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 the continuity or persistence of its use.

Broadly speaking, sustained exposure to an innovation policy instrument may change the conditions from 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).

Some existing research has indeed found that firms' participation in R&D stimulating policies is persistent over time (Aschhoff 2008; Busom, Corchuelo, and Martínez-Ros 2017). That means successful 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.

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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). In general, almost all empirical studies find that R&D subsidies have the potential for encouraging firms to entry into R&D and 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. The bottom line of this is to find to what extent continuous engagement in the innovation policy is explained by firm heterogeneity (think 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 provide the desired innovation outcomes. That is, does continuity in the use of R&D subsidies lead to more 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). In chapter 3, we find that the effect of R&D subsidies lasts longer for firms with more prolonged use of the policy.

The third question is to what extent continuous engagement in R&D subsidization is also reflected in 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 decide to terminate innovation projects (Mohnen, Palm, Van Der Loeff, and Tiwari (2008) for the Netherlands; Radas and Bozic (2012) for the case of Croatian firms. García-Vega and López (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 the degree of persistence into the model. This approach has the advantage of handling the possibility of endogeneity of subsidies in the innovation production function. With the aim of capturing 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 and 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, a distinction is made between SMEs and large firms about the degree of persistence and the impact that continuous engagement in the policy may have on innovation.

From the public policy perspective evaluating the extent to which continuous engagement in a support program leads to changes in innovation outcomes would have implications for the designing and targeting R&D stimulating policies. If continuous use of the policy- as measured by its degree of persistence- leads to higher innovation outcomes, then R&D subsidies should boost firms' continuous use of the policy measure as a way to intensify the effectiveness of R&D regarding innovation results. If R&D subsidy persistence does not derive in higher innovation results or lower probabilities of stopping innovation projects, then there would be no need for encouraging firms to use the policy continuously.

Our main findings are summarized 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. Second, R&D subsidy persistence leads to better innovation outcomes, including a lower probability of abandoning innovation projects. However, there are some striking differences in behavior between SMEs and large firms. In particular, R&D subsidy persistence is associated with achieving new-to-market innovative products for SMEs while it is not for large firms. Thus, from the policy perspective, encouraging continuous use of R&D subsidies in SMEs seems to be particularly more appropriate in fostering innovation results that are far from the market and whose degree of market failure may be higher.

The chapter has the following structure. In section 2 we provide some previous evidence. Section 3 briefly describes the data and the empirical methodology. Section 5 presents and discusses the estimation results. Finally, in Section 6 we conclude.

4.2 Some 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 the 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).[1] Moreover, public agencies might also prioritize firms of particular importance (e.g., smaller firms, young innovative firms, start-ups, high growth firms).

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

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 up due to 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 2008). 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 obtaining subsidies in future applications (Antonelli and Crespi 2013).[2]

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

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

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 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; García-Vega and López 2010 and García-Quevedo et al. 2018 for the Spanish case). Stopping an innovation project could be associated with poor access to critical resources, or because there are barriers revealed in the process of conducting innovation activities.

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. On the other hand, 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).[3] 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 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 due to 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 available if it had to rely on 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 their

[3] 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.

ability to finalize an innovation project. However, the primary focus of the author is to analyze the influence of barriers to innovation on the abandoning of innovative activities, and not to investigate the role of public support.

All these studies, however, overlook the fact that continuous engagement in R&D subsidization can also affect the potential risk of stopping innovation projects. In a profit-maximizing scenario, it is expected that firms embark on those projects that have the highest expected returns (David et al. 2000). Suppose a firm has a portfolio of four projects, three of which can be undertaken with internal financial means. The fourth one entails higher uncertainty and risk which can derive in low or even negative private expected return. Though the project is not profitable for the private investor, it is expected to have positive social returns, increasing the likelihood of getting support. If the firm obtained an R&D subsidy to finance the fourth project and if the firm does not reallocate the available funds within its R&D portfolio, then the risk of stopping it would decrease even if it may not lead to positive private returns.

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.[4] 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.[5] 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

[4] 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.

[5] 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.

not provide information on tax incentives. Busom, Corchuelo, and Martínez-Ros (2014), studying the degree of 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.[6]

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). In order to eliminate all fluctuations among firms, three more filters are carried out: first, we drop firms that experienced merger or takeover processes, as well as drastic employment incidents[7]; companies on a merger or acquisition process; employment regulation or liquidation phase; second, we eliminate observations with anomalies, such as extreme values and null sales.[8] 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

[6] 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.

[7] 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).

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

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 (%)	92.6	7.3
Yes (%)	29.1	70.9
Large firms		
No (%)	92.6	7.3
Yes (%)	29.1	70.9

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.

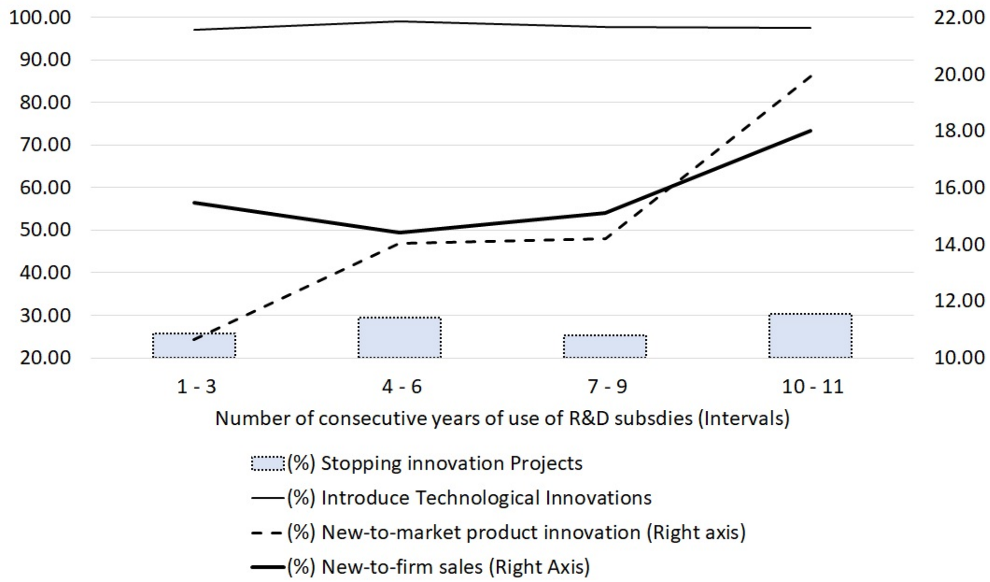
Figure 4.1 (for SMEs) and Figure 4.2 (for large firms) show the relationship between the level of R&D subsidization length (i.e., the number of consecutive years in which firms have been subsidized) and some output indicators including the average proportion of firms abandoning innovation projects. Data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

Looking more closely at the trends, the average SMEs introducing products new to the market increases steadily from 10.63% in years 1 to 3 to 14.21% 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 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%.[9]

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.

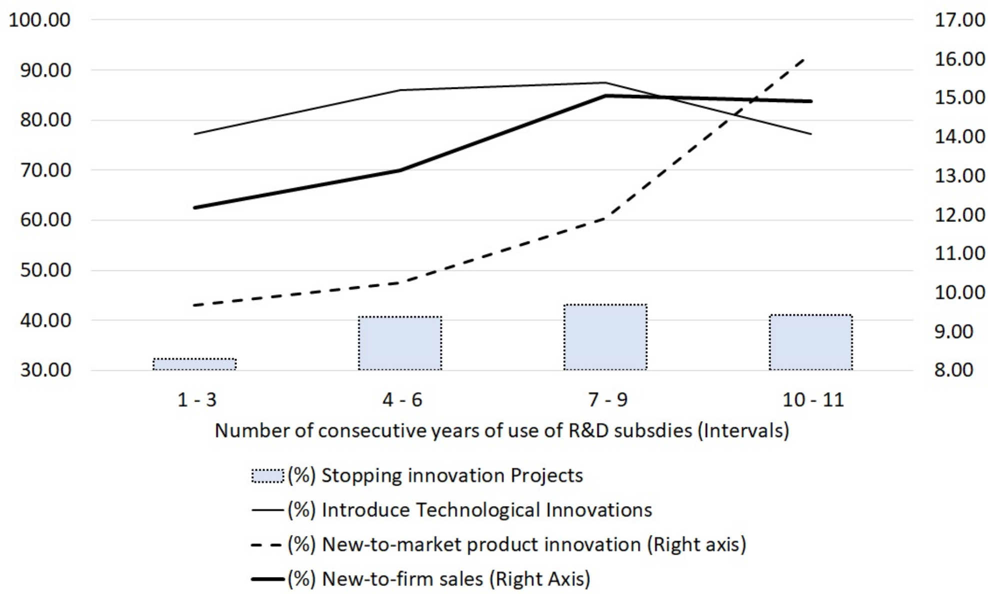
[9] Percentage calculated by the authors using the OECD STI Scoreboard 2017: http://www.oecd.org/sti/inno/inno-stats.htm

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: SMEs



Notes: As in Figure 4.1

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 assume that the duration of an R&D subsidy is treated as a discrete variable since firms can apply for and obtain support repeatedly (on an annual basis).[10] In particular, the model that 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 in order to integrate out the unobserved effect. Hence, we will incorporate unobserved heterogeneity checking its closed form expression. For that aim, we will treat u parametrically and non-parametrically.[11]

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

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

[10] 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)).

[11] 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.

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.[12]

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 [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 [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:

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

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

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 will 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 as well as 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 as well as 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.[13] 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 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).[14]

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[13] 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).

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

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.[15] The latter reflects the number of information sources rated as highly significant. It is expected that the firm might improve the probability of acquiring 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.[16] Thus, it is assumed 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

[15] 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.

[16] 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.

variable indicates if the firm is hampered by financial constraints or not (FC^*_{it}) (Equation [4.7])

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

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.

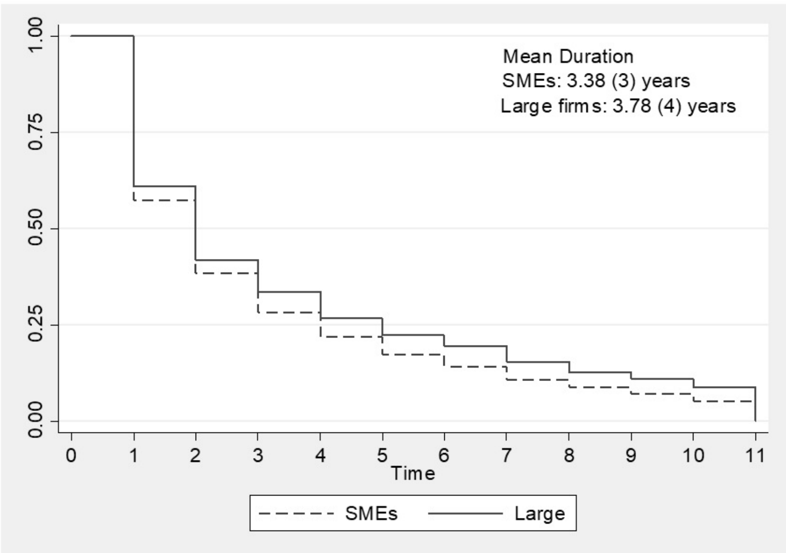
4.4 Results

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 plots a description of the Kaplan-Meir survival estimates. 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.[17] 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.

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.

Table 4.2 reports the results 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) Cloglog model with "mass points"

[17] A log-rank test for equality of survivor functions between SMEs and large firms shows a significance difference between their survival functions (Chi2= 33.1 with pr>chi2=0.000).

in the unobserved heterogeneity distribution (columns 3 and 7).[18] This estimation method treats unobserved heterogeneity non-parametrically; (iv) A standard Random Effects probit model (columns 4 and 8). Coefficients are shown in 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.

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 duration dependence, suggesting that the probability of subsidy spell termination decreases as the firm accumulates experience in the subsidization program. 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 sucessful 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 2008; 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. 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 with a greater share of employees holding higher education as well as with a higher ratio of R&D employees experience a lower probability of subsidy spell ending. This result is expected as

[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.

[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.

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 in 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 of a negative relationship between cooperation for technology activities and persistence 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 result could also be the reflection 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 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 R&D subsidy survival: The smaller the size, the higher the rate of R&D subsidy persistence is (as shown by the negative coefficient of log size). Second, we observe that being a young firm increases the probability of experiencing lengthier subsidy spells. 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, accessing to EU funding has a negative and significant effect on the likelihood of interrupting a spell of R&D subsidization. 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 subsidies spells

	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)
(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	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	-3,501.176	-3,501.176	-3,501.17	-3,464	-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 R&D subsidy survival and the innovation outcomes - the coefficients obtained are in line with the hypothesis that R&D subsidy persistence increase innovation results. Despite the presence of some common features, differences in behavior between both groups of companies are observed: in the case of SMEs, the predicted survival rate increases the likelihood of introducing technological innovations as well as 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 is positive and statistically significant on radical innovation. Although they do not differentiate their results between SMEs and large firms and their data are cross-section.

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	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 data structure, especially for 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.[20] The dependent variable takes the

[20] 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 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.[21] First, size and financial constraints

[21] 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.

4.5 Conclusions

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

Our empirical analysis comprises three reduced-form equations. 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 continuous exposition to innovation policies. This means that a higher number of consecutive years using the policy would also be an input for increasing the rate of innovation success.

Results would seem to suggest that firms receiving public funding for R&D activities could accumulate knowledge and experience that would increase the chances of getting support in latter applications. Results also confirm that continuous R&D performers have a positive likelihood of reducing the hazard of ending an R&D subsidy spell. We also find that new-to-market product innovation is triggered by small firms participating continuously into the R&D subsidization program while for large ones they did not. Besides, survival in R&D subsidization also reduces the likelihood of abandoning R&D projects at either the concept stage or mature stages.

From a policy perspective, the results point towards a so far unexplored effect of R&D subsidization persistence on innovation performance. Even with good intentions R&D stimulating policies risk to misallocate funding for two reasons: First supporting a current wrong set of firms (think of firms that cannot adapt to distinct competitive environment or without the ability to identify and exploit the features and associated benefits of their products or services); second, supporting R&D projects that are not really ambitious and aim to introduce innovations close to the market where market failures are lower. Even though allocating resources to the "right" ones could be a difficult task, observing data and vetting potential sources of subsidy persistence and its effect on innovation could serve as an objective indicator for future policy design — for instance, distinguishing the behavior between firms of different size. According to our results, it seems plausible to encourage continued use of R&D subsidies in SMEs as it could foster radical and risky innovation as well as reducing abandoning. Even though continuous use of R&D subsidies does not render significant effects for innovations far from the market (i.e., radical innovation) for large firms, the effect of subsidy persistence does reduce the likelihood of stopping innovation projects whatever the stage. Notwithstanding, we believe that more work should be done to understand better all the forces driving the heterogeneous effect of subsidy persistence.

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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 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 indicator of participating 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	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-1)	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.

Supplementary Materials

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