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Publication bias in the returns to R&D literature

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Abstract

The returns to R&D literature is large and has been surveyed on several occasions. We complement previous surveys by using formal meta analytic techniques to analyse publication bias. We find evidence consistent with a strong positive bias in the part of the literature that controls for unobserved firm fixed effects. The reason may be that fixed effects specifications are particularly susceptible to measurement errors and therefore have a high probability of producing implausibly low return estimates. Implausible estimates are likely to be filtered out before being reported, and our analysis suggest that 26 % of a hypothetical complete literature is missing. Future reviews should take into account that the full effect of negative specifications biases may be masked by reporting and publication bias.

Keywords: Returns to R&D, Meta-analysis, Publication bias, Funnel asymmetry, Trim-and-fill method, FAT – PET

JEL classification: C83, D24, O31

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1 Introduction

OECD governments spend a substantial amount of public money on programs intended to stimulate innovative activities. The justification for these programs rests on a vast and steadily growing literature that estimates the private and social returns to R&D.

Much of the returns to R&D literature builds on the R&D capital model formalized in Griliches (1973, 1979), and the literature is reviewed in a number of excellent surveys. Mairesse and Mohnen (1990) is an early example. Hall, Mairesse and Mohnen (2010), in a new Elsevier Handbook, is the most recent.[1] All surveys conclude that there are large returns to R&D, although no one computes a combined return estimate using a formal meta-analytic technique.

Most economists have a prior belief that returns to R&D are positive and possibly large, but the returns to R&D literature is prone to problems related to measurement, selection, choice of functional form and appropriate lag lengths. This suggests that there is a danger of publication bias. Reporting and publication bias are widely recognized as threats to the validity of empirical research. This bias may be self-imposed by researchers, or imposed by editors and referees who consider negative, small or non-significant coefficients to be suspicious and of little interest. Studies - and results within studies - where the returns to R&D are overestimated are then more likely to end up reported than results where the returns are underestimated. To the extent that this occurs, the average of estimates from published studies will overestimate the true return. This topic has not been given any attention in previous surveys of the returns to R&D, except for a brief comment by Griliches (1992):

> "The estimated social rates of return look surprisingly uniform in their indication of the importance of [...] spillovers. While one must worry whether this is not just the result of self-imposed publication filters, my own involvement in this work and my acquaintance with many of the other researchers in this area leads me to believe in the overall reality of such findings."

We do not question the "overall reality" of positive returns to R&D, but we complement previous surveys by providing a first analytical investigation of whether the "worry" that Griliches reflects on, is warranted or not. Surveying a related literature, Ientile and Mairesse (2009) find evidence suggesting that "there might be a positive publication bias in the literature on the

[1] Other surveys include Mairesse and Sassenou (1991), Nadiri (1993), the Australian Industry Commission (1995), Hall (1996), Griliches (1995, 2000) and Wieser (2005).

efficiency of R&D tax credits".[2]

The literature on the private and social returns to R&D is large. We base our meta analysis on the recent and comprehensive surveys by Wieser (2005) and Hall et al. (2010).[3] Our focus is on the private returns to R&D estimated on firm level data. Using both funnel graphs, regressions and the "trim and fill"-method, we find evidence consistent with a strong positive bias in the part of the literature that controls for unobserved firm fixed effects. The reason may be that fixed effects specifications are particularly susceptible to measurement errors and therefore have a high probability of producing implausibly low return estimates. Our analysis suggests that as much as 26 % of the results in a hypothetical complete literature is missing. Although it may seem rational for individual researchers to filter out implausible results without reporting them, this number is surprisingly high. Many papers included in the surveys we build on are done by the most merited researchers in the field, and they were in many instances commissioned or invited in some way without being subject to usual publication selection.[4] Moreover, they tend to focus on methodological issues where zero or negative results should be as interesting as positive ones. Given this, one may speculate that the filtering of insignificant and negative results may be at least as large in the complete returns to R&D literature which comprise more studies commissioned by policy makers and studies produced by less merited researchers.[5]

In a subsample that estimates the gross private returns to R&D directly, we find a combined return estimate of 18.2 % before accounting for publication bias. When correcting for publication bias, the combined return estimate drops to 13.8 %. Our analysis, of course, does not imply that 13.8 % is a correct estimate of the true private returns to R&D-investments. In fact, 13.8 % seems implausibly low for a gross rate of return to R&D, as R&D investments are believed to depreciate by at least 15 % per year from a private point of view (Hall et al., 2010). The lesson to be learned from our meta analysis is rather that reporting and publication bias are an issue in the returns to R&D literature, and that negative specification biases, such as measurement

[2]This is supported by a recent and more formal analysis by Casellacci and Lie (2013).

[3]Wieser (2005) includes a formal meta analysis of the private returns to R&D literature, focusing on whether the returns are stable over time and across different countries, industries and econometric specifications. He does not adjust for publication bias, however, but he acknowledges that it "is generally considered to be one of the merits of the procedure".

[4]This was pointed out to us by an early referee, "aware of the research and publication history of many of the papers ".

[5]Mehmet et al. (2013) find that there exists a number of studies and results that are not included in the previous surveys. Brodeur et al. (2013) find that young researchers distort their reported results more in order to achieve statistical significance than tenured and older researchers.

error bias, is likely to interact with publication bias and mask the full effect of the specification bias.

2 The R&D capital model

The R&D capital model of Griliches (1973, 1979) has been the ruling paradigm for researchers wanting to estimate the returns to R&D – despite the many weaknesses that Griliches and others have pointed out. A simple representation of the model is the augmented R&D production function:

$$\log Y_{it} = \beta \log X_{it} + \gamma \log K_{it} + \alpha_i + u_{it} \tag{1}$$

where Y_{it} is output of firm i in year t, typically measured by firm revenue, X_{it} is a vector of standard economic inputs such as labor, materials, machinery, equipment etc. K_{it} is one or more measures of accumulated research efforts or "knowledge capital".[6] The error term is composed of α_i and u_{it} where α_i is a potential firm fixed effect and u_{it} is the idiosyncratic part. The coefficient of main interest is γ, the elasticity of output with respect to knowledge capital. The rate of return to R&D-investments can be calculated as $\gamma \frac{Y_{it}}{K_{it}}$

The knowledge capital stock can be constructed as a weighted sum of past investments in R&D. This can be done by the perpetual inventory method, making the necessary assumptions about how fast the R&D investments impact production and how fast knowledge depreciates from a private point of view.

Replacing levels with growth rates gives an alternative formulation where the marginal returns to R&D can be estimated directly:

$$\Delta \log Y_{it} = \alpha + \beta \Delta \log X + \rho \frac{R_{it}}{Y_{it}} + \Delta u_{it} \tag{2}$$

In this formulation, $\rho = \frac{dY_{it}}{dK_{it}} = \gamma \frac{Y_{it}}{K_{it}}$ and $\Delta \log K_{it}$ is approximated by $\frac{R_{it}}{K_{it}}$. R_{it} is the net investment in R&D, i.e. net of the depreciation of previously accumulated knowledge. Under certain assumptions, see e.g. Hall et al. (2010), ρ can be interpreted as the marginal gross internal rate of return to R&D. Subtracting the private R&D depreciation rate one obtains a

[6]The model can also be specified with labor productivity or total factor productivity as dependent variable.

marginal net rate of return.[7]

3 Sources of publication bias

Ashenfelter, Harmon and Oosterbeek (1999) point out that if published results are selected because they are significant, this implies that surveys of such results suffer from the same sample selection bias that is emphasized as a concern in all econometric text books. In economics, this idea goes back at least to DeLong and Lang (1992), but it has received considerably more attention in other sciences like medicine. Ashenfelter et al. state that publication bias may arise "because of the tendency in virtually all scientific fields to report statistical results that tend to reject the null hypothesis of no effect." They stress that "the existence of any such bias is no reflection on any individual scholar, but is instead the natural working of a scientific process designed to discover important new results."

Card and Krueger (1995) address three potential sources of publication bias. First, scientific journals might favor statistically significant results, as pointed out above. Second, reviewers and editors may use their expectation of the value as an informal test of the validity of estimates. Third, researchers are likely to have an expectation of what the results will look like. Such expectations may be important when evaluating findings, and might influence the subsequent choice of empirical specification. Rather than relying on counterintuitive results, researchers might believe there is something wrong with the specification. Even though this may be true in many cases, selection of this type will still bias the literature.

The various sources of bias might also reinforce each other. When evaluating their results, researchers will consider the probability of having findings published. This implies that they may not only evaluate results on grounds of their own expectations, but also on their understanding of other researchers' expectations.

[7] In equation (2), R is the net investment in R&D, while only gross R&D is available in empirical work. Using an R&D measure that is too large, obviously causes ρ to be underestimated. Hall et al. (2010) show that this bias may be substantial. Eberhart, Helmers and Strauss (2012), on the other hand, show that private returns to R&D estimates may suffer from a positive bias as they are based on specifications that ignore the effect of R&D spillovers. R&D spillovers are positively correlated with private R&D investments. Much of this bias, however, is likely to be absorbed by firm fixed effects.

4 Data

The returns to R&D have been analyzed at the country level, industry level and firm level. We will focus on results from research at the firm level, as this is the most common approach. Our focus is on private returns, not social returns.[8] Following Wieser (2005), we exclude studies based on cost functions (the dual approach). The reason is partly that the number of such studies at the firm level is small, and partly that they vary quite a bit with respect to specification. Beyond a reasonable number of studies, a condition for conducting a meta-analysis is that the studies included share some common aspects that make them comparable in a statistical manner.

Our aim is to complement previous surveys, and we use the data in Wieser (2005), Tables 2, 3 and 4 as our starting point. Table 2 contains "firm level econometric estimates of the rate of return to research and development", Table 3 contains "estimates of the elasticity of research and development from the level dimensions" (including pooled OLS estimates) and Table 4 contains "estimates of the elasticity of research and development based on the temporal dimensions" (i.e. within and difference estimates). We have updated these tables by cross-checking them against Hall et al. (2010), where Tables 3, 2a and 2b correspond to Wieser's Tables 2, 3 and 4, respectively. This resulted in the inclusion of estimates from 18 additional studies, based on 38 samples. In Hall et al. (2010), there is not a standard error attached to every reported estimate. There are also examples where the effect estimate is denoted by an interval, rather than a precise number. In these cases, we collect standard errors and exact estimates from the original source. When the two surveys report results from different versions of the same paper, we collect our estimates from the most recent. If a data set is represented by results from different levels of aggregation of the underlying data, e.g. both an overall estimate and estimates by industry or separate time periods, we only include the results based on the most aggregated sample.

All estimates used are listed in Tables A1–A3 in the appendix.[9] For each study and regression result, we record the coefficient of interest (rate of return or elasticity), the standard error of the coefficient, the number of firms in the sample, the time period covered and the country. Our analysis is based on 41 primary studies, but many of the studies are represented by multiple estimates. When these results represent different specifications estimated on the same sample,

[8]See Karlsson, Warda and Gråsjö (2012) for a formal meta-analysis of the spatial knowledge spillover litterature.

[9]We have also posted our dataset at the meta analysis web page of Chris Doucouliagos, http://www.deakin.edu.au/buslaw/aef/meta-analysis/.

including all would imply that these samples are overweighted. In order to avoid this problem, we only include the median estimate for each sample reported in Tables A1–A3. This reduces our total number of estimates from 197 to 94. Table 1 gives descriptive statistics for the estimates included in our meta-analysis.

Table 1: Sample statistics

	(1) Rate of return to R&D	(2) Elasticity of R&D Level dimension	(3) Elasticity of R&D Temporal dimension
Number of effect estimates	32	32	30
Mean effect estimate	0.19	0.10	0.07
	(0.15)	(0.05)	(0.08)
Median effect estimate	0.210	0.103	0.045
Min. effect estimate	-0.475	0.014	-0.003
Max. effect estimate	0.420	0.216	0.328
Mean number of firms	700	671	642
	(1146)	(1216)	(814)
Median number of firms	269.5	236.5	394
Min. number of firms	3	17	17
Max. number of firms	5240	6145	3830

Standard errors in parentheses. Elasticity estimates based on the level dimension include pooled OLS. Elasticity estimates based on the temporal dimension account for firm fixed effects. Also the rate of return estimates account for firm fixed effects, as they are based on a first difference specification, cf. equation (2).

We do not include moderating variables in our meta analysis as our focus is on publication bias, and Wieser (2005) find very few systematic sources of heterogeneity in his meta analysis.

5 Detecting publication bias

Light and Pillemer (1984) claim that a "funnel graph" holds information on selection bias in scientific literatures. They plot different estimates of the same parameter into a coordinate system. The horizontal axis denotes the size of the coefficient, whereas the vertical axis denotes the sample size of the study. The idea is that the scatter plot should form a symmetric funnel-shaped pattern in the absence of publication bias.

Funnel graphs were quickly adopted to examine clinical trial studies. According to Sutton et al. (2000), this is the most commonly used method to detect publication bias in medical research. In economics, funnel graphs have not been much used until recently, but the survey by Stanley and Doucouliagos (2010) illustrates their simplicity and effectiveness. Stanley and

Doucouliagos argue that the inverse of an estimate's standard error is a better measure of its precision than the sample size. They claim that the funnel graph has two main implications. First, only the most accurate findings will reveal the true value of an estimate. Second, an asymmetric funnel graph suggests publication bias.[10] Funnel graph asymmetry can be tested formally, e.g. by simple linear regression or by the non-parametric method of Duval and Tweedie (2000a, 2000b).

We present funnel graphs in section 7.1, regression based asymmetry tests in section 7.2, and the results from the trim-and-fill method in section 7.3.

6 Correcting for publication bias

Based on the literature, we want to present a best estimate for the overall returns to R&D. When publication bias is detected, however, a combined meta analysis estimate must account for the effect of missing studies. Several techniques have been suggested, and a common approach is the non-parametric trim-and fill method developed by Duval and Tweedie (2000a, 2000b). Even though this procedure is implemented in all large statistical software packages, it has hardly been used in economics.[11] The trim-and-fill method is a relatively simple, rank-based augmentation technique, and the simulation studies in Duval and Tweedie (2000a) suggest that it outperforms more sophisticated methods in many situations.[12]

The trim-and-fill method can be considered a formalization of the funnel graph. It starts out estimating the number of "asymmetric" studies on the right-hand side of the funnel by a non-parametric, iterative procedure. (We assume here that it is the small and negative estimates on the left-hand side of the funnel that may have been filtered out.) Asymmetric studies can broadly be thought of as studies that do not have a left-hand side counterpart. In the next step, the asymmetric studies are removed or "trimmed" away, leaving a symmetric remainder that is used to estimate the true center of the funnel by standard meta-analytic methods. Finally, the

[10] Strictly speaking, there may also be symmetric publication selection in which case Light and Pillemer (1984) suggest using the 'hollowness' of the funnel graph to indicate selection bias. Symmetric selection is less of a concern, since the mean effect found in meta-analyses will remain largely unbiased.

[11] The only studies we know of are by Abreu, de Groot and Florax (2005) who briefly mention the method and present some results based on it, and two very recent paper, Haelermans and Borghans (2012) and Nelson (2013).

[12] A common caveat in this literature, however, is that publication bias is only one possible cause of funnel plot asymmetry, see Sterne and Egger (2005). A cautious interpretation of results based on funnel graph asymmetry, therefore, is to consider them sensitivity analyses showing the potential effect of missing studies. We return to this issue in Section 8.

trimmed studies are replaced and their hypothetical, missing counterparts are imputed as mirror images of the "asymmetric" studies. Using this "filled" sample, an adjusted overall confidence interval can be calculated around the center estimate.[13]

When combining effect estimates to compute the true center of the funnel, one must choose between a fixed effects and a random effects model, see e.g. Borenstein, Hedges and Rothstein (2007). Readers not familiar with meta-analytic models should note that these are not the same as the standard econometric fixed- and random effects models for panel data. The fixed effects model in meta-analysis involves the assumption that there is only one true effect size that is shared by all included studies. The combined effect is then an estimate of this fixed or common effect, and the only reason for estimates to vary across studies is random error within studies. With a large enough sample size, this error will tend to zero. Hence, under the fixed effects model, a large study with high precision will be given a large weight, while small studies with low precision will have little influence on the combined estimate. This implies that the effect of publication bias may not be very severe under the fixed effects model, as the missing estimates typically have low precision.

The random effects model, by contrast, allows the true effect to vary between studies. The studies included in the meta analysis are assumed to be a random sample from the relevant distribution of effects. The estimated combined effect is then an estimate of the mean effect in this distribution. Since each study in the meta analysis is informative about a true effect size drawn from the distribution of effects, the random effects model gives more weight to estimates with low precision than the fixed effects model. Formally, the random effects model can be expressed as

$$\widehat{\theta}_i = \theta_i + \epsilon_i \quad \text{with} \quad \theta_i \sim N(\theta, \tau^2) \quad \text{and} \quad \epsilon_i \sim N(0, \sigma^2). \tag{3}$$

θ is the overall true effect and $\widehat{\theta}_i$ is the effect estimate from study i. The within study variance is σ^2 and the between study variance is τ^2. With $\tau^2 = 0$, the random effects model transforms to the fixed effects model. Note that the normality assumptions are customary,

[13]The algorithm works as follows: The most extreme right-hand side effect sizes are removed one by one. Between each iteration, the overall effect size is estimated, and the procedure goes on until the funnel plot is symmetric around the latest computed overall effect size. This trimming gives an unbiased effect size estimate, but also reduces the variance of the effects. Therefore, the algorithm adds back the original studies and augments the sample with their mirror images before computing the confidence interval.

but not strictly necessary. The variances, σ^2 and τ^2 can be estimated either with maximum likelihood or method-of-moments, cf. e.g DerSimonian and Kacker (2007).[14]

Given estimates of σ^2 and τ^2, the combined meta analysis estimate of θ is simply

$$\widehat{\theta} = \frac{\sum w_i \widehat{\theta}_i}{\sum w_i} \quad \text{where} \quad w_i = (\widehat{\sigma}^2 + \widehat{\tau}^2)^{-1} \quad \text{and} \quad \mathrm{SE}(\widehat{\theta}) = \frac{1}{\sqrt{\sum w_i}} \tag{4}$$

When combining estimates of the return to R&D, it seems obvious that the random effects model is easier to justify than the fixed effects model. The true returns to R&D are likely to vary over time and between industries, countries and even firms. In fact, in the introduction to their survey, Hall et al. (2010) explicitly caution the reader that the returns to R&D should not be thought of as an invariant parameter, but the outcome of a "complex interaction between firm strategy, competitor strategy and a stochastic macro-economic environment". There is therefore "no reason to expect *ex post* returns to be particularly stable".

7 Results

We start out presenting funnel graphs, and then turn to a formal regression analysis. Finally we present combined estimates based on the random effects model where we use the "trim and fill"-method to correct for publication bias.

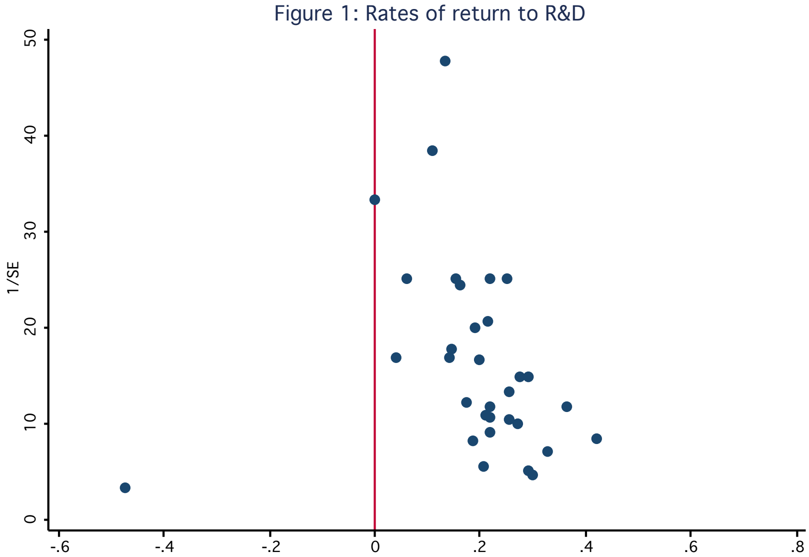
7.1 Funnel graphs

7.1.1 Rate of return results

When looking at direct empirical estimates of the rate of return to R&D, i.e. the direct marginal effect of investments from equation (2), we use a total of 32 results from 23 different studies. In Figure 1, we investigate potential publication bias by plotting the different results. We follow Stanley and Doucouliagos (2010) by measuring the size of the estimates on the horizontal axis, and the inverse standard error of the estimates on the vertical axis.

[14] In the empirical part of this paper we use the distribution free moment-based estimator of DerSimonian and Laird (1986). Kontopantelis and Reeves (2012), in a comprehensive simulation study, conclude that researchers may have "confidence that, whichever method they adopt, results are highly robust against even very severe violations of the assumption of normally distributed effect sizes."

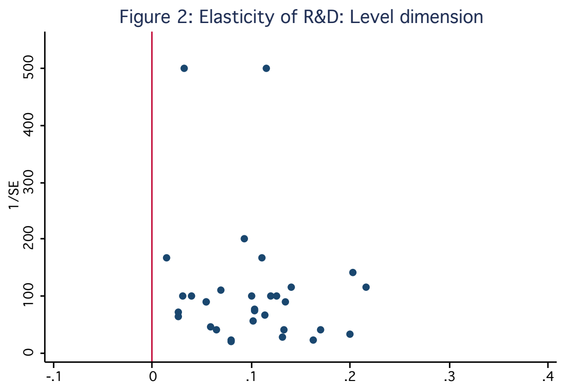
Figure 1: Rates of return to R&D



We see that the estimates vary from about -0.5 to almost 0.5. The most precise findings are clustered relatively close to 0 on the positive part of the horizontal axis. We recall that the most precise findings are those with the highest value at the vertical axis. The tail at the right hand side of the peak is remarkably thicker than the one to the left, and negative results are hardly present. According to the previous discussion of funnel graphs, this clearly suggests publication bias. Wieser (2005) reports an unweighted average rate of return of 28 % based on the significant coefficients in the literature he surveys. The funnel peaks at a substantially lower level, somewhere around 15 %.

7.1.2 Elasticity of R&D investments results

As explained in Section 2, elasticity estimates are also informative about the returns to R&D. Both Wieser (2005) and Hall et al. (2010) distinguish between results estimated from the level dimension of the data and results estimated using time variation. The key difference is that the latter group of studies control for firm fixed effects.



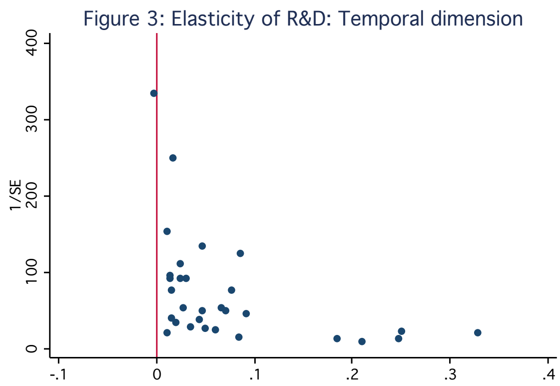


Figure 2 plots 32 results from 23 different studies utilizing the level dimension, and Figure 3 plots 30 results from 18 different studies utilizing the time dimension. A visual inspection of Figure 2 does not suggest serious publication bias, as the plot seems rather symmetric. The elasticity estimates peak around 0.1. A visual inspection of Figure 3, on the other hand, clearly suggests the presence of publication bias. It is striking how the results seem to reach their lower bound around zero. Also, the results tend to get more imprecise as the magnitude of the estimate increases. We will return to the difference between the two plots when we have verified the results using regression analysis.

7.2 Regression analysis

Stanley and Doucouliagos (2010) show by a graphical transformation how the funnel graph corresponds to a simple meta-regression model

$$\text{effect}_\text{i} = \beta_0 + \beta_1 SE_i + \epsilon_i \tag{5}$$

where i is an index referring to different empirical estimates.

Running this regression helps us verify or deny our subjective visual inspection of the funnel graphs presented in the previous section. Due to obvious heteroskedasticity, however, a weighted least squares counterpart of the above model is preferable. This can be obtained by weighting the squared errors by the inverse of the estimates' individual variances, $1/SE_i^2$, and is equivalent to dividing the previous expression by SE_i.

$$t_i = \beta_1 + \beta_0(1/SE_i) + \nu_i \tag{6}$$

Here, t_i is the t-value of each reported effect, and the intercept, β_1, will be zero in the absence of publication bias. This test is widely used and known as the funnel asymmetry test (FAT) or the Egger linear regression test after Egger et al. (1997). Simulations in Stanley (2008) show that this WLS procedure provides both an objective approach to identifying publication bias and a test for the presence of a true effect. If publication bias is not present, estimated effects should be independent of their standard errors, i.e. β_1 should be zero. Moreover, if there is an authentic empirical effect beyond the publication selection effect, β_0 should be positive. Testing the latter hypothesis, i.e. whether the coefficient on 1/SE is positive, is known as the precision effect test (PET).

The results of the described meta regression on the samples plotted in Figure 1, 2 and 3 are reported in Table 2, columns (1), (2) and (3), respectively.[15]

Table 2: WLS Meta-regressions

	(1) Rate of return to R&D	(2) Elasticity of R&D Level dimension	(3) Elasticity of R&D Temporal dimension
Constant (β_1) – FAT	1.422***	2.128	2.698***
	(0.505)	(1.920)	(0.634)
1/SE (β_0) – PET	0.0877***	0.0728***	0.000309
	(0.0263)	(0.0124)	(0.00624)
Observations	32	32	30
R^2	0.270	0.535	0.000

*** is significant at the 1% level, ** is significant at the 5% level. * is significant at the 10% level.
Elasticity estimates based on the level dimension include pooled OLS. Elasticity estimates based on the temporal dimension account for firm fixed effects. Also the rate of return estimates account for firm fixed effects, as they are based on a first difference specification, cf. equation (2).

The tabulated results show that the regressions verify our preliminary conclusions based on the funnel graphs. Both the regressions based on marginal returns to R&D and those based on elasticity estimates from studies utilizing the temporal dimension give β_1-estimates that are significantly different from 0. This suggests that publication bias is present. The regression based on elasticity estimates from studies utilizing the level dimension, on the other hand, does not give a significant β_1-estimate. Hence, publication bias appears not to be a problem in these studies, although the estimated coefficient is clearly positive. As for the (1/SE) term, both the rate of return estimates and the specification with elasticities from the level dimension state a

[15]Leaving out the obvious outlier to the left in Figure 1 does not change the results in column 1 noteworthy.

significant and positive effect of R&D, while this is not the case for elasticities estimated from the time dimension. One should perhaps not place too much emphasis on the lack of a significant, positive result in column (3), however, as Stanley (2008) shows that β_0 is underestimated when publication bias is present.

At first sight it is somewhat surprising that publication bias appears to be a problem in two specifications, but not in the third. We believe this can be explained by other biases that are present. Estimates utilizing the time dimension of the data account for firm fixed effects, but it is well known that this amplifies measurement error bias by increasing the noise-to-signal ratio in the data (Griliches and Hausman, 1986). Since R&D data typically are quite noisy, this implies that accounting for fixed effects increases the likelyhood of producing small estimates that are candidates to be rejected by the researchers themselves or by referees and editors. Studies utilizing the level dimension of the data do not account for unobserved firm fixed effects. Unobserved firm fixed effects may be due to differences in human capital, management quality, market size, previous patents, strength of brand names etc. These are characteristics that typically correlate positively with R&D. Estimates that do not control for fixed effects are therefore likely to be positively biased in absence of measurement errors, and the measurement error bias is likely to be smaller than in fixed effects specifications as explained above. Hence, level estimates will more easily confirm prior beliefs in the profession concerning high, positive returns to R&D.

7.3 Adjusting for publication bias using the trim-and-fill method

In Table 3 we present combined estimates of the returns to R&D based on the random effects model using the formula in equation (4) as implemented in the "metatrim"-algoritm by Steichen (2001). Metatrim also corrects for publication bias using the trim-and-fill method of Duval and Tweedie (2000a, 2000b) described in section 6.[16]

Results for the samples plotted in Figures 1, 2, and 3 are reported in columns (1), (2) and

[16]The algorithm uses the non-iterative moment-based estimator of DerSimonian and Laird (1986) to estimate the between studies variance. Hence, our results in Table 3 do not depend strictly on any distributional assumption regarding the random effect, cf. the discussion in Section 6.

(3), respectively.[17] [18]

From column (1) we see that the combined estimate for the marginal returns to R&D falls from 18.2 % to 13.8 % when publication bias is accounted for. The estimated number of missing studies is 11, i.e. 26 % of the filled sample. Correction for publication bias involves an even larger relative change for the combined elasticity estimates utilizing the temporal dimension. From column (3) we see that the combined elasticity estimate falls from 0.048 to 0.013 when publication bias is accounted for. The estimated number of missing studies is 15, i.e. 33 % of the filled sample. From column (2) we see that the combined elasticity estimates from studies utilizing the level dimension do not change at all that much, although the number of missing studies from this approach is 8, corresponding to 20 % of the filled sample. Correcting for publication bias reduces the combined elasticity estimate from 0.099 to 0.075. These findings are broadly consistent with the meta-regression results in Table 2, although we did not find significant publication bias in the level dimension sample there.

Table 3: Combined random effects estimates

	(1) Rate of return to R&D	(2) Elasticity of R&D Level Dimension	(3) Elasticity of R&D Temporal dimension
No correction for publication bias	0.182***	0.099***	0.048***
Correction for publication bias	0.138***	0.075***	0.013*
Original sample size	32	32	30
Filled sample size	43	40	45
Estimated no. of missing studies	11	8	15

*** is significant at the 1 % level, ** is significant at the 5 % level, * is significant at the 10 % level.
The estimates are calculated using the Stata-routine "metatrim" by Steichen (2001).

8 A caveat

Before concluding, we should stress that the methods used in this paper are indicative of and publication bias, but they do not prove that this is what causes the funnel asymmetry, cf.

[17]Testing the random effects model against the fixed effects model using the so-called Q-test presented in Shadish and Haddock (1994, p. 266), clearly rejects the fixed effects model in all three samples. The fixed effects point estimates before adjusting for potential publication bias are 0.151, 0.082 and 0.019 for columns (1), (2) and (3), respectively. The corresponding estimates with correction for publication bias are 0.128, 0.074 and 0.009. Hence, our results are not highly sensitive to the choice between the fixed effects and random effects model.

[18]Leaving out the obvious outlier to the left in Figure 1 does not change the results in Table 3, column 1 noteworthy.

footnote 12. In the context of medical research Lau et al. (2006) write that

> "Strictly speaking, funnel plots probe whether studies with little precision (small studies) give different results from studies with greater precision (larger studies). Asymmetry in the funnel plot may therefore result not from a systematic under-reporting of negative trials, but from an essential difference between smaller and larger studies that arises from inherent between-study heterogeneity. "

In some settings it is conceivable that small studies have a larger true effect than large studies. This could e.g. happen in medical research if small studies use different populations or different protocols, or if the patients get more attention in small studies. Such concerns seem less relevant in the returns to R&D literature, but it is e.g. conceivable that large sample studies include a more heterogeneous group of firms and therefore, in absence of matching, have more of a problem with R&D investments being an endogenous choice. This could cause a positive correlation between precision and the estimated effect size. In such a case, however, one would expect to see an asymmetric funnel in studies utilising the level dimension and not in studies utilizing within firm variation. We observe the opposite.

Another possible reason for true funnel asymmetry is a case where the true underlying effect distribution is skewed.[19] One can easily argue that the returns to R&D at the firm level are skewed. The potential downside of an R&D project will be limited, while successful projects in rare instances may win a very profitable world marked. Empirical evidence in favor of this view can be found in Scherer and Harhoff (2000), although it should also be noted that the bulk of commercial R&D that form the basis of the returns to R&D literature, is relatively low risk development projects.

We have done explorative simulations showing that skewness of outcomes in the primary research samples will, to some extent, carry over to the funnel plot.[20] This is because samples that happen to include a very successful firm both will produce a high effect estimate and have a large estimated standard error. If this was a main driving force for funnel asymmetry in our analysis, however, we would expect to see at least as much funnel asymmetry in studies utilizing the level dimension of the data as in studies that control for unobserved firm fixed effects. This is not the case.

[19]This possibility is –as far as we know – not previously discussed in the meta-analysis literature.

[20]We are grateful to Jonas Andersson for providing these simulations.

9 Concluding remarks

Publication bias has previously been detected in the literature on minimum wages by Card and Krueger (1995), in the returns to education literature by Ashenfelter, Harmon and Oosterbeek (1999) and in the literature on spillovers from multinational companies by Görg and Strobl (2001) to mention a few.[21] The meta-analysis presented in this paper suggests that publication bias is also present in the returns to R&D literature. Based on a sample of 32 results that directly estimate the gross private returns to R&D, we find a combined estimate of 18.2 % when publication bias is not accounted for. This is reduced to 13.8 % when we use the "trim and fill"-method to adjust for publication bias. The estimated number of missing studies is 11, i.e. 26 % of a hypothetical filled sample. In a sample of 30 studies estimating the elasticity of R&D using the temporal dimension of the data, i.e. accounting for firm fixed effects, we find evidence of even more severe publication bias. The estimated number of missing studies represents 33 % of a hypothetical filled sample, and the combined elasticity estimate falls from 0.048 to 0.013. In a sample of 32 studies estimating the elasticity of R&D using the level dimension of the data, however, we find that publication bias is far less of a problem. Correcting for publication bias using the trim-and-fill method on this sample only reduces the combined elasticity estimate from 0.099 to 0.075, and the Egger test for funnel graph asymmetry shows no significant publication bias at all. When publication bias is less of a problem in studies utilizing the level dimension, it is probably because these studies do not account for firm fixed effects, and therefore are likely to be positively, or at least less negatively, biased at the outset. This implies that they are likely to confirm prior beliefs in the profession concerning high, positive returns to R&D. The two specifications where publication bias is clearly present, on the other hand, control for firm fixed effects and are therefore likely to be negatively biased at the outset because of measurement errors in R&D. Resulting negative and small positive estimates are candidates to be rejected by the researchers themselves, or by referees and editors.

Our combined private returns to R&D estimate of 13.8 % seems implausibly low, as it represents a gross rate of return. R&D investments are believed to depreciate by at least 15 % per year from a private point of view. This suggests that further research on how to estimate

[21] More examples can be found in Stanley and Doucouliagos (2010). Note that Card and Krueger's (1995) conclusion was challenged by Neumark and Wascher (1998), but supported by an extended meta-analysis by Doucouliagos and Stanley (2009).

the returns to R&D is required, either as refinements of the standard R&D capital framework or through more novel generalizations. That being said, we should also stress that meta analysis is a review of the historical literature, not a review of "the truth". Hence, weighting together historical estimates and correcting them for historical publication bias produces a number that does not take into account that much has been learned since the earliest contributions to this literature were published. More recent and methodologically advanced studies would be expected to have estimates that are closer to the true average return. It is in this respect interesting to note that GMM-estimates, which are currently the preferred method of estimation, generally yield results that are close to the level estimates in the previous literature.

Our analysis serves to remind researchers in the field that reporting and publication bias pose a threat to the validity of the empirical literature. In light of this, future reviews should beware that the full effect of specifications problems may be masked by reporting and publication bias.

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Appendix

Table A1. Estimates of the rate of return to R&D

Sample#	Study	Country	Time period	No. of firms	Return	St.dev
1	Bartelsman et al. (1996)	Netherlands	1985-1989	209	0.218	0.085
2	Bartelsman et al. (1996)	Netherlands	1989-1993	159	0.173	0.082
3	Cincera (1998)	World	1987-1994	625	0.38	0.060
3	Cincera (1998)	World	1989-1993	2445 (unbal.)	0.05	0.037
4	Clark & Griliches (1984)	USA	1971-1980	924	0.18	0.005
4	Clark & Griliches (1984)	USA	1971-1980	924	0.18	0.005
4	Clark & Griliches (1984)	USA	1971-1980	924	0.19	0.005
4	Clark & Griliches (1984)	USA	1971-1980	924	0.19	0.005
4	Clark & Griliches (1984)	USA	1971-1980	924	0.20	0.005
4	Clark & Griliches (1984)	USA	1971-1980	924	0.20	0.005
5	Fecher (1990)	Belgium	1981-1983	292	0.04	0.059
6	Goto & Suzuki (1989)	Japan	1976-1984	13	0.42	0.118
7	Goto & Suzuki (1989)	Japan	1976-1984	5	0.22	0.094
8	Goto & Suzuki (1989)	Japan	1976-1984	3	0.33	0.138
9	Griliches & Mairesse (1983)	USA, France	1973-1978	343+185	0.28	0.06
9	Griliches & Mairesse (1983)	USA, France	1973-1978	343+185	0.12	0.06
10	Griliches & Mairesse (1990)	Japan	1973-1980	406	0.56	0.23
10	Griliches & Mairesse (1990)	Japan	1973-1980	406	0.30	0.21
10	Griliches & Mairesse (1990)	Japan	1973-1980	406	0.20	0.21
11	Griliches & Mairesse (1990)	USA	1973-1980	525	0.41	0.09
11	Griliches & Mairesse (1990)	USA	1973-1980	525	0.27	0.10
11	Griliches & Mairesse (1990)	USA	1973-1980	525	0.25	0.10
12	Hall et al. (2009)	USA	1996-1999	1422	0.30	0.08
12	Hall et al. (2009)	USA	1996-1999	1422	0.21	0.07
12	Hall et al. (2009)	USA	1996-1999	1427	0.28	0.07
12	Hall et al. (2009)	USA	1996-1999	1427	0.23	0.08
13	Hall et al. (2009)	USA	2002-2005	1450	0.14	0.03
13	Hall et al. (2009)	USA	2002-2005	1450	0.16	0.04
13	Hall et al. (2009)	USA	2002-2005	1454	0.15	0.04
13	Hall et al. (2009)	USA	2002-2005	1454	0.17	0.05
14	Hall & Mairesse (1995)	France	1980-1987	197	0.231	0.053
14	Hall & Mairesse (1995)	France	1980-1987	197	0.273	0.059
14	Hall & Mairesse (1995)	France	1980-1987	197	0.036	0.053
14	Hall & Mairesse (1995)	France	1980-1987	197	0.065	0.060
15	Harhoff (1998)	Germany	1979-1989	443	0.22	0.04
16	Klette (1991)	Norway	1978-1985	200	0.106	0.026
16	Klette (1991)	Norway	1978-1985	200	0.108	0.026
16	Klette (1991)	Norway	1978-1985	200	0.108	0.026
16	Klette (1991)	Norway	1978-1985	200	0.108	0.026
17	Kwon & Inui (2003)	Japan	1995-1998	3830	0.163	0.041
18	Licthenberg & Siegel (1991)	USA	1972-1985	5240	0.132	0.021
19	Link (1981)	USA	1971-1976	174	-0.00	0.03
20	Link (1983)	USA	1975-1979	302	0.06	0.04
21	Mansfield (1980)	USA	1960-1976	16	0.275	0.067
22	Medda et al. (2003)	Italy	1992-1994	1008	0.29	0.067
23	Medda et al. (2003)	Italy	1995-1997	689	0.364	0.084
24	Minasian (1962)	USA	1947-1957	18	0.25	0.04
25	Odagiri (1983)	Japan	1969-1981	123	0.256	0.096
26	Odagiri (1983)	Japan	1969-1981	247	-0.475	0.295
27	Odagiri & Iwata (1986)	Japan	1966-1973	135	0.201	0.109
27	Odagiri & Iwata (1986)	Japan	1966-1973	135	0.170	0.135
28	Odagiri & Iwata (1986)	Japan	1974-1982	135	0.169	0.059
28	Odagiri & Iwata (1986)	Japan	1974-1982	135	0.113	0.059

Table A1 (cont.): Estimates of the rate of return to R&D

Sample#	Study	Country	Time period	No. of firms	Return	St.dev
29	Rogers (2010)	UK	1989-2000	466	0.178	0.059
29	Rogers (2010)	UK	1989-2000	466	0.172	0.060
29	Rogers (2010)	UK	1989-2000	66	0.246	0.125
29	Rogers (2010)	UK	1989-2000	66	0.249	0.123
30	Rogers (2010)	UK	1989-2000	223	0.227	0.057
30	Rogers (2010)	UK	1989-2000	223	0.184	0.099
30	Rogers (2010)	UK	1989-2000	20	0.215	0.164
30	Rogers (2010)	UK	1989-2000	20	0.201	0.197
31	Sassenou (1988)	Japan	1973-1981	394	0.69	0.19
31	Sassenou (1988)	Japan	1973-1981	394	0.22	0.11
31	Sassenou (1988)	Japan	1973-1981	394	-0.02	0.07
32	Wakelin (2001)	UK	1988-1996	170	0.29	0.19

The rate of return estimates account for firm fixed effects, as it is based on a first difference specification, cf. equation (2). The data can be downloaded from http://www.deakin.edu.au/buslaw/aef/meta-analysis/.

Table A2. Estimates of elasticity of R&D, Level dimension

Sample#	Study	Country	Time period	No. of firms	Elasticity	St.dev
1	Bartelsman et al. (1996)	Netherlands	1985-1989	209	0.008	0.016
1	Bartelsman et al. (1996)	Netherlands	1985-1989	209	0.046	0.015
2	Bartelsman et al. (1996)	Netherlands	1989-1993	159	0.043	0.023
2	Bartelsman et al. (1996)	Netherlands	1989-1993	159	0.165	0.004
3	Bond et al. (2003)	Germany	1988-1996	234	0.079	0.042
4	Bond et al. (2003)	UK	1988-1996	239	0.065	0.024
5	Cincera (1998)	World	1987-1994	625	0.11	0.006
5	Cincera (1998)	World	1987-1994	625	0.19	0.008
5	Cincera (1998)	World	1987-1994	625	0.08	0.006
5	Cincera (1998)	World	1987-1990	625	0.09	0.009
5	Cincera (1998)	World	1991-1994	625	0.12	0.008
6	Crepon et al. (1998)	France	1990	6145	0.12	0.01
7	Cunéo & Mairesse (1984)	France	1972-1977	182	0.203	0.007
8	Griffith et al. (2006)	UK	1990-2000	188	0.03	0.01
9	Griliches (1980)	USA	1963	883	0.069	0.009
10	Griliches (1986)	USA	1972	491	0.115	0.018
10	Griliches (1986)	USA	1972	491	0.089	0.017
11	Griliches & Mairesse (1984)	USA	1966-1977	133	0.054	0.011
12	Hall (1993)	USA	1964-1970	1200	0.032	0.002
13	Hall & Mairesse (1995)	France	1980-1987	197	0.180	0.009
13	Hall & Mairesse (1995)	France	1980-1987	197	0.252	0.008
14	Harhoff (1998)	Germany	1979-1989	443	0.14	0.01
14	Harhoff (1998)	Germany	1979-1989	443	0.11	0.01
15	Kafouros (2005)	UK	1989-2002	78	0.04	0.01
16	Kwon & Inui (2003)	Japan	1995-1998	3830	0.10	0.002
16	Kwon & Inui (2003)	Japan	1995-1998	3830	0.13	0.002
17	Los & Verspagen (2000)	USA	1974-1993	485	0.014	0.006
18	Mairesse & Hall (1996)	USA	1981-1989	1073	0.035	0.005
18	Mairesse & Hall (1996)	USA	1981-1989	1073	0.246	0.012
19	Mairesse & Hall (1996)	France	1981-1989	1232	0.090	0.006
19	Mairesse & Hall (1996)	France	1981-1989	1232	0.093	0.006
19	Mairesse & Hall (1996)	France	1981-1989	1232	0.092	0.004
19	Mairesse & Hall (1996)	France	1981-1989	1232	0.165	0.004
20	Minasian (1962)	USA	1948-1957	17	0.113	0.015

Table A2 (cont): Estimates of elasticity of R&D, Level dimension

Sample#	Study	Country	Time period	No. of firms	Elasticity	St.dev
21	O'Mahony & Vecchi (2000)	Europe, USA	1988-1997	783	0.027	0.014
22	Ortega-Argiles et al. (2009)	EU	2000-2005	532	0.104	0.009
22	Ortega-Argiles et al. (2009)	EU	2000-2005	532	0.104	0.017
23	Rogers (2010)	UK	1989-2000	466	0.123	0.008
23	Rogers (2010)	UK	1989-2000	466	0.124	0.009
23	Rogers (2010)	UK	1989-2000	66	0.158	0.013
23	Rogers (2010)	UK	1989-2000	66	0.146	0.013
24	Rogers (2010)	UK	1989-2000	223	0.123	0.013
24	Rogers (2010)	UK	1989-2000	223	0.120	0.014
24	Rogers (2010)	UK	1989-2000	20	0.234	0.034
24	Rogers (2010)	UK	1989-2000	20	0.218	0.036
25	Sassenou (1988)	Japan	1976	394	0.10	0.01
25	Sassenou (1988)	Japan	1976	112	0.16	0.03
25	Sassenou (1988)	Japan	1976	112	0.07	0.02
26	Schankerman (1981)	USA	1963	110	0.104	0.036
26	Schankerman (1981)	USA	1963	110	0.159	0.035
27	Schankerman (1981)	USA	1963	187	0.018	0.022
27	Schankerman (1981)	USA	1963	187	0.099	0.021
28	Schankerman (1981)	USA	1963	101	0.034	0.020
28	Schankerman (1981)	USA	1963	101	0.232	0.029
29	Schankerman (1981)	USA	1963	34	0.069	0.047
29	Schankerman (1981)	USA	1963	34	0.090	0.046
30	Schankerman (1981)	USA	1963	31	0.032	0.033
30	Schankerman (1981)	USA	1963	31	0.292	0.048
31	Schankerman (1981)	USA	1963	41	0.043	0.011
31	Schankerman (1981)	USA	1963	419	0.065	0.011
32	Wang & Tsai (2003)	Taiwan	1994-2000	136	0.20	0.03

Elasticity estimates based on the level dimension include pooled OLS and do not account for firm fixed effects.The data can be downloaded from http://www.deakin.edu.au/buslaw/aef/meta-analysis/.

Table A3. Estimates of the elasticity of R&D, temporal dimension

Sample#	Study	Country	Time period	No. of firms	Elasticity	St.dev
1	Bartelsman et al. (1996)	Netherlands	1985-1989	209	0.247	0.083
2	Bartelsman et al. (1996)	Netherlands	1989-1993	159	0.185	0.080
3	Bond et al. (2003)	UK	1988-1996	239	-0.296	0.054
3	Bond et al. (2003)	UK	1988-1996	239	0.054	0.072
3	Bond et al. (2003)	UK	1988-1996	239	0.044	0.026
4	Bond et al. (2003)	Germany	1988-1996	234	0.054	0.029
4	Bond et al. (2003)	Germany	1988-1996	234	0.010	0.050
4	Bond et al. (2003)	Germany	1988-1996	234	-0.008	0.044
5	Capron & Cincera (1998)	World	1987-1994	625	0.32	0.04
5	Capron & Cincera (1998)	World	1987-1994	625	0.13	0.05
5	Cincera (1998)	World	1987-1994	625	0.10	0.006
5	Cincera (1998)	World	1987-1994	625	0.33	0.042
5	Cincera (1998)	World	1987-1994	625	0.21	0.094
5	Cincera (1998)	World	1987-1994	625	0.24	0.041
5	Cincera (1998)	World	1987-1990	625	0.38	0.069
5	Cincera (1998)	World	1987-1990	625	0.29	0.069
5	Cincera (1998)	World	1991-1994	625	0.26	0.046
5	Cincera (1998)	World	1991-1994	625	0.24	0.054

Table A3 (continued): Estimates of the elasticity of R&D, temporal dimension

Sample#	Study	Country	Time period	No. of firms	Elasticity	St.dev
5	Cincera (1998)	World	1980-1994	2445 (unbal.)	0.28	0.022
5	Cincera (1998)	World	1980-1994	2445 (unbal.)	0.21	0.010
6	Cunéo & Mairesse (1984)	France	1972-1977	182	0.050	0.039
7	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	289	0.003	0.005
7	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	289	0.025	0.016
8	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	140	0.013	0.006
8	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	140	0.046	0.016
9	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	275	0.018	0.004
9	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	275	0.075	0.011
10	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	132	-0.003	0.008
10	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	132	0.025	0.005
11	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	148	0.009	0.005
11	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	148	0.017	0.017
12	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	304	0.002	0.006
12	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	304	0.046	0.012
13	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	293	0.011	0.008
13	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	293	0.018	0.018
14	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	138	0.018	0.011
14	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	138	0.074	0.030
15	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	160	0.013	0.009
15	Doraszelski & Jaumandreu (2008)	Spain	1991-1999	160	0.041	0.028
16	Griffith et al. (2006)	UK	1990-2000	188	0.024	0.011
17	Griliches (1980)	USA	1957-1965	883	0.076	0.013
18	Griliches & Mairesse (1983)	USA, Japan	1973-1978	343+185	0.02	0.03
19	Griliches & Mairesse (1984)	USA	1966-1977	182	0.091	0.022
20	Hall (1993)	USA	1964-1970	1200	0.06	0.04
21	Hall & Mairesse (1995)	France	1980-1987	197	-0.001	0.036
21	Hall & Mairesse (1995)	France	1980-1987	197	0.069	0.035
22	Harhoff (1998)	Germany	1981-1989	443	0.09	0.02
22	Harhoff (1998)	Germany	1981-1989	443	0.07	0.02
22	Harhoff (1998)	Germany	1981-1989	443	0.1	0.03
23	Kwon & Inui (2003)	Japan	1995-1998	3830	0.084	0.008
23	Kwon & Inui (2003)	Japan	1995-1998	3830	0.087	0.008
23	Kwon & Inui (2003)	Japan	1995-1998	3830	0.149	0.014
23	Kwon & Inui (2003)	Japan	1995-1998	3830	0.147	0.014
23	Kwon & Inui (2003)	Japan	1995-1998	3830	0.053	0.014
23	Kwon & Inui (2003)	Japan	1995-1998	3830	0.052	0.014
24	Los & Verspagen (2000)	USA	1974-1993	485	0.017	0.004
25	Mairesse & Cunéo (1985)	Japan	1974-1979	390	0.21	0.10
26	Mairesse & Hall (1996)	France	1981-1989	1232	-0.003	0.003
26	Mairesse & Hall (1996)	France	1981-1989	1232	-0.003	0.003
26	Mairesse & Hall (1996)	France	1981-1989	1232	-0.005	0.003
26	Mairesse & Hall (1996)	France	1981-1989	1232	0.008	0.011
26	Mairesse & Hall (1996)	France	1981-1989	1232	0.013	0.011
26	Mairesse & Hall (1996)	France	1981-1989	1232	-0.016	0.013
27	Mairesse & Hall (1996)	USA	1981-1989	1073	0.010	0.024
27	Mairesse & Hall (1996)	USA	1981-1989	1073	0.092	0.026
27	Mairesse & Hall (1996)	USA	1981-1989	1073	0.041	0.011
27	Mairesse & Hall (1996)	USA	1981-1989	1073	0.170	0.014
28	Minasian (1962)	USA	1948-1957	17	0.084	0.068
29	O'Mahony & Vecchi (2000)	Europe, USA	1988-1997	783	0.328	0.050
30	Sassenou (1988)	Japan	1973-1981	394	0.04	0.04
30	Sassenou (1988)	Japan	1973-1981	394	-0.01	0.01

Elasticity estimates based on the temporal dimension account for firm fixed effects. The data can be downloaded from http://www.deakin.edu.au/buslaw/aef/meta-analysis/.