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Which design works? A meta-regression analysis of the impacts of R&D tax incentives

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Which design works? A meta-regression analysis of the impacts of R&D tax incentives

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Abstract

A growing interest in R&D tax incentives as a way to sustain research and innovation efforts has given rise to a large number of evaluations. The absence of consensus in the literature about their impact on R&D is intertwined with the variety of underpinning R&D tax incentives designs. Our meta-analysis aims at explaining this heterogeneity by the designs characteristics of R&D tax incentives. We find that the type of design has a distinct impact on R&D demand in the short run. We argue that these distinct effects are the results of managing a trade-off between providing strong incentives for R&D and simplicity to claim R&D deduction. In this respect, incremental and volume-based designs find a balance between both dimensions while hybrid designs lack clarity and predictability in the short run. Their respective effect can be moderated by additional features (i.e. generosity, targeting rules) even if the latter increases complexity and decreases predictability. We conclude by highlighting the importance of having a stable, clear, and simple framework to enhance the effect of R&D tax incentives.

Keywords Meta-analysis - research and innovation policies - tax incentives

JEL codes C08 - O32 - H25 - O38

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1 Introduction

It is well-known that firms under-invest in R&D activities due to the fundamental uncertainty involved and the limited appropriability of knowledge (Arrow, 1972; Nelson, 1959). This market failure combined with the existence of knowledge spillovers justify the need for governmental interventions. Governments have introduced a variety of instruments to promote private research and innovation efforts. R&D grants and tax incentives represent the main instruments to do so. Numerous issues in the allocation (Faccio, 2006) and in the use of R&D grants (Boeing & Peters, 2019) reduce their effectiveness (see Dimos & Pugh, 2016; Ugur *et al.*, 2016, for an illustration). Shifting the subsidization of R&D through the tax system instead of direct grants is thereby more likely to reward innovative firms. Furthermore, R&D tax incentives are supposed to be more neutral on the direction of innovative efforts. R&D tax incentives have been adopted in most of OECD countries, reflected by an increasing number of evaluations across countries and over time. However, the results of the literature remain unclear. While some authors report positive effects of R&D tax incentives on R&D expenditures, others do not find any effect in the short or mid-run (see Straathof *et al.*, 2014, for a review). Two previous meta-analyses investigate this heterogeneity and consider the importance of sectors (see Castellacci & Lie, 2015), and different sources of publications bias (Gaillard-Ladinska *et al.*, 2015) as potential explanations. Besides sample characteristics and methodological choices, we argue that the heterogeneity of the results found in the literature is driven by the specificities of the R&D tax incentive scheme per se. As developed in Thomson (2013), the designs of R&D tax incentives are likely to affect the results found for a given country. Our study proposes to rely on the meta-regression framework to articulate the micro-findings from the literature on R&D tax incentives with a set of variables characterizing the evaluated designs.

We explain this heterogeneity by the designs characteristics of R&D tax incentives. Our study contributes to the literature on innovation policies by deepening our understanding of the impact of R&D tax incentives on firms' demand for R&D. Contrary to previous meta-analyses, we use more rigorous inclusion criteria to focus exclusively on estimates at the firm-level and a strict definition of the user costs to compare the magnitude of the effects of distinct R&D tax incentives designs. Doing so, we aim at answering three main questions: i) is there a genuine effect related to the introduction of R&D tax incentives on the private demand for R&D, and how do methodological variations impact the results found in the literature?, ii) how does this effect vary across countries?, iii) to which extent is this heterogeneity across countries explained by the R&D tax designs?

We find that the type of design has a distinct impact on R&D demand in the short run. We argue that these distinct effects are the results of managing a trade-off between providing strong incentives for R&D and simplicity to claim R&D deduction. In this respect, incremental and volume-based designs find a balance between both dimensions while hybrid designs lack clarity and predictability in the short run. The respective design effect can be moderated by additional features (i.e. generosity, targeting rules). The latter must be carefully considered to avoid losing predictability and clarity which both reduce the firm's capacity to claim R&D deductions. The paper is structured as follows: Section 2 provides the rationale behind the different tax incentives schemes, section 3 develops the empirical strategies and the meta-regression approaches used, section 4 presents the results and robustness checks. Section 5 summarizes the main results and policy conclusions.

2 Heterogeneity of tax incentives schemes

R&D tax incentives constitute an important indirect policy instrument to support private research and innovation efforts. This instrument is based on the underlying theory that the optimal level of private R&D is determined by the intersection of a downward sloping demand for R&D, and an upward sloping supply of R&D inputs. R&D tax incentives act on the latter by decreasing the after-tax cost of R&D inputs via a reduction in corporate tax liability. Ceteris paribus, R&D as input becomes less expensive, firms demand more R&D (Hall, 1993). The reduction in corporate tax liability creates a tax shield for the firm which increases with the amount of eligible R&D expenditures defined by the tax law[1]. As R&D tax incentives depend on the reduction of corporate tax liability, there is an asymmetry in incentivizing profitable and loss-making firms (e.g. SMEs) (Bozeman & Link, 1984). On the one hand, profitable firms having enough profits/tax liability can benefit fully from the reduction. On the other hand, loss-making firms are less likely to claim R&D tax deductions, or at best, benefit from a lower deduction than their profitable counterparts[2].

The magnitude of the deduction does not only depend on the quantity of the firm's R&D expenditures but also on the features of the R&D tax incentive implemented. We can distinguish different types of R&D tax incentives depending on the definition of their base and source of deduction. Regarding the source of deduction, the most common form of R&D tax incentives is the tax credit, which reduces directly the corporate tax liability (Appelt *et al.*, 2016). In contrast, enhanced deductions reduce the tax base (see subsection 2.4). In the next subsections, we mainly focus on tax credit designs and differentiate between the definition of their respective bases. We classify these types of R&D tax incentives based on their opportunity costs in claiming tax deduction (e.g. complexity, incentives for R&D and risk of relabelling).

2.1 Incremental R&D tax incentives

Incremental R&D tax incentive schemes award firms only for the fraction of R&D spending above a pre-defined base. This pre-defined base is usually measured by averaging previous R&D expenditures. Governments originally defined this base on a moving average of past R&D spending to determine the firms' eligibility threshold in a given year. However, this moving average discourages firms to apply to R&D tax incentives as current R&D expenditures increase the future threshold[3]. This base definition can also lead to distortions in firms' R&D planning: firms develop strategies to maximize their tax gain by gradually increasing their R&D investment instead of doing a single large investment (Straathof *et al.*, 2014; Correa *et al.*, 2013). This explains why governments moved towards volume-based schemes to avoid such kind of R&D behaviour (see Table 1). Since this design only rewards the marginal R&D expenditures, it reduces the risk of subsidizing windfall gains for existing R&D investments (Bozeman & Link, 1984). By the same token, it lowers the risk of relabelling of R&D expenditures as it is not sustainable to over- or underestimate R&D expenditures due to the clawback provision of current expenditures (Köhler *et al.*, 2012). Incremental designs cannot fully impede the risk of relabelling if

[1] The definition of eligible R&D expenditures differs among countries. Many countries refer to the Frascati Manual which sets the benchmark for identifying R&D activities.

[2] Governments tackle this asymmetry by providing carry forward options for unused R&D tax incentives as well as a transformation to cash refunds. However, cash refunds are usually provided at a lower incentive rate.

[3] An alternative to this is to introduce base amounts which are unrelated to current spending (e.g. the current US incremental tax credit).

uncertainty remains in the definition of the qualified R&D expenditures (Hall, 2001; Laplante *et al.*, 2019) and if the base definition is disconnected from previous R&D investments.

The combination of reduced risks linked to relabelling and incentives to reward actors who increase their R&D spending make it very attractive for governments. However, this lower budgetary burden comes at the price of high administration costs. From an administrative perspective, firms' applications must be monitored to be qualified as eligible or not. From the firms' perspective, they have to document their R&D expenditures over time and are not necessarily equipped to forecast whether the cost of applying will be overweighted by the tax deduction. In this respect, SMEs are less likely to benefit from such a scheme: first, by having less persistent R&D expenditures due to financial constraints, second, a lower tax liability than large firms, and third, a lack of skilled staff dedicated to know-how to minimize the tax burden. Governments can also decide to target SMEs via the tax design to compensate for this lack of fit, either with a targeted refundability rule, or a more generous tax deduction. With higher financial incentives, SMEs are more likely to bear the application costs for R&D tax incentives.

2.2 Volume-based tax schemes

Volume-based R&D tax incentives proportionally award companies that conduct R&D. In that case, the tax deduction depends only on the total amount of eligible R&D expenditures in a given year. As the R&D tax incentive is independent of past R&D investments, it increases the predictability of the return of R&D tax incentives claimed. This gives firms more freedom to allocate and to plan R&D investments (Spengel, 2009). Moreover, the simplicity in implementing volume-based R&D tax incentives reduces the costs of monitoring by the public administration and decreases the firms' compliance costs (Köhler *et al.*, 2012; Spengel, 2009). In theory, more firms should apply in compare with incremental designs, especially among SMEs. The downside of this design is to leave room for relabelling of R&D expenditures. The more familiar firms are with the claims for R&D tax incentives, the easier it is to label expenditures as eligible R&D. The second risk is to subsidize infra-marginal R&D projects, which would have been conducted even in the absence of the R&D tax incentive. This lack of incentives to substantially boost R&D can be moderated with an incremental component (e.g. hybrid design), or additional features such as an enhanced deduction. The next subsections develop the two possibilities.

2.3 Hybrid tax schemes

Hybrid R&D tax incentives combine a volume-based and an incremental component. As mentioned above, the volume-based component lowers the cost of claiming and sustains the overall R&D efforts. The incremental component aims at rewarding the extra R&D efforts that firms undertake. The combination of both designs aims at benefiting from the best of both worlds (e.g. low application costs, and incentives to stimulate incremental R&D expenditures) but comes at the price of increasing the complexity of the scheme. The definition of the eligibility threshold for the incremental component makes the tax deduction less predictable and more costly to claim. The incremental component implies that firms have to disclose their current R&D expenditures as well as the previous ones to show an increasing trend over time. Consequently, firms have more incentives to apply to the volume-based component, than benefiting from the full scheme. Doing so reduces the incentives to boost R&D and increasing the risk of relabelling. This complexity which is inherent in hybrid as well as incremental R&D tax incentive schemes represents a disincentive for firms to apply (Appelt *et al.*, 2016; Hall, 2019).

Corchuelo & Martínez-Ros (2010) illustrate this by reporting that a large number of Spanish firms do not apply to tax incentives due to the complexity and high compliance costs involved. This explains the persistence of firms claiming after having borne the costs of applications once, especially among SMEs (see Labeaga *et al.* (2018)).

2.4 Alternative to tax credits: enhanced deduction

Besides tax credits, other types of R&D tax incentives consist of a super allowance that reduces the taxable income by more than 100% of the eligible R&D expenditures. In contrast to tax credits, enhanced deductions do not depend on the firms' tax liability. SMEs or non-profitable firms, who would not be able to claim the full amount of their tax credit can increase their loss carry forward with enhanced deductions. However, the expected return related to enhanced deduction is defined by the marginal corporate tax rate. The latter is the result of several factors beyond R&D expenditures. Due to their dependence on the marginal corporate tax rate, enhanced deductions are often not directly considered in the R&D budget of a firm as well as less predictable than R&D tax credits and thus, less likely to encourage additional R&D investments (OECD, 2003). This lack of incentives in using enhanced deductions increases over time considering that nowadays most R&D tax credits provide fast cash refunds to foster the participation of non-profitable firms. In some countries, enhanced deductions have been combined with volume-based and hybrid tax credits to increase R&D incentives. Nevertheless, the combination of both types of R&D tax incentives increases the complexity of benefiting from the former.

2.5 Sources of heterogeneity: publication bias

The meta-analysis framework provides an interesting lens to study the variations found in the literature. We build upon the meta-regression framework developed by Stanley (2012) which split the sources of bias in two categories: publication bias (so-called K variables) and moderators of the studied phenomenon (Z variables). Previous meta-studies about R&D tax incentives have mainly considered the sources of publication bias (e.g. sample characteristics and methodological variations). Castellacci & Lie (2015) find a significant effect of the service sector and SMEs in increasing the effect of R&D tax incentives on R&D demand. Gaillard-Ladinska *et al.* (2015) illustrate the heterogeneity coming from the choice of the outcome variable (R&D stock vs R&D flow). Second, the authors show that publication bias comes from the publication age and the journal ranking. Additional methodological variations such as selection and endogeneity are also considered by the two previous meta-analyses but do not affect the significance of the results[4]. The characteristics of R&D tax incentives designs have been mainly neglected as an explanatory source of variations across studies. Castellacci & Lie (2015) look at the type of designs in their analysis but do not report any statistical effect except in their interactions with the high tech sector. Our analysis aims at extending this first attempt by considering the characteristics of the R&D tax incentives designs in moderating their effectiveness (Z variables).

As developed above, the claiming mechanism behind each design is ,therefore, a source of variations across studies. The wide majority of evaluations assumes that all eligible firms in a given period claim their R&D deduction, and hence, overestimate the actual impact of R&D tax incentives. The latter implies that firms quickly get familiar with the application process. This simplifying assumption is not supported by empirical findings. In a recent OECD report, only

[4]See Gaillard-Ladinska *et al.* (2015) for GMM and Castellacci & Lie (2015) for IV

half of the eligible firms do apply for R&D tax incentives (Appelt *et al.*, October 2019 (final project report forthcoming)). Providing a stable, clear, and simple tax scheme represents a key determinant to make R&D tax incentives effective (Hall, 2001; Bloom *et al.*, 2002; Appelt *et al.*, 2016; Hall, 2019). The period evaluated in our set of studies is on average centred around a few years before and after the introduction of R&D tax incentives. The latter limits the number of legal changes but reduces the analysis to short-term estimates. The focus of our analysis is thereby rather short-term oriented to get a large set of comparable estimates.

3 Methods

Meta-analysis can be thought of as a collection of statistical analyses used to examine results from individual (and independent) studies with the general purpose of integrating their findings (Glass, 1976). Here, we employ a certain meta-analytical approach, which is called meta-regression analysis, that is popular in empirical economics and that was introduced by Stanley & Jarrell (1989) and Stanley (2001). Meta-regression analysis is a multivariate approach, utilizing multiple regressions analysis to explain variations in study outcomes that might be due to different model specifications, study designs etc., but also due to publication bias. The latter is seen as a central threat to the validity of the empirical results: "In our view, the central task of meta-regression analysis is to filter out systematic biases, largely due to misspecification and selection, already contained in economics research" (Stanley, 2012, 13).

3.1 Data collection

We collected estimations from publications by crossing two main sources: Google Scholar, and IDEAS /RePEc. In line with previous meta-analyses, the earliest study composing the sample is from 1993 to take into account the increasing use of econometric techniques (GMM estimations with Arellano- Bond standard errors) in this field. The selection of publication relies on the following strategy: alltitle='R&D tax*' and covers the period 1993-2019. Various trials showed that specifying 'tax credit' or 'tax incentives' did not help in getting more relevant studies[5]. The data was extracted between the 3rd of May 2018 and the 16th of June 2018[6]. The strategy developed to extract publications from IDEAS/RePEc differs slightly by relying on JEL codes[7] standardized across economic fields and countries. According to the JEL code definitions, we combined each query with a keyword search in the whole record ('R&D tax incentive') (see Table 7 in the appendix for more details)[8]. The data was extracted between the 28th of May until the 28th of September 2018. Only French, Spanish, German, and English publications were used. Figure 2 in appendix summarizes the main steps of the selection process.

3.2 Inclusion criteria: structural approaches at the firm level

The empirical assessment of the effectiveness of R&D tax incentives is estimated through parametric and non-parametric methods. Non-parametric approaches, e.g. ATM or ATT, measure

[5]The variation in vocabularies across communities did not lead to the selection of specific keywords. The advantage of 'tax*' is to cover all potential variations of tax credits, tax reforms, tax incentives.

[6]Guceri & Liu (2019) was added after the data collection when the latter got published.

[7]`https://ideas.repec.org/j/`

[8]The drawback associated to our strategy lies in the multiple entries within IDEAS/RePEc due to the use of multiple JEL codes within one publication, and co-authors uploading the paper on multiple depositories, creating several duplicates. However, IDEAS/RePEc helped to complete the initial sample of publications which probably did not refer to R&D taxes in their titles.

the difference in R&D expenditures between eligible and non-eligible firms to R&D tax incentives. The latter represents the additionality effect related to the reduction of R&D costs. We can distinguish two main empirical types of analysis among non-parametric methods: on the one hand, the direct approach which uses a difference and difference framework, and on the other hand, the structural approach which links the reduction of R&D cost coming from R&D tax incentives to the demand for R&D via an elasticity. Consequently, we restrict our sample to estimations based on structural approaches to be able to study the differences in effectiveness across tax designs. Structural approaches can be summarized as follow:

$$RD_{i,t} = \beta_0 + \beta_1 \times UC_{i,t} + \beta_2 \times X_{i,t} + \epsilon_{i,t} \tag{1}$$

In which X refers to firm-specific variables and UC to the user costs of R&D for a given firm (i) and period (t). The most widespread category of user costs can be defined as the "King-Fullerton", or "Jorgenson-Hall" approach. The simplest version of the user cost is defined as: $UC_{i,t} = \frac{1-A_{i,t}}{1-\tau} \times (r_{i,t} + \delta)$. In which r refers to the real interest rate, δ to the depreciation rate of knowledge, τ to the corporate income tax, and A to the net present value of capital allowances and deductions which reflect the reduction in tax liability for each dollar used in R&D. Most of the estimations use a log-log specification to express the user costs as an elasticity. Nevertheless, some authors estimate the user cost as a semi-elasticity or a growth rate. Our data collection and coding scheme take this aspect into account. Structural approaches are criticised to suffer from endogeneity and selection. First, the decision and capacity to claim a tax deduction are not randomly distributed and depend on firms' characteristics. Second, a given firm decides in investing in R&D according to multiple criteria which mainly reflect a firm's strategy and characteristics. The attempts to tackle both issues and their impact on the effectiveness of R&D tax incentives are also discussed in our results. As the literature focuses mostly on short-run effects on R&D, our analysis is mostly bounded on this group to gather enough comparable estimates. The long-run estimates found in some publications have been used to test the persistence of R&D tax incentives on R&D demand. An overview of the publications (and their respective design type) used to extract the short-run estimates is presented in Table 1. Unlike the two previous meta-analyses, we exclusively focus on structural approaches that are more comparable: on the one hand, by focusing exclusively on firm-level estimations, and on the other hand, by comparing estimates which strictly use the definition of the user costs previously defined.

3.3 FAT-PET-PEESE estimation methods

The FAT-PET-PEESE (Funnel Asymmetry Test – Precision Effect Test - Precision Effect Estimate with Standard Error) is widely used in economics and focuses on effect synthesis under conditions of publication bias. Under this approach, publication bias is seen as the selective publication or non-publication of studies based on the direction and statistical significance of the results (Rothstein *et al.*, 2005, 3). In other words, the publication of an effect is a function of the standard error. Concerning modelling the effect estimate under conditions of publication bias, the following equation is a good starting point to illustrate the underlying logic:

$$\text{Estimate}_{i,s} = \beta_{0,i,s} + \beta_{1,i,s} \times \text{SE}_i + \epsilon_{i,s} \tag{2}$$

In this context, i denotes a given estimation coming from a given study s. The term $\beta_{1,i,s} \times \text{SE}_i$ is supposed to capture the publication selection bias, and, when $SE_i \to 0$, then $E(effect_i) \to \beta_0$. The estimate is thus the result of its estimated true effect (β_0) and its estimated publication bias (β_1). The entire FAT-PET-PEESE approach consists of three steps: (1) The FAT, which is also known as the Egger's test (Egger *et al.*, 1997), is employed to test for the existence of publication bias, i.e., it tests $H_0 : \beta_{1,i,s} = 0$ and when we reject the H_0 we would conclude that this might be due to publication bias. (2) The PET tests for the existence (not magnitude) of a real effect after adjusting for publication bias that is assumed to follow a certain selection mechanism ($H_0 : \beta_{0,i,s} = 0$). (3) Finally, PEESE is supposed to provide an effect size estimate that has been "corrected for publication bias", employing a different measurement of publication bias, i.e., instead of SE, the variance SE^2 is used (Stanley, 2012, 78).

However, equation 2 suffers from heteroskedasticity which is a common feature of economic research. Due to the limited sample size, publication fixed effects were impossible to use in the meta-regressions since each study represents one specific tax design[9]. Therefore, we follow the approach described in Stanley (2012) who applies weighted least squares estimation with the inverse of the variance of each estimate as analytical weight. As a robustness check, we also weighted the latter by the inverse of the number of estimates characterizing each study to account for over- or under- representation within the sample (Nelson & Kennedy, 2009). In each estimation, robust and clustered standard errors at the study level are used to account for correlated research choices in the estimation method, data sources, and research practices characterizing a given study.

We start the analysis with the elasticities collected in the literature to document the distribution of the averaged true effect linking R&D tax incentives to R&D demand. Since statistical effects are expressed differently across studies (i.e. elasticities with log-log specifications, semi-elasticities with lin-log elasticities, or even growth rates), we rely on the Partial Correlation Coefficient (PCC) transformation to convert all effect sizes to a common measure to compare the different statistical effects and thereby enlarge the number of observations and tax designs in the sample. Another common transformation in meta-analysis is the t-test but comes with two drawbacks. First, it limits the interpretation of the results to a significance level since the t-test is a scale-free parameter. Second, the t-test is also sensitive to the number of parameters and observations characterising the estimations. The PCC transformation takes into account the power of estimations with the degrees of freedom and allows to interpret the results as the strength of the relationship between the costs and demand of R&D (e.g. the correlation between user costs and R&D demand).

[9] We could only observe variations from the period or the designs in a given country for France, Spain, Canada. The set of related estimates was not large enough to exploit within-country variations.

Table 1: Papers on the Effectiveness of R&D tax incentives on R&D investment Included in the Meta-Analysis

Study	**Authors,Year**	**Status**	**Estimates**	**Country**	**Period**	**Incentive Base**	**Incentive Design**
1	Agrawal *et al.* (2014)	Published	10	Canada	2000-2007	Volume	Tax Credit
2	Baghana & Mohnen (2009)	Published	4	Quebec	1997-2003	Volume	Tax Credit
3	Crespi *et al.* (2016)	Published	18	Argentina	1998-2004	Hybrid	Tax Credit
4	Domínguez (2006)	Published	4	Spain	1991-1999	Hybrid	Tax Credit
5	Domínguez *et al.* (2008)	Published	32	Spain	1991-1999	Hybrid	Tax Credit
6	Fowkes *et al.* (2015)	Working Paper	4	United Kingdom	2003-2013	Volume	Enhanced Allowance
7	Guceri & Liu (2019)	Published	2	United Kingdom	2002-2012	Volume	Enhanced Allowance
8	Hall (1993)	Published	5	United States	1980-1991	Incremental	Tax Credit
9	Harris *et al.* (2009).	Published	1	Northern Ireland	1998-2003	Volume	Tax Credit
10	Jia & Ma (2017)	Published	16	China	2009-2013	Volume	Enhanced Allowance
11	Koga (2003)	Published	6	Japan	1991-1998	Incremental	Tax Credit
12	Labeaga *et al.* (2014)	Working Paper	28	Spain	2001-2008	Hybrid	Tax Credit
13	Lokshin & Mohnen (2007)	Working Paper	5	Netherlands	1996-2004	Volume	Tax Credit
14	Lokshin & Mohnen (2012)	Published	3	Netherlands	1996-2004	Volume	Tax Credit
15	Mulkay & Mairesse (2008)	Working Paper	1	France	1983-2002	Incremental	Tax Credit
16	Mulkay & Mairesse (2011)	Working Paper	6	France	1981-2007	Hybrid	Tax Credit
17	Mulkay & Mairesse (2013)	Published	5	France	2000-2007	Hybrid	Tax Credit
18	Mulkay & Mairesse (2018)	Working Paper	4	France	1999-2007	Hybrid	Tax Credit
					2008-2013	Volume	Tax Credit
19	Rao (2010)	Working Paper	22	United States	1981-1991	Incremental	Tax Credit
20	Rao (2013)	Working Paper	17	United States	1986-1990	Incremental	Tax Credit
21	Rao (2016)	Published	12	United States	1986-1990	Incremental	Tax Credit
22	Thomson (2010)	Published	8	Australia	1990-2005	Hybrid	Enhanced Allowance

However, since partial correlations are usually not reported in primary studies, we have to calculate them based on the information of the primary estimates:

$$\mathrm{PCC}_{i,s} = \frac{\mathrm{t}_{i,s}}{\sqrt{\mathrm{t}_{i,s}^2 + \mathrm{df}_{i,s}}} \tag{3}$$

where t refers to the t-ratio and df to the degrees of freedom of the relevant estimation. The standard error for the PCC transformation is given by $\mathrm{SE}_{PCC} = \sqrt{\frac{(1-PCC^2)}{df}}$. The PCC is quite robust even if there are slight mismeasurements of the degrees of freedom as these are often not explicitly reported in the primary estimates (Stanley, 2012)[10].

3.3.1 Drivers of heterogeneous effects: extended MRA

Numerous characteristics of the sample, or methodological choices, may drive the variations found among the estimated results. Stanley (2012) suggests to extend the simple model in (2) by introducing Z variables, which account for heterogeneity and misspecification bias, and K variables, which tackle publication bias:

$$\mathrm{PCC}_{i,s} = \beta_{0,i,s} + \sum_k \beta_k \times Z_k + \beta_{1,i,s} \times \mathrm{SE}_{PCC,i} + \sum_j \delta_j K_j \times SE_{PCC,i} + \mathrm{v}_{i,s} \tag{4}$$

As mentioned above, several characteristics of the sample and methodology involved in a given publication tend to influence the magnitude and significance of the results attributed to the effect of tax incentives on R&D demand (Gaillard-Ladinska *et al.*, 2015; Castellacci & Lie, 2015). We take into account the latter by building upon the two previous analysis to code our K variables. We develop new variables characterizing the design of the tax incentives evaluated in a given study, assuming that the latter moderate the averaged true effect attributed to tax incentives (Z variables). A detailed coding scheme is provided in Table 2.

3.3.2 Proxies for tax incentive scheme characteristic (Z variables)

Based on the insights gained from the theoretical background in section 2, we focus on these characteristics of the tax scheme to explain the heterogeneity found in the literature. We first address the differences in schemes by defining two main designs: on the one hand, a full incremental scheme, and on the other hand, a full volume-based scheme. Hybrid schemes are used as a reference category in both cases. Additionally, we control for R&D tax incentives using enhanced deductions (Deduction) to control for deviating effects from R&D tax credits. Furthermore, governments often target SMEs to increase the overall take-up of R&D tax incentives. We take into account the latter by adding a dummy Targeted. Furthermore, we aim at measuring the impact of generosity on the averaged true effect. This is done by defining a lower (Min) and upper bound (Max) characterizing a given scheme.[11]

[10] A general concern raised in the context of PCC transformation is the problem of asymmetric distribution if the values get close to -1 and +1. However, the underlying dataset faces no asymmetric distribution.

[11] Refer to section B in appendix for more details on the calculation of the boundaries.

Table 2: Main variables to tackle heterogeneity across studies

Variable	Definition
K variables	
Outcome	
RDflow	1 if the RD outcome variable was RD expenditures (flows), 0 if RD stock of RD intensity
RDstock	1 if the RD outcome variable was RD stock, 0 if RDflow or RD intensity
Study	
Published	1 if published in peer-reviewed journals, 0 if working paper
Modeltype	1 if linear GMM estimations, 0 otherwise
Sample	
Sectors	1 if manufacturing and services/agri are considered, 0 if manufacturing only
Small	1 if only small firms are considered, 0 otherwise
Large	1 if only large firms are considered, 0 otherwise
Z variables	
Tax scheme	
Vol	1 if the tax scheme is volume-based, 0 otherwise (e.g. hybrid and incr)
Incr	1 if the tax scheme is incremental, 0 otherwise (e.g. hybrid and vol)
Min.	normal rate, or the one for large companies
Max.	max rate applied (beyond the normal regime, or for SME)
Deduction	1 if enhanced allowance, 0 if tax credit
Targeted	1 if a given scheme targets SMEs, 0 otherwise

3.4 Descriptive statistics

Our primary publication sample consists of 22 studies from which 226 estimates were extracted. The latter include 116 elasticities, 30 growth rates, 10 semi-elasticities, 44 estimates from linear forms, 8 growth-log, and 18 growth-linear estimations. This variety among the specification forms requires us to transform the estimates into PCCs to be comparable. As shown in Table 9 in the appendix, the distribution of the initial coefficients extracted from the literature is less uneven after the PCC transformation. Our set of R&D tax incentives estimates covers 16 different schemes evaluated over 33 years (e.g. 1980-2013) and across 12 distinct regions[12]. The majority of these evaluations focuses on R&D tax credits instead of enhanced deductions (see Table 1). Hybrid R&D tax incentives constitute the lion share of our sample while 19.5% of the estimations deal with volume-based schemes, and 30.5% with incremental schemes respectively. The type and level of financial incentives to claim R&D tax incentives strongly differ across designs (see Table 3): enhanced deductions are more combined with volume-based designs than schemes with incremental components. Moreover, the spread between the minimum and maximum refund rates differs across schemes: in the incremental designs, the spread is rather low while it increases in the volume related schemes. SMEs benefit on average more from targeted schemes in hybrid or volume-based designs than in incremental ones. Finally, we can see a trend towards more volume-related designs over time: our earliest estimations are related to incremental designs while our most recent set of estimations is related to volume-based estimations (see Table 1). Hybrid designs emerge as a sort of transition between both designs.

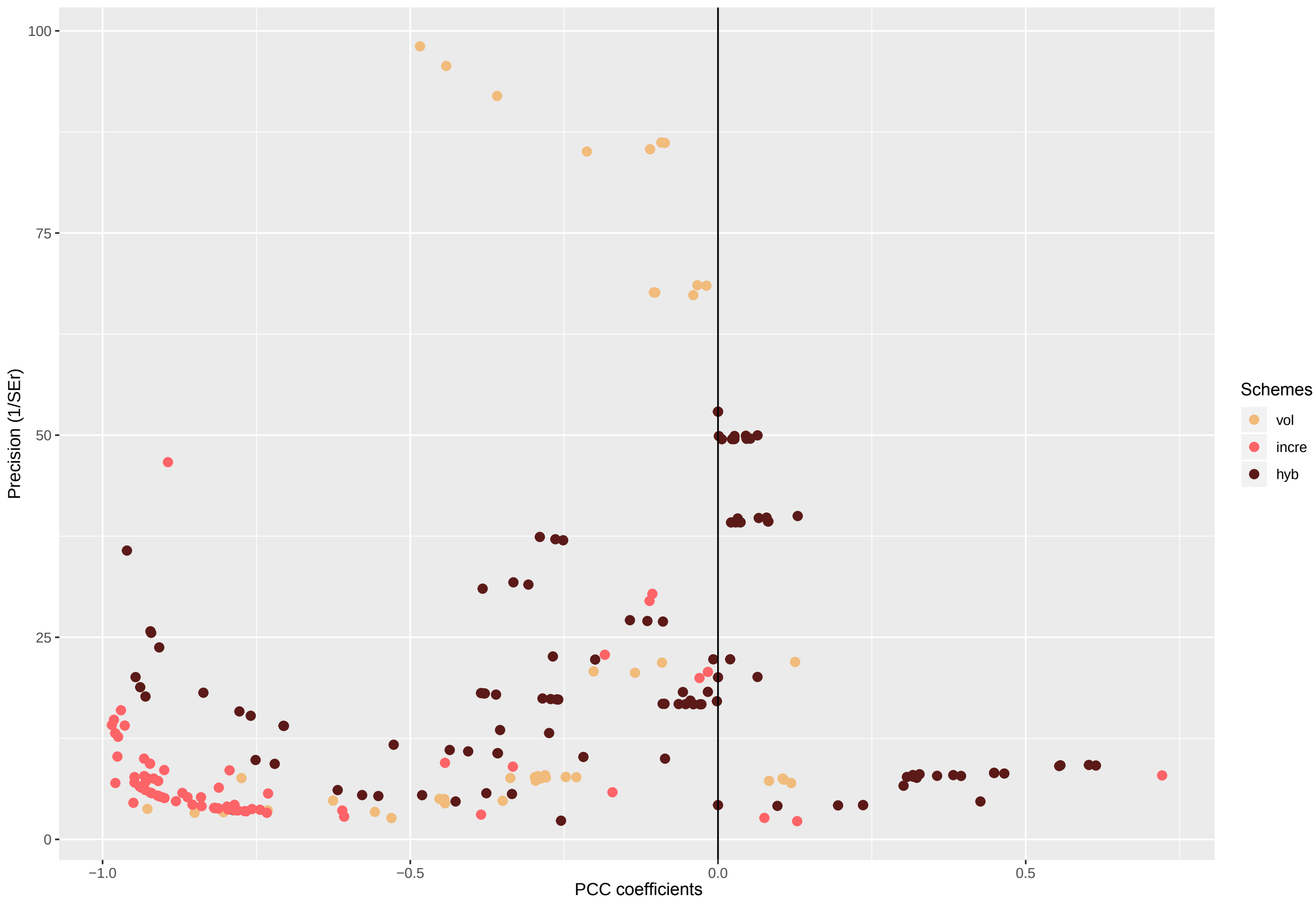
The high level of heterogeneity is reflected in Figure 1 which maps the value of the partial

[12] They correspond to 10 countries and two specific regions, Northern Ireland and Quebec

Table 3: Composition and characteristics of tax incentives schemes

	Incremental	Volume	Hybrid
Estimations	69	44	113
Elasticities	8	24	84
Enhanced Deduction	0	20	8
Tax Credit	69	22	105
Generosity (min)	25.27	14.65	35.42
Generosity (max)	25.72	27.52	57.90
Targeted	6	26	101
Non-Targeted	63	18	12
GMM	7	24	65

Figure 1: Funnel plot with PCC: distribution across designs



correlation coefficients on their precision (1/SE). In absence of publication bias, the funnel plot should depict a symmetrical inverted funnel. The asymmetrical distribution rather suggests that the studies composing our sample are heavily heterogeneous and/or the existence of publication bias (e.g. authors tend to overestimate the actual effect of R&D tax incentives on R&D demand). Each type of design follows a different distribution which shows different levels of efficiency and biases. Besides the diversity coming from the evaluated policy, methodological choices enhance the heterogeneity of results found across evaluations (see Table 9). We observe that most estimates use R&D expenditures in flow as an outcome variable (N=137), 29 R&D stock, and 60 R&D intensity. The nature of the sample differs across studies as well (e.g. sectoral and firm size): the majority of our estimates looks at the manufacturing sector and the overall firm population. Finally, nearly half of our estimates come from GMM estimations to capture the dynamics of R&D investment. As mentioned before, the estimates using GMM strongly overlap with the IV estimations. To avoid multicollinearity we focus mainly on the use of GMM more than considering IV and GMM apart. As suggested in Castellacci & Lie (2015), the use of IV does not correlate with publication bias. Our results confirm this finding (see subsection 4.1.1). Finally, our sample is relatively balanced regarding its composition of published and unpublished result.

4 Results

We present different sets of results that disentangle between the heterogeneity coming from methodological variations and R&D tax incentive designs. First, we motivate our analysis by providing an economic interpretation of the results found in the literature with a subset of elasticities (see Table 4). Second, we use the PCC transformation as an output variable (e.g. correlation score between the R&D demand and the user costs) to enlarge the number of observations and the number of countries (and hence, designs) (see Table 5). Since almost each country represents a single tax design[13], we extend the set of country dummies by splitting the designs of R&D tax incentives across their type, target, and generosity (see Table 6). The results are then discussed by providing a set of robustness checks across R&D tax incentive types to test if the sources of variation are coming from the context of implementation (see Tables 10 and 11 in appendix).

4.1 Averaged effects: heterogeneity across countries and methodologies

Tables 4 and 5 summarize different specifications which successfully disentangle between the variations across R&D tax incentive designs across countries and methodological choices. Both estimations aim at testing: i) the existence of publication bias among the reported estimates in the literature, ii) the averaged true effect of R&D tax incentives on R&D demand. Within this FAT-PET-PEESE framework, the coefficient reflecting publication bias is related to the standard error coefficient, or the variance one. The constant provides the averaged true effect characterising the strength of the correlation between the R&D cost and related demand, net from publication bias. Since the user cost represents the cost (or price) to conduct R&D, R&D demand should increase when the former decreases. Ceteris paribus, if the cost of R&D diminishes with the change in R&D tax incentives, firms will increase their demand for R&D. We, therefore, expect to find that the averaged true effect is negative (and statistically significant). By the same token, publications which overestimate the effect of R&D tax incentives by selecting results should report a negative and significant publication bias.

Disregarding the choice of variable to measure publication bias (e.g. standard error or variance), models 1 and 2 in Tables 4 and 5 respectively confirm the existence of an averaged true effect between the R&D user costs and the demand for R&D. On average, the elasticity of R&D is around 1, meaning that reducing the cost of R&D by one percentage is associated with an increase in R&D expenditures around one percentage (see Tables 4). A dollar invested in reducing the costs of R&D via R&D tax incentives should thereby be translated into one dollar invested in R&D. Our averaged true effect in Table 5 is around 0.15 across the three main models and supports the results found in the subsample of elasticities. The magnitude of our averaged true effect in the case of the PCC represents a large correlation between the user costs and the related R&D demand[14]. However, the models weighted by the number of observations per publication (see models 3 in Tables 4 and 5) depict different trends depending on the output variable used in the meta-regressions: the subsample of elasticities indicates that the averaged true effect is not statistically significant when one controls for over-representation of some studies in the sample. On the contrary, the estimation with PCC shows a higher magnitude regarding the averaged

[13] Our sample has only two countries with estimates characterised by time-varying designs: France and Spain. Therefore, almost each country represents a vector of different tax incentives parameters that we aim at testing.

[14] According to Doucouliagos (2011) an averaged true effect above 0.076 in the field of policy and tax can be considered as large.

true effect. In the next subsections, we test whether these contrasting findings reflect the results of methodological biases or distinct countries (and designs) across our two samples.

4.1.1 Methodological biases in measuring the impact of R&D tax incentives

In Table 4, we successively test whether the definition of the output variable used, and the time-window involved (e.g. short vs long run) affect the results. Model 4 focuses exclusively on estimations which use R&D flow as the way to measure R&D demand. This subsample represents the lion share of our estimations and does not seem to differ much from the overall results. Models 7 and 8 perform the same analysis on estimations which were not part of models 1-3 due to their methodological differences with the rest of the literature (e.g. growth and not elasticities, and long-run estimates). These models aim at understanding whether the effect of R&D tax incentives modifies structurally the R&D demand (model 7) and persists over time (model 8). Despite its low number of observations, model 7 provides a less optimistic picture than previously with elasticity around 0.27 and a significant level of publication bias. Moreover, the few non-null long-run estimates we could find in the literature suggest that the effect of R&D tax incentives collapses in the long-run disregarding whether the lag considered is one or two periods[15]. This lack of persistence characterising R&D tax incentives has been also documented in Gaillard-Ladinska *et al.* (2015).

In Table 5, we compare whether the type of methodology (e.g. to tackle selection and endogeneity) influences the scope of the results. Our results show that estimations taking into account selection effects do not find any averaged true effect but instead reflect a strong publication bias (see column 4). On the contrary, estimations which do not take into account selection show a strong overall effect of R&D tax incentives on R&D demand without publication bias. Our overall results seem thereby driven by the latter. R&D tax incentives seem to increase R&D at the extensive margin more than at the intensive margin. This finding is in line with a recent report of OECD showing that firms in R&D intensive sectors and firms with a high level of R&D react less than their counterparts(Appelt *et al.*, October 2019 (final project report forthcoming)). Similarly, Castellacci & Lie (2015) find that on average firms in high tech sectors exhibit a lower effect than in the overall population. The lack of a long-run effect combined with lower effects measured with R&D growth and GMM estimations suggests that R&D tax incentives are rather used in an opportunist way to decrease the R&D costs in the short-run instead of incentivizing significant changes in R&D strategies. In our sample, most of the GMM estimates are associated with hybrid designs (see Table 3). Therefore, one cannot ignore that this effect might be mostly driven by hybrid estimations.

Model 6 shows that estimations with IV approaches (e.g. financial component in the majority of cases) find a larger effect of R&D tax incentives in reducing the cost of R&D than our overall models (columns 1-3) but seems plagued as well by publication bias. As mentioned in Köhler *et al.* (2012), a limited amount of evaluations benefited from significant variations in the tax scheme that allows disentangling causal mechanisms associated with the use of R&D tax incentives. Using the financial component as an IV approach in this stream of literature became the best way to deal with endogeneity. Despite its popularity, the magnitude of publication bias characterising it is not without ambiguity regarding the effect attributed to R&D tax incentives. The limited impact of using the financial component as an IV strategy was also documented in

[15] Longrun takes the value 1 when the estimation was related to a lag of two periods, 0 if it was only one period.

Castellacci & Lie (2015) who do not find any impact in explaining the variations found among the estimates in the literature. Publications with a large set of estimates provide a similar picture as the one depicted in the case of IV strategy (see model 6). Increasing the comparability of estimates does not affect the significance level of our publication bias and the averaged true effect. The slight increase in the magnitude of the averaged true effect may reflect differences in the country and tax design evaluated.

4.1.2 R&D tax incentives and heterogeneity across countries

Both samples are composed of a large number of Spanish estimates which may bias the results towards this specific country and design. We, therefore, compare our results without Spain (model 6 in Table 4 and model 8 in Table 5) and introduce country dummies by pooling publications associated to the same country[16] (model 5 in Table 4 and model 9 in Table 5). In Table 5, model 8 shows that removing Spanish estimates increases the magnitude of the genuine effect of R&D tax incentives on R&D but at the price of inflating the publication bias. This result is confirmed in model 9 in which the averaged true effect reflects the Spanish case (not significant). Moreover, assuming that one country represents one specific tax design, our results show that the literature depicts a distribution of heterogeneous effects of R&D tax incentives on R&D demand (from -0.7 and -0.2). Similarly, high heterogeneity across countries is underlined in Table 4. Model 6 in Table 4 removes Spanish estimations from the sample and has the Argentinian design as a reference category. The trend previously described is also illustrated among our elasticities: the elasticity of R&D cost and demand varies between 0.3 for Australia to -1.9 for the USA. This result demonstrates that the impact of R&D tax incentives on R&D demand ranges from firms that do not change their R&D demand to firms that double their R&D expenditures. Similar findings are found in model 5 where Spain replaces Argentina as a reference category. The largest effect is still found for the USA with an elasticity around -1.8 and only two other countries (e.g. Argentina and Canada) seem to find a statistical effect of R&D tax incentives on R&D demand. The next section aims at unpacking these country effects by testing the main features of R&D tax incentives evaluated in each publication.

[16]We observe time-varying designs in France and Spain mainly. The other studies may differ in their level of analysis (region vs country).

Table 4: Averaged true effects of tax incentives on RD with elasticities (short vs long runs)

	Dependent variable: Elasticities and growth rates							
	FAT-PET	FAT-PET-PEESE	Weighted	RD flow	Country	Without Spain	Growth	Longrun
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SE	0.147		-5.720^{***}	0.074	-0.915	-1.947^{**}	-1.705^{***}	-3.478^{*}
	(0.990)		(1.060)	(0.937)	(0.684)	(0.900)	(0.206)	(2.066)
Var		-0.272						
		(0.686)						
Argentina					-0.775^{**}			
					(0.325)			
Australia					0.383	1.286^{***}		
					(0.367)	(0.112)		
Canada					-1.469^{***}	-0.784^{***}		
					(0.306)	(0.079)		
China					0.139	0.941^{***}		
					(0.333)	(0.024)		
Japan					-0.354	0.438^{***}		
					(0.330)	(0.015)		
Netherlands					0.111	0.794^{***}		
					(0.305)	(0.080)		
UK					-0.259	1.101^{**}		
					(0.595)	(0.529)		
USA					-1.813^{***}	-1.025^{***}		
					(0.328)	(0.011)		
Longrun								0.133
								(0.100)
Constant	-1.072^{**}	-1.049^{**}	-0.005	-1.068^{**}	-0.275	-0.907^{***}	-0.269^{*}	-0.105
	(0.482)	(0.423)	(0.067)	(0.500)	(0.299)	(0.125)	(0.149)	(0.101)
Observations	116	116	116	98	116	52	30	89
R^2	0.001	0.002	0.242	0.0001	0.534	0.379	0.729	0.274
Adjusted R^2	-0.008	-0.007	0.235	-0.010	0.494	0.264	0.719	0.257
Residual Std. Error	25.265 (df = 114)	25.247 (df = 114)	32.375 (df = 114)	27.151 (df = 96)	17.891 (df = 106)	21.883 (df = 43)	0.368 (df = 28)	0.419 (df = 86)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Robust standard errors and clustered at publication level

Table 5: FAT-PET and FAT-PET-PEESE estimations

	Dependent variable: PCC								
	FAT-PET	FAT-PET-PEESE	Weighted per estimation	GMM	NoGMM	IV	>10	Without Spain	Country
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SE	−1.762		−1.074	-3.300^{**}	−1.157	-2.214^{***}	-2.943^{***}	-2.081^{**}	−0.958
	(1.230)		(1.081)	(1.386)	(2.020)	(0.838)	(0.777)	(0.946)	(1.329)
Var		-7.939^{***}							
		(2.694)							
Argentina									-0.261^{**}
									(0.131)
Australia									0.075
									(0.148)
Canada									-0.196^{*}
									(0.105)
China									−0.037
									(0.247)
France									0.058
									(0.125)
Japan									-0.365^{***}
									(0.126)
Netherlands									−0.126
									(0.171)
UK									0.018
									(0.112)
USA									-0.744^{***}
									(0.243)
Constant	-0.134^{*}	-0.167^{**}	-0.153^{**}	−0.051	-0.154^{**}	-0.210^{***}	-0.222^{***}	-0.186^{***}	−0.028
	(0.076)	(0.071)	(0.063)	(0.139)	(0.068)	(0.020)	(0.027)	(0.036)	(0.094)
Observations	226	226	226	96	130	128	132	154	226
R^2	0.033	0.028	0.016	0.110	0.013	0.079	0.126	0.068	0.331
Adjusted R^2	0.029	0.023	0.011	0.101	0.006	0.072	0.119	0.062	0.300
Residual Std. Error	6.972 (df = 224)	6.993 (df = 224)	2.037 (df = 224)	6.053 (df = 94)	7.550 (df = 128)	6.077 (df = 126)	6.019 (df = 130)	6.127 (df = 152)	5.920 (df = 215)

Note: *p<0.1; **p<0.05; ***p<0.01

Robust standard errors and clustered at study level, FE study level

4.2 Effects of R&D tax incentives: PCC estimations

As mentioned before, our set of estimations is characterised by a high level of heterogeneity. Therefore, one can assume that there might not be one averaged true effect linked to R&D tax incentives but a distribution of true effects that are approximately normally distributed around their mean (Stanley, 2017). Estimations in Table 6 indicate that the magnitude of the averaged true effects depends on the characteristics of the scheme evaluated and of the methodology involved in a given publication. Model 1 in Table 6 examines the existence of publication bias and its methodological sources. Model 2 focuses only on the designs of R&D tax incentives which are then tested successively across types in the appendix to avoid multicollinearity[17]. Our third model combines all dimensions to illustrate potential issues with multicollinearity and explains why we exclude a set of variables from our analysis in columns 4-7 (i.e. Published, Sector, Modeltype).

4.2.1 Drivers of publications bias

The results from Table 6 show that publication bias is mainly coming from the outcome variable. The first model provides the averaged true effect of R&D tax incentives on R&D demand taking into account the specificities of the sample and methodology in a given estimation. In line with Gaillard-Ladinska *et al.* (2015), using R&D stock as an output measure tends to underestimate the results found. This finding is consistent with the effect found previously: since the demand for R&D is mainly stimulated in the short run, the effect estimated with R&D stock which requires rather long run variations is more likely to be lower than the ones estimated with R&D flow, or intensity. Our averaged true effect is still around -0.15, describing a rather large correlation between R&D cost and demand. Unlike Castellacci & Lie (2015), we do not find any statistical effect coming from services and confirm the findings of Gaillard-Ladinska *et al.* (2015). Considering the overlap in terms of publications in our sample, this result suggests that the choice of the response variable and/or the coding scheme used by Castellacci & Lie (2015) are responsible for this difference. Similarly, we do not observe a higher reaction from SMEs to changes in R&D tax incentives than in the overall firms' population. Although our K variables are not statistically significant, only considering Z variables is accompanied by publication bias (model 2). On average, evaluations based on structural approaches tend to overestimate the actual impact of R&D tax incentives. The next subsection discusses the distribution of averaged true effects depending on the specificities of the R&D tax incentive designs and additional sources of biases.

[17] The absence of enhanced deductions in the case of incremental design makes the variable highly correlated with our design type variables

Table 6: Extended MRA estimations with PCC: tax schemes characteristics

	Dependent variable: PCC						
	K	Z	K+Z	Types	US	wo US	Period
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SE	−1.813	−1.928**	0.134	−1.596	1.751	−2.343	3.076
	(1.895)	(0.931)	(1.317)	(1.031)	(3.204)	(3.926)	(3.115)
RDflowSE	2.629		1.143	1.765	−0.647	3.673	−0.909
	(2.412)		(1.490)	(1.952)	(2.382)	(3.571)	(1.678)
RDstockSE	3.696*		3.823**	1.887	−1.297	2.789	−0.586
	(1.951)		(1.607)	(1.159)	(2.846)	(3.238)	(3.044)
PublishedSE	−3.690		−3.908*				
	(2.888)		(2.059)				
SmallSE	−1.548		−2.910	−3.504	−4.218	−4.069	−2.405
	(3.523)		(2.991)	(3.726)	(4.381)	(4.782)	(3.189)
LargeSE	2.883		2.965**	1.483	−0.708	0.511	1.019
	(1.865)		(1.459)	(1.181)	(1.503)	(1.808)	(1.457)
ModeltypeSE	−0.242		−2.461				
	(1.454)		(1.616)				
Incremental		−0.419***	−0.506***	−0.443***		−0.318***	
		(0.137)	(0.123)	(0.125)		(0.089)	
Volume		−0.166*	−0.204***				
		(0.096)	(0.062)				
Deduction		0.205***	0.225***				
		(0.039)	(0.045)				
Targeted		−0.012	0.061				
		(0.121)	(0.111)				
US_SE					−5.880**		
					(2.723)		
PeriodSE							−6.082*
							(3.210)
Constant	−0.158***	−0.031	−0.091	−0.138**	−0.157**	−0.150**	−0.175***
	(0.061)	(0.078)	(0.100)	(0.060)	(0.063)	(0.067)	(0.060)
Observations	226	226	226	226	226	165	213
R^2	0.151	0.241	0.413	0.203	0.144	0.120	0.192
Adjusted R^2	0.123	0.223	0.383	0.181	0.120	0.087	0.168
Residual Std. Error	6.625 (df = 218)	6.235 (df = 220)	5.560 (df = 214)	6.403 (df = 219)	6.636 (df = 219)	7.297 (df = 158)	6.636 (df = 206)

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors and clustered at publication level

4.2.2 Tax design and averaged true effects

Models 2 and 3 suggest that the volume-based estimations seem to have a higher impact than hybrid ones. This finding is in line with Castellacci & Lie (2015) who use a similar set of publications. The correlation between the tax design features in models 3 and 4 puts in doubt the reliability of this effect. As a robustness check, we pool together our subset of hybrid and volume-based estimations to increase their level of comparability (see Table 11 in appendix). Model 4 isolates the main effect associated with the type of design characterising a given evaluation. The averaged effect is absorbed by the incremental dummy which exhibits a larger magnitude than in the overall model. Put in other words, estimations evaluating an incremental design find on average significant effects in stimulating R&D demand by decreasing the costs of R&D. This result holds across our different specifications but we cannot ignore two potential sources of biases. As suggested in Table 1, incremental designs were mostly implemented in the 1980s and early 1990s. Moreover, our observations linked to incremental designs are also biased towards the USA. In the next subsection, we test whether our conclusion about the incremental design is driven by the USA or the evaluated period.

4.2.3 Country, Period bias vs tax design

In model 5, we test whether having the USA as a context of evaluation is a potential source of bias. On average, studies looking at the USA provide more optimistic results regarding the impact of R&D tax incentives than the ones evaluating other countries. Multiple reasons can explain why studies about the USA find stronger results such as the quality of institutions or a more market-based economy. In model 6 we test whether excluding the US estimates from the sample decreases the magnitude of the effects estimated in model 4. The averaged true effect and the significance of the incremental designs remain but we can observe a slight decrease in magnitude. Model 6 confirms what we find in model 5: the US estimates depict higher effects than the ones coming from other countries but do not drive the main results.

As mentioned above, we only observe estimates for the USA in the 1980s and 1990s. This period is of interest because it represents the development of several high tech industries in the USA (i.e. ICT, biotech, semi-conductors) which is enhanced by the birth of venture capital. More broadly speaking, this period was characterised by the liberalization of markets (e.g. capital and goods ones) around the world. This might have played a role in fostering the effect of R&D tax incentives on R&D demand. Several trade agreements were signed in the USA with Canada, Mexico, but also within Europe. The macroeconomic context might have been more rewarding, especially for technological frontier firms, which were increasing R&D due to better access to capital and larger exporting markets (see the “escape competition” scenario Aghion *et al.*, 2005). In parallel, the rise of the Asian tigers went with the intensification of high tech competition at the global level. Consequently, the private R&D demand was strongly stimulated disregarding the existence of R&D tax incentives (see Köhler *et al.*, 2012). In model 7, we introduce a variable splitting our sample into two categories: estimations before 1998 and estimations from early 2000. We chose 1998 as an arbitrary point representing the signature of China to the WTO and the early 2000s as a new phase of globalization. Model 7 indicates only a weak and enhancing statistical effect coming from evaluations using samples from the 1980-1990s. The absence of observations of incremental designs in the 2000s does not allow us to disentangle between the bias from the period and the design type. To measure the magnitude of the difference(s) across designs, we provide a set of robustness checks by splitting our overall sample across design types. Finally, we use these robustness checks to discuss the role of additional tax design features in explaining the heterogeneity of results within each type of design (see Tables 10 and 11).

4.3 Robustness checks: Features across designs

The previous results stress the importance of the type of R&D tax incentive design in explaining the differences across countries. Additional dimensions within the tax design can explain why implementing a similar design in a given country leads to different results. The correlation between enhanced deduction and the design type limited the use of the former in the main results. Moreover, the strong effect coming from the type of design suggests that only variations within the type of design, and not across designs, are relevant to explain the heterogeneity of the results across countries. We conduct a set of robustness checks in Tables 9 and 8 in the appendix for the incremental and volume-related designs (e.g. hybrid and volume-based). We pool together volume-based and hybrid due to the proximity between both designs and periods evaluated. The robustness checks confirm the results previously described (models 1-2 in Tables 8 and 9): we find an averaged true effect in both cases and show that the effect for incremental designs is much higher than in the two other cases. Interestingly, models 3 and 4 in Table 9 contradict this idea by showing that the volume-based estimations drive the overall results in the volume related case. Consistent with our framework and the complexity of the hybrid scheme, the hybrid estimations seem to have on average no effect on R&D demand. The absence of Spanish bias (see model 10 in Table 9) suggests that model 8 in Table 5 exhibits a lower effect due to an increase in the number of hybrid estimations, and not Spanish estimates. The next section discusses the additional tax features which moderate the effect across each type of design.

4.3.1 Targeting & Generosity: incremental design

Generosity seems to explain the variations found in the literature only in the incremental case. A large number of estimations from the USA leads to a significant over-representation of the USA in our sample. Even if the results remain significant by adding a US dummy (see model 6 in Table 8), we cannot ignore a strong bias from the USA among our sub-sample. To cope with this, we weight our estimates with the inverse of the variance of each estimation adjusted by the number of estimates per paper. Doing so, we observe that targeted SME features in the incremental context tend to decrease the overall effect and that there is a linear relationship between the refund rates and efficiency. Nevertheless, the lack of variations in the sample makes our Z variables acting as a dummy US/non-US. Therefore, the averaged true effect reflects the US case and is moderated by features from other countries. Model 3 illustrates the Japanese case which exhibits a weak statistical effect in decreasing the effect of R&D tax incentives. By introducing a special SMEs base definition, the clarity and predictability of the scheme decrease. The negative effects of refund rates (see models 4-5 in Table 10) are associated with observations from France related to the establishment of an additional incremental component in the 1980s. This double incremental component enhances the generosity of the design but at the price of increasing the complexity of obtaining such deduction. The lack of predictability decreases the efficiency of the design.

4.3.2 Targeting & Generosity: volume-based and hybrid designs

In the volume related estimations, only having targeting rules seems to explain the variations across countries. As suggested in Table 3, each design is characterised by a specific level of generosity. The uneven distribution of the refund rates acts as a control for the type of design. Consequently, the averaged true effect sums up the two effects in models 8-9 in Table 11 (e.g. null for hybrid and negative for the volume-based user costs)[18]. Targeting SMEs has different effects depending on the type of R&D tax incentive used. Model 6 shows that designs with enhanced deductions do not affect the magnitude of the averaged true effect. The absence of significance probably reflects the high compliance costs which overweight the uncertain return coming from the lack of predictability. This scenario is confirmed in model 7 in which the magnitude of the constant increases but decreases with enhanced deductions: SMEs who have the choice between a refundable tax credit which is more favourable and an allowance will use the former. As mentioned in the framework, the increased uncertainty linked to the eligibility in enhanced deductions and their disconnection with the R&D budget make them more complex, and hence, less efficient.

5 Conclusion

Nowadays, the majority of OECD countries has adopted R&D tax incentives as an instrument to stimulate the demand for private research and innovation efforts. Yet, the literature provides ambiguous results about their effectiveness. Our meta-regression analysis proposes to consider the R&D tax incentives designs as an explanation for these contradicting results found in the literature. Our study provides four key findings. First, we confirm the existence of a genuine effect of R&D tax incentives on enhancing the private demand for R&D. This effect seems to be short-run oriented and to stimulate R&D rather at the extensive than the intensive margins. Instead of stimulating a significant and permanent increase in R&D expenditures, R&D tax incentives are associated with opportunistic behaviours (e.g. incentives to disclose R&D expenditures, or relabelling). We cannot rule out that hybrid estimations bias this result considering their over-representation in our sample. Second, we quantify this effect: on average, decreasing the cost of R&D by one dollar leads to an increase in R&D expenditures of one dollar. This result varies a lot across countries. Third, we explain this heterogeneity across countries by the characteristics of the R&D tax designs: incremental schemes are related to the highest effect on R&D, followed by volume-based ones. Hybrid estimations do not seem to affect the demand for R&D in the short run, consistent with the opportunistic behaviour described before. Fourth, we show that generosity and targeting have a secondary role in explaining the variations across countries but moderate the averaged true effect in each scheme.

Several important conclusions can be drawn from this analysis. Our findings highlight the trade-off between providing strong R&D incentives and easing the tax claims. Incremental and volume-based R&D tax incentives manage to balance between both at the cost of creating enhanced inequalities between large firms and SMEs, either in terms of providing enough incentives to conduct R&D or to claim R&D deductions. The essence of R&D tax incentives is to reward innovative actors, following a success brings success logic. However, new actors are

[18] Model 8 shows a weak but significant effect in line with the volume-based averaged true effect. This is consistent with the measurement used in the estimation: the minimum refund rate in the hybrid design corresponds to the volume component in the latter. However, model 9 estimates the result of the maximum refund rate comparing the volume case with the incremental component from a hybrid.

hampered by this logic due to their limited tax liability. As we show, moderating this effect by creating differential rewards between SMEs and large firms comes at the cost of increasing complexity. This enhanced complexity seems to explain why we did not find any effect in the case of hybrid designs in the short run. By being at the crossroad between both designs, the hybrid designs reflect that increasing complexity reduces the effectiveness of R&D tax incentives.

The scope of our results is by definition bounded to the studies composing our sample. Besides the specificities of the design, the interaction of R&D tax incentives with other taxes and innovation policies could also explain the contrasting results found across countries. As developed in Hall (2001), the tax rate on capital gains should be considered since the latter rewards risks bore by entrepreneurs and venture capitalists to start innovation projects. Spengel (2009); Akcigit *et al.* (2018) stress the importance of corporate taxation as an instrument to stimulate innovativeness. The literature about the complementarity between R&D subsidies and R&D tax incentives is developing but leads to contradicting results (see Appelt *et al.* (October 2019 (final project report forthcoming)) for a discussion). Beyond country differences, the periods of evaluation might be of interest. R&D tax incentives seem to have a negative effect on R&D demand in case of economic downturns (Aysun & Kabukcuoglu, 2019). The interactions between R&D tax incentives and other policies require further investigations to better understand their asymmetrical treatment of losers and overall effectiveness.

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Appendices

A Data delineation

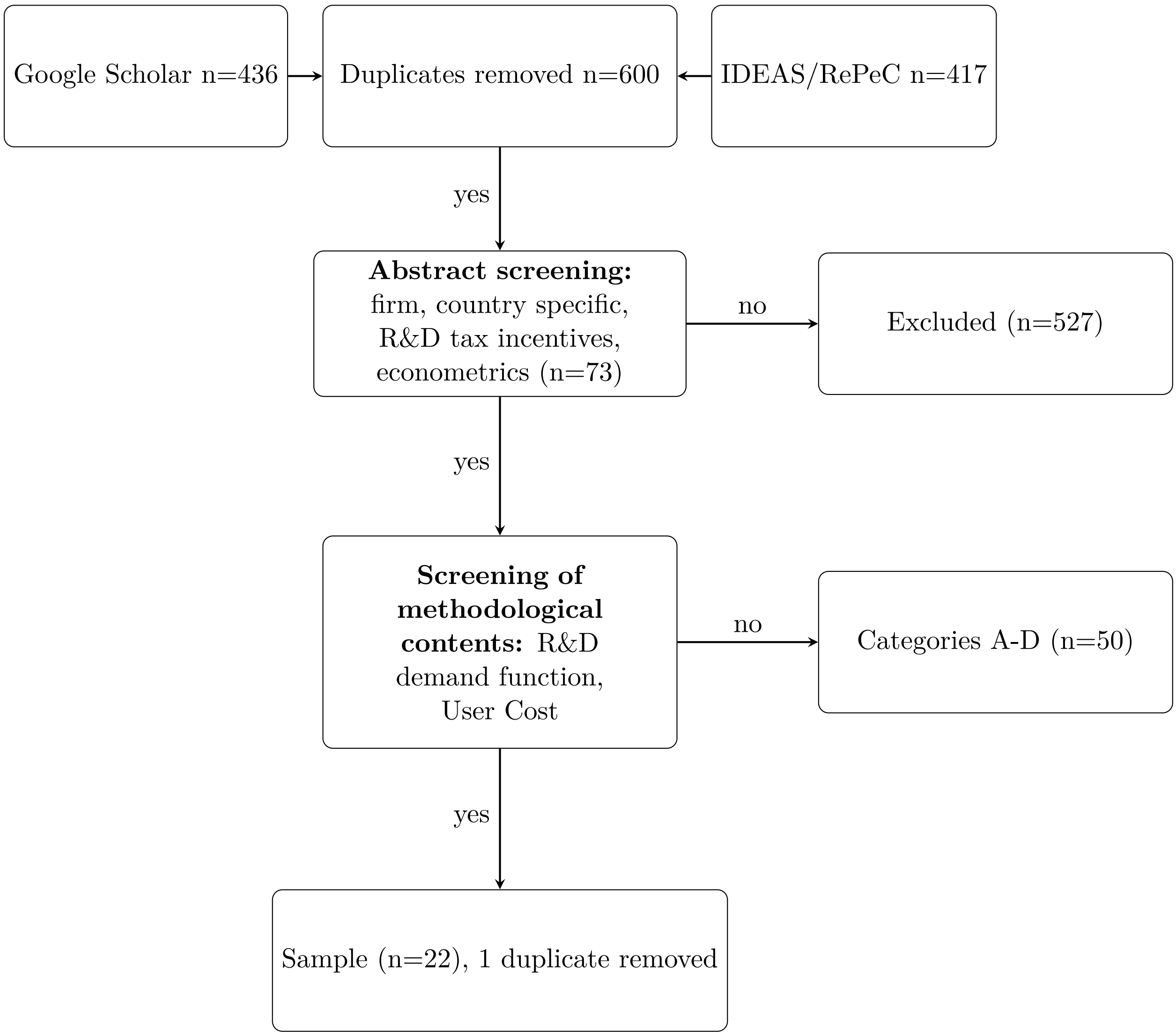

Figure 2: Selection process and inclusion criteria

Table 7: JEL codes

	Category	**Overlap Google**	**Overlap in other JEL**
H25	Business Taxes and Subsidies	15	23 (32)
H32	Firm	4	3 (O38)
H42	Publicly Provided Goods	3	all (H32)
L13	Oligopoly and Other Imperfect Markets	0	1 (O31), 3 (O32)
O38	Government Policy	14	23 (O32)
O32	Management of Technological Innovation and R&D	14	3 (L13), 10 (O31)
O31	Innovation and Intervention: Process and Incentives	4	10 (O32), 1 (L13)

B Definition of the Generosity variables

To approximate for the generosity of a R&D tax incentive scheme, we calculate a minimum and maximum tax credit rate applicable for the respective country (taking into account firm size specific regulations) over the sample period. In case of an enhanced deduction, we transform the deduction to an equivalent tax credit rate by multiplying the enhanced deduction rate with the corporate income tax rate.

Table 8: Generosity

Country	Sample period	Size	Minimum (%)	Maximum (%)
Argentina	1998-2004	all	50	80
Australia	1990-2005	all	43,44	60,81
Canada	2000-2007	all	20	35
		small	20	35
		large	20	20
China	2009-2013	all	12,5	12,5
France	1981-2007	all	4,6	48,45
	1983-2002	all	47,37	80
	1991-2003	all	50	50
	1999-2007	all	42,5	50
	2000-2007	all	2	17
	2004-2007	all	6,35	48,65
	2008-2013	all	30	35
Japan	1991-1998	all	20	20
Netherlands	1996-2004	all	13,45	50
Northern Ireland	1998-2003	all	25	50
Québec	1997-2003	all	19,6	50
		small	39,29	50
		large	19,6	19,6
Spain	1991-1999	all	30	50
Spain	2001-2008	all	40,88	62,18
United Kingdom	2002-2011	all	5,34	18,75
United Kingdom	2003-2012	all	5,4	20,45
United States	1980-1991	all	25	25

Australia:

During the time period covered several changes in the corporate income tax rate occured. 1990-93: 39%, 1994-95: 33%, 1996-2000: 36%, 2001: 34%, 2002-05: 30% The average CIT rate is 34,75%. The super-deduction of 125% (175%) is transformed by multiplying the depreciation rate with the CIT. Therefore the generosity is measured with 43,44% (min) and 60,81% (max).

United Kingdom:

In the United Kingdom the R&D tax incentives is a super-deduction, we have to transform it to an equivalent tax credit to be comparable to other studies. We calculated therefore the average tax credit rate for SME (large companies) for each case of small or large profits. Which gives you the average generosity of each scheme during the sample period.

Canada:

There are two subsamples: either all firms or only small firms are observed. Therefore the minimum rate of 20% and the max rate of 35% is used as proxy. Only in the case of only large firms we would have used 20% as a proxy for min and max.

Québec:

For SMEs a refundable tax credit for salaries and wages of researches exists. The tax credit rate is 37,5% additionally a SME could claim an incremental tax credit on R&D expenditure (1999-2004) of 15%. Therefore we use 37,5% (min) and 52,5% (max) as proxy. For a sample of large firms 17,5% is used as min and max. For a mixed sample 17,5%(min) and 37,5% (max) is used.

Argentina:

For Argentina we proxy the minimum rate with 50%. Law No. 23,877 provides a tax credit on investment in R&D and the available maximum rate is 50%. However, if companies invest in technological modernization a maximum credit of 80% is available, irrespective of the company size.

Spain (1991-1999):

The tax credit was introduced in 1995. The Spanish tax credit consists of a volume-based part and an incremental part. The volume-based rate was 20% and the incremental rate was 40%. The rates changed in 2001.

Spain (2001-2008):

The Spanish tax credit consists of a volume-based part and an incremental part. The rates varied over the sample period. In general all firms could receive the volume-based part. The average tax credit rate of the volume-based part is calculated in the following way: (3*0,2+3*0,3+0,276+0,25)/8 = 25,325% (min) And for the incremental part: (3*0,45+3*0,5+0,46+0,52)/8 = 46,625% (max)

China:

The R&D tax incentives is an enhanced deduction of 150%. In general, 100% is always deductable. Therefore, we transform the additional 50% to an equivalent tax credit of 12,5% (due to a CIT rate of 25%).

Japan:

In general, all firms can apply for the incremental credit of 20%. However, SMEs could alternatively apply for a volume-based tax credit of 10%. Based on the descriptive statistics the majority of companies observed in the data are not classified as SMEs according to Japanese tax law. As a result of this, we do not consider the alternative 10% volume-based tax credit.

Netherlands:

The R&D allowance takes the form of deductions of wage tax and social-insurance contributions. As a rule, the R&D allowance amounts to 40% of the first EUR 68,000/90,756/110,000 of the wage bill for R&D per calendar year, and 15% (on average) of the remaining R&D wage bill. The 40% could be increased for start-ups t0 60-70% (on average 50%).

France:

Evolution from the incremental to the volume-based regime > 50% to 40% from the incremental component from 1984 to 2007 and emergence of the volume-based at 5% in 2004. In 2008, regime totally volume based and around 30% (5 compo as extra). No SMEs discrimination.

C Data description

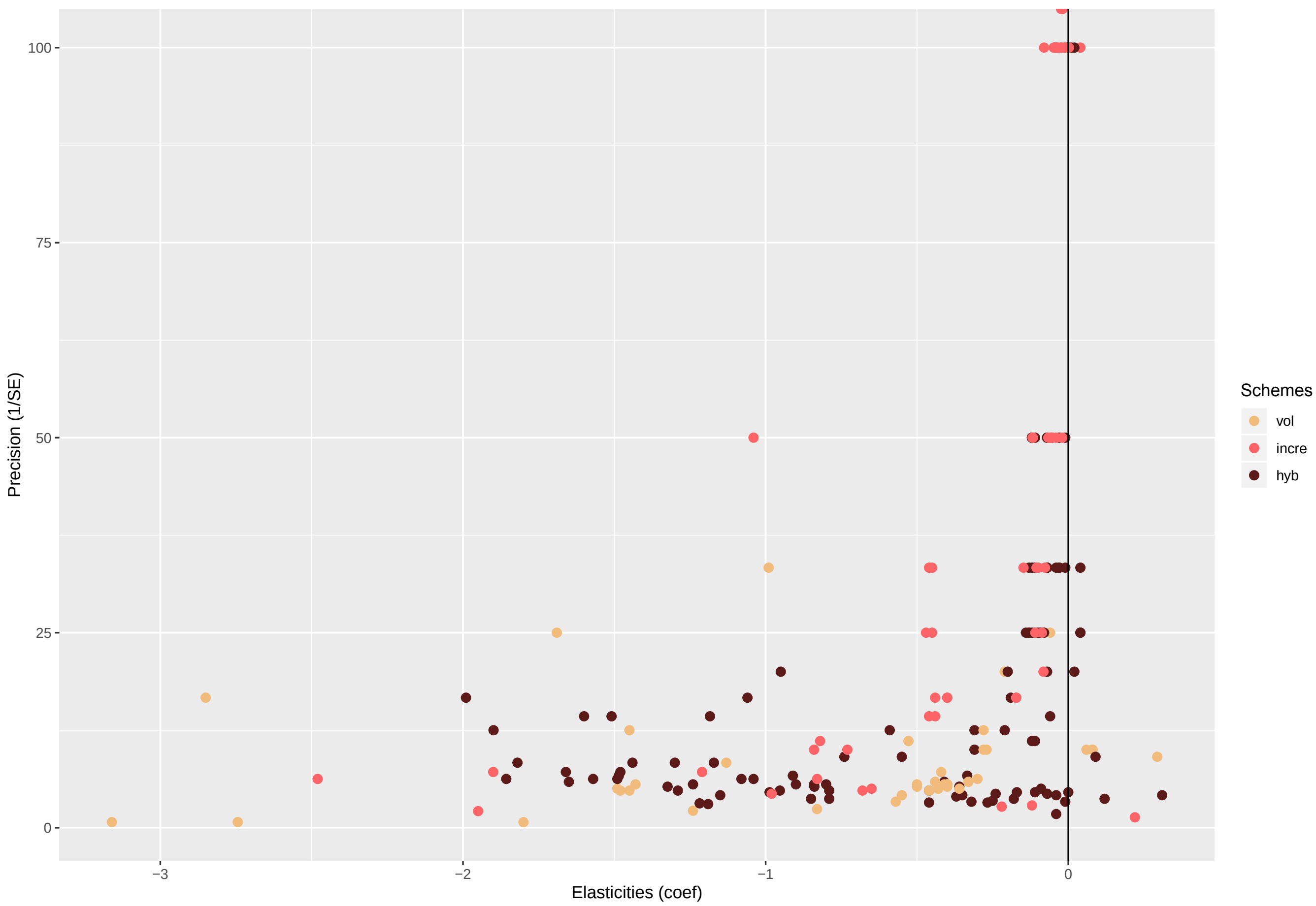

Figure 3: Distribution of the estimated elasticities

Table 9: Summary statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Response variable							
Coef. User Cost	226	−0.479	0.619	−3.160	−0.798	−0.055	0.310
SE User Cost	226	0.128	0.184	0.000	0.030	0.180	1.400
PCC	226	−0.352	0.435	−0.985	−0.787	−0.003	0.722
SE PCC	226	0.121	0.093	0.010	0.046	0.176	0.443
K variables							
RDflow	226	0.606	0.490	0	0	1	1
RDstock	226	0.128	0.335	0	0	0	1
RDintensity	226	0.265	0.443	0	0	1	1
Published	226	0.513	0.501	0	0	1	1
Small	226	0.181	0.386	0	0	0	1
Large	226	0.301	0.460	0	0	1	1
Sector	226	0.549	0.499	0	0	1	1
Modeltype	226	0.425	0.495	0	0	1	1
Z variables							
Incremental	226	0.305	0.462	0	0	1	1
Volume	226	0.195	0.397	0	0	0	1
Enhanced deduction	226	0.133	0.340	0	0	0	1
Targeted	226	0.588	0.493	0	0	1	1
Minimum	226	28.273	12.353	2	20	40.9	50
Maximum	226	42.163	19.992	12	25	60.8	80

D Robustness checks

Table 10: Robustness checks with incremental estimations

	Dependent variable: PCC					
	Avg effect	K	Target	Min	Max	US
	(1)	(2)	(3)	(4)	(5)	(6)
SE	-1.517^{***}	-1.197	3.017	-1.361	-1.738^{**}	3.601
	(0.331)	(0.720)	(2.342)	(1.330)	(0.756)	(2.386)
RDflowSE		-2.284	1.487	-2.365	-2.412	2.530
		(1.748)	(2.850)	(1.977)	(1.728)	(3.014)
SmallSE		0.162	-0.984	0.233	0.448	-0.950
		(0.452)	(0.702)	(0.481)	(0.336)	(0.624)
LargeSE		4.270	1.782	4.373	4.639	1.650
		(4.250)	(2.256)	(4.315)	(4.463)	(3.554)
Targeted			0.712^{***}			
			(0.257)			
Min				0.005		
				(0.036)		
Max					0.014	
					(0.013)	
ModeltypeSE						-0.297
						(3.575)
USdummy						-0.839^{***}
						(0.229)
Constant	-0.485^{***}	-0.529^{***}	-1.338^{***}	-0.620	-0.807^{***}	-0.662^{**}
	(0.089)	(0.142)	(0.465)	(0.704)	(0.285)	(0.274)
Observations	69	69	69	69	69	69
R^2	0.049	0.142	0.351	0.143	0.173	0.452
Adjusted R^2	0.035	0.089	0.300	0.076	0.107	0.399
Residual Std. Error	4.523 (df = 67)	4.394 (df = 64)	3.853 (df = 63)	4.426 (df = 63)	4.349 (df = 63)	3.568 (df = 62)

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors and clustered at publication level

Table 11: Robustness checks with hybrid and volume estimations

	Dependent variable: PCC									
	avg effect	K	Deduction	Targeted	Min	Max	Deduction	Deduc/target	Spain	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SE	−0.181	3.020	0.340	-2.650^{*}	−0.205	−0.441	−0.345	−0.542	−0.524	−2.402
	(1.824)	(3.378)	(0.968)	(1.564)	(2.531)	(1.803)	(2.414)	(1.394)	(1.348)	(2.073)
RDstockSE		2.444								
		(2.107)								
SmallSE		−4.396								
		(4.009)								
LargeSE		1.902								
		(1.528)								
SectorSE		−3.102								
		(2.737)								
ModeltypeSE		-3.732^{*}								
		(2.245)								
Deduction						0.143	0.158^{*}			
						(0.093)	(0.093)			
Min								0.002		
								(0.005)		
Max									0.002	
									(0.004)	
Spain										0.117
										(0.161)
Constant	-0.151^{**}	-0.140^{**}	-0.214^{***}	−0.009	-0.157^{**}	-0.159^{**}	-0.168^{**}	-0.207^{*}	−0.216	−0.101
	(0.075)	(0.064)	(0.043)	(0.059)	(0.077)	(0.074)	(0.073)	(0.124)	(0.155)	(0.116)
Observations	157	157	44	113	127	157	127	157	157	113
R^2	0.0003	0.151	0.001	0.048	0.0003	0.032	0.038	0.017	0.013	0.085
Adjusted R^2	−0.006	0.117	−0.023	0.040	−0.008	0.019	0.022	0.004	0.001	0.068
Residual Std. Error	7.326 (df = 155)	6.863 (df = 150)	7.524 (df = 42)	6.833 (df = 111)	8.055 (df = 125)	7.233 (df = 154)	7.934 (df = 124)	7.287 (df = 154)	7.301 (df = 154)	6.731 (df = 110)

Note: *p<0.1; **p<0.05; ***p<0.01

Robust standard errors and clustered at publication level

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