Do the effects of RD tax credits vary across industries? A meta-regression analysis

Castellacci, Fulvio and Lie, Christine

Norwegian Institute of International Affairs, TIK Centre, University of Oslo

July 2013

Do the effects of R&D tax credits vary across industries? A meta-regression analysis

Fulvio Castellacci and Christine Mee Lie

Norwegian Institute of International Affairs (NUPI) & TIK Centre, University of Oslo

This draft: 1 July 2013

Abstract

This paper presents a survey of the micro-econometric literature on the effects of R&D tax credits on firms' innovation activities. We focus on one specific aspect that has not received sufficient attention in previous research: the sectoral dimension. Our meta-regression analysis (MRA) sets up a new database collecting a large number of firm-level studies on the effects of R&D tax credits and investigates the factors that may explain differences in the estimated effects that are reported in the literature. The main result of the MRA analysis is indeed that *sectors matter*. Micro-econometric studies that have focused on a sub-sample of high-tech industries have on average obtained a *smaller* estimated effect of R&D tax credits. The paper proposes a simple framework to investigate why the effects of R&D tax credits vary across sectors and points out new directions and hypotheses for future research.

JEL codes: H25, H32, O32, O38

Keywords: R&D tax credits; R&D policy; sectors; meta-regression analysis

Corresponding author:
Fulvio Castellacci
Norwegian Institute of International Affairs (NUPI)
Postal address: C.J. Hambros plass 2D, Pb 8159 Dep 0033 Oslo;
Telephone: +47 22 99 40 21; E-mail: fc@nupi.no

1. Introduction

R&D tax credits are a major public policy instrument that has the objective to increase private firms' incentives to invest in innovative activities. They are tax deductions that business enterprises can claim if they are involved in R&D activities, which have the effect of reducing the marginal costs of R&D investments faced by firms (Hall and Van Reenen, 2000).

A large empirical literature has investigated the effects of fiscal incentives to R&D, in the attempt to estimate the extent to which a given amount of tax credits leads to an increase in firms' R&D investments. While the earlier literature focused on a few countries only, and in particular the US, an increasing number of micro-econometric studies on a large number of economies have been presented during the last few years (Parsons and Phillips, 2007; Mohnen and Lokshin, 2009). The exponential growth in the literature is partly due to the increasing popularity of tax credits, which are now adopted in more than 20 OECD countries; but it has also been fostered by the greater availability and diffusion of firm-level data in several countries, and particularly in Europe (Bodas Freitas and von Tunzelmann, 2008; OECD, 2010).

The bulk of this micro-econometric literature provides estimates of the rate at which R&D investments increase due to the introduction of fiscal incentives (additionality ratio) or, correspondingly, the rate at which the marginal costs of R&D investments decrease (user-cost elasticity). One dominant characteristic common to most of the existing studies is that their main objective is to estimate the *average* effect of R&D tax credits in a large sample of firms. So far, however, the literature has not questioned explicitly whether this average estimated parameter may vary among industrial sectors, and the possible reasons for cross-industry differences.

One of the major results in the field of innovation studies is that *sectors matter*. Firms in different industries differ substantially in terms of the innovation strategy they adopt and the technological performance they achieve. The sectoral context provides micro agents (firms) with a set of opportunities and constraints that greatly shape the way in which they organize their innovative activities (Pavitt, 1984; Malerba, 2005). Specifically, the R&D distribution of firms varies greatly by sectors. Other sector-specific factors – such as the degree of market competition, technological opportunities, and the intensity of knowledge diffusion and spillover effects – do also differ substantially across industries. It is therefore reasonable to suspect that firms' responsiveness to fiscal incentives to R&D, and the related innovation and productivity effects, may vary considerably among industries.

So, do the effects of R&D policy support vary systematically by sector, and if so, why? Our paper intends to investigate this new research question by carrying out an updated overview of the literature and a meta-regression analysis to study whether the effects of tax credits differ across industries.

Our meta-regression analysis (MRA) builds up a new database containing information on a large number of recent firm-level studies on the effects of R&D tax credits. We then investigate the factors that may explain differences in the estimated effects that are reported in the literature. In addition to several other control factors, the key explanatory variable that we focus on refers precisely to the sectoral dimension: our MRA regressions investigate whether those studies that have controlled for sectoral characteristics, e.g. by comparing high- and low-tech industries, have on average achieved different results than all other micro-econometric works. The main result of the MRA analysis is surprising: empirical studies that have focused on a sub-sample of high-tech industries have on average obtained a *smaller* estimated effect of R&D tax credits.

This is an interesting pattern that calls for further research. If corroborated by future investigations, this finding would cast some important doubts on the effectiveness of R&D tax incentives. This would in fact imply that fiscal resources intended to stimulate R&D and economic competitiveness have a relatively stronger effect on those industrial sectors that are characterized by low technological opportunities, sluggish demand conditions and weak spillover effects to the rest of the economy. If so, R&D tax incentives mechanisms should be redesigned in order to take into account the sector-specific conditions that shape innovation propensity and dynamics in different industries of the economy, and in particular allocate a greater amount of fiscal incentives to R&D to high-opportunity and technologically dynamic sectors.

There exists a few other thorough overviews of this literature, and in particular Hall and Van Reenen (2000), Parsons and Phillips (2007), Mohnen and Lokshin (2009) and Cerulli (2012). The specific novelty of our survey paper and its intended contribution to the literature are twofold. First, the adoption of the MRA database and methodology opens up for future updates and extensions of this type of analysis of the effects of R&D policy. Secondly, by explicitly investigating the role of the sectoral dimension, we create a bridge between the R&D policy literature, on the one hand, and the important strand of research on sectoral patterns of innovation, on the other.

The paper is organized as follows. Section 2 introduces the literature on the effects of R&D tax incentives. Section 3 presents the MRA database, indicators and econometric methods. Section 4 summarizes the MRA regression results. Section 5 discusses a framework for future research. Section 6 concludes and outlines the implications of the work.

2. The effects of R&D tax credits

Business firms' R&D investments are important for the growth and competitiveness of national economies. Several countries have recently increased their efforts to strengthen innovation performance by means of R&D policy, following e.g. the guidelines of the Lisbon Agenda in EU (Lundvall and Borràs, 2005). R&D policy can basically take two distinct forms: it can either allocate directly public R&D resources through grants or procurement, or alternatively provide indirect support by means of R&D tax incentives.

R&D tax incentives are tax deductions that firms can claim if they are involved in R&D activities, thus providing them with an incentive to increase their innovation efforts. Tax credits are typically directed to all firms in the economy and hence let private agents decide what type of project to apply for. Their effect is to reduce the marginal cost of R&D investments (Hall and Van Reenen, 2000). By contrast, R&D subsidies target specific projects with high social returns and a longer time horizon, and their effect is to raise the marginal rate of return of R&D (David et al., 2000; Czarnitzki and Lopes-Bento, 2013). An advantage of tax incentives *vis-a-vis* subsidies is that the former are less subject to policy inefficiencies, since they are bottom up and based on agents' decisions, whereas subsidies are more likely to incur in policy failure because they are highly dependent on the information available to the policy makers that manage the R&D programme and the strategic priorities set by this.

R&D tax incentives have by now become a popular innovation policy instrument. More than 20 OECD countries currently support private R&D investments through this type of schemes, including not only advanced countries but also developing economies such as Brazil, India, China and South Africa (OECD, 2010). The widespread adoption of this type of R&D support schemes has increasingly attracted the attention of innovation scholars and fostered the development of a large stream of applied research, which investigates the effects of tax credits on firms' R&D expenditures by making use of firm-level data. While most of the early studies focused on enterprises in US States, the literature has recently been fostered by the increasing availability of firm-level datasets in several other countries and particularly in Europe.

Hall and Van Reenen (2000) present a seminal overview of methods and results in this field. Parsons and Phillips (2007) provide an updated survey of the main results in the literature, and Cerulli and Poti (2012) is a comprehensive discussion of econometric methods in R&D policy evaluation. Researchers interested in the effects of R&D tax incentives on firms' innovation have typically adopted two distinct microeconometric approaches. The first is to estimate the following equation:

$$RD_{ij} = \eta + \beta TC_{ij} + \theta X_{ij} + \mu_{ij} \quad (1)$$

where RD_{ij} is the R&D expenditures of firm *i* in industry *j*, TC_{ij} is a variable measuring the tax credit received by the enterprise, and X_{ij} is a vector of firm-specific characteristics affecting its R&D strategies (e.g. past R&D, cash flow and financial conditions, size, technological capabilities). In this specification, the parameter β (expected positive) measures the *additionality ratio*, which indicates the average increase that a tax credit induces in firms' R&D investments.[1]
The second approach estimates instead the following equation:

$$RD_{ij} = \varkappa + \lambda UC_{ij} + \psi X_{ij} + \nu_{ij} \quad (2)$$

in which UC_{ij} is a variable measuring the user cost of R&D (i.e. its marginal costs), and the parameter λ (expected negative) is the elasticity of R&D with respect to its price, measuring by how much R&D will increase when its marginal costs decrease.[2]

The bulk of the R&D policy evaluation literature has so far focused on the estimation of the *average* additionality ratio (in equation 1) or the *average* price elasticity (in equation 2) in each national economy. However, the field has so far neglected the study of the existence and extent of cross-industry differences in these estimated parameters. This is an important research gap and avenue for future research.

One of the major results that has convincingly been shown within the field of innovation studies is that *sectors matter*. Firms in different industries differ substantially in terms of the innovation strategy they adopt and the technological performance they achieve. The sectoral context provides micro agents (firms) with a set of opportunities and constraints that greatly shape the way in which they organize their innovative activities (Pavitt, 1984; Malerba, 2005). The R&D distribution of firms varies greatly by sectors. R&D intensive firms are typically concentrated in technologically advanced industries, whereas enterprises in more traditional sectors do not make use of R&D activities as their dominant strategy to create or implement new technologies. But the innovation literature has also shown that sectors differ along several other dimensions, such as the degree of market competition, technological opportunities, and the intensity of knowledge diffusion and spillover effects.

[1] The additionality ratio is either pointed out as *treatment effect*, if matching or difference-in-difference estimators are used, or simply as *incrementality ratio* through OLS and IV estimators.

[2] Hall and Van Reenen (2000: 467) define the user cost of R&D as the "pre-tax real rate of return on the marginal investment project that is required to earn a minimum rate of return after tax".

Therefore, it is reasonable to ask whether the effects of R&D policy support vary systematically by sector, and if so, why. Our paper intends to investigate this unexplored issue by carrying out an updated overview and a meta-regression analysis of the literature.

3. MRA: data and methods

3.1 Data and indicators

Following the standard MRA methodology (see e.g. Stanley, 2001), the search process for relevant papers to include in the meta-analysis database included: Google- and Google Scholar searches; the EconLit database; the JSTOR-, Ideas- and Science Direct Journal databases; all relevant journals in the innovation field; working paper series; homepages of relevant academics in the field; tables and reference lists in previously published survey papers. Key words used in this literature search were "R&D tax credits", "R&D tax incentives", "effects of R&D tax credits", and "effects of R&D tax incentives".

Only papers that presented an econometric analysis of the effects of R&D tax credits on firm-level innovation, and that provided enough information regarding the effect estimates and their standard errors (or t-statistics), were further considered.[3] Our literature search focused more carefully on those more recent micro-econometric studies produced from 2000 onwards. Earlier studies had been identified and surveyed in previous overview papers, which made some of our data collection tasks easier.[4]

Typically, each study on the effects of R&D fiscal incentives present estimation results for several regressions. There is no clear benchmark or rule in the meta-regression literature for deciding how many and which of these reported regressions should be included in a MRA dataset. In order to have as many observations as possible and thus increase the variability of our sample, the selection criterion we used was somewhat broad. We included all different regressions produced by the same micro-econometric study as different observations in our dataset, as long as these regressions differed between them in some substantial way, e.g. in terms of their sub-sample, time period, model specification, tax-credit measure or dependent variable. This procedure is in line with other recent meta-analysis exercises in other fields of economic research (e.g. Doucouliagos and Stanley 2009; Efendic et al. 2012).

[3] Notice also that we have only focused on papers that study "first-order effects" of fiscal incentives (i.e. their direct effects on R&D investments), and disregard the few studies investigating their effects on other firm-level variables (e.g. innovation output and economic performance).

[4] Hall and Van Reenen (2000), Parsons and Phillips (2007), Mohnen and Lokshin (2009), Hall et al. (2009) and Yang (2011) were the survey papers of direct relevance that we found and that we used during the search process.

This data collection procedure left us with a total of 31 articles, published between 1991 and 2012, and a total of 393 effect estimates. Tables 1 and 2 provide a complete list of references and some of the key characteristics of these 31 articles. Table 1 lists all the papers we found in which the dependent variable is the additionality ratio, estimated by using the model specification pointed out in equation 1 (see section 2). Table 2 lists instead all the articles in our database in which the dependent variable is the user cost elasticity, estimated through equation 2. As explained in section 2, equations 1 and 2 represent two different econometric approaches to estimate the effects of R&D tax incentives, and we will therefore consider them separately in our MRA analysis. The MRA database we have produced is available online, in order to ensure replicability and further extensions of this work in future research.[5]

< Tables 1 and 2 here >

Table 3 provides a list of the indicators we constructed on the MRA database and included in the analysis, along with their definition and descriptive statistics. Two of the indicators measure industry-specific characteristics (when these are considered in the micro-econometric studies): HTECH (dummy for high-tech subsamples) and MANUF (dummy for manufacturing subsamples). These variables test whether the effects of R&D tax credits are higher or lower when they are estimated on different sectoral subsamples. The SME variable (dummy for SMEs subsamples) controls whether small and medium-sized companies have different estimated effects than the overall sample of firms used in each study. We also include three further control variables: RD_{t-1} (dummy for the inclusion of lagged R&D as control variable in each study), SUBSIDY (dummy for the inclusion of R&D subsidies as control variable) and COUNTRY (dummy for the inclusion of country fixed effects). Several more characteristics of each paper and each regression were collected in the meta-database, and are available online for future extensions of this MRA study.

< Table 3 here >

3.2 Econometric methods

The baseline specification of the meta-regression model regresses the effects size of interest (i.e. the estimated additionality ratio, or user-cost elasticity) on an intercept and a measure of statistical precision, typically the standard error (SE):

[5] The database is available at: http://english.nupi.no/Activities/Projects/R-D-Policy-by-Sector-A-Cross-Country-Investigation

$$Effect\ Estimate_{s,i} = \hat{\alpha} + \hat{\beta}_0 * SE_{s,i} + \hat{\varepsilon}_{s,i} \tag{3}$$

where s = 1,…, 31 indexes the studies in the meta-database, and i = 1,…, 393 the individual regression estimates reported. $\hat{\alpha}$, $\hat{\beta}_0$ are estimated, and $\hat{\varepsilon}_{s,i}$ is the error term. To avoid heteroskedasticity, the common practice is to weight equation 3 by the standard error (SE) associated with each observation (Stanley et al. 2008). Equation 4, which is the weighted least squares (WLS) of equation (1), thus yields more efficient estimates:

$$TSTAT_{s,i} = \hat{\alpha} * \left(\frac{1}{SE_{s,i}}\right) + \hat{\beta}_0 + \hat{\varepsilon}_{s,i} * \left(\frac{1}{SE_{s,i}}\right). \tag{4}$$

After this transformation, the dependent variable is now the t-statistic ($TSTAT_{s,i}$) of the effect estimate in equation 3.[6] However, the estimated parameters in equation 4 must still be interpreted in terms of changes in the size of the effect estimate, *not* in terms of changes in statistical significance (changes in t-statistics) (Efentic et al. 2011). Note also that the intercept and the precision coefficient are reversed in equation (4), and so the main variable of interest is now the inverse of the standard error $\left(\frac{1}{SE_{s,i}}\right)$.

Egger et al. (1997) point out that the t-test of the intercept in equation 4 is a test for *publication bias*, which indicates whether some omitted variables in equation 4 (e.g. characteristics of the studies or the researchers that have produced them) may lead to a systematic selection effect and hence a bias in the estimated effect. Stanley (2008) argues that the meta-regression model can be used to test not only for publication selection, but also for estimating the *true empirical effect* after having controlled for publication bias. The first test is referred to as the *funnel asymmetry test (FAT)* and the latter as the *precision-effect test (PET)*. More formally, FAT tests the hypothesis H_0: $\hat{\beta}_0 = 0$, where non-rejection implies lack of publication selection and rejection is consistent with either upward (positive sign) or downward publication bias (negative sign). As for the PET, the hypothesis H_0: $\hat{\alpha} = 0$ is tested, where rejection is consistent with the existence of an authentic empirical effect, and could be interpreted as the true effect *corrected* for any publication bias (Stanley, 2008).

[6] The t-statistics, if not explicitly reported in the original paper, is calculated by using the formula: $TSTAT_{s,i} = (\frac{Effect\ Estimate_{s,i}}{SE_{s,i}})$, and equivalently to find the SE (if not reported): $SE_{s,i} = (\frac{Effect\ Estimate_{s,i}}{TSTAT_{s,i}})$, see e.g. Fischer (1954).

In this paper, in addition to these two standard terms, we are interested to investigate the extent to which different characteristics of the micro-econometric studies of R&D policy (see the indicators in table 3) explain the different estimated effects that are reported in the literature. In particular, we want to focus on the sectoral dimension, and investigate whether running the micro-econometric regressions on different sectoral sub-samples has a systematic influence on the estimated effect of R&D tax credits. We therefore extend the baseline specification in equation (4) to include a set of additional explanatory variables. Our multivariate meta-regression (MRA) model in equation 5 includes a set of k moderator (control) variables:

$$TSTAT_{s,i} = \hat{\alpha} * \left(\frac{1}{SE_{s,i}}\right) + \hat{\beta}_0 + \sum_{1}^{K} \hat{\lambda}_k * \left(\frac{1}{SE_{s,i}}\right) * Z_{k,s,i} + \hat{u}_{s,i} * \left(\frac{1}{SE_{s,i}}\right) \tag{5}$$

where $Z_{k,s,i}$ are the k = 1,…, K moderator variables each weighted by $\left(\frac{1}{SE_{s,i}}\right)$, and $\hat{\lambda}_k$ are the k coefficients to be estimated in the meta-regression. Each of these coefficients measures the impact of the corresponding moderator on the true empirical effect size.

4. MRA results

Tables 4 and 5 present the results of the meta-regression analysis (MRA). Table 4 reports the results for the estimation of equation 5, referring to the empirical approach in which the dependent variable used in previous empirical studies is the additionality ratio (see equation 1, section 2). Table 5 does instead report the estimation results referring to the second model specification that is typically adopted in the literature, which has as dependent variable the user cost elasticity (see equation 2, section 2).

In each of these tables, we progressively include the various explanatory variables, going from the baseline to the complete version of the model. Specification 1 only includes the constant (the *publication bias* effect) and the INVSE variable (measure of the *true empirical effect* of R&D tax incentives). Specification 2 includes the two variables measuring industry-specific characteristics: HTECH (dummy for high-tech subsamples), the variable of our main interest, and the control variable MANUF (dummy for manufacturing subsamples). Specification 3 adds the SME variable (dummy for SMEs subsamples). Specification 4 also includes three further control variables: RD_{t-1} (dummy for the inclusion of lagged R&D as control variable in the study), SUBSIDY (dummy for the inclusion of R&D subsidies as a control variable) and COUNTRY (dummy for the inclusion of country fixed effects).

In both of the tables, the R-squared indicates that the meta-regressions have a relatively good explanatory power, so that the model takes into account some of the most important characteristics that explain variation in the estimated effects of R&D tax credits among different micro-econometric studies available in the literature. Note that the signs of all estimated coefficients in table 4 are just the opposite as those in table 5, for the obvious reason that the former table has a *positive* measure as dependent variable (additionality ratio), whereas the latter makes use of a *negative* one (user cost elasticity).

In both tables 4 and 5, the estimated parameter for the constant is significant, providing evidence of a publication (selection) bias effect. The parameter is positive in table 4 and negative in table 5, indicating that previous studies overestimated the effect of R&D tax credits on firms' innovation activities when they failed to control for a set of ancillary factors that may affect this relationship (and that our MRA regressions try to correct for). However, in spite of this publication bias, there is also significant evidence of a true empirical effect (measured by the variable INVSE), which is obviously positive for the additionality ratio (table 4) and negative for the user cost elasticity (table 5).

Before looking at the results of the estimations for the variable of main interest for this study, HTECH, let us briefly discuss the results for the set of control variables we have included in our MRA model in tables 4 and 5. The variable MANUF is statistically significant in both tables. Its estimated coefficient (positive in table 4 and negative in table 5) indicates that those studies that have run regressions on a sub-sample of manufacturing companies (i.e. excluding service firms) have on average obtained a greater estimated effect of fiscal incentives to R&D. This result is not surprising, since the innovation literature has often pointed out that the bulk of R&D activities is concentrated in manufacturing industries, whereas enterprises in the service sectors innovate through a variety of different strategies among which R&D is certainly not the dominant mode (Castellacci, 2008). It is therefore reasonable to infer that service firms are less responsive to R&D policy schemes than manufacturing companies. Next, the variable SME tests whether the effects of R&D tax credits differ when they are estimated for sub-samples of SMEs. The variable is weakly significant in the full model specification in regressions 4. When estimated with precision, the coefficient indicates that the additionality ratio (user cost elasticity) is smaller (larger) for SMEs than for the whole sample of firms.

The next three variables are control factors that micro-econometric studies in this field should in principle include in the econometric specification but sometimes do not (e.g. due to the lack of available data). When the lagged R&D variable (RD_{t-1}) is included in the specification to alleviate endogeneity issues, the estimated effect of R&D policy is obviously smaller in size. The same effect arises when the control variable SUBSIDY is included in the regression. This is a measure of R&D subsidies received by the firm in addition to the R&D tax credits, so it is reasonable that when this is controlled for the estimated additionality ratio turns out to be lower. Finally, the control variable COUNTRY tests for the inclusion of country fixed effects in the regressions, which are only used by the few studies having availability of firm-level data for more than one country, or States within a country (typically the US). This variable is only significant in table 4. Its estimated sign indicates that the additionality effect is higher for those works including country-fixed effects, and this result is arguably driven by firm-level estimates obtained on US datasets, where fiscal incentives to R&D have a longer tradition and more established effects than in other OECD countries.

Let us now shift the focus to the results for the variable of main interest for our paper: HTECH, the dummy variable indicating whether each micro-econometric regression reported in the literature focuses on a sub-sample of high-tech industries (dummy = 1), or rather considers the whole sample available without any further control for sector-specific differences (dummy = 0). This variable turns out to be statistically significant. Its estimated coefficient is *negative* in table 4 and *positive* in table 5. This means that micro-econometric regressions that have focused on a sub-sample of high-tech industries have on average obtained a *smaller* estimated effect of R&D tax credits (i.e. a lower additionality ratio, or a higher user cost elasticity).

This is an interesting result that has not previously been pointed out in the literature. In our MRA dataset, most of the micro-econometric studies do not control for sectoral characteristics and do not run separate regressions for different groups of industries. Only a limited number of studies do this, either by focusing on specific industries, or by running separate regressions for high-tech and low-tech industries. Specifically, the studies of Wang and Tsai (1998), Huang (2009) and Yang et al. (2012) focus on Taiwanese companies, and find that enterprises in the electronics sector are more responsive to fiscal incentives. Paff (2004 and 2005) and Ho (2006) investigate the effects of the alternate incremental credit (AIC) in various US States, pointing out remarkable differences between two high-tech industries: pharmaceuticals and software. Lee (2011) estimates firm-level regressions for six countries (Canada, Japan, Korea, Taiwan, China and India), and finds among other things that the degree of competition of each industry affects firms' responsiveness to R&D tax credits.[7]

[7] In addition to these studies included in our MRA dataset, notice also that in their seminal paper Bloom and Van Reenen (2002) did also obtain user cost elasticities for all manufacturing industries in their sample. Table 3 in their

However, although providing some interesting and significant evidence that the effects of R&D tax incentives vary across sectors, these few previous studies have mostly treated this as a marginal aspect and not investigated at length whether this is a systematic effect, and what sector-specific factors may explain these patterns. In short, the existing literature contains some clear indications of the existence of cross-industry differences, but it has never explicitly investigated this point. So, how could these patterns be explained? We point out two possible alternative explanations.

The first and most simple one is that it may be natural to expect that firms in low-tech sectors, which have on average a lower R&D intensity than companies in high-tech sectors, may find it relatively easier to increase their R&D expenditures in response to a tax credit scheme. Due to the lower initial conditions, in fact, even a small R&D increase as a response to fiscal incentives will for low-tech firms represent a relatively large additionality effect. By contrast, achieving an additionality effect will be more demanding and difficult for enterprises in high-tech sectors, due to the already high level of R&D commitment they have.

However, this argument is not as obvious as it may appear at first. A large literature in innovation studies has extensively investigated sectoral patterns of innovation, and shown that companies in different branches of the economy follow substantially different innovation modes and strategies (Pavitt, 1984; Malerba, 2005). In particular, in several low-tech and traditional industries, R&D is not a dominant strategy to develop new technologies, and firms rely instead on other channels such as the purchase of new capital machineries, and/or organizational and marketing innovations not based on formal R&D activities. The fact that the R&D propensity of firms varies substantially across sectors casts some doubts on the first explanation we have pointed out.

So, a different reason explaining why tax credits have a stronger additionality effect in low-tech industries than high-tech sectors may be based on the sectoral patterns of innovation literature, and in particular on the concept of *technological and economic opportunities* (Dosi, 1982). Industrial sectors differ in terms of technological opportunities – the ease with which innovative input leads to technological output – as well as demand conditions and economic opportunities. Low-tech and mature sectors are typically characterized by a lower level of technological and economic opportunities and less dynamic demand conditions than high-tech industries (Von Tunzelmann and Acha, 2005). It may be argued that firms in low-tech sectors, due to the lower level of market opportunities they face, are on average more likely to experience financial constraints and, for this reason, they may find it convenient to apply to a tax credits scheme in order to enjoy fiscal benefits. According to this second argument, the higher additionality of companies in low-tech

article indicates that the estimated user cost elasticities are greater for lower-tech sectors and smaller (or not significant) for most high-tech sectors.

sectors could be interpreted not as an indication of technological dynamism and catch up, but rather as a signal that firms in low-tech and traditional industries are eager to apply to tax credit schemes primarily to achieve fiscal benefits and alleviate their financial constraints rather than for increasing their R&D investments in a permanent manner.

These two alternative explanations have not previously been discussed in the literature. It is not possible here to conclude which of them is more plausible, and this discussion does indeed call for future research. We further discuss this issue and propose further avenue for future research in the next section.

< Tables 4 and 5 here >

5. A framework for future research

So, how should future research investigate cross-industry differences in the effects of R&D tax incentives? We provide here a simple framework outlining new directions and hypotheses for future research. Consider an economy with *s* sectors. Each industry *j* has a population of N_j (homogenous) firms, out of which n_j enterprises receive an R&D tax credit at time *t*. The (average) additionality ratio in this sector can be defined as:

$$\alpha_j = (RD_{j;\,t+1} - RD_{j;\,t}) \,/\, RD_{j;\,t} \tag{6}$$

where RD_j is the R&D expenditures of each firm in a given period. The total additional R&D spending induced by the tax incentive scheme in industry *j* is then:

$$\Delta RD_j = n_j\,(RD_{j;\,t+1} - RD_{j;\,t}) \tag{7}$$

This total increment can be rewritten as the product of three factors:

$$\Delta RD_j = \alpha_j \bullet (n_j \,/\, N_j) \bullet (N_j \bullet RD_j) \tag{8}$$

The first factor is the (average) additionality ratio defined above. The second is the share of firms in the industry that have received R&D support, indicating the sector-specific propensity of firms to respond to R&D policy incentives, and/or their ability to apply and receive such fiscal benefits. The third factor is the total R&D pool, i.e. the total amount of R&D expenditures carried out by all enterprises in that sector. The literature surveyed in the previous sections has typically focused on the first factor only. However, if we want to estimate the overall innovation effects of a tax incentive scheme, the second and third factors matter as well. All of the three factors pointed out in equation 8 are arguably *sector-specific*: they can reasonably be expected to vary systematically across industries, and it is therefore important to analyze how variations in sector-specific characteristics shape the effects of R&D policy on firms' innovative activities.

Let us now shift the focus to the economic effects of R&D tax credits. The additional R&D carried out in industry j leads, through the creation of new products and processes, to an increase in the sector's TFP level:

$$\Delta TFP_j = \Delta RD_j \bullet \gamma_j \tag{9}$$

The parameter γ_j defines the level of technological opportunities in the sector, which indicates, as noted in the previous section, the ease with which innovative inputs are translated into innovative output and value added (Dosi, 1982). This is as well-known an industry-specific parameter, which varies substantially across sectors (and historical periods), tending to be high in technologically advanced and emerging sectors, and low in more traditional and mature industries.

Besides, the additional R&D carried out in industry j will also lead to economic and productivity gains in other industries of the economy through a set of inter-industry knowledge spillover effects (Wieser, 2005). These can be defined as:

$$\Delta TFP_k = \Delta RD_j \bullet \delta_j \bullet \pi_{j;k} \tag{10}$$

where k indicates all other sectors of the economy except j ($k = 1, \ldots, s$; $k \neq j$); $\pi_{j;k}$ measures the technological proximity between j and k (i.e. the intensity of the knowledge diffusion from the former to the latter sector); and δ_j represents the *knowledge spillover potential* embodied in industry j. The knowledge spillover potential indicates the extent to which the advanced knowledge produced by firms in sector j has the potential to drive the growth of other industries. This is in other words a measure of the so-called *pervasiveness* of the new technologies produced in sector j, indicating whether they have widespread impacts throughout the whole economic system or rather weak effects on a limited set of related industries. Besides the degree of novelty of the new technologies, sectoral pervasiveness also depends on the position of each industry in the economic system, and the function it plays: upstream industries producing advanced knowledge are likely to lead to stronger spillover effects in the whole economy than downstream (supplier-dominated) industries (Pavitt, 1984; Castellacci, 2008).

In short, while the literature on R&D policy evaluation has so far focused on the estimation of the (average) additionality ratio for the whole economy, the framework described here points out the need to broaden up the focus of future research towards the joint investigation of three related factors: (1) the *total incremental effect* of the tax credit in a given industry (ΔRD_j; equation 8); (2) the *productivity effects* of this in the same industry (ΔTFP_j; equation 9); (3) the *spillover effects* to all other industries (ΔTFP_k; equation 10). From a policy point of view, the estimation of the average additionality ratio on which the literature has so far focused (i.e. the parameter α_j above) does not provide sufficient information to assess the overall innovation and economic effects of an R&D tax incentive scheme. Only the joint consideration of the three dimensions pointed out above can enable a complete assessment of the benefits of R&D policy.[8] And the key point that we want to make here is that all of the three factors are sector-specific, as pointed out in the innovation literature, so that it is reasonable to expect the effects of R&D tax incentives to vary systematically across industries.

Specifically, we outline three directions for future research, and for each of these we formulate a general hypothesis for future theoretical and empirical studies in this field. The first direction refers to the study of the *total incremental effect* of the tax credit in a given industry. Consider equation 8. All of the three terms in this equation are likely to differ substantially across industries. The total R&D pool term ($N_j \bullet RD_j$) is supposedly greater for a high-tech industry than a low-tech sector. The other two terms – the propensity to apply to the tax credits programme (n_j / N_j) and the average additionality ratio in the market (α_j) – are also sector-specific. In fact, a large literature on competition and innovation has previously investigated the relationship between competiton conditions within each industry and the incentives of firms to engage in R&D. This traditional literature has potentially important implications for the study of the effectiveness of R&D policy.

On the one hand, industry-level competition may decrease the monopoly rents of prospective innovative firms, thus reducing their incentives to engage in R&D activities. This is an argument traditionally known as the *Schumpeterian effect*, which postulates the existence of a negative relationship between the degree of competition in an industry and the R&D intensity of firms (Geroski 1990; Nicoletti and Scarpetta 2004; Tang 2006). If this effect holds, then we should

[8] The total benefits of an R&D support scheme should then be compared with its costs, including both the costs in terms of fiscal resources that are devoted to private companies' R&D activities and the administrative costs that policy-makers incur to set up and manage the scheme (David et al., 2000; Hall and Van Reenen, 2000).

arguably expect firms' propensity to apply to a tax credits programme (n_j / N_j) and the average additionality ratio (α_j) to be *lower* in a highly competitive industry than in an oligopolistic market.

On the other hand, more recent research on competition and innovation has also pointed out the possibility that product market competition may also turn out to boost R&D investments, since it may increase the incremental profits that firms obtain by investing in R&D activities (Aghion et al. 1997 and 2005; Castellacci, 2011). This second argument, the *escape-competition effect*, points out that the relationship between the degree of market competition and innovation may hence be positive, and even more so in neck-to-neck industries where competiton between rival firms is fierce. If this effect prevails, we should instead expect that the propensity to apply to a tax credits programme and the additionality ratio is *greater* in a highly competitive industry than in an oligopolistic market.[9] In short, it is not possible to determine *ex-ante* which of these two effects prevails, so that future empirical research should examine how the effects of R&D tax credits on firms' innovation are affected by the degree of competition that characterizes each sector.

The second direction for future research relates to the *productivity effects* of R&D tax credits within a given sector (see equation 9). As pointed out above, the level of technological opportunities in a given industry (the parameter γ_j) is an industry-specific factor that varies substantially across sectors (Dosi, 1982; Castellacci and Zheng, 2010). Opportunities are typically high in technologically advanced and new emerging sectors, and lower in more traditional and mature industries (Von Tunzelmann and Acha, 2005). Hence, it would be reasonable to expect that the productivity effects of R&D tax credits within the same industry is positively related to the level of technological opportunities that characterize the industry at any given time.

Finally, the third direction for future research refers to the *spillover effects* that R&D tax credits in sector j have on all other industries k of the economy (equation 10 above). The literature on sectoral patterns of innovation has previously pointed out sectoral taxonomies that identify some key sector-specific dimensions that characterize the innovative process in each industry and shape its technological trajectory and economic performance over time (Malerba, 2005). One important result in this literature is that some sectors have a high degree of pervasiveness, and hence a strong knowledge spillover potential (the parameter δ_j in equation 7), thus playing a central role as key drivers of the whole economic system. In particular, upstream industries that produce advanced technological knowledge are likely to lead to stronger spillover effects throughout the whole economy than downstream (supplier-dominated) industries (Pavitt, 1984; Castellacci, 2008). In terms of the effectiveness of R&D policy, this would imply that the spillover effects that R&D tax credits in sector j have on all other industries k of the economy should be expected

[9] This hypothesis is also in line with the empirical results of Lee (2011), which finds the degree of market competition to be positively related to the average estimated additionality ratio.

to be substantially stronger for upstream knowledge intensive industries (e.g. knowledge-based services, science-based manufacturing) than for downstream supplier-dominated sectors (e.g. personal goods and service providers).

The three general hypotheses that we have sketched here are not only relevant for future academic research in this field, but do also have an important policy dimension. In fact, the bottom line of our argument is that the total additional R&D spending induced by a tax incentive scheme ($\sum_j \Delta RD_j$) should to the extent possible be concentrated in industries with high technological opportunities and in sectors that lead to strong spillover effects to the rest of the economy. By contrast, if the R&D additionality effect is mainly skewed towards low opportunity mature sectors and/or downstream industries with low pervasiveness and spillover potential, the overall effect of the R&D tax credit scheme in the national economy will be *sub-optimal*.

In this respect, the MRA results presented in the previous section seem to cast some doubts on the efficiency of this type of R&D policy. Those results do in fact suggest that the additionality effects of fiscal incentives to R&D are on average stronger for low-tech industries than for high-tech sectors. If this finding will be corroborated by future empirical research, it would imply that fiscal resources intended to stimulate R&D and economic competitiveness tend to benefit relatively more those branches of the economy that do not have the highest innovative potential and economic impact on the growth of the national economy. If so, R&D tax incentives mechanisms should be redesigned in order to take into account the sector-specific conditions that shape innovation propensity and dynamics in different industries of the economy.

6. Conclusions

The paper has carried out a survey of the micro-econometric literature on the effects of R&D tax incentives on firms' innovation activities. This literature has rapidly expanded in the last few years, due to the increasing popularity of fiscal incentives as a policy tool, and also thanks to the larger availability of firm-level datasets in several countries in the OECD area. This empirical research typically leads to the conclusion that tax credits have a positive effect on corporate R&D investments, by increasing the amount of R&D carried out by each company, and by lowering its marginal costs. Our survey has in particular focused on one specific aspect that has not received sufficient attention in previous research: the sectoral dimension. Out of the large amount of micro-econometric studies in this field, only a limited number of them has controlled for cross-industry differences in the estimated effects of R&D policy, and no previous work has discussed a conceptual framework to investigate whether and why this could be the case.

To study this unexplored question, we have carried out a meta-regression analysis: this has set up and made available a new database collecting a large number of firm-level studies on the effects of R&D tax credits, and then investigated the factors that may explain differences in the estimated effects that are reported in the literature. The key explanatory factor we have focused on is precisely the sectoral dimension: our MRA regressions have investigated whether those studies that have controlled for sectoral characteristics, e.g. by comparing high- and low-tech industries, have on average achieved different results than all other micro-econometric works. The main result of the MRA analysis is indeed that *sectors matter*. Micro-econometric studies that have focused on a sub-sample of high-tech industries have on average obtained a *smaller* estimated effect of R&D tax credits. This is an interesting result that has not previously been pointed out in the literature.

Why may this be the case – why do the effects of R&D tax credits vary across sectors, and what are the possible implications for policy? These questions open up a new avenue for theoretical and empirical research in this field. The second part of our paper has proposed a simple framework to investigate these issues and pointed out some more specific new directions and hypotheses for future research. In short, our argument is that the overall benefits of an R&D tax incentives scheme depend on the complex interplay of three related factors: (1) the total incremental effect of the tax credit in a given industry; (2) the productivity effects of this in the same industry; (3) the spillover effects to all other industries. All of the three factors are sector-specific: firms' responsiveness to fiscal incentives to R&D and their economic effects are arguably closely dependent on sectoral characteristics such as the degree of market competition, the level of technological opportunities, and the intensity of knowledge diffusion and inter-industry spillover effects. Future research should therefore develop a theoretical and empirical framework to understand how these sector-specific characteristics shape firms' responses to R&D policy.

This research task is highly relevant for innovation policy-making. In fact, the bottom line of our argument is that the total additional R&D spending induced by a tax incentive scheme should to the extent possible be concentrated in industries with high technological opportunities and in sectors that lead to strong spillover effects to the rest of the economy. By contrast, if the R&D additionality effect is mainly skewed towards low opportunity mature sectors and/or downstream industries with low pervasiveness and spillover potential, the overall effect of the R&D tax credit scheme in the national economy will be *sub-optimal*.

In fact, our main MRA result – that the additionality effects of fiscal incentives to R&D are on average stronger for low-tech industries than for high-tech sectors – casts some doubts on the efficiency of this type of R&D policy. If this finding will be corroborated by future empirical research, it would imply that fiscal resources intended to stimulate R&D and economic competitiveness tend to benefit relatively more those branches of the economy that do not have the highest innovative potential and economic impact on the growth of the national economy. If so, R&D tax incentives mechanisms should be redesigned in order to take into account the sector-specific conditions that shape innovation propensity and dynamics in different industries of the economy, e.g. by introducing a sectorally differentiated incentive scheme to give stronger support to firms in more innovative and higher-opportunity industries. This policy implication is however far from conclusive, and will necessitate a substantial amount of further comparative research on different countries and industrial sectors.

In addition, two more policy-related considerations will have to be undertaken in order to assess the efficiency, or possible sub-optimality, of R&D policy. First, countries differ substantially in terms of their specialization patterns and industrial structure. Some economies, even in the presence of sub-optimal effects of R&D tax incentives, may still decide to invest in technological upgrading of domestic mature sectors that may be relevant in terms of employment or other policy objectives (e.g. availability of natural resources) – rather than focusing its R&D efforts in the promotion of high-tech industries. The economic efficiency of R&D policy should therefore be balanced with a set of other policy considerations and objectives.

Secondly, the evaluation of the effects of fiscal incentives to R&D should to the extent possible be carried out jointly with the study of the impacts of R&D subsidies. The latter often have a more explicit policy, and hence sectoral, dimension and set of priorities, and this may contribute to re-balance, or strengthen, the national pattern of R&D specialization of each economy. The literature has so far separately studied the effects of R&D tax credits and R&D subsidies. Future research should investigate these jointly, and study how different combinations of them may lead to different technological trajectories and economic outcomes.

Acknowledgment

This paper is produced as part of the R&DPOL project (2013-2015). Financial support from the Norwegian Research Council (FORFI programme) is gratefully acknowledged. The paper was presented at a project workshop in Oslo, June 2013. We wish to thank all participants, and in particular Isabel Bodas Freitas, Tommaso Ciarli, Giovanni Cerulli, Roberto Fontana and Paul Nightingale, for the very helpful comments and suggestions.

References

Aghion, P., et al. (1997). "Competition and growth with step-by-step innovation: an example." *European Economic Review, Papers and Proceedings*: 771-782.

Aghion, P., et al. (2005). "Competition and innovation: an inverted U relationship." *Quarterly Journal of Economics* **120**(2): 701-728.

Baghana, R. and P. Mohnen (2009). "Effectiveness of R&D tax incentives in small and large enterprises in Quèbec." *Small Business Economics* **33**: 91-107.

Berger, P. G. (1993). "Explicit and Implicit Tax Effects of the R&D Tax Credit " *Journal of Accounting Research* **31**(2): 131-171.

Billings, B. A. and Y. Fried (1999). "The effects of taxes and organizational variables on research and development intensity." *R&D Management* **29**(3): 289-301.

Billings, B. A., et al. (2001). "The role of taxes in corporate research and development spending." *R&D Management* **31**(4): 465-477.

Bloom, N., Griffith, R. and Van Reenen, J. (2002): "Do R&D tax credits work? Evidence from a panel of countries 1979-1997", *Journal of Public Economics*, **85**: 1-31.

Bodas Freitas, I. and von Tunzelmann, N. (2008): "Mapping public support for innovation: A comparison of policy alignment in the UK and France", *Research Policy* **37** (9): 1446-1464.

Castellacci, F. (2008). "Technological paradigms, regimes and trajectories: manufacturing and service industries in a new taxonomy of sectoral patterns of innovation." *Research Policy* **37**: 978-994.

Castellacci, F. and J. Zheng (2010). "Technological regimes, Schumpeterian patterns of innovation and firm-level productivity growth." *Industrial and Corporate Change* **19**(6): 1829-1865.

Castellacci, F. (2011). "How does competition affect the relationship between innovation and productivity? Estimation of a CDM model for Norway." *Economics of Innovation and New Technology* **20**(7): 637-658.

Cerulli, G. and B. Poti (2012). "Designing ex-post assessment of corporate RDI policies: conceptualization, indicators and modeling." *World Review of Science, Technology and Sustainable Development* **9**(2-3-4).

Corchuelo, M. B. and E. Martìnez-Ros (2009). "The Effects of Discal Incentives for R&D in Spain." *Business Economic Series Working Paper* **02**.

Czarnitzki, D. and Lopes-Bento, C. (2013): "Value for money? New microeconometric evidence on public R&D grants in Flanders", *Research Policy* **42** (1): 76-89.

Dagenais, M., et al. (1997). "Do Canadian Firms Respond to Fiscal Incentives to Research and Development?" *CIRANO Scientific Series*.

David, P., et al. (2000). "Is public R&D a complement or substitute for private R&D? A review of the econometric evidence." *Research Policy* **29**: 497-529.

Dosi, G. (1982). "Technological paradigms and technological trajectories." *Research Policy* **11**: 147-162.

Doucouliagos, C. and T. D. Stanley (2009). "Publication selection bias in minimum-wage research? A meta regression analysis." *British Journal of Industrial Relations* **47**: 406-428.

Duguet, E. (2012). "The Effect of the R&D Tax Credit on the Private Funding of R&D: En Econometric Evaluation on French Firm Level Data." *ERUDITE Working Paper*.

Egger, M., et al. (1997). "Bias in meta-analysis detected by a simple, graphical test." *British Medical Journal* **316**: 629-634.

Fischer, R. (1954). *Statistical Methods for Research Workers*. Edinburgh, Oliver and Boyd.

Geroski, P. A. (1990). "Innovation, Technological Opportunity and Market Structure." *Oxford Economic Papers* **42**(3): 586-602.

Hall, B. H. (1993). "R&D Tax Policy during the 1980s: Sucess or Failure?" *Tax Policy and the Economy* **7**: 1-35.

Hall, B. and Van Reenen, J. (2000). "How effective are fiscal incentives for R&D? A review of the evidence. *Research Policy* **29**: 449-469.

Hall, Brownyn H., et al. (2009). "Measuring the returns to R&D." *NBER Working Paper Series* 15622

Harris, R., et al. (2009). "Is a higher rate of R&D tax credit a panacea for low levels of R&D in disadvantaged regions?" *Research Policy* **38**: 192-205.

Hines, J. R. (1991). "On the sensitivity of R&D to delicate tax changes: The behaviour of U.S. multinationals in the 1980s." *NBER Working Paper Series* **3930**.

Ho, Y. (2006). Evaluating the effectiveness of state R&D tax credits. Graduate School of Public and International Affairs, University of Pittsburgh.

Huang, C.-H. (2009). Three Essays on the Innovation Behaviour of Taiwan`s Manufacturing Firms. Graduate Institute of Industrial Economics, Taiwan, National Central University.

Hægeland, T. and J. Møen (2007). "Input additionality in the Norwegian R&D tax credit scheme." *Statistics Norway Reports*.

Kasahara, H., et al. (2012). "Does R&D Tax Credit Affect R&D Expenditure? The Japanese Tax Credit Reform in 2003." *Journal of Economic Literature*.

Klassen, K. J., et al. (2004). "A Cross-national Comparison of R&D Expenditure Decisions: Tax Incentives and Financial Constraints." *Contemporary Accounting Research* **21**(3): 639-680.

Koga, T. (2003). "Firm size and R&D tax incentives." *Technovation* **23**: 643-648.

Lee, C.-Y. (2011). "The differential effects of public R&D support on firm R&D: Theory and evidence from multi-country data." *Technovation* **31**(256-269).

Lokshin, B. and P. Mohnen (2007). "Measuring the Effectiveness of R&D tax credits in the Netherlands." *UNU-MERIT Working Paper Series* **025**.

Lokshin, B. and P. Mohnen (2012). "How effective are level-based R&D tax credits? Evidence from the Netherlands." *Applied Economics* **44**(12): 1527-1538.

Lundvall, B. Å. and S. Borràs (2005). Science, technology and innovation policies. The Oxford Handbook of Innovation. J. Fagerberg, D. C. Mowery and R. R. Nelson. Oxford, Oxford University Press.

Malerba, F. (2005). How innovation differ across sectors and industries. The Oxford Handbook of Innovation. J. Fagerberg, D. C. Mowery and R. R. Nelson. Oxford, Oxford University Press.

Mercer-Blackman, V. (2008). "The Impact of Research and Development Tax Incentives on Colombia`s Manufacturing Sector: What Difference Do They Make?" *IMF Working Paper* **178**.

Mohnen, P. and Lokshin, B. (2009). "What Does it Take for an R&D Tax Incentive Policy to be Effective?" *CIRANO Scientific Series* 2009s-11

Mulkay, B. and J. Mairesse (2003). "The Effect of the R&D Tax Credit in France." LEREPS and UNU-MERIT, Preliminary Draft.

Mulkay, B. and J. Mairesse (2008). "Financing R&D Through Tax Credit in France." LEREPS and UNU-MERIT Preliminary Draft.

Nicoletti, G. and S. Scarpetta (2004). "Regulation, Productivity and Growth: OECD Evidence." *Economic Policy* **18**: 9-72.

OECD (2010). R&D tax incentives: rationale, design, evaluation.

Paff, L. A. (2004). "Does the alternate incremental credit affect firm R&D?" *Technovation* **24**: 41-52.

Paff, L. A. (2005). "State-Level R&D Tax Credits: A Firm-Level Analysis." *Topics in Economic Analysis & Policy* **5**(1).

Parisi, M. L. and A. Sembenelli (2003). "Is Private R&D Spending Sensitive to Its Price? Empirical Evidence on Panel Data for Italy." *Empirica* **30**: 357-377.

Parsons, M. and Phillips, N. (2007), "An Evaluation of the Federal Tax Credit for Scientific Research and Experimental Development." *Department of Finance Working Paper* 2007-08

Pavitt, K. (1984). "Sectoral patterns of technical change: towards a taxonomy and a theory." *Research Policy* **13**: 343-373.

Poot, T., et al. (2003). "Evaluation of a major Dutch Tax Credit Scheme (WBSO) aimed at promoting R&D." *Working Paper*.

Rao, N. (2010). "Do Tax Credits Stimulate R&D Spending? Revisiting the Effects of the R&D Tax Credit in its First Decade." The Wagner School New York University.

Stanley, T. D. (2001). "Wheat from chaff: meta-analysis as quantitative literature review." *Journal of Economic Perspectives* **15**: 131-150.

Stanley, T. D. (2008). "Meta-regression methods for detecting and estimating empirical effects in the presence of publication selection." *Oxford Bulleting of Economics and Statistics* **70**: 103-127.

Swenson, C. W. (1992). "Some tests of the incentive effects of the research and experimentation tax credit." *Journal of Public Economics* **49**: 203-218.

Tang, J. (2006). "Competition and Innovation Behaviour." *Research Policy* **35**: 68-82.

Tunzelmann, N. V. and V. Acha (2005). Innovation in 'low-tech' industries. The Oxford Handbook of Innovation. J. Fagerberg, D. C. Mowery and R. R. Nelson. Oxford, Oxford University Press.

Wang, J.-C. and K.-H. Tsai (1998). "The impact of research and development promotion schemes in the Taiwanese electronic component industry." *R&D Management* **28**(2): 119-124.

Wieser, R. (2005). "Research and development productivity and spillovers: empirical evidence at the firm level." *Journal of Economic Surveys* **19**(4): 587-621.

Yang, C.-H., et al. (2012). "Tax incentives and R&D activity: Firm-level evidence from Taiwan." *Research Policy* **41**: 1578-1588.

Yang, I-Hua. (2011) "The Effectiveness of Tax Credits as a Policy Tool to Promote R&D Activity: A Systematic Review and Meta-Regression Analysis." Dissertation, Auckland University of Technology.

Yohei, K. (2011). "Effect of R&D Tax Credits for Small and Medium-sized Enterprises in Japan: Evidence from firm-level data." *RIETI Discussion Paper Series 11-E-066*.

Table 1. List of papers included in the meta-regression database: Positive tax-credit measures (estimates of the additionality ratio)

Art. #	Reference	Country	Time Period*	No. of Obs.**	No. of Firms**	No. of Estimates	Avg. Effect Measure	Avg. Value of t-statisitc
1	Yang et al 2012	Taiwan	2001-2005	2588	.	6	0.1553333	2.21912475
2	Billings et al 2001	US	1992-1998	1848	231	2	0.19065	1.035
3	Paff 2005	California, Massachusetts (US)	1994-1999	780	.	6	0.33563	2.34463485
4	Kasahara et al 2012	Japan	2000-2003	7057	.	48	1.5799792	1.22272662
5	Yohei 2011	Japan	2006	1452	.	21	1.247429	4.89492298
6	Huang 2009	Taiwan	2001-2005	3031	.	9	0.812667	3.33444444
6	Huang 2009	Taiwan	2001-2005	3031	.	3	0.142	2.69785237
7	Lee 2011	Japan, Canada, Korea, Taiwan, China, India	1997	815	.	13	0.176923	1.53461538
8	Klassen et al 2004	US, Canada	1991-1997	821	168	10	1.9092	3.164
9	Wang and Tsai 1998	Taiwan	1997	.	124	2	-12.785	-3.23
10	Billings and Fried 1999	US	1994	.	113	1	0.018	2.25
11	Duguet 2010	France	1993-2003	.	1645	30	0.075233	3.49466667
11	Duguet 2010	France	1993-2003	.	1645	40	0.0333	1.2785
12	Mercer-Blackman 2008	Colombia	2000-2002	2278	.	3	1.066667	2.18333333
13	Berger 1993	US	1975-1989	3551	231	2	0.00065	3.397
14	Swenson 1992	US	1975-1988	5006	.	6	0.03	-0.87833333
15	Ho 2006	US	1975-1999	36977	.	72	3.723458	1.0670643
16	Hægeland and Møen 2007	Norway	1993-2005	8233	.	3	0.496	2.74173385

Notes: *This is the longest time period for which data is available. Some of the estimates in these studies have however been obtained on different sub-periods. **This is the overall number of observations/firms available for each study. Some of the estimates in these studies have however been obtained on smaller sub-samples of observations.

Table 2. List of papers included in the meta-regression database: Negative tax-credit measures (estimates of the user-cost elasticity)

Art. #	Reference	Country	Time Period*	No. of Obs.**	No. of Firms**	No. of Estimates	Avg. Effect Measure	Avg. Value of t-statistic
1	Harris et al 2009	Northern Ireland	1998-2003	2063	563	2	-0.9465	-4.645
2	Lokshin and Mohnen 2012	Netherlands	1996-2004	1185	.	6	-0.503333	-3.11137566
3	Baghana and Mohnen 2009	Canada	1997-2003	1386	.	8	-0.0995	-1.84950352
4	Koga 2003	Japan	1991-1998	6098	904	6	-0.397617	-1.55593022
5	Billings et al 2001	US	1992-1998	1848	231	2	-1.74105	-2.783
6	Paff 2005	California, Massachusetts (US)	1994-1999	780	.	10	-7.37436	-0.54915181
7	Paff 2004	California (US)	1997-1999	249	83	3	21.212233	0.80784899
8	Rao 2010	US	1981-1991	7762	168	11	-0.479818	-7.36414319
9	Hines 1993	US	1984-1989	.	116	8	-1.127038	-2.71886941
10	Daegenais e al 1997	Canada	1975-1992	4859	434	1	-0.0686	-1.632
11	Corchuelo and Martinez-Ros 2009	Spain	1990-2002	898	.	6	-0.465	-1.5833333
11	Corchuelo and Martinez-Ros 2009	Spain	1990-2002	898	.	18	0.658889	1.85555556
12	Hall 1993	US	1980-1991	4360	.	8	-0.48625	-5.73549559
12	Hall 1993	US	1980-1991	4360	.	5	-1.674	-9.4101444
13	Mulkay and Mairesse 2008	France	1983-2002	15977	2431	4	-1.6255	-10.0568749
14	Mulkay and Mairesse 2003	France	1982-1996	6021	765	4	-0.72975	-4.26521144
15	Lokshin and Mohnen 2007	Netherlands	1996-2004	2615	841	10	-0.5517	-2.74173385
16	Parisi and Sembenelli 2003	Italy	1992-1997	4356	.	3	-4.36	-4.16269748
17	Poot et al 2003	Netherlands	1997-1998	.	1751	1	-0.11	-4.5

Notes: *This is the longest time period for which data is available. Some of the estimates in these studies have however been obtained on different sub-periods. **This is the overall number of observations/firms available for each study. Some of the estimates in these studies have however been obtained on smaller sub-samples of observations.

Table 3. Definition of indicators and descriptive statistics

Variable	Definition	Original		Transformed*	
		Mean	SE	Mean	SE
INVSE	The inverse of the standard error (SE) of the effect estimate.	1.3471	4.8797	40.1641	377.3092
HTECH	Dummy: 1 if sub-sample is high-tech firms, 0 otherwise.	0.1399	0.3474	1.1125	5.9341
MANUF	Dummy: 1 if sub-sample is manufacturing firms, 0 otherwise.	0.0102	0.1005	0.0647	0.6814
SME	Dummy: 1 if sub sample is small or medium sized firms (SMEs), 0 otherwise.	0.1730	0.3788	0.8361	3.5357
RD_{t-1}	Dummy: 1 if lagged R&D is included as control in the econometric specification, 0 if not included.	0.2952	0.4567	30.5213	377.7413
COUNTRY	Dummy: 1 if country fixed-effects or country interaction-effects are included as controls in the econometric specification, 0 if not included.	0.1425	0.3500	0.5956	1.8267
SUBSIDY	Dummy: 1 if public R&D subsidies received by firms are included as control in the econometric specification, 0 if not included.	0.2977	0.4578	4.1583	11.3895

Note: *These are transformed according to equation (4) i.e. divided by the effect estimates' standard errors.

Table 4. MRA results: Positive tax-credit measures. Dependent variable: TSTAT (t-statistic of the estimated additionality ratio)

	(1)		(2)		(3)		(4)	
	Robust SE	Cluster SE	Robust SE	Cluster SE	Robust SE	Cluster SE	Robust SE	Cluster SE
CONSTANT	1.891494 (15.29)***	1.891494 (4.88)***	1.899479 (15.11)***	1.899479 (5.51)***	1.916535 (14.79)***	1.916535 (5.50)***	1.444614 (9.35)***	1.444614 (5.87)***
INVSE	0.0003052 (3.08)***	0.0003052 (3.23)***	.0003106 (3.07)***	0.0003106 (3.45)***	0.0003071 (3.03)***	0.0003071 (3.38)***	0.0316881 (3.97)***	0.0316881 (2.89)**
HTECH			-0.0340836 (-3.01)***	-0.0340836 (-2.67)**	-0.0312554 (-2.74)***	-0.0312554 (-2.50)**	-0.0210417 (-1.76)*	-0.0210417 (-1.72)
MANUF			0.8297275 (11.65)***	0.8297275 (12.32)***	0.8263947 (11.51)***	0.8263947 (12.14)***	0.6178825 (6.75)***	0.6178825 (2.93)**
SME					-0.0218241 (-1.40)	-0.0218241 (-1.58)	-0.0036951 (-0.22)	-0.0036951 (-0.27)
RD_{t-1}							-0.0313152 (-3.93)***	-0.0313152 (-2.85)**
COUNTRY							0.2694418 (3.82)***	0.2694418 (1.31)
SUBSIDY							-0.0264371 (-1.76)*	-0.0264371 (-1.28)
R-squared	0.0045	0.0045	0.0654	0.0654	0.0670	0.0670	0.2050	0.2050
Observations	277	277	277	277	277	277	277	277

Notes: Significance levels: *** 1%, ** 5%, * 10%. t-statistic in parentheses.

Table 5 MRA results: Negative tax-credit measures. Dependent variable: TSTAT (t-statistic of the estimated user-cost elasticity)

	(1)		**(2)**		**(3)**		**(4)**	
	Robust SE	Cluster SE	Robust SE	Cluster SE	Robust SE	Cluster SE	Robust SE	Cluster SE
CONSTANT	-1.559303 (-4.63)***	-1.559303 (-1.60)	-1.59566 (-4.63)***	-1.59566 (-1.57)	-1.667683 (-4.76)***	-1.667683 (-1.65)	-2.093408 (-4.77)***	-2.093408 (-3.45)***
INVSE	-0.1455175 (-5.27)***	-0.1455175 (-3.43)***	-0.1427606 (-5.22)***	-0.1427606 (-3.35)***	-0.1439019 (-5.12)***	-0.1439019 (-3.41)***	-0.2342409 (-3.54)***	-0.2342409 (-3.35)***
HTECH			4.465753 (5.37)***	4.465753 (2.34)**	4.601495 (5.37)	4.601495 (2.42)**	6.679015 (5.51)***	6.679015 (4.65)***
MANUF			-0.5464603 (-16.67)***	-0.5464603 (-6.06)***	-.5383328 (-15.78)***	-0.5383328 (-5.92)***	-0.5316152 (-11.74)***	-0.5316152 (-7.77)***
SME					0.1538882 (2.23)**	0.1538882 (1.37)	0.0779268 (1.87)*	0.0779268 (1.34)
RD_{t-1}							0.1249167 (1.86)*	0.1249167 (1.74)
COUNTRY							-1.1981 (-1.20)	-1.1981 (-1.06)
SUBSIDY							1.128952 (5.74)***	1.128952 (6.89)***
R-squared	0.2716	0.2716	0.2973	0.2973	0.3062	0.3062	0.4797	0.4797
Observations	116	116	116	116	116	116	116	116

Notes: Significance levels: *** 1%, ** 5%, * 10%. t-statistic in parentheses.