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Abstract

The volume of work on productivity effects of research and development (R&D) investment has expanded significantly following the contributions of Zvi Griliches and others to microeconometric work in late 1970s and early 1980s. This study aims to meta-analyse the research findings based on OECD firm and industry data, with a view to establish where the balance of the evidence lies and what factors may explain the variation in reported evidence. Drawing on 1,262 estimates from 64 primary studies, we report that the average effect of R&D capital on productivity and the average rate of return on R&D investment are both positive, but smaller than the summary measures reported in previous narrative reviews and meta-analysis studies. We also report that a range of moderating factors have significant effects on the variation among productivity and rates-of-return estimates reported in primary studies. Moderating factors with significant effects include: (i) measurement of inputs and output; (ii) model specifications; (iii) estimation methods; (iv) levels of analysis; (v) countries covered; and (vi) publication type among others.

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1. Introduction

Investment in research and development (R&D) is costly and may remain suboptimal due to positive externalities. In addition, returns on R&D investment are more uncertain compared to other types of investment. Despite these complications, however, R&D investment is considered as a crucial driver of competitiveness. It enables firms and industries to lower production costs and/or provide better-quality goods and services. Given these characteristics, the relationship between R&D investment and productivity has long been a subject of interest for researchers, firm managers and policy makers for a long time.

Innovation is central to Schumpeter's (1942) creative destruction thesis, according to which innovation-driven change is the most important factor that "… revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one'. Solow's (1957) work on growth accounting and decomposition paved the way towards testing Schumpeter's hypothesis at the country and industry levels. At the firm level, the pioneering work is that of Griliches (1973) on R&D capital and productivity and Terleckyj (1974) on R&D and rates of return. The analytical survey of the measurement and estimation issues by Griliches (1979) has instigated a large volume of microeconometric work based mainly on OECD firm and industry data.

The large majority of the empirical work is based on a Cobb-Douglas production function – the so-called approach in which output at the firm or industry level is related to knowledge (R&D) capital in addition to conventional inputs such as labour and physical capital. A minority, on the other hand, has adopted a dual approach, which draws on a system of factor demand equations and cost-function representation of technology. In this meta-analysis, we synthesize the evidence from the *primal approach* only as studies adopting the dual approach are small in number and more heterogeneous in their model specifications.

Several reviews have attempted to synthesize the rich and diverse evidence base. For example, Mairesse and Sassenou (1991) and Mairesse and Mohnen (1994) review the literature on innovation and productivity at the firm and industry levels, respectively. Hall (1996) focuses on rates-of-return estimates, distinguishing between private and social returns to R&D. Cincera (1998) provides systematic summaries of the evidence on both productivity and rates-of-return estimates before presenting own findings based on firm-level data. A recent review by Hall et al. (2010) provides a wide range of summary statistics and a comprehensive evaluation of the analytical and empirical dimensions that characterise the research field. There are also two meta-analysis studies: whilst Wieser (2005) summarises the productivity and rates-of-return estimates at the firm level from 17 primary studies published between 1980-2000; a more recent study by Moen and Thorsen (2013) synthesizes the rate-of-return estimates reported by 41 studies published between 1962-2010.

We have identified a number of issues that may limit the information content and generalizability of the findings reported by existing reviews. First, the latter draw upon a 'representative' or 'preferred' estimate chosen either by authors of the primary studies or by the reviewers themselves. The chosen estimate is usually presented together with a measure of within-study variation, but this practice implies inefficient use of information as a large number of estimates reported in the primary studies are excluded from the analysis. More importantly, however, reliance on a 'preferred' or 'summary' measure may amplify the *publication selection bias* that may be due to preferences of primary study authors or journal editors to publish 'significant effects' (Egger et al., 1997; Stanley and Doucouliagos, 2012).

The second issue relates to a potential sampling bias that may arise from the lack of verifiable criteria used to include (or exclude) primary studies. True, the existing reviews follow a cascading approach, which involves updating the list of previously reviewed studies. Although a properly-conducted cascading approach may allow for replication and extension as methods of verification, the absence of inclusion/exclusion criteria limit the verifiability of the presented syntheses of the evidence base.

The third issue relates to how existing reviews quantify the effects of moderating factors on the variation among primary study estimates. The narrative reviews rely on 'vote counting' to decide whether a moderating factor (e.g., estimation method, measure of inputs or output, sample characteristics, etc.) is associated with systematically larger or smaller estimates. Of the meta-analysis studies, Wieser (2005) controls for a number moderating factors within a multiple meta-regression framework. However, the selective nature of the evidence base raises questions about the robustness of the reported findings. On the other hand, Moen and Thorsen (2013) estimate the degree of publication selection bias; however they do not account for the effects of moderating factors on the heterogeneity of the estimates reported in primary studies.

To address these issues this study is organised in three sections. Section 2 provides an overview of the analytical and empirical frameworks that underpin the productivity and rates-of-return estimates reported in primary studies. In section 3 we present the meta-analysis methodology - including the search and study selection criteria; the data extraction and coding procedures; and the meta-regression methodology used. In section 4 we present the meta-analysis findings, using 1,262 estimates from 64 studies. Of these, 443 are elasticity estimates in the level dimension, 469 are estimates of elasticities in the temporal dimension; and 350 are rates-of-return estimates. The primary study estimates are based on OECD firm or industry data; and are extracted from studies published between 1980 and July 2013.

We focus on studies investigating OECD firms and industries for three reasons. First, we wish to avoid excessive heterogeneity in the evidence base that may be due to wider differences in R&D data quality when both OECD and non-OECD countries are included. Secondly, we wish to control if the elasticity or rates-of-return estimates differ between developed countries because of differences in their R&D intensiveness. Third, studies on OECD firms and industries have been repeated and as such they allow for testing whether the effect-size estimates have changed over time.

2. The analytical and empirical framework of the R&D and productivity literature

The primary studies usually draw on a Cobb-Douglas production function, augmented with knowledge (R&D) capital as a factor of production. Assuming perfect competition in factor markets, unit elasticity of substitution between factors, and separability of the conventional inputs (capital and labour) from past and current R&D investments, the Cobb-Douglas production function can be stated as:

$$Y_{it} = Ae^{\lambda t}C_{it}^{\alpha}L_{it}^{\beta}K_{it}^{\gamma}e^{u_{it}} \tag{1}$$

Where, Y is deflated output (sales or production or value-added); C is deflated physical capital stock; K is deflated knowledge capital; L is labour (number of employees or hours worked); λ is rate of disembodied technological change; and A is a constant. Taking natural logarithms and using lower-case letters to denote logged values, t to denote time and i to denote firm or industry, the econometric model to be estimated can be written as:

$$y_{it} = \eta_i + \lambda t + \alpha c_{it} + \beta l_{it} + \gamma k_{it} + u_{it} \tag{2a}$$

In (2a), the log of technical progress ($Ae^{\lambda t}$) yields a firm- or industry-specific effect (ηi) and a time effect (λt). Although the Cobb-Douglas production function assumes constant returns to scale, model (2a) can be estimated with and without restriction on the coefficients of capital, labour and knowledge capital. Different specification about returns to scale can be tested explicitly through model (2b) below, where logged labour is subtracted from both sides of equation (2a).

$$(y_{it} - l_{it}) = \eta_i + \lambda t + \alpha(c_{it} - l_{it}) + \gamma(k_{it} - l_{it}) + (\mu - 1)l_{it} + u_{it} \tag{2b}$$

Here, $\mu = \alpha+\beta+\gamma$ and it implies constant returns to scale if $\mu =1$ but increasing returns to scale if $\mu >1$ or decreasing returns to scale if $\mu <1$. Both (2a) and (2b) can be estimated to obtain *output elasticities* with respect to knowledge capital (γ) as well as the conventional inputs of capital and labour (α and β, respectively).

Usually, knowledge capital (K) is constructed using the perpetual inventory method (PIM), in which knowledge capital is a linear function of all past R&D investments with no diminishing returns, but subject to depreciation (Griliches, 1979).

$$\begin{aligned} K_{it} &= (1-\delta)K_{i,t-1} + R_{it} \\ &= R_{it} + (1-\delta)R_{i,t-1} + (1-\delta)^2 R_{i,t-2} + (1-\delta)^3 R_{i,t-3} + \cdots \\ &= \textstyle\sum_{\tau=0}^{\infty}(1-\delta)^{\tau} R_{i,t-\tau} \end{aligned} \tag{3a}$$

Here, δ is the rate of depreciation for R&D capital and τ is the number of years in the pre-sample period. Hence, the initial level of knowledge capital can be calculated as follows:

$$K_{i0} = \sum_{\tau=0}^{\infty}(1-\delta)^{\tau} R_{i,0-\tau} = R_{i0} \sum_{\tau=0}^{\infty} \frac{(1-\delta)^{\tau}}{(1-g)} = \frac{R_{i0}}{(g+\delta)} \qquad (3b)$$

where, g is the annual growth rate of R&D investment in the pre-sample period. This is either calculated from the R&D series over a period of τ years prior to initial year in the panel or assumed to be 5% on average if the R&D series is not long enough.

The depreciation rate (δ) is usually assumed at 15%. This assumption is informed by depreciation rates estimated directly in some studies [for example, 10%-15% in Bosworth (1978); 20% or 25% in Klette (1994) or Pakes and Schankerman (1984); 15% - 36% in Hall (2005)]. A number of studies report that elasticity estimates are not sensitive to changes in the depreciation rate assumed (Griliches and Mairesse, 1983, 1984; Harhoff, 1994; Hall and Mairesse, 1995; Bartelsman et al., 1996). Assumed depreciation rate does not affect the rate-of-return estimates either because the latter are based on R&D intensity rather than R&D capital. Hall and Mairesse (1995) demonstrate that the growth rate of R&D investment (g) affects only the initial R&D capital stock. Various studies report that elasticity estimates are not sensitive to assumed growth rate either (Hall and Mairesse, 1995; Bartelsman et al, 1996; Verspagen, 1995).

Two further issues arise when the primal model is used for estimating R&D elasticities: (i) the appropriateness of the perpetual inventory method (PIM) for constructing the R&D capital; and (ii) whether one should assume equality of elasticities or rates of return across firms.

Although PIM remains the most frequently used method for constructing R&D capital, several contributors indicate that alternative specifications constitute a useful avenue for future research (Griliches, 1979; Bitzer and Stephan, 2007; and Hall et al., 2010). Therefore, in this review, we control for different methods of constructing R&D capital to verify if the productivity estimates differ systematically between studies using the PIM or alternative methods.

The constant elasticity assumption overlooks the possibility that firms may choose different factor shares, depending on the competitive equilibria they are faced with. Most contributors relax this assumption and utilise a rates-of-return version of the production function, where rates-of-return equality is assumed. In this review, we synthesize the evidence on both elasticity and rates-of-return estimates separately.

Rates of return estimates are obtained by expressing model (2a) in first-difference instead of levels. This yields:

$$\Delta y_{it} = \Delta\lambda t + \alpha\Delta c_{it} + \beta\Delta l_{it} + \gamma\Delta k_{it} + \Delta u_{it} \qquad (4a)$$

Note that the firm- or industry-specific fixed effect term (η_i) has disappeared and the time effect is now a growth rate effect relative to the initial observation rather than a level effect.

By definition, the elasticity of output with respect to R&D capital is $\gamma = (\delta Y_{it}/\delta K_i)\,(K_{it}/Y_{it})$. Given that $(\delta Y_{it}/\delta K_i) = \rho$ is the marginal productivity of R&D capital, (4a) can be re-written as:

$$\Delta y_{it} = \Delta\lambda t + \alpha\Delta c_{it} + \beta\Delta l_{it} + \rho(K_{it}/Y_{it})\,\Delta k_{it} + \Delta u_{it} \qquad \text{(4a')}$$

The terms for knowledge capital simplify as follows:

$$\rho(K_{it}/Y_{it})\,\Delta k_{it} = \rho(K_{it}/Y_{it})\,(\Delta K_{it}/K_{it}) = \rho(\Delta K_{it}/Y_{it}) = \rho(K_{it} - K_{it-1})/Y_{it}$$

$$= \rho\frac{(1-\delta)K_{it-1} + R_{it} - K_{it-1}}{Y_{it}} = \rho\frac{R_{it} - \delta K_{it-1}}{Y_{it}} \cong \rho\frac{R_{it}}{Y_{it}}$$

If the depreciation rate (δ) is close to zero. Consequently, equation (4a) can be rewritten as (4b) below, where (ρ) is the gross rate of return on R&D investment and (R_{it}/Y_{it}) is R&D intensity.

$$\Delta y_{it} = \Delta\lambda t + \alpha\Delta c_{it} + \beta\Delta l_{it} + \rho\frac{R_{it}}{Y_{it}} + \Delta u_{it} \qquad \text{(4b)}$$

Model (4b) allows for estimating gross rates of return on R&D investment, using output growth. However, (4b) can be manipulated to estimate rates of return based on total factor productivity (TFP) growth. This is done by subtracting the terms for conventional inputs (physical capital and labour) from both sides of (4b), leading to:

$$\Delta TFP_{it} = \Delta\lambda t + \rho\frac{R_{it}}{Y_{it}} + \Delta u_{it} \qquad \text{(4c)}$$

R&D rates of return can also be obtained from the definition of the R&D elasticity (γ). As indicated above: $\gamma = (\delta Y_{it}/\delta K_i)\,(K_{it}/Y_{it}) = \rho(K_{it}/Y_{it})$, where ρ is the marginal product of R&D capital. From here;

$$\rho = \gamma/(K_{it}/Y_{it}) = \gamma(Y_{it}/K_{it}) \qquad \text{(4d)}$$

Here, Y_{it} and K_{it} are sample means of output and R&D capital, respectively. A small number of studies in the sample provide rates-or-return estimates based on (4d). We have included such estimates only if they are reported together with their standard errors (which are calculated by primary study authors using the delta method).

Unlike elasticity estimates that are comparable across studies, caution is required in interpreting rates-of-return estimates for two reasons. First, there is a consensus in the literature that rates-of-return estimates should be considered as excess rates of return when they are obtained indirectly (i.e., in accordance with 4d) (see, Griliches, 1979; Schankerman, 1981; and Hall et al., 2010). Excess returns reflect either a risk premium or a supra-normal rate of profit on R&D investments. However, Griliches (1980a: 389) points out that this interpretation is valid only when the elasticity estimates (γ) are in the level dimension (see below on the difference between 'level' and 'temporal' dimensions).

The second difficulty arises when primary studies try to account for the effect of double-counting on rates-of-return estimates. The double-counting problem arises when R&D capital expenditures and R&D personnel are counted twice: once on their own and once as part of the physical capital (C) and labour (L). Failure to deduct R&D capital and R&D personnel from conventional inputs is associated with a downward bias in the elasticity estimates (Griliches, 1979, 1980a; Schankerman, 1981; Harhoff, 1994; Mairesse and Hall, 1994; and Hall et al., 2010). Therefore, excess rates-of-return estimates will be biased downwards when calculated indirectly in accordance with (4d). Schankerman (1981) demonstrates that the downward bias is usually around 10% and will be observed unless R&D capital and R&D labour remain constant.

However, there has been no systematic effort to verify if this particular type of downward bias also remains when rates of return are estimated directly, using model (4b) or (4c). Therefore, in the multivariate meta-regression, we control for whether primary studies correct the double-counting problem – and we do this not only in elasticity estimates in the level and temporal dimensions but also in rates-of-return estimates based on (4b), (4c) and (4d).

Another dimension of the research field that may affect the reported estimates relates to differences in econometric specifications in the context of panel data models, including: (i) level and first-difference specifications; (ii) static or dynamic production functions; and (iii) differences in the range of control variables used to capture the effects of capacity utilization, spill-overs, and industry/time dummies, etc.

To highlight the difference between the elasticity estimates in 'level' and temporal' dimensions, consider the error term in model (2a). This can be written as:

$$\varepsilon_{it} = \eta_i + \lambda_t + u_{it} \qquad (5)$$

Where, η_i is the cross sectional unit-specific effect (e.g., firm-specific managerial quality or industry-specific technology, etc.); λ_t is the time-specific effect (e.g., technological change or exchange rate variation); and u_{it} is the idiosyncratic error term that captures random sources of errors and disturbances.

One possible approach would be to assume that η_i and λ_t are constant across all units and time periods, respectively Another approach would be to eliminate the time effects by estimating the model for each period (*cross-section estimation*) or taking the average values over a time period (*between estimates*). In the literature, results from both types of estimation are classified as elasticity estimates that emphasize the *c*ross-section variation in the *levels* of the R&D capital and other inputs. In this study, we will refer to such estimates as *elasticity estimates in the level dimension*.

Another approach would be to estimate the model by using *first differences* of the variables or a *within estimator* where the variable's deviation from the individual mean is taken into account. In both cases, the *unit-specific fixed effect* disappears and the elasticity estimates are referred to as *elasticities in the level dimension*.

The elasticity estimates in the *level* and *temporal* dimensions will be consistent and similar if equation (2a) is specified correctly. In practice, however, different control variables are used in addition to inputs. For example, some primary studies control for spill-over effects (e.g., Aiello and Cardamone, 2005: Blanchard et al., 2005; Cincera, 1998; Hanel, 2000; and Los and Verspagen, 2000); whilst others do not (e.g., Bartelsman et al., 1996; Griliches, 1980a and 1980b; Griliches and Lichtenberg, 1984; and Hall, 1993). Also, in contrast to the majority of studies that use a *static* Cobb-Douglas production function specification, some studies use a *dynamic* specification (e.g., Aldieri et al, 2008; Anon and Higon, 2007; Ballot et al, 2006; and Griffith et al., 2004) or a *translog* version of the production function (e.g., Cameron et al., 2005; Lehto, 2007; and Smith et al., 2004). Such specification differences are potential sources of heterogeneity in elasticity estimates reported by primary studies.

The practice in this research field is to pool the elasticity estimates within two clusters reflecting the *level* and *temporal* dimensions; and to treat the rates-of-return estimates as a third cluster where the estimates are based on R&D intensity rather than R&D capital. We will follow this practice and meta-analyse the evidence in three clusters: two clusters encompassing elasticity estimates in *level* and *temporal* dimensions; and one cluster including *rates-of-return* estimates.

However, even if we pool the evidence into three clusters estimates within each cluster can still exhibit a high degree of heterogeneity due to a wide range of *moderating factors* that reflect other dimensions of the research field. Therefore, we conduct multivariate meta-regression analysis (MRA) after having estimated the 'average' elasticity and rates-of-return estimates for each cluster of the evidence base. The MRA model draws on Stanley and Doucouliagos (2012) and allows for explicit modeling of the sources of heterogeneity in the evidence base. The moderating factors that constitute the sources of observed heterogeneity in the evidence base are summarised in Table 1 below.

Table 1: Sources of variation in the evidence base

Moderating factor (source of variation)	Indicator
Publication type	Journal articles; working papers; report; book chapters; etc.
Data time dimension	Mid-year of the time dimension of the data
Country of origin for the data	Firm or industry data from UK, US, France, Germany or other OECD countries
Level of analysis/aggregation	Analysis with firm or industry data
Model specification	Dynamic *versus* static production functions; Cobb-Douglas *versus* Translog production functions; control for spill-over effects or capacity utilisation *versus* no control; and constant *versus* variable returns to scale specification, etc.
Econometric specification	Control for time and industry dummies; control for spillovers, instrumental *versus* non-instrumental estimation methods; etc.
Measures of output	Whether output is measured as sales, production or value-added
Measure of R&D capital	Whether R&D capital is constructed via perpetual inventory or other methods
Sample differences	Different samples for type of R&D (basic *versus* applied research); source of finance for R&D investment (own funds *versus* government funds); R&D-intensity of the firms/industries in the sample; firm size (small *versus* large firms); etc.

Meta-regression is a quantitative method of reviewing the literature in a well-defined research field. It provides quantitative and verifiable answers to four questions about the effects of R&D investment at the firm or industry level: (i) What is the 'average' effect of R&D capital on firm/industry productivity after controlling for publication selection bias? (ii) What is the 'average' rate of return on R&D investment after controlling for publication selection bias? (iii) How do moderating factors that reflect the observable dimensions of the research field affect the elasticity or rates-of-return estimates reported in primary studies? (iv) What are the conditional productivity or rates-of-return estimates when certain assumptions are made about the moderating factors?

3. Meta-analysis: procedures and method

For meta-analysis, we followed the best-practice recommendations that reflect the consensus among the community of meta-analysts in economics, business and public policy fields (Stanley et al., 2013). To locate the relevant studies, we conducted electronic searches in nine (9) databases, using 13 search terms for searches in the *Title* and 20 search terms for searches in the *Abstract* fields. The list of databases and search terms, together with an explanation of the search routine, are given in *Appendix A1*.

We uploaded the search results on to EPPI-Reviewer - a systematic-review-software developed and maintained by the Institute of Education (London).[1] Search results and exclusion decisions at each stage of the selection process are given in Table 2 below.

Table 2: Study selection process: R&D and productivity in OECD firms and industries

Search Results	• Total hits from *electronic searchers*	947
	• Studies located through *handsearch* and *snowballing*	32
	• **Total number of studies in the pool**	**979**
Srage-one decisons	• Studies excluded as *duplicates*	(- 297)
	• Studies that fail one or more *stage-one criteria*	(- 343)
	• **Studies transferred to stage two**	**339**
Stage-two decisions	• Studies that fail one or more *stage-two criteria*	(- 275)
	• **Number of studies included for meta-analysis**	**64**

Stage-one decisions were based on title and abstract information for each study, whereas stage-two decisions were based on full-text information. In both stages, two reviewers read the relevant information and coded the studies in accordance with pre-defined inclusion/exclusion criteria. A study was excluded if it 'satisfied' at least one of the exclusion criteria specified in Table A2.1 in *Appendix A2*. At stage one, 297 duplicate studies were excluded, together with 343 studies that satisfied at least one of the exclusion criteria. The frequencies with which an exclusion criteria have featured in the exclusion decisions are

[1] For information, see http://eppi.ioe.ac.uk/cms/Default.aspx?alias=eppi.ioe.ac.uk/cms/er4.

given in Table A2.2 for stage-one decisions and in Table A2.3 for stage-two decisions (see, *Appendix A2*).

In stage one, the exclusion criteria invoked with high frequency consisted of the following: investigation of an irrelevant independent and/or dependent variables (34.3%); studies that are descriptive in nature (20.7%); theoretical/analytical studies without an empirically-tested model (10.8%); and studies that utilize innovation measures other than R&D investment (12.4%).

At stage two, of the total exclusion criteria invoked 34.8% involved studies that do not follow the primal (production function) approach. The second most common set of exclusion criterion invoked (26.1%) relates to studies that utilize an input-output model of innovation proposed by Crepon et al (1998) – the so-called Crepon-Duguet-Mairesse (CDM) model. In this approach, R&D investment determines innovation output (usually, patents or number of product or process innovations introduced) that in turn affects productivity. This is followed by exclusion decisions that relate to studies investigating the effect of R&D on size distribution of the firms (Gibrat's Law) or those utilizing an R&D dummy only as opposed to R&D capital or R&D intensity.

Two reviewers extracted *all* elasticity and rates-of-return estimates reported in included studies, together with associated standard errors, t-values or p-values as the case may be. Each extracted estimate was coded systematically to capture the wide range of moderating factors that may bear upon its size and standard error. Extracted data and coding was checked systematically to identify and correct any typing or coding error. Data extraction yielded 1,262 estimates in total. Of these, 443 are estimates of level/total elasticities; 469 are estimates of temporal elasticities; and 350 are rates-of-return estimates.

First, we calculate fixed-effect weighted means (FEWMs) per study and for each evidence cluster, calculated in accordance with (6) below.

$$\bar{X}_{fee} = \sum e_i(1/SE_i^2)/\sum(1/SE_i^2) \qquad (6)$$

Here, e_i is the *elasticity* or *rate-of-return* estimate and SE_i is the associated standard error reported in primary studies. The weight $(1/SE_i^2)$ is precision-squared and allows the FEWM to take account of within-study variation by assigning lower weights to estimates with larger standard errors. As a summary measure, FEWMs are better than simple means; however, they cannot be taken as measures of genuine effect if the estimates reported in primary studies are subject to publication selection bias and/or they are affected by within-study dependence due to data overlap. Therefore, we provide FEWMs only to summarise the research field and indicate the extent of heterogeneity therein.

To estimate 'genuine effect' beyond publication selection bias and account for sources of heterogeneity in the evidence base, we draw on recent contributions to meta-regression analysis (MRA) of economics research (Stanley, 2005 and 2008; Doucouliagos and Stanley, 2012 & 2013; and Stanley and Doucouliagos, 2012 & 2013a). These contributions draw on

Egger et al. (1997) who posited that researchers with small samples and large standard errors would search intensely across model specifications, econometric techniques and data measures to find sufficiently large (hence statistically significant) effect-size estimates. Given this assumption, publication selection bias can be expressed as:

$$e_i = \alpha_0 + \beta_0 SE_i + u_i \tag{7}$$

In (7), e_i is the effect-size estimate (elasticity or rates-of-return estimate) reported in primary studies and SE_i is the associated standard error. Rejecting the null hypothesis of $\beta_0 = 0$ indicates the presence of publication bias. This is also known as the funnel-asymmetry test (FAT), which reflects the asymmetry of the funnel graphs that chart the effect-size estimates against their precisions.[2] On the other hand, testing for $\alpha_0 = 0$ is a test for whether genuine effect exists beyond publication selection bias.

However, model (7) suffers from three weaknesses. First, the test for publication selection is known to have low power: it often fails to detect publication selection bias when the latter exists (Egger et al, 1997; Stanley, 2008). Secondly, the model is evidently heteroskedastic because reported estimates have widely different standard errors (and thereby different variances). Therefore the error term (u_i) cannot be assumed as independently and identically distributed (i.i.d.), with the implication that ordinary least-squares (OLS) is not an appropriate estimator. Third, simulations results indicate that the relationship between reported estimates and their standard errors is non-linear. Stanley and Doucouliagos (2012, 2013) argue that it is more appropriate to relate the reported estimates to their variance (SE_i^2) rather than their standard error (SE_i) as originally argued by Egger et al. (1997).

To address these heteroskedasticity and specification issues, Stanely (2008) and Stanley and Doucouliagos (2012) propose two solutions. First, and in line with a long-standing practice in meta-analysis, they propose a weighted least squares (WLS) version of model (6). The WLS version is obtained by weighting both sides of model (6) with the precision ($1/SE_i$) of the primary study estimates, leading to:

$$t_i = \alpha_0 \left({}^{1}\!/_{SE_i} \right) + \beta_0 + v_i \tag{8}$$

Here t_i is the t-value reported in the primary study (or calculated as e_i/SE_i when standard errors are reported instead of t-values); and the error term $v_i = u_i/SE_i$.

Testing for $\beta_0 = 0$ is the test for publication selection bias whereas the test for $\alpha_0 = 0$ is the precision-effect test (PET). The PET allows for establishing whether genuine effect exists beyond publication selection bias. Under the Gauss-Markov theorem, the ordinary least square estimation of the WLS model in (8) yields the best (minimum-variance) linear unbiased estimates. However, further issues need to be addressed while estimating this model.

[2] Funnel graphs for the three evidence clusters are presented in *Appendix 3* to enable visual inspection of the publication selection bias.

The first relates to within-study dependence and study-specific fixed effects. Within-study dependence occurs when multiple estimates reported by one study are based on the same dataset or a subset thereof. The study-specific fixed effect, on the other hand, may be due to a combination of unobservable factors that remain the same within each study and affect each of the estimates reported by that study. To take account of these issues, we estimate model (8) with both cluster-robust standard errors and a fixed-effect (FE) estimator with robust standard errors. If both estimations indicate significance, we can have more confidence in the presence of genuine effect beyond selection bias (Stanley and Doucouliagos, 2012).

The second issue relates to the effects of overly influential observations. To address this issue, we use the DFBETA routine in *Stata*. This routine calculates the difference between the regression coefficient when the i^{th} observation is included and excluded. The difference is scaled by the estimated standard error of the coefficient. Observations with |DFBETA| > 1 are considered to have undue influence and are excluded from the estimation.

The third issue concerns the non-linear relationship between the effect-size estimates and their standard errors reported in primary studies. The WLS model need to take account of this non-linear relationship – particularly when the precision-effect test (PET) from (8) indicates the existence of genuine effect (i.e., when $\alpha_0 \neq 0$)(Stanley and Doucouliagos, 2012 & 2013a). The precision-effect test with standard errors (PEESE) model can be stated as follows:

$$e_i = \alpha_0 + \beta_0 SE_i^2 + u_i \qquad (9a)$$

The weighted least-squares version of which is:

$$t_i = \alpha_0 \left({}^{1}\!/_{SE_i} \right) + \beta_0 SE_i + v_i \qquad (9b)$$

When estimated without a constant term, model (9b) corrects for non-linear relationship between the elasticity or rates-of-return estimates and their standard errors. Moreno et al (2009) state that model (9b) provides a 'novel method to deal with publication biases' and recommend it for taking account of selection bias in published antidepressant clinical trials. It should also be added that the WLS estimator used in estimating models (8) or (9b) does not require that the error term be distributed normally or the variances have any particular structure (Stanley and Doucouliagos, 2013b). Indeed, it allows for modelling heterogeneity through any variance structure (additive or multiplicative) as long as individual variances are known. This condition is satisfied here because the individual variance is nothing but the square of the standard error associated with the reported estimate (SE_i^2).

The PET-FAT routine enables us to verify if R&D capital has a significant effect on productivity or if the rates of return on R&D are positive after controlling for publication selection bias and other types of biases that may be due to within-study dependence and study-specific fixed effects. Doucouliagos and Stanley (2009, 2012) suggest that the selection bias should be considered as substantial if estimation of model (8) yields $|\beta_0| \geq 1$ and as severe if it yields $|\beta_0|$

≥ 2. If $\alpha_0 \neq 0$, we infer genuine effect beyond publication selections bias. However, this effect must be corrected for the non-linear relationship between the effect estimates and their standard errors, using model (9b). In other words, if genuine effect is established in the PET-FAT model of (8), the correct size of the effect is obtained by estimating model (9b) without constant.

The 'average' effect estimated via (9b) is more reliable than the FEWM because it takes account of any publication selection bias. Nevertheless, it generalizability to other contexts is limited for two reasons. First, it measures a 'typical effect' assuming that all moderating variables that affect the primary study findings (apart from precision) are equal to their sample means. Secondly, unobserved heterogeneity may have substantial effect on the variation among primary study findings.

Drawing on Higgins and Thompson (2002: 1546-47), we measure the effect of unobserved heterogeneity (I^2) as follows:

$$I^2 = (MSE - 1)/MSE \qquad (10)$$

where MSE is the mean error sum of squares of the meta-regression model in (9b). Heterogeneity would have substantial effect on between-study variation if it accounts for more than 50% of the variation among the estimates reported in primary studies. However, this benchmark is tentative and "... the practical impact of heterogeneity in a meta-analysis also depends on the size and direction of 'treatment effects'".

Although unobserved heterogeneity limits the generalizability of the PEESE estimate, the latter is more reliable than the fixed-effect weighted means (FEWMs) or any other summary estimate because: (i) it takes account of publication selection bias; (ii) corrects for the non-linear relationship between primary-study estimates and their standard errors; and (iii) takes account of within-study dependence and study-specific fixed effects.

More importantly, however, the meta-regression model can be extended to estimate how observable sources of heterogeneity affect the reported estimates in a consistent manner. The multivariate version of the meta-regression can be stated as follows:

$$t_i = \beta_0 + \alpha_0(1/SE_i) + \sum \alpha_j Z_{ji}/SE_i + \epsilon_i \qquad (11)$$

As before, $1/SE_i$ is precision, Z_{ji} is a vector of moderating factors that capture the sources of variation in the evidence base, and ϵ_i is the disturbance term due to sampling error. All covariates (moderating variables) in (10) are weighted by precision ($1/SE_i$); and the model is estimated with both cluster-robust and fixed-effect estimation to take account of within-study dependence and study-level fixed effects.

In estimating model (11), we minimise the risk of over-specification and multicollinearity by following a general-to-specific estimation procedure, whereby we omit the *most insignificant* variables (variables associated with the largest *p-values*) one at a time until all remaining covariates are statistically significant in the standard WLS estimation. The specific model thus obtained is then estimated with cluster-robust standard errors and heteroskedasticity-robust fixed-effect estimator to take account of within-study dependence and study-specific fixed effects. After estimating the specific model with three specifications, we interpret the estimation results as follows:

a) The effect of the moderating variable on elasticity or rates-of-return estimates is supported by *strong evidence* if the coefficient of the moderating variable in question remains significant across three specifications;
b) The effect of the moderating variable on elasticity or rates-of-return estimates is supported by *moderate evidence* if the coefficient of the moderating variable in question remains significant across two specifications;
c) The effect of the moderating variable on elasticity or rates-of-return estimates is supported by *weak evidence* if the coefficient of the moderating variable in question is significant in one specification only.

We discuss the effect of a moderating factor (a research dimension) and how our finding concerning that affect compares with existing reviews only if the said effect is supported by medium or strong evidence.

4. **Meta-analysis results: R&D effects and sources of heterogeneity**

Fixed-effect weighted means (FEWMs) are presented in Tables 3a – 3c below for: (a) elasticity estimates in the level dimension; (b) elasticity estimates in the temporal dimension; and (c) rates-of-return estimates. The FEWM is 0.053 for elasticities in the level dimension (Table 3a), 0.012 for elasticities in the temporal dimension (Table 3b), and 11.5% for the rates of return (Table 3c). They indicate that knowledge capital has a positive but small effect on productivity, and the average rate of return on R&D investment is 11.5%. These findings are smaller than what is reported in existing reviews. For example Wieser (2005) report an average productivity effect (elasticity) in excess of 0.10 whereas Hall et al (2010) report an average elasticity of 0.08 for the level and temporal dimensions taken together. The rates of return are reported to be in the range of 20% to 30% by Hall et al (2010), at 28.3% on average by Wieser (2005), and at 18.2% in Moen and Thorsen (2013).

Table 3a: Fixed-effect weighted means (FEWMs) for estimates in level dimension

Study	Publication type	Unit of analysis	Country	Observations	FEWM	Std. Dev.	Min	Max
1. Aldieri et al (2008)	Journal article	Firm	US	4	0.271	0.018	0.250	0.290
2. Ballot et al (2006)	Journal article	Firm	OECD-other, France	10	0.054	0.012	0.025	0.135
3. Bartelsman (1990)	Working paper	Firm	US	6	0.006	0.007	-0.005	0.149
4. Bartelsman et al (1996)	Report	Firm	OECD-other, France	12	0.016	0.013	0.003	0.076
5. Blanchard et al (2005)	Journal article	Firm	France	6	0.085	0.018	0.080	0.168
6. Boler et al (2012)	Working paper	Firm	OECD-other, France	5	0.034	0.021	0.020	0.100
7. Bond et al (2002)	Working paper	Firm	UK, Germany	6	0.061	0.010	0.053	0.083
8. Bonte (2003)	Journal article	Industry	Germany	2	0.026	0.002	0.024	0.028
9. Cincera (1998)	Thesis	Firm	OECD-other, France	10	0.136	0.070	0.080	0.470
10. Cuneo and Mairesse (1984)	Working paper	Firm	France	10	0.159	0.060	0.058	0.209
11. Eberhardt et al (2013)	Journal article	Industry	OECD-other, France	15	0.092	0.023	-0.107	0.462
12. Frantzen (2002)	Journal article	Industry	OECD-mixed	7	0.164	0.022	0.147	0.202
13. Griffith et al (2006)	Journal article	Firm	UK	14	0.020	0.008	0.004	0.033
14. Griliches (1980b)	Book chapter	Firm	US	22	0.059	0.019	0.029	0.186
15. Griliches (1998)	Journal article	Firm	US	12	0.122	0.028	0.044	0.247
16. Griliches and Mairesse (1981)	Working paper	Firm	US	14	0.146	0.082	-0.007	0.292
17. Hall (1993)	Journal article	Firm	US	75	0.028	0.029	-0.262	0.648
18. Hall and Mairesse (1995)	Journal article	Firm	US	14	0.230	0.028	0.176	0.254
19. Harhoff (1994)	Working paper	Firm	Germany	13	0.136	0.019	0.090	0.163
20. Hsing (1998)	Journal article	Firm	US	2	0.204	0.000	0.204	0.204
21. Kafourous (2005)	Journal article	Firm	UK	17	0.038	0.041	-0.091	0.152
22. Kwon and Inui (2003)	Journal article	Firm	OECD-mixed	22	0.101	0.018	0.071	0.130
23. Lehto (2007)	Journal article	Firm	OECD-mixed	13	0.033	0.011	0.014	0.059
24. Mairesse and Hall (1996)	Working paper	Firm	France, US	29	0.047	0.047	-0.193	0.246
25. Ortega-Argiles et al (2010)	Journal article	Firm, Industry	OECD-other	8	0.082	0.038	0.017	0.169
26. O'Mahoney and Vecchi (2000)	Book chapter	Firm	OECD-other	1	0.098	n.a.	0.098	0.098
27. Rogers (2010)	Journal article	Firm	UK	12	0.012	0.019	0.009	0.238
28. Schankerman (1981)	Journal article	Firm	US	18	0.069	0.047	0.018	0.292
29. Smith et al (2004)	Journal article	Firm	OECD-other	8	0.090	0.011	0.080	0.125
30. Verspagen (1995)	Journal article	Industry	France, Germany, UK, OECD-other	55	0.022	0.031	-0.024	0.171
Overall	**All**	**All**	**All**	**443**	**0.053**	**0.055**	**-0.262**	**0.648**

Table 3b: Fixed-effect weighted means (FEWMs) for estimates in temporal dimension

Study	Publication type	Unit of analysis	Country	Observations	FEWM	Std. Dev.	Min	Max
1. Aiello and Cardamone (2005)	Journal article	Firm	OECD-other	4	0.055	0.004	0.053	0.090
2. Aldieri et al (2008)	Journal article	Firm	OECD-other, US	12	0.170	0.072	0.090	0.460
3. Anon and Higon (2007)	Journal article	Industry	UK	4	0.307	0.022	0.281	0.331
4. Bartelsman (1990)	Working paper	Firm	US	6	0.033	0.067	-0.005	0.180
5. Bartelsman et al (1996)	Report	Firm	OECD-other	10	0.071	0.045	0.028	0.247
6. Blanchard et al (2005)	Journal	Firm	France	1	0.013	.	0.013	0.013
7. Bond et al (2002)	Working paper	Firm	Germany, UK	6	0.024	0.079	-0.328	0.053
8. Bonte (2003)	Journal article	Industry	Germany	6	0.007	0.002	0.006	0.016
9. Branstetter (1996)	Working paper	Firm	OECD-other, US	2	0.056	0.115	0.013	0.360
10. Cincera (1998)	Thesis	Firm	OECD-other	48	0.192	0.062	0.040	0.480
11. Cuneo and Mairesse (1984)	Working paper	Firm	France	10	0.106	0.061	0.027	0.229
12. Doraszelski and Jaumandreu (2013)	Journal article	Firm	OECD-other	18	0.014	0.015	-0.003	0.075
13. Eberhardt et al (2013)	Journal article	Industry	OECD-other	3	0.053	0.015	0.024	0.063
14. Goto and Suzuki (1989)	Journal article	Industry	OECD-other	21	0.334	0.147	0.190	0.810
15. Griliches (1980a)	Journal article	Industry	US	3	0.050	0.015	0.026	0.067
16. Griliches (1980b)	Book chapter	Firm	US	37	0.073	0.021	0.011	0.232
17. Griliches (1998)	Journal article	Firm	US	5	0.108	0.009	0.095	0.110
18. Griliches and Mairesse (1981)	Working paper	Firm	US	18	0.093	0.079	-0.062	0.270
19. Griliches and Mairesse (1991b)	Book chapter	Firm	OECD-other	2	0.025	0.005	0.020	0.030
20. Hall (1993)	Journal article	Firm	US	10	0.023	0.019	-0.011	0.175
21. Hall and Mairesse (1995)	Journal article	Firm	US	42	0.072	0.057	-0.001	0.320
22. Harhoff (1994)	Working paper	Firm	Germany	46	0.113	0.061	-0.072	0.258
23. Harhoff (2000)	Journal article	Firm	Germany	5	0.068	0.001	0.067	0.069
24. Kwon and Inui (2003)	Working paper	Firm	OECD-mixed	60	0.046	0.038	-0.010	0.149
25. Lehto (2007)	Journal article	Firm	OECD-mixed	5	0.023	0.012	0.003	0.035
26. Los and Verspagen (2000)	Journal article	Firm	US	12	-0.001	0.004	-0.008	0.102
27. Mairesse and Hall (1996)	Working paper	Firm	US, France	34	0.036	0.059	-0.132	0.176
28. Ortega-Argiles et al (2010)	Journal article	Firm, Industry	OECD-other	8	0.041	0.099	-0.120	0.234
29. O'Mahoney and Vecchi (2000)	Book chapter	Firm	OECD-other, US	8	0.266	0.067	0.042	0.354
30. O'Mahoney and Vecchi (2009)	Journal article	Firm	OECD-other	9	0.149	0.116	-0.304	0.251
31. Smith et al (2004)	Journal article	Firm	OECD-other	2	0.086	0.000	0.086	0.088
32. Verspagen (1997)	Journal article	Industry	OECD-other	12	0.076	0.032	0.018	0.177

Overall	**All**	**All**	**All**	**469**	**0.012**	**0.040**	**-0.328**	**0.810**

Table 3c: Fixed-effect weighted means (FEWMs) for rates of return estimates

Study	Publication type	Unit of analysis	Country	Observations	FEWM	Std. Dev.	Min	Max
1. Bartelsman et al (1996)	Report	Firm	OECD-other	9	0.112	0.102	-0.004	0.348
2. Cameron et al (2005)	Journal article	Industry	UK	9	0.635	0.127	0.496	0.901
3. Cincera (1998)	Thesis	Firm	OECD-other	1	0.380	.	0.380	0.380
4. Clark and Griliches (1998)	Book chapter	Firm	US	6	0.190	0.008	0.180	0.200
5. Griffith et al (2004)	Journal article	Industry	OECD-other	15	0.479	0.095	0.343	0.857
6. Griliches (1980a)	Journal article	Industry	US	2	0.042	0.014	0.029	0.058
7. Griliches and Lichtenberg (1984)	Journal article	Firm	US	20	0.178	0.122	0.040	0.762
8. Griliches and Mairesse (1991a)	Book chapter	Firm	OECD-other, US	6	0.316	0.090	0.203	0.562
9. Griliches and Mairesse (1991b)	Book chapter	Firm	OECD-other, France, US	13	0.204	0.135	-0.550	0.450
10. Hall and Mairesse (1995)	Journal article	Firm	US	20	0.169	0.097	-0.013	0.341
11. Hanel (2000)	Journal article	Industry	OECD-other	8	0.168	0.080	0.077	0.338
12. Harhoff (1994)	Working paper	Firm	Germany	6	0.226	0.024	0.189	0.297
13. Heshmati and Hyesung (2011)	Journal article	Firm	OECD-other	2	0.128	0.000	0.128	0.129
14. Klette (1991)	Working paper	Firm	OECD-other	20	0.110	0.012	0.082	0.176
15. Kwon and Inui (2003)	Working paper	Firm	OECD-other	2	0.225	0.069	0.163	0.301
16. Lichtenberg and Siegel (1991)	Journal article	Firm	US	33	0.185	0.168	-0.120	1.926
17. Link (1981)	Journal article	Firm	US	2	0.252	0.360	0.190	2.310
18. Link (1983)	Journal article	Firm	OECD-other	2	0.050	0.007	0.047	0.063
19. Lokshin et al (2008)	Journal article	Firm	OECD-other	4	0.216	0.084	0.137	0.307
20. Mansfield (1980)	Journal article	Firm	US	25	0.063	0.068	-0.180	1.780
21. Mate-Garcia and Rodriguez-Fernandez (2008)	Journal article	Firm	OECD-other	1	0.266	.	0.266	0.266
22. Medda et al (2003)	Working paper	Firm	OECD-other	2	0.319	0.036	0.290	0.364
23. Odagiri (1983)	Journal article	Firm	OECD-other	2	0.185	0.217	-0.475	0.256
24. Odagiri and Iwata (1986)	Journal article	Firm	OECD-other	4	0.150	0.032	0.113	0.201
25. Rogers (2010)	Journal article	Firm	UK	18	0.144	0.064	-0.049	0.610
26. Scherer (1982)	Journal article	Industry	US	4	0.143	0.087	0.001	0.210
27. Scherer (1983)	Journal article	Industry	US	4	0.244	0.080	0.200	0.476
28. Sterlacchini (1989)	Journal article	Industry	UK	6	0.124	0.034	0.090	0.190
29. Sveikauskas (1981)	Journal article	Industry	US	21	0.082	0.077	0.039	0.394
30. Terleckyj (1980)	Book chapter	Industry	US	12	0.156	0.143	-0.180	0.370
31. van Meijl (1997)	Journal article	Industry	France	15	0.118	0.051	0.010	0.190
32. Verspagen (1995)	Journal article	Industry	Fr., Germ. UK, OECD-other	28	0.068	0.036	-0.737	0.524
33. Wakelin (2001)	Journal article	Firm	UK	14	0.269	0.139	-0.210	0.640
34. Wolff and Nadiri (1993)	Journal article	Industry	US	14	0.134	0.102	-0.087	0.612
Overall	**All**	**All**	**All**	**350**	**0.115**	**0.103**	**-0.737**	**2.310**

Smaller but more heterogeneous elasticity estimates in the temporal dimension may be due to various reasons. First, elasticity estimates in the temporal dimension are based on 'within' estimators or 'first-differenced' data. Such estimations may be affected by collinearity between capital (both R&D and physical capital) and the time-effect that reflects autonomous technical change. Secondly, measurement errors are amplified when first-differenced data is used instead of levels. A third reason is related to difficulties in providing appropriate specification for the dynamic evolution and lags of the R&D capital in short panels (see, Hall and Mairesse, 1995; Hall et al., 2010).

Although FEWMs provide more reliable measures compared to simple means, we do not consider them as reliable estimates for reasons indicated in section 3 above. Hence, we estimate the bivariate meta-regression models of (8) and (9b) to obtain 'typical' elasticities and rates-of-returns estimates corrected for publication selection and non-linear relationship between primary study estimates and their standard errors. The results are presented in Table 4 below.

Columns 1 – 3 report the 'average effect' corrected for publication selection bias. This 'average effect' is based on the assumption that all moderating factors apart from the standard error are at their sample means. The significance of these estimates indicate the existence of a 'genuine' effect that is robust to heteroskedasticity (column 2) and study-level fixed effects (column 3).

Column 4 reports the productivity and rates-of-return estimates corrected for publication selection bias and non-linear relationship between primary-study estimates and their standard errors (PEESE). This is the appropriate 'effect size estimate' and is equal to 0.078 in the level dimension, 0.044 in the temporal dimension, and 11.3% for rates of return. These estimates are close to the FEWMs established in Table 3 above. Nevertheless, they are still smaller than those reported in existing reviews. For example, Wieser (2005: 594) report a mean elasticity of 0.121 (with a standard deviation of 0.064) in the level dimension; a mean elasticity of 0.179 (with standard deviation of 0.104) in the temporal dimension; and a rates of return average at 28.3%. Hall et al (2010) report an average elasticity of 0.10 or larger in the level dimension, 0.08 in the level and temporal dimensions taken together, and an average rates-of-return estimate ranging from 20% to 30%. Finally, Moen and Thorsen (2013) report an average rates-of-return at 18.2%.

Table 4: E*lasticity* and *rates-of-return* estimates for R&D

	1	2	3	4
Elasticity estimates in level dimension	**PET WLS**	**PET - WLS Cluster-robust**	**PET-Fixed effects Cluster-robust**	**PEESE Robust**
Precision	0.076***	0.076***	0.050***	0.078***
	(0.003)	(0.017)	(0.011)	(0.008)
St. Error				0.058
				(4.444)
Constant	0.424	0.424	2.706***	
	(0.457)	(1.240)	(0.925)	
Observations	440	440	440	440
R-Squared	0.525	0.525	0.368	0.671
|DFBETA| > 1 for 2 observations, which are excluded from the estimation				
I^2 = (MSE-1)/MSE = 0.98 (Proportion of variation due to unobserved heterogeneity)				

Elasticity estimates in temporal dimension	**PET WLS**	**PET - WLS Cluster-robust**	**PET-Fixed effects Cluster-robust**	**PEESE Robust**
Precision	0.026***	0.026***	0.035***	0.044***
	(0.004)	(0.005)	(0.012)	(0.007)
St. Error				6.566***
				(1.793)
Constant	2.266***	2.266***	1.811***	
	(0.289)	(0.432)	(0.628)	
Observations	468	468	468	468
R-Squared	0.095	0.095	0.116	0.352
|DFBETA| > 1 for 1 observation, which is excluded from estimation				
I^2 = (MSE-1)/MSE = 0.96 (Proportion of variation due to unobserved heterogeneity)				

Rates of return estimates	**PET WLS**	**PET - WLS Cluster-robust**	**PET-Fixed effects Cluster-robust**	**PEESE Robust**
Precision	0.067***	0.067***	0.063***	0.113***
	(0.007)	(0.012)	(0.01)	(0.010)
St. Error				1.12***
				(0.360)
Constant	1.473***	1.473***	1.535***	
	(0.140)	(0.180)	(0.153)	
Observations	350	350	350	350
R-Squared	0.228	0.228	0.214	0.570
|DFBETA| > 1 for 2 observation, which are excluded from the estimation				
I^2 = (MSE-1)/MSE = 0.72 (Proportion of variation due to unobserved heterogeneity)				

- *** Significant at 1 % level
- Estimates in (1), (2) and (3) are based on the precision-effect test (PET) model – estimated with weighted least-squares (WLS). Estimates in (4) are based on the precision-effect test corrected for standard errors (PEESE) model, which is also a WLS model.
- DFBETA influence statistics calculates the difference between the regression coefficient when the i^{th} observation is included and excluded. The difference is scaled by the estimated standard error of the coefficient. Observations with *|DFBETA| > 1* are considered to have undue influence and are excluded from the estimation.
- All estimations except (1) are with heteroskedasticity-robust standard errors.

We argue that the average elasticity and rates-of-return estimates reported in previous reviews are likely to be biased upward for two reasons. First, some are based on simple averages or vote counting – without appropriate weighting that reflects the precision of the estimates reported in primary studies. Secondly, and more importantly, some are based only on primary study estimates that are statistically significant – a choice that is highly likely to propagate any publication selection bias that may contaminate the primary-study estimates.

Indeed, publication selection bias does exist in the estimates reported by primary studies. The constant term in columns 3 of Table 4 (the preferred meta-regression model that takes account of heteroskedastacity and study-level fixed effects) is positive and significant. This indicates that primary studies are more likely to report estimates that are larger than the weighted mean. The selection bias is substantial ($|\beta_0| \geq 1$) in the temporal dimension for elasticities and in the rates-of-return estimates; and it is severe ($|\beta_0| \geq 2$) in the case of elasticity estimates in the level dimension.

At this juncture, it is necessary to discuss the mean rates-of-return estimate, which we report as 11.3% in the bottom panel of Table 4. As indicated above, this is smaller than the typical rates-of-return estimates reported in previous reviews. More importantly, however, it is also smaller than the typical depreciation rate (usually, 15%) that primary studies use for constructing the R&D capital (15%). This raises the question as to whether net rates of return on R&D investment can be negative.

This is a legitimate question, the answer for which is still debated in the literature. According to Griliches and Mairesse (1991a), the rates-of-return estimates reported in primary studies should be considered only as "distant reflections of the relevant 'rate of return' concept" for two reasons. First, the rates-of-return estimate is a short-run measure. It measures the partial effect of R&D intensity in the current period on output growth or total factor productivbity (TFP) growth between the preceding and current periods. This is a naïve measure because R&D projects take several years to complete and the returns on completed R&D projects may not materialise until a few years after completion. Second, the rate-of-return estimate is obtained from *R&D intensity* in one period only. This is in contrast to elasticity estimates, which are based on *R&D capital stock* that takes account of past and current R&D flows. Because of these properties, Griliches and Mairesse (1991a: 389) report that rates-of-return estimates obtained from microeconometric models tend to be biased downward by an order of 50%. However, the question is still open as various studies (e.g., Griliches, 1979; Schankerman, 1981; Griliches and Lichtenberg 1984; and Cuneo and Mairesse, 1984) demonstrate that this interpretation is not compatible with the growth rates of the variables used for estimating rates of return on R&D investment.

Table 4 also reports the proportion of the variation among elasticity and rates-of-return estimates that is due to unobserved heterogeneity (I^2). The proportion is 0.98 for elasticities in the level dimension, 0.96 for elasticities in the temporal dimension and 0.72 for rates-of-return estimates. These are much larger than the benchmark of 50% proposed by Higgins and Thompson (2002). The large impact of the unobserved heterogeneity does not invalidate the estimated elasticities and rates of return, but it calls for caution in generalising these estimates into other contexts.

In what follows, we utilise a multivariate meta-regression model as specified in (10) above to model the sources of heterogeneity and quantify their effects in a systematic manner. The model includes 22 moderating variables that capture the dimensions of the research field. These are dummy variables, with descriptions and summary statistics reported in Tables A4.1 - A4.4 in *Appendix 4*.

We estimate the multivariate meta-regression by following a general-to-specific model estimation routine, whereby the 'most insignificant' variables (i.e., those with the largest *p-value*) are dropped one at a time until all remaining variables are significant in the standard weighted least-squares (WLS) estimation. Then, we re-estimate the specific model with cluster-robust standard errors and with fixed-effect estimators to take account of within-study dependence, heteroskedasticity and study-specific fixed-effects.

Results in Table 5 below indicate that primary studies tend to report *larger elasticity estimates* in the level dimension when they: (i) use firm-level data as opposed industry- or sector-level data; (ii) measure output with value added as opposed to sales or gross production; (iii) control for double counting by deducting the R&D capital and R&D personnel from physical capital and labour; (iv) control for at least one type of spill-over effect; and (v) use a dynamic instead of static model specification. On the other hand, primary studies tend report *smaller elasticity estimates* when they: (i) control for endogeneity by using instrumented estimation techniques; (ii) take account of heterogeneity between firms/industries by using industry dummies; (iii) report elasticities for government-funded R&D as opposed to private R&D; and (iv) use the perpetual inventory method (PIM) to construct the R&D capital.

In our discussion, we consider the evidence as: (a) *strong* if the results are robust across three different estimation methods (standard WLS, cluster-robust-WLS and heteroskedasticity-robust fixed-effect); (b) *medium* if the results are robust across two methods; and (c) *weak* when the results are significant only in one estimation method. We consider the moderating variable to have an effect on reported estimates only when its effect is supported with *strong* or *medium* evidence.

Our findings are congruent with conclusions derived in some primary studies and existing reviews with respect to three moderating factors: control for double-counting, use of instrumented estimation methods, and inclusion of industry dummies.

Control for double-counting involves deduction of R&D capital and personnel from conventional capital and labour inputs. Our finding indicates that studies that control for double-counting tend to report larger elasticity estimates in the level dimension compared to studies that do not. This is in line with Schankerman (1981), Cunéo and Mairesse (1984), Hall and Mairesse (1995), Harhoff (1994), and Mairesse and Hall (1996) who report a substantial downward bias in the R&D elasticity when the conventional inputs are not corrected for R&D double-counting. Schankerman (1981) demonstrates that the bias will be larger the larger are the ratios of R&D capital and R&D personnel to conventional capital and labour respectively.

Table 5: Sources of variation in elasticity estimates: The level dimension

	WLS	*WLS Cluster-robust*	*Fixed-effect Robust St. Ers.*
Working paper	-0.023***	-0.023	0.022
	(0.008)	(0.023)	(0.014)
Perpetual inventory method	-0.123***	-0.123***	-0.019
	(0.010)	(0.029)	(0.016)
Frim-level data	0.082***	0.082***	0.041***
	(0.010)	(0.028)	(0.012)
GMM estimation	-0.045*	-0.045	-0.000
	(0.026)	(0.035)	(0.032)
Dynamic model specification	0.102***	0.102***	0.017
	(0.025)	(0.036)	(0.028)
Instrumented variable estimation	-0.038***	-0.038**	-0.050***
	(0.007)	(0.014)	(0.011)
Output measured as value added	0.036***	0.036**	0.051***
	(0.006)	(0.015)	(0.010)
Data midpoint after 1980	-0.017*	-0.017	-0.003
	(0.009)	(0.018)	(0.007)
UK firm or industry data	-0.051***	-0.051	-0.033
	(0.011)	(0.034)	(0.032)
US firm or industry data	0.041***	0.041	-0.010
	(0.009)	(0.029)	(0.014)
Control for double counting	0.015***	0.015**	0.018***
	(0.005)	(0.006)	(0.003)
Control for spill overs	0.088***	0.088***	-0.011
	(0.012)	(0.031)	(0.022)
Time dummies included	0.025***	0.025	0.015
	(0.008)	(0.016)	(0.012)
Industry dummies included	-0.027***	-0.027***	-0.020***
	(0.004)	(0.009)	(0.004)
Variable returns to scale	0.016***	0.016	-0.001
	(0.004)	(0.014)	(0.003)
Translog production function	-0.040***	-0.040	0.019
	(0.014)	(0.040)	(0.040)
Government-funded R&D	-0.140***	-0.140***	-0.084***
	(0.042)	(0.028)	(0.011)
Constant	1.640***	1.640**	1.851***
	(0.352)	(0.659)	(0.536)
Observations	440	440	440
R-squared	0.804	0.804	0.686

|DFBETA| > 1 for 2 overly influential observations, which are excluded from estimation

Strong evidence *Medium evidence*

Insignificant moderating variables dropped from the general model: *Journal article; German firm or industry data; French firm or industry data; small-firm samples as defined by the author; R&D-intensive firms as defined by the author; and weighted least square (WLS) estimation as opposed to all other types of estimation.*

Endogeneity may arise for three reasons in the estimation of productivity effects of and rates of return on R&D: reverse causality between the firm's output and its decisions concerning R&D investment and other inputs; omitted variable bias; and measurement errors. Some studies address the endogeneity problem by using a semi-reduced form of the production function (Griliches and Mairesse, 1984), some use a general method of moments (GMM) estimator (Mairesse and Hall, 1996; Aldieri et al., 2008; Blanchard et al., 2006; and Griffth et al., 2006) and some others such as Verspagen (1995) use three-stage least-squares (3SLS). The meta-regression result indicates that studies that control for endogeneity through any of these methods report lower elasticity estimates compared to those that do not. Stated differently, elasticity estimates are likely to be biased upward if studies do not control for endogeneity.

A third area of congruence between our findings and those reported in previous reviews concerns the effect of industry/sector dummies on reported elasticity estimates. The negative and significant coefficient we report for industry/sector dummies indicates that elasticities in the level dimension tend to be smaller when primary studies include such dummies in their models. This is in line with Hall et al. (2010: 21-22) who report that estimates based on the level dimension tend to be lower when industry/sector dummies are included in the estimation.

However, it is not clear whether industry/sector dummies correct for potential bias or introduce a bias of their own. On the one hand, industry/sector dummies can correct for potential bias by taking account of sector-specific conditions that are not measured in the data. On the other hand, they may constitute a new source of bias as they capture variations in sector-specific technological opportunities that should be captured by the elasticity estimates themselves. Therefore, it would be good practice in this research field to compare alternative estimates with and without industry/sector dummies.

Results in Table 5 also enable us to report a range of other findings that may be useful in two ways: (i) quantifying the effects of some moderating factors for which there is no consensus in the existing literature or reviews; or (ii) providing an empirical verification of the previous findings based on narrative synthesis only.

One such finding relates to elasticity estimates based on firm data as opposed to industry/sector data. Results in Table 5 indicate that elasticity estimates based on firm-level data are higher than those based on industry/sector data. Hall et al. (2010: 22) report that the literature does not indicate a systematic difference between elasticity estimates based on firm or industry/sector data. However, our finding indicates that this may not be the case when the elasticity estimates are in the level dimension. This can be explained by the relatively higher levels of between-firm variation in the R&D capital stock compared to between-industry variation. This interpretation is supported by the absence of any significant difference between firm-level and industry-level elasticity estimates when estimation is based on the temporal dimension (see Table 6 below). This is to be expected because the temporal dimension emphasizes the within-firm variation of the R&D capital, which is smaller compared to between-firm variation in the level of the R&D capital stock.

Secondly, there is an extensive literature that examines the effects of R&D spillovers as an additive source of productivity gains. Although the partial effects of spillovers on productivity are investigated widely, there is no systematic evaluation of how the estimated productivity effects would differ when primary studies do or do not control for the effects of spillovers in their models. Meta-regression enables us to address this question and the results indicate that studies that control for spillovers in their models tend to report larger elasticity estimates.

This finding should be interpreted with caution because the expectation is to find lower elasticity estimates when spillovers are controlled for. Our finding is likely to be driven by sample differences between studies that do and do not control for spillovers. This is why we do not consider it as an indication of systematic difference between elasticity estimates due to controlling for spillover effects. This interpretation draws support from the absence of any significant effect associated with controlling for spillovers in the sample of temporal elasticity estimates (see Table 6 below).

Four more results from the meta-regression are worth discussing. One concerns the effect of output specification on reported elasticity estimates. We report that studies that use value added as the measure of output tend to report larger elasticity estimates compared to studies that use sales or gross output. This finding is consistent across elasticity estimates in level and temporal dimensions (see Table 6 below).

How does this finding compare with the existing literature? Cunéo and Mairesse (1984) and Mairesse and Hall (1994) report that elasticity estimates based on value-added do not differ from those based on sales without including materials as an additional input. However, Griliches and Mairesse (1984) indicate that elasticity estimates based on value added tend to be smaller than those based on sales without materials. Our finding is not strictly comparable because the reference category for the dummy variable we have consists of gross output as well as sales (with and without including materials as input). Nevertheless, it indicates that the measure of output is highly likely to constitute a source of systematic variation in both level and temporal elasticity estimates. Therefore, it is advisable for researchers and research users to compare the productivity effects of R&D using (or looking at) different measures of output – subject of course to data availability.

Another finding concerns the effect of how R&D capital is measured. As indicated above, the most common method for constructing R&D capital is the perpetual inventory method (PIM), whereby a firm with more knowledge capital in the preceding period carries out less R&D investment in the current period. However, this method is questioned (see, Hall et al., 1986; Klette, 1994). The argument is that the negative correlation between the R&D capital stock in the preceding period and the R&D investment in the current period is not borne out by evidence. On the contrary, it is argued that firms that carry out high levels of R&D investment in the preceding period also tend to do so in the current period. Therefore, some studies (Hall and Hayashi 1989; Klette, 1994; Bitzer and Stephan, 2007) have suggested alternative methods for constructing the R&D capital.

Several authors have acknowledged that such innovations in constructing the R&D capital stock constitute useful avenues for future research (Griliches, 1979; Bitzer and Stephan, 2007; and Hall et al., 2010). However, no attempt is made to evaluate whether productivity estimates differ systematically between studies using the PIM or alternative methods. Our finding indicates strong evidence of downward bias in both level and temporal elasticity estimates when studies construct the R&D capital via PIM as opposed to alternative methods.

The last two findings relate to the effects of dynamic model specification and government-funded R&D on reported estimates. With respect to the former, we report that studies with a dynamic model specification tend to report larger elasticity estimates compared to those utilising static models. With respect to the latter, we report that elasticity estimates based on government-funded R&D tend to be smaller compared to those based on privately funded R&D. Because we also find a similar result for rates of return, we will discuss the finding and its implications below when we consider the meta-regression results on rates-of-return estimates.

We close the discussion on elasticities in the level dimension by commenting on R&D intensiveness of firms and industries as a moderating factor. In our work, R&D intensiveness is found to have no significant effect on reported elasticity estimates. This is in contrast to several studies cited in Hall et al. (2010) as reporting higher R&D elasticities for R&D-intensive firms, particularly in the level dimension. True, studies such as Griliches (1980b); Griliches and Mairesse (1981); Cunéo and Mairesse (1984); Odagiri (1983); Bartelsman (1990) and Hall (1993) do report higher elasticities for R&D-intensive firms or industries. However, multiple findings within each study are not consistent across different samples, model specifications or estimation methods. Therefore, the difference between R&D-intensive and other firms/industries disappears when all reported estimates are included in the meta-analysis.

Meta-regression results for elasticities in the temporal dimension are given in Table 6. With respect to three moderating factors, the results for the temporal dimension are in conformity with those concerning elasticities in the level dimension. Studies that control for double-counting and those that use value added as the measure of output tend to report larger elasticity estimates; whereas studies that construct the R&D capital via PIM tend to report smaller elasticity estimates. We do not elaborate on these findings as we have already done so above.

Beyond that results in Table 6 reveal a wide of range of new moderating factors that affect the elasticity estimates in the level dimension. We find that studies tend to report larger temporal elasticities when: (i) they include time dummies in their models; (ii) they draw on German or US firm/industry data as opposed to data from the rest of OECD countries; and (iii) use a translog production function as opposed to a Cobb-Douglas production function in its static or dynamic versions. On the other hand, studies tend to report smaller elasticity estimates when

Table 6: Sources of variation in elasticity estimates: The temporal dimension

	WLS	*WLS Robust St. Ers.*	*Fixed-effect Robust St. Ers.*
Precision	0.230***	0.230***	0.184**
	(0.024)	(0.042)	(0.069)
Journal article	-0.142***	-0.142***	-0.153***
	(0.010)	(0.018)	(0.016)
Working paper	-0.143***	-0.143***	-0.163***
	(0.013)	(0.022)	(0.027)
Perpetual inventory method	-0.082***	-0.082***	-0.074***
	(0.014)	(0.023)	(0.026)
Firm-level data	-0.049***	-0.049	-0.010
	(0.018)	(0.039)	(0.067)
Output measured as value added	0.017***	0.017**	0.025***
	(0.006)	(0.006)	(0.009)
Data midpoint after 1980	-0.029**	-0.029*	-0.009
	(0.013)	(0.016)	(0.008)
French firm or industry data	-0.016*	-0.016*	-0.027**
	(0.008)	(0.009)	(0.011)
German firm or industry data	0.033*	0.033	0.074**
	(0.017)	(0.021)	(0.031)
US firm or industry data	0.029***	0.029***	0.020
	(0.010)	(0.009)	(0.014)
Control for double counting	0.027***	0.027*	0.029
	(0.007)	(0.015)	(0.018)
Time dummies included	0.026***	0.026**	0.036**
	(0.009)	(0.011)	(0.014)
Variable returns to scale allowed	-0.050***	-0.050***	-0.047***
	(0.008)	(0.009)	(0.007)
Small firms	-0.064***	-0.064***	-0.054***
	(0.023)	(0.013)	(0.005)
Translog production function	0.122***	0.122***	0.032
	(0.020)	(0.024)	(0.036)
Constant	0.988***	0.988***	0.959***
	(0.295)	(0.280)	(0.245)
Observations	468	468	468
R-squared	0.432	0.432	0.401

|DFBETA| > 1 for 1 overly influential observation, which is excluded from estimation

Strong evidence *Medium evidence*

Insignificant moderating variables: *Control for spillovers, instrumented estimation methods, GMM, government-funded R&D, weighted least squares, dynamic model specification, UK data, R&D-intensive firms or industries* they: (i) are published as journal articles or working papers as opposed book chapters or reports; (ii) have a variable-returns-to-scale specification as opposed to constant returns to scale; (iii) draw on panel data with a mid-year after 1980; (iv) draw on data for small firms as defined by the author(s); and (v) draw on data for French firms/industries as opposed firms/industries in other OECD members.

Hall et al. (2010: 12) recommend inclusion of time dummies in productivity estimations at the firm or industry/sector levels. This is to control for variations across time, which may not be related to the effect of R&D on productivity. Such variations could be due to macro-economic shocks, changes in capacity utilisation that may be due to macro-level or sector-specific shocks, errors in deflators that may be common to a sector or the whole economy, or other economy-wide measurement errors. However, time dummies, just as it was the case for industry/sector dummies, may introduce a new source of bias if they capture changes in the effect of R&D over time. Our finding of larger estimates form studies that include time dummies indicate that researchers and research users should provide and/or compare estimation results with and without time dummies.

Unlike the elasticity estimates in the level dimension, there are evident effects associated with countries of origin. While estimates based on German and US data are systematically larger; those based on French data are systematically smaller.[3] The larger elasticity estimates obtained from US and German data may be related to relatively higher levels of R&D intensity (business R&D as percentage of GDP) in those countries. This interpretation draws on case studies indicating that firms/industries in R&D-intensive countries may better able to exploit the returns on own R&D as well as the positive spillover effects of the R&D undertaken by other firms/industries. By the same token, the relatively smaller elasticity estimates based on French data may be related to relatively lower levels of R&D intensity in France.[4] However, this is a tentative interpretation because other OECD countries with R&D intensity over the OECD average (e.g., Japan, Korea, Sweden, etc.) are underrepresented in the research on R&D productivity.

Another set of results relate to publication type, which indicate that studies published as journal articles or working papers tend to report smaller elasticity estimates in the temporal dimension compared to studies published as book chapters or research reports. Given that the expected elasticity is positive and that the coefficient on journal articles is negative (around – 0.14), it appears that journal editors' selection criteria may not be operating as an additional source of selection bias (see Card and Krueger, 1995; Stanley, 2008). Finally, it also indicates that the 'winner's curse' that Costa-Font et al. (2013) point out may not be at work in this research field.[5] This interpretation is also supported by the insignificant coefficient on the journal article variable in the level dimension discussed earlier.

[3] It should be noted here that we also controlled for UK data in all estimations. Although UK data is associated with smaller elasticity estimates in the level dimension (see Table 5 above), the effect is significant only in the standard WLS. The UK data effect was never significant in the temporal elasticity or rates-of-return estimates.
[4] According to OECD figures, business R&D intensity in the US and Germany tends to be higher than the OECD average; whereas business R&D intensity in France and the UK tends to below OECD average (OECD, 2011).
[5] The 'winner's curse' arises when journals with higher levels of perceived quality tend to publish more intensely selected and biased findings to prove or disprove a hypothesis.

Table 7: Sources of variation in rates of return on R&D investment

	WLS	***WLS Robust St. Ers.***	***Fixed-effect Robust St. Ers.***
Precision	0.151***	0.151***	0.280***
	(0.035)	(0.040)	(0.026)
Journal article	-0.082***	-0.082***	-0.203***
	(0.027)	(0.028)	(0.031)
Working paper	0.088**	0.088**	0.121***
	(0.036)	(0.037)	(0.018)
Firm-level data	-0.035*	-0.035*	-0.027
	(0.021)	(0.019)	(0.022)
Estimation with weighted variables	0.148***	0.148***	0.096***
	(0.022)	(0.018)	(0.023)
Output measured as value added	0.052***	0.052***	0.044*
	(0.018)	(0.017)	(0.024)
French firm or industry data	-0.053*	-0.053***	0.132***
	(0.029)	(0.018)	(0.045)
US firm or industry data	-0.036**	-0.036**	-0.056**
	(0.015)	(0.014)	(0.023)
Control for double counting	-0.131***	-0.131***	-0.269***
	(0.036)	(0.036)	(0.024)
Translog production function	0.115***	0.115***	0.256***
	(0.037)	(0.038)	(0.027)
Government-funded R&D	-0.173***	-0.173***	-0.206**
	(0.035)	(0.063)	(0.084)
Constant	1.487***	1.487***	1.289***
	(0.141)	(0.283)	(0.067)
Observations	350	350	350
Studies	33	33	33
R-Squared	0.39	0.39	0.36

No overly influential observations
Strong evidence *Medium evidence*

Insignificant moderating variables: *Industry dummies, time dummies, data mid-point after 1980, control for spillovers, instrumented estimation methods, GMM estimation, small firms, variable returns to scale, dynamic model specification, UK data, German data, R&D-intensive firms or industries.*

The mid-point of the panel data allows for verifying if R&D's productivity effects are systematically larger or smaller after 1980. Controlling for this variable is informed by the debate on whether the productivity effects had fallen in 1970s when R&D investments fell or stagnated compared to the 1960s when they had peaked (see Griliches, 1980a). We have chosen the cut-off year as 1980 instead of 1970 for two reasons: (i) there was no sign of recovery in R&D investments in the 1980s compared to 1970s; and (ii) most OECD countries experienced a prolonged period of structural change in the manufacturing sector. In table 5 above, there was weak evidence of decline in level elasticities after 1980. In the temporal dimension in Table 6, the evidence is medium. Therefore, we conclude that there is some evidence of decline in R&D productivity at least in the temporal dimension. We relate this finding to the structural change in and shrinking of the manufacturing sector over the 1980s and 1990s compared to the services sector.

Meta-regression results for rates-of-return estimates are given in Table 7 above. Rates-of-return estimates have one advantage compared to elasticity estimates: a constant rate of return across firms/industries is more compatible with return equalisation implied by competition. The drawback is that rates-of-return estimates are more likely to be heterogeneous due to differences between direct (models 4b and 4c above) and indirect estimates (model 4d). As a result of this heterogeneity, the meta-regression model for rates-of-return estimates has a lower goodness of fit (a smaller R-squared of 39%) compared to the meta-regression for elasticities in the level or temporal dimensions (with R-squared of 80% and 43%, respectively).

Results in Table 7 are in conformity with the findings about elasticity estimates with respect to four moderating variables. In summary, studies tend to report: (i) *smaller* rate-of-return estimates when they are published as journal articles compared to working papers, book chapters or reports; (ii) *larger* estimates when they use value added as the measure of output compared to others that use sales or gross production; (iii) *larger* estimates when they use a tranlsog production function as opposed to a Cobb-Douglas function; and (iv) *smaller* estimates when they report rates-of-return on government-funded R&D as opposed to private-funded R&D.

We have already commented on the relevance/implications of the first three findings in the context of the elasticity estimates. Therefore, we will limit the discussion here to the last – namely, the smaller rates of return on government-funded R&D. This finding is in conformity with a number of studies that have reported a lower rate of return on government-funded R&D, including Griliches (1980a), Griliches and Lichtenberg (1984), Hanel (2000), Lichtenberg and Siegel (1991) and Mansfield (1980); as well as with the review conclusion in Hall et al. (2010).

Several reasons have been put forward to explain the relatively lower rates of return on government-funded R&D (see, Hall et al., 2010). For one, firms may be less efficient or they may underestimate the risks when they use public funds for research and development purposes. Secondly, the evidence base is generally related to the manufacturing sector and therefore the results may be misrepresenting the true effect of government-funded R&D if a larger chunk of the public funds are spent in the services sector. Third, public funds for R&D may be spent in areas such as health and defence, with high levels of externalities but low potential for the private sector to appropriate such externalities. Finally, the findings may be reflecting diminishing returns on R&D investment. This is likely to be the case if public funds are concentrated in few industries, such as pharmaceuticals and information technologies where returns are lower due to high levels of R&D intensity. Given that these factors may be working at cross purposes, more disaggregated research is needed before passing judgement against government funding of R&D activities.

Four additional findings on the sources of variation in rates-of-return estimates are worth mentioning. First, we find that rates of return tend to be smaller when the underlying data is at firm level as opposed to industry level. This finding is in conformity with Lichtenberg and Siegel (1991), who compare the firm-level rates of return with industry-level equivalents. Industry-level rates of return approximate what is described as 'social rates of return' because they also capture the effects of within-industry spillovers. There may be within-firm spillover effects if the firm is large and multi-unit, but even in large firms the within-firm spillovers are smaller than within-industry spillovers.

The second concerns the effect of using weighted variables on reported estimates. Some studies, form example Bartelsman (1996), Cameron et al. (2005), Hall (1993) and Lichtenberg and Siegel (1991) use weighted variables, where the weight is usually the square-root of R&D intensity.[6] This approach is intended to provide unbiased estimates that take account of between-firm or between-industry heterogeneity. Bartelsman et al. (1996) report that weighted estimations yield lower elasticity but higher rates-of-return estimates; but others do not provide comparative findings. The meta-regression enables us to compare the estimates based on weighted variables with the rest of the sample and confirms Bartelsman et al (1996) with respect rates-of-return estimates. The effect of weighting on elasticity estimates, however, turns out to be insignificant in the samples of elasticity estimates discussed above. Therefore, we suggest that researchers and research users should provide (or look for) both weighted and un-weighted rates-of-return estimates - unless they can demonstrate that they have controlled for excess heterogeneity between firms or industries through other methods.

The third is about relatively smaller rates-of-return estimates based on US and French firm/industry data. The finding concerning the US data can be explained by the law of diminishing returns on investment, as R&D intensity in the US has been higher than OECD average throughout the data periods in the primary studies. However, this interpretation should be taken with caution because it does not hold for Germany, whose R&D intensity is also above OECD average.

The fourth finding relates to smaller estimates reported by studies that control for double counting as opposed to others that do not. This finding is in contradiction to what we have established with respect to elasticity estimates in both level and temporal dimensions. As indicated above, controlling for double-counting is conducive to larger elasticity estimates. This should be associated with larger rates-of-return estimates if the latter are calculated indirectly (i.e., in accordance with model 4d). However, the literature is silent about whether this will hold when rates of return are estimated directly (i.e., in accordance with 4b or 4c above). Given that the large majority of the rates-of-return estimates in our sample are estimated directly, control for double counting is associated with lower rates-of-return estimates if the latter are estimated directly.

[6] Other weights include firm size (Hall, 1993) and industry's share in sectoral value added (Cameron et al., 2005).

What is more important, however, is that the discrepancy can also be interpreted as a question mark about whether rates-of-return estimates measure what they purport to measure. Recall that the estimates are based on R&D intensity rather than R&D capital. In other words, the variable in the numerator of the R&D intensity is a flow variable and *not* corrected for depreciation. This is unlike the R&D capital variable used for estimating elasticities, which is both corrected for depreciation and takes account of past R&D investments. Thus, and as Griliches and Mairesse (1991a: 389) indicate, the rates-of-return estimates 'are only very distant reflections of the relevant "rate of return" concept.' Therefore, the downward bias observed in primary study estimates that take account of double-counting should be interpreted as an indication that further research is required to address the limitations of the rates-of-return estimates in measuring the 'true' rate of return on R&D investment. Particularly, it may be necessary to go beyond contemporaneous estimations where return on R&D in the current period is determined solely by R&D investment (or its ratio to output) in that period. It is necessary to model more accurately the lag structure of the R&D investment with respect to the time spans for: (i) completion of R&D projects; and (ii) accrual of the returns on R&D investment.

Conclusions

We have synthesized the evidence on productivity effects of R&D investment, including elasticity estimates in the level and temporal dimensions and estimates of private returns on R&D investment. The evidence base consists of 1,262 estimates, extracted from 64 studies on OECD firms and industries. We have followed best practice recommendations for meta-analysis, which include a clearly defined search strategy, a clear set of inclusion and exclusion criteria, and transparent documentation of included and excluded studies.

The meta-analysis is based on all estimates reported in the primary studies, as opposed to representative or preferred estimates chosen by the authors of the primary studies or reviewers thereof. We report three sets of evidence, consisting of: (i) fixed-effect weighted means (FEWMs) per study and evidence cluster; (ii) average elasticity and rates-of-return estimates derived from a weighted least squares (WLS) meta-regression for each evidence cluster; and (iii) multivariate meta-regression estimates for the effects of the moderating factors on reported estimates.

The evidence from both (i) and (ii) indicates that the elasticity and rates-of-return estimates are positive but smaller than what is reported in existing reviews. On average, the elasticity of output with respect to R&D capital is 0.08 in the level dimension that exploits the cross-sectional variation in the R&D capital and 0.04 in the temporal dimension that focuses on its evolution within firms or industries; with an average of 0.06 when evidence from both dimensions is pooled together. The average gross rate of return, on the other hand, is 11.3%. We also report that both the estimates reported in primary are associated with a positive and substantial publication selection bias, which indicates that primary studies tend to report larger positive estimates more frequently compared to smaller or negative estimates.

Our second conclusion concerns the effect of heterogeneity on the generalizability of summary measures derived from estimates reported in primary studies. The existing reviews acknowledge the high level of heterogeneity in the evidence base. However, they draw upon preferred or representative estimates to derive conclusions about the size of the productivity effects without evaluating the extent to which their generalizability may be limited by heterogeneity. We report that unobserved heterogeneity has a substantial effect, accounting for 72%-98% of the variation among the estimates reported by primary studies. Although this finding does not invalidate the mean elasticity and rates-of-return estimates, it indicates that their generalizability to other contexts is limited.

Using multivariate meta-regression to account for sources of heterogeneity has enabled us to complement the existing reviews in three ways. First, we have provided quantitative estimates that confirm some of their conclusions about the effects of moderating factors on estimates reported in primary studies. Specifically, we have confirmed the following: (i) failure to control for double-counting of the R&D capital and R&D personnel introduces a downward bias in the elasticity estimates; (ii) inclusion of industry or time dummies has significant effects on reported estimates, but whether the inclusion of dummies correct for existing biases or constitute new sources of bias remains unclear; (iii) reported estimates would tend to be larger if they are based on value added as a measure of output instead of sales or gross production; and (iv) government-funded R&D tends to be associated with lower elasticity and rates-of-return estimates.

Secondly, we provide novel evidence on some moderating factors that are either not quantified in existing reviews or for which the narrative synthesis is ambiguous. For example, we have established that the use of perpetual inventory method for calculating the R&D capital is conducive to a downward bias in the elasticity estimates in both level and temporal dimensions. We have also established that weighting the R&D variables to reduce inter-firm or inter-industry heterogeneity is associated with higher rates-of-return estimates. With respect to the level of analysis, we have found that firm-level data is associated with larger elasticity estimates in the level dimension but does not have a significant effect on elasticities in the temporal dimension or on rates-of-return estimates.

Our third contribution also consists of novel evidence on moderating factors that remain below the radars of the existing reviews. For example, we establish that journal articles tend to report relatively smaller estimates compared to book chapters or reports. This finding suggests that the selection criteria of the journal editors do not necessarily exacerbate the positive publication selection bias observed in the estimates reported by the primary studies. We also find some evidence indicating that data from countries with R&D intensity above the OECD average (e.g., Germany and the US) is usually associated with higher elasticity estimates. This finding, however, applies only partially to rates-of-return estimates where we found diminishing returns in the US (a country with R&D intensity above OECD average) and France (a country with R&D intensity below OECD average). Finally, we find that controlling for spill-overs by adding the weighted or un-weighted sum of the R&D capital in other firms or industries is not effective in addressing the omitted variable problem. In contradiction to expectations, controlling for spill-overs is associated with larger elasticity estimates in the level dimension; but does not have a significant effect on rates-of-return estimates or on elasticity estimates in the temporal dimension.

Overall, our findings suggest that future research can benefit from addressing three issues. First, there is scope for innovation in the method used for calculating R&D capital. Innovative approaches have already been used in some studies such as Hall and Hayashi (1989); Klette (1994, 1996); and Bitzer and Stephan (2007). However, we agree with Hall et al. (2010) that further innovation in this area would enhance our understanding of R&D's effects on productivity. The second issue relates to the method of measuring spillovers, which consists of calculating weighted or un-weighted sums of the R&D capital in other firms/industries. This meta-analysis is not about the effects of R&D spillovers on productivity, which is an extant area of research in its own right. However, we had to address the issue from a different angle – mainly from the perspective of whether the productivity effects of *own R&D* differ when studies control or do not control for spillovers. From this perspectives, we have established that controlling for spillovers through an additive term in the productivity model may create an additional bias in the level dimension instead of resolving the omitted variable bias problem. A more interesting approach would be to build on Eberhardt et al. (2013) and control for spillovers as cross-sectional dependence that affects the error structure. The third issue relates to the use of weighted estimation with a view to reduce inter-firm or inter-industry heterogeneity. We have found that weighted estimation is associated with higher rates-of-return estimates while some primary studies (for example, Bartelsman et al., 1996) report that it is associated with lower elasticity estimates in the level dimension. These findings indicate that the use of weighted estimation has the potential for correcting the upward bias in elasticity estimates and makes the rates-of-return estimates more than a "distant reflections of the relevant 'rate of return' concept." (Griliches and Mairesse, 1991a).

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64. Wolff, E. N., and M. I. Nadiri (1993). Spillover effects, linkage structure, and Research and Development, *Structural Change and Economic Dynamics,* 4(2), 315-331.

APPENDIX

A1. SEARCH PROTOCOL

The aim of the search is to locate studies investigating the relationship innovation and performance at the firm or industry level. Specifically, we are interested in studies that investigate the relationship between research and development (R&D) investments and firm productivity, including rates of return on R&D investment. We aim to focus on studies that utilize firm- or industry-level data from OECD countries for two reasons: (i) minimise the extent of heterogeneity in the evidence base through reliance on studies that utilize firm or industry data the OECD considers as comparable structural and demographic business statistics; and (ii) compare the findings in three types of corporate finance regimes: the equity-market-oriented regime in the US and the UK, the bank-oriented system in Germany and the mixed model in France.

A1.1 Databases

We use a range of search terms to conduct 'Title' and 'Abstract' searches in a range of Business and Economics databases. For journal articles, books and PhD Theses, we search in the following databases:

1. *Business and Economics Databases on EBSCO Host*
   http://web.ebscohost.com/ehost/search/advanced?sid=5dc67460-1145-4c05-9630-42f295da61d6%40sessionmgr11&vid=2&hid=10
2. *International Bibliography of Social Sciences (IBSS)*
   http://search.proquest.com/index?accountid=15997
3. *J-Stor*
   http://www.jstor.org/action/showBasicSearch
4. *Web of Knowledge*
   http://apps.webofknowledge.com/UA_GeneralSearch_input.do?product=UA&search_mode=GeneralSearch&SID=N295pG4HLcP6Pp7Gk7J&preferencesSaved=
5. *EconLit*
   https://www.aeaweb.org/econlit/efm/index.php

For working papers, we search in:

6. Econpapers:
   http://econpapers.repec.org/scripts/search/search.asp?pg=-1
7. SSRN:
   http://papers.ssrn.com/sol3/DisplayAbstractSearch.cfm
8. IMF working papers:

http://www.imf.org/external/publications/pubindadv.htm

9. World Bank Policy Research Working Papers: http://econ.worldbank.org/external/default/main?menuPK=577939&pagePK=64165265&piPK=64165423&theSitePK=469382

A1.2 Search terms

The meta-analysis is designed to address the following research question: What is the effect of research and development (R&D) investment on firm performance in terms of productivity and rates of return at the firm and/or industry level in OECD countries? Productivity performance can be measured as output elasticities estimated using sales, production or value added at the firm or industry level. Rates of return, on the other hand, can be calculated on the basis of partial (i.e., labour) productivity conditional on capital or total factor productivity (TFP). The aim of the search strategy is to locate all studies that investigate the relationship between R&D investment (innovation input) as the independent (explanatory) variable and firm productivity or rates of return as the dependent (outcome) variable. To achieve this aim, we have used the following *search terms*:

For searches in the *Title* field: ***TI("R&D" OR innovat* OR "research and development" OR "research & development" OR patent*) AND (growth OR productivity OR TFP OR sale* OR revenue OR "value added" OR "value-added")***

For searches in the *Abstract* field: ***Ab("R&D" OR innovat* OR "research and development" OR "research & development" OR patent*) AND (growth OR productivity OR TFP OR sale* OR revenue OR "value added" OR "value-added") AND (firm OR company OR industry OR corporat* OR sector OR enterprise OR micro)***

A1.3 Search routine

1. Conduct *Title* and *Abstract* searches , using all databases (4 + 4 = 8 databases)
2. Set 1980 as start year for publication date
3. In databases 1 – 5, exclude magazines, news, reviews, commentaries, etc.
4. In databases 1 –5, DO NOT exclude book chapters or PhD Theses
5. In databases 1 – 5, restrict language to ENGLISH
6. Exports the results from each database search to EndNotes and save separately
7. Keep record of the search results from each database
8. Combine the individual database results in EndNotes
9. Record the results
10. Repeat the same procedure for databases 6 – 9, to obtain hits for working papers or reports.
11. Export results for Databases 1-5 and Databases 6-9 to EPPI-Reviewer. [7]

A2. STUDY SELECTION PROTOCOL

[7] For information, see http://eppi.ioe.ac.uk/cms/Default.aspx?alias=eppi.ioe.ac.uk/cms/er4.

On EPPI-Reviewer, we have created study codes for two stages of the study selection process: stage-one where decisions are based on title and abstract information; and stage-two where decisions are based on full-text information. Each code indicates why a study should be excluded – given the review question. List of codes is given in *Table A2.1* below.

Table A2.1.: Exclusion criteria at stage one and stage two of the study selection process

Stage-one exclusion criteria	Stage-two exclusions criteria
Study addresses irrelevant independent and/or dependent variable	Study follows non-production function approach
Descriptive study	Study utilizes Crépon-Duguet-Mairesse (CDM) model of innovation
Innovation measure is not R&D	Study investigates Gibrat's Law on size distribution
Study is theoretical/analytical only	Study utilizes R&D dummy only
Macro-level study	Missing standard errors or t-values
Study is based on non-OECD data	R&D term is nonlinear or interactive
Study investigates R&D and employment	Ad hoc modeling
Study investigates productivity only	Case study
Study is a review article	Descriptive study
Study investigates spillovers only	Regional rather than industry or firm level data
Study investigates firm survival	Study investigates spillovers only
Publication date is pre-1980	Study investigates R&D volatility
Study is not published in English	Total Factor Productivity measure is not tractable
Study investigates R&D subsidies only	
Study is a meta-analysis	

In both stages, two reviewers read the relevant information and coded the the suides in accordance with exclusion criteria above. A study was excuded if it 'satisfied' at least one of the exlucison criteria spcified. Discrepancies between reviewer decisions were resolved unanimously following joint assessment of the title/abstract or full-text information. The relevance check in stage one and the full-text evaluation process at stage two led to the following decisions in *Table A2.2* and *Table A2.3*.

Table A2.2: Exclusion decisions based on title and abstract information: Stage-one decisions

Exclusion criteria	% of total decisions
Independent and/or dependent variable is irrelevant	34.3
Descriptive study	20.7
Innovation measure is not R&D	12.4
Study is theoretical/analytical only	10.8
Macro-level study	7.5
Study is based on non-OECD data	5.5
Study investigates R&D and employment	3.1
Study investigates performance only	1.5
Study is a review article	1.2
Study investigates spillovers only	1.2
Study investigates firm survival	0.7
Publication date is pre-1980	0.6
Study is not published in English	0.3
Study investigates R&D subsidies only	0.2
Study is a meta-analysis	0.2
Total (%)	**100**

Table A2.3: Exclusion decisions based on full-text information: Stage-two decisions

Exclusion criteria	% of total decisions
Non-production function (including cost function) approach	34.8
Crépon-Duguet-Mairesse (CDM) models of innovation	26.1
Gibrat's Law modeling	6.5
R&D dummy only	6.5
Missing standard errors or t-values	4.4
R&D term is nonlinear or interactive	4.4
Ad hoc modeling	4.4
Case study	2.2
Descriptive study	2.2
Regional rather than industry or firm level data	2.2
Study investigates spillovers only	2.2
R&D volatility	2.2
Unconventional TFP measure	2.2
Total (%)	**100**

A3. FUNNEL GRAPHS FOR ELASTICITY AND RATES-OF-RETURN ESTIMATES

Figure A3.1: Funnel graph of elasticities in level dimension

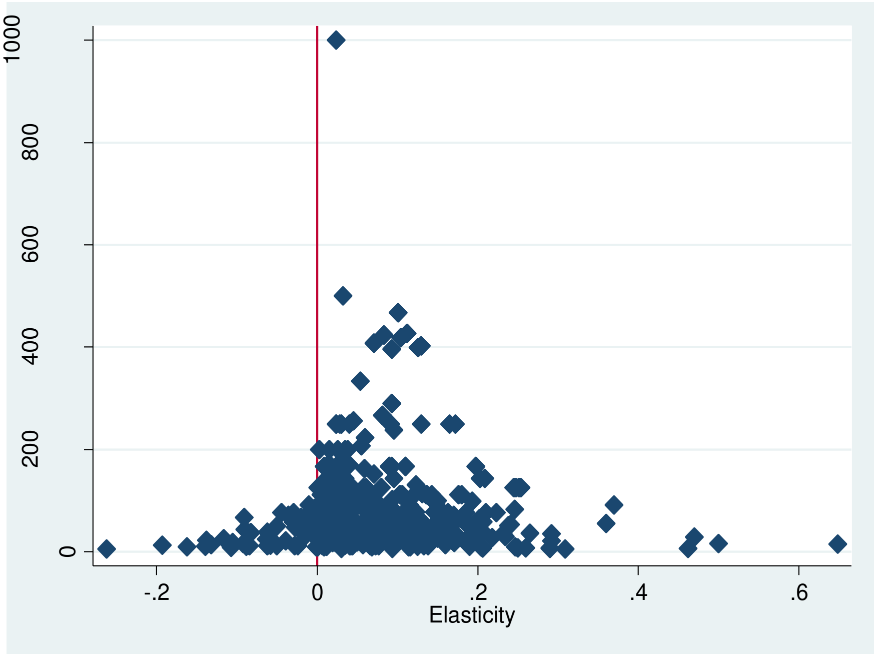


Figure A3.1: Funnel graph of elasticities in temporal dimension

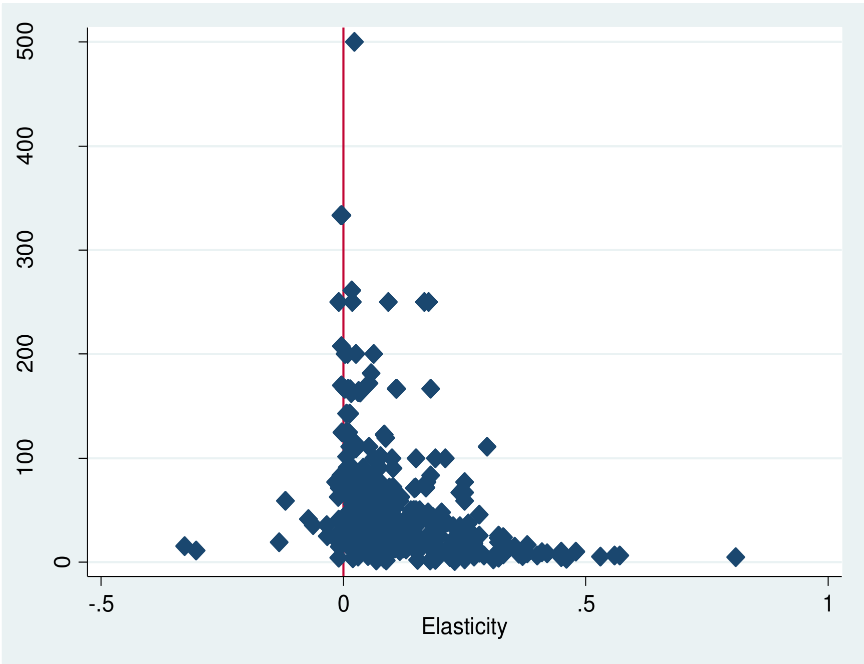
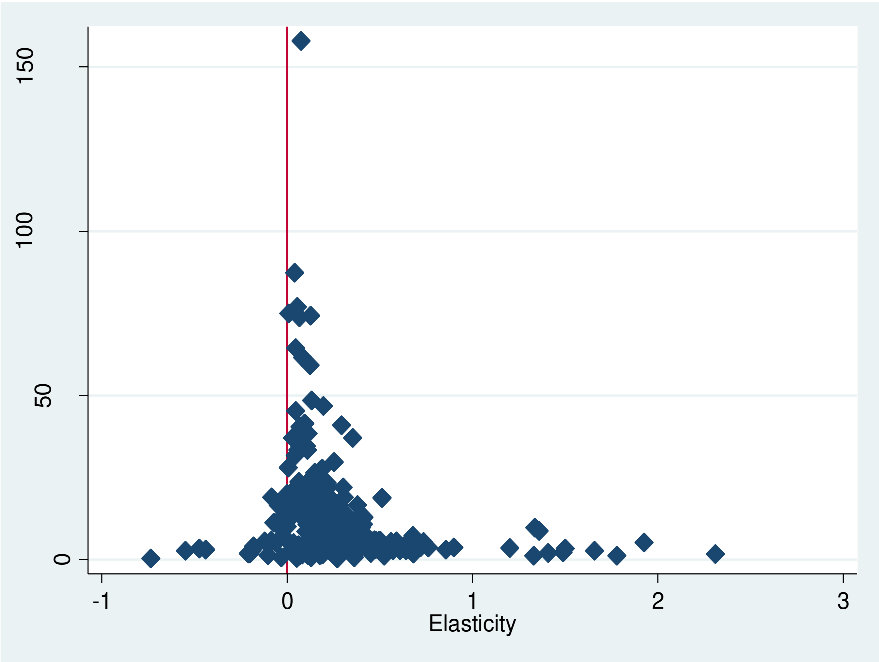


Figure A3.1: Funnel graph of rates-of-return estimates



A4. SUMMARY STATISTICS

Table A4.1: Description of moderating variables and reference categories

Moderating variable	Description and reference category
1. Journal article	Equals 1 if study is published as journal article; 0 for all other publications types
2. Working paper	Equals 1 if study is published as working paper; 0 for all other publications types
3. Firm-level data	Equals 1 if estimate is based on firm- or plant-level data; 0 if it is based on 2-digit or more disaggregated industry data
4. GMM estimation	Equals 1 if estimate is based on system or difference GMM estimation; 0 for all other types of estimation
5. Weighted least square estimation	Equals 1 if estimate is based on weighted least squares (WLS) estimation; 0 for non-WLS estimation
6. Dynamic model	Equals 1 if estimate is based on dynamic model specification; 0 otherwise
7. Instrumented variable estimation	Equals 1 if estimate is based on instrumented (GMM, 2SLS, 3SLS, etc.) estimation; 0 otherwise
8. Output measured as value added	Equals 1 if estimate is based on value added; 0 for output measured as sales or production
9. Data mid-point after 1980	Equals 1 if estimate is based on data panel with amid year = 1980; 0 if the midpoint is larger than 1980
10. French firm or industry data	Equals 1 if estimate is based on French data; 0 for data from ALL other OECD countries
11. German firm or industry data	Equals 1 if estimate is based on German data; 0 for data from ALL other OECD countries
12. UK firm or industry data	Equals 1 if estimate is based on UK data; 0 for data from ALL other OECD countries
13. US firm or industry data	Equals 1 if estimate is based on US data; 0 for data from ALL other OECD countries
14. Control for double counting	Equals 1 if the estimate is derived from a model that controls for double counting; 0 otherwise
15. Control for spillovers	Equals 1 if the estimate is derived from a model that controls for spillovers; 0 otherwise
16. Time dummies included	Equals 1 if the estimate is derived from a model that includes period dummies; 0 otherwise
17. Industry dummies included	Equals 1 if the estimate is derived from a model that includes industry dummies; 0 otherwise
18. Variable returns to scale allowed	Equals 1 if estimate is derived from a model that allows for variable returns to scale; 0 if constant returns are imposed
19. R&D-intensive firms	Equals 1 if estimate relates to R&D-intensive firms/industries as defined by the author; 0 otherwise
20. Small firms	Equals 1 if estimate relates to small firms as defined by the author; 0 otherwise
21. Translog production function	Equals 1 if estimate is based on translog production function; 0 otherwise
22. Government-funded R&D	Equals 1 if estimate is related to level of government-funded R&D; 0 for private funded or source not specified

Table A4.2: Summary statistics for Meta-regression 1: R&D elasticity estimates in level dimension

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
1. Elasticity estimate	443	0.077	0.095	-0.262	0.648
2. Standard error	443	0.030	0.032	0.000	0.210
3. Journal article	443	0.661	0.474	0	1
4. Working paper	443	0.237	0.426	0	1
5. Firm-level data	443	0.810	0.392	0	1
6. GMM estimation	443	0.113	0.317	0	1
7. Weighted least square estimation	443	0.079	0.270	0	1
8. Dynamic model	443	0.104	0.305	0	1
9. Instrumented variable estimation	443	0.269	0.444	0	1
10. Output measured as value added	443	0.476	0.500	0	1
11. Data mid-point after 1980	443	0.587	0.493	0	1
12. French firm or industry data	443	0.095	0.293	0	1
13. German firm or industry data	443	0.054	0.227	0	1
14. UK firm or industry data	443	0.117	0.322	0	1
15. US firm or industry data	443	0.413	0.493	0	1
16. Control for double counting	443	0.253	0.435	0	1
17. Control for spillovers	443	0.156	0.363	0	1
18. Time dummies included	443	0.542	0.499	0	1
19. Industry dummies included	443	0.458	0.499	0	1
20. Variable returns to scale allowed	443	0.485	0.500	0	1
21. R&D-intensive firms	443	0.223	0.417	0	1
22. Small firms	443	0.014	0.116	0	1
23. Translog production function	443	0.183	0.387	0	1
24. Government-funded R&D	443	0.007	0.082	0	1

Table A4.3: Summary statistics for Meta-regression 2: R&D elasticity estimates in temporal dimension

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
1. Elasticity estimate	469	£0.108	£0.114	-0.328	0.810
2. Standard error	469	£0.052	£0.085	0.000	0.920
3. Journal article	469	£0.387	£0.488	0	1
4. Working paper	469	£0.389	£0.488	0	1
5. Firm-level data	469	£0.887	£0.317	0	1
6. GMM estimation	469	£0.055	£0.229	0	1
7. Weighted least square estimation	469	£0.011	£0.103	0	1
8. Dynamic model	469	£0.085	£0.279	0	1
9. Instrumented variable estimation	469	£0.115	£0.319	0	1
10. Output measured as value added	469	£0.351	£0.478	0	1
11. Data mid-point after 1980	469	£0.757	£0.429	0	1
12. French firm or industry data	469	£0.077	£0.266	0	1
13. German firm or industry data	469	£0.128	£0.334	0	1
14. UK firm or industry data	469	£0.015	£0.121	0	1
15. US firm or industry data	469	£0.328	£0.470	0	1
16. Control for double counting	469	£0.319	£0.467	0	1
17. Control for spillovers	469	£0.143	£0.350	0	1
18. Time dummies included	469	£0.504	£0.501	0	1
19. Industry dummies included	469	£0.191	£0.394	0	1
20. Variable returns to scale allowed	469	£0.413	£0.493	0	1
21. R&D-intensive firms	469	£0.172	£0.378	0	1
22. Small firms	469	£0.017	£0.129	0	1
23. Translog production function	469	£0.049	£0.216	0	1
24. Government-funded R&D	469	£0.006	£0.080	0	1

Table A4.4: Summary statistics for Meta-regression 3: Rates of return on R&D investment

Variable	Obs	Mean	Std. Dev.	Min	Max
1. Rate-of-return estimate	350	0.249	0.312	-0.737	2.31
2. Standard error of the estimate	350	0.183	0.299	0.006	2.989
3. Journal article	350	0.778	0.416	0	1
4. Working paper	350	0.085	0.280	0	1
5. Firm-level data	350	0.607	0.489	0	1
6. GMM estimation	350	0.020	0.140	0	1
7. Weighted least squares	350	0.131	0.338	0	1
8. Dynamic production function	350	0.060	0.238	0	1
9. Instrumented var. estimations (GMM+2SLS+3SLS)	350	0.182	0.387	0	1
10. Output measured as value-added	350	0.390	0.489	0	1
11. Data mid-point is after 1980	350	0.436	0.497	0	1
12. French firm or industry data	350	0.066	0.248	0	1
13. German firm or industry data	350	0.026	0.158	0	1
14. UK firm or industry data	350	0.142	0.350	0	1
15. US firm or industry data	350	0.499	0.501	0	1
16. Control for double-counting	350	0.234	0.424	0	1
17. Control for spillovers	350	0.202	0.402	0	1
18. Time dummies included	350	0.319	0.467	0	1
19. Industry dummies included	350	0.464	0.499	0	1
20. Variable returns to scale	350	0.325	0.469	0	1
21. R&D-intensive firm or industry	350	0.037	0.189	0	1
22. Small firm	350	0.009	0.092	0	1
23. Translog production function	350	0.105	0.308	0	1
24. Government-funded R&D	350	0.043	0.203	0	1

A5. EXAMPLES OF EXCLUDED STUDIES

A5.1 Examples of studies excluded for lacking an empirical dimension

Anthony Scott D; Johnson Mark W; Sinfield Joseph V; Altman Elizabeth (2008) Driving Growth Through Innovation. Financial Executive. 24: 38-43.

Barnholt E W; (1997) Fostering business growth with breakthrough innovation. Research-Technology Management. 40: 12-16.

Baumol William J; (2002) Entrepreneurship, Innovation and Growth: The David-Goliath Symbiosis. Journal of Entrepreneurial Finance and Business Ventures. 7(2): 1-10.

Bell Robert R; Burnham John M; (1989) The Paradox of Manufacturing Productivity and Innovation. Business Horizons. 32: 58.

Bianchi Carmine, Winch Graham W; (2009) Supporting value creation in SMEs through capacity building and innovation initiatives: the danger of provoking unsustainable rapid growth. International Journal of Opportunity, Growth and Value Creation. 1: 164-184.

Cantwell John, Fai Felicia (1999) Firms as the source of innovation and growth: the evolution of technological competence. Journal of Evolutionary Economics. 9: 331.

Carlson WBernard, Sammis Stuart K; (2009) Revolution or evolution?: The role of knowledge and organization in the establishment and growth of R & D at Corning. Management & Organizational History. 4: 37-65.

Deplazes Ursula, Deplazes Wolfgang, Boutellier Roman (2010) Engines of growth - the importance of 'routine innovation activities'. International Journal of Entrepreneurship and Innovation Management. 12: 244-269.

Ehrengen Lars (2006) The relationship between R&D, innovation and growth in Europe. International Journal of Management & Decision Making. 7: 692-707.

George Gerard, McGahan Anita M; Prabhu Jaideep (2012) Innovation for Inclusive Growth: Towards a Theoretical Framework and a Research Agenda. Journal of Management Studies. 49: 661-683.

Helo Petri, Takala Josu, Phusavat Kongkiti (2008) Productivity measurement for knowledge work in research and development. International Journal of Productivity and Quality Management. 4: 39-54.

Lee Sungjoo, Kim Moon-soo (2010) Inter-technology networks to support innovation strategy: an analysis of Korea's new growth engines. Innovation: management, policy and practice. 12: 88-104.

Moncada-Housernò-Castello Pietro, Cincera Michele (2012) Enterprises' Growth Potential in the European Union: Implications for Research and Innovation Policy. IUP Journal of Entrepreneurship Development. 9: 7-40.

Oakey R P; (2003) Funding innovation and growth in UK new technology-based firms: some observations on contributions from the public and private sectors. Venture Capital. 5: 161.

Patterson Marvin L; (1998) From Experience: Linking Product Innovation to Business Growth. Journal of Product Innovation Management. 15: 390-402.

Simons Tad, Gupta Arvind, Buchanan Mary (2011) Innovation in R&D: Using design thinking to develop new models of inventiveness, productivity and collaboration. Journal of Commercial Biotechnology. 17: 301-307.

Vaz Teresa de Noronha; Nijkamp Peter (2009) Knowledge and innovation: The strings between global and local dimensions of sustainable growth. Entrepreneurship & Regional Development. 21: 441-455.

Wang Jenn-hwan (2007) From technological catch-up to innovation-based economic growth: South Korea and Taiwan compared. Journal of development studies. 43: 1084-1104.

A5.2 Examples of Studies excluded for lacking a relevant dependent and/or independent variable

Agarwal Rajshree, Bayus Barry L; (2002) The Market Evolution and Sales Takeoff of Product Innovations. Management Science. 48: 1024-1041.

Aghion Philippe, Blundell Richard, Griffifth Rachel, Howitt Peter, Prantl Susanne (2009) The Effects of Entry on Incumbent Innovation and Productivity. Review of Economics & Statistics. 91: 20-32.

Aghion Philippe, Blundell Richard, Griffith Rachel, Howitt Peter, Prantl Susanne (2004) Entry and Productivity Growth: Evidence from Microlevel Panel Data. Journal of the European Economic Association. 2: 265-276.

Ahlstrom David (2010) Innovation and Growth: How Business Contributes to Society. Academy of Management Perspectives. 24: 11-24.

Ang Cecil Y; (2010) Cash is King: Financing the Innovation-Productivity Link at Firm Level. Michigan Journal of Business. 3: 9-44.

Baldwin John R; Wulong G U; (2004) Trade Liberalization: Export-market Participation, Productivity Growth, and Innovation. Oxford Review of Economic Policy. 20: 372-392.

Baumol William J; (2003) Innovations and growth: two common misaprehensions. Journal of Policy Modeling. 25: 435.

Borisova Ginka, Brown James R; (2013) R&D sensitivity to asset sale proceeds: New evidence on financing constraints and intangible investment. Journal of Banking & Finance. 37: 159-173.

Bottazzi Giulio, Dosi Giovanni, Lippi Marco, Pammolli Fabio, Riccaboni Massimo (2001) Innovation and corporate growth in the evolution of the drug industry. International Journal of Industrial Organization. 19: 1161.

Brown James R; Fazzari Steven M; Petersen Bruce C; (2009) Financing Innovation and Growth: Cash Flow, External Equity, and the 1990s R&D Boom. Journal of Finance. 64: 151-185.

Carlin Wendy, Schaffer Mark, Seabright Paul (2004) A Minimum of Rivalry: Evidence from Transition Economies on the Importance of Competition for Innovation and Growth. Contributions to Economic Analysis & Policy. 3: 1-43.

Cohen Wesley M; Klepper Steven (1996) Firm Size and the Nature of Innovation within Industries: The Case of Process and Product R. Review of Economics and Statistics. 78(2): 232-43.

Danzon Patricia M; Nicholson Sean, Pereira Nuno Sousa; (2005) Productivity in pharmaceutical -- biotechnology R&D: the role of experience and alliances. Journal of Health Economics. 24: 317-339.

Davis Colin (2013) Regional integration and innovation offshoring with occupational choice and endogenous growth. Journal of Economics. 108: 59-79.

Filson Darren (2002) Product and Process Innovations in the Life Cycle of an Industry. Journal of Economic Behavior and Organization. 49(1): 97-112.

Griffith Rachel, Redding Stephen, Simpson Helen (2004) Foreign Ownership and Productivity: New Evidence from the Service Sector and the R&D Lab. Oxford Review of Economic Policy. 20: 440-456.

Hamilton Donald I; (2009) Innovation and corporate growth: a study of small and medium scale enterprises in Nigeria. International Journal of Management Practice. 3: 291-303.

Howells Jeremy, Gagliardi Dimitri, Malik Khaleel (2008) The growth and management of R&D outsourcing: evidence from UK pharmaceuticals. R&D Management. 38: 205-219.

Ishii Y (2010) The role of patent, citation and objection stocks in the productivity analysis of R&D - using Japanese company data. International journal of innovation management. 14: 947-963.

Kirchhoff Bruce A; Newbert Scott L; Hasan Iftekhar, Armington Catherine (2007) The Influence of University R & D Expenditures on New Business Formations and Employment Growth. Entrepreneurship: Theory & Practice. 31: 543-559.

Love James H; Roper Stephen, Bryson John R; (2011) Openness, knowledge, innovation and growth in UK business services. Research Policy. 40: 1438-1452.

Mazzucato Mariana (2003) Risk, variety and volatility: growth, innovation and stock prices in early industry evolution. Journal of Evolutionary Economics. 13: 491-512.

Monreal-Pérez Joaquín, Aragón-Sánchez Antonio, Sánchez-Marín Gregorio (2012) A longitudinal study of the relationship between export activity and innovation in the Spanish firm: The moderating role of productivity. International Business Review. 21: 862-877.

Nair Anand, Jones-Farmer L Allison; Swamidass Paul (2009) Modelling the reciprocal and longitudinal effect of return on sales and R&D intensity during economic cycles. International journal of technology management. 49: 2-24.

Nishioka S, Ripoll M (2012) Productivity, trade and the R&D content of intermediate inputs. European Economic Review. 56: 1573-1592.

Peneder Michael (2010) The impact of venture capital on innovation behaviour and firm growth. Venture Capital. 12: 83-107.

Regev Haim (2005) Life Cycle, Innovation and Firm Productivity: Israeli Manufacturing Firms, 1955-1999. Annals of Economics and Statistics / Annales d'Économie et de Statistique. : 405-431.

Sharma Dave, Martini Luigi G; (2013) Austerity vs. growth-The impact of the current financial crisis on pharmaceutical innovation. International Journal of Pharmaceutics. 443: 242-244.

Stainer Alan, Nixon Bill (1997) Productivity and performance measurement in R&D. International Journal of Technology Management. 13: 486.

Wagner Marcus (2010) Acquisitions as a means of innovation sourcing by incumbents and growth of technology-oriented ventures. International journal of technology management. 52: 118-134.

A5.3 Examples of studies excluded for utilizing a CDM model

Anon Higon, Dolores , Manjón Antolín, Miguel (2012) Multinationality, foreignness and institutional distance in the relation between R&D and productivity. Research Policy. 41: 592-601.

Anon Higon, Dolores , Manjón Antolín, Miguel , Mañez Juan A; (2011) Multinationals, R&D, and productivity: evidence for UK manufacturing firms. Industrial & Corporate Change. 20: 641-659.

Antonietti Roberto, Cainelli Giulio (2011) The role of spatial agglomeration in a structural model of innovation, productivity and export: a firm-level analysis. Annals of Regional Science. 46: 577-600.

Benavente Jose Miguel; (2006) The role of research and innovation in promoting productivity in chile. Economics of Innovation & New Technology. 15: 301-315.

Bos J W B, Economidou C, Koetter M (2010) Technology clubs, R&D and growth patterns: Evidence from EU manufacturing. European Economic Review. 54: 60-79.

Crepon Bruno, Duguet Emmanuel, Mairesse Jacques (1998) Research, Innovation and Productivity: An Econometric Analysis at the Firm Level. *Economics of Innovation & New Technology*. 7: 115.

Griffith Rachel, Huergo Elena, Mairesse Jacques, Peters Bettina (2006) INNOVATION AND PRODUCTIVITY ACROSS FOUR EUROPEAN COUNTRIES. Oxford Review of Economic Policy. 22: 483-498.

Higon Dolores Anon; Manjon Antolin, M (2012) Multinationality, foreignness and institutional distance in the relation between R&D and productivity. Research policy. 41: 592-601.

Huergo Elena, Moreno Lourdes (2011) Does history matter for the relationship between R&D, innovation, and productivity?. Industrial & Corporate Change. 20: 1335-1368.

Karafillis Chrysovalantis, Papanagiotou Evaggelos (2011) Innovation and total factor productivity in organic farming. Applied Economics. 43: 3075-3087.

Legros Diégo, Galia Fabrice (2012) Are innovation and R&D the only sources of firms' knowledge that increase productivity? An empirical investigation of French manufacturing firms. Journal of Productivity Analysis. 38: 167-181.

Mairesse Jacques, Mohnen Pierre, Kremp Elisabeth, Kremp Elizabeth (2005) The Importance of R&D and Innovation for Productivity: A Reexamination in Light of the French Innovation Survey. Annals of Economics and Statistics / Annales d'Économie et de Statistique. : 487-527.

A5.4 Examples of studies excluded for NOT following the primal (production function) approach

Amirkhalkhali Saleh, Mukhopadhyay Arun K; (1993) The Influence of Size and R&D on the Growth of Firms in the US. Eastern Economic Journal. 19(2): 223-33.

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