiation phase. According to Hall (1992) and Carreira and Silva (2010), conceptual stages involve larger risks than more mature stages, leading the firm to rely more heavily on internally generated funds. Hence it is expected that the impact of public support is much higher on execution stages as firms are more prone to seek external sources of funding (Kerr and Nanda 2015).

Regarding other controls, results are the following. First, the decision to stop R&D projects is highly persistence (accounted by the corresponding one-year lag of the stopping condition). Second, we do not find evidence that financial constraints increase the probability of abandoning a project. Nevertheless, time-average values of the financial constraints show a positive and significant effect on the probability of stopping projects in the conception stage, meaning that firms facing financial barriers in the long-run have larger probability of stopping innovation projects in the initiation phase.

Third, the results show that the abandoning decision is mainly driven by firms with the most innovative activity -the ones with the highest average R&D intensity and that have protected their innovations. These results are expected in the sense that uncertainty and risk characterize R&D activities, increasing the chances of stopping innovation projects (Dasgupta and Stiglitz 1980; Hall and Lerner 2010). Fourth, those firms that rely on an external source of knowledge are more likely to abandon innovation projects. This may explain a potential learning effect from external sources of information, making the firm more able to introduce rapid changes in its investment decisions (Lhuillery and Pfister 2009).

Table 4.4: Stopping Innovations (Marginal Effects)

	SMEs			Large Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
	Stop conception	Stop Implem.	Stop overall	Stop conception	Stop Implem.	Stop overall
$\hat{S}$ (Survival Predicted)	-0.062***	-0.082***	-0.074***	-0.058	-0.097***	-0.085**
	(0.019)	(0.020)	(0.023)	(0.036)	(0.035)	(0.039)
Stop $(t-1)$	0.311***	0.280***	0.344***	0.370***	0.338***	0.389***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.009)	(0.008)
R&D expenditures (log) $(t-2)$	0.001	0.009***	0.010***	0.000	0.007***	0.006***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
R&D employees $(t-2)$	0.007	0.002	-0.022	0.022	0.002	0.019
	(0.024)	(0.026)	(0.029)	(0.050)	(0.052)	(0.056)
Higher education $(t-2)$	0.026	-0.001	0.020	0.074*	-0.017	0.067*
	(0.019)	(0.020)	(0.024)	(0.038)	(0.040)	(0.040)
IP protect $(t-2)$	0.020***	0.014**	0.021***	0.027**	0.042***	0.044***
	(0.006)	(0.006)	(0.007)	(0.011)	(0.011)	(0.013)
Cooperation $(t-2)$	0.004	0.009	0.014**	0.028**	0.013	0.040***
	(0.006)	(0.006)	(0.007)	(0.013)	(0.013)	(0.014)
Depth 0-10	-0.001	-0.002	-0.001	0.008**	0.002	0.005
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
Breadth 0-10	0.008***	0.003***	0.005***	0.011***	0.001	0.005**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Size (log) $(t-2)$	0.009	0.004	0.005	0.046	0.039	0.057*
	(0.012)	(0.012)	(0.014)	(0.029)	(0.027)	(0.031)
Young	0.001	0.017	0.006	0.028	0.014	0.050*
	(0.011)	(0.011)	(0.013)	(0.027)	(0.029)	(0.029)
Sales growth	0.006	-0.009	-0.004	0.008	0.012	0.018
	(0.007)	(0.008)	(0.010)	(0.025)	(0.026)	(0.027)
Group $(t-2)$	-0.001	0.006	0.001	-0.017	0.005	-0.009
	(0.007)	(0.007)	(0.008)	(0.019)	(0.018)	(0.020)
Foreign	0.003	0.001	0.001	0.023	0.005	0.009
	(0.014)	(0.014)	(0.017)	(0.016)	(0.015)	(0.018)
Exporter $(t-2)$	-0.007	-0.001	-0.005	0.031	0.004	0.029
	(0.008)	(0.008)	(0.009)	(0.019)	(0.018)	(0.019)
Financial Constraints $(t-2)$	-0.010	0.002	-0.004	-0.013	-0.002	-0.001
	(0.008)	(0.009)	(0.010)	(0.020)	(0.018)	(0.020)
Knowledge Barriers $(t-2)$	0.003	-0.011	-0.003	-0.014	-0.000	-0.026
	(0.008)	(0.008)	(0.009)	(0.020)	(0.020)	(0.022)
Mkt Barriers: Dominated $(t-2)$	0.009	-0.004	0.002	-0.013	-0.011	-0.019
	(0.009)	(0.008)	(0.011)	(0.025)	(0.022)	(0.026)
Mkt Barriers: Uncertainty $(t-2)$	-0.005	-0.005	-0.006	-0.001	0.033*	0.028
	(0.009)	(0.008)	(0.010)	(0.020)	(0.019)	(0.021)
Financial Constraints t_0	0.005	-0.002	0.000	-0.032*	0.009	-0.027

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Table 4.4 – Continued

	SMEs			Large Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
	Stop conception	Stop Implem.	Stop overall	Stop conception	Stop Implem.	Stop overall
	(0.007)	(0.006)	(0.008)	(0.017)	(0.016)	(0.018)
Initial value t_0	0.064***	0.052***	0.077***	0.066***	0.055***	0.071***
	(0.007)	(0.006)	(0.008)	(0.013)	(0.012)	(0.015)
Time averages						
M.size	0.002	-0.005	-0.003	-0.031	-0.034	-0.050
	(0.012)	(0.012)	(0.014)	(0.030)	(0.028)	(0.032)
M.age	0.003	0.003	0.004	-0.009	-0.005	-0.012
	(0.007)	(0.006)	(0.008)	(0.010)	(0.010)	(0.011)
M.R&D	0.006***	-0.005***	-0.003	0.005	-0.004	-0.001
	(0.002)	(0.002)	(0.002)	(0.005)	(0.004)	(0.005)
M.higher education	-0.032	0.001	-0.015	-0.072	0.085*	-0.046
	(0.026)	(0.026)	(0.031)	(0.054)	(0.050)	(0.056)
M.Financial constraints	0.035***	0.016	0.030**	0.028	-0.007	0.019
	(0.013)	(0.012)	(0.015)	(0.027)	(0.025)	(0.029)
M.Knowledge barriers	-0.003	0.028**	0.014	0.053	0.008	0.046
	(0.014)	(0.014)	(0.016)	(0.033)	(0.034)	(0.037)
M.dominated barriers	-0.003	0.004	0.011	0.036	0.008	0.050
	(0.016)	(0.015)	(0.019)	(0.034)	(0.033)	(0.036)
M.uncertainty barriers	0.048***	0.033**	0.052***	0.028	-0.012	-0.001
	(0.015)	(0.014)	(0.017)	(0.030)	(0.029)	(0.032)
N	4,848	4,848	4,848	1,594	1,594	1,594

Notes: Standard errors clustered at the firm level in parentheses; Estimations control for time and industry dummies. Marginal effects are reported at sample means. For dummy variables, the marginal effect corresponds to the discrete change from 0 to 1. Simultaneous estimation using CMP STATA command by Roodman (2018). Significance levels: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$; All models include year and industry dummies.

Fifth, we do not find evidence that the performance of the firm (proxied by sales growth) is correlated with innovation abandonment regardless of the stage. However, the time-average values of market barriers due to the uncertainty in demand for innovative shows a positive and significant effect on the probability of stopping innovation projects regardless of the stage. Thus, SMEs that reported facing difficulties due to the uncertainty in demand for innovative are more likely to abandon innovation projects. This result may indicate that market uncertainty may be an essential barrier capturing not only the aggregate macro-conditions of demand but also the characteristics of the innovative products and their reinforcing effect on the abandon of innovation-related activities (D'Este, Iammarino, Savona, and von Tunzelmann 2012). García-Vega and López (2010) and D'Este et al. (2017) also find that demand uncertainty increases the likelihood of abandoning.

Regarding equation [4.6] the reduced form equation for financial constraints, some of the results confirm previous evidence.[23] First, size and financial constraints

[23] Results are in the second part of Table 4.A5.

are negatively correlated, especially for the case of SMEs. Second, other perceived barriers to innovation seem to explain the probability of perceiving financial constraints positively. This implies that obstacles are interdependent or reinforce each other (Galia and Legros 2004). Third, as in García-Quevedo et al. (2018), we do not find that firms investing more heavily in R&D are more likely to face financial constraints. Fourth, the instrument used (average of financial constraints) is always statistically significant. Finally, interestingly survival in R&D subsidization always reduces the likelihood of stopping projects regardless of the stage and size, supporting the idea that continuous engagement into a policy may ease financial constraints.

4.4.4 Robustness across Industries

As a robustness check, we analyze differences across industries by using the industry classification of Eurostat: non-knowledge-intensive services (NKIS), knowledge-intensive services (KIS), low-tech manufacturing (LTM), medium low-tech manufacturing (MLTM), medium-high-tech manufacturing (MHTM), high-tech manufacturing (HTM).[24]

We find that results have a broadly similar pattern across industries considered. Firstly, according to the estimates of the hazard function (Table 4.A6 in the appendix), our results are consistent with the existence of negative duration dependence in the use of R&D subsidies. Second, in the case of KIS and medium-high-tech manufacturing, the predicted survival rate is positively correlated with the introduction of technological innovations and sales due to new market innovations (see tables 4.A7 and 4.A8 in the Appendix). The correlation however does not hold for firms in low-tech sectors. Finally, the decision to stop innovation projects at both the conception stage and implementation stage is negatively associated with the predicted survival. Overall, these results might suggest that the agency's selection of projects is more oriented to industries intensive in technology (see tables 4.A9 and 4.A10 in the Appendix).

4.5 Concluding Remarks

This essay contributes to the existing literature on the effects of R&D stimulating policies on innovation. We evaluate the drivers of R&D subsidization persistence and analyzed the extent to which continuous participation in R&D subsidy programs

[24] The correspondence between PITEC industries and the Eurostat classification is carried out according to NACE Rev. 2 at 2-digit level. See here: https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf. The working sample corresponds to 2,251 firms of which 29% are KIS, 8% NKIS, 7% HTM, 24% MHTM, 15% MLTM and 16% LTM.

increases the effectiveness of R&D outcomes and reduces the probability of slowing down innovation projects.

The empirical analysis comprises three reduced-form equations in order to answer each of the three questions. First, we determine survival in R&D subsidies using discrete-time duration models. Second, we analyze the potential effect of continuous use of R&D subsidies on innovation outcomes by introducing the degree of persistence into the model and testing the effect on three variables: technological innovation, turnovers for new-to-market and New-to-firm innovation. Third, we estimate the effect of continuous use of R&D subsidies on the probability of stopping innovation projects. We interpret that the increase in innovation outcomes is the reflection of both the firm's capabilities and the ability of the public agency to identify high quality projects that take some time to fully develop.

The first question in this study seeks to identify the drivers of persistence in the use of R&D subsidies. We find that firms receiving public funding for R&D activities could accumulate knowledge and experience that would increase the chances of getting support in later applications. This finding supports the idea that the firms participating in direct public support programs are more likely to accumulate experience yielding a self-sustained process. Results also confirm that continuous R&D performers have a positive likelihood of reducing the hazard of ending an R&D subsidy spell.

The second question of the study aims to analyze the extent to which continuity in the use of R&D subsidies leads to better, more innovative outcomes. We find that among SMEs, continued program participation is positively correlated with new-to-market product innovation. In contrast, we do not find this correlation to be significant in the case of large firms.

Finally, this chapter looks at the extent to which continuous engagement in R&D subsidization is associated with the firm's decision to stop innovation projects. We find that survival in R&D subsidization also reduces the likelihood of abandoning R&D projects at either the concept stage or mature stages. For both SMEs and large firms, the effect is negative and significant, showing that firms with continuous use of the policy could to a certain extent neutralize the risk of abandoning projects in the course of innovation.

The findings in this study are subject to a number of limitations. First, the lack of information on the duration of a subsidy award from a single application may lead to an overestimation of persistence in project subsidization. Second, it is not possible to identify subsidy application costs and how they might change over time because of lack of information on all applications, including those that have been rejected. Third, when analyzing the decision to stop innovation projects we could not control for the number or type of projects a firm is conducting.

With these considerations in mind, these findings may provide some insights for innovation policies. When designing programs policymakers could take into account that firm participation is to a good extent a self-sustained process, in part maybe because application costs fall, in part because once a firm engages in R&D the cost of producing new ideas and further innovations falls, or a combination of both. Identifying the factors that determine application costs could be useful, especially if the policy aims at encouraging the spread of socially beneficial innovation activities across firms. The finding that new-to-market product innovation is triggered by SMEs participating continuously into the R&D subsidization program suggests that the agency's selection of projects is successful in identifying truly innovative projects. The social benefits of occasional participation would not be obvious though.

A number of issues would deserve further research. One is investigating how persistence in R&D subsidization is reinforced by persistence in performing R&D activities, that is, what mechanisms are driving the reinforcement process. The second would involve estimating the social returns of innovation subsidies, in line with work by Takalo, Tanayama, and Toivanen (2013) for Finland and Koehler (2018) for Germany.

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Appendix

Table 4.A1: Definition of Variables

Variable Name	**Variable Definition**
R&D subsidy spell	Discrete-time hazard rate for firm i in the time interval j to leave the subsidy scheme (subsidized or non-subsidized)
(θ) Persistence (log)	Log of survival time (baseline hazard). Survival time ranges from 1 to 11 years.
Tech Innovation	Binary; firm has introduced any new or significantly improved goods, services or improved process for producing or supplying goods or services over the last three years.
Turnover: Market	Percentage of sales derived from products or services newly introduced that are a novelty for the market over the last three years.
Turnover: firm	Percentage of sales derived from products or services newly introduced that are a novelty for the firm over the last three years.
Novelty Market	Binary; firm has introduced a new or significantly improved product onto the market before its competitors.
Novelty Firm	Binary; firm has introduced a new or significantly improved product that was already available in the market.
Stop overall	Binary; firm has abandoned any innovation project either in the conception phase or implementation phase.
Stop conception	Binary; firm abandons any innovation project either in the conception phase.
Stop implementation	Binary; firm abandons any innovation project either in the implementation phase.
R&D expenditures	Log of innovation investment in constant prices
Continuous R&D performer	Binary; firm engages in R&D activities on a continuous basis
R&D employees	Percentage of R&D employees over the total workforce of the firm.
Higher education	The share of employees with higher education
IP protect	Binary; Firm uses formal IP mechanisms
Cooperation	Binary; firm reports active cooperation for innovation activities with other firms or institutions
Breadth	Ranges from 0 to 10, based on the number of sources of information for innovation used by the firm.
Depth	Ranges from 0 to 10, based on the number of sources of information the firm rated as highly important.
Size (log)	Log of Firm Size
Young	Firm is young (age¡10 years)
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.
Fixed investment	Binary; firm has invested in fixed capital.
Financial constraints	Binary: Firm declares that access to internal and external funding is an important obstacle for innovating
Knowledge barriers	Binary; Firm declares that knowledge barriers are an important obstacle for innovating: availability of skilled personnel, information on technology, markets and lack of innovation partners.
Mkt. barriers: dominated	Binary; Firm declares that markets being dominated by incumbents is an important obstacle for innovating.
Mkt. barriers: Demand Uncertainty	Binary; Firm declares that demand uncertainty is an important obstacle for innovating
Group	Binary; Firm belongs to a business group.
Foreign	Binary; for multinational firms with participation of foreign capital greater than 50%
Export	Binary; Firm has sold products and/or services in the international market (European and third party).

Continued on next page

Table 4.A1 – continued from previous page

Variable Name	Variable Definition
EU support	Binary; Firm participates in public support programs from the European Union.
High-tech Manufac.	Binary; firm belongs to the Manufacturing sectors: pharmacy, IT products, electronic and optical products, aeronautical and space industries.
Medium-Tech Manufac	Binary; firm belongs to the Manufacturing sectors: chemicals, mechanical and electrical equipment, other machinery, motor vehicles, naval construction.
Other Manufacturing	Binary; firm belongs to remaining manufacturing sectors: food, beverages and tobacco, textiles, clothing, leather and footwear, wood and cork, cardboard and paper, rubber and plastics, metal manufactures, other transport equipment, furniture, other manufacturing activities, graphic arts.
High-Tech Services	Binary; firm belongs to the High Technology Services sectors: telecommunications, programming, consulting and other information activities, other information and communications services, R&D services.
Other Services	Binary; firm belongs to other Services sectors: repair and installation of machinery and equipment, commerce, transportation and storage, hotels and accommodation, financial and insurance activities, real estate activities, administrative activities and auxiliary services, education, sanitary activities and social services, artistic, recreational and entertainment activities, other services.

Table 4.A2: Sample Distribution by type of Spells

	SMEs	**Large**
Completed	37.60%	19.62%
Right Censored	10.98%	18.43%
Left censored	33.40%	21.27%
Left-right censored	16.40%	40.67%
Total Spells (No. Obs)	**7,195**	**2,181**

Table 4.A3: Kaplan-Meier Analysis

SMEs with public support= 1,549					
Time (years)	(N) Firms whose R&D subsidy spell ends	Survivor Function	Std. Error	[95% Conf. Int.]	
1	1070	0.574	0.0099	0.5545	0.5931
2	479	0.3828	0.0097	0.3638	0.4018
3	251	0.2825	0.009	0.265	0.3003
4	162	0.2174	0.0082	0.2015	0.2338
5	110	0.1732	0.0076	0.1587	0.1883
6	80	0.1411	0.007	0.1277	0.155
7	85	0.107	0.0062	0.0953	0.1195
8	50	0.0867	0.0056	0.0761	0.0982
9	41	0.0705	0.0051	0.0609	0.081
10	47	0.0516	0.0044	0.0434	0.0607
11	130	0	.	.	.
Large firms with public support= 406					
Time (years)	Firms whose R&D subsidy spell ends	Survivor Function	Std. Error	[95% Conf. Int.]	
1	292	0.6091	0.0179	0.5731	0.6431
2	144	0.418	0.018	0.3826	0.453
3	62	0.336	0.0172	0.3024	0.3698
4	53	0.267	0.0161	0.236	0.2989
5	34	0.2227	0.0151	0.1938	0.2529
6	22	0.194	0.0143	0.1668	0.2229
7	31	0.1534	0.0131	0.1288	0.18
8	21	0.1266	0.012	0.1042	0.1512
9	13	0.1091	0.0113	0.0882	0.1324
10	17	0.087	0.0102	0.0684	0.1083
11	65	0	.	.	.

Note: Sample of firms that invested in innovation at least once and obtained public support.

Table 4.A4: Innovation Outputs

	SMEs			Large Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
	Turnover Mkt and firm	Novelty market	Novelty firm	Turnover Mkt and firm	Novelty market	Novelty firm
$\hat{S}$ (Survival Predicted)	4.630*	0.142	0.403***	0.939	0.142	0.483**
	(2.373)	(0.114)	(0.119)	(3.289)	(0.201)	(0.210)
Innovation output (first lag)	0.516***	1.535***	1.665***	0.545***	1.538***	1.923***
	(0.021)	(0.057)	(0.060)	(0.035)	(0.109)	(0.122)
R&D expenditures (log) (t-2)	0.166	-0.048	0.001	-0.946	0.164**	-0.191**
	(0.890)	(0.043)	(0.044)	(1.255)	(0.075)	(0.078)
R&D employees (t-2)	3.302	-0.187	-0.032	16.164**	-0.302	0.249
	(3.712)	(0.171)	(0.175)	(6.785)	(0.398)	(0.477)
Higher education (t-2)	-0.255	-0.270	-0.043	4.450	0.254	-0.155
	(3.526)	(0.172)	(0.181)	(4.886)	(0.300)	(0.308)
IP protect (t-2)	1.663	0.054	0.254***	-3.080*	0.203**	0.172*
	(1.088)	(0.051)	(0.053)	(1.644)	(0.098)	(0.103)
Cooperation (t-2)	-1.888	-0.021	0.091	2.888	0.109	0.094
	(1.158)	(0.054)	(0.056)	(1.866)	(0.108)	(0.113)
Depth 0-10	-0.093	0.008	-0.004	0.063	0.042*	0.060**
	(0.288)	(0.013)	(0.014)	(0.399)	(0.024)	(0.026)
Breadth 0-10	0.796***	0.038***	0.047***	0.340	0.040*	0.019
	(0.223)	(0.010)	(0.011)	(0.367)	(0.021)	(0.023)
Size (log) (t-2)	-0.034	0.033	-0.080	-0.460	-0.045	-0.004
	(2.428)	(0.118)	(0.125)	(3.532)	(0.208)	(0.228)
Young	0.695	-0.027	0.118	4.097	-0.202	0.081
	(1.737)	(0.083)	(0.086)	(3.953)	(0.234)	(0.263)
Sales growth	1.163	-0.139*	0.120	2.677	0.194	-0.320*
	(1.571)	(0.078)	(0.076)	(2.738)	(0.160)	(0.187)
Group (t-2)	4.048***	0.164***	-0.088	-1.656	-0.090	0.122
	(1.336)	(0.060)	(0.061)	(2.341)	(0.139)	(0.146)
Foreign	-6.528**	-0.010	0.142	3.757*	0.106	0.126
	(2.882)	(0.132)	(0.138)	(2.188)	(0.127)	(0.138)
Exporter (t-2)	-1.283	0.059	-0.043	-1.169	-0.075	0.005
	(1.407)	(0.064)	(0.066)	(2.795)	(0.162)	(0.172)
Initial value (t_0)	0.087***	0.159**	0.303***	0.087***	0.355***	0.380***
	(0.020)	(0.062)	(0.069)	(0.031)	(0.125)	(0.147)
Time averages						
M.Size	-0.943	0.097	0.176	1.628	-0.048	0.308
	(2.485)	(0.119)	(0.127)	(3.704)	(0.219)	(0.239)
M.age	0.131	-0.106*	-0.039	1.445	0.022	-0.042
	(1.307)	(0.059)	(0.060)	(1.401)	(0.084)	(0.088)
M.R&D	1.934*	0.157***	0.065	0.827	-0.115	0.194**
	(1.115)	(0.051)	(0.053)	(1.461)	(0.087)	(0.093)
M.Higher education	2.130	0.162	-0.051	-4.266	-0.496	0.056
	(4.659)	(0.216)	(0.225)	(6.875)	(0.409)	(0.439)
Constant	-11.396	-2.155***	-2.470***	1.446	-1.831***	-2.424***
	(8.895)	(0.397)	(0.411)	(10.393)	(0.613)	(0.664)
lnsig2u		-1.778***	-1.820***		-2.005***	-1.995***
		(0.260)	(0.299)		(0.579)	(0.644)

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Table 4.A4 – Continued

	SMEs			Large Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
	Turnover Mkt and firm	Novelty market	Novelty firm	Turnover Mkt and firm	Novelty market	Novelty firm
sigma_u	12.281***	0.411***	0.402***	7.117***	0.367***	0.3688***
	(0.899)	(0.053)	(0.060)	(1.531)	(0.106)	(0.119)
sigma_e	29.974***			26.412***		
	(0.394)			(0.583)		
Rho	0.144***	0.145***	0.139***	0.068***	0.119***	0.119**
	(0.019)	(0.032)	(0.036)	(0.028)	(0.0605)	(0.0679)
N	4,848	4,848	4,848	1,594	1,594	1,594
Firms	1,095	1,095	1,095	305	305	305
Uncensored observations	4,172			1,452		
Censored observations	679			142		

Notes: Standard errors in parentheses; Standard errors are clustered at the firm level. Columns 1, 4, and 7 report estimates from a random effect probit model. Remaining columns report random-effects Tobit regressions with right censoring. Significance levels: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; All models include year and industry dummies.

Table 4.A5: Stopping Innovations (Coefficients)

	SMEs			Large Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
	Stop conception	Stop Implem.	Stop overall	Stop conception	Stop Implem.	Stop overall
main						
$\hat{S}$ (Survival predicted)	-0.329***	-0.454***	-0.311***	-0.282	-0.512***	-0.368**
	(0.099)	(0.108)	(0.097)	(0.172)	(0.184)	(0.170)
lagconsin1	1.649***	1.543***	1.445***	1.795***	1.776***	1.685***
	(0.038)	(0.040)	(0.034)	(0.065)	(0.072)	(0.062)
R&D expenditures (log) (t-2)	0.007	0.050***	0.041***	0.001	0.038***	0.025***
	(0.005)	(0.005)	(0.004)	(0.009)	(0.010)	(0.009)
R&D employees (t-2)	0.039	0.013	-0.091	0.109	0.011	0.082
	(0.127)	(0.143)	(0.122)	(0.243)	(0.274)	(0.244)
Higher education (t-2)	0.135	-0.003	0.086	0.360*	-0.089	0.289*
	(0.103)	(0.108)	(0.099)	(0.184)	(0.210)	(0.173)
IP protect (t-2)	0.105***	0.078**	0.090***	0.129**	0.220***	0.189***
	(0.032)	(0.032)	(0.029)	(0.056)	(0.060)	(0.055)
Cooperation (t-2)	0.020	0.050	0.059**	0.135**	0.070	0.171***
	(0.033)	(0.032)	(0.030)	(0.063)	(0.067)	(0.059)
Depth 0-10	-0.004	-0.013	-0.006	0.037**	0.010	0.021
	(0.010)	(0.010)	(0.009)	(0.018)	(0.019)	(0.018)
Breadth 0-10	0.042***	0.016***	0.020***	0.051***	0.004	0.024**
	(0.006)	(0.006)	(0.005)	(0.012)	(0.012)	(0.011)
Size (log) (t-2)	0.046	0.020	0.020	0.222	0.206	0.249*
	(0.062)	(0.064)	(0.058)	(0.139)	(0.142)	(0.135)
Young	0.006	0.095	0.027	0.135	0.071	0.216*
	(0.057)	(0.061)	(0.053)	(0.132)	(0.152)	(0.126)
Sales growth	0.034	-0.050	-0.016	0.038	0.063	0.079
	(0.039)	(0.046)	(0.041)	(0.121)	(0.138)	(0.116)
Group (t-2)	-0.005	0.035	0.003	-0.084	0.024	-0.040
	(0.038)	(0.039)	(0.035)	(0.090)	(0.094)	(0.087)
Foreign	0.015	0.006	0.003	0.112	0.029	0.040
	(0.076)	(0.076)	(0.073)	(0.077)	(0.080)	(0.076)
Exporter (t-2)	-0.038	-0.006	-0.022	0.151	0.021	0.124
	(0.042)	(0.042)	(0.038)	(0.092)	(0.096)	(0.083)
Financial Constraints (t-2)	-0.053	0.011	-0.019	-0.063	-0.009	-0.004
	(0.043)	(0.047)	(0.041)	(0.095)	(0.093)	(0.085)
Knowledge Barriers (t-2)	0.016	-0.060	-0.014	-0.069	-0.001	-0.114
	(0.043)	(0.044)	(0.040)	(0.096)	(0.103)	(0.094)
Mkt Barriers: Dominated (t-1)	0.050	-0.023	0.008	-0.065	-0.057	-0.080
	(0.050)	(0.047)	(0.044)	(0.123)	(0.114)	(0.113)
Mkt Barriers: Uncertainty (t-1)	-0.027	-0.029	-0.026	-0.005	0.172*	0.121
	(0.047)	(0.046)	(0.041)	(0.096)	(0.102)	(0.091)
Time averages						
M.size	0.012	-0.028	-0.014	-0.152	-0.179	-0.215
	(0.065)	(0.066)	(0.061)	(0.144)	(0.146)	(0.140)
M.age	0.015	0.018	0.019	-0.044	-0.025	-0.050
	(0.036)	(0.034)	(0.032)	(0.049)	(0.050)	(0.047)
M.R&D	0.034***	-0.029***	-0.012	0.026	-0.020	-0.005
	(0.009)	(0.009)	(0.008)	(0.022)	(0.022)	(0.020)

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Table 4.A5 – Continued

	SMEs			Large Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
	Stop conception	Stop Implem.	Stop overall	Stop conception	Stop Implem.	Stop overall
M.higher education	-0.171	0.004	-0.064	-0.347	0.445*	-0.200
	(0.137)	(0.143)	(0.130)	(0.260)	(0.264)	(0.241)
M.Financial constraints	0.184***	0.089	0.127**	0.137	-0.035	0.082
	(0.069)	(0.069)	(0.063)	(0.132)	(0.133)	(0.126)
M.Knowledge barriers	-0.017	0.155**	0.057	0.260	0.042	0.198
	(0.072)	(0.075)	(0.068)	(0.159)	(0.181)	(0.162)
M.dominated barriers	-0.018	0.020	0.045	0.174	0.043	0.215
	(0.086)	(0.082)	(0.079)	(0.165)	(0.173)	(0.155)
M.uncertainty barriers	0.256***	0.184**	0.217***	0.138	-0.064	-0.002
	(0.080)	(0.077)	(0.072)	(0.143)	(0.153)	(0.138)
Financial Constraints t_0	0.026	-0.012	0.001	-0.156*	0.047	-0.118
	(0.036)	(0.035)	(0.033)	(0.083)	(0.082)	(0.078)
Stop t_0	0.340***	0.285***	0.324***	0.322***	0.289***	0.306***
	(0.036)	(0.036)	(0.034)	(0.064)	(0.065)	(0.065)
Constant	-2.076***	-1.893***	-1.685***	-2.529***	-2.015***	-1.988***
	(0.156)	(0.155)	(0.140)	(0.323)	(0.329)	(0.319)
Financial constraints						
$\hat{S}$ (Survival predicted)	-0.396***	-0.399***	-0.397***	-0.375**	-0.377**	-0.375**
	(0.089)	(0.089)	(0.089)	(0.169)	(0.169)	(0.169)
Avg. Financial Constraints	0.581***	0.597***	0.590***	0.937***	0.927***	0.934***
	(0.180)	(0.179)	(0.180)	(0.224)	(0.225)	(0.224)
R&D expenditures (log) (t-2)	0.004	0.004	0.004	0.020*	0.020*	0.020*
	(0.005)	(0.005)	(0.005)	(0.010)	(0.010)	(0.010)
R&D employees (t-2)	0.036	0.036	0.036	0.134	0.138	0.135
	(0.093)	(0.093)	(0.093)	(0.191)	(0.190)	(0.191)
Higher education (t-2)	-0.181	-0.182	-0.179	-0.364	-0.362	-0.364
	(0.124)	(0.124)	(0.124)	(0.250)	(0.249)	(0.250)
IP protect (t-2)	0.033	0.032	0.033	-0.010	-0.009	-0.010
	(0.030)	(0.030)	(0.030)	(0.060)	(0.060)	(0.060)
Cooperation (t-2)	-0.012	-0.011	-0.012	0.061	0.060	0.061
	(0.030)	(0.030)	(0.030)	(0.071)	(0.071)	(0.071)
Size (log) (t-2)	-0.284***	-0.285***	-0.284***	0.126	0.123	0.126
	(0.088)	(0.088)	(0.088)	(0.230)	(0.230)	(0.230)
young	0.008	0.010	0.008	0.176	0.178	0.178
	(0.064)	(0.064)	(0.064)	(0.174)	(0.174)	(0.174)
Sales growth	0.006	0.005	0.006	-0.045	-0.044	-0.046
	(0.056)	(0.056)	(0.056)	(0.136)	(0.136)	(0.136)
Group (t-2)	-0.016	-0.016	-0.016	0.091	0.090	0.091
	(0.026)	(0.026)	(0.026)	(0.068)	(0.068)	(0.068)
Foreign	-0.035	-0.035	-0.033	-0.138**	-0.136**	-0.137**
	(0.049)	(0.050)	(0.049)	(0.061)	(0.061)	(0.061)
Exporter (t-2)	-0.051*	-0.051*	-0.051*	0.217***	0.216***	0.217***
	(0.030)	(0.030)	(0.030)	(0.067)	(0.067)	(0.067)
Knowledge Barriers (t-2)	0.122**	0.123**	0.121**	-0.150	-0.150	-0.150
	(0.051)	(0.051)	(0.051)	(0.121)	(0.121)	(0.121)
Mkt Barriers: Dominated (t-2)	0.207***	0.209***	0.207***	0.231	0.231	0.231
	(0.056)	(0.056)	(0.056)	(0.149)	(0.149)	(0.149)

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Table 4.A5 – Continued

	SMEs			Large Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
	Stop conception	Stop Implem.	Stop overall	Stop conception	Stop Implem.	Stop overall
Mkt Barriers: Uncertainty (t-1)	0.136***	0.136***	0.137***	0.292**	0.292**	0.291**
	(0.053)	(0.053)	(0.053)	(0.120)	(0.120)	(0.120)
Time averages						
M.size	0.298***	0.299***	0.297***	-0.139	-0.137	-0.140
	(0.087)	(0.087)	(0.087)	(0.230)	(0.231)	(0.230)
M.age	-0.034	-0.032	-0.034	0.014	0.015	0.015
	(0.022)	(0.022)	(0.022)	(0.038)	(0.038)	(0.038)
M.R&D	0.001	0.001	0.001	-0.048**	-0.048**	-0.048**
	(0.007)	(0.007)	(0.007)	(0.021)	(0.021)	(0.021)
M.Higher education	0.116	0.118	0.113	0.335	0.332	0.333
	(0.130)	(0.130)	(0.130)	(0.260)	(0.259)	(0.260)
M.Financial constraints	3.715***	3.715***	3.715***	3.983***	3.983***	3.983***
	(0.030)	(0.030)	(0.030)	(0.084)	(0.084)	(0.084)
M.Knowledge barriers	-0.149***	-0.150***	-0.148***	0.177	0.177	0.176
	(0.057)	(0.057)	(0.057)	(0.144)	(0.144)	(0.144)
M.dominated barriers	-0.155**	-0.156**	-0.155**	-0.214	-0.216	-0.213
	(0.061)	(0.062)	(0.061)	(0.158)	(0.159)	(0.158)
M.uncertainty barriers	-0.131**	-0.132**	-0.132**	-0.351***	-0.347***	-0.349***
	(0.058)	(0.058)	(0.058)	(0.129)	(0.129)	(0.129)
Financial Constraints t_0	0.041***	0.042***	0.041***	0.071*	0.072*	0.071*
	(0.013)	(0.013)	(0.013)	(0.038)	(0.038)	(0.038)
Constant	-2.080***	-2.090***	-2.082***	-3.013***	-3.015***	-3.014***
	(0.122)	(0.121)	(0.121)	(0.272)	(0.273)	(0.272)
atanhrho_12	0.103***	0.102***	0.108***	0.035	0.048	0.028
	(0.026)	(0.026)	(0.024)	(0.054)	(0.050)	(0.049)
N	4,848	4,848	4,848	1,594	1,594	1,594

Notes: Standard errors clustered at the firm level in parentheses; Estimations control for time and industry dummies. Marginal effects are reported at sample means. For dummy variables, the marginal effect corresponds to the discrete change from 0 to 1. Simultaneous estimation using CMP STATA command by Roodman (2018). Significance levels: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$; All models include year and industry dummies.

Table 4.A6: Robustness across Industries: ML Estimates for Discrete Time Proportional Hazard models- R&D Subsidies Spells

	(1) KIS	(2) NKIS	(3) HTM	(4) MHTM	(5) MLTM	(6) LTM
(θ) Persistence (log)	-0.199***	-0.467***	-0.256**	-0.205***	-0.334***	-0.268***
	(0.055)	(0.143)	(0.121)	(0.061)	(0.081)	(0.084)
R&D expenditures (log) ($t-1$)	-0.009	0.040	-0.004	0.005	0.009	-0.004
	(0.013)	(0.027)	(0.037)	(0.015)	(0.016)	(0.016)
Continuous R&D performer	-0.388***	-0.486**	0.261	-0.254**	-0.228*	-0.419***
	(0.103)	(0.200)	(0.306)	(0.117)	(0.135)	(0.134)
Technological innovation ($t-1$)	0.077	0.140	-0.293	-0.193	0.047	-0.151
	(0.097)	(0.240)	(0.249)	(0.140)	(0.153)	(0.161)
R&D employees ($t-1$)	-0.383**	-0.287	-1.832**	-0.452	-2.779*	-1.922*
	(0.191)	(1.026)	(0.796)	(0.639)	(1.620)	(0.993)
Higher education ($t-1$)	-0.357***	-0.472	0.358	-0.167	-0.598*	-0.484
	(0.138)	(0.375)	(0.357)	(0.228)	(0.358)	(0.347)
IP protect ($t-1$)	0.006	0.343*	-0.123	0.026	0.147	0.041
	(0.078)	(0.191)	(0.165)	(0.081)	(0.105)	(0.104)
Cooperation ($t-1$)	-0.212***	-0.035	-0.260	-0.385***	-0.271***	-0.242**
	(0.079)	(0.177)	(0.159)	(0.082)	(0.104)	(0.107)
Size (log) ($t-1$)	-0.081***	0.051	-0.028	-0.151***	-0.184***	-0.101*
	(0.029)	(0.075)	(0.089)	(0.044)	(0.058)	(0.054)
young	-0.143	0.022	-0.268	0.040	-0.179	0.222
	(0.108)	(0.324)	(0.336)	(0.181)	(0.234)	(0.187)
Sales growth	-0.039	-0.323	0.115	0.080	0.043	-0.145
	(0.061)	(0.295)	(0.249)	(0.150)	(0.217)	(0.237)
Fixed investment ($t-1$)	-0.277***	-0.603***	-0.362	-0.061	0.092	-0.074
	(0.095)	(0.211)	(0.262)	(0.125)	(0.157)	(0.155)
Financial Constraints ($t-1$)	0.061	0.032	-0.046	0.065	0.069	-0.024
	(0.073)	(0.174)	(0.155)	(0.081)	(0.103)	(0.104)

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Table 4.A6 – Continued

	(1) KIS	(2) NKIS	(3) HTM	(4) MHTM	(5) MLTM	(6) LTM
Mkt Barriers: Dominated $(t-1)$	-0.086	-0.224	-0.160	0.105	-0.102	-0.179
	(0.088)	(0.272)	(0.180)	(0.096)	(0.156)	(0.135)
Mkt Barriers: Uncertainty $(t-1)$	0.062	0.166	0.117	0.015	-0.171	0.152
	(0.084)	(0.218)	(0.170)	(0.096)	(0.129)	(0.122)
Group $(t-1)$	-0.072	0.226	-0.273	-0.091	0.204*	-0.097
	(0.080)	(0.211)	(0.183)	(0.096)	(0.119)	(0.120)
Foreign	0.306*	-0.246	0.234	0.373***	-0.118	0.353*
	(0.170)	(0.334)	(0.235)	(0.120)	(0.174)	(0.189)
Exporter $(t-1)$	0.050	0.043	-0.470	0.182	-0.087	0.013
	(0.076)	(0.181)	(0.319)	(0.174)	(0.184)	(0.195)
UE funding $(t-1)$	-0.455***	-0.898***	0.086	-0.289*	-0.133	0.061
	(0.097)	(0.279)	(0.238)	(0.164)	(0.233)	(0.208)
Left censoring	-0.493***	-0.023	-0.249	-0.487***	-0.370***	-0.215**
	(0.079)	(0.195)	(0.171)	(0.086)	(0.116)	(0.107)
Constant	2.163***	0.851*	1.830***	1.761***	1.691***	2.027***
	(0.210)	(0.477)	(0.551)	(0.285)	(0.346)	(0.333)
lnsig2u	-12.833	-12.595	-12.567	-13.469	-13.175	-12.128
	(15.429)	(15.294)	(15.761)	(19.230)	(17.706)	(16.664)
N	3603	474	634	2157	1296	1160

Notes: All estimations were run with bootstrapped errors. All models include year dummies. Estimation method: A Complementary Log-Log Model (*Cloglog*) with gamma distribution. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.A7: Robustness across Industries: Innovation Outputs I

	KIS			NKIS			HTM		
Variables	(1) Tech innovation	(2) Turnover Market	(3) Turnover firm	(1) Tech innovation	(2) Turnover Market	(3) Turnover firm	(1) Tech innovation	(2) Turnover Market	(3) Turnover firm
$\hat{S}$ (Survival Predicted)	1.065***	3.577*	6.459**	0.411	1.118	-12.748	1.151*	4.743	8.637
	(0.209)	(1.995)	(3.169)	(0.589)	(5.308)	(12.724)	(0.642)	(4.959)	(7.046)
Innovation output (first lag)	1.835***	0.480***	0.546***	1.964***	0.507***	0.484***	2.146***	0.457***	0.549***
	(0.115)	(0.023)	(0.029)	(0.295)	(0.053)	(0.126)	(0.463)	(0.042)	(0.087)
R&D expenditures (log) $(t-2)$	0.079	-0.187	2.282**	-0.631**	-1.399	-2.213	-0.088	3.039	-0.137
	(0.071)	(0.738)	(1.127)	(0.262)	(2.253)	(4.902)	(0.283)	(2.585)	(3.835)
R&D employees $(t-2)$	-0.162	2.916	-4.951	0.467	-7.748	5.480	4.187**	10.933	20.006
	(0.226)	(2.379)	(3.917)	(1.420)	(10.851)	(29.029)	(1.712)	(10.306)	(15.353)
Higher education $(t-2)$	-0.083	2.885	-3.705	0.724	0.518	-23.133	-0.281	-15.453*	0.213
	(0.243)	(2.467)	(3.732)	(1.041)	(9.442)	(18.161)	(1.134)	(9.339)	(12.586)
IP protect $(t-2)$	0.063	0.860	1.368	0.527*	-0.317	3.040	0.135	3.434	-1.994
	(0.094)	(0.968)	(1.558)	(0.305)	(2.339)	(5.914)	(0.313)	(2.421)	(3.617)
Cooperation $(t-2)$	0.268***	0.165	1.874	0.282	1.308	3.311	0.104	-1.775	1.303
	(0.095)	(1.078)	(1.782)	(0.259)	(2.310)	(5.589)	(0.275)	(2.251)	(3.313)
Depth 0-10	0.010	0.154	0.481	0.029	-0.182	2.941*	0.039	0.230	0.368
	(0.022)	(0.231)	(0.377)	(0.068)	(0.611)	(1.503)	(0.069)	(0.516)	(0.766)
Breadth 0-10	0.050***	0.372*	1.430***	0.044	0.822*	1.016	0.034	0.207	2.128***
	(0.017)	(0.206)	(0.357)	(0.044)	(0.450)	(1.154)	(0.059)	(0.513)	(0.817)
Size (log) $(t-2)$	0.078	-0.904	-2.035	-0.415	5.605	-30.030**	-0.007	0.488	5.180
	(0.174)	(1.764)	(2.724)	(0.791)	(6.596)	(14.908)	(0.719)	(6.003)	(8.243)
Young	0.016	0.413	-0.008	-0.088	-0.669	-11.082	-1.041*	3.083	-8.002
	(0.135)	(1.361)	(2.131)	(0.501)	(4.733)	(12.003)	(0.570)	(4.657)	(7.095)
Sales growth	0.003	1.110	-1.881	0.136	2.339	2.017	-0.293	8.445**	5.851
	(0.069)	(0.770)	(1.203)	(0.361)	(3.502)	(7.258)	(0.429)	(3.590)	(4.872)
Group $t-2$	-0.106	1.082	1.230	0.189	-0.927	16.902**	0.161	2.159	0.652
	(0.109)	(1.160)	(2.039)	(0.337)	(2.913)	(8.303)	(0.330)	(2.722)	(4.107)
Foreign	0.171	-3.285	-5.299	0.291	-5.267	8.420	0.258	4.579	2.364
	(0.266)	(2.553)	(4.525)	(0.509)	(4.342)	(10.491)	(0.504)	(3.319)	(5.153)

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Table 4.A7 – Continued

	KIS			NKIS			HTM		
Variables	(1) Tech innovation	(2) Turnover Market	(3) Turnover firm	(1) Tech innovation	(2) Turnover Market	(3) Turnover firm	(1) Tech innovation	(2) Turnover Market	(3) Turnover firm
Exporter $(t-2)$	-0.089	-0.782	0.757	0.013	-1.652	-8.915	0.442	2.341	3.748
	(0.098)	(1.037)	(1.731)	(0.271)	(2.434)	(6.541)	(0.509)	(5.072)	(7.630)
Initial value (t_0)	0.176	0.089***	0.033	0.052	0.164**	0.218	0.569	0.079	0.258***
	(0.158)	(0.022)	(0.040)	(0.328)	(0.066)	(0.189)	(0.624)	(0.056)	(0.078)
Time Averages									
M.Size	-0.037	1.774	-0.290	1.154	-5.026	35.501**	0.149	-3.856	-8.965
	(0.172)	(1.742)	(2.722)	(0.842)	(6.950)	(15.701)	(0.695)	(5.959)	(8.448)
M.age	0.012	-0.868	-0.137	0.025	3.588	-10.509	-0.422	-4.498*	4.397
	(0.109)	(1.162)	(2.187)	(0.258)	(2.332)	(7.148)	(0.279)	(2.301)	(3.675)
M.R&D	-0.067	1.734**	-0.532	0.495*	0.772	12.092**	-0.289	-4.410*	-3.872
	(0.080)	(0.863)	(1.448)	(0.289)	(2.525)	(6.076)	(0.329)	(2.647)	(3.946)
M.Higher education	0.050	-2.639	4.360	-0.063	4.963	8.753	-0.027	5.249	0.862
	(0.323)	(3.565)	(6.312)	(1.153)	(10.201)	(24.585)	(1.237)	(10.067)	(14.036)
Constant	-1.860***	-12.720*	-41.404***	-0.826	-4.863	-93.391**	2.178	29.806**	9.732
	(0.632)	(6.584)	(12.323)	(1.675)	(15.170)	(45.888)	(1.889)	(15.081)	(23.724)
lnsig2u	-1.373**			-14.279			-3.132		
	(0.402)			(350.620)			(5.536)		
sigma_u		7.843***	18.362***		0.000	24.553***		0.000	8.490***
		(0.769)	(1.262)		(3.305)	(5.025)		(6.125)	(3.201)
sigma_e		21.029***	27.430***		18.933***	28.331***		22.023***	27.344***
		(0.312)	(0.541)		(0.735)	(2.211)		(0.709)	(1.327)
N	3011	3011	3011	332	332	332	483	483	483
Firms	537	537	537	95	95	95	120	120	120

Notes: As in Table 4.3

Table 4.A8: Robustness across Industries: Innovation Outputs II

Variables	MHTM (1) Tech innovation	MHTM (2) Turnover Market	MHTM (3) Turnover firm	MLTM (1) Tech innovation	MLTM (2) Turnover Market	MLTM (3) Turnover firm	LTM (1) Tech innovation	LTM (2) Turnover Market	LTM (3) Turnover firm
$\hat{S}$ (Survival Predicted)	0.611**	0.109	5.663*	0.010	9.172***	-1.337	0.721	2.180	-4.105
	(0.299)	(2.273)	(3.367)	(0.448)	(3.245)	(5.456)	(0.445)	(3.115)	(5.754)
Innovation output (first lag)	2.206***	0.431***	0.520***	2.383***	0.460***	0.481***	1.835***	0.355***	0.505***
	(0.175)	(0.032)	(0.040)	(0.258)	(0.031)	(0.051)	(0.249)	(0.051)	(0.066)
R&D expenditures (log) $(t-2)$	-0.066	0.127	-2.237	0.010	-0.177	1.815	-0.034	0.226	-0.766
	(0.122)	(0.966)	(1.402)	(0.150)	(1.195)	(1.890)	(0.145)	(1.148)	(2.089)
R&D employees $(t-2)$	0.130	-1.693	6.862	0.920	-12.135	-2.141	-1.643	15.111	-32.572
	(1.016)	(8.383)	(13.227)	(2.211)	(16.144)	(32.557)	(1.105)	(10.627)	(22.509)
Higher education $(t-2)$	-0.959	1.311	-6.949	0.369	1.406	6.044	-0.109	-0.256	-16.527
	(0.630)	(4.831)	(6.930)	(0.816)	(6.044)	(8.952)	(1.096)	(6.749)	(11.490)
IP protect $(t-2)$	0.320**	0.228	1.916	0.115	0.435	-1.641	0.165	1.438	1.993
	(0.140)	(1.063)	(1.643)	(0.199)	(1.443)	(2.678)	(0.185)	(1.401)	(2.646)
Cooperation $(t-2)$	0.025	3.217***	0.766	0.240	-1.029	-2.677	0.067	-1.365	2.040
	(0.137)	(1.144)	(1.808)	(0.192)	(1.539)	(2.880)	(0.183)	(1.515)	(2.897)
Depth 0-10	0.022	-0.075	0.817*	-0.068	0.019	-0.627	0.024	-0.544	-0.429
	(0.041)	(0.303)	(0.477)	(0.052)	(0.397)	(0.766)	(0.051)	(0.368)	(0.709)
Breadth 0-10	0.069***	-0.024	0.516	0.102***	0.318	1.833***	0.004	0.246	0.643
	(0.024)	(0.228)	(0.368)	(0.036)	(0.298)	(0.577)	(0.033)	(0.303)	(0.599)
Size (log) $(t-2)$	0.219	-2.310	-4.471	0.036	-2.881	7.993	1.006*	-0.081	-9.401
	(0.476)	(3.378)	(4.835)	(0.479)	(3.435)	(4.985)	(0.594)	(4.297)	(7.870)
Young	0.960**	1.774	3.164	0.398	-1.107	6.843	0.878**	4.032	3.496
	(0.423)	(2.669)	(4.068)	(0.427)	(3.323)	(5.840)	(0.441)	(2.984)	(5.830)
Sales growth	-0.279	-0.727	-2.714	-0.155	-0.864	2.313	-0.023	-3.492	4.826
	(0.251)	(2.071)	(2.973)	(0.334)	(2.574)	(3.893)	(0.433)	(3.147)	(5.797)
Group $(t-2)$	-0.088	0.124	2.153	0.179	3.034*	2.009	-0.378*	-1.469	-3.977
	(0.154)	(1.276)	(2.107)	(0.230)	(1.732)	(3.615)	(0.207)	(1.729)	(3.455)
Foreign	0.479**	-0.822	1.528	0.062	3.869*	11.087**	0.891	6.765**	-3.810
	(0.236)	(1.602)	(2.732)	(0.320)	(2.238)	(4.495)	(0.758)	(3.134)	(6.213)

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Table 4.A8 – Continued

	MHTM			MLTM			LTM		
Variables	(1) Tech innovation	(2) Turnover Market	(3) Turnover firm	(1) Tech innovation	(2) Turnover Market	(3) Turnover firm	(1) Tech innovation	(2) Turnover Market	(3) Turnover firm
Exporter $(t-2)$	-0.324	-5.000**	2.950	0.226	-1.500	0.528	-0.510	-1.665	-2.664
	(0.286)	(2.320)	(3.636)	(0.304)	(2.684)	(5.392)	(0.397)	(2.764)	(5.196)
Initial value (t_0)	-0.088	0.050*	0.090**	0.237	0.083**	0.186***	0.285	0.032	0.160**
	(0.231)	(0.026)	(0.042)	(0.383)	(0.033)	(0.065)	(0.287)	(0.045)	(0.073)
Time Averages									
M.Size	-0.120	3.001	6.127	0.036	1.699	-10.558**	-0.511	0.861	14.426*
	(0.483)	(3.429)	(4.949)	(0.490)	(3.527)	(5.329)	(0.581)	(4.290)	(7.850)
M.age	0.116	1.141	-1.535	-0.008	0.033	5.174*	0.000	0.675	-4.928*
	(0.127)	(1.067)	(1.822)	(0.164)	(1.235)	(2.809)	(0.151)	(1.346)	(2.811)
M.R&D	0.012	1.036	1.784	-0.004	1.534	-2.673	0.346**	-1.085	5.320**
	(0.139)	(1.121)	(1.755)	(0.184)	(1.465)	(2.767)	(0.164)	(1.326)	(2.590)
M.Higher education	1.057	0.767	-5.472	-1.299	-7.059	10.232	0.701	14.698*	8.470
	(0.750)	(5.738)	(8.839)	(1.011)	(8.000)	(15.274)	(1.246)	(8.469)	(15.772)
Constant	-0.974	-8.503	0.057	-2.072	-4.408	-31.114	-4.754***	3.323	-43.777**
	(0.916)	(7.786)	(13.497)	(1.388)	(10.327)	(24.048)	(1.284)	(9.528)	(19.759)
lnsig2u	-11.726			-2.446			-12.594		
	(186.188)			(2.209)			(233.804)		
sigma_u		2.437	9.479***		0.000	15.471***		5.433***	14.154***
		(1.838)	(1.427)		(2.029)	(1.985)		(1.737)	(2.413)
sigma_e		19.303***	25.264***		19.447***	25.444***		16.664***	26.441***
		(0.407)	(0.637)		(0.459)	(0.907)		(0.584)	(1.058)
N	1558	1558	1558	897	897	897	791	791	791
Firms	385	385	385	224	224	224	190	190	190

Notes: As in Table 4.3

Table 4.A9: Robustness across Industries: Stopping Innovations (Marginal Effects)

	KIS			NKIS			HTM		
	(1) Stop Conception	(2) Stop Implem	(3) Stop Overall	(4) Stop Conception	(5) Stop Implem	(6) Stop Overall	(7) Stop Conception	(8) Stop Implem	(9) Stop Overall
$\hat{S}$ (Survival Predicted)	-0.036	-0.068**	-0.047	-0.053	-0.056	-0.041	-0.164***	-0.220***	-0.204***
	(0.027)	(0.027)	(0.032)	(0.065)	(0.060)	(0.084)	(0.063)	(0.063)	(0.070)
Stop $(t-1)$	0.325***	0.286***	0.359***	0.189***	0.161***	0.210***	0.369***	0.376***	0.402***
	(0.007)	(0.009)	(0.008)	(0.016)	(0.021)	(0.022)	(0.013)	(0.013)	(0.014)
R&D expenditures (log) $(t-2)$	0.003*	0.008***	0.009***	0.005**	0.010***	0.012***	0.001	0.012**	0.010*
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)
R&D employees $(t-2)$	-0.007	0.006	-0.024	-0.013	-0.099	-0.063	0.198**	0.102	0.147
	(0.023)	(0.024)	(0.028)	(0.071)	(0.083)	(0.100)	(0.093)	(0.123)	(0.115)
Higher education $(t-2)$	0.050**	0.008	0.049*	-0.089	-0.092	-0.110	-0.043	-0.030	-0.005
	(0.022)	(0.023)	(0.028)	(0.058)	(0.058)	(0.070)	(0.061)	(0.067)	(0.072)
IP protect $(t-2)$	0.008	0.014*	0.016	0.014	0.006	-0.011	0.029	0.026	0.022
	(0.009)	(0.009)	(0.011)	(0.017)	(0.017)	(0.022)	(0.021)	(0.020)	(0.022)
Cooperation $(t-2)$	0.022**	0.024***	0.042***	-0.017	0.025	0.023	0.066***	0.010	0.059***
	(0.010)	(0.009)	(0.011)	(0.018)	(0.017)	(0.022)	(0.022)	(0.019)	(0.022)
Depth 0-10	0.003	0.001	0.003	-0.005	-0.011*	-0.010	-0.003	0.004	-0.003
	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)	(0.007)	(0.006)	(0.005)	(0.006)
Breadth 0-10	0.006***	0.000	0.002	0.005**	-0.002	-0.000	0.012***	0.004	0.005
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)
Size (log) $(t-2)$	0.017	0.010	0.011	-0.004	0.064	0.044	0.031	-0.022	0.004
	(0.015)	(0.014)	(0.017)	(0.033)	(0.043)	(0.041)	(0.038)	(0.030)	(0.039)
Young	-0.007	0.003	0.001	-0.080**	-0.036	-0.060	0.037	0.100**	0.084**
	(0.014)	(0.014)	(0.016)	(0.037)	(0.043)	(0.053)	(0.037)	(0.039)	(0.043)
Sales growth	0.011	-0.009	-0.000	0.020	0.043	0.056*	-0.042	-0.065*	-0.094***
	(0.007)	(0.007)	(0.008)	(0.024)	(0.026)	(0.029)	(0.037)	(0.036)	(0.037)
Group $(t-2)$	-0.014	0.005	-0.006	-0.010	0.011	-0.004	-0.050*	-0.034	-0.039

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Table 4.A9 – Continued

	KIS			NKIS			HTM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Stop	Stop	Stop	Stop	Stop	Stop	Stop	Stop	Stop
	Conception	Implem	Overall	Conception	Implem	Overall	Conception	Implem	Overall
	(0.011)	(0.010)	(0.012)	(0.021)	(0.021)	(0.026)	(0.026)	(0.029)	(0.029)
Foreign	-0.006	0.003	-0.022	-0.053	-0.088**	-0.084*	-0.011	-0.002	-0.026
	(0.024)	(0.024)	(0.029)	(0.048)	(0.040)	(0.051)	(0.035)	(0.031)	(0.037)
Exporter $(t-2)$	-0.004	-0.007	-0.003	-0.022	-0.025	-0.034*	0.024	-0.016	0.003
	(0.009)	(0.009)	(0.011)	(0.016)	(0.018)	(0.020)	(0.044)	(0.033)	(0.041)
Financial Constraints $(t-2)$	-0.012	0.008	-0.005	-0.002	-0.017	-0.014	-0.001	-0.053*	0.004
	(0.014)	(0.013)	(0.016)	(0.021)	(0.020)	(0.026)	(0.028)	(0.030)	(0.032)
Knowledge Barriers $(t-2)$	-0.007	-0.021*	-0.018	0.006	-0.001	0.019	-0.053*	-0.050*	-0.060**
	(0.012)	(0.012)	(0.015)	(0.024)	(0.031)	(0.037)	(0.027)	(0.027)	(0.028)
Mkt Barriers: Dominated $(t-2)$	0.022	-0.013	0.013	0.007	-0.036	-0.019	-0.032	0.006	-0.017
	(0.015)	(0.014)	(0.016)	(0.031)	(0.032)	(0.039)	(0.032)	(0.030)	(0.037)
Mkt Barriers: Uncertainty $(t-2)$	0.001	0.007	0.004	-0.029	0.003	-0.036	0.009	0.024	0.012
	(0.013)	(0.013)	(0.015)	(0.027)	(0.029)	(0.032)	(0.028)	(0.027)	(0.029)
Financial Constraints t_0	-0.002	0.001	-0.005	-0.026	-0.004	-0.017	0.025	0.018	0.029
	(0.011)	(0.010)	(0.012)	(0.020)	(0.022)	(0.026)	(0.027)	(0.026)	(0.030)
Initial value t_0	0.051***	0.042***	0.067***	0.090***	0.080***	0.126***	0.084***	0.062***	0.091***
	(0.010)	(0.010)	(0.012)	(0.021)	(0.022)	(0.030)	(0.024)	(0.021)	(0.025)
Time averages									
M.size	-0.000	-0.007	-0.004	0.020	-0.058	-0.030	0.005	0.042	0.026
	(0.016)	(0.014)	(0.017)	(0.033)	(0.044)	(0.042)	(0.037)	(0.032)	(0.038)
M.age	-0.013	-0.021**	-0.016	-0.016	-0.013	-0.019	-0.024	0.002	-0.003
	(0.010)	(0.010)	(0.011)	(0.017)	(0.016)	(0.021)	(0.023)	(0.020)	(0.022)
M.R&D	0.002	-0.006**	-0.005*	0.001	0.000	-0.004	0.006	-0.006	-0.002
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.008)	(0.008)	(0.009)
M.higher education	-0.030	0.002	-0.039	0.134**	0.137*	0.171**	-0.100	0.047	-0.037
	(0.032)	(0.031)	(0.038)	(0.065)	(0.073)	(0.083)	(0.086)	(0.095)	(0.102)

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Table 4.A9 – Continued

	KIS			NKIS			HTM		
	(1) Stop Conception	(2) Stop Implem	(3) Stop Overall	(4) Stop Conception	(5) Stop Implem	(6) Stop Overall	(7) Stop Conception	(8) Stop Implem	(9) Stop Overall
M.Financial constraints	0.041**	0.004	0.035	0.017	0.054*	0.043	-0.009	0.004	-0.036
	(0.020)	(0.019)	(0.023)	(0.033)	(0.029)	(0.042)	(0.045)	(0.043)	(0.049)
M.Knowledge barriers	0.019	0.043**	0.034	0.038	-0.045	0.000	0.087*	0.149***	0.133***
	(0.020)	(0.020)	(0.024)	(0.041)	(0.049)	(0.058)	(0.047)	(0.048)	(0.050)
M.dominated barriers	-0.047**	0.007	-0.038	-0.005	0.025	-0.005	0.022	-0.058	0.010
	(0.023)	(0.020)	(0.026)	(0.052)	(0.051)	(0.069)	(0.047)	(0.044)	(0.051)
M.uncertainty barriers	0.061***	0.031	0.070***	0.131***	0.097**	0.189***	0.037	-0.034	-0.005
	(0.020)	(0.020)	(0.023)	(0.043)	(0.047)	(0.051)	(0.047)	(0.045)	(0.051)
N	3011	3011	3011	332	332	332	483	483	483

Notes: Standard errors clustered at the firm level in parentheses; Estimations control for time and industry dummies. Marginal effects are reported at sample means. For dummy variables, the marginal effect corresponds to the discrete change from 0 to 1. Simultaneous estimation using CMP STATA command by Roodman (2018). Significance levels: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$; All models include year and industry dummies.

Table 4.A10: Robustness across Industries: Stopping Innovations (Marginal Effects)

	MHTM			MLTM			LTM		
	(1) Stop Conception	(2) Stop Implem	(3) Stop Overall	(4) Stop Conception	(5) Stop Implem	(6) Stop Overall	(7) Stop Conception	(8) Stop Implem	(9) Stop Overall
$\hat{S}$ (Survival Predicted)	-0.049	-0.060*	-0.071*	-0.004	-0.044	-0.002	-0.050	-0.070	-0.051
	(0.035)	(0.035)	(0.041)	(0.037)	(0.040)	(0.045)	(0.042)	(0.049)	(0.054)
Stop $(t-1)$	0.367***	0.324***	0.388***	0.303***	0.269***	0.341***	0.293***	0.269***	0.322***
	(0.008)	(0.009)	(0.008)	(0.010)	(0.013)	(0.011)	(0.010)	(0.012)	(0.012)
R&D expenditures (log) $(t-2)$	0.002	0.010***	0.010***	0.001	0.009***	0.010***	-0.003**	0.007***	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
R&D employees $(t-2)$	0.011	-0.065	-0.050	-0.115	-0.026	0.014	-0.018	0.013	-0.072
	(0.085)	(0.082)	(0.093)	(0.169)	(0.159)	(0.184)	(0.105)	(0.116)	(0.127)
Higher education $(t-2)$	0.025	-0.021	0.009	0.149***	-0.013	0.092	-0.006	0.049	0.021
	(0.043)	(0.042)	(0.047)	(0.043)	(0.058)	(0.060)	(0.061)	(0.060)	(0.070)
IP protect $(t-2)$	0.007	0.014	0.015	0.046***	0.032**	0.050***	0.029**	0.029**	0.039***
	(0.011)	(0.010)	(0.012)	(0.013)	(0.013)	(0.015)	(0.012)	(0.013)	(0.014)
Cooperation $(t-2)$	0.012	0.004	0.021*	-0.016	0.011	-0.013	0.004	-0.010	0.008
	(0.011)	(0.010)	(0.012)	(0.014)	(0.012)	(0.015)	(0.012)	(0.013)	(0.014)
Depth 0-10	0.004	-0.000	0.003	-0.005	-0.001	-0.003	0.002	-0.004	-0.004
	(0.004)	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Breadth 0-10	0.009***	0.004*	0.005**	0.011***	0.003	0.008***	0.012***	0.005**	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Size (log) $(t-2)$	0.040*	0.008	0.038	0.039	0.012	0.023	0.003	0.007	0.023
	(0.023)	(0.021)	(0.025)	(0.030)	(0.028)	(0.034)	(0.029)	(0.028)	(0.034)
Young	0.018	-0.019	-0.002	-0.019	-0.034	-0.032	0.008	0.021	-0.003
	(0.029)	(0.025)	(0.031)	(0.034)	(0.034)	(0.038)	(0.025)	(0.029)	(0.031)
Sales growth	0.029	0.007	0.008	-0.047*	-0.017	-0.028	0.006	-0.002	0.006
	(0.023)	(0.021)	(0.024)	(0.025)	(0.028)	(0.032)	(0.026)	(0.024)	(0.028)
Group $(t-2)$	0.014	0.022*	0.027*	0.006	-0.001	-0.005	0.005	0.007	-0.002

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Table 4.A10 – Continued

	MHTM			MLTM			LTM		
	(1) Stop Conception	(2) Stop Implem	(3) Stop Overall	(4) Stop Conception	(5) Stop Implem	(6) Stop Overall	(7) Stop Conception	(8) Stop Implem	(9) Stop Overall
	(0.015)	(0.013)	(0.016)	(0.016)	(0.015)	(0.018)	(0.016)	(0.015)	(0.019)
Foreign	0.034*	0.014	0.034*	0.020	0.020	0.026	-0.010	-0.028	-0.022
	(0.017)	(0.016)	(0.020)	(0.020)	(0.020)	(0.023)	(0.024)	(0.023)	(0.028)
Exporter $(t-2)$	-0.008	-0.007	-0.022	-0.002	0.016	0.007	0.004	-0.004	0.011
	(0.021)	(0.021)	(0.023)	(0.023)	(0.019)	(0.025)	(0.023)	(0.022)	(0.025)
Financial Constraints $(t-2)$	-0.011	0.003	-0.006	-0.032*	-0.027	-0.036	0.022	0.043**	0.045**
	(0.016)	(0.016)	(0.018)	(0.019)	(0.018)	(0.022)	(0.016)	(0.018)	(0.020)
Knowledge Barriers $(t-2)$	0.014	0.008	0.007	-0.001	-0.020	-0.023	0.005	-0.015	-0.006
	(0.016)	(0.015)	(0.017)	(0.018)	(0.017)	(0.020)	(0.019)	(0.019)	(0.021)
Mkt Barriers: Dominated $(t-2)$	-0.025	-0.003	-0.014	0.002	0.026	0.009	0.011	-0.012	-0.032
	(0.019)	(0.016)	(0.019)	(0.025)	(0.022)	(0.025)	(0.021)	(0.020)	(0.025)
Mkt Barriers: Uncertainty $(t-2)$	0.013	0.024	0.023	0.015	0.008	0.022	-0.036**	-0.045**	-0.033
	(0.018)	(0.015)	(0.018)	(0.020)	(0.017)	(0.021)	(0.017)	(0.020)	(0.020)
Financial Constraints t_0	0.014	0.009	0.007	0.024	0.020	0.025	0.004	0.001	-0.001
	(0.013)	(0.012)	(0.015)	(0.017)	(0.017)	(0.019)	(0.015)	(0.016)	(0.018)
Initial value t_0	0.060***	0.057***	0.072***	0.045***	0.030**	0.042**	0.080***	0.065***	0.086***
	(0.012)	(0.011)	(0.014)	(0.015)	(0.014)	(0.017)	(0.014)	(0.014)	(0.017)
Time averages									
M.size	-0.042*	-0.020	-0.051**	-0.025	-0.015	-0.018	0.022	0.010	0.003
	(0.023)	(0.022)	(0.025)	(0.031)	(0.028)	(0.035)	(0.030)	(0.029)	(0.035)
M.age	0.017	0.017	0.013	0.009	0.014	0.007	-0.007	0.004	-0.004
	(0.012)	(0.011)	(0.013)	(0.012)	(0.012)	(0.014)	(0.011)	(0.011)	(0.013)
M.R&D	0.006	-0.009***	-0.004	0.009**	-0.010***	-0.009**	0.009***	-0.001	0.004
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
M.higher education	-0.087	0.055	-0.050	-0.017	0.092	0.068	0.077	0.069	0.104
	(0.057)	(0.056)	(0.064)	(0.064)	(0.069)	(0.079)	(0.078)	(0.077)	(0.087)

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Table 4.A10 – Continued

	MHTM			MLTM			LTM		
	(1) Stop Conception	(2) Stop Implem	(3) Stop Overall	(4) Stop Conception	(5) Stop Implem	(6) Stop Overall	(7) Stop Conception	(8) Stop Implem	(9) Stop Overall
M.Financial constraints	0.026	0.011	0.019	0.029	0.016	0.027	-0.001	-0.045*	-0.028
	(0.024)	(0.024)	(0.027)	(0.027)	(0.027)	(0.032)	(0.026)	(0.027)	(0.033)
M.Knowledge barriers	0.010	0.003	0.012	0.010	0.032	0.034	-0.031	0.036	-0.010
	(0.027)	(0.025)	(0.030)	(0.030)	(0.029)	(0.034)	(0.030)	(0.036)	(0.040)
M.dominated barriers	0.093***	0.022	0.096***	0.010	-0.040	0.000	-0.014	0.004	0.029
	(0.031)	(0.027)	(0.035)	(0.045)	(0.036)	(0.049)	(0.035)	(0.035)	(0.041)
M.uncertainty barriers	-0.049*	-0.026	-0.064**	0.029	-0.003	0.015	0.075***	0.100***	0.083**
	(0.029)	(0.025)	(0.032)	(0.036)	(0.029)	(0.038)	(0.029)	(0.032)	(0.036)
N	1558	1558	1558	897	897	897	791	791	791

Notes: Standard errors clustered at the firm level in parentheses; Estimations control for time and industry dummies. Marginal effects are reported at sample means. For dummy variables, the marginal effect corresponds to the discrete change from 0 to 1. Simultaneous estimation using CMP STATA command by Roodman (2018).. Significance levels: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$; All models include year and industry dummies.

Supplementary Materials

Supplementary materials are available in the following repository: https://github.com/velezjorgea/Paper_Subsidy_Persistence