10[ème] Congrès de l'Académie de l'Entrepreneuriat et de l'Innovation
AEI DAKAR – 6,7 et 8 décembre 2017

Are Public R&D Subsidies Effective? Some New Evidences from a Meta-Analysis of the Literature

Syoum Negassi
Université Paris 1 Panthéon-Sorbonne
PRISM Sorbonne
17, rue de la Sorbonne
75005 Paris, France
E-mail: Syoum.Negassi@univ-paris1.fr

Jean-François Sattin
(Corresponding author)
Université Paris 1 Panthéon-Sorbonne
PRISM Sorbonne
17, rue de la Sorbonne
75005 Paris, France
Tel : (+33) 1 44 07 83 21
E-mail: Jean-Francois.Sattin@univ-paris1.fr

October 2016

Abstract: This paper aims to review the present knowledge about the public subsidization of private R&D. We provide a meta-analysis of the literature by implementing some tests on a database built from past researches on this topics. Our results emphasize the main role played by the methodological design, as well as the contrasted role of the level of public financing on the efficiency of the system.

Key words: Subsidies, R&D
JEL classification: H22, O32

Work in progress-Please do not quote

1. Introduction

Support for R&D and innovation by government plays a central role in technology policies. OECD countries policy makers have been concerned about the technological performance of their countries for large parts of the twentieth Century. The economic theory and empirical evidence indicate that technological innovation is an important determinant of long-term economic development. Various country policies have been launched in favour of private research and development (R&D) with economic development as the main objective. There is no doubt that jobs and income are ultimate goals in countries innovation-based economic development. However, increasing private spending on R&D in one country is a necessary intermediate step toward these final goals.

Governments, therefore, take different actions to support private technological activities with R&D subsidies being one of the most frequently adopted tools (direct subsidies vs. tax incentives, patent laws…etc.). Although the reasons for public support to private R&D are well established and its effectiveness needs to be examined. In recent years, public policy evaluation has acquired growing importance and although the results are not entirely conclusive. Recent literature reviews (David et al., 2000; García-Quevedo, 2004) indicate that, in the case of R&D subsidies, the existence of an additional effect is the most frequent outcome. Most studies evaluating R&D direct subsidies tend to analyze the average effects of these subsidies on recipient firms. The degree of effectiveness of R&D policy can differ substantially depending on the allocation procedure and on the characteristics of R&D direct subsidies. Among these characteristics, the amount and intensity of the public direct subsidy has been justified in several ways.

First, governments are responsible for providing new or improved technology for public sector functions (security, health, and communications) and R&D for these tasks may be performed in public research laboratories or contracted out to private firms and funded by public revenues.

The second justification for public direct subsidies is to correct for market failures which would hamper firms from reaching the socially optimal level of R&D (Arrow, 1962; Stiglitz, 1988). Most countries have decided to correct for the presence of market failures by supporting business-funded R&D via direct grants, tax incentives, or a mixture of the two. There is a considerable body of international experience with all types of instruments used to support business R&D. The arguments in favor of one or the other policy measure are based generally on evidence from factual situations in a specific country or industrial context. Market failures in real and financial markets offer scope and justification for public direct support, as the return may be not sufficient to justify private investment. The broad consensus on the use of public direct support is based on the inefficiencies of the market. The neoclassical theory based on a positive externality argument explains that, because of the 'public good' characteristics of R&D activities, the firms are prevented from completely appropriating the potential benefits from the innovations generated from their R&D activities as other firms would have the opportunity to free ride. Consequently, the level of private R&D expenditure would be systematically lower than the socially optimal level. These create a gap between private and social return on R&D and as a result we have at a country less than optimal levels of research. Incomplete appropriability of research output and externalities deriving from the public good nature of R&D are at the base of this (Nelson, 1959; Arrow, 1962). Even if innovation could be fully appropriated, the existence of capital market imperfections may also lead private firms to disregard socially valuable R&D projects (Griliches, 1986; Hall, 2002). Thus, the characteristics of imperfect appropriability and imperfect excludability lead to the under-provision of innovation outputs by private decision makers in a market environment. This occurs since the benefits associated with R&D activities are easily and freely available to firms that are not engaged in R&D efforts. Indeed, the lack of full appropriability of R&D outcomes reduces the incentive to do R&D on the part of private firms so that, as in a classical Pigouvian context, government intervention through direct subsidies can reduce the extent of this 'market failure'. This argument has been widely criticized by several scholars. From an evolutionary perspective Cohen and Levinthal (1989) argued that knowledge cannot be so easily absorbed unless imitative firms in turn invest in a certain level of R&D effort: imitation is not costless and needs some pre-existing 'hard core' R&D activity. This standpoint could lead to a paradoxical consequence: in an environment characterized by significant spillover effects, firms could have greater incentives to perform R&D since, in doing so, they might expand their absorptive capacity, i.e. their ability to benefit from the R&D efforts of others. In this way, they could more easily imitate and exploit market surpluses. As a consequence, the level of R&D could be too high (rather than too low), since many firms could undertake more R&D effort than that required to reach the optimal social results (e.g. by an increase of duplications in R&D expenditure).

The third reason for public R&D support is the existence of asymmetric information about the expected outcome of R&D investments and sunk costs because most of the investment goes into wages of R&D staff. Moreover investment in R&D is riskier than investment in physical assets, and as a result there are likely to be more financial constrained (Hyytinen and Tovainen, 2005; Czarnitzki, 2006). Due to the risk associated with R&D activities and information asymmetries between borrowers and lenders, the financial opportunities to engage in R&D activities are limited. Policymakers could then contribute to reducing the cost of riskier but socially valuable R&D projects, by increasing the firms' expected return to such R&D projects. Direct public investment is designed to encourage firms to carry out R&D by lowering marginal costs and decreasing the uncertainties that are typically connected to this activity. In addition to these direct effects at the firm level, positive indirect impacts are also expected to spillover to other firms in the system.

Thus, the objective of governments R&D direct subsidies is to reduce the gap between the private investment and the socially desirable investment as well as in order to ensure national competitiveness and to provide new and improved technology for public sector functions. By doing this the governments reduce the price of socially valuable R&D projects for private investors to a level at which it becomes profitable to invest. But, the key question is whether the policy is appropriate, efficient and effective.

The aim of this paper is thus twofold. We first seek to explain if a government R&D direct subsidies stimulate private R&D (firm level) in different OECD countries. In order to do that we rely on a meta-approach of the microeconomic literature (not on macroeconomic level as in Montmartin and Herrera, 2015) in order to explain the relationship between the characteristics of the subsidies and their outcome like additionality effect (crowding-in) or substitution effect (crowding-out)[1].

The study is organised as follows. The second section provides a review of the empirical literature about the link between public R&D support and company-financed R&D, and we use this baseline to posit our research assumptions. The third and fourth sections present the methods and the results. The paper ends with our concluding remarks and suggestions for future research.

2. Theory and hypotheses

2.1. Research design of previous studies on subsidies

The majority of works in the effects of public policies on firm R&D expenditure seem to have chosen to measure the presence ⁄absence of 'additionality' of public incentives by skipping, at least implicitly, the essential step of going into an explicit theoretical framework to explain this causal relation (also without entering too much into the analysis of other types of additionality, such as that based on output variables: productivity, profitability, innovation performance, etc.). This explain the great variability of the research designs implemented in the previous studies.

This point is quite clear regarding the definition of the R&D itself (internal, private, or not). This is also true regarding the dependent and the explicative variables implemented. For instance, some studies focus on a level analysis and try to shed light on the absolute return in R&D $ of grants while others investigates relative R&D ratios (as R&D/sales, R&D/ turnover or R&D/ number of employees for instance). Moreover the main explicative variable could be the project financed or the amount of subsidies granted, or the percentage of increase of the grant. This point is also true regarding the other explicative variables (for instance the presence or absence of sectoral or time dummies), as well as regarding the sample retained for the analysis (innovative firms or not, SME or large firms).

Last but not least, previous papers have implemented different kinds of empirical analysis in order to assess the additionality effect while coping with the sample selection problem. Firms given grants may have been be chosen by public agencies because they are likely to carry out successful research projects. Agencies are, indeed, likely to "pick the winners" and support attractive project proposals (Wallsten, 2000). If the criteria for allocating public funds are linked to high expected rates of return on private R&D funding (David et al 2000), then the probability of been chosen depends on current R&D spending. If this is the case, then public funding becomes endogenous, and estimates will be biased and inconsistent if they are not addressed in an econometric framework. The literature on the econometrics of evaluation offers different ways of tackling the existence of an endogenous subsidy variable in policy evaluations. These include: 1) regressions models (regressions with controls, fixed effects or difference-in-difference models, or instrument variable estimators) 2) sample selection models, and (3) non-

[1] Contrary to our study, we can find an increase studies that analyse the relationship between R&D subsidies and their effects on firms' on cluster (Nishimura and Okamuro, 2011), on cash flow (Colombo, A. Croce and M. Guerini, 2013), or external financing (Meuleman and Maeseneire, 2012).

parametric matching of treated and untreated firms. All this techniques can be run on panel or cross-section samples.

In all to all, a striking question deals with the sensitivity of the results to the research design implemented. This leads us to write our first proposition.

Proposition 1 (Meta-analysis hypothesis): The research design of the compiled studies on subsidies impacts on their results regarding the size of the additionnality effect.

2.2. R&D grant policy

David and Hall (2000) tried to provide more sound theoretical bases for the understanding of the effect of public policies on private R&D investment. They explicit a structural model that identifies the optimal level of R&D investment for the firm. Relying on a classic profit maximization strategy, they define the optimum as the point at which marginal rate of returns (MRR) and marginal capital costs (MCC) associated with R&D investments are equal. The MCC curve, reflects opportunity costs of investment funds, at any level of R&D. This curve has an upward slope due to the assumption that, as soon as the number of projects to implement increases, firms have to shift from financing them through retained earnings to equity and ⁄ or debt funding (i.e. from internal to external and more costly sources). The MRR curve instead, derives from sorting R&D projects according to their internal rate of return, as in a usual investment plan. This curve is a decreasing function of the overall R&D expenditure, since firms will first implement projects with higher internal rates of return and then those presenting lower rates[2]. It follows from their model is that public policies regarding subsidies should experience decreasing return as the amount of available grants increases and the profitability of the financed projects decrease. We can thus state the proposition 2 below:

Proposition 2 (Decreasing return hypothesis): The efficiency of public subsidies is negatively correlated with the amount of public R&D subsidies granted in the surveyed countries.

2.3. Fiscal incentives

The fiscal incentives for R&D can take various forms. First of all, some countries provide R&D tax credits. These are deducted from the corporate income tax and are applicable either to the level of R&D expenditures or to the increase in these expenditures with respect to a given base. In addition, some countries allow for the accelerated depreciation of investment in machinery, equipment, and buildings devoted to R&D activities (Negassi and Sattin, 2014). The generosity of R&D tax incentives can be measured by the B index (Warda 1996, 2002; Thomson, 2012). This is a composite index computed as the present value of pre-tax income necessary to cover the initial cost of an R&D investment and to pay corporate income tax, so that it becomes profitable to perform research activities. Algebraically, the B index is equal to the after-tax cost of a one

2 Moreover both curves depend on a number of variables that can move them either downward or upward. MRR depends of technological opportunities; state of demand; and appropriability conditions and MCC of technological policy tools; macroeconomic conditions; external costs of funds; and venture capital availability.

euro expenditure on R&D, divided by one less the corporate income tax rate. The after-tax cost is the net cost of investing in R&D, taking account of all the available tax incentives (corporate income tax rates, R&D tax credits and allowances, depreciation rates).

Tax incentives are typically used to deliver assistance to a broad range of sectors. Conversely to subsidies, with tax incentives, each firm can decide alone on which R&D projects to carry out. As fiscal incentives can be less costly and less burdensome to manage than direct R&D subsidies, the relative efficiency of the two instrument has to be questioned, the typical question being about the complementarity or the substituability of tax credit and subsidies scheme.

Proposition 3a (Complementarity hypothesis): The efficiency of public subsidies is positively correlated with the fiscal generosity toward R&D in the surveyed countries.

Proposition 3b (Substitution hypothesis): The efficiency of public subsidies is negatively correlated with the fiscal generosity toward R&D in the surveyed countries.

3. Methods

3.1. Data and sample

The data used come from a sample of 63 articles that attempted to assess the effectiveness of R&D grants in various countries, and that focused on the impact of the public grant on firm's R&D expenses. The complete list of the surveyed papers is displayed in the annex 1.

We have tried to collect the most important articles in each field, relying on a set of key criteria. In order to be selected for our analysis, a paper should:
1/ Focus on the relationship between public grant and private R&D. Papers focusing on output additionnality were then discarded from our analysis.
2/ Develop a quantitative analysis and report estimates of a size effect. Qualitative analysis as well as results arising from simulations were not taken into account.
3/ Display results in absolute form relative to R&D or to R&D intensity. This point led us to cancel estimates that were reported in variation, which diminished our potential sample in a sensible way. Nevertheless it was required in order to ensure the homogeneity of our pooled sample.
4/ Have an independent variable which is the subsidy amount or the subsidy receipt. Ratios were not allowed on the right hand side of the equation.
5/ Not be too old, i.e. be published after 2000

Indeed as quoted by David et al. (2000) who surveyed studies on that topic, most of the estimations they reviewed are subject to a potential selection bias as recipients for subsidies might be chosen by the government because they are more promising candidates in succeeding their research projects. Recent works implement various techniques to overcome this problem, but old studies (i.e. before 2000) should be examined with caution regarding this last point. That point was taken into account, and only papers issued after 2000 were considered here.

The sample was then restricted due to missing macroeconomic data. Each paper into the database has then been read in a meticulous way in order to track down the result and the context of the research. The remaining papers were quite diversified regarding to the number of estimations provided. Differences in estimations results in a same paper could be grounded on different samples and/or different empirical procedures. On average there were 10 estimates per articles, but with great variations amongst papers (from 2 to 40 (!) estimates for one paper). Finally our panel encompasses 429 point estimates of additionality effects, coming from 42 articles.

One difficulty encountered arises from the fact that the papers implemented different kinds of empirical models, leading to somewhat diversified measures of additionality. In order to enable the comparability of the results, the additionality parameters were classified into subgroups depending of the model they were derived from. We dropped two subgroup that did not encompass enough observation to be statistically significant (less than 30 observations), as well as the measures that focused on the R&D by employees, as they were not comparable to the other ratios implemented (in euro). Moreover, inside each category, the coefficient were rescaled when needed, taking into account the presence of percentage and the currency rates. Tables 1 describe the different estimation groups:

Table 1. "Bang for the Buck" and other measures of R&D additionality and/or crowding-out

Group Number	*Output assessed*	*Mean effect size (unweighted)*			*Number of observations*
		Matching models	*Regression models*	*Selection models*	
1	Amount of supplementary R&D per euro invested	-	2.91 euros [-4.59,16.42]	1.55 euro [1.04,2.53]	76
2	Amount of supplementary R&D per project financed	1.34 million euros [0.03,28.78]	1.91 million euros [0.07,12.18]	1.23 million euros [-0.17,5.39]	104
3	Percentage of supplementary R&D per 1% increase of the grant	3.10% [-0.20, 0.26]	2.41% [-9.34, 8.59]	-	36
4	Amount of supplementary R&D intensity per project financed	2.37% [-6.66,44.61]	2.22% [-9.34,8.59]	0.08% [0.08,0.08]	213

3.2. Meta-analysis

The basic model of meta-analysis is grounded on the assumption is that the true effect size is the same for all the studies. When this is the case, the differences between the estimated effect sizes can only occur because of some sampling error, and a fixed-effects model can be used to estimate the weighted mean effect size and its standard error. We have then:

$$EM = \frac{\sum(wiESi)}{\sum wi}$$

where EM is the weighted mean effect size, ES_i is the individual effect size for i = 1 to k (where k here is the number of effect sizes observed), SEi is the standard error of effect size for i, and wi is the individual weight for ESi . The inverse variance is commonly used to weight the studies in meta-analysis. When this option is chosen, we have the following:

$$wi = 1/SEi^2$$

The assumption that the effect size distribution is random requires homogeneity, a property of the sample that is assessed with the Q-statistic below:

$$Q=\sum wi\ (ESi - EM)^2$$

The Q-statistic is distributed as a chi-square, with k -1 degrees of freedom (Hedges and Olskin 1985), with k the number of studies included. When Q is found to be significant, the null hypothesis of homogeneity is rejected, and the fixed effect model is not the best estimation method, as it ignores the extra variability due to differences between studies in addition to the sampling error.

One common way of solving this is using the random-effects model for the estimation of the weighted mean effect size. The random-effects method assumes that each observed effect size differs from the population means by subject level sampling error plus a value that represents other sources of variability assumed randomly distributed (Lipsey and Wilson, 2000). Incorporating both sampling error levels gives us a different inverse variance weight and therefore a different effect size. For the random effects method one needs to calculate a new value of the variance, which is the sum of the subject-level sampling error and the random-effects variance sr^2, with :

$$sr^2 = \frac{Q-(k-1)}{\sum wi-(\sum \quad wi^2/\sum wi)}$$

The new value of the variance, gives us a new standard error and a new inverse variance of every effect size. Re-estimating the equations above using the new formula for the inverse variance gives us a new weighted mean effect size.

3.3. Publication bias

Publication bias is a type of selection bias, which can arise because not all research that has been done with respect to the subject at hand is published or reported. The reasons for this could be that researchers and publishers do not trust the results or do not value the results properly. This particular type of bias is likely to influence the results of a meta-analysis. Publication bias in a meta-analysis means that there are studies that cannot be found in common databases or books, which are ‘missing’ in the dataset of studies created for the meta-analysis. Due to these ‘missing’ studies, the weighted mean effect size might be biased. In our case, it is that the weighted mean effect size is upward biased, as almost all values of the effect size are significant, and around or just above zero.

Tests for publication bias investigate whether the effect size is related to the sample size or the standard error of the estimate. If studies with a high t-value or a low p-value are more likely to be published, the bias will decrease with the standard error or sample size. Begg’s test is an adjusted-rank correlation test, to check whether the effect size and its variance are correlated. Egger’s test is based on a regression of the effect size on its inverse variance, and tests whether the intercept is significantly different from zero. Due to the parametric structure, it is more powerful than Begg's test.

Publication bias can be corrected by estimating the effect size, controlling for the correlation between estimated effect size and the standard error of the estimate. In a nonparametric setting, this correction can be based on the so-called 'trim and fill' method (Duval and Tweedie 2000). This method copes with publication bias by trimming extreme positive studies and by adding some studies to the study database that appear to be missing, to make the dataset symmetric. After that, the weighted mean effect size is calculated again. The regression that is used to detect the relationship between the estimated effect size and its standard error, in a parametric setting, can also be used to estimate the average effect size where the standard error is 0, and thus publication bias can be assumed to be absent. This approach has been developed by Doucouliagos and Stanley (2009), and can easily be extended to a meta-regression context.

3.4. Meta-regressions

In a meta-regression, all the explanatory variables that are created during the coding stage can be regressed on the main variable, our case, the estimated effect size of subsidies on R&D (for each estimation, we have the estimated coefficient between subsidy variable and R&D variable). A standard meta-regression is a random-effects regression in which the relation between the background and the study characteristics and the effect size can be tested quantitatively. One of the advantages of a meta-regression is that it has a multivariate context (Doucouliagos and Laroche 2003). Meta-regressions make it possible to investigate the relation between the effect size and one or more of the key variables, where the other variables, the study characteristics, can be used as controls.

Because it is likely that the chance of being published is largely influenced by the significance level of the results of a study, an extra aspect has to be added to the meta-regression to account for this chance of publication. One way to cope with this problem is to use the FAT publication bias test as a basis for a meta-regression (Doucouliagos and Stanley, 2009). In this test, publication bias is assumed to be a linear function of the standard error of the study. Therefore they propose to control for publication bias by including the standard deviation (or the variance) of the effect size in the meta-regressions. When this is done, Doucouliagos and Stanley (2009) argue that the coefficient of precision is the 'true effect' corrected for publication bias. They also suggest to implement this method by using the metareg algorithm in Stata.

3.5. Variables

Dependant variable
Our variable of interest is the effect size of subsidies on R&D in the surveyed papers (for each estimation, we have the estimated coefficient between subsidy variable and R&D variable). As quoted above, these measures have been harmonized amongst estimation groups, while heterogeneity between groups is grasped with a set of dummy group variables.

Explicative variables

The explicative variables are of three kinds (see Table 3). We first try to explain the measured effect size by studies' characteristics. The kind of model implemented is grasped by the group variables. We further control for the sample characteristics into several dimensions (number of observations, panel or cross section data, kinds of firms surveyed, etc.), for inclusion of specific variables into the estimations (time-lag, sectoral and time dummies) as well as for the estimation technique (estimation type). Last but not least, the incidence of fiscal incentives for R&D is grasped by the mean of the beta variable that refer to the B-index relevant for each studies; while the grant policy is assessed by the means of the two variables Subsidy Intensity and Subsidy Intensity² in order to check the presence of some quadratic effect between subsidies and firms R&D.

All the explicative variables are summarized in the table 2 below.

Table2. Explicative variables and descriptive statistics

VARIABLE	DESCRIPTION	MEAN	SD	MIN	MAX
Standard deviation	Standard deviation of the study	0,819	0.933	0,001	8,002
Group 1	Dummy variable equals to 1 if the effects comes from an estimation that belongs to the group 1	0,177	0,382	0	1
Group 2	Dummy variable equals to 1 if the effects comes from an estimation that belongs to the group 2	0,242	0,429	0	1
Group 3	Dummy variable equals to 1 if the effects comes from an estimation that belongs to the group 3	0.084	0.277	0	1
Estimation type	Dummy variable equals to 1 if the effect is estimated using matching techniques	0,398	0,490	0	1
Data type	Dummy variable equals to 0 if the database is cross sectional, and 1 if it is a panel	0,629	0,483	0	1
Manufacturing sector	Dummy variable equals to 1 if the database focuses on the manufacturing sector	0,580	0,494	0	1
Services sector	Dummy variable equals to 1 if the database focuses on the service sector	0,972	0,165	0	1
Number of observations	Number of observations in the database	2069.133	7070.485	51	98366
Innovative firms	Dummy variable equals to 1 if the database encompasses only innovative firms	0,151	0,358	0	1
SME	Dummy variable equals to 1 if the database encompasses SMEs	0,911	0,284	0	1
Large firms	Dummy variable equals to 1 if the database encompasses large firms	0,841	0,365	0	1
Date of the paper	Year when is issued the paper	2007,193	2,818	2000	2013
Lagged Subsidies	Dummy variable equals to 1 if the model encompasses lagged subsidies	0,174	0,380	0	1
Industry dummies	Dummy variable equals to 1 if the model encompasses industries dummies	0,771	0,420	0	1
Time dummies	Dummy variable equals to 1 if the model encompasses time dummies	0,519	0,500	0	1
Private R&D	Dummy variable equals to 1 if the model focus on private or internal R&D	0,477	0,500	0	1
Beta index	Mean of the country beta index over the period covered by the database of the paper	0,955	0,132	0,566	1,059
Labor	Mean of the current and labour components of the country beta index over the period covered by the database of the paper	0,930	0,132	0,497	1
Mechanicals	Mean of the mechanicals component of the country beta index over the period covered by the database of the paper	1,030	0,214	0,571	1,563
Buildings	Mean of the building component of the country beta index over the period covered by the database of the paper	1,340	0,269	0,867	1,941

Subsidies intensity	Mean the ratio subsidies / business R&D over the period covered by the database of the paper	0,098	0,062	0,006	0,308
Subsidies intensity ²	Mean the ratio subsidies / business R&D over the period covered by the database of the paper squared	0,013	0.017	0.001	0.095

4. Results

4.1. Publication bias and meta-analysic results

In order to test our theoretical propositions, we first have to investigate the presence of some publication bias in our sample. This will lead us to set up a nonparametric analysis of the effect size, before to go into the meta-regression analysis.

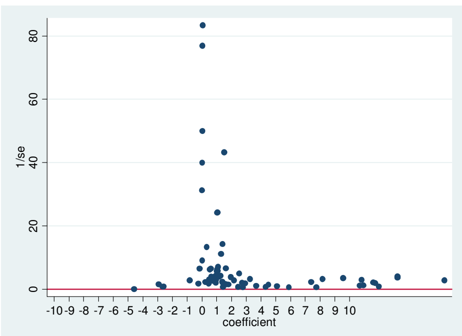
Publication bias analysis

Table 3. Eigger's and Begg's tests for publication bias

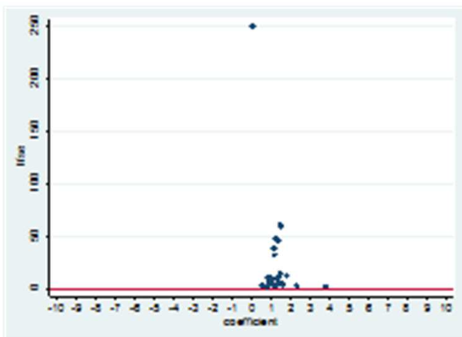
Group	Number of observations	Begg's score	s.d.	Begg's z continuity corrected	p	Egger's bias	p
1	76	22	222.97	0.09	0.925	4.95	0.000
2	104	1321	356.03	3.71	0.000	4.35	0.005
3	36	-92	73.38	1.24	0.215	1.08	0.000
4	213	5418	1039.82	5.21	0.000	5.03	0.070
Overall	429	6669	1123.86	5.93	0.000	1.12	0.000

The results of Begg's and Egger's tests for publication bias are reported in the table 3. The two tests suggests that publication bias is present in our pooled sample. Nevertheless, we note that they display different conclusions on our group subsamples. Even if the Egger's test is somewhat more powerful than the Begg's procedure, it is impossible to reject the proposition that there is no publication bias without looking for further information with the FAT analysis (Doucouliagos and Stanley, 2009).

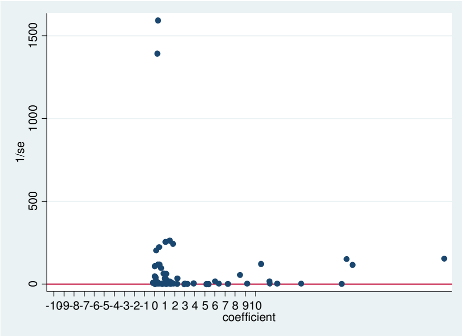
The visual inspection of the plot of the effect size versus the standard error of the effect size in Figure 1 also suggest the existence of some publication bias, at least in subsamples 2 and 4. Even if evidences regarding groups 1 and 3 appear to be more mixed, we therefore conclude that publication bias need to be controlled for in our dataset.



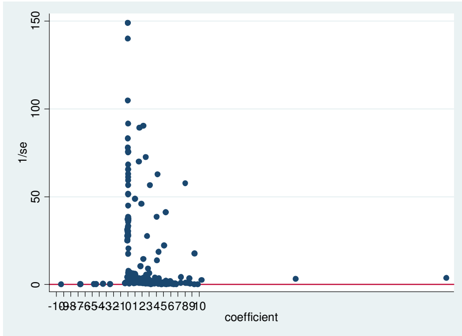
Funnel plot : Group 1



Funnel plot : Group 3



Funnel plot : Group 2



Funnel plot : Group 4

Figure 1. Funnel plots by subsamples

Trim and fill analysis

To correct for publication bias, we use what is called the 'trim and fill' method. Results are presented in table 6. The 'trim and fill' algorithm try to detect the missing studies (i.e. the unpublished ones) by looking to the funnel asymmetry and in order to correct the 'files drawer' effect. In order to assess a corrected mean effect size it added 30 studies in our first subsample, 40 in the second one, 19 in the third one, and 72 in the last one.

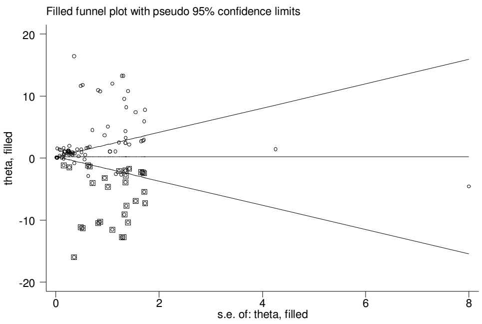
We see that the Q statistic is significant even after having controlled the publication bias. There is still heterogeneity in the various subsamples, leading us to prefer the random estimates over the fixed effect measures.

Table 4. The 'trim and fill' analysis

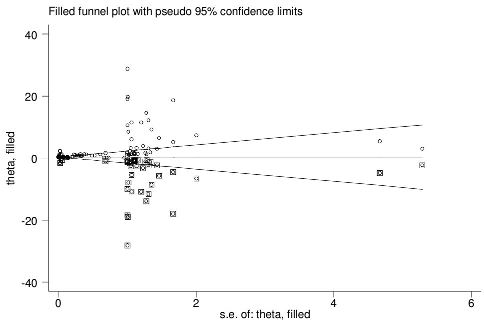
	Weighted estimates		Trimmed weighted estimates		Q sig
group	FE	RE	FE	RE	
1	0,239***	2.038***	0.219***	0.429***	***
2	0,307***	0,547***	0.306***	0.333***	***
3	0,011***	0,223***	0.011***	0.223***	***
4	0.481***	1.825***	0.298***	0.544***	***

*** p<0.01 **p<0.05 *p<0.1

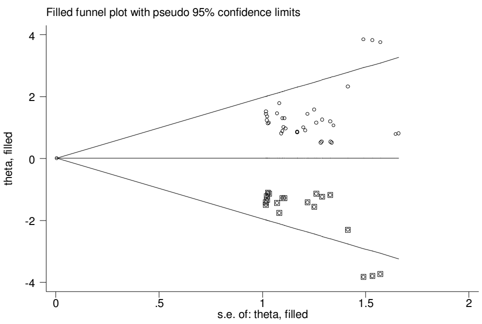
The trimming analysis confirm that there is an upward bias in the published articles, that leads to right-side biases in the funnels plots. Added studies were then on average on the bottom of the filled funnel plots in Figure 2. Finally, the trimming procedure results in lowered estimates for each subsamples, that go far away from those presented in table 1. On average, if we follow the random coefficient model and before controlling the other covariates, 1 euro subsidy adds 0.429 euro in the R&D budget, and one project financed increases up to 333 000 euros the firm's R&D expenses or to 0.54 % the R&D intensity. We note here that there is no formal correspondence between these two results (the average subsidy being far less than 1 million euro), because the two kinds of studies having chance to exhibit different characteristics. This point highlight the necessity to go one step beyond into the analysis, by investigating the other factor that can also explain the effect sizes of R&D additionality in the literature.

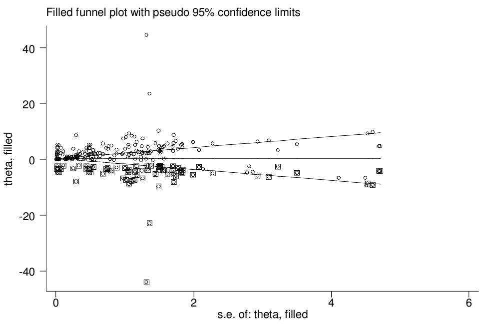


Trimmed funnel plot (weighted): Group 1



Trimmed funnel plot (weighted): Group 2





Trimmed funnel plot (weighted): Group 3

Trimmed funnel plot (weighted): Group 4

Figure 2. Trimmed funnel plots by subsamples

4.2. Meta-regressions results

Our estimates comes from the random effect meta-regression implemented with the metareg routine in Stata. It is a weighted regression implemented with REML and that allow for some random variation amongst observations (Models 1-6). The publication bias has been taken into account through the inclusion of the standard deviation of the effect size in the estimations. The coefficient of this variable is always highly significant. As such it confirms the need to control for publication bias with our data. Moreover some robustness checks, not reported here, have been done with a random panel model (i.e. without weighting) in order confirm our main results. The pseudo R^2 ranges from 0.12 to 0.30, and is thus acceptable for this kind of analysis. Moreover all the model are significant at the 1% level, and are presented in table 5 below.

Table 5. The empirical results: Meta-regressions

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model6
Standard deviation	1,622***	1,301***	0.947***	0.908***	0.954***	0.993***
	6,14	*4.64*	*3.33*	*3.22*	*3.39*	*3.45*
Group 1	0,563	3.200***	3.743***	3.768***	3.676***	3.642***
	1,07	*4.30*	*4.83*	*4.93*	*4.99*	*4.93*
Group 2	0,351	1.035**	0.771	0.601	0.288	0.276
	0,75	*2.16*	1.51	1.19	0.58	0.56
Group 3	-1,800**	0.076	0.124	0.157	0.505	0.856
	-2,46	*0.09*	*0.15*	*0.20*	*0.63*	*1.04*
Estimation type		-1.916***	-1.308**	-1.615***	-1.483***	-1.462***
		-3.47	*-2.37*	*-2.92*	*-2.76*	*-2.73*
Data type		*1.518****	1.560***	1.123*	0.780	0.680
		3.00	*2.67*	*1.90*	*1.36*	*1.18*
Manufacturing sector		*0.877***	0.280	0.223	-0.012	0.351
		2.10	*0.65*	*0.53*	*-0.03*	*0.74*
Services sector		*1.532*	1.011	0.172	-0.727	-0.563
		1.21	*0.79*	*0.13*	*-0.58*	*-0.44*
Number of observations		*0.001***	0.001**	0.001**	0.001***	0.001***
		2.42	*2.36*	*2.30*	*2.88*	*2.63*
Innovative firms		-0.324	-0.345	-0.245	-0.548	-0.387
		-0.61	*-0.64*	*-0.48*	*-1.06*	*-0.72*
SME		1.206	0.773	0.535	1.037	0.900
		1.47	*1.13*	*0.79*	*1.57*	*1.35*
Large firms		0.849	0.686	0.858	1.200**	0.994*
		1.61	*1.29*	*1.25*	*2.33*	*1.89*
Date of the paper		0.081	0.078	0.141*	0.193**	0.187***
		1.08	*1.03*	*1.83*	*2.51*	*2.44*
Lagged Subsidies			0.174	0.904	0.786	0.846
			0.29	*1.42*	*1.27*	*1.29*
Industry dummies			2.254***	2.657***	2.115***	1.743***
			4.37	*5.08*	*3.95*	*2.92*
Time dummies			-1.426***	-1.730***	-2.344***	-2.234***
			-3.11	*-3.75*	*-5.10*	*-4.74*
Private R&D			-0.571	-0.690*	-0.140	-0.147
			-1.41	*-1.74*	*-0.35*	*-0.37*
Beta index				6.104***	7.911***	
				3.41	*4.15*	
Wages						7.856***
						3.42
Mechanicals						-2.430
						-1.21
Buildings						2.735**
						2.12
Subsidies intensity					52.364***	43.795***
					5.44	*4.07*
Subsidies intensity ²					-172.400***	-144.571***
					-5.57	*-4.20*
Constant	1.168***	-165.966	-159.995	-291.120*	-397.923**	-387.334**
	3.58	*-1.11*	*-1.05*	*-1.87*	*-2.57*	*-2.51*
Number of observations	429	429	429	429	429	429
F-test	*10.36****	*6.58****	*7.67****	*7.50****	*8.84****	*8.22****
Adj. R²	*12.62%*	*18.36%*	*23.11%*	*25.30%*	*30.74%*	*30.95%*

t stats between parenthesis *** p<0.01 **p<0.05 *p<0.1

We use a step-by-step analysis to investigate our proposition. The model 1 encompasses only the group dummies next to the standard deviation. The model 2 adds the characteristics of the sample and method, while the model 3 adds the other characteristics of the research design. The models 4 to 6 focus then on the public policy variables. The model 4 adds the measure of the beta index, and the model 5 the proportion of subsidized business R&D at the macroeconomic level. Finally the model 6 refine our analysis of the fiscal policy by disaggregating the beta index on 3 components (respectively wages, mechanicals and building sub-indexes) that assess the R&D tax advantages allowed to firms depending on the nature of their spending.

Impact of the research design on the result of past researches

Our econometric results seems to validate our proposition 1, with some variable relative to former studies on subsidies being significantly different from 0.

The models 1 to 6 show the coefficients associated with the various group variable are most often significant and of opposite signs. This is the case in models 5 and 6 that are the more important regarding this point, as they are our final estimation with all the covariates. Not surprisingly then, the kind of output assessed has a robust impact on the effect size measured. This is important as the validity of our other results relies on the capacity of these dummies to grasp the residual heterogeneity in the effect size that are not due to the other covariate in our models.

Our estimations can then help to depict the characteristics of an 'ideal' research that concluded to the presence of crowding-in with subsidies. First of all this paper appears to be recent, as suggested by the date variable and even when controlled for publication bias. A possible explanation of is results can rooted on the increased quality of the datasets given to researchers by public institutions. Better quality estimates can thus be computed by scholars. But his point also questions the possibility of a homogenization of the results as time passes and as public institutions are more demanding toward positive results in order to validate the policies they implement.

Moreover, in all our models the variables estimation type is significant. They suggest that papers that relied on matching procedures displayed more often positive results than the average article. On this ground we note that the data type seems to be more influential than the estimation type on the effect size. This point is interesting as the potentiality of the panels can only be exploited using regressions techniques. As such, most of the time, matching comes with a cross section analysis.

Furthermore we quote the strong impact of the number of observations variable. Studies that rely on important dataset are more subject to conclude to the efficiency of public subsidies, even when controlled for the other dataset characteristics (panel or not). Even more surprisingly, innovative firms as well as SMEs do not appear to be more sensitive to public subsidization than the average, when controlling for other covariates. This is a striking point as past researches have concluded than these two subgroups of firms should be the main beneficiary of such policies.

When turning to the characteristics of the econometric model implemented, estimations 3 to 6 show that the presence of some time lag is important in order to estimate the true effect size. Moreover, industry dummies were found to be also significant in our analysis, but not time dummies. One should be cautious when interpretating this last result as time dummies are specific to cross-section data, and as the possible control of time variation could have been grasped by the data type variable. Last but not least the fact to focus on private or internal R&D do not appear to have a significant impact on the effect size, everything equals. This suggests that estimation over all forms of R&D could qualify in order to assess the effect size of additionality.

Implications for public policy

Estimations 4 to 6 encompass the public policies variables, and seems to validate the propositions 2 and 3b. First of all the coefficient of the beta variable is positive and always significant in the models 4 and 5. As such our analysis suggest that there is a negative relationship between the fiscal generosity toward R&D and the efficiency of R&D subsidies[3]. Tax credit and subsidies systems appear then to be at least partial substitutes in order to foster R&D investment. The more generous the tax system becomes, the less efficient will be the subsidization of firms. As estimation 6 shows, the effect of fiscal generosity is mainly rooted in the fiscal advantages displayed toward current spending and salaries, while tax credit on building and other mechanicals do not appears to have a significant impact on the mean effect size of subsidies. This point is not surprising when one think to the cost structure of R&D activities in firms, and to the main importance of the researcher's wages and of current spending for the companies.

In line with this result, estimation 5 and 6 exhibit a quadratic relationship (as an inverted U-shape) between the subsidies intensity and the effect size of such policies. While small level of subsidization of business R&D appears to foster firms' R&D, such policies appears to quickly meet decreasing returns. As such, high level of subsidization appears to be inefficient as they are most of the time associated with crowding out effects.

5. Concluding remarks

In this article, we have presented a meta-analysis of public subsidies effects on firms R&D. Relying on past researches estimates on this topic, we have showed that public support toward companies R&D experienced two kinds of decreasing returns. On the one hand, at the macroeconomic level, the efficiency of the subsidies appears to be negatively linked to subsidies intensity. The more important the part of private R&D publicly financed, the less efficient are the subsidies. On the other hand, we have also found that this relationship is true even if public subsidization comes from fiscal policies implemented. The more generous is the tax system toward R&D, the less efficient are the subsidies.

3 Fiscal generosity is commonly assessed by 1-Beta (Warda, 1996, 2002).

Last but not least, we have also showed that the methodology and the quality of the data used for an analysis play a major role in determining the return to public R&D subsidization. By studying the research designs of previous studies, we were able to depict the researches that were more to find a positive results to grant policies.

To conclude, it is important to note that this meta-analysis has been carried out using relatively few studies of the effects subsidies because these studies are scarce, and because meta-analysis requires some homogeneity in the assessed effect size in order not to sum up together 'oranges and apples' . More solid research on this subject would therefore be very useful. Our study has shown that the use of methods to correct publication bias is important, so this should explicitly be taken into account. Furthermore, to better compare studies on this topic, more precise information on macroeconomic context, as well as on the research designs could also help to improve our understanding of the determinants successful public policies in order to foster R&D.

Acknowledgment

We would like to thank the Dr Russel Thomson (U. of Melbourne) that gave us access to his database on B-indexes, as well as the members of the PRISM-Sorbonne for helpful comments.

References

Aerts, K., 2008. Who writes the pay slip? Do R&D subsidies merely increase researcher wages?, K.U.Leuven Discussion Paper, forthcoming.

Aerts and Czarnitzki, (2004) Using innovation survey data to evaluate R&D policy: The case of Belgium, ZEW Discussion Paper 04-55, Mannheim. Also appeared as Research Report OR 0439, K.U.Leuven, Dept. of Applied Economics, Leuven

Aerts, K., Czarnitzki, D., (2006) The impact of public R&D funding in Flanders, IWT M&A Study 54, Brussels

Aerts, K. and Schmidt, T., 2008. Two for the price of one? Additionality effects of R&Dsubsidies: a comparison between Flanders and Germany. Research Policy 37,806–822.

Aerts and Thorwarth, 2008 Additionality Effects of Public R&D Funding: "R" versus "D", mimeo.

Almus, M. and D. Czarnitzki (2003), The Effects of Public R&D Subsidies on Firms' Innovation Activities: The Case of Eastern Germany, *Journal of Business and Economic Statistics*, 21(2), 226-236.

Arqué et Mohen, (2010) R&D subsidies and permanent inducement effects, mimeo.

Arrow, K.J. (1962) Economic welfare and the allocation of resources to invention. In Nelson, R.R. (ed.), The Rate and Direction of Inventive Activity: Economic and Social Factors (pp. 609-625). Princeton University Press.

Cerulli, G., and Poti, B. (2010): “The differential impact of privately and publicly funded R&D on R&D investment and innovation: The Italian case”, Working Papers 10, Doctoral School of Economics, Sapienza University of Rome, revised
2010.

Cohen, W.M., D.A. Levinthal. 1989. Innovation and Learning: The Two Faces of R & D. The Economic Journal 99 569-596.

Czarnitzki, D., 2001. Die Auswirkungen der Forschungs- und Technologiepolitik auf die Innovationsaktivitäten ostdeutscher Unternehmen, Schmollers Jahrbuch - Zeitschrift für Wirtschafts- und Sozialwissenschaften 121(4), 1-22.

Czarnitzki D. (2006): “Research and development in small and medium-sized German enterprises: The role of financial constraints and public funding”, *Scottish Journal of Political Economy*, 53 (3), 335-357.

Czarnitzki, D. and Fier, A. (2002): “Do innovation subsidies crowd out private investment: evidence from the German service sector”, *Applied Economics Quarterly*, 48(1), 1–25.

Czarnitzki, D., Hussinger, K., 2004. The link between R&D subsidies, R&D input and technological performance, ZEW Discussion Paper 04-56, Mannheim.

Czarnitzki & Toole, 2007 Business R&D and the interplay of R&D subsidies and product market uncertainty. Review of Industrial Organization 31(3): 169-181.

Czarnitzki, Hottentot & Thorwarth, 2011 Industrial research versus development investment: the implications of financial constraints. Cambridge Journal of Economics, 35(3): 527-544.

Czarnitzki, D., Ebersberger, B., Fier, A., 2007. The relationship between R&D collaboration, subsidies and R&D performance: empirical evidence from Finland and Germany. Journal of Applied Econometrics 22 (7), 1347–1366.

Czarnitzki, D., Licht, G., 2006. Additionality of public R&D grants in a transition economy: the case of Eastern Germany. Economics of Transition 14 (1), 101–131.

Czarnitzki, D., Lopes-Bento, C., 2011. Innovation subsidies: Does the funding source matter for innovation intensity and performance? Empirical evidence from Germany

Dasgupta, P., and Stiglitz, J. (1980): “Industrial structure and the nature of innovative activity”, *Economic Journal*, 90, 266-293.

David, P.A., Hall, B.H. and Toole, A.A. (2000) Is public R&D a complement or substitute for private R&D? A review of econometric evidence. Research Policy 29(4-5): 497-529

Doucouliagos, C. and Laroche, P. (2003). ‘What do unions do to productivity? A meta-analysis’. Industrial Relations, 42 (4): 650–91.

Doucouliagos C. and Stanley, T. D. (2009). ‘Publication selection bias in minimum-wage research? A meta-regression analysis’. *British Journal of Industrial Relations*, 47 (2): 406–28.

Duch-Brown, Garcma-Quevedo & Montolio, 2011, The link between public support and private R&D effort: what is the optimal subsidy?

Duguet, E. (2004), Are R&D Subsidies a Substitute or a Complement to Privately Funded R&D? Evidence from France Using Propensity Score Methods for Non Experimental Data, *Revue d'Economie Politique*, 114(2), 263-292.

Duval, S. and Tweedie, R. (2000). 'Trim and fill: a simple funnel-plot-based method of testing and adjusting for publication bias in meta-analysis'. *Biometrics*, 56: 455–63.

Ebersberger, B. (2005), The Impact of Public R&D Funding, VTT Publications 588.

García-Quevedo, J. (2004) Do public subsidies complement business R&D? A meta-analysis of the econometric evidence. *KYKLOS* 57(1): 87-102

González, X., Jaumandreu, J., and Pazó, C. (2005): "Barriers to Innovation and Subsidy Effectiveness", *Rand Journal of Economics,* 36(4), 930-949.

González, X. and Pazó C. (2008): "Do public subsidies stimulate private R&D activities?", *Research Policy*, 37(3), 371-389.

Gorg and Strobl (2007) The effect of R&D subsidies on private R&D, *Economica* 74(294), 215-234

Griliches, Z. (1986) Productivity, R&D, and the basic research at the firm level in the 1970's. *American Economic Review* 76(1): 141-54

Hall, B. H. (2002) The financing of research and development. *Oxford Review of Economic Policy* 18(1): 35-51.

Heijs, J. and L. Herrera (2004), The distribution of R&D subsidies and its effect on the final outcome of innovation policy, Working paper Instituto de Análisis Industrial y Financiero 46, Madrid.

Henningsen, Heagland and Moen, 2011, Estimating the additionality of R&D subsidies using proposal evaluation data to control for firms' R&D intensions, mimeo.

Herrera and Ibarra, 2010 Distribution and effect of R&D subsidies: A comparative analysis according to firm size, *Intangible Capital*, 6(2), 272-299

Hussinger, K. (2008), "R&D and subsidies at the firm level: an application of parametric and semiparametric two-step selection models". *Journal of Applied Econometrics*, 23, 729-747.

Kaiser, U. (2004), Private R&D and public R&D subsidies: Microeconometric evidence from Denmark, CEBR Discussion Paper 19, Denmark.

Klette and Moen, 2011 R&D Investment Responses to R&D Subsidies: A Theoretical Analysis and a Microeconomic Study. Preliminary draft presented at the NBER Summer Institute, july

Lach, S. (2002): "Do R&D subsidies stimulate or displace private R&D? Evidence from nIsrael", *Journal of industrial economics*, 50(4), 369-390.

Licht & Stadler, 2003 Auswirkung offentlicher Forschungsforderung auf die private F&E-Tdtigkeit: Eine mikroekonometrische Evaluatio in Empirische Wirtschaftsforschung: Methoden und Anwendungen, pp. 213-240. Tubingen

Meeusen & Janssen, 2001 Substitution versus additionality: econometric evaluation by means of micro-economic data of the efficacy and efficiency of R&D subsidies to firms in the Flemish region. CESIT discussion paper No 2001/01, University of Antwerp.

Negassi, S., Sattin, JF (2014) Evaluation of public R&D policy: A meta-regression analysis, PRISM Working paper, University Paris 1.

Nelson, R. R. (1959), 'The Simple Economics of Basic Scientific Research', *Journal of Political Economy*, 67 (3) 297-306.

Nishimura and Okamuro (2011) Subsidy and networking: The effects of direct and indirect support programs of the cluster policy, *Research Policy*, 40, 714-727

Reinhowski, Alecke, Mitze & Untiedt, 2010, Effectiveness of Public R&D Subsidies in East Germany-Is it a mMatter of Firm Size ?, mimeo

Stanley, T.D., 2008, Meta-regression methods for detecting and estimating empirical effects in the presence of publication selection, *Oxford Bulletin of Economics and Statistics*, vol. 70, no. 1, pp. 103-127.

Tandogan & Pamukçu, 2011 Evaluating the effectiveness of public support to R&D in Turkey through concets of input and output additionality

Thomson, R. (2012), Measures of R&D Tax Incentives for OECD Countries, WP 17/12, University of Melbourne.

Wallsten, S.J. (2000) The effects of government-industry R&D programs on private R&D: the case of the small business innovation research program. *RAND Journal of Economics* 31(1): 82-100.

Warda, J. (2002). Measuring the Value of R&D Tax Treatment in OECD Countries*, Science and technology Review* No. 27. Paris OECD. 27: 185-211.

Annex 1. Source for Meta-analysis

	Author(s)	**Publication date**	**Country**	**Time window**		**Output(s) assessed in the paper**			
				Beginning	**Ending**	**Amount of supplementary R&D per euro invested**	**Amount of supplementary R&D per project financed**	**Percentage of R&D increase per 1% increase of subsidy**	**Amount of supplementary R&D intensity per project financed**
1	Aerts	2008	Belgium	2003	2005	X	X	X	X
2	Aerts & Czarnitzki	2004	Belgium	1998	2000		X		X
3	Aerts & Czarnitzki	2006	Belgium	1998	2000	X	X	X	X
4	Aerts & Schmidt	2008	Belgium / Germany	1998	2004		X		X
5	Aerts & Thorwarth	2008	Belgium	2002	2006	X	X		
6	Ali-Yrkko	2005	Finland	1996	2002	X			
7	Almus & Czarnitzki	2003	Germany	1993	2001				X

8	Arqué et Mohen	2010	Spain	1990	2002	X			
9	Cerulli & Poti	2010	Italy	2000	2004		X		
10	Czarnitzki	2001	Germany	1996	1998				X
11	Czarnitzki & Fier	2002	Germany	1996	1998		X		X
12	Czarnitzki & Hussinger	2004	Germany	1992	2000		X		X
13	Czarnitzki & Licht	2005	Germany	1993	1999		X		X
14	Czarnitzki & Lopes Bento	2011	Germany	1992	2006				X
15	Czarnitzki & Toole	2007	Germany	1998	2000	X			
16	Czarnitzki, Ebersberger & Fier	2007	Finland / Germany	1996	2000				X
17	Czarnitzki, Hottentot & Thorwarth	2011	Belgium	1999	2007				X
18	Duch-Brown, Garcma-Quevedo & Montolio	2011	Spain	2005	2006	X			
19	Duguet	2004	France	1986	1997				X
20	Ebersberger	2005	Finland	1994	2000		X		X
21	Gonzalez & Pazo	2008	Spain	1990	1999		X		X
22	Gonzalez , Jamendreu & Pazo	2005	Spain	1990	1999	X			
23	Heijs & Herrera	2006	Spain	1998	2000				X
24	Henningsen, Heagland & Moen	2011	Norway	2001	2007	X		X	
25	Herrera & Ibarra	2010	Spain	1999	2000				X
26	Kaiser	2004	Denmark	2001	2001				X
27	Klette & Moen	2011	Norway	1982	1995	X			
28	Lach	2002	Israel	1990	1995	X		X	
29	Lopes Bento & Czarnitzki	2010	Luxembourg / Germany / Belgium / Spain / South Africa	2002	2004				X
30	Lopes Bento & Czarnitzki	2013	Belgium	2002	2008				X
31	Meeusen & Janssen	2001	Belgium	1992	1997	X			
32	Streicher,Schibany & Gretzmacher	2004	Austria	1997	2002	X			
33	Tandogan & Pamukçu	2011	Turkey	2005	2006				X
34	Toivanen & Hyytinen	2005	Finland	2002	2002		X		
35	Vzgelik & Taymaz	2008	Turkey	1993	2001				X
36	Wallsten	2000	USA	1990	1993	X			
37	Bloch & Graversen	2012	Denmark	1995	2005		X		
38	Hussiger	2008	Germany	1992	2000		X		
39	Licht & stadler	2003	Germany	1999	2000		X		

40	Clausen	2007	Norway	1999	2001			X	
41	Gorg & Strobl	2007	Ireland	1998	2002			X	
42	Reinhowski, Alecke, Mitze & Untiedt	2010	Germany	2001	2003				X