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Participation inertia in R&D tax incentive and subsidy programs

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Abstract We examine how persistent firms' participation is in R&D subsidy and tax incentive programs, and whether persistence is driven by individual heterogeneity—observed and unobserved—or by state dependence. Using a panel of Spanish manufacturing firms over the period 2001–2008, we estimate a set of dynamic models of program participation. True state dependence of participation in each program is found to be significant, while unobserved heterogeneity accounts for about 41 and 29 % of observed persistence in subsidy and tax credit programs, respectively. Both tend to reach mostly stable R&D performers. We also identify significant differences across programs. Highly productive firms within a given industry are more likely to obtain subsidies; the use of tax credits, in contrast, is unrelated to a firm's productivity. Our results suggest that R&D tax incentives and R&D subsidies are not substitutes and that any unintended misallocation of support is likely to persist.

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1 Introduction

Governments in developed countries allocate public resources—up to 0.4 % of gross domestic product in 2011 (OECD 2013)—to support business research and development (R&D) through tax incentive and subsidy programs. Total public support for business R&D has increased since 2006, especially the share of government funds for R&D accounted for by tax incentive schemes (OECD 2014). In most OECD countries, they are offered simultaneously, although with varying emphasis. While in the USA, the share of tax incentives on total government support for business R&D was about 23 % in 2011, in France, this share was as high as 70 % (OECD 2013). As with any policy intervention, a number of questions arise concerning the features of firms that benefit from each program, the efficiency of each individually and as policy package and their final impact on productivity growth at the micro- and macrolevels.

The ultimate justification of both policies is their potential ability to address market failures associated with the production of knowledge by the private sector. Whether it is best to rely on tax incentives or on direct support or on a combination of both to reach this goal is a controversial issue. Claims in favor of each have been made, yet extant evidence does not offer a conclusive answer to this question. Most empirical studies have focused on testing for potential crowding-out and crowding-in effects of each type of support separately (Castellacci and Lie 2015, Dimos and Pugh 2016). These impact estimates—or *additionality*, as they are known in this literature—provide a useful but partial picture of the ex post efficiency of R&D subsidy and tax incentive programs. In particular, the analysis of how support is allocated across firms, or participation stage, is not the main focus of most studies. Yet, we believe that doing so can bring insights about how each policy works and reveal some potential limitations (Haapanen et al. 2014; Yin 2009; Budish et al. 2015).

We contribute to the debate by analyzing the dynamics of participation patterns in each program. We address two main questions: (1) Is the pool of firms that benefit from each policy always the same, or are entry and exit rates significant? and (2) does receiving a subsidy increase the chances a firm will use tax incentives in the future and vice versa? The first question involves testing whether participation in one of these programs predicts future participation in the same program, that is, the extent of inertia or state dependence. Participation persistence may simply reflect that some firms' R&D projects always involve significant spillovers or innovativeness and are thus permanently eligible for public support. On the negative side, persistence may signal that once a firm participates, further participation follows irrespective of project features, suggesting that the practical implementation of the policy is not fully aligned with its purpose. Disentangling the relative weight of heterogeneity and of true state dependence in driving persistence is thus relevant to improving policy design and efficiency.

The second question we address deals with the dynamic interaction between R&D subsidies and tax incentives, or potential dynamic cross-program spillovers: Participation in one program may predict future participation in the other. High cross-persistence from subsidies to tax credits would imply that the first program has long-term budgetary consequences that should be taken into account when designing the subsidy program. Cross-persistence from tax credits to subsidies would instead suggest that firms that invest in privately profitable R&D are able to undertake R&D projects that match the public agency's preferences, a desirable policy outcome.

To investigate these issues, we analyze a longitudinal firm-level dataset of Spanish manufacturing firms over the period 2001–2008 which includes information on participants and non-participants in R&D support programs.[1] R&D subsidies and tax credits have been in place simultaneously in Spain since before 1995, when a new corporate tax law substantially increased tax incentives for R&D investment. We estimate a reduced form of the application and granting process, both for subsidies and tax credits. Our results show that true state dependence and some observed firm characteristics drive most of the participation persistence: Participating once increases the likelihood of doing so the following period, conditional on observed and unobserved firm features. Unobserved individual heterogeneity accounts for about 41 % of persistence in the case of subsidies and 29 % in the case of tax credits. Finding evidence of true persistence may not be fully satisfactory from a policy perspective, as it could suggest that over time either the base of firms with genuine innovating projects—with high spillover potential—is not expanding, or that if it is, public support might not be reaching them. It may also reflect that repeated participation—especially in tax incentive programs—is unrelated, to a good extent, to project features, as accounted for by individual unobserved heterogeneity. Other mechanisms to provide public support might be more appropriate for some types of firms such as start-ups and young knowledge-based firms, or for some types of projects (riskier and lengthier than those the market would produce).

Our findings also suggest that, given macroeconomic and other framework conditions prevailing during the period analyzed, R&D tax incentives and subsidy programs reach mostly incumbents—firms

[1] Participants are defined as firms that obtain an R&D subsidy or claim a tax credit a given year. We do not analyze separately the dynamics of applying for support from the dynamics of obtaining it conditional on applying, since the data set does not contain information about unsuccessful applications.

that were already performing R&D—large firms and those in high-tech industries. We finally identify some differences across both programs. Highly productive firms within a given industry are more likely to obtain subsidies, while the use of tax credits, in contrast, is unrelated to a firm's productivity. A plausible explanation is that high-productivity firms are more likely to undertake high-quality innovation projects and to apply for direct support and therefore more likely to succeed at the public agency selecting them. Claiming tax credits, in contrast, does not usually require passing this filter.

The paper layout is as follows. In Sect. 2, we explain how R&D subsidies and tax incentives have been analyzed in previous work and present our arguments for analyzing the evolution of program participation over time. In Sect. 3, we describe the data as well as the institutional setting. Section 4 outlines the empirical model; we describe the estimation results in Sect. 5. In Sect. 6, we discuss our findings and their implications and conclude in Sect. 7.

2 Analyzing public support to business R&D: some questions

The high relevance of innovation for growth and social welfare, the close association between innovation and R&D investment and the extent of private underinvestment in some types of R&D projects—those that generate important spillovers—or by some types of firms—young, knowledge based, financially constrained—have been widely documented by many empirical studies. This body of research provides a solid ground for designing appropriate policies to support innovation (Hall et al. 2010; Hall and Lerner 2010). However, implementing them is not an easy task for several reasons. A substantial one is that an efficient allocation requires two conditions: (1) sufficient information to identify R&D projects that are socially desirable but either generate too low private returns or cannot obtain private funding and, (2) the ability to match support to relevant project features.

Because of imperfect and asymmetric information, unintended mistakes in policy design and implementation can be easily made (Haapanen et al. 2014; Yin 2009). Analyzing the allocation of support and its impact on a set of relevant variables can help identify unanticipated policy limitations. Some questions that can be raised in this regard are the following: (1) Do R&D tax incentives and subsidies crowd-out private R&D investment? (2) To what extent is firms' participation in these programs correlated with market failures? and (3) Who benefits from R&D tax credits and subsidies over time: Do the same firms always benefit from each program? We next clarify the relevance of each question, briefly comment existing evidence and explain how we extend previous work.

2.1 The crowding-out question

The main focus of most empirical research has been testing whether R&D subsidy and tax incentive programs induce substitution of private for public funding, or on the contrary, they contribute to increasing private R&D effort.[2] To this end, samples of participating and non-participating firms in a particular program have been analyzed and compared using a variety of empirical methods to control for the endogeneity and selection issues that arise when program participation is not random.[3] What many studies have not explicitly accounted for is that these two programs may be available at the same time in a country. Consequently, estimates for individual programs may be upward biased. In the case of R&D subsidies, studies for the few countries where tax incentives are not offered reject the hypothesis of full replacement of private by public funding (Czarnitzki et al. 2007).

Aggregate estimates of the impact of R&D tax incentives suggest that they increase private R&D intensity (Bloom et al. 2002), but recent micro-level studies are more nuanced. Results might depend on the specific tax relief design. Lokshin and Mohnen (2012) find evidence of partial crowding out when beneficiaries are large firms in the Netherlands. Cappelen et al.

[2] This is known in the literature as input additionality. Some studies also estimate the impact of each program on outcomes such as patenting and on the introduction of product and process innovations (output additionality) or on the type of R&D conducted (behavioral additionality).

[3] A popular method used to control for selection into treatment is the estimation of the propensity score (probability of receiving a grant) in order to obtain a comparable control group for the treated. For recent examples, see Czarnitzki and Lopes-Bento (2013), Hottenrott and Lopes-Bento (2014) and Hud and Hussinger (2015).

(2012) find that the Norwegian SkatteFUNN tax credit scheme increases the introduction of products new to the firm and new processes, but not major product innovations. In contrast, Dechezleprêtre et al. (2016), exploiting a policy reform of the R&D tax scheme in the UK, find that it has large effects on R&D and patenting activity.[4]

Complementing this work, some studies investigate whether R&D subsidies—or subsidized loans—induce firms that were not previously investing in R&D to do so, and whether they prevent firms from stopping R&D, that is, whether they have an effect on the extensive margin (González et al. 2005; Arqué-Castells 2013; Huergo et al. 2015). Others have estimated the impact of support on patenting and on the introduction of innovations by firms that benefit from these programs. For example, Bronzini and Iachini (2014), Bronzini and Piselli (2016) find that R&D subsidies increase R&D investment and the number of patent applications only by small firms, adding evidence to the hypothesis that the effects of support are not homogeneous across firms. The literature is quite extensive by now; the surveys by Cerulli (2010), Correa et al. (2013) and Zuñiga-Vicente et al. (2014) provide systematic overviews of empirical methods and findings of this line of research. In addition, Dimos and Pugh (2016) and Castellacci and Lie (2015) use meta-regression analysis of existing micro-level studies to find a representative effect of subsidies and tax incentives, respectively, taking into account publication bias and several sources of heterogeneity in the design of empirical strategies.

There are, however, some limitations to focusing exclusively on additionality estimates to assess each policy, as discussed in Takalo et al. (2013a, b) and Busom et al. (2014). First, these estimates do not inform about the success of each program in addressing the potential market failures that are associated with some types of innovation activities that justify public support. For example, R&D projects that generate high spillovers should not be expected to induce high additional private investment (high input additionality) precisely because spillovers limit private returns. Or some firms might increase their R&D investment because support lowers the cost of R&D, but the social value of these projects might be lower than their social cost. In fact, additionality estimates do not necessarily provide a measure of the net welfare gains induced by the policy, as Takalo et al. (2013a, b) show through a formal model. Second, additionality estimates do not reveal whether potential and unintended barriers to program participation exist. In particular, a program might systematically reach only a narrow subset of the population of targeted firms or might repeatedly benefit the same set of firms, irrespective of R&D project features. To answer these questions, the allocation of support, or firm participation stage, has to be addressed as well, both from a static and a dynamic perspective.

2.2 Allocation of support and market failures

Although program participation has not been the main focus of most research on innovation policies, a small number of studies have analyzed it for some R&D subsidy programs. Two of them use firm- and project-level information. Takalo et al. (2013a, b) use data from Tekes, the Finnish funding agency for innovation, to estimate the determinants of allocation process considering both the application by firms and the awarding decisions by the public agency. They find that exporters and larger firms are more likely to apply and that the public agency awards grants according to the quality of submitted proposals. Huergo and Trenado (2010) perform a similar analysis for the case of Spain and find comparable results. While this research shows that a firm's presence in export markets increases both the probability to apply and the probability to obtain support, an explicit consideration of the role of project or firm features connected to market failures is not made in this work.[5]

Recently, Busom et al. (2014) have investigated the extent to which two indicators of market failures:

[4] In the UK, the scheme provides an enhanced deduction of R&D from taxable income and allows for a higher deduction for SMEs. In addition, SMEs investing in R&D but not making (enough) profits can claim the refundable tax credit. See also Bond and Guceri (2012), Fowkes et al. (2015), Guceri and Liu (2015) and Wallis (2016).

[5] See also Colombo et al. (2016), who investigate the participation of new technology-based firms in EU-funded partnerships and find that venture capital backing increases the likelihood that a firm will participate in this type of program. Dai and Cheng (2015), Corchuelo and Martínez-Ros (2010), Marín and Siotis (2008) and Blanes and Busom (2004) study participation in other R&D programs.

Financing constraints faced by firms to conduct innovative projects, and appropriability of returns, are correlated with firms' access to R&D subsidies and to R&D tax credits. They find that both for SMEs and large firms, facing innovation-specific financing constraints increases the probability of obtaining R&D subsidies, while it decreases the probability of claiming tax credits for R&D. This result lends support to the idea that these two policies are not equivalent or substitutes and suggests that if financing constraints were the only cause of underinvestment in R&D, R&D tax incentives, as designed, would not appear to be an appropriate policy to address this particular market failure, while R&D subsidies would be.

The studies reported here take a basically static approach, as they show how some firm-specific factors explain participation in R&D support programs at a point in time. The next question to ask is how participation evolves over time: whether it is intermittent or persistent, whether recurring participation is driven by individual features and whether participating once leads to further participation irrespective of firm or R&D project properties. Answers to these issues may convey further information about potential policy inefficiencies or unintended mistakes.

2.3 Persistence of participation in R&D support programs

From a policy perspective, firms' continued participation in R&D support programs is desirable to the extent that underlying obstacles to carry out socially valuable innovation projects that would not be pursued otherwise persist. Because these obstacles are project and firm specific, we should expect any observed persistence to be associated with financing constraints, firm's age or size and appropriability issues, that is, to be driven by individual heterogeneity. If persistence is instead driven exclusively by previous participation and is independent of any other factors, we would suspect that some failure in the policy design or implementation might be at work.

Well-intended public support can distort private R&D decisions in such a way that global welfare is reduced instead of increased. Since changing the rules once they are in place can be hard, welfare losses may accumulate. Recent work by Akcigit et al. (2014) illustrates the first point by modeling alternative innovation policies within the framework of an endogenous growth model. The authors assume that research projects differ in their potential for generating spillovers; the standard classification into basic and applied research approximates this idea, as well as the concepts of radical or generic versus incremental innovations. Two of the policies they investigate are a project type-dependent research subsidy—a selective subsidy—and a uniform private research subsidy, where a fraction of each firm's total R&D investment is subsidized.[6] In the competitive equilibrium, firms overinvest in applied research and under-invest in basic research. The first best policy is to provide differentiated subsidy rates for different types of projects. A uniform subsidy accentuates overinvestment in applied research and lowers total welfare relative to selective subsidies. They use French firm-level information to estimate their impact on the aggregate economy. From their results, we can conjecture that a sustained uniform subsidy would generate cumulative welfare losses; this strengthens the case for exploring how the allocation of support evolves over time.[7]

Our data allow us to compare two programs that differ in their ability to discriminate across types of R&D projects, as well as in terms of eligibility requirements, volume and timing of public support. R&D subsidy schemes allow the public agency to select R&D projects, while tax incentive schemes do not or much less so.[8] Direct R&D subsidies are allocated to projects that fulfill some specific conditions set by the public agency: Either the project is socially valuable but not sufficiently profitable for the firm—because of knowledge spillovers or of technical

[6] In their model, they also consider the optimal public funding for academic research, which consists of basic research.

[7] See also González et al. (forthcoming), who show that market incentives might lead pharmaceutical firms to overinvest in incremental R&D relative to radical R&D, in which case a non-discriminatory subsidy (tax credit) would induce welfare losses.

[8] There is a high variety of possible tax incentive designs. Some may offer tax breaks from the corporate income tax, others from payroll and social security taxes, or from the value-added tax. Some countries offer combinations of all. In addition, they may be based on R&D volume or on incremental expenditure; they may include special provisions for young firms and SMEs or for firms that collaborate with public research centers; they can contemplate cash refunds, carry-forwards and caps to deductions. All of these may affect the degree of discrimination across R&D types as well as the subset of effective beneficiaries.

risk—or the firm faces innovation-specific financing constraints. Usually, awarding agencies match the volume of support to project features and provide initial funding for carrying it out. To be able to benefit from tax incentives, a firm has to first fund an R&D project that complies with the tax authority definition of R&D. This entails fulfilling the requirement that this investment leads to the development of a product or process that provides substantial novelty at the market level. The firm, however, does not have to show that the social value of the project is higher than private return or that it cannot fund the project; tax authorities do not have to verify this either.[9]

When the tax incentive is designed as a deduction from the firm's corporate tax liability, only firms with positive taxable income and ability to finance—with own or with external funds—their R&D investment will be able to claim it. Conditional on this, any R&D project will qualify, whether it generates spillovers or not. Firms that lack internal or external funding to start valuable R&D projects are unlikely to benefit from this scheme.

It is reasonable to expect that the differences just described between both policies will affect participation dynamics. When tax incentives are implemented through the corporate income tax, several factors may lead to participation persistence. Large or diversified firms and established firms, those with a limited number of competitors and some market power, are all more likely to benefit repeatedly from R&D tax incentives—conditional on investing in R&D—because they usually generate positive taxable income on a regular basis, in contrast to SMEs, firms with many competitors or young firms. The concern that tax incentive persistence may signal that this scheme could protect incumbents against innovative entrants has been pointed out by Bravo Biosca et al. (2013).[10] Criscuolo et al. (2016) also argue that when the government has imperfect monitoring ability, firms (especially large firms) will use support to fund inframarginal investments that the firm would have made even in the absence of government intervention.

In addition, incumbents and large firms are less likely to suffer from innovation barriers and more likely to engage in incremental—exploitation—R&D. Innovations by firms whose R&D projects generate appropriable returns not only increase revenues, but also the firm's internal funds and consequently increase their ability to keep investing in R&D. This mechanism is consistent with the hypothesis of "success-breeds-success"; a tax incentive scheme would reinforce it.

Participation persistence in R&D subsidy programs is a priori indeterminate. On the one hand, the government agency may target mostly firms in one or several of the following categories: new knowledge-based firms; firms that face high R&D fixed costs; firms that are financially constrained to innovate; and firms whose projects exhibit limited appropriability but have high social value. In these cases, support may be intended as a temporary lever for firms to embark in innovation or to perform specific types of projects, like those of an exploratory nature. We would expect firm participation turnover to be high and therefore persistence to be low on average. On the other hand, public agencies may select ambitious, long-term R&D projects exhibiting technical uncertainty, fixed costs and widespread spillovers; these projects may require continuous funding to keep them going; public support would then involve continued participation.

Finally, dynamic cross-program interactions may take place. Recipients of direct support could be in a position to claim tax credits in future periods, especially if support allows the firm to make profits from resulting innovations, as would be expected if the subsidy aims at easing funding constraints rather than compensating for limited appropriability. R&D subsidies may then lead to cross-persistence of tax credits with respect to subsidies. On the other hand, some of the firms that enjoy tax credits may be interested in undertaking projects that fulfill the requirements of the public agency, in particular if at some point, they face financing constraints.

Aschhoff (2010) is the only study we know of about participation persistence in direct support programs. She investigates whether in Germany firms that obtain R&D subsidies do so repeatedly, becoming a

[9] In Spain, the corporate tax code distinguishes between market- and firm-level novelty. In the second case, a firm that adopts an innovation can still claim a tax credit, but the rate is lower.

[10] This may depend on the specific design of R&D tax incentives. For instance, in the UK, if firms make no taxable profits, the tax credit turns into a subsidy. This may encourage young firms and SMEs to participate in the tax relief scheme. See HMRC (2014).

stable group, or whether the composition of the pool of participants changes over time. She finds that participation is very stable and that entry rate into the program is very low. In her sample, however, over 40 % of the firms were observed only once and very few over two consecutive years; she could not therefore estimate a truly dynamic model to control for unobserved heterogeneity as a potential driver of persistence. Our main contribution is that we are the first to estimate a dynamic model for participation in each program, tax credits and subsidies, disentangling the sources of persistence and testing for potential cross-program spillovers. We now turn to explaining the institutional setting and the data.

3 Institutional setting and data

We use a rich longitudinal data set of manufacturing firms in Spain to study the dynamics of participation of firms in both R&D support programs over the period 2001–2008. We first summarize the main features of these programs in Spain and then describe the dynamic patterns we observe in our data.

3.1 Institutional setting

Both R&D subsidy schemes and R&D tax incentives have been in place in Spain since the 1980s. The main public agency providing funds for firms' R&D and innovation projects is the Center for the Development of Industrial Technology (CDTI), created in 1977 by the central government. Its budget to support business projects increased substantially in 2003 and following years, from €236 Million to €1090 Million in 2007, with a temporary drop to €766 Million in 2008. CDTI runs several types of programs: Some provide refundable low-interest loans and others a direct grant, depending on the nature of the project—whether firms cooperate with public research centers, whether firms are young and/or small and the degree of novelty, are, with project quality, some of the attributes that CDTI takes into account. In 2008, 1926 applications were submitted; about 60 % of these projects obtained support. Firms with 50 or less employees had submitted about 47 % of the approved projects. Almost one thousand (967 firms) obtained support in 2008. In aggregate terms, the volume of public support provided represented 50–60 % of the full project cost.[11]

Regional governments and the European Union also provide direct support for business R&D projects. In this paper, however, we focus exclusively on the first source of funding because for Spanish firms it is the main source of funds, because differences in goals across jurisdictions are likely to generate different dynamics, and because it is the more appropriate program to compare with R&D tax incentives.

Spain's R&D tax incentive scheme, exclusively offered by the central government, allows firms to deduct a given percentage of their R&D expenditures from their corporate tax liability.[12] The definition of R&D is based on the OECD's Frascati Manual. The scheme is designed as a hybrid system, combining volume and incremental based deductions, and is applicable to both SMEs and large firms. Firms can deduct 25 % of their qualifying expenditures and an additional 42 % (50 % until 2007 included) of their incremental expenditure. There is a cap to the total amount of credits that can be claimed in the tax period, 35 % of the tax liability. In case of insufficient tax liability, a firm can claim the credit in the next 15 tax periods. There are no refunds for firms that do not have positive taxable income.[13]

In 2008, about 3150 firms claimed tax credits for a total of €326 Million, which account for roughly 4 % of in-house business R&D investment. About 75 % of this volume was claimed by large firms. Although absolute magnitudes are much larger in the USA, in relative terms the picture is not much different: According to a report from the US Government Accountability Office, in 2005 the net credit claimed accounted for about 4.5 % of qualified research expenses (US GAO 2009).[14] During the period 2001–2008, the volume of subsidies provided through

[11] This information is available in the annual reports of CDTI, accessible in Spanish at: http://www.cdti.es.

[12] Although available since 1978, a major change in the corporate tax act in 1995 introduced substantial changes in tax incentives, increasing their appeal for businesses.

[13] See http://www.oecd.org/sti/rd-tax-stats.htm#design for a detailed comparative description of R&D tax schemes in OECD countries. According to OECD estimates, the implied tax subsidy rates for Spain are among the highest within member countries.

[14] See United States Government Accountability Office (US GAO 2009, Table 3, page 53).

CDTI was about three times as large as that of tax credits, a proportion also similar to that of the US schemes.

3.2 Data

Our data source is a firm-level annual survey of manufacturing firms sponsored by the Ministry of Industry of Spain since 1990, the *Encuesta Sobre Estrategias Empresariales* (ESEE hereafter). All firms with more than 200 employees are surveyed; those between 10 and 200 employees are selected through a stratified, proportional and systematic sampling; firms with less than 10 employees are not included.[15] The survey contains information on firms' products, employment, markets and technological activities. Since its inception, it includes questions on a firm's R&D investment and use of direct public support (loans and grants); in 2001, questions relative to the use of tax incentives were added.[16] To compare the use of both policy instruments, we use data from 2001 to 2008, which was a period of economic growth up to 2007.

Our initial sample consists of an unbalanced panel of about 2000 firms from 2001 to 2008, although the number of firms was smaller some of these years.[17] About 30 % of them have more than 200 employees, and 21 % are in high- or medium-technology industries. On average, in this period 36 % conduct R&D, whether internal or external; 13 % claim R&D tax credits (one-third of those engaging in R&D), and 10 % participate in subsidy programs.

From this sample, we extract a balanced panel of 779 firms that account for 6232 observations (47 % of all observations). Firm size and industry composition of both panels are very similar, as tables below will show. Figure 1 shows the evolution of the share of firms benefiting from each type of support. Notice that the share of firms that use tax credits is higher than the share of firms that use subsidies up to 2006, when it falls. In contrast, the share of those participating in the subsidy program increases over this period. The drop of the participation rate in tax credits possibly mirrors a fall in the firms' taxable income as the economic crisis was just starting.[18]

With two R&D programs and two participation options, each firm will be each year in one of four possible situations: not participating in any program, participating in both or participating in only one of them. To describe transition rates that capture own and cross-persistence effects, we define a participation status variable that reflects a firm's state in a given year. Table 1 below shows the transition rates across participation states, that is, the probability of a firm changing or remaining in the same status across two consecutive periods. The table highlights that (1) the vast majority of non-participants (96 % of them) remain in that state the following year; only 4 % change status; (2) among firms that participate exclusively in one of the programs, the chances of remaining in the same program are still high—about 60 %—but about one-fourth lose all support the following period; (3) there are no remarkable differences between participants in exclusively one of the programs; and (4) firms that participate in both programs are quite likely to stay in this status. Note that probability cells are very similar for both the unbalanced and balanced panels. The general observed pattern is thus one of strong own persistence and low cross-persistence.[19]

We find differences in transition patterns across firm size: SMEs that did not benefit from subsidies at time t have a probability of 2.6 % of doing so the following year (independently of whether firms also obtain tax credits); for large firms, this probability is quite higher (6.6 %). Likewise, the likelihood of exiting the program varies across firm size: 32 % for

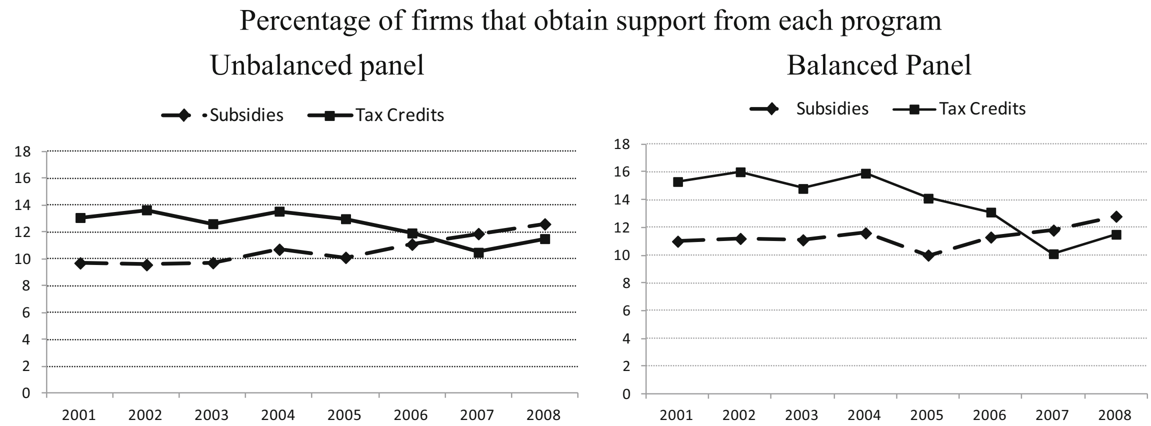
[15] Because of the sampling procedure, in our empirical analysis we will define large firms those with more than 200 employees, instead of the usual 250 threshold. Those with 200 or less employees (but at least with 10) will be considered to be SMEs.

[16] This is one of the few data sets providing information on a firm's access to both types of support. A full description of the data set can be found at https://www.fundacionsepi.es/esee/en/epresentacion.asp. Questionnaires and annual reports are available as well from this site.

[17] In the unbalanced panel, the number of firms each year oscillates from 1300 in 2001–2023 in 2006.

[18] Official statistics from the tax authorities (Agencia Estatal de la Administración Tributaria and Dirección General de Tributos) confirm this trend: While 3621 firms claimed R&D tax credits in 2006, their number fell to 3150 in 2008. Earnings before interests and taxes also fell in 2008 for manufacturing firms.

[19] The survey does not provide information on subsidy duration or on the firm's use of carry-forward provisions when claiming tax credits. Observed persistence might be partially attributable to ongoing rather than repeated participation. We take this into account in Sect. 5.



Note: The evolution of the percentage of non-participants in any support program, not shown in this figure, is very stable, with around 82% of firms not participating in any of the programs over these years. Data source: ESEE.

Fig. 1 Evolution of participation 2001–2008

Table 1 Transition rates across participation states

Status in *t*	Num observ.	Status in $t + 1$				
		No support	Only subsidy	Only tax credit	Both	Total
A. Unbalanced panel						
No support	8630	95.9	1.6	1.9	0.5	100
Only subs	508	23.4	59.7	3.0	14.0	100
Only tax credit	726	27.2	1.9	60.4	10.5	100
Both	613	6.4	14.0	11.1	68.5	100
Total	10,477	82.4	5.2	6.6	5.6	100
B. Balanced panel						
No support	4429	95.8	1.6	2.1	0.5	100
Only subs	249	22.9	61.8	1.2	14.1	100
Only tax credit	416	27.6	1.0	61.3	10.1	100
Both	359	6.7	11.7	11.4	70.2	100
Total	5453	81.4	4.9	7.2	6.5	100

The total number of observations here is smaller than the number in Fig. 1 because firms that do not remain in the panel for at least two consecutive years had to be dropped. *Data source*: ESEE

SMEs and 28 % for large firms. With respect to tax credits, the probability of claiming them when not doing so the previous period is 3 % for SMEs, and the probability of stopping claiming is 25 %; for large firms, these probabilities are 8 and 22 %, respectively. There seems to be a significant difference at the entry stage across firm size and less at the exit stage.

It is suitable to compare the continuity of participation in R&D programs with the extent of persistence in performing R&D. Previous studies have found persistence in R&D and innovation to be very high (Peters 2009; Peters et al. 2013; Martínez and Labeaga 2009; Raymond et al. 2010; Huergo and Moreno 2011; Antonelli et al. 2012). Several explanations for this fact have been proposed. Some authors underline the importance of entry and exit fixed costs (Mañez et al. 2015; Arqué and Mohnen 2015); others emphasize the role of competition (Woerter 2014) and of learning effects (Geroski et al. 1997; Triguero et al. 2014). An additional channel may be that when R&D results in a successful innovation, it provides firms with increased internal funds, alleviating innovation-specific financing constraints and allowing the firm to fund future R&D projects. These considerations suggest that R&D persistence may carry over to participation in R&D support programs.

In our unbalanced panel, we find a high persistence of R&D investment: 96 % of firm observations not engaging in R&D remain in the same situation the following period; among those engaged in R&D in a year, 90 % remain so.[20] These percentages are averages that hide significant differences across firm size. One-fifth of SMEs invest in R&D, and their chances of switching from not doing to doing so is only 3 %; similarly, the likelihood of stopping is high (16 %). In contrast, about 70 % of large firms perform R&D, and the likelihood of switching from not doing to doing is higher (10 %), while the likelihood of discontinuing is lower (6 %). This description is consistent with the well-known hypothesis that SMEs face significant hurdles to engage in and sustain R&D investment.

We next investigate the participation patterns of the subsample of firms that invest in R&D at least once during this period, which is about one-third of firms in the sample. About 40 % of these benefit from tax credits and 35 % from subsidies. That less than half of potential beneficiaries of tax credits actually claim them, when in principle the procedure to do it is simple, suggests the presence of some barriers to using this type of R&D support. Not having positive taxable income is one of them. Administrative data from tax authorities show that 55 % of all industrial firms that filed for the corporate tax had positive taxable income in 2002.[21] This percentage fell over the period, to 43 % in 2008. Differences between large (more than 250 employees) and small firms are significant: In 2008, 66 % of large firms had positive taxable income, while only 37 % of SMEs did.[22] Another factor that could explain this behavior is that some firms perform a type of R&D that may not conform to the tax authorities' definition. For instance, R&D investments that aim at adapting some technology without introducing a significant novelty would not qualify.

When computing the transition probabilities for the subset of R&D performers at time t, we observe that switching from no support into some support status is more likely than for the whole sample. This suggests that firms that already have some experience in R&D are more likely to benefit from support. As for program interactions, we do not observe significant differences with respect to the whole sample. Table 2 shows these transitions, which are again comparable across the balanced and unbalanced panels.

4 Empirical strategy

4.1 Model specification

We specify a random effects dynamic bivariate probit model to analyze the extent and origins of persistence of a firm's participation in each R&D program. We observe two binary dependent variables: Whether a firm has obtained an R&D subsidy from the public agency in year t, and whether a firm has claimed an R&D tax credit in year *t*. That is, we do not observe whether firms have applied for but not obtained a subsidy; we only observe whether a firm has been a successful applicant. The same remark applies to R&D tax credits.[23] Each of these discrete variables (y_{1it}, which refers to firm *i*'s status regarding R&D subsidies in year *t*, and y_{2it}, which refers to status with respect to tax credits) is related to a corresponding underlying latent variable (y^*_{1it} and y^*_{2it}, respectively) that is a function of the firm's participation state in each program the previous year, y_{jit-1}, with $j = 1, 2$; of a set of lagged observable variables x_{jit-1}; of an unobservable time-invariant firm-specific effect, η_{ji}

[20] R&D transition rates are very similar to those obtained by Huergo and Moreno (2011), who use the ESEE for the period 1990–2005.

[21] See Agencia Tributaria (Spanish Internal Revenue Service), *Cuentas Anuales en el Impuesto sobre Sociedades*, available at http://www.agenciatributaria.es/AEAT.internet/datosabiertos/catalogo/hacienda/Cuentas_anuales_en_el_Impuesto_sobre_Sociedades.shtml.

[22] For tax authorities, the definition of large firms includes those with 250 or more employees. In our data, the threshold is 200 employees because of the sampling procedure.

[23] Disentangling the differences between determinants of applying and of granting support is also an interesting issue of its own; it has been explored by Takalo et al. (2008) and Huergo and Trenado (2010) as explained in Sect. 2.2. It is not, however, the main focus of our research here. Analogously, we do not explore here the determinants of the volume of support, which may require R&D project-specific information that is not available in our data.

Table 2 Firms that invest in R&D: participation transition rates

Status in t	N observ	Status in $t+1$				
		No support	Only subs	Only tax credit	Both	Total
A. Unbalanced panel						
No support	1260	83.3	6.3	7.5	2.9	100
Only subs	422	17.8	64.5	3.3	14.5	100
Only tax credit	601	22.3	2.2	64.4	11.2	100
Both	584	4.6	14.0	10.6	70.7	100
Total	2867	44.9	15.6	19.5	20.1	100
B. Balanced panel						
No support	730	83.3	6.2	8.1	2.5	100
Only subs	214	18.2	65.4	0.9	15.4	100
Only tax credit	357	22.7	1.1	65.3	10.9	100
Both	345	4.4	11.6	11.3	72.8	100
Total	1646	45.1	13.9	20.2	20.7	100

Subsample of firms with positive R&D expenditure at t

and of a time-varying idiosyncratic random error term u_{jit}. u_{1it} and u_{2it} are assumed to be independent over time and to follow a bivariate normal distribution with zero means, unit variances and cross-equation covariance ρ_u. The individual specific unobserved permanent component η_{ji} allows individuals who are homogenous in their observed characteristics to be heterogeneous in unobserved permanent features. η_{1i} and η_{2i} are assumed to follow a bivariate normal distribution with variances $\sigma^2_{\eta 1}$, $\sigma^2_{\eta 2}$ and covariance $\rho_\eta\ \sigma_{\eta 1}\ \sigma_{\eta 2}$.

The model is the following:

$$\begin{aligned} y^*_{1it} &= \gamma_{11} y_{1it-1} + \gamma_{12} y_{2it-1} + \beta_1 x_{1it-1} + \eta_{1i} + u_{1it} \\ y^*_{2it} &= \gamma_{21} y_{1it-1} + \gamma_{22} y_{2it-1} + \beta_2 x_{2it-1} + \eta_{2i} + u_{2it} \end{aligned} \qquad ([1])$$

$$\text{with } y_{jit} = \begin{cases} 1 & y^*_{jit} > 0 \\ 0 & \text{else} \end{cases} \quad \text{and} \quad \Sigma_u = \begin{pmatrix} 1 & \rho_u \\ \rho_u & 1 \end{pmatrix}$$

The two-equation model satisfies the coherency—or logical consistency—conditions established by Schmidt (1981) for discrete models, as illustrated in applications by Hajivassiliou and Ioannides (2007) and Ayllón (2015). These conditions provide exclusion restrictions, so that contemporaneous y_{2t} does not enter the equation for y_{1t}, and viceversa, facilitating identification. Variables x_{jit-1} are assumed to be exogenous with respect to u_{jit}, but may be endogenous with respect to unobserved individual effects: η_{ji} may be correlated with observable characteristics as well as with the initial condition y_{ji0}. To consistently estimate this type of discrete random effects dynamic models, Wooldridge (2005) proposed a conditional maximum likelihood approach, where the individual effect is assumed to depend on the initial conditions, y_{ji0} and all lagged values of each exogenous variable—excluding the initial value for x_i, x_{i0}. In practice, researchers often use a constrained version of the model where the lags of exogenous variables are replaced by the time average of each exogenous variable, $\bar{x}_{ki}$.[24] For the bivariate case, the specification is:

$$\begin{aligned} \eta_{1i} &= \alpha_{10} + \alpha_{11} y_{1i0} + \alpha_{12} y_{2i0} + \alpha_{13} \bar{x}_{1i} + \varepsilon_{1i} \\ \eta_{2i} &= \alpha_{20} + \alpha_{21} y_{1i0} + \alpha_{22} y_{2i0} + \alpha_{23} \bar{x}_{2i} + \varepsilon_{2i} \end{aligned} \qquad ([2])$$

The covariance matrix of the random effects ε_{ji} is:

$$\Sigma_\varepsilon = \begin{pmatrix} \sigma^2_{\varepsilon 1} & \rho_\varepsilon \sigma_{\varepsilon 1} \sigma_{\varepsilon 2} \\ \rho_\varepsilon \sigma_{\varepsilon 1} \sigma_{\varepsilon 2} & \sigma^2_{\varepsilon 2} \end{pmatrix} \qquad ([3])$$

Inserting [2] into [1], we obtain the full model to estimate. The contribution of unobserved heterogeneity to total variance of each equation is measured by $\rho = \sigma^2_{\varepsilon j}/(\sigma^2_{\varepsilon j} + \sigma^2_{uj})$. The parameters that will inform about true state dependence and about cross-program interactions are γ_{11}, γ_{12}, γ_{21} and γ_{22}.

Rabe-Hesketh and Skrondal (2013) have suggested that using Mundlak means $\bar{x}_{ji}$ might be overly restrictive, because it imposes the same coefficient

[24] This term, known as Mundlak means, refers to Mundlak's (1978) proposal to relax the assumption that observed and unobserved variables are uncorrelated.

on the initial value of x and remaining periods. They show that for short panels this may lead to biased estimates and propose including the initial values of independent variables separately from their mean in subsequent periods.[25] We will estimate and compare both specifications using the balanced panel and conditional maximum simulated likelihood methods.

4.2 Independent variables

In addition to testing the influence that past participation may have on current participation, we will check whether some specific observed features of firms, included in vector x_{ijt-1}, are correlated with program participation. These are variables that are likely to affect the expected benefits and costs of performing R&D (and innovating) with and without support. They are, in the first place, firm size and the firm's industry type, as well as the firm's average productivity (Peters et al. 2013; Roberts and Vuong 2013; Máñez et al. 2015). A second group of observed variables that are known to influence costs and benefits of investing in R&D are the following: (1) the firm's age and previous experience in R&D; (2) the firm's human capital; (3) the availability of own funds relative to its short-run debt; and (4) variables that describe the firm's market environment: extent of product diversification, the firm's position in the market and perceived market share growth. All variables are defined in Table 8 in the Appendix.

Table 3 below provides a description of the sample by support status. We observe differences across participants and non-participants for any of the two programs. For instance, the average size, age and relative productivity of non-participants are smaller than those of participants. Human capital is higher among participants, as well as exporting activity. There are more market leaders among participants than among non-participants. The share of young firms among R&D subsidy beneficiaries is higher than that in other categories.

[25] Rabe-Hesketh and Skrondal (2013) show through a series of Monte Carlo experiments that when the initial period of explanatory variables is included in the model, the bias practically disappears.

5 Estimation results

We describe in this section the set of models we estimate and show estimation results in Tables 4, 5, 6 and 7. In the next section, we interpret and discuss our results.

5.1 The baseline model

The model specified in [1], a random effects dynamic bivariate probit, is estimated using the two alternative ways to model individual unobserved heterogeneity. For comparison, a pooled bivariate probit that does not account for heterogeneity is estimated as well.[26] The vector of observed time-varying variables includes the (log of) average productivity of the firm relative to that of its industry (*Relative productivity*); two time-invariant variables are added: industry (*High Tech*) and size (*Size +200*). Table 4 shows the estimation results for these three models. In Model 1, we use the standard Mundlak's specification for unobserved individual effects, while in Model 2 we use Rabe-Hesketh and Skrondal's approach. Estimates obtained by Model 1 and Model 2 are very similar, suggesting that using Mundlak's means does not produce biased results in our case. Model 3, the pooled probit, overestimates true own and cross-persistence as found in the literature. We therefore will base our discussion below on Model 1.

5.2 Exploring additional sources of observed heterogeneity

We sequentially add to Model 1—our baseline model—a set of observable variables described in Sect. 4.[27] We investigate the influence of previous R&D experience on participation in each program through two different indicators: whether the firm was investing in R&D at the beginning of the period ($R\&D_{t0}$) (Model 4) and the firm's R&D intensity ($R\&D\ Effort_{t-1}$) (Model 5). The binary indicator for

[26] For other examples of bivariate probit dynamic models, see Esteve-Perez and Rodriguez (2013) and Devicienti and Poggi (2011). Our estimates are obtained by maximum simulated likelihood estimation, as in Devicienti and Poggi, whose Stata code we adapt to our case.

[27] We follow this procedure to save degrees of freedom while still obtaining consistent results. We have to keep in mind that the number of firms that participate in each program is a small percentage of all firms.

Table 3 Descriptive statistics

Variable	No subsidy		Subsidy		No tax credit		Claim tax credit	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Employees	199.20	569.45	833.80	1504.20	221.66	722.03	579.45	932.01
Size +200	0.24	0.43	0.73	0.44	0.24	0.43	0.67	0.47
Age	29.20	21.70	36.34	23.70	28.85	21.55	37.24	23.72
Relative productivity	1.07	1.02	1.35	1.03	1.07	1.21	1.36	0.99
% Employees higher education	0.05	0.08	0.11	0.10	0.05	0.08	0.10	0.09
Top 3 in market	0.17	0.38	0.30	0.46	0.16	0.37	0.36	0.48
Atomistic market	0.18	0.39	0.07	0.26	0.18	0.39	0.09	0.28
DMktmis[a]	0.55	0.50	0.46	0.50	0.56	0.50	0.41	0.49
Use IP	0.05	0.21	0.24	0.43	0.04	0.21	0.21	0.41
High tech	0.07	0.25	0.20	0.40	0.06	0.23	0.24	0.43
Growing market share	0.22	0.42	0.28	0.45	0.22	0.42	0.28	0.45
Young	0.06	0.25	0.09	0.28	0.07	0.25	0.05	0.22
Not diversified[b]	0.87	0.34	0.80	0.40	0.87	0.33	0.79	0.40
Export[b]	0.64	0.48	0.94	0.23	0.62	0.48	0.97	0.18
Doing R&D[b]	0.30	0.46	1.00	0.00	0.28	0.45	0.99	0.11
R&D/sales[b]	0.46	1.96	3.27	4.58	0.45	2.07	2.82	3.98
Innovative exporter[b]	0.15	0.36	0.54	0.50	0.14	0.35	0.52	0.50
Exports/sales of product innovators[b]	0.05	0.15	0.23	0.30	0.05	0.16	0.19	0.27
Own funds/short term debt[b]	2.45	12.75	1.60	2.39	2.43	12.93	1.86	2.53

Balanced panel: 779 firms, 6232 firm-year observations

[a] A substantial number of firms did not report every year their position in their main market; this binary variable indicates whether this information is missing

[b] Some firms did not report a value for this variable some year. The number of firm-year observations lost is at most 140

whether a firm performed R&D in $t-1$ or not has very little time variation in our sample, reflecting the high persistence of R&D found in many previous studies; we include instead the firm's initial R&D status. The second indicator is R&D intensity, a continuous, time-varying variable, lagged one period. In Model 6, we explore whether being a young firm (*Young*) affects participation in these programs; this will inform on the ability of each program to favor entrants or incumbents. In Model 7, we test the influence of the firm's human capital through a binary indicator that identifies firms that do not have employees with higher education (*No high educ empl*). Estimation results are shown in Table 5.

We look into the influence of some strategic variables that are often correlated with the private returns of investing in R&D and with program participation decisions. Model 8 includes an indicator of a firm's extent of product diversification; we define it such that it identifies firms that are single product (*Not diversified*). Diversification may increase the private returns to its investment in R&D because of its higher potential for generating cross-product, within-firm spillovers (Akcigit et al. 2014). This would increase in turn the likelihood of benefiting from tax credits and possibly of subsidies as well. In Model 9, we explore whether participation is more likely for firms that experience a growing market share, relative to firms that face a losing or stagnant market position (*Market share*). In Model 10, we include an indicator of whether the firm holds one of the top three positions in the market (*Top 3 position*). Table 6 displays the results we obtain.

Finally, we investigate whether an indicator of the financial situation of the firm affects program participation. Many studies provide evidence that access to

Table 4 Dynamic bivariate probit estimation I. Baseline

	Model 1 Mundlak-baseline		Model 2 Rabe-Hesketh & Skrondal		Model 3 Pooled bivariate probit	
	Subsidy	Tax credit	Subsidy	Tax credit	Subsidy	Tax credit
Tax credit$_{t-1}$	0.120	1.552***	0.123	1.554***	0.215**	1.954***
	(0.145)	(0.109)	(0.147)	(0.109)	(0.098)	(0.086)
Tax credit$_{t0}$	0.508***	0.913***	0.504***	0.911***	0.211**	0.424***
	(0.166)	(0.151)	(0.167)	(0.151)	(0.104)	(0.091)
Subsidy$_{t-1}$	1.360***	0.070	1.362***	0.074	2.012***	0.228**
	(0.129)	0.142)	(0.129)	(0.143)	(0.117)	(0.099)
Subsidy$_{t0}$	1.592***	0.575***	1.581***	0.563***	0.654***	0.269***
	(0.215)	(0.158)	(0.215)	(0.157)	(0.113)	(0.108)
Relative productivity$_{t-1}$	0.403**	0.012	0.409**	0.031	0.330**	0.035
	(0.183)	(0.148)	(0.183)	(0.148)	(0.147)	(0.136)
MRel productivity	−0.133	0.359**			−0.168	0.234
	(0.207)	(0.166)			(0.157)	(0.149)
Relative productivity$_{t0}$			−0.231	−0.301*		
			(0.221)	(0.176)		
RRel productivity			0.081	0.622***		
			(0.271)	(0.215)		
Size more than 200	0.569***	0.439***	0.568***	0.433***	0.403***	0.331***
	(0.118)	(0.096)	(0.118)	(0.096)	(0.083)	(0.073)
High tech	0.480***	0.716***	0.489***	0.735***	0.324***	0.504***
	(0.182)	(0.140)	(0.183)	(0.141)	(0.117)	(0.097)
Constant	−2.82***	−2.47***	−2.85***	−2.51***	−2.20***	−2.08***
	(0.147)	(0.110)	(0.151)	(0.114)	(0.056)	(0.054)
Rho	0.483***		0.485***		0.458***	
	(0.085)		(0.085)		(0.066)	
Sigma ε_1	0.847***		0.842***			
	(0.106)		(0.106)			
Sigma ε_2	0.643***		0.629***			
	(0.088)		(0.087)			
Rho ε	0.467***		0.455***			
	(0.162)		(0.169)			
LogLikelihood	−1760.12		−1757.99		−1799.07	
N observations (firms)	5443 (779)		5453 (779)		5453 (779)	

(1) Standard errors in parenthesis. (2) In Model 1, the unobserved effect accounts for about 41 % = $0.847^2/(1 + 0.847^2)$ of the composite error in the subsidy equation and 29 % in the tax credit equation. In Model 2, they are practically identical to those of Model 1. (3) MRel productivity is the within mean of the log of relative productivity from period 0 to T. (4) RRel productivity is the within mean of the log of relative productivity from period 1 to T

finance is an important limitation for firms with R&D investment plans. In Model 11, we use the ratio of own funds to short-run debt, a continuous time-varying variable, as an indicator of financing constraints (*Own funds/SR debt*$_{t-1}$). Although this is an imperfect proxy, as often discussed in the literature, recent research by López-García et al. (2013) shows that in the case of Spanish firms, the firm's leverage ratio is

Table 5 Dynamic bivariate probit estimation II

	Model 4 Control: Initial R&D		Model 5 Control: R&D effort		Model 6 Control: Young		Model 7 Control: No high educ employees	
	Subsidy	Tax credit	Subsidy	Tax credit	Subsidy	Tax credit	Subsidy	Tax credit
Tax credit$_{t-1}$	0.108	1.534***	0.153	1.555***	0.122	1.548***	0.118	1.537***
	(0.148)	(0.110)	(0.146)	(0.113)	(0.144)	(0.108)	(0.144)	0.109
Tax credit$_{t0}$	0.256	0.612***	0.382**	0.854***	0.509***	0.914***	0.435*	0.837***
	(0.161)	(0.136)	(0.159)	(0.155)	(0.166)	(0.151)	(0.163)	0.149
Subsidy$_{t-1}$	1.368***	0.079	1.340***	0.040	1.353***	0.075	1.375***	0.088
	(0.130)	(0.147)	(0.132)	(0.151)	(0.129)	(0.142)	(0.127)	0.142
Subsidy$_{t0}$	1.325***	0.281*	1.340***	0.402***	1.596***	0.584***	1.527***	0.528***
	(0.208)	(0.150)	(0.208)	(0.160)	(0.216)	(0.159)	(0.210)	0.157
Relative Productivity $_{t-1}$	0.396**	−0.012	0.364*	−0.031	0.404**	0.008	0.391**	0.005
	(0.187)	(0.150)	(0.188)	(0.150)	(0.183)	(0.148)	(0.182)	0.147
MRel productivity	−0.180	0.308*	−0.126	0.412**	−0.133	0.364**	−0.189	0.284*
	(0.210)	(0.168)	(0.209)	(0.171)	(0.207)	(0.166)	(0.205)	0.166
R&D$_{t0}$	0.747***	0.827***						
	(0.153)	(0.115)						
R&D effort$_{t-1}$			−0.014	−0.021				
			(0.022)	(0.020)				
MR&D effort			0.128***	0.104***				
			(0.032)	(0.027)				
Young					0.073	−0.361		
					(0.295)	(0.285)		
No high educ employees							−0.498***	−0.689***
							(0.178)	(0.166)
Size more than 200	0.428***	0.285***	0.588***	0.478***	0.568***	0.434***	0.467***	0.323***
	(0.119)	(0.094)	(0.118)	(0.101)	(0.118)	(0.096)	(0.119)	(0.097)
High tech	0.372**	0.547***	0.347*	0.644***	0.482***	0.713***	0.416**	0.645***
	(0.175)	(0.134)	(0.173)	(0.147)	(0.183)	(0.140)	(0.179)	(0.138)
Constant	−3.01***	−2.64***	−2.86***	−2.54***	−2.83***	−2.46***	−2.63***	−2.27***
	(0.168)	(0.123)	(0.154)	(0.119)	(0.148)	(0.110)	(0.146)	(0.109)
Rho	0.479***		0.479***		0.485***		0.483***	
	(0.088)		(0.089)		(0.085)		(0.085)	
Sigma ε_1	0.815***		0.802***		0.848***		0.827***	
	(0.109)		(0.107)		(0.106)		(0.104)	
Sigma ε_2	0.549***		0.651***		0.642***		0.630***	
	(0.090)		(0.091)		(0.087)		(0.089)	
Rho ε	0.360*		0.368**		0.468***		0.430**	
	(0.205)		(0.173)		(0.162)		(0.167)	
LogLikelihood	−1701.28		−1686.20		−1759.08		−1747.25	
N observations (firms)	5432		5362		5453		5453	
	(776)		(766)		(779)		(779)	

(1) Standard errors in parenthesis. (2) MRel productivity is the within mean of the log of relative productivity. (3) MR&D effort is the within mean of R&D effort

Table 6 Dynamic bivariate probit estimation III

	Model 8 Control: Not diversifying		Model 9 Control: Growing market share		Model 10 Control: Market position	
	Subsidies	Tax credits	Subsidies	Tax credits	Subsidies	Tax credits
Tax credit$_{t-1}$	0.136	1.564***	0.126	1.560***	0.128	1.551***
	(0.146)	(0.109)	(0.147)	(0.109)	(0.148)	(0.109)
Tax credit$_{t0}$	0.510***	0.905***	0.477**	0.880***	0.485**	0.869***
	(0,168)	(0.150)	(0.166)	(0.150)	(0.167)	(0.147)
Subsidy$_{t-1}$	1.340***	0.059	1.371***	0.086	1.366***	0.074
	(0.128)	(0.142)	(0.129)	(0.144)	(0.129)	(0.144)
Subsidy$_{t0}$	1.625***	0.582***	1567***	0.538***	1.579***	0.542***
	(0.218)	(0.159)	(0.213)	(0.156)	(0.215)	(0.156)
Relative Productivity$_{t-1}$	0.402**	0.012	0.408*	0.023	0.402*	0.008
	(0.184)	(0.148)	(0.184)	(0.148)	(0.183)	(0.147)
MRel productivity	−0.126	0.357**	−0.151	0.333*	−0.137	0.335*
	(0.208)	(0.167)	(0.207)	(0.166)	(0.207)	(0.166)
No Diversification$_{t-1}$	−0.245	−0.330**				
	(0.179)	(0.155)				
MNo Diversification	0.399	0.249				
	(0.269)	(0.216)				
Market share$_{t-1}$			0.113	0.122		
			(0.108)	(0.095)		
MMarket share			0.334	0.489*		
			(0.266)	(0.212)		
Top 3 position					−0.046	0.042
					(0.143)	(0.123)
MTop 3 position					0.147	0.408*
					(0.231)	(0.187)
DMissing Top 3					−0.017	−0.168
					(0.102)	(0.086)
Size more than 200	0.573***	0.434***	0.581***	0.464***	0.554***	0.389***
	(0.119)	(0.096)	(0.118)	(0.095)	(0.118)	(0.095)
High tech	0.476***	0.717***	0.497**	0.748***	0.503**	0.749***
	(0.186)	(0.140)	(0.181)	(0.140)	(0.182)	(0.141)
Constant	−2.977***	−2.409***	−2.914***	−2.607***	−2.822***	−2.445***
	(0.234)	(0.163)	(0.162)	(0.123)	(0.165)	(0.125)
Rho	0.481***		0.487***		0.490***	
	(0.085)		(0.086)		(0.087)	
Sigma ε_1	0.860***		0.831***		0.837***	
	(0.107)		(0.105)		(0.105)	
Sigma ε_2	0.643***		0.616***		0.607***	
	(0.087)		(0.086)		(0.087)	
Rho ε	0.475***		0.437*		0.458*	
	(0.162)		(0.174)		(0.181)	
LogLikelihood	−1756.45		−1752.50		−1748.62	
N observations (firms)	5446 (778)		5453 (779)		5453 (779)	

Notes: (1) Standard errors in parenthesis. (2) MRel productivity is the within mean of the log of relative productivity. (3) MNo Diversification, MMarket share and MTop 3 position are the within means of the corresponding variables. (4) Model 9 includes a dummy variable that accounts for missing values for the variable Top 3

Table 7 Dynamic bivariate probit estimation IV

	Model 11 Own funds/Short run debt		Model 12: Subsample Firms that do R&D at least once during the period		Model 13 Exporters that introduced a new product	
	Subsidies	Tax Credits	Subsidies	Tax Credits	Subsidies	Tax Credits
Tax credit$_{t_1}$	0.110	1.573***	0.217	1.584***	0.212	1.561***
	(0.150)	(0.114)	(0.141)	(0.114)	(0.156)	(0.112)
Tax credit$_{t0}$	0.482***	0.901***	0.136**	0.522***	0.363**	0.773***
	(0,168)	(0.158)	(0.152)	(0.133)	(0.163)	(0.151)
Subsidy$_{t_1}$	1.391***	0.082	1.329***	0.170	1.385***	0.135
	(0.135)	(0.155)	(0.129)	(0.145)	(0.141)	(0.160)
Subsidy$_{t0}$	1.556***	0.501***	1.234***	0.261*	1.604***	0.484***
	(0.230)	(0.170)	(0.198)	(0.138)	(0.242)	(0.164)
Relative productivity$_{t-1}$	0.392**	−0.020	0.411**	0.016	0.399**	−0.005
	(0.192)	(0.150)	(0.193)	(0.157)	(0.186)	(0.149)
MRel productivity	−0.104	0.337*	−0.365*	0.200	−0.116	0.358***
	(0.214)	(0.170)	(0.220)	(0.176)	(0.209)	(0.170)
Own funds/SRdebt$_{t-1}$	0.007	−0.022				
	(0.020)	(0.018)				
MOfunds/SRdebt	−0.097	0.006				
	(0.039)	(0.019)				
Innovative exporters					0.204	0.391***
					(0.129)	(0.102)
Size +200	0.524***	0.459***	0.299**	0.184**	0.461***	0.425***
	(0.119)	(0.099)	(0.117)	(0.092)	(0.119)	(0.099)
High tech	0.436***	0.662***	0.350**	0.568***	0.647***	0.805***
	(0.169)	(0.142)	(0.162)	(0.129)	(0.171)	(0.147)
Constant	−2.589***	−2.395***	−2.064***	−1.791***	−2.810***	−2.558***
	(0.151)	(0.113)	(0.124)	(0.093)	(0.157)	(0.121)
Rho	0.506***		0.514***		0.470***	
	(0.090)		(0.087)		(0.098)	
Sigma ε_1	0.806***		0.727***		0.795***	
	(0.112)		(0.107)		(0.121)	
Sigma ε_2	0.613***		0.458***		0.615***	
	(0.092)		(0.098)		(0.092)	
Rho ε	0.479***		0.050		0.259	
	(0.188)		(0.225)		(0.198)	
LogLikelihood	−1663.59		1563.03		1649.93	
N observations (firms)	5061 (723)		2485 (355)		5278 (754)	

(1) Standard errors in parenthesis. (2) MRel productivity is the within mean of the log of relative productivity. (3) MOfunds/SRdebt is the within mean of own funds/short-run debt. (4) In models 11 and 13, a small number of observations is lost because of missing data for the relevant variable. (5) Model 12 does not account for potential sample selection bias

correlated with the probability of facing financing obstacles for investing in innovation.[28] In Model 12, we run the baseline model with the subsample of firms that are invested in R&D at least once during the period; this provides a test for the robustness of the baseline to sample composition. Finally in Model 13, we explore whether firms that are innovative exporters are more likely to participate in each program (*InnovExport*). Table 7 reports estimation results.

5.3 Sensitivity to an alternative lag specification

We consider adding a second lag of each dependent variable for two reasons. First, firms can carry forward tax credit deductions when these exceed the legal threshold percentage of their tax liability. In our balanced panel, a small percentage (about 9 %) of firms that obtain a tax credit at t did not perform R&D at $t-1$, suggesting that these firms were possibly making use of the carry-forward provision allowed for. Second, subsidies may be awarded in some cases for more than one year. If these two conditions are frequent, then the estimated coefficients of the lagged dependent variables in the baseline model would overestimate the extent of true state dependence. The survey we use does not provide information on subsidy duration or on the use of carry-forward provisions, but an indirect way to check whether they might be driving observed persistence is to estimate the baseline model adding a second lag of each dependent variable. If participation exhibits true state dependence, then we would expect the second lag to be significant as well. Table A3 shows two-lag transition probabilities for each program and Table A4 the number of years firms benefited from them. Table A5 reports estimation results. The second lag of the respective dependent variable is highly significant, although smaller in magnitude than that of the first lag; this supports the hypothesis of true state dependence. The significance and magnitude of the coefficients of relative productivity, firm size and industry do not experience important changes, while the weight of unobserved heterogeneity falls, especially for tax credits.[29]

6 Discussion

We focus now on the interpretation and implications of these results for understanding persistence and cross-persistence in firms' participation in R&D support programs. From our baseline model (Model 1), we can conclude that program participation exhibits positive own state dependence: The coefficient of lagged subsidy in the subsidy equation and of lagged tax credit in the tax credit equation are highly significant, meaning that the probability of participating in one of these programs is higher for firms that have previously participated than for identical firms that have not.[30] Another way to put it is that firms that participate at any time are very likely to become stable beneficiaries of support independently of other variables, including unobservable effects such as the nature of their projects.[31] We thus find true state dependence as Aschhoff (2010) did for participants in subsidy programs in Germany. Learning and reputation effects might be sources of this persistence: Firms get better organized and more productive at managing their R&D portfolio as they benefit from support, which enables them to keep benefiting; the public agency learns about the quality and reliability of a firm's proposals, in the case of subsidies. But unless project features—those that should make it eligible for support from a social efficiency perspective and that are in our case integrated within the individual heterogeneity term—play a significant role, this persistence may be a sign of policy failure.

The variance of individual unobserved effects in each program's equation is highly significant.

[28] López-García et al. (2013) obtain this result by using two sources of data: the Spanish version of the Community Innovation Survey and the Bank of Spain's Central Balance Sheet Data. From the first, they obtain a variable that measures the degree of financing constraints faced by firms with innovation projects; from the second, they obtain the leverage ratio. They then estimate a model for the perceived degree of innovation-specific financing constraints using as explanatory variables the leverage ratio and firm's age, size and industry.

[29] Given the relatively limited number of firms, however, this specification may be over-fitting our data.

[30] The initial value of subsidy status (tax credit status) in the subsidy equation (tax credit equation) is also highly significant, which indicates that unobserved heterogeneity and the initial condition of the corresponding dependent variable are correlated.

[31] Note that we can only state that having benefited from one program in the past increases the probability of benefiting in the future. This has to be the outcome of both the firms' repeatedly applying for and repeatedly obtaining support.

Unobserved heterogeneity, which accounts for less than one half of the unexplained variance of the composite error, $\varepsilon_{ji} + u_{ji}$ in both programs, is higher in the case of subsidies (41 %) than in that of tax credits (29 %). We interpret this as suggesting that the subsidy policy has a higher ability to take into account the unobserved specific project features than tax credits and therefore to discriminate across projects over time. This result lends support to our hypotheses. The correlation between unobserved individual effects across programs is significant and positive, suggesting that what drives a firm to participate in one of the programs will also drive it to participate in the other.

Interestingly, we do not find evidence of cross-program interactions, once we control for relative labor productivity, size and industry as well as unobserved heterogeneity. This means that obtaining a subsidy at $t - 1$ does not mechanically lead a firm to claim a tax credit at t and conversely. A simple explanation is that firms that are supported through subsidies may not be able to generate sufficient taxable income in the short run so as to be able to claim a tax credit, especially if they conduct projects of an exploratory nature. On the other hand, firms that benefit from tax credits at t may do so because they invest in R&D projects of an incremental nature, allowing the firm to introduce resulting innovations quickly in the market and increase revenues; they would not automatically change the nature of their R&D projects just to obtain a subsidy.

Turning to the observable firm characteristics we have included in our estimations, our results provide several insights on firms' participation patterns. First, highly productive firms within a given industry are more likely to obtain subsidies, while this feature does not appear to influence the likelihood of obtaining tax credits. This may be the outcome of high-productivity firms being more likely to undertake high-quality projects and to apply for support and succeeding at the public agency selecting them.[32] Thus, publicly funded projects may have in general different qualities than those that entitle firms to R&D tax credits.

A larger firm size increases the likelihood of participating in any of the two programs, holding everything else constant. Huergo and Trenado (2010), who study the determinants of applying for subsidies and then obtaining them with a different data set, find that large firms are more likely to apply. Our results on participation are consistent with theirs. In the case of tax credits, this result may be specific to their design in Spain, where the low taxable income of many SMEs may hinder their ability to benefit from this kind of support. In the case of subsidy programs, it is likely that SMEs are less likely to apply for support—and therefore obtain it—not so much because of size itself, but because many of them do not have sufficient human capital. In our sample, even in high-tech industries the median of the percentage of employees with higher education is 16 % for firms with more than 200 employees, while it is 9 % for SMEs. As expected, firms in the high-tech industries also are more likely to participate in these programs. The results regarding persistence and cross-persistence just described hold for all the additional specifications we estimate.

An issue of relevance from a policy perspective is whether R&D support programs contribute to increase the number of firms that engage in R&D on top of reaching those that have been previously active in R&D. Our results show that firms that were investing in R&D at the beginning in the period are indeed more likely to participate in either of these programs than non-performers at that time. However, the intensity of R&D effort during the previous year does not appear to be directly correlated with participation. The first of these variables seems to better capture the relevance of R&D experience. Both programs are very similar in this respect, suggesting that at least during the period we study it was hard to widen the base of R&D performers significantly through these tools. The same conclusion would apply to participation of young firms.

The main results of remaining estimations provide complementary insights. We find that availability of human capital is significantly correlated with participation in both programs. This is not surprising, as the ability to spot new product or process opportunities and to implement an appropriate R&D plan depend on the human capital of the firm. It is unlikely that firms that lack some minimum level of these skills will either apply or obtain public support. In our sample, about one-third of manufacturing firms did not have employees with higher education. This percentage changes very little during the period, with only 3 % of

[32] Previous research shows that these firms are more likely to invest in R&D; for a study using with the same data source, see Máñez et al. (2015) on the relationship between R&D, exports and productivity.

firms that initially had no highly educated employees changing their state. For those that did, the median share of educated employees was 5 % in 2001 and 6 % in 2008. This shows that improvements of human capital were quite small over this period, at least for these firms, a fact that can be expected to result in little variation in R&D capabilities and therefore in program participation potential.

We find that some firm features are correlated with claiming tax credits but not with obtaining subsidies: Diversified firms and innovative exporters are more likely to claim tax credits, while these qualities are uncorrelated with obtaining subsidies. Finally, we do not find a significant correlation between participation in any of the programs and the indicator of financing constraints, the firm's position in the market leader or the evolution of its market share.

The global conclusion that emerges from this analysis is that both programs tend to benefit on average firms that have R&D experience and that end up participating continuously. Furthermore, we identify some differences between participants in subsidy and tax incentive programs: While a high productivity increases the chances of benefiting from the former, diversified, innovative exporters are more likely to benefit from the latter. To some extent, this suggests that the R&D projects supported by each program have different properties. To investigate this further would require having access to some information about R&D projects, such as their scope, duration and extent of novelty.

7 Concluding remarks

Understanding which firms participate in R&D support programs, whether participating at a point in time leads to continued participation and whether benefiting from a particular program triggers participation in a second one are important issues for a comprehensive policy evaluation. In this paper, we extend current research on innovation policies by bringing the focus on the dynamics of firm participation in two R&D support programs, explicitly comparing R&D subsidies—direct support—and R&D tax incentives—indirect support.

Standard impact analysis—the extent of input or output additionality associated with public support—is not sufficient to make inferences about the ability of these policies to increasing welfare by reducing market failures. The support allocation mechanism itself is of interest, because it may contribute evidence to assess whether there is a link between potential causes of market failures and becoming a beneficiary of support. We have extended here existing work by looking into participation from a dynamic perspective, asking the extent to which continued participation may be driven by true state dependence, by some observed firm characteristics or by individual specific unobserved features. In other words, whether a stable pool of firms systematically benefits from each program, and whether participating in one of the programs acts as a springboard for participating in the other.

Our main conclusions and their implications are summarized as follows. First, we find significant true state persistence of participation in R&D subsidy and tax credit programs; unobserved heterogeneity accounts for about 41 % of the unexplained variance of the composite error in the case of subsidies and 29 % in the case of tax credits. The smaller weight of heterogeneity in accounting for persistence in benefiting from tax credits, the lack of correlation between productivity and participation and the high significance of past participation suggests that the projects' beneficiary firms engage in would possibly have been carried out even without support. In income-based tax credit designs, the ability to claim derives from market success; therefore, these firms must enjoy sufficient appropriability mechanisms so that innovation effort is not deterred. Consequently, there is room for some misallocation of public resources; true state dependence implies that any misallocation incurred in at one point in time is likely to persist, inducing negative welfare effects in the long run. When we estimate the model with one and two period lags of the dependent variables, we still find a significant extent of true persistence.[33] Second, our results also highlight the importance of human capital for program participation. Lack of it may be a major constraint to the success of both R&D subsidies and tax credits programs in increasing a country's innovativeness,

[33] Mistakes in the allocation of subsidies may be more easily corrected than those of tax credits, as the public agency decides on a case-by-case basis and has more information on the nature of R&D projects as well as the ability to monitor the project at different stages, particularly when the duration of a project is longer than 1 year.

especially where the share of SMEs is high. Therefore, these policies should be implemented in association with others that push firms to increase their human capital.

These reflections would call for an encompassing ex post evaluation of each policy tool, including both participation—allocation—and impact analysis in order to reveal systematic misallocation as well as the role of complementary policies. As a first step, information on the type of R&D projects' firms that claim tax credits carry out, particularly their duration and indicators of their nature—exploratory and/or generic versus incremental—would be very valuable.

Finally, we acknowledge that the study faces some limitations. First, our results are based on a balanced panel of about 800 manufacturing firms; service firms are not included because the data source we use does not sample them. This is important because knowledge-intensive service firms also benefit from R&D support programs and results might be affected if they were included. Second, although firms in our sample are similar in many observed dimensions to those in the unbalanced panel, they may still differ in unobserved characteristics. Third, our indicators of human capital and financing constraints are only gross approximations to these variables. And fourth, we cannot disentangle application from granting behavior in the case of R&D subsidy programs, nor control for the duration of a granted subsidy or use of carry-forward provisions when claiming tax incentives. We hope that data will improve in the future as public institutions become more involved with policy evaluation.

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Appendix

See Tables 8, 9, 10, 11 and 12.

Table 8 Variable definition

Variable	Definition
Tax credit	Binary; 1 if the firm claims a tax credit in year t
Subsidy	Binary; 1 if the firm receives a subsidy in year t
Tax credit$_{t_1}$	Binary; 1 if the firm claimed a tax credit in year $t-1$
Tax credit$_{t0}$	Binary; 1 if the firm claimed a tax credit in year 2001
Subsidy$_{t_1}$	Binary; 1 if the firm received a s subsidy in year $t-1$
Subsidy t_0	Binary; 1 if the firm received a subsidy in the initial period
Relative productivity$_{t_1}$	Log of the firm's sales per employee/average sales per employee of firms in the same industry at $t-1$
M Rel productivity	Mundlak mean: within mean of the log of relative productivity
Relative productivity t_0	Log of relative productivity at initial period
R rel productivity	Mundlak mean: within mean of the log of relative productivity
Young	Binary; 1 if firm was born after 1995
R&D t_0	Binary; 1 if firm was investing in R&D at initial period
R&D effort $t-1$	R&D expenditures/sales at $t-1$
MR&D effort	Mundlak mean: within mean of R&D effort
No diversification$_{t_1}$	Binary; 1 if firm is single product line; it does not diversify at $t-1$
MNo diversification	Mundlak mean: within mean of not diversifying
Market share$_{t-1}$	Binary; 1 if the firm's market share is growing
MMarket share	Mundlak mean: within mean of growing market share
Top 3 position$_{t-1}$	Binary; 1 if firm is one of the top 3 in its market at $t-1$

Table 8 continued

Variable	Definition
MTop 3	Mundlak mean: within mean of top 3 position
Own funds/SRdebt$_{t-1}$	Ratio of own funds to short-run debt at $t-1$
MOwn funds/SRDebt	Within mean of the ratio of own funds to short-run debt
No high educ. employees	Binary; 1 if firm does not have higher education graduates
Innovative exporter$_{t-1}$	Binary; 1 if the firm introduced product innovations and exported
Size +200	Binary; 1 if the firm has more than 200 employees
High tech	Binary; 1 if the firm is in a high-tech industry

Table 9 One-lag transition rates of subsidies, tax credits and R&D

Status at $t-1$	Subsidy status at t		Tax credit status at t		R&D status at t	
	No (%)	Yes (%)	No (%)	Yes (%)	No (%)	Yes (%)
Unbalanced panel						
No	97	3	97	3	96	4
Yes	22	78	25	75	10	90
Balanced panel						
No	97	3	97	3	97	3
Yes	20	80	24	76	8	92
Balanced panel						
Firms that conduct R&D at least one year						
No	92	8	91	9	86	14
Yes	21	79	26	74	6	94

Table 10 Two-lag transition rates of subsidies and tax credits

Status at $t-2$	Subsidy status at t		Tax credit status at t	
	No (%)	Yes (%)	No (%)	Yes (%)
No	96	4	96	4
Yes	27	73	35	65

Table 11 Frequency of participation over the period

	Unbalanced panel 2824 firms		Balanced panel 779 firms	
	R&D subsidy (%)	R&D tax incentives (%)	R&D subsidy (%)	R&D tax incentives (%)
1 year	36	33	33	22
2 years	25	25	17	21
3 years	12	12	10	11
4 years or more	27	30	41	46
Total	100	100	100	100

Table 12 Dynamic bivariate probit estimation with two lags

	Subsidies	Tax credits
Subsidies		
Tax credit$_{t_1}$	0.179	1.786***
	(0.142)	(0.104)
Tax credit$_{t_2}$	−0.001	0.382***
	(0.135)	(0.110)
Tax credit$_{t0}$	0.219*	0.362***
	(0.127)	(0.120)
Subsidy$_{t_1}$	1.747***	0.085
	(0.129)	(0.145)
Subsidy$_{t_2}$	0.535***	0.159
	(0.130)	(0.142)
Subsidy$_{t0}$	0.643***	0.229*
	(0.177)	(0.137)
Rel productivity$_{t_1}$	0.453**	0.027
	(0.180)	(0.153)
MM rel prod	−0.267	0.261
	(0.194)	(0.165)
Large firm	0.402***	0.290***
	(0.090)	(0.079)
High-tech	0.320**	0.448***
	(0.125)	(0.111)
Constant	−2.305***	−2.160***
	(0.111)	(0.085)
Rho	0.518***	
	(0.088)	
Sigma ε1	0.266*	
	(0.154)	
Sigma ε2	0.166	
	(0.175)	
Rho ε	0.615	
	(1.667)	
LogLikelihood	−1471.65	
N obs (firms)	4674 (779)	

The number of firm-year observations is smaller than in other estimations because an additional year is lost when adding a second lag of dependent variables

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