**What do we know about R&D spillovers and productivity?**
**Meta-analysis evidence on heterogeneity and statistical power**

## ONLINE APPENDIX

### Box 1: Sources of heterogeneity in the evidence base

We extract information to identify a wide range of moderating factors that may explain the variation in reported effect-size estimates. These factors are modelled through a set of binary ($Z$) variables that moderate the magnitude of the effect-size estimates and a set of continuous ($X$) variables that capture the sources of selection bias. Box 1 below provides a summary of the moderating factors and their relevance in the research field.

First, R&D spillovers are not observable in the data at hand. The common practice is to construct an external R&D (knowledge) stock, $S$, which may generate different spillover types depending on the channels through which external knowledge is diffused (Griliches, 1992; Hall et al., 2010).

One channel is technological proximity between the sources and recipients of the spillover effects. In this case, the spillover pool is constructed by using weights that reflect proximity in the technology space. Such pools are considered as sources of *knowledge spillovers* because the latter are not mediated through bilateral transactions between the sources and recipients of knowledge externalities (Cincera and Van Pottelsberghe de La Potterie, 2001; Griliches, 1992; Hall et al., 2010; Mohnen, 1996; Verspagen, 1997). The reported estimate is also described as knowledge spillover effect when the spillover pool is constructed with equal weights (pure knowledge spillovers) or with weights that reflect geographical distance (spatial knowledge spillovers).

Country-level studies use bilateral import shares (see, Coe and Helpman, 1995) whereas some industry-level utilise intermediate input flows between industries (see, Biatour et al., 2011). In line with the literature, we classify the evidence based on such weights as *rent spillover effects*, which arise from the wedge between market prices paid by the buyers and the quality-adjusted true prices not observed in the data (Griliches, 1979; 1992).[1]

There is less clarity about how to characterise the external knowledge pools when the weights capture the intensity of bilateral transactions in knowledge-intensive goods/services (e.g., patent flows/citations; R&D collaborations, movements of R&D personnel, etc.). Mohnen (1996) and Verspagen (1997) classify such pools as knowledge spillovers. However, Griliches (1992) and Hall et al. (2010) argue that such externalities do not fit the theoretical concept of knowledge externality.

Some primary studies (e.g., Keller, 1998; Krammer, 2010) argue for double weighting in the construction of international spillovers: one weight to capture the intensity of bilateral import shares and one to reflect the spillover recipient's openness to 'trade'. The latter assumes that a country that is more open to trade would derive a higher level of benefit from R&D externalities compared to another faced with the same pool but is less open to trade. Hence a further source of heterogeneity is whether the spillover pool is single-weighted (eq. 1a) or double-weighted (eq. 1b).

[1] Market prices are expected to be lower than quality-adjusted prices unless the innovative supplier has monopoly power.

A third source of heterogeneity is the unit of analysis – i.e., whether the data is at the firm, industry or country/region levels. At each level, the productivity effects of the external R&D stock may co-exist with adverse effects stemming from: (i) technological obsolescence (creative destruction) caused by competitors' R&D investments (Aghion et al., 2014; Aghion and Howitt, 1992; Schumpeter, 1942); and (ii) product-market competition whereby R&D investors expand their market shares at the expense of non-investors (Bloom et al., 2013). Hence, the net productivity effects due to spillovers may differ depending on the level of analysis and the speed with which the countervailing effects unfolds at each level.

Finally, heterogeneity in the evidence base can result from between-study and within-study variations with respect to sample characteristics (e.g., high *versus* low R&D-intensity firms or industries), model specification (e.g., number of spillover types included in the model), estimation methods (standard OLS, dynamic OLS, panel cointegration, instrumental variable estimations, etc.), data period (relatively old or recent data), and publication types (journal articles, working papers, reports, etc.).

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**Box 2: Hierarchical specifications for bivariate and multi-variate meta-regression models**

We propose a hierarchical model (HM) estimator to take account of a well-known feature of the meta-analysis data, where primary studies report multiple effect-size estimates and the latter may be correlated due to dependence on a given data source, estimator or time period or a combination thereof. The HM takes account of such dependencies by allowing for a more general covariance structure where effect-size estimates from the same study can be correlated.

The underlying model for the average effect size is that of Egger et al. (1997):

$$effect\_size_i = \beta + \alpha SE_i + \xi_i \qquad \text{(A1)}$$

Using the inverse of the squared standard error as weights to address heteroskedasticity, the precision-effect and funnel-asymmetry tests (PET/FAT) are based on:

$$t_i = \alpha + \beta\left(1/_{SE_i}\right) + \omega_i \qquad \text{(A2)}$$

The common practice is to estimate A1 with ordinary least squares (OLS). However, OLS would be inappropriate if within-study dependence (i.e., intra-study correlation) exists. This is because: (i) the sample size is exaggerated due to treatment of all effect-size estimates as independent observations; and (ii) the risk of rejecting the null hypothesis erroneously (type-I error) is higher (Snijders and Bosker, 2012).

To address these issues, the bivariate hierarchical models (HMs) for PET/FAT can be stated as follows:

$$t_{ij} = \alpha^{RI2} + \beta^{RI2}\left(1/_{SE_{ij}}\right) + h_{0j}^{RI2} + u_{ij}^{RI2} \qquad \text{(A3)}$$

$$t_{ij} = \alpha^{RIS2} + \beta^{RIS2}\left(1/_{SE_{ij}}\right) + h_{0j}^{RIS2} + h_{1j}^{RIS2}\left(1/_{SE_{ij}}\right) + u_{ij}^{RIS2} \qquad \text{(A4)}$$

Here, subscript *i* denotes effect-size estimate (level-1 observation) and *j* denotes primary-study (level-2 cluster). The random-effect components ($h_{\ddot{0}}$) denote study-specific intercepts whereas those with subscript denote study-specific slopes for the relationship between the t-value and precisions. Finally, of the superscripts, *RI2* indicates two-level HM with random intercepts only in (A3) and *RIS2* indicates two-level HM with random-intercepts and slopes in (A4).

If the HM in A3 or A4 is preferred against a weighted least squares (WLS) specification and if the average effect-size estimate is statistically significant, the PEESE versions of the HM specifications can be stated as follows:

$$t_{ij} = \gamma^{RI2}\left(1/_{SE_i}\right) + \varphi^{RI2} SE_i + h_{0j}^{RI2} + u_{ij}^{RI2} \qquad \text{(A5)}$$

$$t_{ij} = \gamma^{RIS2}\left(1/_{SE_i}\right) + \varphi^{RIS2} SE_i + h_{0j}^{RIS2} + h_{1j}^{RIS2}\left(1/_{SE_{ij}}\right) + u_{ij}^{RIS2} \qquad \text{(A6)}$$

We rely on likelihood ratio (LR) tests to choose between HMs and WLS or between different HM specifications. The test compares different assumptions about the variance of the reported effect-size estimates, which is assumed to be distributed around the 'true' effect ($\gamma$) with a variance of $\theta_i$.

$$effect\_size_i \sim N(\gamma, \theta_i) \tag{A7}$$

The WLS assume that individual variances are just a multiple of the idiosyncratic error variance ($\emptyset\sigma_i^2$). In contrast, the hierarchical models assume an additive variance structure in which the random-effect variances ($\tau^2$) correspond to different assumptions about between-study heterogeneity. These assumptions can be stated as follows:

| | |
|---|---|
| $\theta_i^{WLS} = \emptyset\sigma_i^2$ | WLS |
| $\theta_i^{RI2} = \sigma_i^2 + \tau_{01}^2$ | Two-level HM with random intercepts at the study level |
| $\theta_i^{RIS2} = \sigma_i^2 + \tau_{01}^2 + \tau_{11}^2$ | Two-level HM with random intercepts and random slopes |

The null hypothesis in the LR tests is that the restricted model (the model with one or several random-effect variances restricted to zero) is nested within the unrestricted model. A rejection of the null hypothesis indicates that the unrestricted model (the HM with more complex heterogeneity structure) fits the data better than the restricted model, which can be a WLS model with no additive term for heterogeneity or a HM with a relatively simpler heterogeneity structure.

One drawback of the HMs is that they assume normality of the model residuals and this is more explicit compared to WLS. However, violation of the normality assumption affects the confidence intervals but not the coefficient estimates. Therefore, we are of the view that HMs are capable of addressing a wide range of estimation issues with little or no cost in terms of consistency (Demidenko, 2004; McCulloch et al., 2008; Snijder and Bosker, 2012).

The HM framework for the bivariate meta-regression outlined above applies directly to a multivariate meta-regression context that allows for modelling the observed sources of heterogeneity. Augmented with covariates that capture observed sources of heterogeneity, the WLS and HM versions of the multivariate meta-regression can be stated as follows:

$$t_{ij} = \alpha^{WLS} + \beta^{WLS}(1/SE_{ij}) + \sum_m \gamma_m^{WLS} Z_m(1/SE_{ij}) + \sum_k \gamma_k^{WLS} X_k + \varepsilon_{ij}^{WLS} \tag{A8}$$

$$t_{ij} = \alpha^{HM} + \beta^{HM}(1/SE_{ij}) + \sum_m \gamma_m^{HM} Z_m(1/SE_{ij}) + \sum_k \gamma_k^{HM} X_k + h_{0j} + h_{1j}(1/SE_{ij}) + \varepsilon_{ij}^{HM} \tag{A9}$$

Here *Z* is a vector of *M* binary variables that control for moderating factors that affect the reported effect sizes; whereas *X* is a vector of continuous variables that affect the selection bias. The *Z* variables are divided with the standard error of the primary-study estimates to capture their effects on the average effect. The X variables, however, are not divided by the standard errors to capture their effects on selection bias. Equation A6 is a two-level HM with random intercepts; whereas A7 is a two-level HM with random intercepts and slopes at the study level. The choice between restricted and unrestricted models is based on LR tests indicated above.

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## Table A1 - Spillovers and Productivity: Overview of the Evidence Base

| Study | Pub type | Data type | Estimation method | Unit of analysis | Unit count | Country | Data start | Data end | Mean effect size | Median effect size | median t-value | No. of est. | Spillover type | Spillover weight |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Acharya and Keller (2009) | Jnl | Panel | OLS | Country/Industry | 17 | Mixed | 1973 | 2002 | 0.151 | 0.129 | 5.083 | 102 | Knowledge | Unweighted |
| Adam and Jaffe (1996) | Jnl | Panel | Non-Linear LS | Firm | 80 | US | 1974 | 1988 | 0.175 | 0.215 | 9.150 | 6 | Knowledge | Tech proximity |
| Aiello and Cardarmone (2005) | Jnl | Panel | GLS/GMM | Firm | 1017 | Italy | 1995 | 2000 | 0.011 | 0.012 | 3.995 | 4 | Knowledge | Tech proximity |
| Aldieri and Cincera (2009) | Jnl | Panel | GMM | Firm | 808 | US | 1988 | 1997 | 0.500 | 0.500 | 17.777 | 4 | Knowledge | Tech proximity/Distance |
| Belitz and Molders (2016) | Jnl | Panel | Cointegration/FE | Country | 77 | Mixed | 1990 | 2008 | 0.034 | 0.036 | 3.500 | 19 | Knowledge/Rent | FDI/Import shares |
| Biatour et al (2011) | WP | Panel | Dynamic | Industry | 21 | Belgium | 1987 | 2007 | 0.089 | 0.090 | 1.630 | 27 | Mixed/Rent | Patent/Input-Output Flows |
| Bitzer and Geishecker (2006) | Jnl | Panel | GLS | Industry_Country | 170 | Mixed | 1973 | 2000 | 0.009 | 0.017 | 4.375 | 8 | Rent | Import shares |
| Bitzer and Kerekes (2008) | Jnl | Panel | GLS | Industry_country | 10 | Mixed | 1973 | 2000 | 0.019 | 0.015 | 7.103 | 18 | Rent/Knowledge | Import shares shares/FDI |
| Bloch (2013) | Jnl | Panel | FE | Firm | n.a. | Denmark | 1997 | 2005 | 0.052 | 0.062 | 2.952 | 5 | Knowledge | Tech proximity |
| Bloom et al. (2013) | Jnl | Panel | OLS/2SLS | Firm | n.a. | US | 1981 | 2001 | 0.165 | 0.191 | 4.125 | 5 | Knowledge | Tech proximity |
| Braconier and Sjoholm (1998) | Jnl | Panel | OLS | Industry | 49 | Mixed | 1979 | 1991 | -0.015 | -0.014 | 1.260 | 7 | Knowledge | Unweighted |
| Braconier et al. (2001) | Jnl | Panel | OLS/FE/RE | Firm | 66 | Sweden | 1978 | 1994 | 0.009 | 0.017 | 0.850 | 19 | Knowledge | Tech proximity/FDI |
| Branstetter (2001) | Jnl | Panel | Diff | Firm | 209 | Japan/US | 1985 | 1989 | 0.371 | 0.449 | 1.412 | 4 | Mixed | Patent |
| Bronzini and Piselli (2009) | Jnl | Panel | Cointegration | Region | 19 | Italy | 1985 | 2001 | 0.405 | 0.405 | 13.824 | 2 | Knowledge | Distance |
| Cincera (2005) | Jnl | Panel | Diff/GMM/FE | Firm | 625 | Mixed | 1988 | 1994 | 0.573 | 0.590 | 3.582 | 9 | Knowledge | Tech proximity |
| Coe et al (1997) | Jnl | Panel | Diff | Country | 77 | Mixed | 1971 | 1990 | -0.010 | 0.061 | 2.813 | 15 | Rent/Knowledge | Import shares /Unweighted |
| Coe et al (2009) | Jnl | Panel | FE | Country | 24 | Mixed | 1971 | 2004 | 0.079 | 0.049 | 3.300 | 24 | Knowledge/Rent | Unweighted/Import shares |
| del Barrio-Castro et al (2002) | Jnl | Panel | Cointegration | Country | 21 | Mixed | 1966 | 1995 | 0.117 | 0.117 | 2.485 | 2 | Rent | Import shares |
| Edmond (2001) | Jnl | Panel | FE | Country | 21 | Mixed | 1971 | 1990 | 0.222 | 0.200 | 8.429 | 7 | Rent/Knowledge | Import shares/Unweighted |
| Engelbrecht (1997) | Jnl | Panel | GLS/OLS | Country | 21 | Mixed | 1971 | 1985 | 0.280 | 0.249 | 4.304 | 11 | Rent | Import shares |
| Frantzen (2000) | Jnl | Panel | Cointegration/OLS | Country | 21 | Mixed | 1991 | 1980 | 0.271 | 0.219 | 3.914 | 10 | Rent | Import shares |
| Frantzen (2002) | Jnl | Panel | Cointegration/OLS | Industry_Country | 308 | Mixed | 1972 | 1994 | 0.169 | 0.164 | 9.765 | 42 | Rent | Import shares |
| Funk (2001) | Jnl | Panel | Cointegration/OLS | Country | 22 | Mixed | 1971 | 1990 | 0.112 | 0.059 | 2.530 | 15 | Rent | Import shares |
| Griffith et al (2006) | Jnl | Panel | GMM/OLS | Firm | 188 | UK | 1990 | 2000 | 0.174 | 0.154 | 1.582 | 46 | Mixed/Knowledge | Patent/Unweighted |
| Guellec and Van Pottelsberghe (2001) | Jnl | Panel | 3SLS/GLS | Country | 16 | Mixed | 1980 | 1998 | 0.094 | 0.092 | 7.885 | 6 | Knowledge | Tech proximity |
| Guellec and Van Pottelsberghe (2004) | Jnl | Panel | 3SLS | Country | 16 | Mixed | 1980 | 1998 | 0.398 | 0.398 | 39.015 | 2 | Knowledge | Tech proximity |
| Gutierrez and Gutierrez (2003) | Jnl | Panel | Coint./FM/DOLS | Country | 47 | Mixed | 1970 | 1992 | 0.517 | 0.531 | 3.068 | 4 | Rent | Import shares |
| Harhoff (2000) | Jnl | Survey | OLS | Firm | 439 | Germany | 1977 | 1989 | -0.016 | -0.013 | -0.412 | 4 | Knowledge | Tech proximity |
| Hejazi and Safarian (1999) | Jnl | Panel | OLS | Country | 20 | Mixed | 1971 | 1990 | 0.081 | 0.089 | 3.615 | 8 | Rent/Knowledge | Import shares/FDI |
| Higon (2007) | Jnl | Panel | Coint/MG/PMG | Industry | 8 | UK | 1970 | 1997 | 0.598 | 0.215 | 0.578 | 8 | Rent | Import shares |
| Jacobs et al (2002) | Jnl | Panel | FE | Industry | 11 | Netherlands | 1973 | 1992 | 0.962 | 0.926 | 5.144 | 5 | Rent | Import shares/Input-Output Flows |
| Jaffe (1988) | Jnl | CrS | OLS | Firm | 391 | US | 1972 | 1977 | 0.082 | 0.094 | 2.102 | 4 | Knowledge | Tech proximity |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Jaffe (1989) | Jnl | Panel | OLS | Firm | 432 | US | 1973 | 1979 | 0.128 | 0.128 | 3.368 | 1 | Knowledge | Tech proximity |
| Johnson and Evenson (1999) | Jnl | Panel | OLS | Country | 6 | Mixed | 1973 | 1987 | 0.143 | 0.143 | 2.875 | 2 | Knowledge | Unweighted |
| Kao et al. (1999) | Jnl | Panel | Coint/Dyn/OLS | Country | 22 | Mixed | 1971 | 1990 | 0.167 | 0.114 | 3.269 | 16 | Rent | Import shares |
| Ke and Luger (1996) | Jnl | CrS | OLS | Firm | 210 | US | 1991 | 1991 | 0.094 | 0.093 | 1.529 | 6 | Knowledge | Unweighted |
| Keller (1998) | Jnl | Panel | OLS | Country | 22 | Mixed | 1971 | 1990 | 0.186 | 0.156 | 11.167 | 9 | Rent | Import shares |
| Krammer (2010) | Jnl | Panel | Cointegration/FE | Country | 47 | Mixed | 1990 | 2006 | 0.065 | 0.029 | 4.322 | 42 | Rent/Knowledge | Import shares/FDI |
| Kwon (2004) | WP | Panel | GLS | Industry | 34 | Japan | 1970 | 1998 | -0.440 | -0.378 | -0.595 | 8 | Knowledge/Rent | Tech proximity/Input-Output Flows |
| Lee (2005) | Jnl | Panel | Coint/OLS/Dyn/FE | Country | 17 | Mixed | 1971 | 2000 | 0.031 | 0.032 | 2.569 | 40 | Mixed/Knowledge/Rent | Patent/Tech Proximity/Import shares |
| Lee (2006) | Jnl | Panel | Cointegration/OLS | Country | 16 | Mixed | 1981 | 2000 | 0.049 | 0.031 | 2.302 | 27 | Rent/Knowledge | Import shares/FDI |
| Lehto (2007) | Jnl | Panel | 2SLS/OLS/GLS | Firm | 2171 | Finland | 1987 | 1998 | -0.013 | 0.014 | 3.400 | 39 | Knowledge | Unweighted |
| Lichtenberg and Van Pottelsberghe (1998) | Jnl | Panel | FE | Country | 22 | Mixed | 1971 | 1990 | -0.514 | 0.058 | 2.926 | 14 | Rent | Import shares |
| Lopez-Pueyo et al (2008) | Jnl | Panel | Cointegration/OLS | Industry_country | 10 | Mixed | 1979 | 2000 | 0.125 | 0.123 | 3.962 | 26 | Knowledge | Tech proximity |
| Los and Verspagen (2000) | Jnl | Panel | Unspecified/FE/RE | Firm | 680 | US | 1977 | 1991 | 0.389 | 0.393 | 8.485 | 48 | Knowledge/Mixed | Tech proximity/Unweighted/Patent |
| Lumenga-Neso et al (2005) | Jnl | Panel | OLS | Country | 22 | Mixed | 1971 | 1990 | 0.156 | 0.200 | 3.774 | 9 | Rent/Knowledge | Import shares/Unweighted |
| Lychagin et al (2016) | Jnl | Panel | OLS/GMM | Firm | 1383 | US | 1970 | 2000 | 0.462 | 0.654 | 3.250 | 29 | Knowledge | Tech proximity/Distance |
| Mcvicar (2002) | Jnl | Panel | Non-Linear LS | Industry | 7 | UK | 1973 | 1992 | 0.464 | -0.288 | -1.889 | 4 | Rent/Knowledge | Import shares/FDI/Unweighted |
| Negassi (2009) | Jnl | Panel | 3SLS | Firm | 2763 | France | 1990 | 1996 | 0.093 | 0.094 | 1.806 | 6 | Knowledge/Rent | Tech proximity/Import shares |
| Orlando (2004) | Jnl | Panel/CrS | Diff/FE/OLS | Firm | 515 | US | 1972 | 1995 | 0.006 | 0.003 | 0.875 | 24 | Knowledge | Unweighted/Distance |
| Ornaghi (2006) | Jnl | Panel | GMM | Firm | 3151 | Spain | 1991 | 1999 | 0.033 | 0.019 | 2.035 | 12 | Knowledge | Size proximity |
| Parameswaran (2009) | Jnl | Panel | Unspecified | Firm | 2100 | India | 1992 | 2001 | 0.057 | 0.044 | 3.192 | 3 | Knowledge | Tech proximity |
| Park (1995) | Jnl | Panel | RE/OLS/FE | Country | 10 | Mixed | 1970 | 1987 | 0.167 | 0.172 | 2.679 | 16 | Knowledge | Tech proximity |
| Park (2004) | Jnl | Panel | OLS | Country | 22 | Mixed | 1971 | 1990 | 0.079 | 0.072 | 5.224 | 14 | Rent/Knowledge | Import shares/Student Flows |
| Raut (1995) | Jnl | Panel | RE/FE/OLS/3SLS | Firm | 192 | India | 1975 | 1986 | 0.120 | 0.095 | 3.340 | 19 | Knowledge | Unweighted |
| Van Pottelsberghe and Lichtenberg (2001) | Jnl | Panel | Diff/FE | Country | 13 | Mixed | 1971 | 1990 | 0.065 | 0.053 | 5.308 | 19 | Rent/Knowledge | Import shares/FDI |
| Verspagen (1997) | Jnl | Panel | FE/RE | Industry_country | 22 | Mixed | 1974 | 1992 | 0.073 | 0.061 | 2.905 | 48 | Knowledge/Mixed | Tech proximity/Patent |
| Wang and Chao 2008 | Jnl | Panel | OLS | Firm | 72 | Taiwan | 1994 | 2000 | 0.195 | 0.195 | 1.710 | 2 | Knowledge | Unweighted |
| Xu and Wang (1999) | Jnl | Panel | OLS | Country | 21 | Mixed | 1983 | 1990 | 0.063 | 0.062 | 2.241 | 30 | Knowledge/Rent | Distance/Import shares/Export |
| Zhu and Jeon (2007) | Jnl | Panel | Cointegration/OLS | Country | 22 | Mixed | 1981 | 1998 | 0.072 | 0.064 | 5.525 | 18 | Knowledge/Rent | FDI/Import shares/Total Trade |
| **TOTAL** | | | | | | | | | **0.126** | **0.070** | **3.323** | **983** | | |

Notes: Jnl is Journal article, WP is working paper, CrS is Cross Section

## Table A2 - Own R&D and Productivity: Overview of the Evidence Base

| Study | Pub type | Data type | Estimation method | Unit of analysis | Unit count | Country | Data start | Data end | Mean effect size | Median effect size | median t-value | No. of est. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Acharya and Keller (2009) | Jnl | Panel | OLS | Country | 17 | Mixed | 1973 | 2002 | 0.112 | 0.108 | 7.286 | 45 |
| Adam and Jaffe (1996) | Jnl | Panel | Non-Linear LS | Firm | 80 | US | 1974 | 1988 | 0.043 | 0.040 | 8.750 | 6 |
| Aiello and Cardarmone (2005) | Jnl | Panel | GLS/GMM | Firm | 1017 | Italy | 1995 | 2000 | 0.070 | 0.068 | 5.410 | 4 |
| Aldieri and Cincera (2009) | Jnl | Panel | GMM | Firm | 808 | US | 1988 | 1997 | 0.230 | 0.230 | 14.706 | 3 |
| Belitz and Molders (2016) | Jnl | Panel | Cointegration/FE | Country | 77 | Mixed | 1990 | 2008 | 0.008 | 0.009 | 1.550 | 14 |
| Biatour et al. (2011) | WP | Panel | Dynamic | Industry | 21 | Belgium | 1987 | 2007 | 0.076 | -0.030 | -0.460 | 11 |
| Bitzer and Geishecker (2006) | Jnl | Panel | GLS | Industry_Country | 170 | Mixed | 1973 | 2000 | 0.043 | 0.043 | 3.720 | 5 |
| Bloch (2013) | Jnl | Panel | FE | Firm | n.a. | Denmark | 1997 | 2005 | 0.212 | 0.206 | 6.629 | 4 |
| Bloom et al. (2013) | Jnl | Panel | OLS/2SLS | Firm | n.a. | US | 1981 | 2000 | 0.046 | 0.043 | 6.143 | 5 |
| Braconier and Sjoholm (1998) | Jnl | Panel | OLS | Industry | 49 | Mixed | 1979 | 1991 | -0.071 | -0.062 | 1.820 | 6 |
| Braconier et al. (2001) | Jnl | Panel | RE/FE/OLS | Firm | 66 | Sweden | 1978 | 1994 | 0.038 | 0.043 | 4.150 | 8 |
| Branstetter (2001) | Jnl | Panel | Diff | Firm | 209 | Japan/US | 1985 | 1989 | 0.187 | 0.187 | 1.607 | 2 |
| Bronzini and Piselli (2009) | Jnl | Panel | Cointegration | Region | 19 | Italy | 1985 | 2001 | 0.029 | 0.029 | 71.25 | 2 |
| Cincera (2005) | Jnl | Panel | FE/diff/GMM | Firm | 625 | Mixed | 1988 | 1994 | 0.250 | 0.245 | 11.074 | 6 |
| Coe et al (2009) | Jnl | Panel | FE | Country | 24 | Mixed | 1971 | 2004 | 0.098 | 0.096 | 8.685 | 22 |
| del Barrio-Castro et al (2002) | Jnl | Panel | Cointergration | Country | 21 | Mixed | 1966 | 1995 | 0.043 | 0.043 | 1.298 | 2 |
| Edmond (2001) | Jnl | Panel | FE | Country | 21 | Mixed | 1971 | 1990 | 0.060 | 0.064 | 7.789 | 8 |
| Engelbrecht (1997) | Jnl | Panel | GLS/OLS | Country | 21 | Mixed | 1971 | 1985 | 0.090 | 0.090 | 6.700 | 11 |
| Frantzen (2000) | Jnl | Panel | Cointegration/OLS | Country | 21 | Mixed | 1991 | 1980 | 0.079 | 0.091 | 3.176 | 10 |
| Funk (2001) | Jnl | Panel | Cointegration/OLS | Country | 22 | Mixed | 1971 | 1990 | 0.077 | 0.075 | 5.080 | 12 |
| Griffith et al (2006) | Jnl | Panel | GMM/OLS | Firm | 188 | UK | 1990 | 2000 | 0.022 | 0.024 | 2.039 | 12 |
| Guellec and Van Pottelsberghe (2001) | Jnl | Panel | GLS/3SLS | Country | 16 | Mixed | 1980 | 1998 | 0.024 | 0.024 | 5.400 | 6 |
| Guellec and Van Pottelsberghe (2004) | Jnl | Panel | 3SLS | Country | 16 | Mixed | 1980 | 1998 | 0.116 | 0.116 | 61.190 | 2 |
| Gutierrez and Gutierrez (2003) | Jnl | Panel | Coint./FM/DOLS | Country | 47 | Mixed | 1970 | 1992 | 0.236 | 0.062 | 3.046 | 4 |
| Harhoff (2000) | Jnl | Survey | OLS | Firm | 439 | Germany | 1977 | 1989 | 0.068 | 0.068 | 2.429 | 4 |
| Hejazi and Safarian (1999) | Jnl | Panel | OLS | Country | 20 | Mixed | 1971 | 1990 | 0.097 | 0.096 | 8.665 | 6 |
| Higon (2007) | Jnl | Panel | Coint/MG/PMG | Industry | 8 | UK | 1970 | 1997 | 0.309 | 0.313 | 2.617 | 4 |
| Jacobs et al. (2002) | Jnl | Panel | FE | Industry | 11 | Netherland | 1973 | 1992 | 0.315 | 0.336 | 8.205 | 4 |
| Jaffe (1989) | Jnl | Panel | OLS | Firm | 432 | US | 1973 | 1979 | 0.031 | 0.031 | 2.583 | 1 |
| Johnson and Evenson (1999) | Jnl | Panel | OLS | Country | 6 | Mixed | 1973 | 1987 | 0.052 | 0.052 | 4.410 | 1 |
| Kao et al. (1999) | Jnl | Panel | Coint/Dyn/OLS | Country | 22 | Mixed | 1971 | 1990 | 0.089 | 0.091 | 4.688 | 16 |
| Keller (1998) | Jnl | Panel | OLS | Country | 22 | Mixed | 1971 | 1990 | 0.054 | 0.047 | 10.778 | 9 |
| Krammer (2010) | Jnl | Panel | Cointegration/FE | Country | 47 | Mixed | 1990 | 2006 | 0.071 | 0.063 | 4.286 | 21 |
| Lee (2005) | Jnl | Panel | Coint/Dyn/OLS/FE | Country | 17 | Mixed | 1971 | 2000 | 0.040 | 0.026 | 3.922 | 20 |
| Lee (2006) | Jnl | Panel | Cointegration/OLS | Country | 16 | Mixed | 1981 | 2000 | 0.039 | 0.033 | 0.848 | 10 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Lehto (2007) | Jnl | Panel | 2SLS/OLS/GLS | Firm | 2171 | Finland | 1987 | 1998 | 0.028 | 0.031 | 5.200 | 15 |
| Lichtenberg and Van Pottelsberghe (1998) | Jnl | Panel | FE | Country | 22 | Mixed | 1971 | 1990 | 0.077 | 0.082 | 9.556 | 10 |
| Lopez-Pueyo et al. (2008) | Jnl | Panel | Cointegration/OLS | Industry_Country | 10 | Mixed | 1979 | 2000 | 0.335 | 0.158 | 10.489 | 12 |
| Lumenga-Neso et al. (2005) | Jnl | Panel | OLS | Country | 22 | Mixed | 1971 | 1990 | 0.042 | 0.023 | 0.852 | 9 |
| Lychagin et al. (2016) | Jnl | Panel | OLS/GMM | Firm | 1383 | US | 1970 | 2000 | 0.019 | 0.006 | 0.720 | 15 |
| Mcvicar (2002) | Jnl | Panel | Non-Linear LS | Industry | 7 | UK | 1973 | 1992 | 0.032 | 0.032 | 2.286 | 1 |
| Negassi (2009) | Jnl | Panel | 3SLS | Firm | 2763 | France | 1990 | 1996 | 0.157 | 0.157 | 1.809 | 2 |
| Orlando (2004) | Jnl | Panel | Diff/FE/OLS | Firm | 515 | US | 1972 | 1995 | -0.005 | 0.039 | 3.194 | 6 |
| Ornaghi (2006) | Jnl | Panel | GMM | Firm | 3151 | Spain | 1991 | 1999 | 0.093 | 0.098 | 4.261 | 9 |
| Parameswaran (2009) | Jnl | Panel | Unspecified | Firm | 2100 | India | 1992 | 2001 | 0.001 | 0.002 | 2.000 | 3 |
| Park (1995) | Jnl | Panel | RE/OLS/FE | Country | 10 | Mixed | 1970 | 1987 | 0.096 | 0.091 | 2.014 | 16 |
| Park (2004) | Jnl | Panel | OLS | Country | 22 | Mixed | 1971 | 1990 | 0.049 | 0.057 | 5.750 | 8 |
| Raut (1995) | Jnl | Panel | RE/FE/OLS/3SLS | Firm | 192 | India | 1975 | 1986 | 0.008 | 0.008 | 1.490 | 19 |
| Van Pottelsberghe and Lichtenberg (2001) | Jnl | Panel | Diff/FE | Country | 13 | Mixed | 1971 | 1990 | 0.052 | 0.048 | 3.575 | 14 |
| Verspagen (1997) | Jnl | Panel | FE/RE | Industry_Country | 22 | Mixed | 1974 | 1992 | 0.076 | 0.076 | 3.665 | 24 |
| Wang and Chao (2008) | Jnl | Panel | OLS | Firm | 72 | Taiwan | 1994 | 2000 | 0.118 | 0.118 | 5.345 | 2 |
| Xu and Wang (1999) | Jnl | Panel | OLS | Country | 21 | Mixed | 1983 | 1990 | 0.051 | 0.029 | 1.493 | 20 |
| Zhu and Jeon (2007) | Jnl | Panel | Cointegration/OLS | Country | 22 | Mixed | 1981 | 1998 | 0.060 | 0.061 | 7.720 | 12 |
| TOTAL | | | | | | | | | **0.078** | **0.061** | **4.261** | **503** |

Notes: Jnl is Journal article, WP is working paper, CrS is Cross Section

**Table A3 – Effects size estimates by spillover types (frequency-weighted)**

| Dependent variable: t-value | Panel A - PET/FAT | | | | | Panel B - PEESE | |
|---|---|---|---|---|---|---|---|
| | (A1) | (A2) | (A3) | (A4) | (A5) | (B1) | (B4) |
| Effect (β in PET/FAT, γ in PEESE) | 0.064** | 0.052 | -0.097 | 0.058*** | 0.043 | 0.097*** | 0.073*** |
| | (0.028) | (0.037) | (0.099) | (0.012) | (0.033) | (0.026) | (0.011) |
| Selection bias | 1.900*** | 1.259*** | 2.932*** | 1.231*** | 2.285*** | | |
| | (0.473) | (0.418) | (0.765) | (0.346) | (0.339) | | |
| Standard error | | | | | | 1.424 | 3.203** |
| | | | | | | (1.479) | (1.587) |
| Obs. | 557 | 96 | 327 | 501 | 983 | 557 | 501 |
| Studies | 46 | 6 | 30 | 26 | 60 | 46 | 26 |
| Log-likelihood (LL) | -1760.941 | -306.995 | -932.755 | -1472.789 | -3064.777 | -1766.875 | -1474.265 |
| LL (comp. model) | -1853.435 | -323.953 | -1051.853 | -1685.547 | -3321.677 | -1933.186 | -1714.120 |
| LR $chi^2$ | 184.987 | 33.915 | 238.196 | 425.516 | 513.8 | 332.623 | 479.709 |
| P > $LRc^2$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Intra-class correlation | 0.103 | 9.30e-18 | 0.252 | 1.51e-13 | 0.063 | 0.170 | 3.32e-14 |

***, **, * indicates significance at 1%, 5% and 10%. LR $chi^2$ is based on likelihood ratio test where the null hypothesis is that the linear model is nested within the multi-level model. (1) is knowledge spillovers; (2) is mixed spillovers; (3) is rent spillovers; (4) is own R&D; (5) is all spillovers types

**Table A4 - Effects size estimates by unit of analysis (frequency-weighted)**

| **Dependent variable: t-value** | **Panel A - PET/FAT** | | | | | | **Panel B - PEESE** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | (A1) | (A2) | (A3) | (A4) | (A5) | (A6) | (B1) | (B2) | (B3) | (B4) | (B6) |
| Effect (β in PET/FAT, γ in PEESE) | 0.102** | -0.106* | 0.030*** | 0.049*** | 0.048 | 0.059*** | 0.135*** | -0.078 | 0.069*** | 0.055*** | 0.073*** |
| | (0.050) | (0.062) | (0.010) | (0.008) | (0.041) | (0.020) | (0.027) | (0.060) | (0.003) | (0.006) | (0.019) |
| Selection bias | 1.822** | 2.513*** | 2.501*** | 0.898** | 2.059** | 1.263*** | | | | | |
| | (0.825) | (0.648) | (0.480) | (0.441) | (1.011) | (0.409) | | | | | |
| Standard error | | | | | | | -0.004 | 2.516*** | -0.226 | 18.257** | 0.655 |
| | | | | | | | (0.931) | (0.619) | (0.911) | (7.584) | (1.002) |
| Obs. | 459 | 223 | 299 | 283 | 89 | 126 | 459 | 223 | 299 | 283 | 126 |
| Studies | 26 | 12 | 22 | 25 | 9 | 19 | 26 | 17 | 22 | 25 | 19 |
| Log-likelihood (LL) | -1408.742 | -678.214 | -955.515 | -705.504 | -313.91 | -265.875 | -1408.742 | -678.214 | -955.515 | -705.504 | -265.875 |
| LL (comp. model) | -1541.737 | -756.472 | -1008.283 | -817.222 | -333.312 | -342.706 | -1541.737 | -756.472 | -1008.283 | -817.222 | -342.706 |
| LR chi$^2$ | 265.989 | 156.515 | 105.535 | 223.437 | 38.805 | 153.662 | 265.989 | 156.515 | 105.535 | 223.437 | 153.662 |
| P > LRc$^2$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Intra-class correlation | 0.037 | 0.242 | 0.019 | 2.55e-16 | 5.00e-16 | 0.396 | 0.100 | 0.403 | 0.248 | 1.13e-15 | 0.617 |

***, **, * indicates significance at 1%, 5% and 10%. LR chi$^2$ is based on likelihood ratio test where the null hypothesis is that the linear model is nested within the multi-level model. (1) is spillovers - country; (2) is spillovers - industry; (3) is spillovers - firm; (4) is own R&D - country; (5) is own R&D – industry; and (6) is own R&D – firm. (1) to (3) is inter-unit only while (4) to (6) is intra-unit only.

## Table A5. Summary statistics for and description of variables

| | Obs. | Mean | Std Dev | Min | Max | Reference Category |
|---|---|---|---|---|---|---|
| **Effect-size indicators** | | | | | | |
| Effect size (elasticity) | 983 | 0.126 | 0.352 | -3.014 | 4.060 | N/A |
| Standard error of effect size | 983 | 0.055 | 0.144 | 0.001 | 2.276 | N/A |
| t-value | 983 | 4.712 | 7.109 | -64.857 | 65.8 | N/A |
| Precision | 983 | 86.169 | 146.319 | 0.439 | 999 | N/A |
| **Continuous variables** | | | | | | |
| Log (h-index, journal) | 983 | 3.901 | 1.049 | 0 | 5.407 | N/A |
| Log (citations per study per year) | 983 | 5.116 | 1.252 | 0 | 7.885 | N/A |
| Log (number of observations) | 983 | 7.004 | 1.547 | 3.807 | 9.870 | N/A |
| Log (number of years in data) | 983 | 2.835 | 0.492 | 0 | 3.497 | N/A |
| **Publication characteristics** | | | | | | |
| Journal article | 983 | 0.964 | 0.185 | 0 | 1 | Working papers |
| Publication date after 2000 | 983 | 0.721 | 0.449 | 0 | 1 | Publication date <=2000 |
| **Model specification in primary study** | | | | | | |
| TFP - Dependent variable is total factor productivity | 983 | 0.586 | 0.493 | 0 | 1 | Dependent variable is output or net sales |
| SPO coefficients in model <=2 | 983 | 0.687 | 0.464 | 0 | 1 | SPO coefficients in model >2 |
| Firm, industry, country dummy in model | 983 | 0.774 | 0.418 | 0 | 1 | Firm, industry, country dummy not in model |
| Control for own R&D in model | 983 | 0.846 | 0.361 | 0 | 1 | No control for own R&D in model |
| Time dummy in model | 983 | 0.586 | 0.493 | 0 | 1 | No control for time dummy in model |
| Control for capital in model | 983 | 0.184 | 0.388 | 0 | 1 | No control for time capital in model |
| Cobb Douglas human capital model | 983 | 0.057 | 0.232 | 0 | 1 | Cobb Douglas standard model |
| **Data and sample characteristics** | | | | | | |
| Data mid-point <= 1991 | 983 | 0.783 | 0.412 | 0 | 1 | Data mid-point > 1991 |
| Unit of analysis: country | 983 | 0.467 | 0.499 | 0 | 1 | Unit of analysis is industry or firm |
| Unit of analysis: industry | 983 | 0.060 | 0.238 | 0 | 1 | United of analysis is country or firm |
| High R&D-intensity firm, industry | 983 | 0.208 | 0.406 | 0 | 1 | Low or mixed R&D intensity firm, industry |
| North American (US and Canada) data | 983 | 0.131 | 0.338 | 0 | 1 | Non-North American sample |
| South Asian data | 983 | 0.103 | 0.304 | 0 | 1 | Non-South Asian data sample |
| OECD data | 983 | 0.729 | 0.444 | 0 | 1 | Non-OECD sample |
| Panel data | 983 | 0.982 | 0.134 | 0 | 1 | Cross-section |
| **Spillover characteristics** | | | | | | |
| Based on asymmetric weights | 983 | 0.195 | 0.397 | 0 | 1 | Symmetric weights |

| | | | | | | |
|---|---|---|---|---|---|---|
| Unweighted | 983 | 0.251 | 0.434 | 0 | 1 | Weighted |
| Based on R&D investment | 983 | 0.109 | 0.313 | 0 | 1 | R&D capital |
| Knowledge spillover | 983 | 0.567 | 0.496 | 0 | 1 | Mixed and rent spillover |
| Rent spillover | 983 | 0.336 | 0.471 | 0 | 1 | Mixed and knowledge spillover |
| **Estimation method** | | | | | | |
| Panel cointegration | 983 | 0.172 | 0.378 | 0 | 1 | Estimation is not based on panel cointegration |
| Instrumental variable (IV) estimation | 983 | 0.033 | 0.178 | 0 | 1 | Estimation is not based on an IV |
| Estimation with differenced data | 983 | 0.044 | 0.205 | 0 | 1 | Estimations is not with differenced data |
| GMM estimation | 983 | 0.072 | 0.289 | 0 | 1 | Estimation is not GMM based |

Notes: N/A- not applicable. Reference category is identified when the binary variable is zero.

**Table A6 - Multivariate meta-regression analysis (general model)**

| **Dependent Variable: *t*-Value** | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Precision | 0.217** | 0.112 | 0.250*** | 0.213** |
| | (0.103) | (0.127) | (0.047) | (0.106) |
| **Publication characteristics** | | | | |
| Journal article | -0.199** | -0.129 | -0.240*** | -0.236*** |
| | (0.083) | (0.088) | (0.036) | (0.069) |
| Log of H index | 0.458 | 0.495*** | 0.142 | 0.083 |
| | (0.386) | (0.156) | (0.683) | (0.911) |
| Publication date after 2000 | -0.047 | -0.011 | -0.106*** | -0.134*** |
| | (0.032) | (0.043) | (0.012) | (0.035) |
| Log of citations | -0.318 | 0.097 | -0.285 | 0.863 |
| | (0.345) | (0.271) | (0.574) | (1.078) |
| **Model specification** | | | | |
| TFP - Dependent variable is total factor productivity | -0.005 | -0.024 | 0.002 | -0.065* |
| | (0.026) | (0.038) | (0.015) | (0.037) |
| SPO coefficients in model <=2 | 0.040*** | 0.025** | 0.045*** | 0.055** |
| | (0.010) | (0.012) | (0.008) | (0.021) |
| Control for own R&D in model | -0.059*** | -0.025 | -0.034*** | 0.011 |
| | (0.019) | (0.019) | (0.012) | (0.027) |
| Firm/Industry/country dummies in model | 0.035 | 0.078*** | 0.029** | 0.056** |
| | (0.032) | (0.025) | (0.011) | (0.022) |
| Year dummies in model | 0.046 | 0.113** | 0.034*** | 0.060*** |
| | (0.032) | (0.044) | (0.008) | (0.022) |
| Cobb Douglas human capital model | -0.035 | -0.056 | 0.007 | 0.029 |
| | (0.049) | (0.045) | (0.014) | (0.027) |
| Control for capital in model | -0.003 | 0.004 | 0.001 | 0.017 |

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | (0.010) | (0.009) | (0.010) | (0.020) |
| **Data and sample characteristics** | | | | |
| Unit of analysis: country | 0.077** | 0.153*** | 0.033** | 0.087** |
| | (0.032) | (0.055) | (0.014) | (0.043) |
| Unit of analysis: industry | -0.197*** | -0.150* | -0.213*** | -0.169** |
| | (0.062) | (0.084) | (0.026) | (0.066) |
| High R&D-intensity firm, industry | -0.031 | -0.055** | -0.025* | -0.031 |
| | (0.025) | (0.027) | (0.014) | (0.032) |
| North American (US&Canada) data | 0.005 | -0.001 | 0.003 | -0.024 |
| | (0.007) | (0.008) | (0.007) | (0.029) |
| South Asian data | 0.054 | 0.010 | 0.098*** | 0.108** |
| | (0.037) | (0.054) | (0.015) | (0.045) |
| OECD data | 0.122** | 0.084 | 0.152*** | 0.125** |
| | (0.054) | (0.068) | (0.025) | (0.061) |
| Data mid-point <= 1991 | -0.069** | -0.105** | -0.050*** | -0.065** |
| | (0.034) | (0.051) | (0.012) | (0.030) |
| Panel data | 0.000 | 0.000 | -0.001 | -0.001 |
| | (0.005) | (0.001) | (0.005) | (0.002) |
| Log of number observations | 0.305 | 0.291 | 0.613 | 0.809* |
| | (0.249) | (0.218) | (0.384) | (0.460) |
| Log of number of years of data used | 0.011 | 0.270 | -0.342 | 0.733 |
| | (0.625) | (0.394) | (0.942) | (0.823) |
| **Spillover characteristics** | | | | |
| Based on asymmetric weights | 0.025*** | 0.049 | 0.024*** | 0.045 |
| | (0.007) | (0.041) | (0.006) | (0.028) |
| Unweighted | 0.002 | 0.003 | 0.005 | 0.003 |
| | (0.003) | (0.004) | (0.003) | (0.004) |
| Knowledge spillover | -0.007 | -0.020 | -0.007 | -0.013 |
| | (0.013) | (0.035) | (0.012) | (0.023) |
| Rent spillover | -0.012 | -0.031 | -0.019 | -0.047* |
| | (0.014) | (0.040) | (0.012) | (0.024) |
| Based on R&D investment | 0.076 | 0.015 | 0.192*** | -0.029 |
| | (0.064) | (0.048) | (0.029) | (0.106) |
| **Estimation method** | | | | |
| Estimation with differenced data | -0.005 | -0.005*** | -0.005 | -0.005*** |
| | (0.003) | (0.002) | (0.003) | (0.002) |
| Estimation takes account of panel cointegration | -0.008 | -0.008*** | -0.010* | -0.014 |
| | (0.005) | (0.002) | (0.005) | (0.009) |
| Instrumental variable (IV) estimation | -0.011 | 0.007 | -0.003 | 0.038 |
| | (0.007) | (0.019) | (0.007) | (0.039) |
| GMM estimation | 0.002 | 0.002 | -0.002 | -0.003 |
| | (0.014) | (0.002) | (0.015) | (0.005) |
| Constant | 0.238 | -2.204 | 0.230 | -8.014* |
| | (2.635) | (1.845) | (4.157) | (4.496) |
| Observations | 983 | 983 | 983 | 983 |
| Studies | 60 | 60 | 60 | 60 |
| Log-likelihood (HM) | -3010.995 | -173.779 | -3047.347 | -183.794 |
| LR Test chi2 | 106.157 | 2075.594 | 414.352 | 4481.363 |
| P> chi2 | 0.000 | 0.000 | 0.000 | 0.000 |
| converged | Yes | Yes | Yes | Yes |
| Log-likelihood (least-sqaures) | -3119.523 | NA† | -3119.523 | NA† |

*** p<0.01, ** p<0.05, * p<0.1. (1) is random intercepts and slopes HM, **without** frequency weights; (2) is random intercepts and slopes HM, **with** frequency weights; (3) is random intercepts only HM, **without** frequency weights; (4) is random intercepts only HM, **with** frequency weights. † log-likelihood statistics for the comparative model is not reported when the HM is estimated with frequency weights. 3-level HM specification was rejected by LR test.

**Box 3: Choosing the model averaging technique**

Multivariate meta-regression model selection has either been ad hoc or reliant on a general-to-specific (g-t-s) modelling routine where insignificant variables are dropped one at a time until all remaining variables are significant. Nevertheless, the g-t-s routine overlooks the fact that model selection and parameter estimation are a combined exercise and that model selection influences the estimated parameters (Magnus et al., 2010: 1331). Several studies demonstrate that biases associated with ignoring model selection can be serious (Danilov and Magnus, 2004; Leeb and Pötscher, 2005; 2006). Therefore, in this study, we rely on a weighted-average least squares (WALS) routine that addresses model uncertainty by combining ideas from Bayesian and frequentist model averaging methods. The box below summarises the methodological issues involved and the evidence on relative performance of the WALS routine.

The Bayesian model-averaging (BMA) method for addressing model uncertainty in multi-variate meta-regression has been suggested by Iršová and Havránek (2013) and Havránek (2015) among others. Other applications of the BMA method in meta-analysis of economics and business research include Awaworyi Churchill and Yew (2017), Campos et al. (2019), and Cuaresma et al. (2014). The method's main advantage is that it takes account of model and parameter uncertainty at the same time. However, it requires information about prior beliefs and different prior distributions can lead to different results in terms of posterior means for the coefficients and posterior inclusion probabilities for the covariates. In addition, the BMA is computationally intensive. Meta-analysts tend to reduce the computation time cost by selecting a large set of *focus variables* - i.e., by keeping the set of *auxiliary variables* small. However, this choice may exacerbate the prior belief problem because there is no theoretical guidance on which moderating factors should be considered as focus variables.

In this study, we utilise a weighted-average least squares (WALS) routine, which is a combination of Bayesian and frequentist approaches to model selection. It is frequentist in that it executes preliminary orthogonal transformations of the auxiliary regressors by constrained least squares. It is also Bayesian because it uses a Bayesian weighting scheme to obtain desirable theoretical properties after implementing a semi-orthogonal transformation to the auxiliary regressors. Both the WALS and BMA compute a weighted average of the conditional estimates, taking account of the focus variables and all possible combinations of the auxiliary variables (De Luca and Magnus, 2011). Whereas BMA calculates posterior inclusion probabilities (*PIPs*) to indicate which auxiliary variables should be included in the 'true' model, WALS rely on t-values. The common rule is to include covariates with PIPs > 0.5 in BMA and with t-values of |1| or greater in WALS. This criterion is based on Masanjala and Papageorgiou (2008), who demonstrate that a *t-ratio* of |1| in WALS corresponds to a *PIP* of 0.5 in BMA.

Amini and Parmeter (2012) compare the performance of BMA, WALS and the frequentist Mallows model averaging (MMA) method in the context of growth regressions. They demonstrate that all three successfully replicate 3 earlier studies based on BMA, producing coefficient estimates that are similar in sign and magnitude. Furthermore, the standard errors obtained from WALS lie between the BMA standard errors at the low end and the MMA standard errors at the top end. In addition, WALS is based on transparent ignorance about the auxiliary covariates (moderating factors) and its model space is a linear function of the auxiliary parameters to be estimated (De Luca and Magnus, 2011; Magnus et al., 2010). Therefore, WALS has a much lower computational time cost compared to BMA, where the model space is exponential in the number of auxiliary variables.

In the context of meta-analysis, Havranek et al. (2017) compares BMA with frequentist Mallow model averaging (MMA) routine whereas Campos et al. (2019) compares BMA with WALS. Both studies report that results from Bayesian and frequentists methods generally concur. [2] These findings are in line with others comparing BMA and WALS in the context of empirical growth models.[3] We therefore prefer WALS because of its bounded risk profile and the transparent ignorance it allows for in the selection of the focus variable(s). The latter quality is particularly important in the context of multivariate meta-regression because there is no theoretical guidance about the relevant set of focus regressors. The only focus regressor for which consensus exists is precision (the inverse of the standard error), which is carried over from the bivariate meta-regression model (model 4b in the main text). Therefore, we use precision as the focus regressor and allow for model uncertainty by treating all moderating variables as auxiliary regressors. The latter consist of 26 binary indicators and 4 continuous variables, which we code from the research field to measure the observable sources of heterogeneity.[4]

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[2] Greco et al. (2015) compare Bayesian and frequentist model averaging approaches in a meta-analysis of the evidence on mortality effects of anaesthetic drugs. The authors report that the results from the frequentist multi-level network meta-analysis (NMA) are comparable to those obtained with the Bayesian NMA approach.

[3] De Luca and Magnus (2011) and Magnus et al. (2010) report that WALS provides similar results to BMA but with a better risk profile and lower computational time costs.

[4] It must be noted that neither the WALS nor the BMA routine precludes the risk of multicollinearity, which could lead to well-known statistical problems such as unstable coefficients, large standard errors, and sign reversals in least squares estimators. However, simulation results have shown that HMs have better tolerance to multicollinearity (see, Shieh and Fouladi, 2003; Yu et al., 2015).

**Box 4: Publication probabilities and 'true' effects based on Andrews and Kasy (2019)**

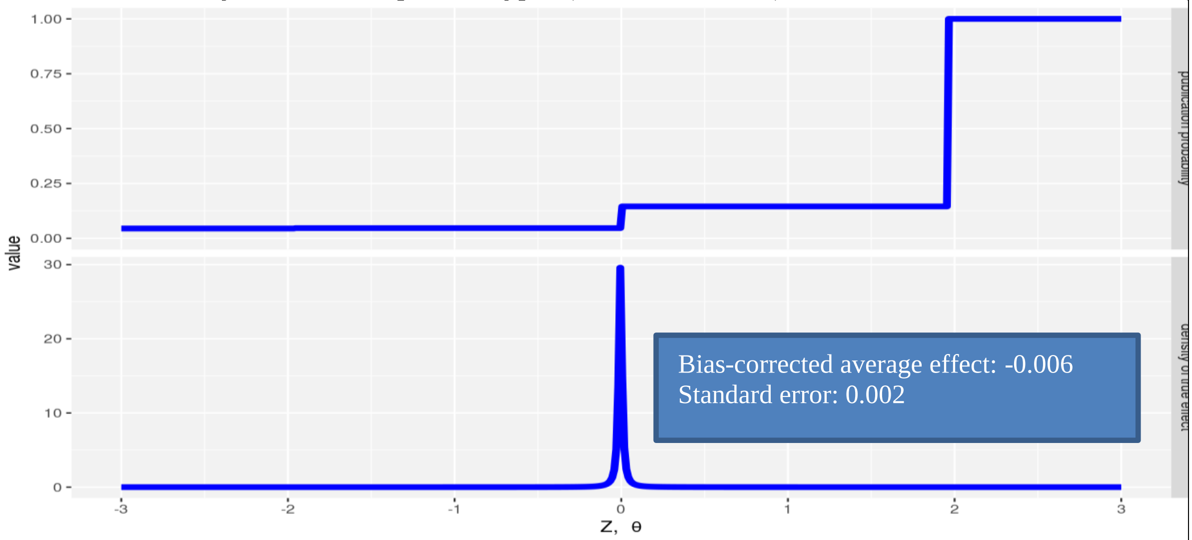
The graphs below are produced using the application provided by Andrews and Kasy (2019), which can be accessed at: https://maxkasy.github.io/home/metastudy/

The underlying non-parametric model allows for: (i) obtaining the probability of publication given the t-statistic associated with each effect-size estimate, and (2) the distribution of true effects in the latent population of studies.

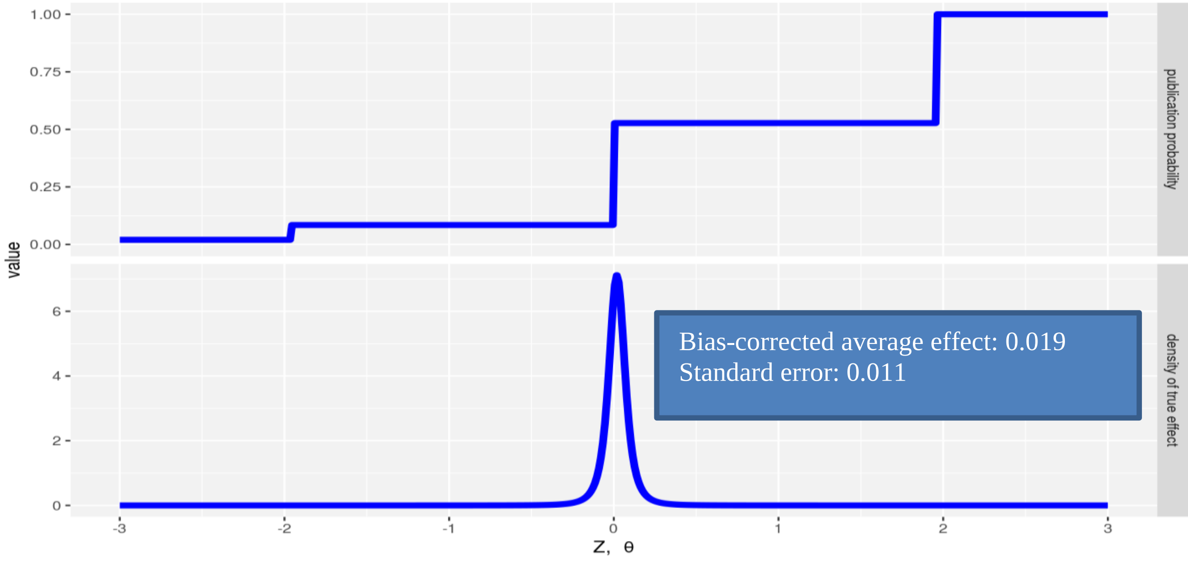
The graphs are produced by allowing for both positive and negative t-values as some primary studies report negative spillovers or own-R&D effects; and the latter are not excluded from the hierarchical model estimations we provide in the main text.

The results indicate that the productivity effect of spillovers is negative (-0.006) and significant! Indeed only the productivity effect of own R&D (0.019) is positive and significant at 10%. This is in line with our finding that the productivity effects of own R&D are usually larger than the spillover effects. However, we are of the view that the estimator proposed by Andrews and Kasy (2019) is susceptible to downward bias – as argued in main text.

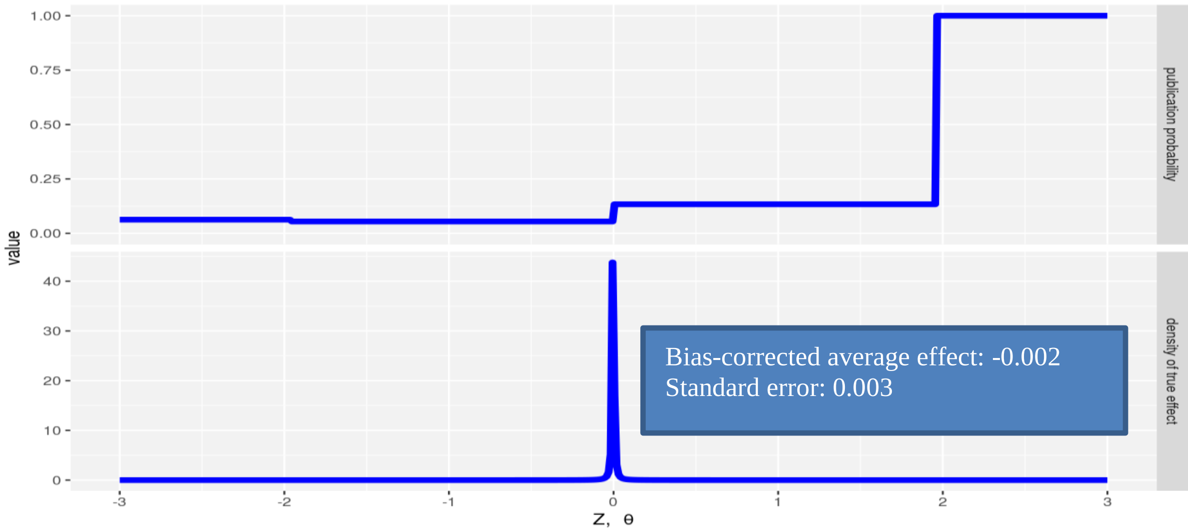
1. Productivity effect of all spillover types (983 observations)



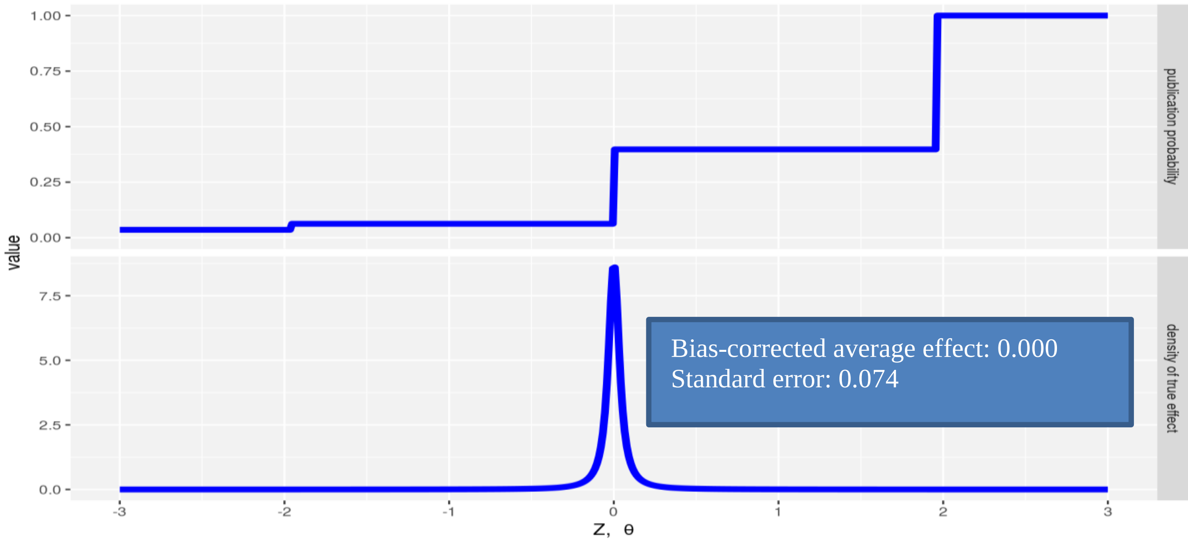

2. Productivity effects of own R&D (501 observations)



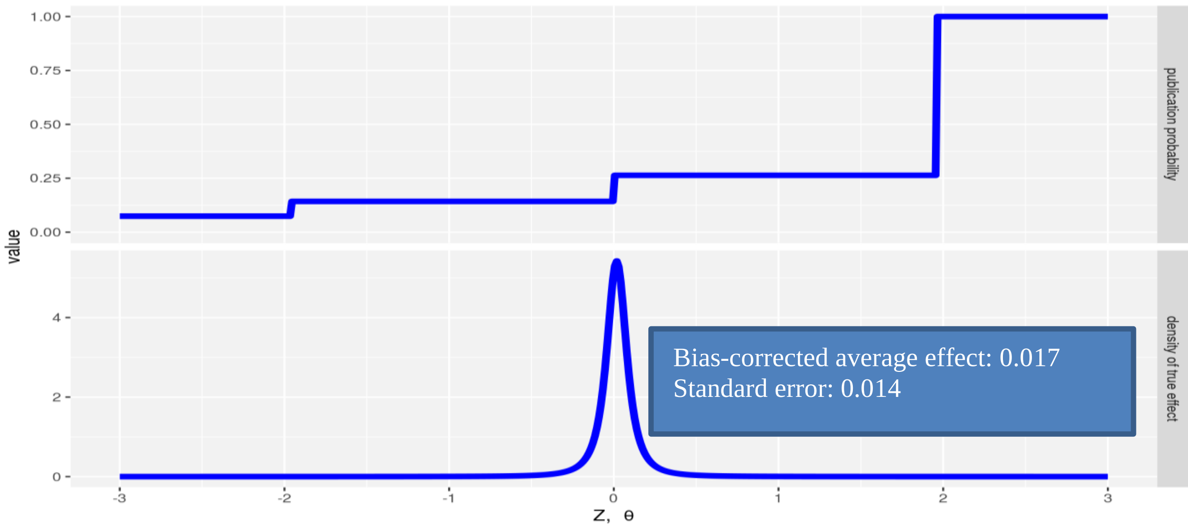

3. Productivity effects of knowledge spillovers (557 observations)




4. Productivity effects of mixed spillovers (96 observations)




5. Productivity effects of rent spillovers (327 observations)



**Box 5: Primary studies included in the meta-analysis**

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