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How Does the Evolution of R&D Tax Incentives Schemes Impact Their Effectiveness? Evidence From a Meta-Analysis.

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How does the evolution of R&D tax incentives schemes impact their effectiveness? Evidence from a meta-analysis.

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Abstract

A growing interest in R&D tax incentive policies has given rise to a large number of evaluations, which provide contrasting results about their effectiveness. Our meta-analysis aims to explain the heterogeneity found in the R&D tax incentive evaluations by the features of tax incentives. We document that on average R&D tax incentives stimulate R&D expenditures across two streams of empirical studies. However, this averaged effect is moderated by the underpinning features of tax incentives. Our samples evidence that the estimations linked to incremental bases and related to targeted rules towards SMEs drive the positive results found in the literature. Introducing a cap or a pre-approval process does not decrease the effectiveness of R&D tax incentives, allowing governments to monitor the indirect support needed to stimulate private R&D expenditures. Our results highlight the importance of setting up a clear and stable tax incentives framework. Sources of uncertainty regarding the time-span, the amount of the financial returns from tax claims but also the main criteria to apply are likely to decrease their effectiveness in the short run.

Keywords Meta-analysis - R&D tax incentives 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 justifies the need for governmental interventions. Governments use 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; Boeing, 2016) as well as in the use and compliance linked to R&D grants (Czarnitzki & Fier, 2002; 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 and to be more neutral on the direction of innovative efforts.

Due to these reasons, governments in many countries have adopted R&D tax incentives to support innovation. A growing number of evaluations across countries and over time reflects this increasing adoption. However, the results found in the literature remain unclear: Hall (1993); Agrawal *et al.* (2020); Guceri & Liu (2019) find a strong and significant effect of R&D tax incentives on R&D demand in the short run while Labeaga *et al.* (2014); Thomson (2009); Mulkay & Mairesse (2013) find no effect with a few positive results in the long run (Mulkay & Mairesse, 2013; Labeaga *et al.*, 2020). Thomson (2013) argues that the specificities of R&D tax incentives implemented across countries explain the variations found in the literature.

We propose investigating the role of R&D tax incentives designs in a meta-analysis framework to explain the discrepancies found across studies. We articulate dedicated variables characterising the design of R&D tax incentives with the set of micro-econometric results found in the two streams of literature composing the empirical evaluations of R&D tax incentives on R&D demand. By doing so, we supplement the meta-analysis of Castellacci & Lie (2015) by providing an alternative source of explanation about the heterogeneity found across studies. Besides an update of the literature, we further enhance the comparability of the estimates by transforming them through a common metric (e.g. Partial Correlation Coefficients) and applying more conservative inclusion criteria. We perform our analysis on micro-estimates exclusively reflecting R&D demand evaluated in a given country and period to isolate the characteristics of the underpinning R&D tax incentives scheme.

We find that on average R&D tax incentives stimulate the private R&D demand even if their effects vary across tax schemes. Overall, our analysis underlines that recent estimates find a decrease in the magnitude and significance level of the relationship between R&D tax incentives and demand. This trend is reflected by a base definition that moderates the policy effectiveness:

incremental base estimates show higher results than hybrid and volume-based ones. Those are less likely to substantially affect R&D demand than incremental estimates. However, volume and hybrid estimates show a significant impact on R&D demand when the underlying schemes focus on SMEs via an immediate refund rule or a specific incentive rate. Relying on a cap to target SMEs does not seem to alter the effectiveness of the policy, but it does not decrease it either. Results are more ambiguous regarding the role of refund rules and the type of tax incentive depending on the reference category taken into account. Finally, our results show that governments can increase the predictability of the amount of foregone revenue through the use of a pre-approval process or caps.

On the whole, our analysis stresses the importance of creating and sustaining a clear institutional framework to enhance the predictability of the firm's financial returns from the tax claims. Doing so raises the firms' incentives to claim R&D deductions in the short run. 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 performed on the structural estimates. Section 5 discusses the previous results by replicating the analysis with the direct estimates as robustness checks. Section 6 summarizes the main results, limitations, and further avenues.

2 Tax incentives: theory and empirical evaluations

R&D tax incentives constitute an important indirect policy instrument to support private research and innovation efforts. It relies on the following theory: the intersection of a downward sloping demand for R&D, and an upward sloping supply of R&D inputs determines the optimal level of private R&D. Ceteris paribus, R&D as an economic input becomes less expensive via the reduction of the corporate tax burden linked to R&D tax incentives, as it stimulates firms' demand for R&D (Hall, 1993). The reduction in corporate tax liability creates a tax shield, which increases with the amount of eligible R&D expenditures defined by the tax law[1]. The main advantages of R&D tax incentives lie in their stability and predictability. Contrary to subsidies, they do neither require a budget, nor administrative units to monitor their use, and are independent of political agendas (Bozeman & Link, 1984). Moreover, R&D tax incentives reward innovative actors and reduce the risk of "picking losers" (Bozeman & Link, 1984; Dechezleprêtre *et al.*, 2016). Firms receive financial rewards after and not before conducting R&D activities. As it will become evident in the following subsections, firms' incentives differ a lot across schemes.

[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.

2.1 Evolution of tax incentives over time

The design of R&D tax incentives reflects the approach that governments decide to develop in order to tackle a changing global innovation environment. In the 1980s, governments heavily relied on R&D subsidies as a key mechanism to sustain innovation efforts. In this context, direct governmental interventions were justified by the need to sustain domestic firms' innovation efforts in an environment that became increasingly internationally competitive (see Spencer & Brander, 1983). Globalization brought additional opportunities and pressures for domestic firms in improving, or maintaining their position in international markets. The rise of the Asian Tigers over this period provided the conditions for a boost in innovation efforts in high tech sectors. In that sense, global R&D competition fell in line with Arrow's argument according to which competition provides incentives to efficiently organize production, lower costs, and stimulate innovation (Arrow, 1972). Over this decade, the first tax incentives designs had mostly an incremental base with carry-forward rules without differentiating between SMEs and large firms.

In the 1990s, capital mobility intensified as a result of financial globalization (Rodrik, 1998). International organizations, such as the WTO, played a leading role in this process. In this respect, the accession of China to the WTO marked a turning point in the nature of the international competition in high tech sectors. While firms at the frontier benefit from this trade liberalization, laggards tend to suffer from an increase in international trade (Shu & Steinwender, 2019). The heterogeneity of this trade liberalization (see Aghion *et al.*, 2005, for a theoretical explanation) reduced on average the incentives to innovate. To lower costs, an increasing share of manufacturing activities has been relocated from the Western world to eastern or Asian countries. This trend has focused the competition on lowering costs more than enhancing quality and has put governments under pressure to increase their location attractiveness by reducing the overall tax burden (Overesch & Rincke, 2011). This changing set of incentives at the international level combined with the increasing competition to attract capital investments creates the prerequisite for the development of tax competition. This has been translated by a decreasing trend in corporate income taxes to attract high tax income activities related to high tech sectors (e.g. "smart tax competition")(Bräutigam *et al.*, 2018). R&D tax incentives were then used as an additional tool to maintain innovation efforts in a given country.

2.1.1 Types of R&D tax incentives: tax credits and super deductions

The most popular types of R&D tax incentives are tax credits, directly followed by super deductions (Straathof *et al.*, 2014). Super deductions reduce the corporate taxable income (e.g. by more than 100% of eligible R&D expenditures) while tax credits allow firms to deduct a given percentage of their R&D expenditures from their corporate tax liability. These differences in the source and timing of the tax relief impact its predictability. With regard to tax credits, firms only need to know the planned R&D spending and the applicable incentive rate to determine the financial benefit. In contrast, to estimate the financial benefit of super deductions firms need additional information on their overall expected tax position at the end of the year [2]. Therefore, R&D tax credits are easier to forecast than super deductions, which eases their integration within firms' R&D investment decisions (OECD, 2003). This argument has motivated countries to shift from super deductions to tax credits, such as the British example in 2015[3]. The predictability of the financial return of tax incentives is further influenced by the base definition, and the refund rules. Those determinants are discussed in the following subsections.

2.1.2 Bases of R&D tax incentives: Incremental, volume or hybrid R&D tax incentives

As mentioned in subsection 2.1, the initial R&D tax incentives schemes were mostly incremental. An incremental base implies that only firms performing R&D expenditures above a given threshold are eligible to claim R&D tax incentives. By the same token, it lowers the risk of relabelling R&D expenditures as it is not sustainable to over- or underestimate R&D expenditures in the long term (Larédo *et al.*, 2016)[4]. The eligibility threshold is usually measured via the averaged past R&D expenditures. Since this base only rewards additional R&D spending, it reduces the risk of subsidizing windfall gains for existing R&D investments (Bozeman & Link, 1984). However, the reliance on a pre-defined threshold is a major drawback: the moving average of past R&D spending discourages firms to persistently increase R&D activities as current R&D expenditures raise the future threshold[5]. This base definition tends to distort firms' R&D planning, as firms develop strategies to maximize their tax gains by gradually increasing their R&D investment instead of doing a single large investment (Straathof *et al.*, 2014; Correa *et al.*, 2013). The complexity of incremental tax incentives increases the compliance costs for both governments and firms, who could even refrain from participating if the application costs are perceived to be higher than the uncertain benefits.

The drawbacks of incremental bases listed above motivated the shift towards a volume-based definition by considering the total amount of current R&D expenditures. By doing so, govern-

[2]The financial benefit of super deductions is the product of the additional deduction of taxable income and the applicable marginal corporate income tax rate. The marginal tax rate is a result from several factors beyond R&D expenditures which makes it difficult to plan over the long-term. In case of losses a firm's applicable tax rate is zero in the year the loss is incurred and, potentially, future years.

[3]R&D tax credits do not reduce the reported profitability of firms (reflected in pre-tax earnings). A public consultation highlighted that especially multinational firms value the higher visibility of R&D tax credits, as group capital is typically allocated based on firm performance, measured by pre-tax earings (HMTreasury, 2012).

[4]However, even within incremental designs there is the risk of relabelling if uncertainty remains in the definition of qualifying R&D expenditures (Hall, 2001; Laplante *et al.*, 2019) and if there is no direct connection to previous R&D investments in the base definition.

[5]An alternative is the introduction of base amounts which are unrelated to current spending (e.g. the current US incremental tax credit), increasing the risk of relabeling.

ments decrease the administrations' and the firms' compliance costs related to tax incentives (Larédo *et al.*, 2016; Spengel, 2009). Likewise, the financial benefits of tax credits are more generous and predictable from the firms' perspective. In theory, more firms should hence claim R&D tax credits under a volume-based scheme than in the case of incremental ones. This is particularly true for SMEs with less persistent R&D efforts as they are more cash constraint than larger firms (stronger market failure). The downside of this design is that it leaves more room for R&D expenditures to be relabeled if applicants become more familiar with the application procedure. In addition to this, there is an increased risk of subsidizing infra-marginal R&D projects, which would have been conducted even in the absence of the R&D tax incentives. To enhance extra R&D efforts, governments can extend volume bases with an incremental component (e.g. hybrid bases). The combination of both base components 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. This complexity and the higher threshold in R&D spending, which is inherent in hybrid as well as incremental R&D tax incentives, represents a disincentive for firms to apply (Appelt *et al.*, 2016; Hall, 2019).

2.1.3 Predictability and generosity schemes from the firms' perspective

Additional features such as refund rules, caps, and pre-approval affect the predictability and generosity of R&D tax incentives, and therefore, their overall effectiveness. One reason to explain the popularity of volume-based schemes lies in their attempt to better target SMEs. R&D tax incentives are by definition addressed to firms with sufficient tax liabilities, creating serious disparities between large and small firms in their capacity to benefit from this type of policy. As highlighted in Bozeman & Link (1984), new firms may not be profitable and hence, do not have enough tax liability in the early years in which they commercialize their first products. Moreover, the risks involved in R&D activities may imply that large firms are more equipped than SMEs to survive in the subsequent years to reap the tax benefits of innovation activities (Bozeman & Link, 1984). To minimize these disparities between large and small firms, governments can use two different refund options: carryforwards and immediate cash refunds. Nowadays, most governments rely on carrying forward rules to benefit from unused R&D tax credits in future periods[6]. As a result, firms do not lose the tax benefit due to insufficient tax liability over a given year. However, since there is a considerable time lag between R&D investments and expected revenues, small firms are more likely to benefit from an immediate cash refund than carry-forward rules. Immediate refund rules work like a direct subsidy by relaxing the financial constraints, typically higher among SMEs (Elschner *et al.*, 2011)[7]. In

[6] This treatment is equivalent to loss-carryforwards in case of super deductions.

[7] Agrawal *et al.* (2019) show that SMEs are especially responsive to cash refunds as these companies face limited amounts of free cash flow or do not have enough tax liability to make use of the R&D tax credit.

addition to this, an immediate refund increases the predictability of the tax benefits, helping its consideration within R&D investment strategies. Schemes without such refund rules are less likely to be efficient. Even if firms are in principle eligible (based on their R&D spending), they are less likely to claim a reduction of their tax burden if they do not have enough tax liability (Hall & Van Reenen, 2000). Governments can also decide to target SMEs directly, considering that they are less likely than large firms to benefit from R&D tax incentives. To do so, governments could restrict the aforementioned cash refund to SMEs only, or simply provide a higher funding rate than the one for large firms. With higher financial incentives, SMEs should be more likely to bear the initial application costs for R&D tax incentives and to start participating regularly.

2.1.4 Predictability for governments

While R&D tax incentives represent an instrument to sustain innovation efforts, they also imply a large amount of foregone revenues for governments. To forecast this amount, governments can introduce different rules to limit or monitor firms' claims and to plan expenditures accordingly. A first approach consists of introducing a cap in the amount of the possible tax benefit per company. Doing so applies the binding constraints on the largest players but does not legally discriminate across actors. However, such a limitation can severely reduce the incentives to expand innovation activities, especially for firms that already spend a lot on research or are approaching the cap (Appelt *et al.*, 2016). Various countries that have implemented such caps seem to reconsider the optimal level to boost incentives for medium-sized companies (Mulkay & Mairesse, 2013; Agrawal *et al.*, 2020; Cappelen *et al.*, 2012). An alternative to closely monitoring the amount of foregone tax relies on a pre-approval of the eligibility of the R&D expenditures. Before being able to claim R&D tax deductions, firms have to apply to document the nature of their R&D activities to be considered as eligible. Pre-approval increases the predictability of the amount of eligible R&D expenditures for the government and for the claiming companies as well. Nevertheless, pre-approval can be a costly process for both parties to audit the relevancy of the project submitted. As previously seen, the interactions of several tax incentives features are likely to provide different incentives to firms, and in turn, affect the magnitude and significance of the results found in the literature. Our set of variables takes into account this diversity across our samples.

2.2 Evaluating the impact of R&D tax incentives on R&D demand

Introducing a tax incentive means changing the relative costs of conducting R&D which should increase firms' incentives to intensify the R&D activities conducted. This type of evaluation is called input additionality, in the sense that it looks at an increase in R&D as an input for innovation. We can distinguish two main approaches to evaluate the impact of tax incentives.

The first approach being structural and the second direct. In the former, the impact of tax incentives is captured via a parameter, the user cost, which takes into account the reduction of R&D costs. Doing so directly links the cost and demand for R&D and is typically measured via an elasticity (e.g. log-log specification). Thus, structural approaches measure the percentage change in R&D resulting from the tax relief for every percentage change in its after-tax price ("the user cost of R&D"). The simplest version of user cost is defined as: $UC_{i,t} = \frac{1-A_{i,t}}{1-\tau} \times (r_{i,t}+\delta)$, where 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. In general, structural estimations can be summarized as follows:

$$RD_{i,t} = \beta_0 + \beta_1 \times UC_{i,t} + \beta_2 \times X_i + \beta_3 \times T_t + \epsilon_{i,t} \tag{1}$$

In which X_i refers to firm fixed effects and T_t to year fixed effects (in a panel setting) and UC to the user costs of R&D for a given firm (i) and period (t). The coefficient of interest is β_1, estimating the R&D price elasticity. Estimations may vary if the researcher uses cross-sectional data, relying on other firm controls than in a fixed effect approach. While very appealing to economically interpret the impact of tax incentives on firms' R&D demand, structural approaches suffer from endogeneity and selection. For this reason, authors increasingly rely on direct approaches (e.g. difference-in-difference, RDD and quasi-experiments). While selection is not always tackled, the direct approach framework better tackles endogeneity by exploiting variations from the eligibility, or from the tax scheme change criteria to assess the actual impact of tax incentives on R&D demand. In the literature concerning direct approaches, R&D expenditures are directly regressed on a variable that serves as an indicator of the strength of R&D tax incentives ($D_{i,t}$) firm (i) faces in period (t). Whereas most authors rely on a binary indicator ($D_{i,t}$) either reflecting the general eligibility for the tax incentive or the actual treatment of the firm (e.g. applied for tax incentives, received or eligible tax incentives), some authors use the absolute firm-specific amount of R&D tax incentive received. Most of the evaluations in this stream of literature relies on a difference and difference framework to estimate β_1 as input additionality by comparing the effect across a treatment and control groups.

$$RD_{i,t} = \beta_0 + \beta_1 \times D_{i,t} + \beta_2 \times X_i + \beta_3 \times T_t + \epsilon_{i,t} \tag{2}$$

β_1 interpretation is less straightforward than in the case of structural approaches that provides an economic interpretation of the introduction of, or change within, the R&D tax incentive scheme. However, the shift towards more causal interpretations in economic research made direct approaches, and more especially diff-and-diff, the most popular way to assess input additionality linked to tax incentives over the most recent period. Consequently, the two streams of literature differ not only in terms of methodological contents but also through the types of R&D tax incentives evaluated. The design of R&D tax incentives has also evolved over time (see subsection 2.1) and the respective samples composing our study are both biased towards specific designs (e.g. hybrid and incremental mostly evaluated in structural approaches and volume-based among direct approaches). Combining both streams of evaluations allows us to reduce those biases in order to provide a more accurate picture of the effect(s) of different designs.

3 Methods

Meta-analysis can be thought of as a collection of statistical analyses used to examine results from individual studies with the general purpose of integrating findings of a given stream of literature (Glass, 1976). Here, we rely on the meta-regression analysis framework introduced by Stanley & Jarrell (1989) and Stanley (2001). Meta-regression analysis is a multivariate approach that aims to assess the existence of a genuine statistical effect characterizing the evaluated set of studies and underpinning sources of variations (i.e. the context of implementation, methodology). Doing so provides an averaged effect of the relationship studied in a stream of literature, corrected from a potential publication bias. The meta-analysis framework questions the validity of the empirical results by "filter[ing] 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. The selection of publication on Google Scholar relies on the following semantic strategy: alltitle='R&D tax*[8]. The strategy developed to extract publications from IDEAS/RePEc differs slightly by relying on JEL codes[9] standardized across economic fields and countries. In accordance with 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)[10]. Figure 2 in the Appendix summarizes the main steps of the selection process. The data collection was performed between 3rd of May 2018 and 28th of September 2018[11]. Only French, Spanish, German, and English publications were used. Finally, we bound the analysis to studies released between 1992-2020 to take into account the increasing use of econometric techniques (GMM estimations with Arellano- Bond standard errors for structural approaches

[8]Various trials showed that specifying 'tax credit' or 'tax incentives' did not help in getting more relevant studies. 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.

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

[10]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.

[11]We updated the data collection when new versions of manuscripts got released

and diff-and-diff in direct approaches) in this field.

3.2 Inclusion criteria: structural and direct approaches

We collected the parameter of interest (e.g. β_1 and its respective standard errors in Equation 1 and 2) linking R&D tax incentives and R&D demand. The data collection has been performed on a subset of literature in both approaches following different criteria: i) the estimations must be at the firm level and for a given country, ii) the estimations are only parametric (exclusion of non-parametric estimations such as ATT). Parametric approaches control for other macroeconomic shocks affecting both treatment and control groups and any differences between the two groups of firms that would be constant over time (Bozio *et al.*, 2014). By doing so, we compare more homogeneous estimates and can tackle the specificities of the tax incentives designs characterizing a given country at the studied period. We added another restriction on structural approaches by relying on estimations, which exclusively use the "King-Fullerton", or "Jorgenson-Hall" approach to estimate the user cost of R&D. The detailed steps involved in the data collection and inclusion criteria are described in the PRISMA charts (see Figure 2 in the Appendix).

Overall, our samples comprise 21 (structural) and 28 (direct) publications respectively from which we gathered 227 and 502 estimates across the different studies (see Table 1). An overview of the publications used to extract the short-term estimates is presented in Table 8 for structural approaches and in Table 9 for direct approaches in the Appendix. As the literature focuses mostly on short run effects on R&D, we restrict our analysis to this subset of comparable short-term effects linked to the introduction or change(s) in R&D tax incentive designs. A few studies do not find significant results in the short run because they consider the existence of adjustment costs in claiming tax incentives and adapting the R&D activities (see Labeaga *et al.*, 2014, for an illustration). Those studies tend to rather find significant results in the long run. However, the limited amount of literature that was available did not enable us to conduct the analysis within this time frame.

3.3 Meta-Regression Analyis: framework, and modelling choices

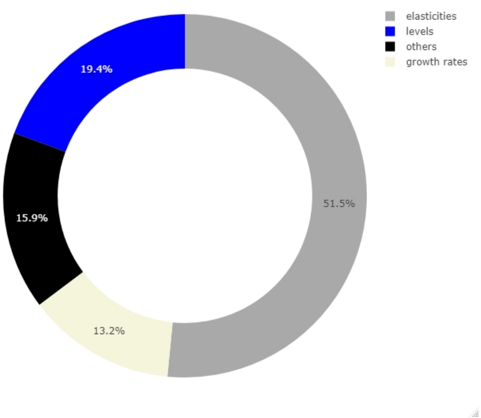
The FAT-PET-PEESE (Funnel Asymmetry Test – Precision Effect Test - Precision Effect Estimate with Standard Error) is widely used in economics. This approach decomposes the value of a given estimate in two key parameters. On the one hand, publication bias (FAT) and on the other hand, the averaged true effect through a measure of precision (PET). Publication bias represents a measure for the selectivity of the reported results characterising a subset of studies based on the direction and statistical significance of the results (Rothstein *et al.*, 2005, 3). In this modelling context, the publication bias is a function of the standard error. Consequently, the averaged true effect measures the statistical relationship characterising the underpinning subset of literature, net from publication bias. 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, e.g. $H_0 : \beta_{1,i} = 0$. This test relies on the assumption that researchers with small sample sizes select the most interesting model(s). It postulates that reported estimates correlate with the size of their standard errors. The net effect measured via the constant provides then the actual averaged (or true) effect associated with the reported estimates characterising the underpinning subset of literature (PET).

$$\text{Estimate}_i = \beta_0 + \beta_{1,i} \times \text{SE}_i + \epsilon_i \tag{3}$$

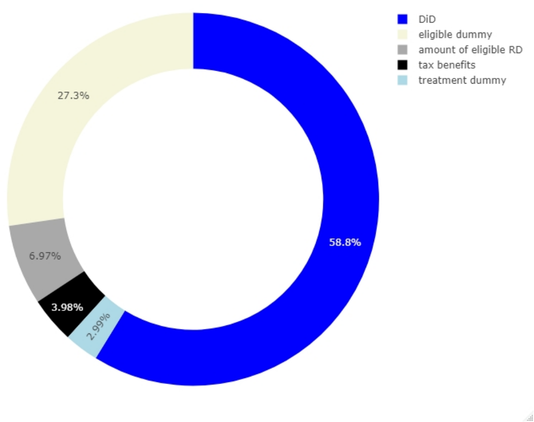
In this context, a given estimate i can be decomposed into a publication selection bias, $\beta_{1,i}$, and β_0 the true statistical effect.

3.4 PCC transformation

The diversity of methodologies in both streams of literature (i.e. elasticities with log-log specifications, semi-elasticities with lin-log elasticities, or even growth rates among structural approaches and DiD or treatment dummies among direct approaches) must be tackled to be able to compare the statistical relationships between tax incentives and R&D demand. Figure 1 shows the high diversity characterising the methodologies used to evaluate the impact of R&D tax incentives across the two streams of literature. To be able to compare the statistical effect found across studies, we convert the estimates to a common scale, e.g. Partial Correlation Coefficient (PCC).



(a) Structural approaches



(b) Direct approaches

Figure 1: Distribution of the methodologies across the two samples

The PCC transformation takes into account the power of estimations with the degrees of freedom and measures the statistical strength of the relationship between R&D tax incentives and demand for R&D.

$$\mathrm{PCC}_i = \frac{\mathrm{t}_i}{\sqrt{\mathrm{t}_i^2 + \mathrm{df}_i}} \tag{4}$$

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)[12]. In line with the previous subsection, the constant β_0 remains the averaged true effect and β_1 measures the publication bias. Our equation 3 becomes:

$$\mathrm{PCC}_i = \beta_0 + \beta_1 \times \mathrm{SE}_{PCC,i} + \epsilon_i \tag{5}$$

The drawback of using PCC lies in its interpretation: the estimations depict the *strength* of the correlation between the two variables studied (e.g. introduction of tax incentives vs R&D price and R&D demand). Doucouliagos (2011) conducts a meta-evaluation of the economic literature to determine the distribution of PCC across subfields. In the case of politics and taxes, Doucouliagos (2011) finds on average that a PCC under 0.015 refers to a weak statistical correlation, between 0.015 and 0.037 the effect is medium, between 0.037 and 0.076 is high, and above 0.076 is very high[13].

3.5 Modelling approach

Following the framework developed by Stanley (2012, 2017), we use a weighted least squares estimation of Equation 5 to account for the heteroskedasticity in the standard-errors composing our samples and the existence of correlation of estimates coming from the same study s (see Equation 6). With this transformation, the constant (β_0) measures the publication bias while β_1 becomes the averaged true effect measured in a stream of literature. Equation 7 introduces the extended meta-regression analysis in which additional variables are added to test their role in moderating the averaged true effect, and explaining the variations found in the literature. The Z variables are described in Table 1 and refer to the features of the R&D tax incentives evaluated in a given study.

$$\text{T-stat}_{i,s} = \beta_0 \times \frac{1}{\mathrm{SE}_{PCC,i,s}} + \beta_1 + \mathrm{v}_{i,s} \tag{6}$$

[12]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 datasets face no asymmetric distribution.

[13]For more details, see Table 4 in (Doucouliagos, 2011)

$$\text{T-stat}_{i,s} = \beta_0 \times \frac{1}{\mathrm{SE}_{PCC,i,s}} + \beta_1 + \sum_j \delta_j Z_j \times \frac{1}{\mathrm{SE}_{PCC,i,s}} + \mathrm{v}_{i,s} \tag{7}$$

We use the inverse of the standard errors as a weight and make a robustness check with the inverse of the variance (PEESE approach)[14]. If not indicated otherwise, we use robust and clustered standard errors at the study level to account for correlation among estimates from the same study. This correlation might be the result of research choices in the estimation method, or data sources for example. In our context of analysis, it is even more important to account for dependencies within studies considering the diversity of the tax incentives schemes evaluated. For the same reason, we do not add publication fixed effects which would make it impossible to then test the specificities of the tax incentives designs evaluated[15].

3.6 Summary statistics

The results of the data collection at the study level is summarized for both streams of literature in the Appendix (see Tables 8 and 9). Table 1 describes the key variables for the analysis of our study. As expected, estimates from structural approaches tend to find a negative relationship between the price of R&D and its related demand. By contrast, direct approach estimates find a positive relationship between decreasing the R&D costs and the related amount of R&D performed. We observe that on average, structural approaches reveal more statistically significant results than direct approaches, which corresponds to the shift of the literature towards more causal interpretations in economic evaluations. Table 2 suggests an alternative source of variation between the two streams regarding their significance level. As indicated in the second column, the majority of our estimates for structural approaches belongs to countries evaluated in the 1980s and 1990s[16].

On the contrary, direct approaches are rather concerned by the evaluations of recent schemes (in the 2000s). Therefore, both samples have the advantage of being consistent with regard to the underpinning macro trends in innovation policies and trade. Structural estimates are therefore more likely to be associated with hybrid and incremental base evaluations than direct estimates, focusing on volume-based evaluations. We take advantage of these specificities across samples to get a more accurate picture of the evolution of tax schemes features and their respective levels of efficiency. Alongside an over-representation of specific bases, our samples also face an over-representation in a few select countries (US and Spanish estimates in structural approaches, Belgium and British estimates in direct approaches). For this reason, we take those in the results into account through various robustness checks. The shift towards volume-based schemes is also

[14] This PEESE approach is supposed to be more efficient in presence of heteroskedasticity (Stanley, 2012, 78)

[15] 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.

[16] 29 percent of the Canadian and all Dutch estimates evaluate a period which overlaps too much between the late 1990s and the early 2000s to be able to code them in a category.

underlined in Figures 3 and 4 in Appendix that map the respective values of the PCC coefficients and their level of precision. Figure 3 suggests that incremental estimates among structural approaches tend to find higher results even if they seem less precise than other evaluated bases. Figure 4 supports this idea even if the volume-based estimates are over-represented in this sample and exhibit a very high heterogeneity in terms of precision and efficiency.

Table 1: Description and summary statistics of moderating variables

Variable	**Definition**	**Obs.**	**Mean**	**St. Dev.**	**Min**	**Max**
Structural						
Outcome characteristics						
PCC	Partial correlation coefficient	227	−0.42	0.37	−0.99	0.72
TSTAT	Estimated t-statistics of effect size	227	−5.04	6.88	−48	6
prec	Inverse of the PCC standard error	227	18.33	19.70	2.26	98.09
prec_sq	Inverse of the PCC variance	227	722.21	1,599.45	5	9,622
Tax scheme: Dummy variables are weighted by the inverse of the standard error of PCC						
VolSE	1 if the tax scheme is volume-based, 0 otherwise	227	5.50	18.37	0	98.09
IncrSE	1 if the tax scheme is incremental, 0 otherwise	227	2.53	5.61	0	47
HybSE	1 if the tax scheme is hybrid, 0 otherwise	227	10.302	14.60	0	53
DeductionSE	1 if enhanced allowance, 0 if tax credit	227	2.19	7.82	0	69
CarryforwardSE	1 if carryforward available, 0 otherwise	227	14.75	20.54	0	98.09
ApprovalSE	1 if pre-approval required, 0 otherwise	227	3.412	7.923	0	37
CapSE	1 if overall tax benefit is limited, 0 otherwise	227	12.38	13.93	0	53
TargetedSE	1 if a given scheme targets SMEs, 0 otherwise	227	15.29	21.12	0	98.09
Direct						
Outcome characteristics						
PCC	Partial correlation coefficient	502	0.03	0.05	−0.17	0.277
TSTAT	Estimated t-statistics of effect size	502	1.99	3.31	−8.03	31.05
prec	Inverse of the PCC standard error	502	71.27	37.71	6.01	203.53
prec_sq	Inverse of the PCC variance	502	6,499.22	7,732.73	36.09	41,426
Tax scheme: Dummy variables are weighted by the inverse of the standard error of PCC						
VolSE	1 if the tax scheme is volume-based, 0 otherwise	502	63.04	40.69	0	203.53
DeductionSE	1 if enhanced allowance, 0 if tax credit	502	42.43	41.21	0	182
CarryforwardSE	1 if carryforward available, 0 otherwise	502	65.89	41.87	0	203.53
ApprovalSE	1 if pre-approval required, 0 otherwise	502	5.89	20.35	0	112
CapSE	1 if overall tax benefit is limited, 0 otherwise	502	53.08	39.67	0	182
TargetedSE	1 if a given scheme targets SMEs, 0 otherwise	502	54.19	46.28	0	203.53
BaseSE	1 if a base scheme shifted towards volume, 0 otherwise	502	8.64	22.65	0	155

Note: The descriptive statistics are successively presented for our main sample of structural and direct approaches.

Table 2: Composition of the samples at the country level (in share of observations)

		Base definition			Type	Refund rules				
Country	**Post2000**	**incremental**	**hybrid**	**volume**	**deduction**	**carry-forward**	**targeted**	**cap**	**approval**	**Obs.**
Structural										
Argentina	1.00	0.00	1.00	0.00	0.00	0.00	1.00	1.00	1.00	0.08
Australia	0.00	0.00	1.00	0.00	1.00	1.00	1.00	0.00	1.00	0.04
Canada	0.71	0.00	0.21	0.79	0.00	0.71	1.00	0.00	0.00	0.06
China	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00	0.07
France	0.19	0.12	0.75	0.12	0.00	0.88	0.00	0.88	0.00	0.07
Japan	0.00	1.00	0.00	0.00	0.00	0.00	1.00	1.00	0.00	0.03
Netherlands	-	0.00	0.00	1.00	0.00	0.00	1.00	1.00	1.00	0.04
Spain	0.50	0.00	1.00	0.00	0.00	1.00	1.00	1.00	0.00	0.32
UK	1.00	0.00	0.00	1.00	1.00	1.00	1.00	0.00	0.00	0.04
USA	0.00	1.00	0.00	0.00	0.00	1.00	0.00	1.00	0.00	0.27
Direct										
Australia	1.00	0.00	0.25	0.75	0.25	1.00	1.00	0.17	0.00	0.02
Belgium	1.00	0.00	0.00	1.00	1.00	1.00	0.00	0.04	0.00	0.14
Canada	1.00	0.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.04
France	1.00	0.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.01
Ireland	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.02
Italy	1.00	0.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	0.01
Japan	1.00	0.00	0.00	1.00	0.00	1.00	1.00	1.00	0.00	0.14
Mexico	1.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.01
Norway	1.00	0.00	0.00	1.00	0.00	0.00	1.00	1.00	1.00	0.07
Slovenia	1.00	0.00	0.00	1.00	1.00	1.00	0.00	0.00	0.00	0.001
Spain	1.00	0.00	1.00	0.00	0.00	1.00	1.00	1.00	0.00	0.01
Taiwan	1.00	0.00	0.67	0.33	0.00	1.00	0.00	0.33	1.00	0.02
UK	1.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	0.00	0.44
USA	0.07	1.00	0.00	0.00	0.00	1.00	0.00	1.00	0.00	0.08

4 Results

We first present the main results from the meta-regression analysis linked to structural approaches (see Table 3) and discuss those in light of the specificities of the tax scheme designs (see Table 4). We then extend the analysis by conducting the same tests with direct approaches (see Tables 5 and 6). Crossing both sources of estimates allows us to provide a picture of the chronological evolution of tax incentives design. The different country biases are discussed across tables.

4.1 Structural approaches: overall effect over time

Table 3 provides the main results testing the existence of an averaged true effect linking the impact of R&D tax incentives on R&D demand among structural approaches. We find a very high, negative and significant effect of the averaged true effect across the different specifications in columns 1 to 7. Put in other words, tax incentives associated with a reduction in the price of R&D lead to a significant increase in its relative demand. The diverging results in columns 1 and 2 suggest a high level of heterogeneity in our sample, which is tackled differently across the first two estimations (e.g. weighting with standard errors versus variance). As shown in Table 2, the large share of US and Spanish estimates may create biases towards those countries. We test those in columns 3 to 7 by using a country dummy weighted by standard errors[17]. We find that Spanish estimates tend to overestimate the impact of tax incentives on R&D demand (see column 3) while the US estimates increase the averaged true effect of tax incentives (see columns 4-5). The proximity of the results estimated in columns 1 and 3 suggests that the estimation in column 1 suffers from a bias related to Spanish estimates. Likewise, the estimation in column 2 via its variance weight gives a stronger role to the US estimates that results in a higher effect than the rest of the sample. As a robustness check, we remove all unpublished estimates from Rao to keep only Hall (1993) and Rao (2016) in column 5, ultimately limiting the over-representation of US estimates in our sample. The results are not altered and the magnitude of the averaged true effect is almost identical.

The last two columns (6 and 7) estimate the extent to which the country effects previously described rather reflect specific evaluated periods (see Table 2). As suggested in subsection 2.1, the designs of R&D tax incentives evolved towards volume-based schemes in the most recent years. We chose the year 2000 as an arbitrary point to delineate between, on the one hand, the early estimates from the 1980s and 1990s, and on the other hand, estimates from the 2000s[18].

[17] We thereby assume that the specificities of the Spanish and US tax incentive schemes are likely to affect the averaged true effect.

[18] 12 observations related to three papers (i.e. Baghana & Mohnen (2009); Lokshin & Mohnen (2007, 2012)) are dropped as they cannot be clearly assigned to either the late 1990s or 2000s. The estimates for the Netherlands are therefore dropped and 29% of the Canadian estimates is not considered in the sample split across the two

We find a significant and negative effect characterising the strength between the R&D price and its relative demand. However, the reported effect is lower in the 2000s than in the 1980s and 1990s. Furthermore, the Spanish bias predominantly arises from the estimates in the 2000s (see column 7). Column 6 shows that on average the estimates related to the Spanish tax incentives for the 1990s do not statistically affect the magnitude of the averaged true effect. Different empirical evaluations of the Spanish R&D tax incentives in the early 2000s support our result from column 7. Busom *et al.* (2014) list various determinants (i.e. unawareness, administrative costs due to the complexity of the application process as well as a higher risk of an inspection by tax authorities) as the main barriers for using R&D tax incentives. Consequently, firms have few incentives to bear the cost of applying for tax credits and mostly use R&D subsidies to sustain innovation efforts (Martínez-Azúa & Ros, 2009)[19]. The results from columns 6 and 7 show that the averaged efficiency across the two periods differs, which supports the idea that the evolution of the designs relates to ambiguous results in the literature (see Table 2). The next estimations sequentially assess the role played by the different R&D tax design features in explaining the variations observed across the two periods.

4.2 Structural approaches: extended MRA with design features

Table 4 summarises the respective effect of the R&D tax incentives designs in moderating the averaged true effects estimated in the literature linked to structural approaches. To control for the country biases described before, we keep the same strategy by restricting our US estimates to published ones. This allows us to control for (or drop in columns 6, 8-10) the recent Spanish estimates depending on multicollinearity characterising the variables across the different models (see Table 10 in the Appendix).

We start the analysis by testing the importance of the base definition in resolving the discrepancy in the results found across the two studied periods (columns 1-5). Column 1 shows that estimates related to an incremental base definition tend to find higher results than those related to hybrid or volume-based estimates. On average, the magnitude of the averaged true effect of incremental estimates is twice as large as the average true effect estimated for other base estimates. The magnitude of the incremental estimates is in line with the one estimated in column 6 in Table 3. Our results suggest that all schemes on average find an effect of R&D tax incentives on R&D demand but this effect is only statistically different in the case of an incremental base (see column 1). The limited amount of volume-based observations within the sample reduces the chance to observe significant results related to this base definition (see col-

periods.

[19]Labeaga *et al.* (2020) report that claiming firms are rather motivated by reducing the corporate tax burden than substantially increasing R&D expenditures. However, they also argue that if companies once bear the high costs of learning how to claim, firms persistently claim R&D tax credits. This learning effect could explain the higher effectiveness of long-run estimations found by Labeaga *et al.* (2014).

umn 2). We extend the discussion on tax incentive bases in the subsample of direct approaches shown in Table 5, in which volume-based estimates are more represented than among structural approaches. Further, the results from column 3 show that only targeted hybrid and volume-based schemes find significant results. To increase the comparability of the sample, we first control for the US estimates (column 4) and exclude them as a robustness check (column 5). We confirm that the US estimates exhibit much higher effectiveness than other countries' estimates. Moreover, we confirm the role played by incremental and targeted schemes estimates in explaining the variations found in the literature.

Columns 6-10 test additional features that are likely to affect the predictability of the financial returns associated with R&D tax incentives. Carry-forward rules are tested in column 6 and do not seem to affect the magnitude of the averaged true effect. More interestingly, columns 7 and 8 do not find a detrimental effect linked to introducing either a pre-approval process to apply and a cap in R&D expenditures. From a governmental perspective, both determinants can help to monitor and forecast the amount of the budget needed to support innovation efforts without having a detrimental effect on the averaged effectiveness of R&D tax incentives. Finally, columns 9 and 10 focus on estimates linked to hybrid and volume bases to avoid reflecting a base effect[20]. We find that relying on super deductions tend to reduce the averaged true effect of R&D tax incentives. The estimation in column 10 supports the results found in columns 3 and 9. Only targeted schemes and schemes based on tax credits find a statistically significant effect among hybrid and volume-based estimates. Table 4 supports the idea developed before: the higher averaged true effect estimated among early estimates is mostly driven by the definition of the tax incentive base. The limited amount of volume-based observations within the sample reduces the chance of observing significant results related to this base definition. Therefore, we extend the discussion on tax incentive bases in the subsample of direct approaches shown in Table 5, in which volume-based estimates are more represented than among structural approaches.

[20]Our sample does not provide estimates which combine an incremental base with a super deduction, and only 6 estimations combining a targeted and incremental scheme (see Table 2).

Table 3: FAT-PET estimations on structural approaches estimates

	Dependent variable: t-value (PCC)						
	FATPET	PEESE	Spain	US	Published US	Pre2000	Post2000
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
prec	-0.142^{**}		-0.171^{***}	-0.170^{***}	-0.166^{**}	-0.380^{**}	-0.187^{***}
	(0.066)		(0.039)	(0.063)	(0.065)	(0.173)	(0.045)
prec_sq		-0.227^{***}					
		(0.044)					
SpainSE			0.113			-0.090	0.169^{***}
			(0.093)			(0.139)	(0.036)
USSE				-0.613^{***}	-0.583^{***}		
				(0.120)	(0.143)		
Constant	-2.433^{**}	16.238	-2.694^{***}	-0.867	-1.061	-0.787	-1.302
	(0.957)	(34.882)	(0.829)	(1.088)	(1.188)	(1.677)	(1.370)
Obs.	227	227	227	227	183	114	101
R^2	0.167	0.540	0.208	0.247	0.218	0.276	0.397
Adjusted R^2	0.163	0.538	0.201	0.240	0.209	0.263	0.385

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

Robust standard errors and clustered at study level

Table 4: Extended MRA: tax incentives designs (structural approaches)

	Dependent variable: t-value (PCC)									
	Incremental	Volume	Targeted	US	wo US	Carry	Approval	Cap	Type	Hybrid-Volume
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
prec	-0.201^{***}	-0.283^{***}	-0.009	0.037	0.039	-0.251^{***}	-0.202^{***}	-0.209^{***}	-0.221^{***}	0.076
	(0.034)	(0.106)	(0.076)	(0.048)	(0.056)	(0.054)	(0.035)	(0.043)	(0.014)	(0.067)
CarryforwardSE						0.044				
						(0.063)				
IncrementalSE	-0.214^{***}		-0.277^{***}		-0.206^{***}	-0.195^{**}	-0.210^{***}			
	(0.065)		(0.083)		(0.059)	(0.081)	(0.068)			
VolumeSE		0.089								
		(0.098)								
ApprovalSE							0.015			
							(0.093)			
SpainpostSE	0.185^{***}	0.257^{***}					0.187^{***}			
	(0.035)	(0.088)					(0.040)			
CapSE								-0.147		
								(0.107)		
USSE				-0.745^{***}				-0.573^{***}		
				(0.133)				(0.087)		
TargetedSE			-0.145^{*}	-0.204^{***}	-0.199^{***}					-0.298^{***}
			(0.075)	(0.057)	(0.060)					(0.076)
HybridSE									-0.036	-0.085
									(0.104)	(0.080)
DeductionSE									0.239^{***}	0.236^{***}
									(0.030)	(0.039)
Constant	-1.369	-0.991	-1.558	-1.413	-1.393	-0.853	-1.439	0.489	-1.427	-1.556
	(0.878)	(1.035)	(1.144)	(1.095)	(1.257)	(1.047)	(0.902)	(1.149)	(0.964)	(1.015)
Obs.	182	182	182	182	165	146	182	146	122	122
R^2	0.331	0.321	0.245	0.244	0.251	0.326	0.332	0.363	0.409	0.472
Adjusted R^2	0.320	0.309	0.232	0.231	0.237	0.311	0.317	0.349	0.394	0.453

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

5 Robustness checks with direct approaches

Estimations in Table 5 assess to which extent the results found in the literature on direct approaches are significant. In contrast to structural approaches, the magnitude of the averaged true effect linked to R&D tax incentives decreases: our models depict a medium relationship and not more a very high statistical relationship. This decreases in magnitude is consistent with the use of more accurate methods to assess the causal impact of R&D tax incentives. Column 1 (FAT-PET approach) shows that these evaluations find on average a positive and significant effect of R&D tax incentives on R&D demand. Whereas the PEESE estimation in column 2 provides contrasting results, in which the positive effect from column 1 vanishes. Column 2 suggests that the initial result in column 1 reflects publication bias. As in Table 3, the variance weight catches the heterogeneity differently across studies and signals a bias from an over-representation of countries (here, the UK). To account for this, we compute an averaged true effect for all UK estimates related to one specific tax incentive scheme (e.g. new eligibility criteria for medium-sized companies to benefit from a higher credit rate) evaluated by two groups of co-authors (Guceri, Dechezlepretre et al.) in column 3[21]. This model includes publication fixed effects and clusters standard errors at the co-authors' group level to account for dependencies across different versions of the manuscripts. Column 4 estimates a model for all other countries. The UK shows a much higher level of statistical significance characterising the averaged true effect than other countries. However, this higher significance is also affected by a stronger publication bias. The working papers related to the evaluation of this scheme may create some noise in the estimations. For that reason, we exclude those and keep only the most recent manuscripts of Guceri & Liu (2019) and Dechezleprêtre *et al.* (2020) in columns 5-7. Columns 5-7 focus on estimates belonging to the 2000s in order to replicate what we did in Table 3.

We find that on average recent estimates find a significant effect of R&D tax incentives in stimulating the demand for R&D but differs across base definitions (see column 5): among our recent estimates, we find that volume-based estimates show less significant results on R&D demand than hybrid or incremental ones, in line with the results found in Table 4. The effect of the volume-based definition is then divided into the related effect of shifting towards a volume-based definition (column 6) and introducing a volume-based tax credit (column 7). Column 6 pools observations evaluating a change in a volume-based scheme (i.e. changing eligibility threshold, rate, or base definition towards volume) while column 7 estimates a model linked to the evaluation of the introduction of a volume-based scheme.

Splitting between the shift versus introduction of volume-based estimates substantially re-

[21] This set of estimations excludes the effects estimated in Guceri & others (2013) looking at the introduction of R&D tax incentives to large UK firms. Doing so, we have more homogeneous estimates which mostly differ by the output used to measure the R&D demand.

duces the number of observations in each model, and hence leads to some country biases in each sample. This bias is really strong in the last column in which half of the estimates relate to Belgium. For this reason, we introduce a dummy to account for its over-representation in the results[22]. Despite a lower number of observations, column 7 still shows a weak but significant effect of the introduction of volume-based schemes while column 6 suggests that on average estimations related to a shift within an existing tax incentive scheme do not find significant results and are not more affected by a change in the base definition. This is consistent with the idea that uncertainty reduces the effectiveness of R&D tax incentives (see subsection 2.1.3); numerous changes over a short period of time create uncertainty and firms must adapt and learn about this changing institutional landscape to benefit from R&D tax incentives (OECD, 2014). Beyond the type of volume-based phenomenon evaluated, additional features correlated with the volume base definition could also explain the heterogeneity of the results found in the literature. Next, we focus mostly on volume-based estimates to extend the results of the previous subsection and to examine the role of additional features within a more homogeneous sample.

Table 6 primarily focuses on volume-based estimates (see columns 1-5) to disentangle between the effect(s) from the volume base definition versus additional features of the evaluated schemes[23]. Considering that dropping potential UK duplicates attenuates the UK bias (see column 5 in Table 5), we maintain the same strategy in Table 6. Our analysis starts by testing the existence of a significant effect of volume-based estimates in stimulating R&D demand. Column 1 shows that on average volume-based estimates exhibit a small but significant positive impact on R&D spending. The magnitude is in line with the results presented in Table 5. The next estimations aim at unravelling the effect of additional features indirectly measured by the volume base definition, explaining the lower averaged effect found for the 2000s in comparison to the earlier periods.

Like Table 4, the estimation in column 2 shows that a pre-approval process does not impact the averaged true effect[24]. Similarly, the results estimated in column 3 support the results found in Table 4 and specify the initial result from column 1: volume-based schemes with targeted features enhancing SMEs applications find significant results. Column 5 also supports the results found with structural estimations regarding the introduction of a cap: discriminating indirectly between large firms and SMEs does not affect the averaged effectiveness of R&D tax incentives, and even tends to enhance their effect. However, column 4 contradicts the results found in Table

[22]Even if the same shock is evaluated by two consequent reports, the estimates refer to distinct periods. We decide to consider our Belgium control as a context of implementation, like a source of publication bias

[23]Column 6 adds incremental and hybrid observations to test the link between the type of tax incentive and their effectiveness due to the limited amount of countries implementing super deductions in our sample. Column 7 relies on hybrid and volume-based estimates as a robustness check.

[24]The large share of Norwegian estimates implies to add a country dummy to catch the effect of pre-approval and not of the Norwegian scheme.

4 regarding the role of carry-forward rules. Using a carry-forward rule decreases the averaged effectiveness of R&D tax incentives on R&D demand. This difference is mostly explained by the reference categories that have been taken into account. In the first sample, we compare the effect of carry-forwards to no specific possibilities to postpone the tax return. In the second sample, we mostly compare carry-forwards vis-à-vis immediate refund rules. In line with our estimation in column 3, immediate refund rules tend to increase the significance level of the averaged true effect, which vanishes in the case of estimates related to carry-forward rules. Finally, column 6 re-introduces hybrid and incremental estimates in order to obtain enough variations in the sample to test the role of the type of incentives. Among our set of direct estimates, we do not find a statistical impact linked to using super deductions and not tax credits on the relationship of tax incentives and R&D demand. Column 7 restricts the estimates to hybrid and volume-based to test if the increase in the averaged true effect is driven by incremental estimates. This last robustness check confirms the absence of the role played by the type of incentive (tax credit versus super deduction) in explaining the variations observed in our direct sample and the stronger effectiveness of incremental estimates in comparison to hybrid and volume-based ones.

Table 5: FAT-PET estimations

	Dependent variable: t-value (PCC transformation)						
	FATPET	PEESE	UK ctrl	wo UK	Post2000 schemes	Shift towards volume base	Intro volume recent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
prec	0.026**		0.025***	0.031*	0.096***	0.027	0.090*
	(0.012)		(0.0004)	(0.016)	(0.034)	(0.019)	(0.048)
prec_sq		0.0001*					
		(0.0001)					
VolumeSE					−0.064*		
					(0.036)		
BaseSE						−0.015	
						(0.010)	
Belgium							−4.545***
							(1.225)
Constant	0.164	1.224***	0.418***	−0.083	−0.175	0.725	−0.885
	(0.589)	(0.366)	(0.029)	(0.751)	(0.780)	(0.733)	(2.497)
Obs.	502	502	202	280	310	168	133
R^2	0.085	0.075	0.170	0.109	0.214	0.174	0.398
Adjusted R^2	0.083	0.073	0.140	0.106	0.209	0.164	0.389

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors and clustered at study level
Col 3 with study fixed effects and clustered standard errors at the co-authors' level

Table 6: Extended MRA: tax incentives designs (direct approaches)

	Dependent variable: t-value (PCC)						
	Volume	Approval	Targeted	Carry	Cap	Type	Type volume
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
prec	0.025*	0.018***	0.003	0.100***	0.024***	0.030**	0.037*
	(0.014)	(0.003)	(0.010)	(0.012)	(0.008)	(0.015)	(0.021)
ApplicationSE		0.104**					
		(0.050)					
Norway		−2.396					
		(3.399)					
TargetedSE			0.024**				
			(0.011)				
CarryforwardSE				−0.079***			
				(0.008)			
CapSE					0.041*		
					(0.021)		
DeductionSE						0.007	0.003
						(0.020)	(0.023)
Constant	0.415	0.228	0.724	−0.016	−0.976	−0.131	−0.333
	(0.644)	(0.353)	(0.696)	(0.608)	(0.948)	(0.826)	(1.011)
Obs.	295	295	295	295	295	348	307
R^2	0.080	0.400	0.122	0.377	0.229	0.107	0.136
Adjusted R^2	0.076	0.394	0.116	0.372	0.223	0.102	0.131

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

6 Conclusion

Our meta-analysis aims to explain the reasons behind the heterogeneous results found in the R&D tax incentives literature. We assess to what extent R&D tax incentives relate to an increase in R&D expenditures and investigate the role of tax incentives features as an explanation for the contrasting results found across evaluations. We supplement the meta-analysis published by Castellacci & Lie (2015) by providing an alternative explanation related to the evolution of R&D tax designs as the main source of variations found in the literature and by enhancing the comparability of the estimates composing our samples.

We document with two streams of literature a positive impact of R&D tax incentives on R&D demand. However, this effect is different across the studied period (before the 2000s and after the 2000s) and depends on the evaluated designs. Estimates linked to incremental bases find higher effects than hybrid or volume-based estimates. Our samples show that schemes implementing an immediate refund rule, or a more generous credit rate to SMEs enhance their effectiveness. Estimates related to more uncertain schemes (i.e. shift in the scheme features, super deductions instead of tax credits, carry-forward versus immediate refund rules) find on average less significant results than estimates associated to more clear and stable tax schemes. Furthermore, introducing a cap or a pre-approval process does not relate to a decrease in the averaged effectiveness of R&D tax incentives. Hence, both can be used by governments to better plan the revenue foregone associated with R&D tax incentives. Overall, the results across our samples highlight the importance of creating a clear and stable institutional framework to claim R&D tax incentives in order to enhance its effectiveness. A specific attention to SMEs, who are more likely to face financial constraints in funding their R&D activities, seems to be an important driver in explaining their comparatively stronger response to tax incentives found in the literature (see Agrawal *et al.*, 2020; Guceri & Liu, 2019; Cappelen *et al.*, 2010, for example).

Our study is not without limitations regarding the scope of our results, bounded to a limited number of countries and schemes. Despite numerous robustness checks, several countries stand out as outliers. The large share of Spanish estimates related to hybrid schemes implies that the reduced effectiveness of this scheme must be read with some caution. Moreover, each sample is to some extent biased towards a specific base (incremental in structural and volume-based in direct approaches), reflecting a trend in economics towards causal inference over time. This methodological shift limits the comparative analysis of their respective effect(s) within one stream of literature. This raises important questions how the way to evaluate the impact of R&D tax incentives. Economists should conduct both types of analysis (i.e. structural and direct) to provide causal effect(s) linked to R&D tax incentives on R&D demand but also quantify their economic magnitude. Doing so would help to compare the effects of tax incentives across countries. Standardizing methodologies would also be needed to increase the comparability of estimates. A better standardization of empirical evaluations would help to address further sources of variations in a meta-analysis framework such as the interactions of R&D tax incentives with other innovation, or tax policies. Ongoing efforts at the OECD may provide an interesting source of estimations to perform an additional meta-analysis on the topic (OECD, 2020).

Finally, reviewing the dedicated literature on R&D tax incentives shows that fewer evaluations look at the long-term effect on R&D additionality (see Mulkay & Mairesse, 2013; Labeaga *et al.*, 2014, as an illustration). This bulk of studies stresses the importance of adjustment costs in learning how to claim, and the persistence of using this indirect instrument after bearing the initial costs of claiming (Labeaga *et al.*, 2020). Further research may also examine more systematically the impact of R&D tax incentives on output additionality. Evidence remains scant (Czarnitzki *et al.*, 2011; Dechezleprêtre *et al.*, 2020) and intensifying the efforts would provide an interesting lens to discuss R&D relabelling issues across schemes.

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Appendices

A Data collection

Table 7: JEL codes

	Category
H25	Business Taxes and Subsidies
H32	Firm
H42	Publicly Provided Goods
L13	Oligopoly and Other Imperfect Markets
O38	Government Policy
O32	Management of Technological Innovation and R&D
O31	Innovation and Intervention: Process and Incentives

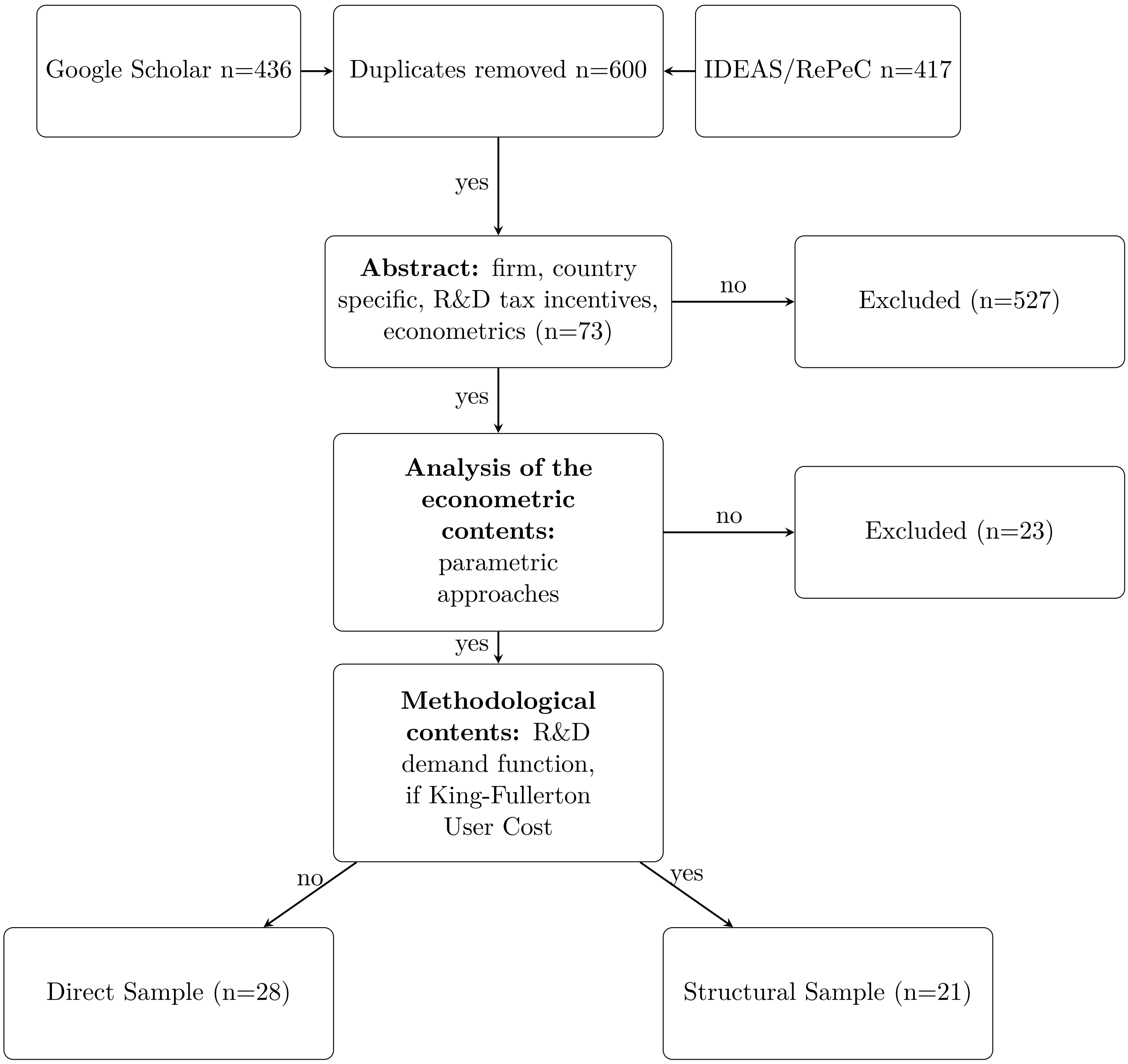

Figure 2: Selection process and inclusion criteria

B Estimates across publications and periods

Table 8: Composition of the structural approach sample: periods evaluated across studies

Study	Country	Period	avg_PCCtstat	obs
Agrawal *et al.* (2014)	Canada	2000-2007	-18.23	10
Baghana & Mohnen (2009)	Canada	1997-2003	-2.01	4
Crespi *et al.* (2016)	Argentina	1998-2004	-8.76	18
Domínguez (2006)	Spain	1991-1999	-2.54	4
Domínguez *et al.* (2008)	Spain	1991-1999	-7.56	32
Fowkes *et al.* (2015)	UK	2003-2012	-1.96	4
Guceri & Liu (2019)	UK	2002-2011	-0,9	3
Hall (1993)	USA	1980-1991	-9.41	5
Harris *et al.* (2009)	UK	1998-2003	-5.87	1
Jia & Ma (2017)	China	2009-2013	-1.43	16
Koga (2003)	Japan	1991-1998	-8.89	6
Labeaga *et al.* (2014)	Spain	2001-2008	-2.61	36
Lokshin & Mohnen (2007)	Netherlands	1996-2004	-2.71	5
Lokshin & Mohnen (2012)	Netherlands	1996-2004	-3.33	3
Mulkay & Mairesse (2008)	France	1983-2002	5.71	1
Mulkay & Mairesse (2011)	France	1981-2007	2.00	1
Mulkay & Mairesse (2011)	France	1991-2003	-1.00	1
Mulkay & Mairesse (2011)	France	2004-2007	0.81	4
Mulkay & Mairesse (2013)	France	2000-2007	0.00	5
Mulkay & Mairesse (2018)	France	1999-2007	-3.20	2
Mulkay & Mairesse (2018)	France	2008-2013	-1.95	2
Rao (2010)	USA	1981-1991	-8.99	2
Rao (2010)	USA	1982, 1986-1990	-6.71	20
Rao (2013)	USA	1986-1990	-4.11	22
Rao (2016)	USA	1986-1990	-3.69	12
Thomson (2010)	Australia	1990-2005	-0.07	8

Note: French estimates consider R&D adjustment costs in their estimations, exhibiting an increase in R&D in the long run.

Table 9: Composition of the direct approach sample: periods evaluated across studies

Study	Country	Period	avg_PCCtstat	obs
Acheson & Malone (2020)	Ireland	2007-2014	0.60	8
Agrawal *et al.* (2020)	Canada	2000-2007	3.27	18
Aristei *et al.* (2015)	Spain	2007-2009	1.85	3
Berger (1993)	USA	1975-1989	3.40	2
Billings *et al.* (2001)	USA	1992-98	1.04	2
Billings & Fried (1999)	USA	1994	2.25	1
Bozio *et al.* (2014)	France	2004-2010	2.87	6
Cantabene & Nascia (2014)	Italy	2007-2009	2.34	4
Calderón-Madrid (2010)	Mexico	2004-2007	2.46	6
Chen & Li (2018)	Taiwan	2006-2014	4.12	3
Dechezleprêtre *et al.* (2020)	UK	2006-2011	1.92	1
Dechezleprêtre *et al.* (2020)	UK	2009	1.89	1
Dechezleprêtre *et al.* (2020)	UK	2009-2011	2.63	34
Dechezleprêtre *et al.* (2020)	UK	2010	2.50	1
Dechezleprêtre *et al.* (2020)	UK	2011	2.52	1
Dechezleprêtre *et al.* (2016)	UK	2006-2008, 2009-2011	1.42	5
Dechezleprêtre *et al.* (2016)	UK	2009	2.05	1
Dechezleprêtre *et al.* (2016)	UK	2009-2011	2.07	27
Dechezleprêtre *et al.* (2016)	UK	2010	2.69	1
Dechezleprêtre *et al.* (2016)	UK	2011	2.55	1
Dumont (2015)	Belgium	2003-2011	0.13	35
Dumont (2019)	Belgium	2003-2015	0.74	33
Guceri (2015)	UK	1999-2007, 2009-2013	2.02	5
Guceri (2015)	UK	2003-2006, 2008-2012	1.66	1
Guceri (2015)	UK	2003-2006, 2009-2012	1.41	1
Guceri (2015)	UK	2003-2007, 2009-2012	2.79	6
Guceri (2016)	UK	2003-2006, 2009-2012	1.14	10
Guceri (2016)	UK	2003-2006, 2010-2012	0.70	10
Guceri (2016)	UK	2003-2012	1.50	10
Guceri (2013)	UK	1998-2001, 2004-2006	1.50	10
Guceri (2013)	UK	1998-2006	1.70	10
Guceri & Liu (2015)	UK	2002-2006, 2009-2011	2.07	8
Guceri & Liu (2015)	UK	2002-2011	1.01	30
Guceri & Liu (2017)	UK	2002-2006, 2009-2011	2.53	8
Guceri & Liu (2017)	UK	2002-2011	2.24	30
Guceri & Liu (2019)	UK	2002-2006, 2009-2011	2.37	3
Guceri & Liu (2019)	UK	2002-2007, 2009-2011	2.43	7
Haegeland & Møen (2007)	Norway	1993-2005	6.22	35
Ho (2006)	USA	1981-2013	1.43	24
Kasahara *et al.* (2014)	Japan	2001-2003	1.11	20
Kobayashi (2014)	Japan	2000-2003	1.01	12
Kobayashi (2014)	Japan	2003	1.29	36
Paff (2005)	USA	1994-1999	2.34	6
Ravšelj & Aristovnik (2020)	Slovenia	2012-2016	3.76	2
Swenson (1992)	USA	1975-1985	-1.10	3
Swenson (1992)	USA	1975-1988	0.36	3
Thomson & Skali (2016)	Australia	2005-2011	21.55	3
Thomson & Skali (2016)	Australia	2011-2012	2.34	2
Thomson & Skali (2016)	Australia	2012	1.14	7
Yang *et al.* (2012)	Taiwan	2001-2005	2.22	6

Note: Chen & Li (2018)'s have been multiplied by -1,
accounting for the nature of the shock (abolition of tax incentives).

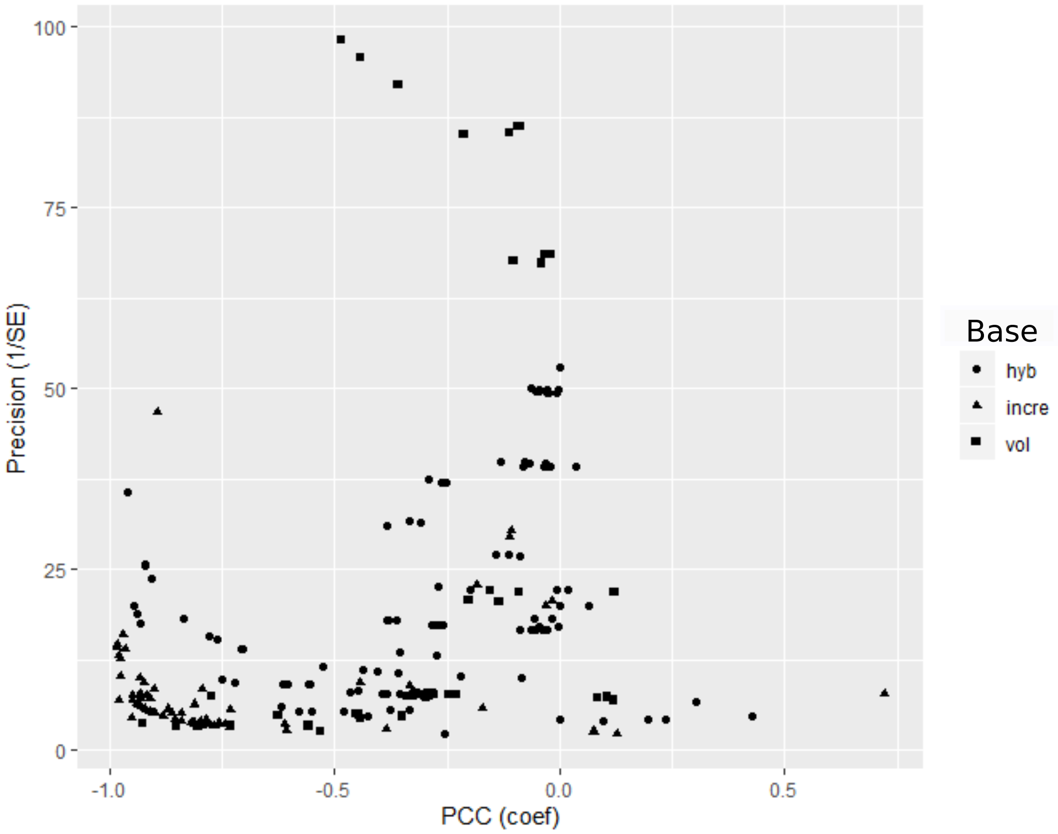

Figure 3: Funnel plot: PCC transformation of structural estimates

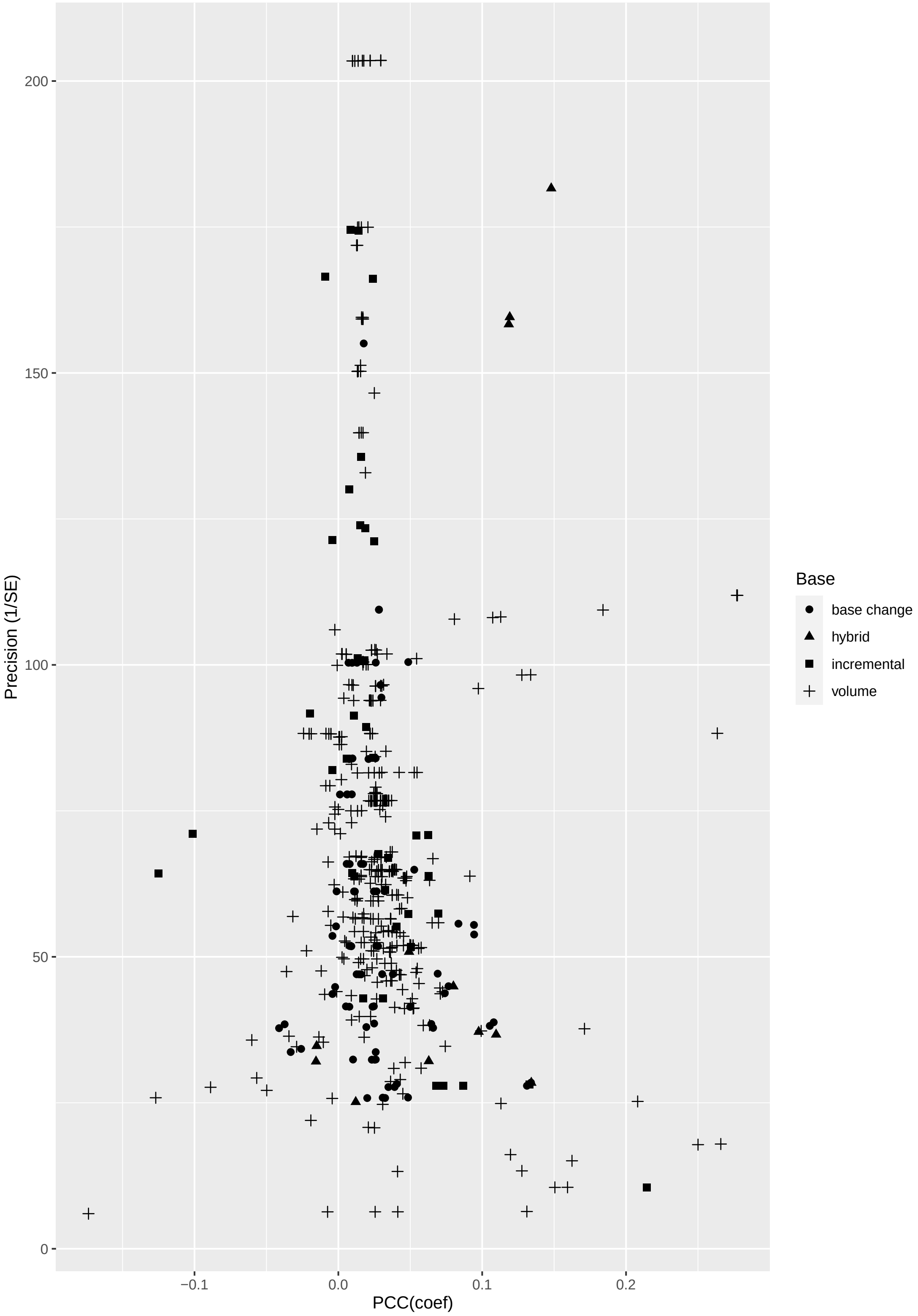

Figure 4: Funnel plot: PCC transformation of direct estimates

C Correlation matrices

Table 10: Correlation matrix of the key variables in the structural approaches sample without US unpublished studies

	incSE	targetedSE	volSE	dedSE	carrySE	appSE	capSE	hybSE
incSE								
targetedSE	-0.01							
volSE	-0.09	0.72****						
dedSE	-0.09	0.13	0.26**					
carrySE	-0.17*	0.86****	0.73****	0.16*				
appSE	-0.14	0.04	-0.11	0.15*	-0.28**			
capSE	0.15*	0.36****	-0.29****	-0.28**	0.26**	0.09		
hybSE	-0.24**	0.36****	-0.28**	-0.13	0.34****	0.21**	0.88****	
SpainpostSE	-0.11	0.39****	-0.13	-0.12	0.43****	-0.20**	0.71****	0.73****

*p<0.05; **p<0.01 ; ***p<0.001 ; ****p<0.0001

Table 11: Correlation matrix of the key variables in the direct approaches sample without UK unpublished studies

	targetedSE	incSE	volSE	dedSE	carrySE	appSE	capSE
incSE	-0.29****						
volSE	0.73****	-0.42****					
dedSE	-0.07	-0.24****	0.17**				
carrySE	0.46****	0.31****	0.53****	0.24****			
appSE	0.16**	-0.11*	0.14**	-0.26****	-0.39****		
capSE	0.17**	0.50****	-0.14*	-0.05	0.12*	0.28****	
hybSE	0.19**	-0.05	-0.19**	0.30****	0.18**	0.01	0.12*

*p<0.05; **p<0.01 ; ***p<0.001 ; ****p<0.0001

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