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The possible adverse impact of innovation subsidies: some evidence from a bivariate switching model

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Abstract

The impact of public funding is estimated using firm-level Italian data. Results from a bivariate endogenous switching model show that innovative productivity is negatively affected by the innovation subsidy; far from 'doing better' as a result of government intervention, supported firms appear to exhaust their advantage through merely increasing their innovative expenditures.

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1. Introduction

Despite the wide diffusion of innovation subsidies, there is still little consensus regarding their true effectiveness in spurring innovation; indeed, while theoretical arguments can be invoked to support the possibility of both a positive and a negative impact of government intervention on firms' innovative activity (Garcia-Quevedo, 2004), empirical studies do not clearly discriminate between them (Capron and Van Pottelsberghe, 1997). Moreover, political interests seem to have driven the analysis mainly towards the issue of additionality - *i.e.* assessing whether an R&D subsidy involves additional R&D expenditures by the receiving firm - neglecting both the importance of the allocation process and the possibility that such input-side additionality does not translate into proportionally higher innovative outputs.

This work tries to move one step further, combining the two (input and output) dimensions of innovation in a unique efficiency perspective: to this end, the impact of public funding on the ratio between total innovative sales and total innovative expenditures, considered as a measure of innovative productivity, is investigated. This change of perspective is a response to the need for evaluation of whether supported firms are really doing *better*, not just *more*, than non-supported ones, 'doing better' having more to do with the efficient use of innovative inputs rather than with the absolute value of the innovative expenditures.

The definition of this productivity variable, together with the description of data and indicators used in the empirical analysis, can be found in Section 3; in Section 4 a bivariate-switching model is developed, the main novelty of which consists in getting rid of both selection bias and endogeneity of the treatment (subsidy) variable, while at the same time checking for possible simultaneity. Econometric results are presented and discussed in Section 5, while Section 6 briefly concludes.

2. Previous literature

Although in absolute terms public funding appears to foster both the input and the output sides of innovation, a crowding out effect also seems to operate, totally or partially displacing privately-funded innovation activities. For instance, using a dataset of firms which benefited from the Small Business Innovation Research Program, Wallsten (2000) comes to the conclusion that R&D grants completely crowd out firm-financed R&D spending, dollar for dollar.

Much more optimistic is the view of Gonzales *et al.* (2005), who found no evidence of crowding out: using an unbalanced panel of more than 2,000 Spanish manufacturing firms, the authors show government intervention as stimulating R&D activities.

Midway between such extreme results, the majority of existing empirical literature on the subject shows that public support is indeed fostering innovation, with crowding out effects operating only partially (see Busom, 2000). In particular, previous studies (see Capron and Van Pottelsberghe, 1997) show that the magnitude of the crowding out depends on factors such as: 1) the level of aggregation of the analysis (a positive effect of public support is seen much more clearly at the industry than at the firm level); 2) the adopted econometric methodology; 3) the size of the investigated firms[1] and 4) the geographical area considered.

Most of these studies, however, do not depart from the standard additionality issue: does public support really add to what the subsidised firm would have invested had it not taken part in a policy program? What this literature seems to neglect is the final impact of government intervention on firms' innovative performance: does the (possibly) higher input level induced by public support lead to a correspondingly higher innovative performance in terms of input-output efficiency? Czarnitzki (2002) rightly raises this question, without fully addressing it.

Bérubé and Mohnen (2009) deal with it partially, exploring the impact that government intervention has on alternative measures of innovative output. However, the input dimension is not taken into account, thus making it impossible to figure out which fraction of the innovative output increase is due merely to an indirect effect of higher innovative inputs induced by public support, and which part, instead, reflects a direct impact of government intervention on firms' innovative productivity.

An interesting step in this direction has been taken by Garcia and Mohnen (2010): using cross-sectional firm-level data taken from the third Austrian CIS, the authors show how no (significant) direct effect of government intervention on the share of innovative turnover emerges once the indirect effect of a higher level of R&D expenditures has been accounted for[2]. However, while allowing for a different intercept to characterize the supported and non-supported sub-samples, the authors do not explicitly investigate the possibility that public funding also affects the marginal effect of R&D on innovative output.

3. Dataset, sample selection and descriptive statistics

Empirical analysis investigating the impact government intervention may have on innovative productivity has been carried out using firm-level data drawn from the third Italian Community Innovation Survey (CIS 3) conducted over a three-year period (1998-2000) by the Italian National Institute of Statistics (ISTAT). A 53% response rate determined the full sample size of 15,512[3] firms. We focus on 9,034 of them, those belonging to the manufacturing sector. Once cleaned of outliers and firms which were either newborn or had recorded an output variation of at least 10% due to M&A, the adopted sub-sample was of 7,965 observations. The dataset comprises a set of general information, together with a much larger set of innovation variables. In particular, firms were asked to answer the question *"Has your enterprise received any kind of public support for innovation-related activities in the last three years?"*.

[1] Lach (2002), for example, finds that small firms enjoy positive dynamic total effects from a subsidy, which seem to fade away as soon as large firms are considered.

[2] See also Branstetter and Sakakibara (1998).

[3] Thanks to a weighting procedure assigning weights according to the reciprocal of the probability of each observation being sampled, this sample is representative, at both sector and firm size level, of the entire population of Italian firms with more than 10 employees.

We can thus introduce a public-support dummy variable (**funding**), equal to 1 if a given innovative firm received some kind of financial support to innovation, and equal to 0 otherwise. The filter-based nature of the CIS questionnaire requires firms to answer the full set of innovative questions, including the one concerning funding, only if they have either started innovative projects (then abandoned or still to be completed) or introduced innovation outputs. As a consequence, our empirical analysis is limited to investigating the efficiency impact of public funding *within* a sample of innovative firms, while we are unable to consider its role in making a firm innovative. Therefore, our sample reduces to 2,855 innovative firms, generating an obvious problem of sample selection that we have to bear in mind when dealing with our core question: are the firms that received public support (funding=1) 'doing better' than those which did not get access to public funding (funding=0)?

In this framework, a first necessary step is that of defining an adequate measure of innovative performance: what do we really mean by 'doing better'.As highlighted in Section 2, this paper aims to go beyond the policy evaluation literature just focusing on the input- or the output-side effect of funding; with this purpose in mind, the impact of public funding on the ratio between total innovative sales and total innovative expenditures is explored. From now on, this ratio will be referred to as our innovative productivity variable (**pdtv**), measuring how many €s of innovative sales (i.e. sales due to innovative products) a firm realizes for each € spent on innovative inputs. Adopting a productivity measure fully matches our aim, which is not to evaluate whether subsidized firms invest more in innovation, but whether they are more efficient in transforming innovative inputs into innovative outputs.

One of the main limitations of CIS is that the only continuous measure of innovative output is turnover due to innovative products (*turninn*), which is used to construct our key productivity variable **pdtv**. This limitation further reduces the extent of our analysis from the 2,855 firms engaged in process and/or product innovation to the sub-sample of firms reporting product innovations only (746 observations)[4]. Of these, 389 firms (52.14%)[5] declared they had received some kind of public financial support (i.e. were 'treated') during the previous three years, while the remaining 357 observations (47.86%) were not supported ('non-treated').

A preliminary, descriptive comparison of these two sub-samples is provided below (Table 1), showing the quantitative (unconditional) effect that the subsidy produces on: 1) the share of turnover due to innovative sales (turninn(%) = sales from new products/total sales); 2) the total innovative expenditure intensity (tot_inn intensity(%) = total innovative expenditures/ total sales); and 3) the productivity measure we obtain upon dividing the first measure by the second (pdtv = sales due to new products / total innovation expenditures).

[4] Because a continuous output measure of process innovation is not available in the adopted dataset, firms engaged in this form of innovation have to be excluded, otherwise the observed effect of funding on **pdtv** would be biased either downward (in the case of firms reporting process innovation only, the innovative productivity of which would be zero) or unpredictably downward/upward, in accordance with the effect of the subsidy on the qualitative composition of the innovation output (this is the case of firms declaring they had introduced both product and process innovations).

[5] Such a high share of supported firms in the total is explained by the selection of innovative firms only.

Table 1: Descriptive statistics.

	Sample means			Mean differences	
	All firms N = 746	**Non-supported firms N_0 = 357**	**Supported firms N_1 = 389**	**Difference: mean(N_1)-mean(N_0)**	**% Difference: mean(N_1)-mean(N_0)**
Turninn (%)	26.474	23.871	28.864	**4.993**** (0.011)	+ 20.91%
tot_inn intensity (%)	4.802	3.95	5.584	**1.633**** (0.002)	+ 41.35%
pdtv[6]	10.938	11.86	10.09	**-1.771*** (0.081)	– 14.93%

Notes: in the case of tot_inn intensity and pdtv, two-sample t-tests with unequal variances were computed, since the null of equal variances was rejected by Bartlett's test for equal variances; p-values in brackets: *** = 1% significant; ** = 5% significant; * = 10% significant

Then the mean differences in the three innovation measures between supported and non-supported firms, the so-called 'treatment-control comparison', were computed. These differences, which provide us with preliminary estimates of the effects generated by the subsidy, are reported in the last two columns of Table 1, together with the corresponding p-values from the two-sample t-tests of their significance.

However, the previous descriptive statistics do not control for the possibility that the negative impact of the subsidy over **pdtv** may be driven either by selection biases or by *ex ante* sources of firm heterogeneity. The following econometric setting is thus devoted to testing whether the negative impact of funding on innovative productivity persists once we have checked for the role that exogenous factors can play in differentiating the two sub-samples of supported and non-supported firms[7], as well as for the two sequential selection biases affecting our analysis (the first concerning the selection of the 2,855 innovative firms from the total 7,965 surveyed, and the second

[6] It must be noticed that:

$$\text{Avg (pdtv}_i\text{)} = \text{Avg}\left(\frac{tot\_inn\_expenditure_i}{turninn_i}\right) = \text{average of the ratios}$$

Therefore, the pdtv values shown in table 1 (third row) are not equal to the ratio between the two averages reported in the two rows above.

[7] See Table A1 in Appendix 1 for an exhaustive list of the observable factors introduced as controls, together with the other variables relevant to this study.

concerning the further selection of the 746 companies characterised by product innovation only)[8].

4. The endogeneity problem: a bivariate switching solution

The main difficulty affecting policy evaluation is the potential endogeneity of the subsidy, the assignment of which fails to satisfy the randomness property that should characterize pure social experiments. Indeed, an evaluation of the expected innovative outcome (by both the firm which has to decide whether to apply for the subsidy and the public agency which must decide which projects to subsidise) is likely to precede the allocation process (Lichtenberg, 1984). This makes public funding an endogenous variable with respect to innovation itself.

The existing treatment evaluation literature offers alternative methodologies to deal with such potential endogeneity, however each of them imposes more or less restrictive conditions[9]. In particular, these approaches rely on the hypothesis that depending on a set of observable explanatory factors X, the alternative outcomes y_1 (with the treatment) and y_0 (without) are orthogonal to the treatment (D):

$$y_0, y_1 \perp D \mid X \qquad \textbf{(1)}$$

These approaches neglect the possibility that observable factors may simultaneously affect both the treatment (D) and the adopted performance measure (y). Simultaneous equation systems accomplish this aim, jointly taking into account the treatment assignment process and its outcome, i.e. checking whether the funding allocation process is partially determined by the same factors affecting the innovative process (endogeneity). In this framework, an endogenous dummy variable (D) becomes the dependent variable of a participation equation where the subsidy can be explained by the same factors affecting firms' innovative performance (see Busom, 2000). In other words, two different 'regimes' for the innovative performance are allowed, public support playing the role of endogenously switching firms from one regime to the other. Therefore, the resulting switching model can be written as:

[8] In particular, while the first source of sample selection can be dealt with through a standard Heckman correction (i.e. by including the inverse Mills ratio obtained from a probit selection equation among the control variables), this is no longer the case when the second selection is considered. In fact, government intervention and the qualitative composition of the innovative output can be seen as simultaneous decisions, this rendering the selection of firms only engaged in product innovation potentially endogenous. A methodological solution allowing us to deal with all these issues simultaneously is developed in Section 4.

[9] See Cameron and Trivedi (2005) and Blundell and Costa Dias (2000) for a complete overview of the evaluation problem.

$$\begin{cases} D_i^* = \alpha' z_i + u_i; \quad D_i = 1 \text{ if } D_i^* > 0,\ 0 \text{ otherwise.} & \textbf{(2)} \\ y_{1i} = \beta_1' x_i + \varepsilon_{1i} \qquad \varepsilon_{1i} \sim \mathrm{N}(0,\ \sigma_{11}) & \textbf{(3)} \\ y_{0i} = \beta_0' x_i + \varepsilon_{0i} \qquad \varepsilon_{0i} \sim \mathrm{N}(0,\ \sigma_{00}) & \textbf{(4)} \\ corr\left[u_i, \varepsilon_{1i}\right] = \rho_{u1}; \quad corr\left[u_i, \varepsilon_{0i}\right] = \rho_{u0} & \end{cases}$$

where the set z of factors determining D partially overlaps the set x that explains the innovative outcome level y; the last row accounts for the likely correlation between the treatment-equation and the performance-equation error terms (endogeneity).

Such a simultaneous model fulfils two needs: firstly, it allows us to correct for funding endogeneity, producing consistent estimates of the performance equation (separately estimated on the two sub-samples of treated and non-treated firms); secondly, it solves the missing-data problem affecting the treatment evaluation literature; indeed, although we cannot directly observe how supported firms would have behaved had they not received the subsidy, we can nevertheless estimate the relevant model on the non-supported firms. The average treatment effect on treated firms can thus be computed consistently as:

$$ATET = E\left[y_{1i} \mid x, D_i = 1\right] - E\left[y_{0i} \mid x, D_i = 1\right] \qquad \textbf{(5)}$$

where the estimated coefficients obtained using the sub-sample of non-supported firms are applied to the supported ones, in order to achieve an estimate of the potential productivity the supported firms would have reached had they not received the subsidy.

This approach is here further developed in order to take into account a second source of endogeneity arising from the possible simultaneity between government intervention and the qualitative composition of the innovative output. Indeed, while receiving a subsidy is likely to foster one innovative typology at the expense of the others, it appears equally plausible that the qualitative composition of the innovation a firm has realised may affect the probability of receiving such a subsidy. This two-way simultaneous relationship should be taken into account when correcting for the selection of product innovators only. This is why we replace the participation equation identifying the switching in the standard endogenous switching models (eq. 2), with a bivariate model (eqs. 6 and 7). Therefore the estimated 'bivariate switching model' will be:

$$\begin{cases} funding_i^* = \alpha_a' z_{ai} + u_{ai} \text{ ; } funding = 1 \text{ if } funding^* > 0 \text{, 0 otherwise;} & \textbf{(6)} \\ PDT\_ONLY_i^* = \alpha_b' z_{bi} + u_{bi} \text{ ; } PDT\_ONLY_i = 1 \text{ if } PDT\_ONLY_i^* > 0 \text{, 0 otherwise} & \textbf{(7)} \end{cases}$$

$$pdtv_i = \begin{cases} \beta_{11}' x_i + \varepsilon_i & \text{if funding=1 \& PDT\_ONLY=1} \\ \beta_{01}' x_i + \varepsilon_i & \text{if funding=0 \& PDT\_ONLY=1} \\ \beta_{10}' x_i + \varepsilon_i & \text{if funding=1 \& PDT\_ONLY=0} \\ \beta_{00}' x_i + \varepsilon_i & \text{if funding=0 \& PDT\_ONLY=0} \end{cases} \qquad \textbf{(8)}$$

The first system thus accounts for the “double switching” (i.e. the joint probability of getting the subsidy and of engaging in product innovation only) that endogenously affects the productivity equation (second system). ε, u_a and u_b follow a trivariate normal distribution with variances σ^2, 1 and 1 respectively, and correlations ρ_{ab}, $\rho_{\varepsilon a}$ and $\rho_{\varepsilon b}$ defined as follows:

$$\rho_{ab} = corr(u_a, u_b)\text{; } \rho_{\varepsilon a} = corr(u_a, \varepsilon)\text{; } \rho_{\varepsilon b} = corr(u_b, \varepsilon)\text{;}$$

The first two selection equations can thus be correlated with each other besides each being individually correlated to the main productivity equation; this fully incorporates the correction for the product-only sample selection into the bivariate switching model. Of course, once a bivariate (rather than a univariate) selection is implemented, four instead of just two different regimes are identified, accounting for the potential specificities that characterize each possible combination of the two ‘switching’ variables: (1, 1); (0, 1); (1, 0) and (0, 0).

From a computational point of view, four productivity equations should be estimated, each of them augmented by two additional terms (inverse Mills ratios) correcting for the double selection bias. Thus, for instance, focusing on the sub-sample identified by the combination (funding=1 & PDT_ONLY=1), the estimated performance equation will be:

$$pdtv_i = \beta_{11}' x_i + \theta_a \lambda_a + \theta_b \lambda_b + \varepsilon_i \text{ ;}$$

where:

$$\theta_a = \sigma \rho_{\varepsilon a}\text{; } \theta_b = \sigma \rho_{\varepsilon b}\text{;}$$

$$\lambda_a = \phi(w_a)\Phi\left[\left(w_b - \rho_{ab}\ funding\right)/\left(1-\rho_{ab}^2\right)^{1/2}\right]/\Phi_2;$$

$$\lambda_b = \phi(w_b)\Phi\left[\left(w_a - \rho_{ab}\ PDT\_ONLY\right)/\left(1-\rho_{ab}^2\right)^{1/2}\right]/\Phi_2;$$

where $w_a = -\alpha_a' funding$, $w_b = -\alpha_b' PDT\_ONLY$ and ρ_{ab} all being obtained from the bivariate probit estimates and then used to compute $\Phi_2 = \Phi\left(w_a, w_b, \rho_{ab}\right)$. The same procedure applies to the other three sub-samples. For our purposes, the relevant ATET will be:

$$E\left[pdtv_{1i} \mid x, Funding_i = 1 \& PDT\_ONLY = 1\right] - E\left[pdtv_{0i} \mid x, Funding_i = 1 \& PDT\_ONLY = 1\right] \quad \textbf{(9)}$$

where, following the same procedure adopted for the univariate endogenous switching model, the coefficients obtained on the sub-sample of non-supported product innovators will be applied to the supported ones in order to obtain an estimate of their potential productivity had they not received the subsidy (counterfactual).

5. Empirical results

The bivariate switching model presented in Section 4 is here estimated in order to properly test and measure the possible negative impact of the subsidy which emerged from the preliminary descriptive evidence reported in Table 1. Four sequential steps have to be performed.

Firstly, the sample selection of 2,855 firms out of the 7,965 surveyed firms has to be taken into account by a standard Heckman procedure[10], generating the inverse Mills ratio (lambda inn) which will be included in the following estimates.

Secondly, the probability of receiving public support and that of being product-only innovators were jointly estimated by means of a bivariate probit (eqs. 6 and 7). As can be seen in Table 2, the probability of obtaining the subsidy and of being a product-only innovator are inversely correlated (this is not surprising, given that the majority of the other 2,109 firms are more committed innovators, performing both product and process innovation). Of a firm's characteristics, the availability of scientific sources of information, export orientation, and cooperation with universities and/or research institutes all increase both the probability of being a product innovator and that of getting a public subsidy. Not surprisingly, the aim of lowering labour costs is negatively related to the likelihood of being product-only, in fact being the main purpose of process innovation.

[10] Results not reported for saving space, but available under request; while all the firm characteristics listed in Table A1 were initially included, only the significant regressors were retained in the final estimated probit specification.

Table 2: Bivariate switching model: the selection equations

	Funding	PDT_ONLY
Funding	-	**-1.496***** (0.000)
PDT_ONLY	**-1.389***** (0.000)	-
logEmp(1998)	0.110 (0.360)	-0.041 (0.229)
logEmp1998^2	-0.013 (0.308)	-
Avgbasic	**0.155***** (0.002)	**0.097**** (0.048)
Avgmkt	-0.025 (0.498)	-
Exp_int	**0.247**** (0.050)	**0.232*** (0.065)
Mkt_extent	-0.014 (0.557)	-
Gp	-0.042 (0.551)	-
Ext_gp	**-0.179*** (0.091)	-
Cobasic	**0.547***** (0.000)	**0.414*** (0.000)
e_flexibility	-0.028 (0.244)	-
e_labour	-	**-0.120***** (0.000)
pro_formal	-	0.055 (0.458)
pro_strategic	-	-0.006 (0.951)
tot_inn intensity	-	-0.420 (0.237)
Growth_emp	-	-0.058 (0.777)
Hecon	-	-0.001 (0.983)
lambda_inn	-0.088 (0.274)	-0.039 (0.819)
Pavitt2	-0.062 (0.710)	-0.024 (0.895)
Pavitt3	0.157 (0.293)	0.164 (0.307)
Pavitt4	**0.262**** (0.041)	**0.225*** (0.093)
Strategies	-	Included
Industry dummies	included	Included
Constant	0.046 (0.895)	0.301 (0.489)
N	2855	
Log-L	-2684.432	
Rho	**0.9998***** (0.000)	

Notes: P-values in brackets: * significant at 10%; ** significant at 5%; significant at 1%.

Table 3: Bivariate switching model: the main equations

Pdtv	**E(pdtv|funding=1 & PDT_ONLY=1)**	**E(pdtv|funding=0 & PDT_ONLY =1)**
logEmp(2000)	0.595 (0.492)	0.776 (0.471)
Exp_int	0.629 (0.817)	3.764 (0.287)
pdt_quality	**2.623***** (0.000)	**3.247***** (0.000)
e_market	1.106 (0.114)	**1.616**** (0.063**)**
e_capacity	0.844 (0.278)	-1.324 (0.202)
mkt_novelty	2.301 (0.160)	**0.360*** (0.079)
Otherinn	3.364 (0.220)	1.964 (0.580)
pro_formal	0.953 (0.599)	-0.333 (0.887)
pro_strategic	-0.045 (0.986)	**5.064*** (0.096)
Hinternal	1.080 (0.265)	-0.979 (0.368)
Hecon	-0.168 (0.834)	**-1.604*** (0.097)
lambda_inn	-0.516 (0.932)	4.049 (0.572)
Pavitt2	1.342 (0.775)	-2.675 (0.570)
Pavitt3	2.697 (0.478)	-2.860 (0.549)
Pavitt4	0.634 (0.842)	-2.647 (0.526)
Strategies	Included	Included
Industry dummies	Included	Included
Constant	-4.126 (0.792)	6.560 (0.696)
LAMBDA-A	-3.750 (0.338)	3.923 (0.630)
LAMBDA-B	-3.305 (0.406)	-5.991 (0.508)
N	389	357
R-squared	0.2877	0.2866
F test	F(50, 338) = **2.73*** **	F(50, 306) = **2.46*** **
Log-likelihood	-1447.5735	-1380.4640

Notes: P-values in brackets: * significant at 10%; ** significant at 5%; significant at 1%.

Thirdly, the innovative productivity measure was separately regressed on the sub-samples of firms identified by the switching variables, using the two inverse Mills ratios LAMBDA-A and LAMBDA-B from the bivariate probit estimates. However, given that our productivity measure is only available for the product-only innovators (see Section 3), only the first two classes (1, 1) and (0, 1) must be considered, comparing subsidized and non-subsidized firms, conditional on them being product innovators. Results from this third step are reported in Table 3.

As can be seen, an above-average expectation of the innovative impact on the quality of the products emerges as the major driver of innovative productivity[11].

Fourthy, turning our attention to the main purpose of this study, the average treatment effect of the subsidy (ATET) is computed in accordance with eq. 10. The results of this fourth step are reported in Table 4.

Table 4: ATET from the bivariate switching model

Supported product-only innovators	**A** $E\left[pdtv_{1i} \mid x, F_i = 1 \& PDT\_ONLY = 1\right]$	**B** $E\left[pdtv_{0i} \mid x, F_i = 1 \& PDT\_ONLY = 1\right]$	**Treatment effect estimate (A-B)**
N = 389	10.091	15.043	**-4.953***** (0.000)
Notes: p-values in brackets; *** = 1% significant.			

Far from being rejected, the efficiency loss highlighted by the preliminary descriptive statistics discussed in Section 3.2 (Table 1) above turns out to be even greater (and much more significant), once firms' characteristics and all the possible sources of sample selection and endogeneity have been taken into account fully.

Therefore, our suspicion of an efficiency loss being associated with government intervention is strongly confirmed: far from 'doing better' as a result of the subsidy, supported firms turn out to increase both their innovation inputs and their innovation outputs, but the latter effect is less than proportional with respect to the former.

6. Conclusions

Once cleared of any source of firm heterogeneity due to different sources of sample selection, as well as being checked for possible simultaneity between public support and the qualitative composition of a firm's innovative activity (bivariate switching model), the impact of an innovation subsidy turns out to be counterproductive.

Despite it being current common practice to publicly support innovation, government intervention actually appears to just induce higher expenses, while the efficiency associated with such innovative expenditures is affected negatively.

[11] This is not surprising, since an innovation able to increase the quality of the final products significantly is likely to increase the share of turnover due to innovative products and hence our **pdtv** measure.

Appendix

Table A1: List and definitions of the dependent and explanatory variables

Dependent variables	
funding	Dummy = 1 if the firm has received a financial subsidy in support of innovation, 0 otherwise
Pdtv	Innovative productivity (total innovative sales/total innovative expenditure)
INNOVATIVE	Dummy = 1 if the firm invested in innovative activities in the period 1998-2000 and has realised a product and/or a process innovation, or it has undertaken an innovative project (later dropped or still to be completed at December 31st, 2000)
PDT_ONLY	Dummy = 1 if the firm has realised product innovations only
Firm characteristics and other controls	
logEmp1998 (logEmp2000)	Logarithmic transformation of firm's employees at December 31st, 1998 (2000)
Growth_emp	Employees - rate of growth (1998-2000)
Exp_int	Export intensity (turnover from export/turnover) in 2000.
mkt_extent	Prevailing (geographical) market extent, ranging from 0 (local) to 7 (Extra-UE)
Gp	Belonging to an industrial group (dummy variable)
ext_gp	Belonging to an industrial group with foreign headquarters (dummy variable)
Industry dummies	23 Industry dummies defined according to the two-digit ATECO 91 classification

Pavitt1-Pavitt4	Dummies mapping the three-digit ATECO 91 codes onto the four categories identified by Pavitt's (1984) taxonomy:
	pavitt1=1 for science-based firms, 0 otherwise;
	pavitt2=1 for supplier-dominated firms, 0 otherwise;
	pavitt3=1 for scale-intensive firms, 0 otherwise;
	pavitt4=1 for specialized suppliers, 0 otherwise

lambda_inn	Inverse Mills ratio correcting for the selection of innovative firms only
Innovation-relevant information	
log(tot_exp)	Logarithmic transformation of total innovative expenditures in 2000
tot_inn intensity	Intensity of total innovative expenditures in 2000 (total innovative expenditure/turnover)
Turninn	Sales due to new products
Avgbasic	Average importance of basic sources of information (universities, research institutes, conferences) for the innovative process: from 0 to 3
Avgmkt	Average importance of market sources of information (competitors, customers, suppliers) for the innovative process: from 0 to 3
Cobasic	Cooperation agreements with universities and/or research institutes (dummy variable)
e_market	Innovation addressed to entering new markets or raising a firm's market share: from 0 to 3
e_capacity	Innovation addressed to raising production capacity: from 0 to 3
e_flexibility	Innovation addressed to raising production flexibility: from 0 to 3
e_labour	Innovation addressed to lowering the cost of labour: from 0 to 3
Hinternal	Average relevance of internal hurdles (lack of information, lack of skilled personnel, organizational rigidities) in hampering innovation (1998-2000): from 0 to 3

Hecon	Average relevance of financial hurdles (economic costs and/or risks too high, no sources of financial support) in hampering innovation (1998-2000): from 0 to 3
pro_formal	Dummy = 1 if patents, copyright or registration of brands are perceived by the firm as useful ways to increase appropriability
pro_strategic	Dummy = 1 if secrecy, complexity or lead time are perceived by the firm as useful ways to increase appropriability
patent	Dummy = 1 if the firm registered at least one patent over the period 1998-2000
pdt_quality	Evaluation of the innovative effect on product quality: from 0 to 3
mkt_novelty	Dummy = 1 if product innovations are new to the market
Otherinn	Dummy = 1 if the firm realised managerial, strategic and/or organizational innovations (1998-2000)
Strategies	Sixteen innovative strategy dummies covering all the possible combinations of the four main innovative inputs firms can choose from: internal R&D; external R&D; embodied technological acquisition in innovative machinery; disembodied technological acquisition such as licences

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