Departament d'Economia Aplicada

Dynamics of firm participation in R&D tax credit and subsidy programs

Isabel Busom, Beatriz Corchuelo, Ester Martínez-Ros

DOCUMENT DE TREBALL

15.03

Universitat Autònoma de Barcelona

Facultat d'Economia i Empresa

Aquest document pertany al Departament d'Economia Aplicada.

Data de publicació : **Març 2015**

Departament d'Economia Aplicada
Edifici B
Campus de Bellaterra
08193 Bellaterra

Telèfon: 93 581 1680
Fax: 93 581 2292
E-mail: d.econ.aplicada@uab.es
http://www.uab.cat/departament/economia-aplicada/

DYNAMICS OF FIRM PARTICIPATION IN R&D TAX CREDIT AND SUBSIDY PROGRAMS

Isabel Busom [a*], Beatriz Corchuelo [b] and Ester Martínez-Ros [c]

March 12, 2015

[a*]*Universidad Autónoma de Barcelona, Departament d'Economia Aplicada, Edifici B, 08193 Bellaterra, Spain. Corresponding author.*
[b]*Universidad de Extremadura, Departamento de Economía, Avda Elvas, Badajoz, Spain*
[c]*Universidad Carlos III de Madrid, Departamento de Economía de la Empresa, Getafe, Spain*

Abstract

We provide comparative evidence on R&D tax credit and subsidy programs by studying whether firms' participation in each program exhibits state dependence and whether cross program interactions exist and are significant. We use a panel of manufacturing Spanish firms, which could use both types of support, to estimate a random effects bivariate dynamic probit model of program participation. We find that true state dependence of participation in R&D subsidy and tax credit programs accounts respectively for about 55% and 60% of observed persistence. In contrast, we do not find evidence of cross program interaction, suggesting that each tool is used by firms with different profiles. Digging on the role of some observable variables, we find that both programs reach on average stable R&D performers, and that they do not foster participation of young firms relative to older ones. We also identify significant differences across programs: while diversified and commercially successful firms are more likely to use tax incentives, those with high productivity are more likely to obtain subsidies. We discuss some policy implications of these findings.

Keywords: R&D, innovation policy, tax incentives, subsidies, persistence, dynamic random effects, bivariate probit.

JEL:O31,

Acknowledgements: We are grateful to Cristina López-Mayan, Bettina Peters, Dirk Czarnitzki and Georg Licht for very useful comments. All errors are ours. This research has been funded by grants from the Ministry of Economy and Competitiveness (Projects nº ECO2012-33427; ECO2013-00043) and Junta de Extremadura (Project IB10013).

1. Introduction.

Governments in developed countries allocate public resources -up to 0.4% of Gross Domestic Product- to support business research and development (R&D) through tax incentive and subsidy programs, alongside with intellectual property protection. The first two policy instruments are currently offered simultaneously in most OECD countries, although with varying emphasis: while in the US the tax incentive share of total government support for R&D was about 23% in 2011, in France this share was 70% (OECD (2014)). As with any policy intervention, a number of questions arise concerning the efficiency of each tool individually and as policy mix and their ex post impact on productivity growth both at the micro and macro levels arise.

A particularly controversial issue is whether it is best to rely on tax incentives than on direct support or vice versa. Extant evidence does not yet offer an answer to this question. Most studies have analyzed separately these two forms of support, disregarding the fact that in many countries both programs are simultaneously available to firms and consequently producing potentially biased impact estimates.[1] Their main focus has been testing whether R&D subsidy or tax incentive programs induce substitution of private for public funding, or on the contrary they induce positive additional private R&D effort.[2] In the case of direct funding studies for countries where tax incentives are not offered reject the hypothesis of full replacement of private by public funding. As for R&D tax incentives, aggregate estimates of the impact of tax incentives have suggested they may increase R&D intensity (Bloom et al. (2002)) but recent micro level studies find evidence of partial crowding out when beneficiaries are large firms (Lokshin and Mohnen (2012)). In addition there is no country where no direct support but only tax incentives are offered, so these estimates may be potentially biased.

In addition to the potential bias just referred to, impact estimates, although valuable as they are to discard crowding out effects, do not provide a complete picture of the ex-post efficiency of R&D subsidy and tax incentive programs. First, they do not inform

[1]An exception is the study by Haegeland and Moen (2007) for the Norwegian case.
[2] In this literature, the ability of public support to induce more private R&D investment is known as input additionality. Some also estimate the impact of each program on outcomes such as patenting and innovation, known as output additionality.

about the success of each program in addressing the potential market failures that are associated with some types of R&D or other innovation activities that justify public support, as discussed in Toivanen et al. (2013) and Busom et al. (2014). Second, additionality estimates do not reveal whether potential and unintended barriers to program take up exist. In particular, a program might systematically reach only a subset of targeted firms; or both programs might repeatedly benefit the same set of firms, which could potentially signal allocation inefficiencies, especially if potentially eligible entrants are excluded. Comparative evidence on how these instruments interact, the profiles of firms each effectively reaches, and which are their long-term effects, is virtually missing.

We contribute to the field by performing a joint examination of participation patterns in each program and their dynamics.[3] We address two main questions: i) is the pool of firms that benefit from each policy always the same, or are entry and exit rates significant?; and ii) 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. Strong state dependence would suggest that the same firms repeatedly benefit from that particular program. On the positive side this may simply reflect that some firms' R&D projects always involve significant spillovers 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, potentially reflecting success at rent-seeking; it also would indicate that the program fails at attracting potentially eligible new firms. The later cases warn that allocation mistakes become permanent, with the subsequent welfare costs. Where the purpose of the policy is to increase the number of firms that invest in R&D (the extensive margin) rather than the investment effort of those that already invest (the intensive margin), program persistence would hint at a policy failure.

[3] Program participation has not been the main focus of evaluation research, with some exceptions (Blanes and Busom (2004); Aschhoff (2010), Huergo and Trenado (2010); Busom et al. (2014), Czarnitzki et al. (2014)). Aschhoff (2010) is the only study on participation persistence in direct support programs. She investigates whether in Germany firms that obtain subsidies are always the same, 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, concluding that the scheme seemingly failed at attracting SMEs, which was one of the aims of the program.

The second question bears on the dynamic interaction between R&D subsidies and tax incentives: participation in one program may predict future participation in the other - the extent of cross-persistence. 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 already invest in R&D are able to undertake R&D projects that match the public agency's preferences, beyond private profit considerations, which would be a desirable policy outcome.

To investigate these issues we analyze a longitudinal firm-level dataset of Spanish manufacturing firms, with yearly observations from 2001 to 2008. R&D subsidies and tax credits have been in place simultaneously since before 1995, when a new corporate tax law substantially increased incentives for R&D investment. The panel nature of the data allows us to identify the extent of state dependence for both programs, controlling for unobserved individual heterogeneity. Our results show that participation in R&D tax credit and subsidy programs is only partially driven by unobserved heterogeneity and that true state-dependence accounts for about 55% of observed persistence in the case of subsidies, and 60% in the case of tax credits. No evidence of cross-program spillovers is found. In addition, some observed firm features appear to have a different effect on the likelihood of participating in each program: higher productivity than the industry average is positively correlated with participating in R&D subsidy programs, but not with claiming tax credits. A firm's position as a market leader and an increasing market share contribute to the firm's claiming tax incentives, but not to the probability of obtaining subsidies. Young firms are not more or less likely to participate in any of these programs than older firms, but firms that were performing R&D at the beginning of the period are more likely to participate in both, as well as large firms.

These results suggest that, given macroeconomic and other framework conditions prevailing during the period analyzed, R&D tax incentives and subsidy programs in Spain were attractive mostly for incumbents -firms that were already performing R&D-, and that tax incentives appealed particularly to commercially successful firms, casting doubts on the ability of the latter to correct market failures.

The paper layout is as follows. In section 2 we discuss previous evidence on the dynamics of R&D and present some hypotheses regarding R&D policy participation. Section 3 describes the data we use in this investigation, while in section 4 we outline the empirical model. In section 5 we discuss our set of estimation results and conclude in section 6.

2. The dynamics of R&D and R&D program participation.

Empirical research has uncovered a number of regularities related to business R&D investment. One of them is the positive association between firm size and the probability of investing in R&D, and an often negative one between size and R&D intensity.[4] More recently, empirical studies have found a high level of persistence of R&D investment and innovation (Peters (2009) and Peters et al. (2013)); Martínez-Ros and Labeaga (2009); Raymond et al. (2010), Huergo and Moreno (2011); Antonelli et al (2012)). Several explanations have been proposed for observed persistence. Some authors argue that R&D investment involves entry and exit fixed costs lead to state-dependence (Mañez et al (2009); Arqué and Mohnen (2015)); others show that persistence is correlated with features such as the number of competitors (Woerter (2014)); or suggest to learning effects (Geroski et al. (1997); Triguero et al. (2014)). In addition, commercially successful innovation may foster more R&D investment because it provides firms with internal funds, alleviating innovation-specific financing constraints. These considerations suggest that R&D persistence may carry over to participation in R&D support programs: these may be more attractive to firms that are regular R&D performers; in addition, benefiting once from a program would make it more likely to keep benefiting from it over time, unless the program places some restrictions to continued support and favoring new entrants.

Whether participation persistence is a positive outcome or not will depend on whether it is associated to some permanent underlying market failure, which is what justifies the program's existence. For instance, Busom et al. (2014) find that firms that face difficulties to finance innovation, whether from internal or external sources, are more likely to obtain subsidies, and less likely to claim tax credits, suggesting that the latter

[4] See for instance the results of empirical research based on the well known Crepon-Duguet-Mairesse model, which distinguishes between firms' decision to invest on R&D from the intensity of R&D effort.

may not be an appropriate tool to address this specific problem. Then, unless a tax credit provides some compensation for limited appropriability, then such a scheme would only provide windfall gains to firms, at a social cost. This cost would be higher for volume-based tax incentive systems than for incremental systems. If participation in an R&D tax credit program exhibits persistence, then program design or implementation mistakes are likely to endure, involving negative welfare effects. Consequently, this finding would underscore the need for careful program design and ex-post evaluation.

Ongoing work on endogenous growth theory illustrates the relevance of a careful choice of innovation policy instrument. In particular, Akcigit et al. (2014) develop a model to evaluate alternative innovation policies that differ in their ability to discriminate across R&D types: a uniform subsidy and a selective subsidy. Their model incorporates some observed empirical regularities on the nature of R&D activities. These are, first, the heterogeneity of R&D projects in terms of their spillover potential -the standard classification into basic and applied research, or into exploration versus exploitation, approximates this idea. And second one refers to the diversity in the extent of product diversification, size and market position as entrant or incumbent across firms. This heterogeneity is expected to shape incentives to pursue each type of R&D, which in turn will influence for the optimal innovation policy instrument choice. Akcigit et al. compare the impact of each policy on firms' allocation of resources to basic and applied research, on productivity growth and on welfare. Using French firm level data, they find that a uniform subsidy leads to overinvestment in applied research and lower welfare than policies that discriminate between different innovation types.

In a similar vein, Akcigit and Kerr (2010, 2012), assume two possible types of R&D: exploration and exploitation activities. Exploration R&D aims at introducing new products to obtain technology leadership and yield higher spillovers than exploitation R&D, whose purpose is to improve existing product lines. Akcigit and Kerr establish that SMEs (entrants) have a comparative advantage for exploration R&D; therefore, an efficient innovation policy should target mostly the former type of firms. Consequently, we should expect low to moderate persistence of support if a policy succeeds at promoting more exploration than exploitation activities.

In our case, the two programs we compare also differ in the extent of discrimination across R&D projects. Direct support through subsidies allows the public agency to select those that fulfill some specific conditions: either the project is socially valuable but not sufficiently profitable for the firm -because of spillovers or technical risk- or the firm faces innovation specific financing constraints. To be eligible for support through tax incentives a firm has to show that its R&D investment aims at developing a product or process that provides substantial novelty at the market level, but not that the social value of the project is higher than private return or that it cannot fund the project.[5]

We expect participation dynamics across these two programs to differ because, even if both R&D subsidies and tax credits decrease the private cost of investing in R&D, features such as actual eligibility, timing, certainty and quantity of support they provide firms vary across programs (Busom et al. (2014)). Tax incentives are a non-discriminatory policy that will be attractive to firms that are able to finance -with own or external funds- their R&D investment and obtain positive taxable income.[6] Tax credits are claimed after successful R&D investment; in addition, the amount claimed can be constrained by the magnitude of profits. R&D subsidies, on the contrary, are intended to be discriminatory -based on the quality, cost and other attributes of a firm's R&D project- and offer upfront, partially non-repayable funding to approved projects. These differences may not only affect incentives to participate in each program, but participation trajectories as well.

In the case of tax incentives we expect participation persistence to be high for the following reasons. Established firms with a limited number of competitors, large or diversified firms, might benefit repeatedly from R&D tax incentives simply because they are less likely to suffer from innovation barriers, more likely to embark in an exploitation type of R&D, and more likely to generate positive taxable income on a regular basis than SMEs, firms with many competitors or new firms, all of which

[5] In Spain the 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 much lower.

[6] Within tax incentive schemes, there is a high variety of designs. Some 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 incremental expenditure; include special provisions for young firms and SMEs; contemplate cash refunds, carry-forwards, ceilings to deductions.... Here we assume that incentives are based on corporate income tax deductions, because this is the design affecting firms in our dataset.

frequently obtain lower profits. In addition, successful innovations not only increase profits but also the firm's internal funds, and consequently its ability to keep investing in R&D. This mechanism is consistent with the hypothesis of "success-breeds-success", and a tax incentive scheme would reinforce it.[7]

Participation persistence in R&D subsidy programs is a priori indeterminate. On one hand, the government agency may mostly target firms in one or several of the following categories: new firms; firms that face high R&D fixed costs; firms that lack funding for innovation, 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 low. On the other hand public agencies may select ambitious, lengthy R&D projects exhibiting technical uncertainty, fixed costs and long term spillovers; these projects may require continuous funding to keep them going, and public support would induce persistence in participation.[8]

Cross-program interactions may take place. Recipients of direct support may 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. In this case R&D subsidies may enable firms to use tax credits in the future, leading 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. We now turn to testing these hypotheses.

[7] The concern that tax incentive persistence may signal that this scheme could protect incumbents against innovative entrants has been pointed out by Bravo Biosca, Criscuolo and Menon (2012).

[8] This is a plausible situation when projects involve pre-competitive research, and when renewal of support is conditional on the project's technical or scientific results. Arqué and Mohnen (2014), who study the effects of public support on private R&D investment, conclude that for sustained R&D investment some firms may need continuation subsidies. This would breed persistence in direct support. Information on product duration would be needed to disentangle this source of persistence from true state dependence.

3. Data

Our data source is a firm-level annual survey sponsored by the Ministry of Industry of Spain since 1990, the *Encuesta Sobre Estrategias Empresariales* (ESEE hereafter). It samples manufacturing firms with 10 or more employees, contains information on firms' products, employment, markets and technological activities, and is a true panel. Since its inception it includes questions on a firm's R&D investment and use of direct public support (loans and grants); in 2001 new questions concerning the use of tax incentives were added.[9] Since our purpose is to compare the use of both policy instruments, we use data from 2001 to 2008, which was a period of economic growth.

Spain's R&D tax incentive scheme, exclusively offered by the central government, is designed as a hybrid system, combining volume and incremental based deductions from the firm's owed tax. The amount of deduction that can be claimed cannot exceed a ceiling that varies according to firm size, but any excess claim can be carried over to future periods. There are no refunds for firms without positive taxable income.[10] In 2008, about 3150 firms claimed tax credits for a total of 326Mio€, which account for roughly 4% of in-house R&D investment. About 75% of this volume was claimed by large firms. Although absolute magnitudes are much larger in the US, 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 (GAO (2009)).[11]

Unlike R&D tax credits, three jurisdictions offer R&D subsidies: Spain's central administration, regional governments and the European Union. In this paper we focus exclusively on the first source of funding because for Spanish firms it is the main source of funds and because differences in each jurisdiction goals are likely to generate different dynamics. During 2001 to 2008, the volume of subsidies provided through the

[9] In ESEE, all firms with more than 200 employees are surveyed as well as a random sample of firms with 10 to 200 employees, stratified by activity and size intervals defined by employment (10-20, 21-50, 51-100 and 101-200). A complete description of sampling procedures and questionnaires can be found in https://www.fundacionsepi.es/esee/en/epresentacion.asp . It is possibly one of the few data sets that provide information on a firm's use of both types of support.

[10] For a detailed comparative description of R&D tax schemes in OECD countries, see http://www.oecd.org/sti/rd-tax-stats.htm#design. According to OECD estimates, the implied tax subsidy rates for Spain are among the highest among member countries. There are no additional tax incentives from regional or local administrations in Spain.

[11] See GAO (2009), Table 3, page 53.

specialized government agency, the CDTI, was about three times as large as that of tax credits, a proportion similar to the US.[12]

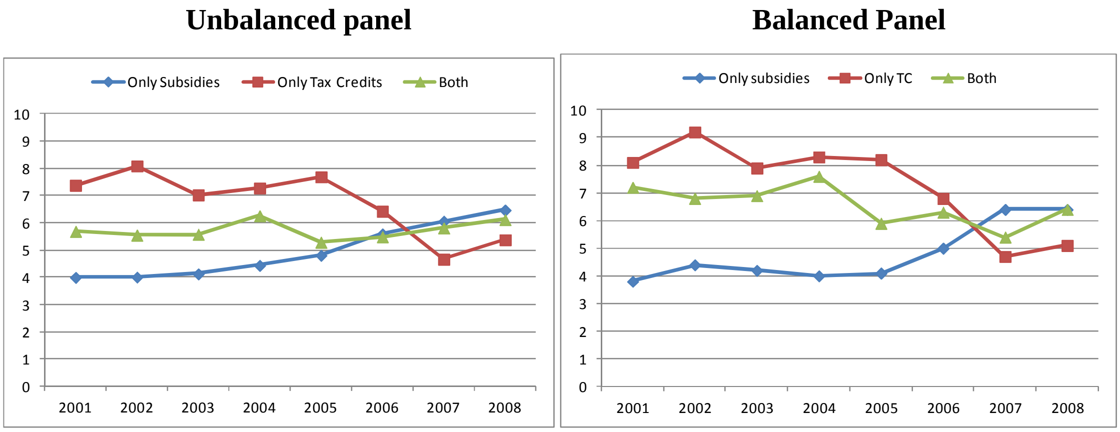
Our initial sample consists of an unbalanced panel of 2827 firms from 2001 to 2008 with a total of about 13000 observations of 2827 firms. 29% of them have more than 200 employees, and 21 % are in high or medium technology industries. On average, 36% conduct R&D, whether internal or external; 12% claim R&D tax credits and 7% participate in subsidy programs over the whole period. We extract from this sample 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.

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, participating in only one of them. We thus define a participation status variable that reflects a firm's state in a given year. Figure 1 shows the evolution of the share of firms in each possible state.[13] Notice that the share of firms that use only tax credits is higher than the share of firms that use only subsidies or both types of support up to 2006, when it falls. In contrast, the share of those participating exclusively in the subsidy program increases over this period; although lowest in 2001, it overtakes the remaining shares at the end of the period. The drop of the participation rate in tax credits possibly reflects to some extent a fall in profits as the economic crisis was just starting.

[12] Different types of subsidies are offered by the public agency; some are loans with or without non-returnable part and some are grants.
[13] We observe that each year about 1373 firms (82% of the total) did not participate in any of the programs, 85 obtained subsidies, 110 obtained tax credits, and 95 obtained both.

Figure 1. Evolution of participation status

Percentage of firms that obtain support by type



In the unbalanced panel, the number of firms each year oscillates from 1300 in 2001 to 2023 in 2006; the average is 1664 firms. The balanced panel contains 779 firms.
Data source: ESEE

Table 1 shows the transition rates across participation state, that is, the probability of a firm changing or remaining in the same status across two consecutive periods. The table highlights that i) the vast majority of non-participants (96%) remain in that state the following year; only 4% change status; ii) 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; iii) there are no remarkable differences between participants in exclusively one of the programs; and iv) 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 pattern is thus of strong persistence, which may be driven by heterogeneity or by true state dependence. In the next section we'll try to disentangle this.

Table 1. Transition rates across participation status.

		Status in t+1				
Status in t	Num observ.	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	10477	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

Note: the total number of observations here is smaller than the number in Figure 1 because firms that do not remain in the panel for at least two consecutive years had to be dropped.

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 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.

We observe that persistence in performing R&D is very high in our unbalanced panel: 96% of non-doing firm-observations remain in the same situation the following period, and of R&D doers, 90% remain so.[14] Again 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 find a comparable pattern if we focus on firm age.

We now focus on the transition patterns of the subsample of firms that invest in R&D at least once during this period, which is about one third of firms. 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

[14] R&D transition rates are very similar to those obtained by Huergo and Moreno (2011) for the period 1990-2005. Exit is more frequently observed than entry.

is easy, suggests the presence of some barriers to program participation. When we compute transition probabilities for the subset of R&D performers at time t, we observe patterns that are similar to those obtained with the whole sample of firms; the main difference being that there is now more entry from no support into some support status, in particular to tax credits. Table 2 shows the results, which are again comparable across the balanced and unbalanced panels.

Table 2. Transition rates across participation status.

Subsample of firms with positive R&D expenditure at t

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

4. Estimation Strategy

We specify a two-equation dynamic model to analyze the extent and origins of persistence of a firm's participation in R&D programs. The dependent variables are the unobserved likelihood of participating in the subsidy scheme, and the unobserved likelihood of participating in the tax credit scheme. Since we only observe participation status, we define two binary indicator variables y_{jit} where j=1 refers to firm i' s status regarding R&D subsidies in year t, and j=2 refers to status with respect to tax credits. We assume that both latent variables are a function of the firm's participation in each program the previous year, y_{jit-1}; a set of lagged observable variables x_{jit-1}[15]; unobservable time-invariant firm-specific effects, η_{ji} and a time-varying random error term u_{jit}. The model is:

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

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

The individual specific unobserved permanent component η_{ji} allows individuals who are homogenous in their observed characteristics to be heterogeneous in unobserved permanent features. They are assumed to be bivariate normal with variances $\sigma^2_{\eta 1}$, $\sigma^2_{\eta 2}$ and covariance $\rho_\eta\ \sigma_{\eta 1}\ \sigma_{\eta 2}$.

Unobserved individual effects, η_{ji}, may be correlated with observable characteristics as well as with the initial condition y_{ji0}. To consistently estimate the univariate dynamic model, 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, $\overline{x}_{ki}$[16]: For the bivariate case, the specification is:

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

Rabe-Hesketh and Skrondal (2013) suggest that using Mundlak means $\overline{x}_{ji}$ might be overly restrictive, because it imposes the same coefficient on the initial value of x and remaining periods. They show that for short panels this may lead to biased estimates,

[15] We include lagged instead of current values of explanatory variables so that they can be considered as predetermined.

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

and propose including the initial values of independent variables separately from their mean in subsequent periods.[17] Thus, for the bivariate case,

$$\begin{aligned} \eta_{1i} &= \alpha_{10} + \alpha_{11} y_{1i0} + \alpha_{12} y_{2i0} + \alpha_{13} x_{1i0} + \alpha_{14} \overline{x_{1i}}' + \varepsilon_{1i} \\ \eta_{2i} &= \alpha_{20} + \alpha_{21} y_{1i0} + \alpha_{22} y_{2i0} + \alpha_{23} x_{2i0} + \alpha_{24} \overline{x_{2i}}' + \varepsilon_{1i} \end{aligned} \qquad [3]$$

where x_{ji0} and $\overline{x_{ji}}'$ are, respectively the initial values of independent variables and the within-mean of each independent variable excluding the initial period. The covariance matrix of the random effects ε_{ji} is:

$$\Sigma_\varepsilon = \begin{pmatrix} \sigma^2_{\varepsilon 1} & \rho_\varepsilon \sigma_{\varepsilon 1} \sigma_{\varepsilon 2} \\ \rho_\varepsilon \sigma_{\varepsilon 1} \sigma_{\varepsilon 2} & \sigma^2_{\varepsilon 2} \end{pmatrix}$$

Inserting [2] into [1] we obtain:

$$\begin{aligned} y^*_{1it} &= \gamma_{11} y_{1it-1} + \gamma_{12} y_{2it-1} + \beta_1 x_{1it-1} + \alpha_{10} + \alpha_{11} y_{1i0} + \alpha_{21} y_{2i0} + \alpha_{13} x_{1i0} + \alpha_{14} \overline{x_{1i}}' + \varepsilon_{1i} + u_{1it} \\ y^*_{2it} &= \gamma_{21} y_{1it-1} + \gamma_{22} y_{2it-1} + \beta_2 x_{2it-1} + \alpha_{20} + \alpha_{21} y_{1i0} + \alpha_{22} y_{2i0} + \alpha_{23} x_{2i0} + \alpha_{24} \overline{x_{2i}}' + \varepsilon_{2i} + u_{2it} \end{aligned} \qquad [3]$$

The contribution of unobserved heterogeneity to total variance of each equation is measured by $\rho = \sigma^2_{\varepsilon j} / \left(\sigma^2_{\varepsilon j} + \sigma^2_{uj} \right)$. The main parameters of interest are γ_{11}, γ_{12}, γ_{21} and γ_{22}. We also wish to test the role of some observed characteristics of firms in explaining program participation. These are mainly relative productivity, human capital, firm size and age, which jointly with industry type are standard predictors of R&D and innovation activities (Peters et al. (2013)).

We first estimate and compare specifications [2] and [3].[18] We will later consider adding a second lag of each dependent variable for two main reasons. First, firms can carry-forward tax credit deductions when these exceed the legal threshold percentage – the ceiling- of their tax liability. In our balanced panel, about 9% (6%) of firms that obtain a tax credit at t did not perform R&D at t-1 (t), which is an indicator of the extent

[17] Rabe-Hesketh and Skrondal (2013) show through a series of Monte Carlo experiments that when the initial period of explanatory variables are included in the model the bias practically disappears.
[18] For an application of [4] see Devicienti and Poggi (2011). We adapt their Stata code, publicly available at http://web.econ.unito.it/fdevic/programs.htm, to our case. Estimation of the random effects bivariate dynamic probit model is performed by simulated maximum likelihood.

of the use of carry-forward opportunities. Second, subsidies may be awarded for more than one year. Both situations might be a source of second-order state dependence. Table 3 shows the frequency of participation over the period: we observe that only about one third of firms obtained a subsidy or a tax credit once, and that in the balanced panel a high percentage of firms did so four years or more.

Table 3. Frequency of participation over the period.

	Unbalanced panel		Balanced panel	
	R&D Subsidy	R&D Tax Incentives	R&D Subsidy	R&D Tax Incentives
One year	36%	33%	33%	22%
Two years	25%	25%	17%	21%
Three years	12%	12%	10%	11%
Four years or more	27%	30%	41%	46%
Total	100	100	100	100

Note: In the unbalanced panel 17% of firms obtain subsidies, and 19% claim tax credits. In the balanced panel, the percentages are 21% and 26% respectively.

5. Results.

We estimate the random effects dynamic model specified in equation [2] above (Model 1), as well as the less restrictive version proposed by Rabe-Hesketh and Skrondal in equation [3] (Model 2). Vector x contains time-varying variables; in our case we include the log of the average productivity of the firm relative to that of its industry, as an indicator of the firms proximity to the industry productivity frontier (*Log Rel Prod*). Time constant variables such as industry (*High Tech*) and size (*Size +200*) dummies among others can be included as well, although in this case their coefficients will capture a combination of the correlation with the unobserved individual effect and the partial effect on y.[19]

Table 4 shows these results, and for comparison, those of a pooled bivariate probit (Model 3). Estimates of Model 1 show that program participation exhibits positive state-dependence: the coefficient of lagged subsidy in the subsidy equation, and of lagged tax credit in the tax credit equation, are highly significant. True persistence accounts for about 55% of the variance of the composite error in the case of subsidies, and for 60% in the case of tax credits. This result supports the hypothesis of success-breeds-success.

[19] All variable definitions are shown on Table A1 in the appendix.

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. Unobserved heterogeneity accounts for a substantial share of persistence: 45% in the case of subsidies and 39% in that of tax credits.

[INSERT TABLE 4]

It turns out that 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. The public agency ends up providing support to firms that are closer to the technology frontier, suggesting that possibly publicly funded projects are of an exploratory nature. We do not observe this association in the case of tax credits, hinting that they are less likely to discriminate across projects. Since firms will on average choose projects that maximize expected private profits, exploitation rather than exploration projects are more likely to be preferred. In line with Ackcigit et al. (2014), this would lead to overinvestment in projects that generate less spillovers, and therefore to inefficient allocations.

We do not find significant cross-program feedback effects, as we cannot reject the hypothesis that $\gamma_{12} = \gamma_{22} = 0$: having participated in one program does not make participation in the other more likely, once we control for observed and unobserved individual characteristics. We interpret this result as evidence that on average each program reaches different types of firms whose projects are likely to be heterogeneous as well. Firms that engage in privately profitable R&D would benefit from tax credits and would not have a further incentive to engage in projects eligible for direct support. On the other hand, firms whose projects benefit from direct support would not, on average, claim tax credits possibly because they may not obtain profits in the short run. This would be consistent with the public agency selecting projects that generate knowledge spillovers but have limited immediate private returns. [20]

[20] Note that the error terms u_{1i} and u_{2i} are positively correlated, implying that joint estimation of both equations is more efficient than individual estimation.

Some further results provide interesting insights on firms' participation patterns. First, firm size increases the likelihood of participating in any of the two programs; on average these do not seem to be able to offset the barriers that SMEs face to engage in R&D. Low profits and application costs may respectively harm their access to tax credits and subsidies, but it is also possible that entry costs are higher than the expected tax deduction or expected subsidy. Second, being in a high-tech industry is also correlated with the probability of participation in any program. These results are consistent with Roberts and Vuong (2013), who through a simulation exercise find that the expected benefits from R&D investment vary across firms with different productivity levels, and across high-tech and low tech industries, and that R&D cost reductions affect them differently. This would show up in program participation incentives.

When we estimate the Rabe-Hesketh and Skrondal version of the model, allowing for different coefficients for the initial period of relative productivity (Model 2), we find that the main parameters' estimates are practically the same.[21] Both in Model 1 and Model 2 we find strong, significant state dependence of each instrument, but no evidence of cross-program effects. Model 3 shows that a simple pooled bivariate model overestimates own state-dependence as well as cross-program dependence, a standard result when individual heterogeneity is ignored.

We test whether other observed firm features are associated to the probability of participating in each program, besides relative productivity Some are time-invariant. The first is the condition of performing R&D at the beginning of the period (*RD_t0*). This variable can inform on the ability of the programs to attract non-performers relative to incumbents. We find that participation in any of the programs is highly correlated with being an R&D performer at the beginning of the period, supporting the hypothesis that incumbents are more likely to benefit from these tools (Model 4 in Table 5).

We next investigate whether being a young firm -a firm born after 1995, so that at the beginning of our period it would be 6 years old or younger- is associated with

[21]Relative productivity is the only time-varying independent variable included in this specification.

participation (Model 5 in Table 5). According to our estimation, the probability of young firms participating is not different from that of older firms. These results point that both programs do not succeed at attracting more manufacturing firms to engage in R&D activities, at least during this period, although they might have helped incumbent firms to maintain their investment.[22] They also highlight the importance of broader framework conditions for the success of innovation-specific policies, as research suggests. [23]

[INSERT TABLE 5]

Other firm observed features that may shape program participation incentives are a firm's human capital -an indicator of ability to undertake creative, high quality projects-, the extent of diversification -an indicator of incentives to engage in exploitation rather than exploration R&D, according to Akcigit and Kerr (2014)-, and the firm's market share or its evolution. Models 6 in Table 5 and Models 7 to 9 in Table 6 show our estimation results. A time invariant, binary indicator of having no employees with higher education (*No humanK*) shows a negative and significant coefficient;[24] interestingly, having more than one product line (*Diversify*) is positively correlated with the likelihood of using tax credits, while has no significant relation with obtaining direct support. This result is again consistent with Akcigit and Kerr's: diversified firms are likely to engage in exploitation R&D, which is a safer activity and more likely to generate profits in the short run, against which tax credits can be claimed. In contrast, diversification is not associated with obtaining subsidies.

Experiencing a growing market share (*Mkt Share*), and the firm's perception of being among the top three firms in its market (*Top 3 pos*) do not appear to be related to participation in subsidy programs. However, in the tax credit participation equation they are correlated with individual heterogeneity (Models 8 and 9 in Table 6).

Many studies have documented that a firm's ability to innovate is affected by the availability of own funds. We would thus expect constrained firms to be more likely to

[22] In that respect, it is important to recall that at that time Spain was experiencing a strong growth period that was driven mostly by the expansion of the construction industry, where returns to investment where very high and innovation opportunities low. The two innovation instruments analyzed would not able to offset this effect. We unfortunately cannot perform this same analysis for service sector firms.
[23] See for instance Westmore (2013) and Wang (2013).
[24]The percent of employees with a higher education degree shows practically no within variation.

use anyone or both support programs. To test this we define and include in our estimation an indicator of the firm's situation in this respect: the ratio between own funds and its short run debt (*Own funds/Debt*). We find that although this variable is not directly related to participation, it shows a negative correlation with the individual heterogeneity term in the case of subsidies, implying that firms with own funds are less likely to apply for direct support (Model 10 in Table 7). This result is consistent with Busom et al. (2014), who find that the likelihood of obtaining R&D subsidies is positively related to innovation-specific financing constraints.

[INSERT TABLE 6]

As an additional control for the possibility that participation dependence is driven mostly by R&D persistence, we estimate the model restricting the sample to those firms that perform R&D at least once during the 2002-2008 period (Model 11 in Table 7). This cuts down the sample in half, as 355 out of 779 firms (46% of the balanced panel) fulfill this condition.[25] About 30% of them claim tax deductions (107 firms) and 25% (90 firms) obtain a subsidy. We find that our main coefficients of interest, state dependence and cross program interaction barely change, as estimates are very close to those obtained with Model 1. The conclusions that previous program participation increases the likelihood of continued participation, that cross-program spillovers are quite weak, and that a high relative productivity increases the likelihood of receiving subsidies but not of claiming tax credits, hold.

We finally explore whether a particular type of firms, those that export and innovate, are more likely to participate in an R&D program (Model 12 in Table 7). In the period studied the corresponding indicator practically does not vary, so we include it as time-invariant variable. We find that there is a positive correlation between this indicator and claiming R&D tax credits, but not with subsidies. We interpret this result as support for the hypothesis that commercially successful innovators are more likely to claim tax credits because the returns of their R&D projects are sufficiently appropriable, and are unlikely to exhibit significant spillovers.

[25] Half of them, in turn, conduct R&D every year of the period.

As a final exercise, we look into the possibility that participation is driven by higher order dynamic process. As explained above, two arguments would justify estimating a model that includes a second lag of each dependent variable. The first is that firms may carryover tax credit claims, and the second is that direct support may be awarded for more than one year. Both would tend to generate state dependence. Given our relatively limited number of firms, however, our results (shown in appendix 2) suggest that this specification may be over-fitting our data: the non-significance of the variance of the individual random effect in the tax equation may reflect model misspecification.

[INSERT TABLE 7]

6. Conclusions

Understanding why and which firms participate in R&D program support programs, whether participation leads to continued participation, and whether 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 the effectiveness of innovation policies by bringing the focus on the dynamics of firm participation in R&D support programs, explicitly comparing R&D subsidies -direct support- with 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 contribution of these policies to increasing welfare. Crowding out -negative additionality- clearly reduces welfare, but positive additionality does not necessarily increase it, and given the opportunity cost of public resources, it might even reduce it. This will depend on the nature of underlying market failures -limited appropriability, financing constraints- and on the success of the support allocation mechanism in spotting the R&D projects most affected by them. Hence, the support allocation mechanism itself is of interest. We here extend work by Busom et al. (2014 by asking 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. This may contribute to uncover potential and unwanted distortions in the allocation of public resources to supporting private innovation.

Our main contributions and their implications can be summarized as follows. First, we find significant true state persistence of participation in R&D subsidy and tax credit programs; it accounts for about 55% of the unexplained variance of the composite error in the case of subsidies, and 60% in the case of tax credits –the rest being driven by unobserved heterogeneity. Second, we do not find evidence of cross-program interactions, controlling for other variables. The extent of state dependence particularly in the use of tax credits, their limited ability to induce the use of subsidies, and their correlation with market success indicators suggests that the projects beneficiary firms engage in would possibly have been carried out even without support. In income-based designs the ability to claim derives from commercial success; therefore, knowledge spillovers are likely to be small enough not to deter innovation effort in the first place. Consequently, there is room for misallocation of public resources, and our results show that any misallocation incurred in at one point in time is likely to persist, inducing long run negative welfare effects.[26] When tax incentives are income based, as is the case in Spain and many other countries, looking into the nature of claimants' R&D projects would be of particular interest. Furthermore, given that firms must be able to finance their projects with internal or external funds before claiming tax credits, it is also likely that most of them do not face serious financing constraints for innovating. There would thus be in principle little point in using this type of scheme unless it is restricted to pre-competitive R&D –often associated to collaborative R&D.

Among different observed firm features, firm size, being in a high tech industry, human capital and being an R&D performer at the beginning of the period, all increase the probability of participating in any of the two programs. Incumbents are thus more likely to respond to both types of incentives, as Aschhoff found in the German case. We also find that the correlation between some observable firm features and the probability of using on program or the other varies across programs. Higher productivity than the industry average is associated with obtaining R&D subsidies, but not with claiming tax credits. Participation in a subsidy program is also indirectly related to experiencing financing constraints. In the same vein, some factors increase the likelihood of claiming

[26] Mistakes in the allocation of subsidies may be more easily corrected, 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 one year.

R&D tax credits but not subsidies: these are whether the firm has more than one production line -which is presumably associated with exploitation R&D projects (Akcigit and Kerr (2013))-, experiencing a growing market share and being among the market leaders.

These reflections would call for a careful ex-post evaluation of each policy tool, encompassing both participation and impact analysis in order to uncover systematic misallocations. By pinpointing the high persistence of program participation, our findings highlight the need to extend ex-post evaluation of innovation policy effects beyond conventional measures of additionality and integrating allocation analysis in these studies.[27] To this end, information on the type of R&D projects firms that claim tax credits carry out, particularly their duration and indicators of their nature –exploratory versus exploitation content-, would be very valuable.

[27] While subsidy schemes may easily allow for adjusting eligibility requirements such that allocations errors can be corrected, this may be harder to achieve with R&D tax credits.

Table 4. Dynamic Bivariate Probit Estimation I. Baseline.

	Model 1 Mundlak-Baseline			Model 2 Rabe-Hesketh& Skrondal			Model 3 Pooled Bivariate Probit		
	Coef	s.e.	z	Coef	s.e.	z	Coef	s.e.	z
Subsidies									
Tax credit $_{t\_1}$	0.120	0.145	0.83	0.123	0.147	0.84	0.215**	0.098	2.19
Tax credit $_{t0}$	0.508***	0.166	3.05	0.504***	0.167	3.01	0.211**	0.104	2.04
Subv $_{t\_1}$	1.360***	0.129	10.56	1.362***	0.129	10.57	2.012***	0.117	17.18
subv$_{t0}$	1.592***	0.215	7.41	1.581***	0.215	7.37	0.654***	0.113	5.79
Log Rel Prod	0.403**	0.183	2.2	0.409**	0.183	2.23	0.330**	0.147	2.24
Mdistprod	-0.133	0.207	-0.64				-0.168	0.157	-1.07
Log Rel Prod $_{t0}$				-0.231	0.221	-1.04			
Rdistprod				0.081	0.271	0.3			
Size +200	0.569***	0.118	4.83	0.568***	0.118	4.82	0.403***	0.083	4.84
High Tech	0.480***	0.182	2.63	0.489***	0.183	2.67	0.324***	0.117	2.78
Cons	-2.826***	0.147	-19.19	-2.851***	0.151	-18.82	-2.201***	0.056	-39.08
Tax Credits									
Tax credit $_{t\_1}$	1.552***	0.109	14.25	1.554***	0.109	14.25	1.954***	0.086	22.7
Tax credit $_{t0}$	0.913***	0.151	6.02	0.911***	0.151	6.04	0.424***	0.091	4.67
Subv $_{t\_1}$	0.070	0.142	0.5	0.074	0.143	0.52	0.228**	0.099	2.31
subv$_{t0}$	0.575***	0.158	3.63	0.563***	0.157	3.57	0.269***	0.108	2.5
Log Rel Prod	0.012	0.148	0.08	0.031	0.148	0.21	0.035	0.136	0.25
Mdistprod	0.359**	0.166	2.16				0.234	0.149	1.57
Log Rel Prod $_{t0}$				-0.301*	0.176	-1.71			
Rdistprod				0.622***	0.215	2.89			
Size +200	0.439***	0.096	4.56	0.433***	0.096	4.52	0.331***	0.073	4.51
High Tech	0.716***	0.140	5.1	0.735***	0.141	5.22	0.504***	0.097	5.21
_cons	-2.476***	0.110	-22.46	-2.516***	0.114	-22.05	-2.089***	0.054	-38.56
Rho	0.483***	0.085	5.69	0.485***	0.085	5.68	0.458***	0.066	6.87
Sigma ε1	0.847***	0.106	8.01	0.842***	0.106	7.96			
Sigma ε2	0.643***	0.088	7.34	0.629***	0.087	7.23			
Rho ε	0.467***	0.162	2.87	0.455***	0.169	2.69			
LogLik	-1760.12			-1757.99			-1799.07		
N obs (firms)	5453 (779)			5453 (779)			5453 (779)		

Notes: The correlation of individual effects for subsidy equation in Model 1 is $rho_{\varepsilon1}$ = corr(ε1t,ε1s) = .84/(1+.84) = 45%; $rho_{\varepsilon2}$ = corr(ε2t,ε2s) = .64/(1+.64)= 39%. In Model 2 they are practically identical to those of Model 1.

Table 5. Dynamic Bivariate Probit Estimation II.

	Model 4 Control for Initial RD			Model 5 Control for Young			Model 6 Control for lack of skill		
	Coef	s.e.	z	Coef	s.e.	z	Coef	s.e.	z
Subsidies									
Tax credit $_{t-1}$	0.108	0.148	0.72	0.122	0.144	0.85	0.118	0.144	0.82
Tax credit $_{t0}$	0.256	0.161	1.59	0.509***	0.166	3.06	0.435*	0.163	2.67
Subv $_{t\_1}$	1.368***	0.130	10.51	1.353***	0.129	10.52	1.375***	0.127	10.77
subv$_{t0}$	1.325***	0.208	6.38	1.596***	0.216	7.4	1.527***	0.210	7.24
Log Rel Prod	0.396**	0.187	2.12	0.404**	0.183	2.2	0.391**	0.182	2.14
Mdistprod	-0.180	0.210	-0.86	-0.133	0.207	-0.64	-0.189	0.205	-0.92
No humanK							-0.498***	0.178	-2.79
Young				0.073	0.295	0.25			
RD t0	0.747***	0.153	4.88						
Size +200	0.428***	0.119	3.59	0.568***	0.118	4.82	0.467***	0.119	3.9
High Tech	0.372**	0.175	2.13	0.482***	0.183	2.64	0.416**	0.179	2.33
Cons	-3.007***	0.168	-17.89	-2.831***	0.148	-	-2.637***	0.146	-17.96
				.					
Tax Credits									
Tax credit t_1	1.534***	0.110	13.94	1.548***	0.108	14.29	1.537***	0.109	14.1
Tax credit $_{t0}$	0.612***	0.136	4.49	0.914***	0.151	6.06	0.837***	0.149	5.59
Subv $_{t\_1}$	0.079	0.147	0.54	0.075	0.142	0.53	0.088	0.142	0.62
subv$_{t0}$	0.281*	0.150	1.87	0.584***	0.159	3.67	0.528***	0.157	3.36
Log Rel Prod	-0.012	0.150	-0.08	0.008	0.148	0.06	0.005	0.147	0.04
Mdistprod	0.308*	0.168	1.84	0.364**	0.166	2.19	0.284*	0.166	1.71
No humanK							-0.689***	0.166	-4.14
Young				-0.361	0.285	-1.26			
RD t0	0.827***	0.115	7.21						
Size +200	0.285***	0.094	3.03	0.434***	0.096	4.52	0.323***	0.097	3.32
High Tech	0.547***	0.134	4.07	0.713***	0.140	5.08	0.645***	0.138	4.64
Cons	-2.645***	0.123	-21.44	-2.465***	0.110	-22.51	-2.272***	0.109	-20.72
Rho	0.479***	0.088	5.42	0.485***	0.085	5.72	0.483***	0.085	5.66
Sigma ε1	0.815***	0.109	7.45	0.848***	0.106	8.03	0.827***	0.104	7.9
Sigma ε2	0.549***	0.090	6.08	0.642***	0.087	7.42	0.630***	0.089	7.05
Rho ε	0.360*	0.205	1.76	0.468***	0.162	2.9	0.430**	0.167	2.57
LogLik	-1701.28			-1759.08			-1747.25		
N obs (firms)	5432 (776)			5453 (779)			5453 (779)		

Table 6. Dynamic Bivariate Probit Estimation III.

	Model 7 Control for Not diversifying			Model 8 Growing market share			Model 9 Market position		
	Coef	s.e.	z	Coef	s.e.	z	Coef	s.e.	z
Subsidies									
Tax credit $_{t\_1}$	0.123	0.143	0.86	0.104	0.142	0.73	0.109	0.142	0.77
Tax credit $_{t0}$	0.514***	0.168	3.06	0.496***	0.164	3.02	0.500***	0.164	3.04
Subv $_{t\_1}$	1.342***	0.127	10.57	1.392***	0.128	10.84	1.383***	0.128	10.79
subv$_{t0}$	1.649***	0.218	7.57	1.542***	0.211	7.3	1.564***	0.215	7.27
Divers $_{t\_1}$	-0.228	0.183	-1.25						
MDivers	0.365	0.265	1.38						
Mkt Share $_{t-1}$				0.112	0.108	1.03			
MMkt Share				0.369	0.261	1.42			
Top 3 pos							0.208	0.223	0.93
MTop 3							-0.010	0.119	-0.09
Size +200	0.689***	0.117	5.9	0.653***	0.113	5.79	0.624***	0.114	5.43
High Tech	0.435**	0.187	2.32	0.438**	0.177	2.48	0.450**	0.179	2.51
Cons	-3.024***	0.229	-13.23	-2.943***	0.158	-18.64	-2.866***	0.167	-17.10
Tax Credits									
Tax credit $_{t\_1}$	1.534***	0.108	14.17	1.555***	0.109	14.24	1.555***	0.108	14.39
Tax credit $_{t0}$	0.977***	0.157	6.24	0.921***	0.155	5.96	0.898***	0.150	5.96
Subv $_{t\_1}$	0.073	0.142	0.51	0.087	0.142	0.61	0.076	0.142	0.54
subv$_{t0}$	0.566***	0.161	3.52	0.544***	0.158	3.44	0.547***	0.158	3.46
Divers $_{t\_1}$	-0.340**	0.156	-2.18						
MDivers	0.230	0.218	1.05						
Mkt Share $_{t-1}$				0.121	0.096	1.27			
Mkt Share				0.547**	0.214	2.56			
Top 3 pos							0.044	0.145	0.31
MTop3							0.577***	0.182	3.16
Size +200	0.590***	0.099	5.98	0.588***	0.095	6.19	0.479***	0.094	5.06
High Tech	0.700***	0.144	4.85	0.700***	0.141	4.95	0.700***	0.141	4.97
Const	-2.490***	0.169	-14.71	-2.693***	0.128	-21.09	-2.616**	0.138	-18.86
Rho	0.485***	0.084	5.75	0.479***	0.083	5.75	0.480***	0.083	5.75
Sigma ε1	0.866***	0.104	8.36	0.815***	0.104	7.86	0.825***	0.104	7.98
Sigma ε2	0.687***	0.088	7.85	0.649***	0.089	7.28	0.632***	0.087	7.25
Rho ε	0.442***	0.145	3.05	0.461***	0.160	2.89	0.481***	0.163	2.94
LogLik	-1774.37			-1769.40			-1750.34		
N obs (firms)	5453 (779)			5453 (779)			5453 (779)		

Note: Model 9 includes a dummy variable to take into account missing values for the variable Top 3 in order to keep the same number of observations as in the other models.

Table 7. Dynamic Bivariate Probit Estimation IV

	Model 10 Own funds/Short run debt			Model 11: subsample Firms that do R&D at least once during the period			Model 12 Exporters that introduced a new product		
	Coef	s.e.	z	Coef	s.e.	z	Coef	s.e.	z
Subsidies									
Tax credit $_{t\_1}$	0.134	0.145	0.93	0.217	0.141	1.53	0.212	0.156	1.36
Tax credit $_{t0}$	0.504***	0.170	2.96	0.136	0.152	0.9	0.363**	0.163	2.23
Subv $_{t\_1}$	1.363***	0.133	10.23	1.329***	0.129	10.24	1.385***	0.141	9.82
subv$_{t0}$	1.557***	0.227	6.86	1.234***	0.198	6.22	1.604***	0.242	6.62
Log Rel Prod				0.411**	0.193	2.13	0.399**	0.186	2.15
Mdistprod				-0.365*	0.220	-1.66	-0.116	0.209	-0.56
Own funds/SRdebt $_{t-1}$	0.007	0.020	0.32						
MOf/SRdebt	-0.092***	0.038	-2.39						
InnovExport							0.204	0.129	1.59
Size +200	0.622***	0.116	5.36	0.299**	0.117	2.55	0.461***	0.119	3.89
High Tech	0.391**	0.168	2.32	0.350**	0.162	2.16	0.647***	0.171	3.8
cons	-2.654***	0.150	-17.72	-2.064***	0.124	-16.64	-2.81***	0.157	-17.95
Tax Credits									
Tax credit $_{t\_1}$	1.576***	0.114	13.88	1.584***	0.114	13.89	1.561***	0.112	13.88
Tax credit $_{t0}$	0.911***	0.158	5.78	0.522****	0.133	3.93	0.773***	0.151	5.12
Subv $_{t\_1}$	0.104	0.157	0.66	0.170	0.145	1.18	0.135	0.160	0.85
subv$_{t0}$	0.513***	0.170	3.02	0.261*	0.138	1.89	0.484***	0.164	2.96
Log Rel Prod				0.016	0.157	0.1	-0.005	0.149	-0.03
Mdistprod				0.200	0.176	1.14	0.358***	0.170	2.11
Own funds/SRdebt	-0.022	0.018	-1.22						
MOf/SRdebt	0.006	0.019	0.31						
InnovExport							0.391***	0.102	3.82
Size +200	0.570***	0.098	5.84	0.184**	0.092	2.0	0.425***	0.099	4.29
High Tech	0.617***	0.142	4.35	0.569***	0.129	4.39	0.805***	0.147	5.46
cons	-2.450***	0.115	-21.37	-1.791***	0.093	-19.15	-2.558***	0.121	-21.23
Rho	0.517***	0.089	5.83	0.514***	0.087	5.89	0.47***	0.098	4.81
Sigma ε1	0.804***	0.103	7.81	0.727***	0.107	6.78	0.795***	0.121	6.58
Sigma ε2	0.626***	0.090	6.93	0.458***	0.0976	4.69	0.615***	0.092	6.7
Rho ε	0.430***	0.171	2.51	0.050	0.2246	0.23	0.259	0.198	1.31
LogLik	-1673.02			-1563.03			-1649.93		
N obs (firms)	5054 (722)			2485 (355)			5278 (754)		

Note: In some models a small number of observations are lost because of missing data for the relevant variable.

References

Ackcigit, Ufuk and William Kerr (2010), "Growth through Heterogeneous Innovations", NBER WP Number 16443. R&R for JPE

Akcigit, Ufuk; Douglas Hanley and Nicolas Serrano-Velarde (2014), "Back to Basics: Basic Research Spillovers, Innovation Policy and Growth", NBER WP Number 19473.

Antonelli, Cristiano & Crespi, Francesco & Scellato, Giuseppe, 2012. "Inside innovation persistence: New evidence from Italian micro-data," *Structural Change and Economic Dynamics*, Elsevier, vol. 23(4), pages 341-353.

Arqué-Castells, Pere (2013) Persistence in R&D Performance and its Implications for the Granting of Subsidies. *Review of Industrial Organization*, forthcoming.

Arqué, Pere and Pierre Mohnen (2013), "Sunk costs, extensive R&D subsidies and permanent inducement effects", *Journal of Industrial Economics*, forthcoming.

Aschhoff, Birgit 2010. "Who Gets the Money? The Dynamics of R&D Project Subsidies in Germany," *Journal of Economics and Statistics* (Jahrbuecher fuer Nationaloekonomie und Statistik), Justus-Liebig University Giessen, Department of Statistics and Economics, vol. 230(5), pages 522-546.

Arulampalam, W. and Stewart, M. (2009). "Simplified implementation of the Heckman estimator of the dynamic probit model and a comparison with alternative estimators", *Oxford Bulletin of Economics and Statistics*, 71, 5,

Aw, B. Y., M. J. Roberts, and D. Y. Xu (2011). "R&d investment, exporting, and productivity dynamics", *American Economic Review*, 101 (4), pp. 1312-44.

Bérubé, Charles and Pierre Mohnen, 2009. "Are firms that receive R&D subsidies more innovative?," *Canadian Journal of Economics*, Canadian Economics Association, vol. 42(1), pages 206-225.

Nick Bloom, Rachel Griffith, John Van Reenen, 2002, Do R&D tax credits work? Evidence from a panel of countries 1979–1997, *Journal of Public Economics*, Vol.85 (1),pp. 1-31

Bravo Biosca, Albert; Chiara Criscuolo and Carlo Menon(2013), "What Drives the Dynamics of Business Growth?," OECD Science, Technology and Industry Policy Papers 1, OECD Publishing.

Busom, Isabel, Beatriz Corchuelo and Ester Martínez Ros (2014), "Tax Incentives or Subsidies for R&D?", *Small Business Economics*.

Cerulli, G. (2010) Modelling and measuring the effect of public subsidies on business R&D: a critical review of the econometric literature. *The Economic Record* 86(274), 421–449.

Correa, Paulo; Luis Andrés and Christian Borja-Vega (2013), "The Impact of Government Support on Firm R&D Investments. A Meta-Analysis", World Bank Research Working Paper 6532.

Devicienti, Francesco and Ambra Poggi,(2011), "Income poverty and social exclusion: two sides of the same coin or dynamically interrelated processes?", *Applied Economics*, vol. 43 (25).

Huergo, E. and L. Moreno (2011), "Does history matter for the relationship between R&D, innovation and productivity", *Industrial and Corporate Change*, 20(5), 1335-1368.

Huergo, E. and Trenado, M. (2010). "The application for and the awarding of low interest credits to finance R&D projects", *Review of Industrial Organization*, 37, 237-259.

Czarnitzki, Dirk; Elena Huergo; Mila Kohler, Pierre Mohnen, Sebastian Pacher ,Tuomas Takalo, Otto Toivanen (2014), " Structural estimation of targeted R&D subsidies: International evidence", mimeo, downloaded from www.ihs.ac.at/conferences/cepr2015/files/TOIVANEN---Structural-estimation-of-targeted-R-D-subsidies....

Lokshin, Boris & Pierre Mohnen, 2012. "How effective are level-based R&D tax credits? Evidence from the Netherlands," *Applied Economics*, Taylor & Francis Journals, vol. 44(12), pp. 1527-1538

Mairesse, J. and Ientile, D. (2009), A Policy to Boost R&D: Does the R&D Tax Credit Work?, European Investment Bank Papers, vol. 14, no. 1

Martínez, Ester and Jose M. Labeaga (2009) Product and Process Innovation: Persistence and complementarities, *European Management Review*, Vol. 6(1), pp. 64-75.

OECD (2013), Supporting Investment in Knowledge Capital, Growth and Innovation, OECD Publishing, DOI:10.1787/9789264193307-en

Peters, Bettina (2009), Persistence of Innovation: Stylized facts and panel data evidence, *Journal of Technology Transfer* 34(2), 226-243.

Peters; Bettina; Mark J. Roberts; Van Anh Vuong and Helmut Fryges (2013), Estimating dynamic R&D demand: an analysis of costs and long-run benefits, NBER WP 19374.

Rabe-Hesketh, Sophia and Anders Skrondal (2013), Avoiding biased versions of Wooldridge's simple solution to the initial conditions problem, *Economics Letters* 120, pp. 346-349.

Raymond, Wladimir; Pierre Mohnen; Franz Palm and Sybrand Schim van der Loeff, 2010. "Persistence of Innovation in Dutch Manufacturing: Is It Spurious?," *The Review of Economics and Statistics*, MIT Press, vol. 92(3), pp. 495-504

Raymond, Wladimir; Jacques Mairesse; Pierre Mohnen and Franz Palm (2013), "Dynamic Models of R&D, Innovation and Productivity: Panel Data Evidence for Dutch and French Manufacturing", CESifo WP 4290.

Roberts, Mark J. and VanAnh Vuong (2013), "Empirical Modeling of R&D Demand in a Dynamic Framework", *Applied Economic Perspectives and Policy*, 35 (2), pp. 185-205.

Takalo, Tuomas & Tanayama, Tanja & Toivanen, Otto, 2013. "Market failures and the additionality effects of public support to private R&D: Theory and empirical implications," *International Journal of Industrial Organization*, vol. 31(5), 634-642.

Wang, Cong (2013), "Can institutions explain cross country differences in innovative activity?", *Journal of Macroeconomics*, 37, pp. 128-145.

Westmore, Ben (2013), "Innovation and Growth: Considertions for Public Policy", *Review of Economics and Institutions*, 4(3), pp. 1-50.

Wooldridge, J.M. (2005), "Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity", *Journal of Applied Econometrics*, 20, 30-59.

Wu, Yonghong, David Popp and Stuart Bretschneider (2007), "The Effects of Innovation Policies on Private R&D Investment: A Cross-national Empirical Study", *Economics of Innovation and New Technology*, 16(4), 237–253.

Zuñiga-Vicente, J.A., C Alonso-Borrego, F. Forcadell and J.I. Galan (2014), "Assessing the effect of public subsidies on firm R&D investment: A survey", *Journal of Economic Surveys*, 28(1), 36-67.

Woerter, Martin 2014,. "Competition and Persistence of R&D", *Economics of Innovation and New Technology*, 23 (5-6), 469-489.

APPENDIX

Table A1. Variable definition

Variable	
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 year 2001
Subv t_1	Binary; 1 if the firm received a s subsidy in year t-1
subvt0	Binary; 1 if the firm received a subsidy in initial period
Log Rel Prod t_1	Log of relative productivity: log of sales per employee/average sales peremployee of firms in the same industry, at t-1
Mdistprod	Within mean of the log of relative productivity from t0 to T.
Log Rel Prod t0	Log of relative productivity at initial period
Rdistprod	Within mean of the log of relative productivity from t1 to T
Young	Binary; 1 if firm was born after 1995
RD t0	Binary; 1 if firm was investing in R&D at t0
$NoDivers_{t\_1}$	Binary; 1 if firm does not diversify products
MDivers	Within mean of not diversifying
Mkt Share $_{t-1}$	Binary; 1 if market share is growing
MMkt Share	Within mean of growing market share
Top 3 $position_{t-1}$	Binary; 1 if firm is one of the top 3 in its market
MTop 3	Within mean of Top 3 position
Own funds/SRdebt $_{t-1}$	Ratio of own funds to short run debt
MOf/SRD	Within mean of the ratio of own funds to short run debt
No humanK	Binary; 1 if firm does not have higher education graduates
Innov*Export	Binary; 1 if the firm introduced a innovation and exported at t-1
Size +200	Binary; 1 if the firm has more than 200 employees
High Tech	Binary; 1 if the firm is in the high tech industries

Table A2. One-lag transition rates

	Subsidy status at t+1		Tax Credit status at t+1		R&D status at t+1	
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 A3. Two-lag transition rates.

		Status at t+2				
Status at t	N. Observ	No support	Only Subs	Only Tax Credit	Both	Total
Unbalanced panel						
No support	6463	94.4	2.2	2.6	0.8	100
Only Subs	356	33.4	44.7	3.4	18.5	100
Only Tax Credit	590	38.1	3.4	45.9	12.5	100
Both	477	10.9	16.9	12.6	59.5	100
Total Obs	7886					
Balanced panel						
No support	3779	94.3	2.2	2.7	0.8	100
Only Subs	205	32.7	48.3	1.5	17.6	100
Only Tax Credit	379	40.6	2.4	46.4	10.5	100
Both	317	10.4	16.1	12	61.5	100
Total Obs	4680	81.6	5.1	6.9	6.4	100

Table A4. Dynamic Bivariate Probit Estimation. Balanced Panel.

	Model 1: RE biv, 1lag			Model 2: RE biv 2lags			Model 3: Pooled biv probit		
	Coef	Sd	t-stat	Coef	Sd	t-stat	Coef	Sd	t-stat
Subsidies									
Tax credit t_1	0.120	0.145	0.83	0.179	0.142	1.25	0.185	0.126	1.46
Tax credit t_2				-0.001	0.135	-0.01	0.005	0.131	0.04
Tax credit t0	0.508***	0.166	3.05	0.219*	0.127	1.72	0.185*	0.111	1.67
Subv t_1	1.360***	0.129	10.56	1.747***	0.129	13.47	1.810***	0.111	16.19
Subv t_2				0.535***	0.130	4.11	0.570***	0.118	4.82
Subv t0	1.592***	0.215	7.41	0.643***	0.177	3.63	0.521***	0.118	4.4
Log Rel Prod t_1	0.403**	0.183	2.2	0.453**	0.180	2.51	0.444***	0.170	2.6
MLog Rel Prod	-0.133	0.207	-0.64	-0.267	0.194	-1.38	-0.270	0.175	-1.54
Large firm	0.569***	0.118	4.83	0.402***	0.090	4.45	0.373***	0.083	4.46
High-Tech	0.480***	0.182	2.63	0.320**	0.125	2.56	0.289**	0.123	2.35
constant	-2.826***	0.147	-19.19	-	0.111	-20.64	-2.222***	0.057	-38.37
Tax Credits									
Tax credit t_1	1.552***	0.109	14.25	1.786***	0.104	17.06	1.803***	0.101	17.81
Tax credit t_2				0.382***	0.110	3.46	0.396***	0.112	3.51
Tax credit t0	0.913***	0.151	6.02	0.362***	0.120	3.01	0.326***	0.095	3.44
Subv t_1	0.070	0.142	0.5	0.085	0.145	0.59	0.114	0.132	0.86
Subv t_2				0.159	0.142	1.12	0.169	0.126	1.34
Subv t0	0.575***	0.158	3.63	0.229*	0.137	1.66	0.190*	0.107	1.78
Log Rel Prod t_1	0.012	0.148	0.08	0.027	0.153	0.18	0.035	0.155	0.23
MLog Rel Prod0	0.359**	0.166	2.16	0.261	0.165	1.58	0.245	0.169	1.45
Large firm	0.439***	0.096	4.56	0.290***	0.079	3.66	0.277***	0.075	3.68
High tech sector	0.716***	0.140	5.1	0.448***	0.111	4.01	0.428***	0.096	4.42
constant	-2.476***	0.110	-22.46	-	0.085	-25.14	-2.128***	0.056	-37.87
Rho	0.483***	0.085	5.69	0.518***	0.088	5.87	0.478***	0.054	
Sigma ε1	0.847***	0.106	8.01	0.266*	0.154	1.73			
Sigma ε2	0.643***	0.088	7.34	0.166	0.175	0.95			
Rho ε	0.467***	0.162	2.87	0.615	1.667	0.37			
LogLikelihood	-1760.12			-1471.65			-1472.37		
N obs (firms)	5453 (779)			4674 (779)			4674 (779)		

Notes: The correlation of individual effects for subsidy equation in Model 1 is $rho_{\varepsilon 1}$ = corr(ε1t,ε1s) = .811/(1+.811) = 45%; $rho_{\varepsilon 2}$ = corr(ε2t,ε2s) = .553/(1+.553)= 36%. Model 2: $rho_{\varepsilon 1}$ = corr(ε1t,ε1s)== .26/(1+.26) = 21%; $rho_{\varepsilon 2}$ is not significant.

Últims documents de treball publicats

NUM	TÍTOL	AUTOR	DATA
15.02	Teaching styles and achievement: Student and teacher perspectives	Ana Hidalgo-Cabrillana, Cristina Lopez-Mayan	Febrer 2015
15.01	The Long-Term Impact of Inequality on Entrepreneurship and Job Creation	Roxana Gutiérrez Romero, Luciana Méndez Errico	Gener 2015
14.10	The good, the bad and the ugly: The socio-economic impact of drug cartels and their violence in Mexico	Roxana Gutiérrez Romero, Mónica Oviedo León	Octubre 2014
14.09	Estimating the impact of Mexican drug cartels on crime	Roxana Gutiérrez Romero, Alessandra Conte	Setembre 2014
14.05	Real unit labour costs in Eurozone countries: Drivers and clusters	Javier Ordóñez, Hector Sala, José I. Silva	Juny 2014
14.04	The determinants of capital intensity in Japan and the U.S.	Dario Judzik, Hector Sala	Maig 2014
14.03	EFFECTS OF INSTITUTIONAL ENVIRONMENT AND TECHNOLOGY DEVELOPMENT ON PAYMENT CHOICE	Francisco J. Callado-Muñoz, Jana Hromcová, Natalia Utrero-González	Maig 2014
14.02	The causal factors of international inequality in CO2 emissions per capita: A regression-based inequality decomposition analysis.	Juan Antonio Duro, Jordi Teixidó-Figuerasa, Emilio Padilla	Abril 2014
14.01	Energy Intensity in Road Freight Transport of Heavy Goods Vehicles in Spain	Lidia Andres Delgado, Emilio Padilla	Abril 2014
13.06	The materiality of the immaterial. Services sectors and CO2 emissions in Uruguay	Matías Piaggio, Vicent Alcántara, Emilio Padilla	Setembre 2013
13.05	Empirics of the international inequality in CO2 emissions intensity: explanatory factors according to complementary decomposition methodologies	Juan Antonio Duro, Jordi Teixidó-Figueras, Emilio Padilla	Juny 2013
13.04	Empirical Welfare Analysis: When Preferences Matter	Jean-François Carpantier, Christelle Sapata	Juny 2013
13.03	How effective are policies to reduce gasoline consumption? Evaluating a quasi-natural experiment in Spain	Javier Asensio, Andrés Gómez-Lobo, Anna Matas	Febrer 2013
13.02	Performance in Post-compulsory Education: Evidence from Vocational and Academic Tracks	Cristina Lopez-Mayan	Febrer 2013
13.01	The Impacts of Social Networks on Immigrants' Employment Prospects: The Spanish Case 1997-2007	Luciana Méndez Errico	Gener 2013