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Spillovers in the production of knowledge: A meta-regression analysis☆

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ABSTRACT

The production of knowledge was subjected to quantitative analysis in the second half of the twentieth century, following Arrow (1962). The determinants of knowledge and the externalities present in the innovation process were discussed with immediate policy influence. In particular, the presence and strength of the spillover of the pool of past knowledge has encouraged high subsidization of R&D in the most developed countries. We survey the empirical literature on the spillover effect in the production of knowledge and implement a meta-analytic regression. We discover that the average spillover effect is less than but close to one and is highly significant. We also find that the spillover effect tends to be greater when the estimation of knowledge production accounts for foreign inputs, and it tends to be lower when the estimation includes only rich economies, regional data are used, and the pool of knowledge is not the patent stock.

1. Introduction

The knowledge or ideas production function is the cornerstone of innovation theory and is the crucial element to define possible policies that provide optimal (or improved) allocations (Arrow, 1962). Pakes and Griliches (1984) were probably the first to formalize a knowledge production function (k.p.f.). According to their approach, the production of knowledge depends on resources allocated to the R&D activity and to an error disturbance. Jaffe (1986) introduces to the knowledge process the influence of the knowledge pool or spillover, relating it to the effect that firms' knowledge may have on other firms. The ideas borrowed by a research team from another team's research results in a technological park such as the Silicon Valley which is the typical example of such effects. These effects are pure knowledge spillovers, which should be distinguished from the rent spillovers deriving from the exchange of goods in which knowledge can be embodied (see, e.g. Griliches, 1979, for a clear distinction between pure knowledge spillovers and rent spillovers).

In fact, when inventors rely and build on the ideas of others to innovate, they are "standing upon the shoulders of giants", an expression attributed to Isaac Newton that has been used in the literature as a synonym of pure knowledge spillover – see, e.g. Caballero and Jaffe (1993).[1] These authors highlight the quantitative importance of those spillovers using patents and the respective citations. Romer (1990) includes some of Arrow's ideas on the market structure needed to promote innovation and devises the first endogenous growth model in which the k.p.f. depends on a stock of past knowledge. These spillovers imply that the market equilibrium provides less innovation than the optimal allocation, which is the base for arguing in favor of government subsidies to R&D. This literature has been the scientific argument behind the high subsidization of R&D in developed countries. For example, according to OECD statistics, the USA subsidized on average 6.6% of private R&D expenditures in 2007.[2]

This idea is transversal to the first generation of endogenous growth models in the line of Grossman and Helpman (1991) and Aghion and Howitt (1992), in which the most counterfactual implication was that growth has scale effects, i.e. the economic growth rate depends positively on the level of population.[3] The so-called scale-effects have been addressed by the second generation of endogenous growth models, i.e. the semi-endogenous growth model of Jones (1995) and Segerstrom (1998). Within this semi-endogenous theory, the spillover has no distortionary effects on the economic growth rate but only on the

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[1] This pure knowledge spillover or "standing-on-the-shoulders" effect is quite distinct from the effect (or elasticity) of inputs to R&D to the production of new ideas, which has also been called the "stepping-on-toes" effect (Jones and Williams, 2000).

[2] OECD Science, Technology and Industry: Scoreboard 2007 (Section C.3).

[3] This prediction would imply that, for example, India should always grow more than Singapore or that today the world should be growing more than in the 1950s, simply because it is now more densely populated than ever before.

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allocation of resources, namely on R&D investments. Also, the spillover effect, together with other externalities' strength, would determine if the economy underinvests or overinvests in R&D. Thus, optimal allocations may call for subsidization or taxation of R&D activities but with null effects on long-run growth rates. Nevertheless, the economic growth rate is positively dependent on the growth rate of population.[4] The third wave of endogenous growth theory, also named Schumpeterian theory, has examples in Aghion and Howitt (1998); Peretto (1998), Howitt (1999) and Peretto and Smulders (2002). Schumpeterian models tend to reconcile theory and evidence, eliminating effects of both the population size and the population growth on economic growth, while also recovering the effects of endogenous variables and policies on growth. In particular, according to these theories economic growth should depend on an interplay of firms', families', and government choices.

In fact, the magnitude and significance of the spillover effect have important implications for theory and policy. First, the findings would lend support to endogenous growth theory (with or without population growth) if the hypothesis that the spillover effect is unity cannot be rejected. If the value of the spillover effect is significantly less than one (as reported in Ang and Madsen, 2015, for example), the evidence lends support to semi-endogenous growth theory. Second, and in terms of policy, a positive and significant spillover effect calls for tax relief or subsidies as well as specific tax rates as suggested in Jones and Williams (2000). However, such policy decisions should consider not only the extent of spillovers but also other sources of externalities and market imperfections that may cause upward or downward departures from the optimal levels of investment in innovation. Finally, positive and significant spillover effects have important implications for growth and welfare, even under the semi-endogenous growth framework due to strong transitional effects (e.g. Gomez and Sequeira, 2014; Grossmann et al., 2013).

The estimates of the spillover effect present a high degree of variability, with a minimum near -0.1 and maximum near 2. Therefore, we utilize evidence synthesis methods not only to estimate an average effect size but also to account for sources of heterogeneity in the evidence base. Meta-regression analysis is a particular type of evidence synthesis method that allows for summarizing the evidence and investigating the sources of variation in the results reported in a specific literature. It has been extensively used in several areas of economics research in recent years (Stanley et al., 2008).

We discover that the average spillover (or standing-on-the-shoulders) effect is on average less than one. Its value tends to be higher once the knowledge production estimation accounts for foreign inputs (imports or more generally, foreign influence). It tends to be lower when the estimation includes only rich economies, regional data are used, and the pool of knowledge is not the patent stock. These results are robust to several different specifications. The identification of several moderating factors influencing the spillover effect is of special relevance for the future empirical research on the k.p.f.

The paper is structured as follows. In Section 2 we explain our search protocol and survey the literature on spillovers in the knowledge production function. In Section 3 we describe the data for our meta-regression analysis. In Section 4 we discuss the evidence on the publication bias and on the average estimate of the spillover effect. In Section 5 we present and analyze the results of the multivariate Ameta-regression analysis. Section 6 concludes and presents policy implications and prospects for future work.

2. Spillover effects on the knowledge production function

Through a thorough review of the literature on the knowledge production function (k.p.f.), we identified five different branches of the literature associated with the estimation of the k.p.f.: (1) a literature dealing with spatial spillovers; (2) a literature dealing with the estimation of knowlegde production functions in firms and industries, which usually does not include a spillover effect (often associated with the seminal paper of Crepon et al., 1998); (3) a literature estimating a knowledge production function following Aghion and Howitt (1992), which does not provide estimations of the spillover effect; (4) a literature using time-series approaches to estimate the long-run relationship between aggregated knowledge and resources in which a spillover effect is not estimated, and finally, (5) the literature that estimates a knowledge production function with an intertemporal knowledge spillover effect. Our meta-analysis focuses on this fifth branch of the literature.

In order to put the articles that we will meta-analyze in perspective with the related literature, we present a brief review of each of the five branches presented above. The literature that estimates regional or spatial spillovers has an example in Bottazzi and Peri (2003).[5] It refers to the knowledge produced in one space that, because of various mechanisms, spills over into neighboring spaces. In doing so, most papers within this literature weight the estimated coefficient on resources allocated to the production of knowledge or on the pool of knowledge by distance between different regions. This literature often calculates these effects assuming that they are dependent on the geographical distances between regions or countries.

The second branch of the literature, abbreviated as CDM (after Crepon et al., 1998) is marked by a step-wise use of the idea of the k.p.f. that explains productivity by innovation output and the latter by research investment. In general, binary or ordered dependent variables are used but a very wide variety of econometric methods have been implemented (for a recent survey, see Lööf et al., 2017).[6] Additionally, this literature focuses on estimating the effects of inputs to the R&D process, thus on the stepping-on-toes effect.

The third branch of literature (e.g. Zachariadis, 2003; Venturini, 2012a; Minniti and Venturini, 2014) estimates a framework based on Aghion and Howitt (1992) such as:

$$\iota = \delta \frac{L_A}{x} \tag{1}$$

where ι is the rate of innovation (or knowledge production), δ is an exogenous productivity parameter, L_A is the amount of resources allocated to knowledge production, and x is the difficulty associated with the knowledge production. If a significant relationship between the rate of knowledge production ι and the relative resources to the difficulty effect $\frac{L_A}{x}$ is obtained, then the non-scale fully endogenous growth model is supported. In general, this is the result reported in these papers. However, neither a stepping-on-toes nor a standing-on-shoulders coefficient is estimated within this literature.

The fourth branch of literature applies time-series (unit-root tests and/or cointegration) techniques to the k.p.f., and its estimations are therefore valid in the long run. This literature does not estimate a coefficient of the knowledge pool (spillover) either. Laincz and Peretto (2006); Ha and Howitt (2007); Bottazzi and Peri (2007), Madsen (2008) and Sedgley and Elmslie (2010) are in this group, and their results tend to support Schumpeterian theory. Generally, the authors find that while TFP growth has been stationary, R&D expenditure has shown a downward trend, and thus this relationship contradicts semi-endogenous growth. Bottazzi and Peri, 2007 also take into account the international spillovers, and Madsen (2008) applies the same type of tests to a longer time series. Sedgley and Elmslie (2010) extend previous work to account for transitional dynamics.

[4] This would imply, e.g. that the economic growth in the first half of the 20th century should have been fast due to the faster population growth experienced in that time.

[5] A more recent example of this branch is Cabrer-borras and Serrano-domingo (2007).

[6] Although Crepon et al. (1998) also have estimations for equations of patents flows, they never regress them on the stock of patents, nor do they include alternative pools of knowledge.

However, most contributions to the estimation of a knowledge production function depart from a functional form *à la* Romer (1990) as in the following:

$$\dot{A} = F(A, L_A) = \delta A^{\phi} L_A^{\lambda} \tag{2}$$

where δ is an exogenous productivity parameter; A is the stock of knowledge; L_A is the amount of physical resources allocated to the knowledge production which may include physical or human capital, labor, or final goods; ϕ measures the effect of the knowledge pool on the accumulation of knowledge (the so-called standing-on-shoulders effect); and λ measures the degree of decreasing returns to scale relating to labor allocated to R&D activities (the so-called duplication or stepping-on-toes effect). This function can be enlarged to include the international effects (international knowledge, imports, foreign direct investment, or convergence effects, usually refereed to as distance to the frontier) and also difficulty or dilution effects usually considered in the Schumpeterian growth theory. Note that the third, fourth and fifth branches of the literature described above are based on an intertemporal concept of spillovers, meaning that a pure knowledge spillover (or "standing-on-the-shoulders" effect) depends on past knowledge. According to this notion of spillovers, inventors rely and build on the stock of existing ideas to expand the knowledge frontier.

In this paper we focus our attention on the fifth branch of the literature, which estimates the knowledge spillover parameter ϕ from a k.p.f. with a specification similar to the logarithmic form of Eq. (2), using the flow of patents to measure the production of knowledge, $\dot{A}$. With this we restrict the analysis to a relatively uniform specification of the k.p.f. In the branches of the literature described earlier, a spillover (coefficient of a given knowledge pool) is not estimated or a k.p.f. is estimated for a dependent variable other than the flow of patents.

Jaffe (1986) was the first to estimate a knowledge production function comparable to the logarithmic version of Eq. (2), using industrial data. The knowledge pool is constructed using patent data by firms and the proximity of firms in the technology space. His research found a significantly positive effect of the knowledge pool on the flow of patents. Jaffe (1989) estimated effects of industrial and academic research in knowledge output (patents). In this paper, the knowledge pool is proxied by the population in parallel with the growth scale effect obtained in the first generation of endogenous growth models. Building on Jaffe's contributions, Peri (2003) estimates the effect of firms' own R &D stock on the flow of patents, obtaining significant effects of around 0.6. In the same line, Venturini (2012b) and Bloom et al. (2013) also use industrial and firm data (respectively) to estimate spillovers. While the former estimates an equation derived from the third generation of endogenous growth model, obtaining estimates of the spillover around one (1), the concept of spillovers in the latter is close to Jaffe's, as it uses distances between firms in the technological space to weight patents. In this case the coefficients of the spillovers are nearly 0.5.

Using a panel-data of countries, Porter and Stern (2000) claim to have found evidence for the validity of the Romer (1990) model, as the coefficient of A in the knowledge production function tends to be one (1) or close to it. The consequence of this is that the level of population would positively influence economic growth, a result that was rejected by the empirical evidence presented, e.g. in Jones (1995). In Porter and Stern (2000), however, the semi-endogenous growth model is not clearly rejected in many specifications, as the Romer (1990) model demands that the coefficient of A in the knowledge production function is at least one (1) and this does not happen in all of the specifications in that paper. Porter and Stern (2000) use an alternative approach to estimate the k.p.f. in which the final good production function is solved with respect to A – called the inversion approach. However, in this case it is impossible to disentangle the spillover effect (i.e. the coefficient of the knowledge pool) from the gains from specialization (the coefficient of A in the final good production function). Because of this, this approach will be disregarded in the meta-regression performed below.

When considering variables linked to the national innovation capacity (e.g. industrial clusters, university capacities), Furman et al.'s (2002) estimates favor semi-endogenous growth, a conclusion also obtained by Furman and Hayes (2004) and Ramzi and Salah (2015) using the same framework. On the contrary, Hu and Mathews (2005, 2008) and Ying (2008) estimate the knowledge production function with similar controls for the Asian countries and China and find support for strong spillovers. In these papers, the knowledge pool is associated with the national innovation capacity, which is proxied by a stock of patents, by GDP, or by GDP *per capita*. Using a time span more recent than Porter and Stern (2000) and a larger set of countries, Pessoa (2005) obtained estimates of the spillover less than one (1), which he claims to be more consistent with the Jones (1995) semi-endogenous model. Luintel and Khan (2009) use a new dataset of patents, highly intensive in research, and obtain high values for the domestic spillover effects, thereby supporting an unbalanced path with increasing population. Luintel and Khan (2012) estimate a knowledge production function for a set of emerging countries and reach conclusions along the same line. Ulku (2007a) and Ulku (2007b) evaluates a non-scale endogenous growth model in which the scale-effects are diluted by a difficulty effect measured by the population size. His results tend to validate the model as he obtains increasing returns to scale toward A in Eq. (2) and also validates the relative research intensity term. However, this last condition holds only in the larger OECD countries, meaning that for other samples the first generation endogenous growth model is as described by the data.

Ang and Madsen (2015) extend the knowledge production function to consider several international effects as well as a larger time span, from 1870 to 2010. They found a domestic spillover very close to or greater than one and a difficulty effect statistically significant and with the sign that is predicted by the non-scale endogenous theory. Thus, this paper strongly supports the Schumpeterian theory. The same authors (Ang and Madsen, 2011) reach the same conclusion for a set of six Asian countries. The contributions surveyed so far estimate different functional forms for Eq. (2) and present point estimates for the degree of the returns to scale with respect to past knowledge – the standing-on-the-shoulders or spillovers effect.

3. The search protocol and data

In order to select the studies to be included in the meta-analysis and complement the literature review presented in the previous Section, we searched in the Web of Science and Scopus databases for papers estimating a knowledge production function (k.p.f.), using the keywords "knowledge production function" *and* "spillovers" *or* "national innovative capacity" in the whole texts, *or* "ideas production" *or* "ideas driven growth" in titles of indexed publications.[7] We restricted the analysis to fields of "Economics", "Planning and Development", and "Economics, Econometrics and Finance" and obtained 312 articles or conference papers. Of 312 papers, the great majority fall within the literatures described in (1) and (2). There are 18 papers falling within groups (3), (4) and (5). In order to enlarge the possible sample, we used Google Scholar together with the analysis of the cited and citing references of the selected papers. Both published articles and working papers were considered. With this strategy we obtained an additional 15 papers, which resulted in a total of 33 papers that estimate intertemporal knowledge production functions. Of those, only 23 provide estimates of the intertemporal spillover, thus falling within the fifth branch of the literature mentioned above.

Table 1 systematizes the articles presented in the literature review of Section 2, complemented with the results of the search protocol

[7] With this search we want to differentiate from a relatively close literature on *international knowledge spillovers*. The aim of this literature is to estimate the elasticity of total factor productivity to the stock of knowledge (e.g. Coe and Helpman, 1995), rather than a spillovers effect within a knowledge production function. This literature was meta-analyzed by Ugur et al. (2016).

Table 1
Classification of articles or papers by the type of k.p.f., spillovers and the aggregation level.

	Regional and CDM 1st and 2nd branches	Specification equation (1) 3rd branch	Time-series methods 4th branch	Specification equation (2) 5th branch
Ma			Bottazzi and Peri (2007) Dinopoulos and Thompson (1998) Ha and Howitt (2007) Madsen (2008) Ramzi and Salah (2015) Sedgley and Elmslie (2010)	Abdih and Joutz (2005) Ang and Madsen (2011, 2015) Furman et al. (2002) Furman and Hayes (2004) Hu and Mathews (2005, 2008) Luintel and Khan (2009, 2012) Madsen (2016) Pessoa (2005) Porter and Stern (2000) Ramzi and Salah (2015) Ulku (2007b) Ying (2008)
Me	Agostino et al. (2012) Peri (2003) Cabrer-borras and Serrano-domingo (2007) Charlot et al. (2015) Jaffe et al. (1993) Acs et al. (2002) Parent (2012) Gumbau-Albert and Maudos (2009)			
Mi	Crepon et al. (1998) Lööf et al. (2017) Ramani et al. (2008) Zheng (2015)	Minniti and Venturini (2014) Venturini (2012a) Zachariadis (2003)	Malerba et al. (2013)	Ulku (2007a) Jaffe (1986, 1989) Bloom et al. (2013) Venturini (2012b) Mancusi (2008) Montobbio and Sterzi (2011)

Note: CDM stands for Crepon et al. (1998). Ma, Me, Mi stands for Macroeconomic, Mesoeconomic and Microeconomic, respectively.

describe above, and classifies the contributions to the literature according to the different branches dealing with the k.p.f. In order to further detail our classification of papers, we have also distinguished the contributions according to their micro (firm and market), meso or macroeconomic approaches. Column (1) includes several examples of papers dealing with regional spillovers and the CDM approach to the k.p.f. In this case the list is far from exhaustive, as there are several contributions on these branches. Column (2) lists papers following the Aghion and Howitt (1992) specification. Column (3) lists contributions applying unit-root and/or cointegration techniques. Common to all these sets of contributions is the fact that they do not estimate a spillover effect on a knowledge pool. Finally, column (4) lists the papers estimating a k.p.f. *à la* Romer (1990), from which a spillover coefficient estimate can be obtained. Table 1 shows that in the first, second and third branches there is a predominance of meso and microeconomic studies while macroeconomic studies are the majority on the fourth and fifth branches.

We select the primary studies to be meta-analyzed from the list of 23 contributions in column (4). In particular, we consider those that present estimates for the coefficient (and the standard error or the *t*-statistic) associated with the stock of knowledge, i.e. an estimate of ϕ, in the estimation of a log version of Eq. (2). Some of these articles also include other covariates in the regression, such as foreign patent stocks, openness related variables, institutional variables and time effects. They also employ different estimation methods (see Tables 2, Table A.1 and Table A.2).

Ang and Madsen (2011), Hu and Mathews (2008), Ying (2008) and Ramzi and Salah (2015) were excluded because they do not report the values of the standard-error of the coefficient. In addition, three regressions using total GDP as the pool of knowledge in Hu and Mathews (2005) were eliminated as they are strong outliers for the coefficient value.[8] This primary study includes data from a small set of East Asian countries (Taiwan, Korea, Singapore, Hong Kong and China) and we attribute the results for GDP coefficient (a scale dependent variable) to the disproportionate size of China when compared to the other countries considered. Furthermore, in order to keep in the sample a set of papers that coherently estimate comparable functional forms of Eq. (2), we include in the baseline analysis only the estimations which also provide a stepping-on-toes or duplication effect. This led to the elimination of Peri, 2003 and Mancusi (2008).

Thus, for our baseline analysis, our database comprises 170 estimates of the effect-size – the spillover effect, ϕ, from 15 different primary studies. Table 2 provides information about their main characteristics.

In an alternative analysis shown in the Appendix we present the results from regressions in which the four papers that do not provide estimations for the duplication effect are considered. In this case, the estimated value of the duplication effect is replaced by a dummy variable, which takes the value 1 if the estimation of the duplication effect in the primary study is present.[9]

The estimates of ϕ in the baseline sample range between a minimum of -0.128 (by Jaffe, 1989) and a maximum of 2.121 (by Furman and Hayes, 2004), with a median of 0.831. In 57 observations (34%), ϕ is equal to or greater than one, while it is less than one in 113 observations (66%). However, we should note that in many observations the spillover coefficient is very close to one and in some cases the upper limit of the confidence interval is above one. In fact, of all 170 observations, 74 present confidence intervals with an upper limit equal to or greater than one, while in 96 the upper limit of the confidence interval is less than one. In general, the spillover estimates in the primary studies tend to be high, meaning a substantial and statistically significant standing-on-shoulders effect. More than 71% of the point estimates (121) are above the value of 0.7 and only 6% (8) are below 0.1. In fact, 97% of the point estimates are positive and 92% are statistically

[8] In fact, these are the only three observations of the spillover that are above the third quantile plus three times the interquartile range, the usual definition for a strong outlier.

[9] We want to thank a referee for the suggestion of this alternative approach.

Table 2
Summary of studies' main characteristics.

Study	Code	Nr. of estimates	Mean of coefficients' estimates	Mean of *SE* of estimates	Sample of countries	Data level	Data structure	Type of publication
Jaffe (1986)	13	5	0.456	0.098	Rich	Firm/Industry	Panel	Article
Jaffe (1989)	14	20	0.201	0.092	Rich	Regional	Mixed	Article
Porter and Stern (2000)	8	15	0.875	0.056	Mixed	Country	Panel	Working-Paper
Furman et al. (2002)	6	15	0.778	0.109	Rich	Country	Panel	Journal
Furman and Hayes (2004)	5	7	1.067	0.123	Mixed	Country	Panel	Journal
Abdih and Joutz (2005)	15	1	1.436	0.062	Rich	Country	Time-Series	Working-Paper
Hu and Mathews (2005)	7	6	0.861	0.035	East Asia	Country	Panel	Journal
Pessoa (2005)	2	16	0.766	0.066	Mixed	Country	Panel; Cross-Section	Journal
Ulku (2007a)	4	10	0.857	0.144	Rich	Country	Panel	Journal
Ulku (2007b)	12	4	1.037	0.045	Rich	Firm/Industry	Panel	Journal
Luintel and Khan (2009)	9	4	0.149	0.042	Rich	Country	Panel	Journal
Luintel and Khan (2012)	3	7	1.562	0.081	Emerging	Country	Panel	Working-Paper
Venturini (2012b)	11	16	0.982	0.009	Rich	Firm/Industry	Panel	Journal
Ang and Madsen (2015)	1	38	0.989	0.004	Mixed	Country	Panel	Journal
Madsen (2016)	10	6	1.055	0.018	Rich	Country	Panel	Journal

Note: Code is the identifier in the database. *SE* stands for standard-error.

significant at the 5% level, presenting a t-statistic equal to or greater than 1.96.

In the knowledge pool used by primary studies as a base to measure the spillovers, most observations (75%) use the stock of patents. In fact, Griliches (1990) argued in favor of the use of patent data to measure knowledge stocks. Of these, 87.5% use unweighted patents. Although Jaffe et al. (1993) argued in favor of using citations to weight patents as a base for the construction of the knowledge pool, most researchers opted to use unweighted patents. Far fewer of the primary studies use GDP, GDP *per capita*, or value added (10%) or population (12%). There is also some discussion in the literature on the advantages and disadvantages of weighting patents (namely with citation data), e.g. in Luintel and Khan (2009).

To evaluate the degree of heterogeneity in the reported estimates of the spillover effect, we calculate" the classic Cochran's Q-statistic and the I^2 index. The Q-statistic measures the weighted sum squares of the differences between study estimates and the fixed effects average estimate. The I^2 index is equal to $(Q - (n - 1))/Q$ and quantifies the proportion of total variation in the estimates that is due to heterogeneity between studies, as opposed to sampling variability (Higgins and Thompson, 2002; Higgins et al., 2003). In our dataset, $Q = 18,291.83$ and $I^2 = 99\%$, which denotes a very high degree of heterogeneity. This means that there is substantial variation between studies' estimates that should be accounted for. In Section 5 we employ meta-regression analysis to provide explanations for this variation.

4. Publication bias and average estimate of the spillover effect

Before explaining the variation in studies' estimates, we compute the average estimate of the spillover effect and test for the presence of publication bias in this literature.

In meta-analyses the combined estimate of the effect-size is often obtained using either fixed effects or random effects estimators. They are both weighted averages of the effect-sizes reported in the primary studies. The fixed effects estimator assumes that there is only one true effect-size, common to all studies, and that the observed variability in the reported estimates comes only from sampling variation. On the contrary, the random effects estimator accounts for the presence of heterogeneity, as it considers that studies have different true effect-sizes; consequently, the observed variability in the reported estimates comes not only from sampling error – within studies variation – but also from differences in studies' true effect-sizes – between studies variation.[10] Due to the heterogeneity detected in the previous section, we employ the random effects specification in the estimations performed throughout the paper.

Publication bias has long been recognized as an important problem in empirical research. In its most frequent form, publication bias arises when statistically significant results are more likely to be produced and published by authors and journals than non-significant results. This leads to a distortion in empirical results, as the effect under analysis tends to be overestimated. Publication bias has been abundantly addressed in meta-analyses in many research areas, including economics (Card and Krueger, 1995; Doucouliagos, 2005; Doucouliagos et al., 2005; Stanley, 2005; Stanley et al., 2008).

The funnel plot is a tool widely used to detect the presence of publication bias and simultaneously to obtain an idea of the average effect. Popularized by Egger et al. (1997), the funnel plot is a scatter diagram that displays the estimates of the effect-size in the horizontal axis and their precision (usually measured by the inverse of the standard errors reported in the primary studies) on the vertical axis. As thoroughly explained by Stanley (2005), in the absence of publication bias, estimates of the effect-size will vary randomly and symmetrically around the mean, the dispersion being higher in studies with lower precision. In this case the diagram will take the shape of a symmetrical inverted funnel. But if there is publication bias favoring a certain direction, studies with higher standard errors (lower precision) tend to present estimates with a higher magnitude and biased toward that direction. In this case the diagram will be asymmetrical especially in its lower part. Thus, the (a)symmetry of the funnel plot is the key to assessing publication bias. Fig. 1 shows the funnel plots for our dataset, one with $precision = 1/SE_i$ on the y-axis (Fig. 1a) and another in which precision appears in log scale for better visualization due to its high amplitude (Fig. 1b).

There seems to be no evidence of publication bias, as the point estimates of the spillover effect are symmetrically distributed around the average (0.83), which is less than one. The conclusions revealed by visual inspection of the funnel plot can be formally tested by running a simple regression of the effect-sizes on the respective standard errors:

[10] For further details on the fixed and random effects estimators in the context of meta-analyses, see Hedges and Olkin (1985) and Borenstein et al. (2009).

(a) Funnel Plot 1 (b) Funnel Plot 2 (log scale)

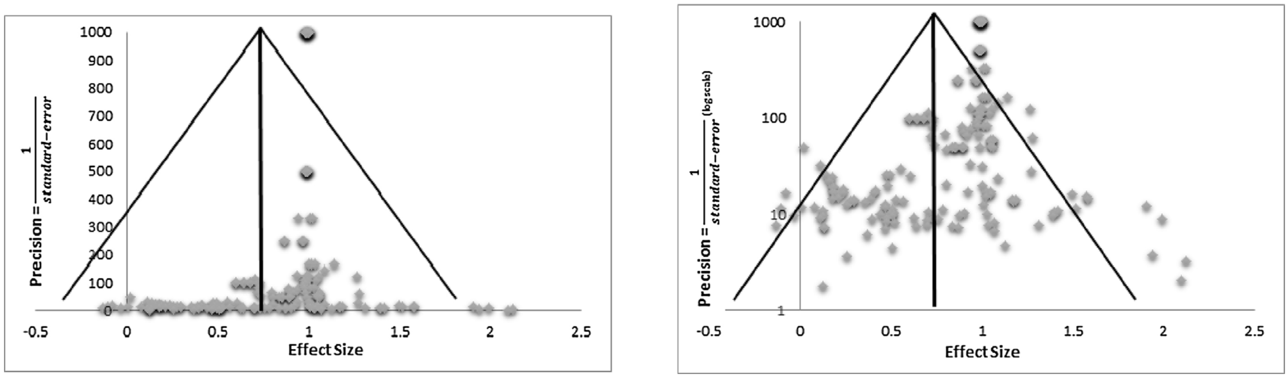

Fig. 1. Funnel plots.

$$\phi_i = \alpha_0 + \alpha_1 \mathrm{SE}_i + u_i \tag{3}$$

In the presence of publication bias, authors of studies with small samples and higher standard errors will tend to search more intensively (from datasets, estimation techniques, and model specifications) for higher estimates of the effect-size in order to report statistically significant results. Thus, ϕ will be correlated with *SE*. In the absence of publication bias, ϕ will be uncorrelated with *SE*, as the reported estimates will vary randomly around the average effect, α_0, regardless of the standard errors (Stanley, 2005).

Eq. (3) can thus be used to test for the presence of publication bias and simultaneously to estimate the average of the effect-size after controlling for publication bias. However, its estimation by OLS has two main problems. First, given that each reported effect has its own standard error, the disturbances u_i are heteroskedastic. This problem can be easily corrected by implementing the usual procedure of dividing both sides of Eq. (3) by *SE* (Stanley, 2005), which leads to:

$$t_i = \alpha_0 \mathrm{precision}_i + \alpha_1 + e_i \tag{4}$$

where $t_i = \phi_i/SE_i$ is the conventional t-statistic associated with ϕ_i reported in the primary studies and $precision = 1/SE_i$. Given that the coefficients are now reversed, testing for the intercept in Eq. (4), α_1, being equal to zero is a test for the presence of publication bias (Funnel Asymmetry Test – FAT), while testing for the slope, α_0, being equal to zero is a test for the presence of a significant average effect beyond publication bias (Precision Effect Test – PET) (Egger et al., 1997; Stanley, 2005; Ugur et al., 2016). However, some authors (e.g. Moreno et al., 2009; Stanley and Doucouliagos, 2012, Ch. 4) have suggested that a specification based on a quadratic relationship between the effect-sizes and their standard errors is more appropriate than a linear specification to correct for publication bias when there is significant average effect. In this case, the *precision-effect estimate with standard error* (PEESE) may be preferred to the PET/FAT. The equation estimated under the PEESE specification is (Stanley and Doucouliagos, 2012, Ch. 4; Ugur et al. 2016):

$$t_i = \alpha_0 \mathrm{precision}_i + \alpha_1 \mathrm{SE}_i + \epsilon_i \tag{5}$$

The second problem in estimating Eq. (3) by OLS is the presence of statistical dependence. When several observations are drawn from the same study, they share the same datasets, specifications or estimation procedures, and therefore are likely to be correlated (Hunter and Schmidt, 1990; Nelson and Kennedy, 2009). In this case, OLS produces biased estimates. The easiest way to address this issue is to choose only one estimate from each study (Stanley, 2001; Lipsey and Wilson, 2001). However, this would generally lead to a considerable reduction in the size of the meta-sample, which is not desirable when the number of studies is limited. If several observations from each study are to be used in the meta-analysis, then hierarchical models, panel data estimators, clustered data analysis, or bootstrapped standard errors can be employed to address the problem of within-study correlation (Nelson and Kennedy, 2009; Doucouliagos and Laroche, 2009). We choose to estimate Eqs. (4) and (5) using hierarchical linear models, since they not only correct the standard errors for within-study correlation, but also estimate the regression coefficients allowing for the presence of heterogeneity between studies (Ugur et al., 2016). Examples of meta-analyses in economics that have used hierarchical linear models are Bateman and Jones (2003); Johnston et al. (2005) and Ugur et al. (2016).

In the hierarchical models, observations are nested into groups with different characteristics. Thus, differences in individual observations can be attributed to both within-group variation and between-group variation. The model's coefficients are allowed to vary randomly between groups. In its most generic form, a hierarchical linear univariate model of the dependent variable $Y_{i,j}$ on explanatory variables $X_{i,j}$ can be written as:

$$Y_{i,j} = (\beta_0 + \gamma_{0,j}) + (\beta_1 + \gamma_{1,j})X_{i,j} + \varepsilon_{ij} \tag{6}$$

where subscript *i* refers to observations and subscript *j* refers to groups; β_0 and β_1 are the fixed-effects intercept and slope, respectively; $\gamma_{0,j}$ and $\gamma_{1,j}$ are the group-specific intercept and slope, respectively, which are assumed to follow a normal distribution. This generic version is called the random intercept and slope model, as it allows both the intercept and the slope to vary randomly across groups. If only the intercept is allowed to vary across groups (in which case the slope is assumed to be fixed and the variance of $\gamma_{1,j}$ is zero), we have a random intercept model; if only the slope is allowed to vary across groups (in which case the intercept is assumed to be fixed and the variance of $\gamma_{0,j}$ is zero), we have a random slope model.

The hierarchical structure can be applied in meta-analysis, as the observations (estimates of the effect size) are nested in groups (studies), that have different characteristics (random variation). We thus estimate Eqs. (4) and (5) using hierarchical linear models following the PET/FAT and PEESE specifications. The results are reported in Table 3.

The upper part of the table shows the results of the estimation of coefficients α_1 and α_0 using as random the slope associated with variable *precision*. Estimations are obtained by maximum likelihood. In both PET/FAT and PEESE specifications, we do not reject that $\alpha_1 = 0$, which confirms that there is no evidence of publication bias in the empirical literature estimating the spillover effect, as suggested by the visual inspection of the funnel plot. In addition, the averages of the spillover are 0.852 (FAT/PET) and 0.804 (PEESE), meaning that overall primary studies indicate, on average, a high but less-than-one standing-on-shoulders effect. As a consequence for the theory, this would validate the semi-endogenous theory. As a consequence for policy recommendations, this may indicate that subsidies to R&D are probably

Table 3
Estimation of Eq. (4): dependent variable: *t*.

Coefficients for:	FAT/PET	PEESE
Precision	0.852***	0.804***
	(0.096)	(0.096)
constant	−0.918	–
	(1.010)	
SE	–	5.248
		(7.612)
RE variances		
Var(*Precision*)	0.097	0.111
	[0.038; 0.250]	[0.045; 0.274]
Var(*residuals*)	52.52	52.08
	[41.97; 65.73]	[41.64; 65.15]
N. obs. (N. Studies)	170 (15)	170 (15)
Log likelihood	−601.66	−601.82
Wald Test	78.05***	75.98***
LR test (random α_0 and α_1 vs. random α_0)	0.000	0.000
LR test (random α_0 and α_1 vs. random α_1)	33.29***	30.06***
LR test (HM vs. OLS)	53.71***	68.57***

Notes: Estimation by maximum likelihood. Standard errors for coefficient estimators are in parentheses (). 95% confidence intervals for random effects variances are in brackets []. Level of significance: *** for *p*-value < 0.01; **for *p*-value < 0.05;* for *p*-value < 0.01. N. Obs is Number of Observations; N. Studies is Number of Studies. RE variances mean Random Effects variances.

justified and may have welfare effects.

The middle part of the table presents the estimates of the variances of the random slopes associated with *precision*, α_0, and of the residuals, as well as the respective confidence intervals at 95%. In both specifications the confidence interval for the variance of the slope associated with *precision* suggests that it is significant, which further confirms the adequacy of the random slope model adopted and the existence of heterogeneity in the reported effect-sizes.[11]

The lower part of the table shows the results of a battery of tests that lend support to our estimation choices. The likelihood ratio (LR) test presented in the last line clearly shows that the hierarchical models are preferred to a simple OLS model. The two other LR tests reported in the table provide evidence that favors the random slope model over other hierarchical specifications. This is an expected result, because, since the coefficients are reversed in Eqs. (4) and (5), a model with a random slope associated with *precision* applied to (4) and (5) allows for random variation between studies in the average spillover effect, α_0. This is the essence of the heterogeneity detected in Section 3.

Table A.7, in the Appendix, presents the same analysis applied to the larger sample, which includes articles that do not estimate the duplication effect in the analysis. Despite that, results are remarkably stable: the average effect-size is between 0.7 and 0.8 and highly significant and there is no evidence of publication bias.

5. Multivariate meta-regression analysis

In this section we estimate a multivariate meta-regression in order to examine if and how differences in the methodological characteristics of the primary studies explain the variation in the reported spillover ϕ estimates. The methodological characteristics are mostly captured through dummy variables and are classified as analytical or empirical dimensions of the research field.

The moderating variables linked with the analytical dimension of the research field are all related to the specification of the knowledge production function (Eq. (2)) used in the primary studies. They include: (1) the value of the estimate of the *duplication* effect, λ,[12] reported in the primary studies; (2) a set of dummies that identify the variable used to measure the domestic knowledge pool, *A* (dummies *Patent*, *GDP,* and *Population* take the value 1 if the primary study uses, respectively, the stock of patents, the GDP/GDP *per capita*/Value Added, or the population as proxies for the knowledge pool), as discussed in Section 3; (3) a dummy for the inclusion in primary regressions of alternative measures of the pool of knowledge (i.e. interactions with the baseline pool variable or other different variable for the pool); dummies for the inclusion of (4) foreign knowlegde, (5) imports, and (6) the distance to frontier as explanatory variables in the estimation of the k.p.f., capturing foreign influence in the production of knowledge – dummies *Foreign knowledge*, *Imports*, and *Distance* take the value 1 if the primary study includes, respectively, the foreign knowledge (usually measured by the foreign stock of patents) imports[13] and the distance to frontier as explanatory variables in Eq. (2). Following our discussion in Section 3 on the use of weighted and unweighted variables to measure the stock of knowledge, we also include in alternative specifications dummies for: (i) *unweighted* and *weighted patents* as proxies of the domestic knowledge pool (weights may be citations or technological distance between firms); (ii) *unweighted* and *weighted foreign influence* (foreign influence is weighted when some variable linked with the openness of the economy is weighted by other, typically foreign knowledge weighted by trade or foreign direct investment). In these two alternative specifications, we replace dummies *Patent*, *Foreign knowledge*, *Imports,* and *Distance* by the respective *unweighted* and *weighted* dummies.

The moderating variables linked with the empirical dimension of the research field are dummies for: (1) the inclusion of *time effects*[14] in the estimation of the k.p.f. by the primary studies; (2) the sample being composed of only *rich countries*; (3) the estimation of the k.p.f. employing instrumental variables *(IV) methods*; (4) the sample using *industrial data*; (5) the sample using *regional* data; (6) the *publication* type being a published article. Finally, the *number of observations* and the *number of countries* included in each regression are also considered as moderating variables.[15]

For the estimation of the multivariate meta-regression we use the random slope version of the hierarchical model, based on LR tests.[16] In Appendix A.3 we present the regressions that include all the covariates detailed above (Tables A.4–Table A.6). However, in order to reduce multicollinearity between covariates, we follow a strategy similar to that in Ugur et al. (2016) for depurating the models presented in the main text.[17] In particular, in each regression we eliminate one by one the covariates that have higher variance inflation factor (VIFs).

Table 4 shows the estimation results of the specific model with the PET/FAT specification (the estimation results of the corresponding general model are reported in Table A.4). Column (1) presents the baseline estimation, obtained by maximum-likelihood. In column (2) the estimation is performed by restricted maximum-likelihood. This approach tends to reduce the bias of the maximum-likelihood, especially for small samples. In column (3) the estimation is performed as in

[11] We do not report the variance of α_1 since we are estimating a model in which only the slope associated with *precision*, α_0, is assumed to be random. However, in both PET/FAT and PEESE specifications, the estimation of a model that allows both α_0 and α_1 to be random reveals that the variance of α_1 is practically zero, which confirms that there is no random variation in the intercept of Eq. (4) and in the coefficient associated with *SE* in Eq. (5).

[12] If λ < 1, there is some degree of duplication in the production of ideas in that some of the knowledge that is created may not be entirely new. This variable will be replaced by a dummy that takes the value 1 if the primary observation contains an estimation for the duplication effect in an alternative analysis, the results of which are presented in the Appendix.

[13] Or, in a more general view, openness to international trade or external financial dependence.

[14] Time dummies, time-trend variables, or year-fixed effects

[15] More details on the covariates of the meta-regression, including their description and summary statistics, are provided in Table A.3 in Appendix A.

[16] LR tests were performed on individual covariates in order to decide which ones should enter with random slopes. The tests suggest that the specification in which covariates *GDP* as proxy for the knowledge pool, *IV method,* and *duplication* enter with random slopes is the most appropriate. Results are available upon request.

[17] We thank an anonymous referee for this suggestion.

Table 4
Estimation of the multivariate meta-regression (FAT/PET). Dependent variable: t_i.

Coefficients for:	(1)	(2)	(3)	(4)	(5)
Precision	0.999*** (0.005)	0.999*** (0.005)	1.092*** (0.024)	0.999*** (0.005)	0.992*** (0.005)
Duplication	−0.459** (0.138)	−0.451*** (0.158)	−0.405* (0.175)	−0.460*** (0.138)	−0.469*** (0.138)
Patent	–	–	–	–	–
Unweighted Patent	–	–	–	–	–
Weighted Patent	–	–	–	0.020* (0.011)	–
GDP	−0.080 (0.406)	−0.070 (0.501)	−0.024 (0.443)	–	−0.082 (0.410)
Population	–	–	−0.659* (0.357)	−0.645** (0.285)	–
Add. variable for pool	−0.425** (0.195)	−0.422 ** (0.209)	−0.376** (0.187)	−0.425** (0.195)	−0.422** (0.191)
Foreign know.	–	–	0.013 (0.032)	–	–
Unweighted foreign Inf.	–	–	–	–	0.031*** (0.004)
Weighted foreign Inf.	–	–	–	–	0.021*** (0.005)
Imports	0.021*** (0.003)	0.022*** (0.004)	0.036 (0.033)	0.021*** (0.003)	–
Distance	0.000 (0.003)	−0.000 (0.003)	−0.025 (0.016)	0.000 (0.003)	–
Time effects	–	–	–	–	–
Rich countries	−0.021** (0.010)	−0.021* (0.011)	−0.045*** (0.017)	−0.020** (0.010)	−0.021** (0.010)
IV methods	−0.267* (0.158)	−0.270 (0.175)	−0.271* (0.162)	−0.263* (0.158)	−0.281* (0.158)
Panel	–	–	–	–	–
Observations	−0.000 (0.000)	−0.000 (0.000)	−0.000*** (0.000)	−0.000 (0.000)	−0.000 (0.000)
Regional data	−0.647** (0.284)	−0.656** (0.327)	–	–	−0.642** (0.286)
Industrial data	0.020* (0.011)	0.020* (0.011)	−0.018 (0.019)	–	0.027** (0.011)
Publication	–	–	–	–	–
Constant	2.793*** (0.857)	2.805*** (0.885)	1.776* (0.956)	2.774*** (0.851)	2.896*** (0.821)
Var(duplication)	0.122	0.176	0.247	0.122	0.127
	[0.035; 0.423]	[0.049; 0.630]	[0.086; 0.712]	[0.035; 0.424]	[0.038; 0.420]
Var(IV methods)	0.113	0.147	0.132	0.114	0.115
	[0.027; 0.481]	[0.033; 0.658]	[0.035; 0.495]	[0.027; 0.485]	[0.028; 0.480]
Var(GDP)	0.388	0.639	0.507	0.398	0.405
	[0.052; 2.927]	[0.065; 6.330]	[0.081; 3.190]	[0.054; 2.298]	[0.056; 2.920]
Var(residuals)	34.408	36.051	23.724	34.398	31.882
	[27.36; 43.27]	[28.53; 45.55]	[18.41; 30.56]	[27.35; 43.26]	[25.36; 40.08]
Log likelihood	−561.06	−597.37	−457.51	−561.11	−555.44
VIF	3.64	3.64	3.20	3.88	3.77

Notes: Moderator variables are divided by the standard errors reported in the primary studies. Estimation by maximum likelihood in columns (1), (3), (4), and (5), restricted maximum likelihood in column (2) Standard errors for coefficient estimators are in parentheses (). 95% confidence intervals for random effects variances are in brackets []. Level of significance: *** for p-value < 0.01; **for p-value < 0.05;* for p-value < 0.01. Wald Test for global significance always rejects with high significance. LR Test is HM vs. OLS and always rejects with high significance. Var() means Random Effects variances. Number of observations is 170 for 15 primary studies except in column (3), where the number of observations is 144.

(1), but excluding outliers in the dependent variable.[18] With this we wish to confirm that the effects of moderating variables are not due to the presence of outliers. In order to check if using weighted or unweighted patents and foreign knowledge is relevant for explaining the heterogeneity in the spillover estimates, we run two alternative regressions in columns (4) and (5). In column (4) we replace the dummy patents by unweighted and weighted patents, and in column (5) we replace variables linked with the foreign influence by unweighted and weighted foreign knowledge.

Results in Table 4 indicate that studies that report larger duplication effects (i.e. larger coefficients on the duplication measure) tend to report smaller spillover effects. This is an expected result, as, for a given evolution of the knowledge dynamics and for given inputs, the greater the duplication effect (stepping-on-toes), the less should be the spillover effect (standing-on-the-shoulders). It is remarkable that this effect is robust to different estimation methods and accounts for cross-study heterogeneity. As seen in Table 4, a one-unit increase in the duplication effect reduces the spillover effect by around 0.45 units.

Moreover, accounting for imports in the estimation of domestic knowledge production increases the estimation of the standing-on-shoulders effect. This significant effect highlights the importance of considering linkages between countries in estimating the knowledge production function. This is also confirmed by the results reported in column (5), in which both unweighted and weighted foreign influence are very significant and present a positive coefficient estimate. In particular, studies that use unweighted foreign knowledge tend to report higher estimates than studies that use weighted foreign knowledge. This reinforces our result according to which the consideration of international linkages in the k.p.f. plays an important role in explaining the variability in spillovers estimates.

As mentioned before, the knowledge pool can be proxied by measures of technological sophistication other than patents, such as population, GDP, GDP *per capita*, or value added. These alternative measures tend to have a negative effect in the estimation of the spillover, especially population, which turns out to be statistically significant. This suggests that the use of patents as a proxy for the pool of knowledge tends to increase the spillovers. However, when a second variable that proxies the pool of knowledge is considered in the regression, the spillover estimate is naturally reduced.

Concerning the sample features in the primary studies, we find that the spillover effect tends to be lower when only rich countries are included and regional data are used and higher when industrial data are used. In our dataset, primary studies that do not include only rich countries in the sample (and thus are classified as 0 in the dummy *rich countries*) consider emerging countries, such as Latin American or South Asian ones. Our result means that R&D in those emerging countries benefits more from their own past knowledge than R&D in the group of rich countries. In addition, the consideration of instrumental variables in the estimations of the primary studies tends to decrease the reported effect sizes. This means that endogeneity tends to upwardly bias the coefficient of the spillover effect.

In order to account for possible nonlinearities in the relationship between the spillover estimates and the respective standard errors, we also present the PEESE specification of the specific model in Table 5. As in Table 4, we show a baseline specification in column (1), a restricted

[18] Weak outliers are usually defined as observations for which the value of the variable is below $Q_1 - 1.5(Q_3 - Q_1)$ or higher than $Q_3 + 1.5(Q_3 - Q_1)$.

Table 5
Estimation of the multivariate meta-regression (PEESE). Dependent variable: t_i.

Coefficients for:	(1)	(2)	(3)	(4)	(5)
Precision	1.003*** (0.005)	1.003*** (0.005)	1.111*** (0.022)	1.003*** (0.005)	0.995*** (0.005)
Duplication	−0.346** (0.137)	−0.330** (0.161)	−0.340* (0.180)	−0.347** (0.137)	−0.349** (0.140)
Patent	–	–	–	–	–
Unweighted Patent	–	–	–	–	–
Weighted Patent	–	–	–	0.011 (0.011)	–
GDP	−0.013 (0.377)	0.000 (0.466)	0.019 (0.430)	–	−0.008 (0.381)
Population	–	—	–	−0.592** (0.294)	–
Add. variable for pool	−0.392** (0.195)	−0.387* (0.211)	−0.353* (0.187)	−0.392** (0.195)	−387** (0.192)
Foreign know.	–	–	0.015 (0.032)	–	–
Unweigheted Foreign Inf.	–	–	–	–	0.030*** (0.004)
Weighted Foreign Inf.	–	–	–	–	0.019*** (0.005)
Imports	0.021*** (0.004)	0.021*** (0.004)	0.036 (0.034)	0.021*** (0.04)	–
Distance	−0.001 (0.003)	−0.001 (0.004)	−0.025 (0.016)	−0.001 (0.003)	–
Time effects	–	–	–	–	–
Rich countries	−0.012 (0.010)	−0.012 (0.011)	−0.046*** (0.017)	−0.012 (0.010)	−0.012 (0.010)
IV methods	−0.213 (0.145)	−0.217 (0.162)	−0.243 (0.154)	−0.211 (0.146)	−0.224 (0.144)
Panel	–	–	–	–	–
Observations	−0.000 (0.000)	−0.000 (0.000)	−0.000*** (0.000)	−0.000 (0.000)	−0.000 (0.000)
Countries	–	–	–	–	–
Regional data	−0.592** (0.294)	−0.603* (0.343)	−0.624* (0.373)	–	−0.584** (0.298)
Industrial data	0.012 (0.011)	0.011 (0.011)	−0.016 (0.020)	–	0.019* (0.011)
Publication	–	–	—	–	–
Standard-error	9.916 (6.691)	9.478 (6.879)	5.941 (5.552)	9.887 (6.612)	9.745 (6.483)
Var(duplication)	0.132	0.196	0.280	0.132	0.140
	[0.034; 0.504]	[0.051; 0.754]	[0.099; 0.795]	[0.034; 0.505]	[0.039; 0.510]
Var(IV methods)	0.089	0.118	0.117	0.090	0.089
	[0.019; 0.414]	[0.024; 0.569]	[0.031; 0.447]	[0.019; 0.417]	[0.019; 0.408]
Var(GDP)	0.314	0.529	0.472	0.315	0.327
	[0.037; 2.687]	[0.049; 5.730]	[0.073; 3.038]	[0.037; 2.669]	[0.040; 2.656]
Var(residuals)	36.437	38.095	24.036	36.433	34.088
	[28.93; 45.89]	[30.12; 48.19]	[18.65; 30.98]	[28.93; 45.89]	[27.07; 42.92]
Log likelihood	−564.99	−599.15	−458.56	−565.01	−560.16
VIF	3.82	3.82	3.72	4.04	3.96

Notes: Moderator variables are divided by the standard errors reported in the primary studies. Estimation by maximum likelihood in columns (1), (3), (4), and (5), restricted maximum likelihood in column (2) Standard errors for coefficient estimators are in parentheses (). 95% confidence intervals for random effects variances are in brackets []. Level of significance: *** for p-value < 0.01; **for p-value < 0.05;* for p-value < 0.01. Wald Test is for global significance and always rejects with high significance. LR Test is HM vs. OLS and always rejects with high significance. Var() means Random Effects variances. Number of observations is 170 for 15 primary studies except in column (3) where the number of observations is 144.

maximum likelihood estimation in column (2), an estimation excluding outliers in column (3), a specification including unweighted and weighted patents as proxies of the knowledge pool in column (4), and finally in column (5) a specification including unweighted and weighted foreign influences. The complete model estimation is presented in Table A.5. The main conclusions from the analysis of the FAT/PET model are maintained, which shows the robustness of our results. The only two (minor) differences are that the precision effect is now greater than one (1) even when outliers are excluded, and variable *IV methods* is not significant. All the other results of Table 5 are in line with those of Table 4.

In sum, given the results presented in Tables 4 and Table 5, we can see that the most significant (i.e statistically significant in at least four out of five columns) sources of spillover variations are the *duplication* effect, the consideration of *imports* (or *foreign influence* in columns (5)) in the k.p.f., the use of *rich countries*, *regional data* and *industrial data* in the sample, the use of *population* to measure the knowledge stock, or the consideration of an *additional variable for pool*. Significant effects should have implications for future research on the knowledge production function, as the presence of these moderating factors is now known to have influence on the estimation of the spillover coefficient. Except for *imports* (or *foreign influence*), and *industrial data*, which have a positive and significant sign, all the other significant moderating factors tend to reduce the spillover effect. Finally, neither the use of *GDP*" as the knowledge pool, nor the number of *observations* are relevant in explaining the variation of the spillover effect, as the respective moderating variables are either nonsignificant in all regressions or are significant in just one regression.

In an alternative approach, we consider the estimation of the meta-regression replacing the value of the duplication effect by a dummy that takes the value 1 when the primary study estimates a duplication effect and zero when the primary study does not estimate a duplication effect. In this alternative analysis, further primary studies (those that do not estimate duplication effects) can be included, allowing us to consider a larger sample. Furthermore, if we consider that the *best practice* is to estimate the knowledge production function with both spillovers and duplication effect, the sum of the precision effect and the duplication dummy coefficients will give us the true effect-size of the literature best practice. The results of this analysis (which are presented in the Appendix in Tables A.8 and Table A.9 for FAT/PET and PEESE models respectively) confirm that the effect-size from the literature *best practice* of considering the estimation of the duplication effect is slightly above one (1). This also means that the primary studies estimating the duplication effect tend to report higher values for the spillover. Furthermore, the analysis also consistently confirms that the spillover tends to be higher with the consideration of *foreign knowledge* and *foreign influence* dummies in primary studies' estimations while it tends to be lower when *distance to frontier* is included in those estimations. These estimations also highlight negative effects of the *patents*, *GDP*, *population* and *IV methods* dummies.

5.1. Robustness

In order to further establish the robustness of our results, we present two additional specifications following again the PET/FAT and PEESE models. First, the Luintel and Khan (2009) article uses a GMM panel

Table 6
Robustness analysis (FAT/PET; PEESE). Dependent variable: t_i.

Coefficients for:	FAT/PET (1)	FAT/PET (2)	PEESE (3)	PEESE (4)
Precision	0.999*** (0.004)	0.999*** (0.396)	1.003*** (0.004)	1.003*** (0.005)
Duplication	−0.392*** (0.138)	−0.459*** (0.138)	−0.280** (0.140)	−0.346** (0.137)
Patent	–	–	–	–
GDP	−0.071 (0.409)	−0.080 (0.406)	−0.012 (0.378)	−0.013 (0.377)
Population	−0.702* (0.380)	−0.647** (0.284)	−0.698** (0.336)	-
Add. Variable for pool	−0.399** (0.194)	−0.425** (0.195)	−0.344* (0.200)	−0.392** (0.195)
Foreign know.	–	–	–	–
Imports	0.022*** (0.003)	0.021*** (0.003)	0.021*** (0.003)	0.021*** (0.004)
Distance	0.000 (0.003)	0.000 (0.003)	−0.001 (0.003)	−0.001 (0.003)
Time effects	–	–	–	–
Rich countries	−0.021** (0.009)	−0.021** (0.010)	−0.012 (0.009)	−0.012 (0.010)
IV methods	−0.251 (0.164)	−0.267* (0.158)	−0.192 (0.148)	−0.213 (0.145)
Panel	–	–	–	–
Observations	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
Countries	–	–	–	–
Industrial data	0.196** (0.009)	0.020* (0.011)	0.011 (0.009)	0.012 (0.011)
Regional data	0.010 (0.492)	–	0.061 (0.465)	−0.592** (0.294)-
Publication	–	–	–	–
Schumpeterian Dummy	–	–	–	–
Constant/standard-error	2.808*** (0.667)	2.793 (0.857)***	10.636** (5.428)	9.916 (6.691)
Var(duplication)	0.165 [0.059; 0.466]	0.122 [0.035; 0.423]	0.178 [0.060; 0.530]	0.132 [0.034; 0.504]
Var(IV methods)	0.116 [0.066; 2.761]	0.113 [0.027; 0.481]	0.089 [0.022; 0.367]	0.089 [0.019; 0.414]
Var(GDP)	0.427 [0.066; 2.761]	0.388 [0.052; 2.927]	0.347 [0.049; 2.434]	0.314 [0.037; 2.687]
Var(residuals)	23.25 [19.26; 28.07]	34.408 [27.36; 43.27]	24.758 [20.50; 29.91]	36.437 [28.93; 45.89]
Log likelihood	−750.50	−561.06	−756.95	−564.99
VIF	3.78	3.64	4.07	3.82

Moderator variables are divided by the standard errors reported in the primary studies. Estimation by maximum likelihood. Standard errors for coefficient estimators are in parentheses (). 95% confidence intervals for random effects variances are in brackets []. Level of significance: *** for p-value < 0.01; **for p-value < 0.05;* for p-value < 0.01. Wald Test is for global significance and always rejects with high significance. LR Test is HM vs. OLS and always rejects with high significance. Var() means Random Effects variances. Number of observations is 242 in columns (1) and (3) and 170 in columns (2) and (4), for 15 primary studies.

data estimator with several within-country averages that allow the authors to compute individual spillovers for 19 different countries. In the baseline database described until now, and following the literature on heterogeneous panel data econometrics, we picked the averaged coefficients for all the countries. In this literature, the individual coefficients are usually neglected due to small sample bias. However, alternatively and with the necessary adaptations, we can also consider each and every country's coefficient.[19] This has the advantage of substantially increasing our sample of spillover coefficients (from 170 to 242 observations), albeit at the expense of potential bias affecting the primary study estimates.

Second, we wish to address a possible selection bias. This can arise from the fact that most recent literature argues in favor of the Schumpeterian theory, although the spillover estimates in that literature tend to be less than one (1).[20] The questions we wish to answer are whether or not papers that explicitly argue in favor of the Schumpeterian theory explain the heterogeneity of the spillover, or contribute to increasing it, displacing the significance of the other moderating factors. To this end we include a dummy that assumes the value 1 for articles that explicitly took the stance of the Schumpeterian theory (Ang and Madsen, 2015; Madsen, 2016; Ulku, 2007a,b; Venturini, 2012b). The results of these robustness tests are presented in Table 6 for the specific model and in Table A.6 for the complete model. Table A.10 has the counterpart results in which a duplication dummy is considered instead of the duplication value.

Columns (1) and (3) show the results of the meta-regression estimation (using the PET/FAT and the PESSE specifications, respectively), with the additional observations from Luintel and Khan (2009). The results are basically the same as those presented in Tables 4 and Table 5. There is only one difference worth noting: both the constant (in the PET/FAT specification) and the coefficient associated with the standard error (in the PEESE specification) are statistically different from zero, which suggests the presence of some degree of publication bias in both specifications. This occurs because most of the additional country-specific estimations from Luintel and Khan (2009) are considerably lower than the estimates collected from the other primary studies, which tends to generate some bias in the sample of spillover coefficients. Nevertheless, once accounting for the presence of publication bias, most moderator variables keep their statistical significance and coefficient signs from the baseline estimations.

Columns (2) and (4) show the results of the meta-regression estimation which in the complete model includes the "Schumpeterian dummy" (see Table A.6). In the results of the complete model, this dummy is significant at 1% and its coefficient is negative, meaning that studies that argue in favor of the Schumpeterian theory tend to present lower estimates of the spillover, for the same values of the other covariates. This may suggest that those studies that stand explicitly for the Schumpeterian theory may also include some elements of the semi-endogenous theory. It also rules out a potential upward bias in our estimates of the spillover that could possibly arise due to the presence of such studies in the meta-analysis. However, our specific model eliminates the "Schumpeterian dummy" as it is highly correlated with the precision effect. Note that in Table 6 (columns 2 and 4) we confirm the results obtained before (cf Tables 4 and Table 5), namely the positive significant sign for *imports* and for *industrial data* (only in column (2)), and the negative significant signs for *population*, *additional variable*

[19] We thank an anonymous referee for this suggestion.

[20] We also thank an anonymous referee for this suggestion.

for pool, *rich countries* and *IV methods* (in this case only in column (2)).

The robustness analysis presented in this section was also implemented for the case in which we replace the value of the duplication effect by a dummy that takes the value 1 when the primary study estimates a duplication effect and zero when the primary study does not estimate a duplication effect. The results, reported in Table A.10 are consistent with those in Tables A.8 and Table A.9 with two minor differences: the "Schumpeterian dummy" is no longer statistically significant and there is no evidence of publication bias (as the constant and the coefficient for the standard error are no longer significant). The nonsignificance of the "Schumpeterian dummy" means that the fact that some primary studies take the stance for the Schumpeterian theory is not affecting the average value of the spillover effect.

From the robustness analysis we conclude that the results from Tables 4 and Table 5 are in general robust to the introduction of Luintel and Khan's (2009) country-specific spillover estimations and to the inclusion of the "Schumpeterian dummy". We emphasize a relatively high average effect for the spillover and again with high statistical significance.

6. Conclusions

The metaphor *standing on the shoulders of giants* means discovering new ideas by building on previous discoveries and goes back to the middle ages, being immortalized by Isaac Newton in a letter (Keith et al., 2016). In economics of innovation, Caballero and Jaffe (1993) used it as the title of a well-known paper about the spillovers in the R&D activity. Since the contributions of Jaffe (1986) many others have quantified the level of spillovers using different samples of data, countries, econometric methods, and so on. The influence of spillovers of the current stock (or pool) of knowledge on the progress of ideas has been noted in both theory and policy. All endogenous growth theories since Romer (1990) have attributed a central role to spillovers. As a positive externality, the presence of spillovers has implied that welfare levels provided by the market tend to be below the efficiency level. This has an influence on the recommended policies: R&D should be subsidized. This policy recommendation has been taken so seriously by policy makers that almost every country subsidizes R&D activities.

In this paper we review the literature on the spillover effect in a knowledge production function, using meta-regression analysis through hierarchical estimation methods. The analysis of our baseline sample of spillover estimates reveals that on average the spillover effect is high and statistically significant, but less than one (1), and that there is no publication bias. Moreover, we obtain several important sources of spillover variations: the *duplication* effect, the consideration of *imports and foreign influence* in the estimated knowledge production function, the inclusion of alternative measures of the pool of knowledge (e.g. *population*) in the knowledge production function, the inclusion of only *Rich Countries* in the sample and the use of *Regional Data*. Most results are very robust to different specifications of the meta-regression, changes in the set of the moderating factors, and different estimation methods.

These results have implications for policy, theory and the empirics of the knowledge production function. As the average effect is relatively high (and highly statistically significant), subsidies to R&D may be justified and have positive transitional effects in both growth rates and allocations. However in the long run subsidies to R&D may be neutral in growth rates. All in all, positive effects in welfare are expected. A caveat must be noted. Since this study, like most existing evidence, is based on patented new knowledge, that conclusion may be overturned if a great proportion of new knowledge is not patented. Furthermore, the heterogeneity found in estimates suggests that precise policy implications may be obtained from industry specific studies. This would reduce uncertainty about the policy prediction that would otherwise affect studies analyzing more heterogeneous data (such as different industries or countries). For theory, the average values obtained in this paper may be used as a source for calibration exercises of endogenous growth models. Additionally, a value less than 1 may support semi-endogenous growth models. For the empirics of the knowledge production function, new research may take into account the significant moderating factors we highlight, both those linked with theory (e.g. the duplication effect and international linkages) and those linked with estimation and specification (e.g. time effects).

This work also opens new avenues of research in both meta-analysis and endogenous growth models. First, other aspects of the knowledge production function (namely the *stepping-on-toes effect*) may be investigated. Furthermore, as some of the recent evidence using long historical series (namely those in Madsen, 2008) supports fully endogenous theory, it may be worth combining semi-endogenous and Schumpeterian elements in new growth theories and take the models to data for validation.

Appendix A. Additional features of the primary sources

A.1 Additional features of the primary sources

Table A.1
Summary of studies' main characteristics: studies with no duplication effect.

Study	Code	Nr. of estimates	Mean of coefficients' estimates	Mean of *SE* of estimates	Sample of countries	Data level	Data structure	Publication
Peri (2003)	13	12	0.456	0.098	Rich	Regional	Panel	Working-Paper
Mancusi (2008)	20	5	0.778	0.109	Rich	Industry	Panel	Article
Montobbio and Sterzi (2011)	19	26	0.875	0.056	Latin American	Country	Panel	Article
Bloom et al. (2013)	15	8	0.201	0.009	Rich	Industry	Panel	Article

Note: Code is the identifier in the database.

A.2 Moderating variables – description

Table A.2
Other characteristics of the primary studies.

Study	Knowledge pool (or stock)	Estimation methods	Foreign knowlegde	Open economies variables
Jaffe (1986)	Weighted patent stock	OLS, 3SLS	No	No
Jaffe (1989)	Population	OLS, 3SLS	No	No
Porter and Stern (2000)	Patent stock	OLS, FE	Yes	No
Furman et al. (2002)	Patent stock, GDP	OLS, FE	No	Yes
Furman and Hayes (2004)	Patent stock, GDP	OLS, FE	No	Yes
Hu and Mathews (2005)	Patent stock, GDP	OLS, FE	No	Yes
Pessoa (2005)	Patent stock	OLS, GLS, SUR	No	No
Ulku (2007a)	Patent stock	GMM	No	Yes
Ulku (2007b)	Patent stock	FE, GMM	No	Yes
Mancusi (2008)	Weighted patent stock	Neg. Binomial	Yes	No
Luintel and Khan (2009)	Patent stock	GMM	Yes	No
Luintel and Khan (2012)	Patent stock	FMOLS	Yes	Yes
Venturini (2012a)	Weighted patent stock	Panel Cointegration	No	Yes
Ang and Madsen (2015)	Patent stock	FGLS	Yes	Yes
Madsen (2016)	Patent stock	FGLS	Yes	Yes
Abdih and Joutz (2005)	Patent stock	Cointegration	No	No
Peri (2003)	Weighted and unweighted patent stock	OLS, FE, Binomial	Yes	No
Bloom et al. (2013)	Weighted patent stock	OLS, IV, Binomial	No	No
Montobbio and Sterzi (2011)	GDP	FE, GMM, Binomial	Yes	No

Notes: GDP aggregates GDP, GDP *per capita* and value added. Estimation methods are aggregated into IV methods and Panel in the database and a single estimation may be both an IV method (IV, 2SLS, GMM) and classified as panel. Weighted patent stocks include weights being citations and technological distances.

A.3 Multivariate meta-regression analysis: general models

Table A.3
Moderating variables.

Variable	Type	Measure	Mean	Standard deviation	Observations
Variables linked with the production of knowledge equation					
Duplication	Estimate value	Value of the coefficient of DRS in physical factors in the k.p.f in the primary study	0.32	0.36	170
Patents	Dummy	1 if *A* is measured with patent data; 0 otherwise	0.75	0.43	170
GDP	Dummy	1 if *A* is measured with GDP or GDP per capita data; 0 otherwise	0.10	0.30	170
Population	Dummy	1 if *A* is measured with population data; 0 otherwise	0.12	0.32	170
Add. variable for pool	Dummy	1 if *A* has more than one proxy in the regression; 0 otherwise	0.08	0.27	170
Foreign Know.	Dummy	1 if econometric specification of k.p.f. includes foreign knowledge; 0 otherwise	0.35	0.48	170
Imports	Dummy	1 if econometric specification of k.p.f. includes imports; 0 otherwise	0.36	0.48	170
Distance	Dummy	1 if econometric specification of k.p.f. includes distance to the frontier; 0 otherwise	0.14	0.35	170
Time effects	Dummy	1 if econometric specification of k.p.f. includes time effects; 0 otherwise	0.80	0.40	170
Variables linked with the sample					
Rich Countries	Dummy	1 if sample includes only Rich Countries; 0 otherwise	0.65	0.48	170
IV methods	Dummy	1 if estimation is with IV methods; 0 otherwise	0.15	0.36	170
Panel	Dummy	1 if sample is a panel database; 0 otherwise	0.94	0.25	170
Industrial data	Dummy	1 if sample is for industrial or firm data; 0 otherwise (country or regional data)	0.15	0.36	170
Regional data	Dummy	1 if sample is for regional data; 0 otherwise (country or industrial/firm data)	0.12	0.32	170
Observations	Count	Number of observations in each estimation	396	329	170
Countries	Count	Number of countries in each estimation	14.58	9.51	170
Variable linked with the primary source					
Publication	Dummy	1 if primary source is a published article; 0 otherwise	0.86	0.34	170

Notes: Descriptive statistics are for the baseline sample and values are before division by the *SE* of the spillover estimate. In some additional specifications, weighted patents, unweighted patents, unweighted foreign influence, and weighted foreign influence are included. Weighted patents is 1 in every case in which patents figures are weighted by citations or technological distance. Weighted foreign influence is 1 in every case in which some foreign variable is weighted by another variable (e.g. foreign knowledge measured by foreign patents weighted by trade flows).

A.4 Results of the meta-analysis of the alternative sample: including primary sources with no duplication effect

Table A.4
Estimation of the multivariate meta-regression (FAT/PET). Dependent variable: t_i.

Coefficients for:	(1)	(2)	(3)	(4)	(5)
Precision	1.046*** (0.408)	1.014** (0.444)	0.910** (0.400)	0.628* (0.376)	1.043*** (0.407)
Duplication	−0.367** (0.162)	−0.361** 0.183)	−0.401** (0.182)	−0.378** (0.160)	−0.374** (0.159)
Patent	0.266 (0.376)	0.299 (0.410)	0.381 (0.369)	–	0.257 (0.374)
Unweighted Patent	–	–	–	0.689** (0.326)	–
Weighted Patent	–	–	–	0.299 (0.509)	–
GDP	0.248 (0.569)	0.289 (0.665)	0.321 (0.591)	0.675 (0.528)	0.234 (0.573)
Population	−0.422 (0.490)	−0.388 (0.542)	−0.291 (0.506)	–	−0.424 (0.485)
Add. variable for pool	−0.283 (0.209)	−0.275 (0.222)	−0.264 (0.189)	−0.351** (0.176)	−0.282 (0.209)
Foreign know.	0.023*** (0.005)	0.023*** (0.005)	−0.021 (0.031)	0.023*** (0.005)	–
Unweighted foreign Inf.	–	–	–	–	0.032*** (0.004)
Weighted foreign Inf.	–	–	–	–	0.023*** (0.004)
Imports	0.012*** (0.003)	0.012*** (0.004)	0.080** (0.031)	0.012*** (0.004)	–
Distance	−0.006** (0.003)	−0.006* (0.003)	−0.029** (0.013)	−0.006** (0.003)	–
Time effects	0.084** (0.035)	0.084** (0.036)	0.101** (0.033)	0.085** (0.034)	0.084** (0.035)
Rich countries	−0.052*** (0.009)	−0.052*** (0.010)	−0.063** (0.014)	−0.052*** (0.009)	−0.051*** (0.009)
IV methods	−0.243 (0.168)	−0.245 (0.186)	−0.252 (0.170)	−0.297* (0.169)	−0.249 (0.165)
Panel	−0.024 (0.135)	−0.023 (0.142)	−0.034 (0.122)	−0.027 (0.135)	−0.026 (0.137)
Observations	−0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
Countries	−0.006*** (0.001)	−0.006*** (0.001)	−0.006*** (0.001)	−0.006*** (0.001)	−0.006*** (0.001)
Industrial data	−0.097*** (0.019)	−0.097*** (0.020)	−0.095*** (0.026)	0.292 (0.396)	−0.090*** (0.020)
Publication	−0.217*** (0.070)	−0.219** (0.074)	−0.258*** (0.072)	−0.218*** (0.070)	−0.211*** (0.071)
Constant	0.810 (0.813)	0.798 (0.856)	1.505* (0.902)	0.729 (0.815)	0.853 (0.818)
Var(duplication)	0.207	0.276	0.295	0.201	0.195
	[0.081; 0.531]	[0.100; 0.762]	[0.120; 0.728]	[0.080; 0.505]	[0.075; 0.507]
Var(IV methods)	0.146	0.183	0.159	0.118	0.139
	[0.041; 0.521]	[0.047; 0.709]	[0.047; 0.535]	[0.032; 0.435]	[0.038; 0.506]
Var(GDP)	0.471	0.735	0.574	0.468	0.488
	[0.076; 2.911]	[0.085; 6.327]	[0.101; 3.277]	[0.075; 2.901]	[0.079; 3.011]
Var(residuals)	20.653	22.637	15.056	20.802	21.241
	[16.45; 25.92]	[17.85; 28.70]	[11.71; 19.36]	[16.58; 26.10]	[16.92; 26.66]
Log likelihood	−525.43	−578.81	−430.71	−525.23	−527.17

Notes: Moderator variables are divided by the standard errors reported in the primary studies. Estimation by maximum likelihood in columns (1), (3), (4), and (5), restricted maximum likelihood in column (2) Standard errors for coefficient estimators are in parentheses (). 95% confidence intervals for random effects variances are in brackets []. Level of significance: *** for p-value < 0.01; **for p-value < 0.05;* for p-value < 0.01. Wald Test for global significance always rejects with high significance. LR Test is HM vs. OLS and always rejects with high significance. Var() means Random Effects variances. Number of observations is 170 for 15 primary studies except in column (3), where the number of observations is 144.

Table A.5
Estimation of the multivariate meta-regression (PEESE). Dependent variable: t_i.

Coefficients for:	(1)	(2)	(3)	(4)	(5)
Precision	1.091*** (0.401)	1.060** (0.436)	1.032*** (0.395)	0.668* (0.365)	1.092*** (0.400)
Duplication	−0.349** (0.161)	−0.343* (0.182)	−0.370** (0.184)	−0.362** (0.158)	−0.355** (0.159)
Patent	0.259 (0.376)	0.291 (0.410)	0.361 (0.373)	–	0.251 (0.375)
Unweighted Patent	–	–	–	0.681** (0.326)	–
Weighted Patent	–	–	–	0.277 (0.503)	–
GDP	0.240 (0.562)	0.279 (0.656)	0.344 (0.588)	0.661 (0.522)	0.228 (0.566)
Population	−0.416 (0.491)	−0.383 (0.543)	−0.262 (0.513)	–	−0.418 (0.486)
Add. variable for pool	−0.278 (0.208)	−0.270 (0.221)	−0.240 (0.188)	−0.345** (0.174)	−0.276 (0.209)
Foreign know.	0.023*** (0.005)	0.023*** (0.005)	−0.025 (0.031)	0.023*** (0.005)	–
Unweigheted Foreign Inf.	–	–	–	–	0.032*** (0.004)
Weighted Foreign Inf.	–	–	–	–	0.023*** (0.004)
Imports	0.012*** (0.003)	0.012*** (0.004)	0.086*** (0.031)	0.012*** (0.004)	–
Distance	−0.007** (0.003)	−0.007** (0.003)	−0.293** (0.013)	−0.007** (0.003)	–
Time effects	0.079** (0.034)	0.079** (0.036)	0.097*** (0.033)	0.080** (0.034)	0.079** (0.035)
Rich countries	−0.051*** (0.009)	−0.051*** (0.010)	−0.064*** (0.014)	−0.051*** (0.009)	−0.051*** (0.009)
IV methods	−0.231 (0.166)	−0.233 (0.183)	−0.226 (0.164)	−0.290* (0.166)	−0.237 (0.162)
Panel	−0.036 (0.131)	−0.036 (0.137)	−0.060 (0.116)	−0.036 (0.131)	−0.041 (0.132)
Observations	−0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
Countries	−0.006*** (0.001)	−0.007*** (0.001)	−0.006*** (0.001)	−0.007*** (0.001)	−0.006*** (0.001)
Industrial data	−0.104*** (0.018)	−0.104*** (0.018)	−0.091*** (0.026)	0.299 (0.390)	−0.098*** (0.018)
Publication	−0.229*** (0.068)	−0.232*** (0.072)	−0.286*** (0.071)	−0.230*** (0.069)	−0.225*** (0.069)
Standard-error	5.499 (5.352)	5.313 (5.618)	4.622 (4.645)	5.300 (5.364)	5.439 (5.424)
Var(duplication)	0.209	0.278	0.310	0.202	0.198
	[0.082; 0.533]	[0.101; 0.763]	[0.127; 0.759]	[0.081; 0.507]	[0.077; 0.511]
Var(IV methods)	0.144	0.179	0.146	0.114	0.136
	[0.040; 0.512]	[0.046; 0.696]	[0.043; 0.494]	[0.031; 0.420]	[0.037; 0.494]

(*continued on next page*)

Table A.5 (*continued*)

Coefficients for:	(1)	(2)	(3)	(4)	(5)
Var(GDP)	0.444	0.696	0.552	0.443	0.461
	[0.071; 2.789]	[0.080; 6.067]	[0.096; 3.178]	[0.070; 2.786]	[0.074; 2.888]
Var(residuals)	20.666	22.657	15.272	20.808	21.272
	[16.46; 25.94]	[17.87; 28.73]	[11.88; 19.63]	[16.59; 26.10]	[16.94; 26.70]
Log likelihood	−525.39	−576.91	−431.57	−525.14	−527.21

Notes: Moderator variables are divided by the standard errors reported in the primary studies. Estimation by maximum likelihood in columns (1), (3), (4), and (5), restricted maximum likelihood in column (2) Standard errors for coefficient estimators are in parentheses (). 95% confidence intervals for random effects variances are in brackets []. Level of significance: *** for p-value $<$ 0.01; **for p-value $<$ 0.05;* for p-value $<$ 0.01. Wald Test is for global significance and always rejects with high significance. LR Test is HM vs. OLS and always rejects with high significance. Var() means Random Effects variances. Number of observations is 170 for 15 primary studies except in column (3) where the number of observations is 144.

Table A.6
Robustness analysis (FAT/PET; PEESE). Dependent variable: t_i.

Coefficients for:	FAT/PET (1)	FAT/PET (2)	PEESE (3)	PEESE (4)
Precision	0.843** (0.373)	0.830** (0.396)	0.923** (0.370)	0.892** (0.389)
Duplication	−0.322** (0.149)	−0.398** (0.163)	−0.296** (0.149)	−0.376** (0.162)
Patent	0.422 (0.349)	0.390 (0.364)	0.410 (0.350)	0.379 (0.364)
GDP	0.387 (0.554)	0.385 (0.583)	0.381 (0.544)	0.376 (0.575)
Population	−0.742* (0.429)	−0.346 (0.481)	−0.780* (0.419)	−0.341 (0.482)
Add. variable for pool	−0.219 (0.196)	−0.318 (0.197)	−0.204 (0.197)	−0.311 (0.196)
Foreign know.	0.024*** (0.004)	0.023*** (0.005)	0.024*** (0.004)	0.023*** (0.005)
Imports	0.012*** (0.003)	0.011*** (0.003)	0.0122*** (0.003)	0.011*** (0.003)
Distance	−0.006** (0.003)	−0.006** (0.003)	−0.007** (0.003)	−0.007** (0.003)
Time effects	0.088*** (0.029)	0.085*** (0.032)	0.079*** (0.029)	0.079** (0.032)
Rich countries	−0.052*** (0.008)	−0.025** (0.010)	−0.051*** (0.008)	−0.024** (0.010)
IV methods	−0.211 (0.171)	−0.290* (0.161)	−0.190 (0.167)	−0.274* (0.158)
Panel	0.071 (0.112)	−0.026 (0.126)	−0.020 (0.110)	−0.045 (0.122)
Observations	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
Countries	−0.006*** (0.001)	−0.002 (0.001)	−0.007*** (0.001)	−0.002* (0.001)
Industrial data	−0.093*** (0.016)	−0.009 (0.026)	−0.104*** (0.015)	−0.018 (0.024)
Regional data	0.445 (0.640)	-	0.496 (0.634)	-
Publication	−0.208*** (0.059)	−0.101 (0.070)	−0.229*** (0.058)	−0.117* (0.069)
Schumpeterian Dummy	-	−0.143*** (0.030)	-	−0.142*** (0.030)
Constant/standard-error	1.239** (0.614)	0.946 (0.760)	7.204* (4.351)	5.665 (4.993)
Var(duplication)	0.214	0.218	0.215	0.220
	[0.090; 0.508]	[0.085; 0.559]	[0.091; 0.510]	[0.086; 0.561]
Var(IV methods)	0.140	0.135	0.133	0.130
	[0.042; 0.469]	[0.038; 0.487]	[0.040; 0.449]	[0.036; 0.471]
Var(GDP)	0.494	0.553	0.458	0.522
	[0.006; 2.844]	[0.094; 3.240]	[0.078; 2.672]	[0.088; 3.095]
Var(residuals)	14.256	17.843	14.365	17.905
	[11.82; 17.19]	[14.20; 22.42]	[11.91; 17.32]	[14.25; 22.49]
Log likelihood	−698.20	−514.64	−698.85	−514.77

Notes: Moderator variables are divided by the standard errors reported in the primary studies. Estimation by maximum likelihood. Standard errors for coefficient estimators are in parentheses (). 95% confidence intervals for random effects variances are in brackets []. Level of significance: *** for p-value $<$ 0.01; **for p-value $<$ 0.05;* for p-value $<$ 0.01. Wald Test is for global significance and always rejects with high significance. LR Test is HM vs. OLS and always rejects with high significance. Var() means Random Effects variances. Number of observations is 242 in columns (1) and (3) and 170 in columns (2) and (4), for 15 primary studies.

Table A.7
Estimation of Eq. (4): dependent variable: t.

Coefficients for:	FAT/PET	PEESE
Precision	0.768***	0.719***
	(0.093)	(0.091)
constant	−1.041	–
	(0.817)	
SE	–	0.970
		(3.341)
RE variances		
Var(*Precision*)	0.123	0.134
	[0.058; 0.259]	[0.064; 0.280]
Var(*residuals*)	41.80	41.83
	[34.38; 50.82]	[34.41; 50.85]

(*continued on next page*)

Table A.7 (*continued*)

Coefficients for:	FAT/PET	PEESE
N. obs. (N. Studies)	221 (19)	221 (19)
Log likelihood	−758.66	−759.42
Wald Test	67.77***	65.10***
LR test (random α_0 and α_1 vs. random α_0)	0.000	0.090
LR test (random α_0 and α_1 vs. random α_1)	86.12***	81.29***
LR test (HM vs. OLS)	209.01***	249.16***

Notes: Estimation by maximum likelihood. Standard errors for coefficient estimators are in parentheses (). 95% confidence intervals for random effects variances are in brackets []. Level of significance: *** for p-value < 0.01; **for p-value < 0.05;* for p-value < 0.01. N. Obs. is Number of Observations; N. Studies is Number of Studies. RE variances mean Random Effects variances.

Table A.8
Estimation of the multivariate meta-regression (FAT/PET). Dependent variable: t_i.

Coefficients for:	(1)	(2)	(3)	(4)	(5)
Precision	0.495 (0.359)	0.527 (0.405)	−0.404 (0.369)	−0.520 (0.558)	0.443 (0.357)
Duplication Dummy	0.750*** (0.178)	0.746*** (0.214)	1.170*** (0.181)	−0.812*** (0.170)	0.755*** (0.175)
Patent	−0.487*** (0.158)	−0.507*** (0.165)	−0.008 (0.192)	–	−0.458*** (0.158)
Unweighted Patent	–	–	–	0.456 (0.531)	–
Weighted Patent	–	–	–	0.045 (0.037)	–
GDP	−0.601* (0.327)	−0.616 (0.379)	−0.097 (0.377)	0.310 (0.594)	−0.582* (0.329)
Population	−1.627*** (0.386)	−1.615*** (0.468)	−1.446*** (0.323)	−0.773 (0.674)	−1.616*** (0.380)
Add. variable for pool	−0.084 (0.085)	−0.080 (0.089)	−0.071 (0.057)	0.010 (0.08)	−0.085 (0.086)
Foreign know.	0.019*** (0.006)	0.019*** (0.006)	0.050 (0.035)	0.018*** (0.005)	–
Unweigheted foreign Inf.	–	–	–	–	0.019*** (0.004)
Weighted foreign Inf.	–	–	–	–	0.009** (0.004)
Imports	0.006 (0.004)	0.006 (0.004)	−0.051 (0.040)	0.006 (0.004)	–
Distance	−0.012*** (0.003)	−0.012*** (0.004)	0.028 (0.030)	−0.011*** (0.004)	–
Time effects	0.605*** (0.082)	0.619*** (0.087)	0.605*** (0.059)	0.565*** (0.081)	0.604*** (0.082)
Rich countries	0.002 (0.013)	0.002 (0.013)	−0.045** (0.019)	−0.002 (0.002)	0.002 (0.013)
IV methods	−0.251 (0.163)	−0.245 (0.171)	−0.262* (0.155)	−0.289 (0.182)	−0.253 (0.162)
Panel	−0.189 (0.151)	−0.192 (0.158)	−0.222** (0.105)	−0.173 (0.153)	−0.180 (0.151)
Observations	−0.000* (0.000)	−0.000* (0.000)	0.000*** (0.000)	−0.000 (0.000)	−0.000 (0.000)
Countries	0.001 (0.002)	0.001 (0.002)	0.002 (0.002)	0.000 (0.001)	0.001 (0.001)
Regional data	0.232 (0.243)	0.209 (0.295)	0.508** (0.209)	0.303 (0.229)	0.250 (0.240)
Industrial data	−0.334* (0.194)	−0.335 (0.236)	−0.224 (0.170)	0.150 (0.508)	−0.318* (0.191)
Publication	0.031 (0.191)	0.004 (0.235)	0.070 (0.157)	0.044 (0.175)	0.026 (0.188)
Constant	−1.097 (0.810)	−1.131 (0.845)	−0.699 (0.703)	−0.542 (0.802)	−0.913 (0.812)
Var(Duplication dummy)	0.053	0.088	0.037	0.041	0.050
	[0.019; 0.149]	[0.027; 0.278]	[0.015; 0.093]	[0.015; 0.117]	[0.018; 0.143]
Var(IV methods)	0.145	0.154	0.164	0.167	0.142
	[0.033; 0.629]	[0.029; 0.824]	[0.048; 0.554]	[0.044; 0.641]	[0.033; 0.611]
Var(GDP)	0.247	0.372	0.357	0.236	0.250
	[0.041; 1.476]	[0.054; 2.569]	[0.078; 1.625]	[0.038; 1.157]	[0.042; 1.496]
Var(residuals)	25.885	27.643	11.154	27.042	26.282
	[21.24; 31.54]	[22.55; 33.89]	[8.99; 13.84]	[22.19; 32.95]	[21.57; 32.02]
Log likelihood	−706.43	−755.72	−533.26	−709.88	−707.64

Notes: Moderator variables are divided by the standard errors reported in the primary studies. Estimation by maximum likelihood in columns (1), (3), (4), and (5), restricted maximum likelihood in column (2) Standard errors for coefficient estimators are in parentheses (). 95% confidence intervals for random effects variances are in brackets []. Level of significance: *** for p-value < 0.01; **for p-value < 0.05;* for p-value < 0.01. Wald Test is for global significance and always rejects with high significance. LR Test is HM vs. OLS and always rejects with high significance. Var() means Random Effects variances. Number of observations is 221 for 19 primary studies except in column (3) where the number of observations is 189.

Table A.9
Estimation of the multivariate meta-regression (PEESE). Dependent variable: t_i.

Coefficients for:	(1)	(2)	(3)	(4)	(5)
Precision	0.293 (0.336)	0.325 (0.383)	−0.557 (0.345)	−0.600 (0.548)	0.272 (0.333)
Duplication Dummy	0.775*** (0.176)	0.770*** (0.213)	1.191*** (0.180)	0.820*** (0.169)	0.776*** (0.173)
Patent	−0.432*** (0.155)	−0.453*** (0.162)	0.048 (0.186)	–	−0.412*** (0.155)
Unweighted Patent	–	–	–	0.454 (0.526)	–
Weighted Patent	–	–	–	0.045 (0.037)	–
GDP	−0.656** (0.321)	−0.671* (0.373)	−0.111 (0.372)	0.229 (0.582)	−0.630* (0.323)
Population	−1.680*** (0.382)	−1.664*** (0.465)	−1.460*** (0.322)	−0.835 (0.665)	−1.661*** (0.376)
Add. variable for pool	−0.091 (0.086)	−0.086 (0.089)	−0.074 (0.057)	−0.001 (0.081)	−0.091 (0.086)
Foreign know.	0.019*** (0.006)	0.019*** (0.006)	0.051 (0.036)	0.018*** (0.006)	–
Unweigheted foreign Inf.	–	–	–	–	0.019*** (0.004)

(*continued on next page*)

Table A.9 (*continued*)

Coefficients for:	(1)	(2)	(3)	(4)	(5)
Weighted foreign Inf.	–	–	–	–	0.009** (0.004)
Imports	0.006 (0.004)	0.006 (0.004)	−0.054 (0.040)	0.006 (0.004)	–
Distance	−0.011*** (0.004)	−0.011*** (0.004)	0.027 (0.030)	−0.011*** (0.004)	–
Time effects	0.598*** (0.082)	0.611*** (0.088)	0.598*** (0.059)	0.563*** (0.081)	0.598*** (0.082)
Rich countries	0.002 (0.013)	0.002 (0.013)	−0.045** (0.019)	−0.001 (0.013)	0.002 (0.013)
IV methods	−0.276* (0.162)	−0.268 (0.169)	−0.281* (0.152)	−0.309* (0.180)	−0.275* (0.161)
Panel	−0.113 (0.144)	−0.112 (0.151)	−0.172* (0.097)	−0.125 (0.146)	−0.114 (0.145)
Observations	−0.000* (0.000)	−0.000* (0.000)	0.000*** (0.000)	−0.000 (0.000)	−0.000 (0.000)
Countries	0.001 (0.002)	0.001 (0.002)	0.002 (0.002)	0.001 (0.002)	0.001 (0.002)
Regional data	0.293 (0.238)	0.267 (0.291)	0.546*** (0.205)	0.332 (0.225)	0.301 (0.235)
Industrial data	−0.295 (0.191)	−0.294 (0.234)	−0.197 (0.167)	0.162 (0.503)	−0.285 (0.188)
Publication	0.040 (0.189)	0.009 (0.234)	0.075 (0.155)	0.051 (0.174)	0.034 (0.186)
Standard-error	1.318 (2.858)	1.264 (2.961)	1.198 (1.908)	2.028 (2.897)	1.335 (2.874)
Var(Duplication Dummy)	0.052	0.087	0.037	0.041	0.049
	[0.018; 0.150]	[0.027; 0.281]	[0.015; 0.093]	[0.014; 0.117]	[0.017; 0.143]
Var(IV methods)	0.141	0.148	0.154	0.163	0.139
	[0.033; 0.607]	[0.028; 0.792]	[0.046; 0.523]	[0.043; 0.621]	[0.033; 0.592]
Var(GDP)	0.232	0.354	0.339	0.221	0.236
	[0.038; 1.432]	[0.050; 2.497]	[0.074; 1.555]	[0.035; 1.413]	[0.038; 1.453]
Var(residuals)	26.172	27.940	11.244	27.100	26.489
	[21.48; 31.89]	[22.79; 34.25]	[9.06; 13.95]	[22.24; 33.02]	[21.74; 32.28]
Log likelihood	−707.24	−755.27	−533.55	−709.87	−708.16

Notes: Moderator variables are divided by the standard errors reported in the primary studies. Estimation by maximum likelihood in columns (1), (3), (4), and (5), restricted maximum likelihood in column (2) Standard errors for coefficient estimators are in parentheses (). 95% confidence intervals for random effects variances are in brackets []. Level of significance: *** for p-value < 0.01; **for p-value < 0.05;* for p-value < 0.01. Wald Test is for global significance and always rejects with high significance. LR Test is HM vs. OLS and always rejects with high significance. Var() means Random Effects variances. Number of observations is 221 for 19 primary studies except in column (3) where the number of observations is 189.

Table A.10
Robustness analysis (FAT/PET; PEESE). Dependent variable: t_i.

Coefficients for:	FAT/PET (1)	FAT/PET (2)	PEESE (3)	PEESE (4)
Precision	0.616* (0.317)	0.515 (0.358)	0.519* (0.307)	0.318 (0.335)
Duplication Dummy	0.641*** (0.171)	0.725*** (0.180)	0.646*** (0.172)	0.747*** (0.177)
Patent	−0.412*** (0.137)	−0.487*** (0.158)	−0.379*** (0.134)	−0.432*** (0.155)
GDP	−0.609* (0.315)	−0.600* (0.327)	−0.643** (0.314)	−0.653** (0.322)
Population	−1.206*** (0.310)	−1.583*** (0.386)	−1.198*** (0.312)	−1.631*** (0.381)
Add. Variable for pool	−0.054 (0.075)	−0.083 (0.085)	−0.058 (0.075)	−0.089 (0.086)
Foreign know.	0.019*** (0.005)	0.019*** (0.006)	0.019*** (0.005)	0.019*** (0.006)
Imports	0.006* (0.003)	0.006 (0.004)	0.006* (0.003)	0.006 (0.004)
Distance	−0.011*** (0.003)	−0.012*** (0.003)	−0.011*** (0.003)	−0.011*** (0.003)
Time effects	0.600*** (0.073)	0.602*** (0.082)	0.595*** (0.073)	0.595*** (0.082)
Rich countries	0.001 (0.011)	0.002 (0.013)	0.002 (0.011)	0.002 (0.013)
IV methods	−0.071 (0.154)	−0.248 (0.164)	−0.082 (0.155)	−0.272* (0.163)
Panel	−0.202 (0.128)	−0.187 (0.150)	−0.159 (0.124)	−0.111 (0.144)
Observations	−0.000** (0.000)	−0.000* (0.000)	−0.000** (0.000)	−0.000* (0.000)
Countries	0.001 (0.001)	0.001 (0.002)	0.001 (0.001)	0.001 (0.002)
Regional data	0.046** (0.226)	0.211 (0.242)	0.063 (0.227)	0.269 (0.237)
Industrial data	−0.463** (0.194)	−0.336* (0.191)	−0.446** (0.195)	−0.298 (0.187)
Publication	−0.040 (0.191)	0.010 (0.191)	−0.046 (0.192)	0.018 (0.189)
Schumpeterian Dummy	-	0.045 (0.071)	-	0.048 (0.071)
Constant/standard-error	−0.575 (0.646)	−1.077 (0.809)	1.356 (2.466)	1.301 (2.860)
Var(Duplication Dummy)	0.060	0.050	0.062	0.048
	[0.022; 0.162]	[0.017; 0.143]	[0.022; 0.170]	[0.016; 0.143]
Var(IV methods)	0.134	0.148	0.135	0.145
	[0.028; 0.637]	[0.035; 0.629]	[0.027; 0.664]	[0.034; 0.609]
Var(GDP)	0.257	0.248	0.253	0.234
	[0.048; 1.377]	[0.042; 1.481]	[0.047; 1.365]	[0.038; 1.438]
Var(residuals)	19.573	25.899	19.590	26.187
	[16.52; 23.18]	[21.25; 31.56]	[16.54; 23.20]	[21.49; 31.91]
Log likelihood	−889.70	−706.24	−889.94	−707.01

Notes: Moderator variables are divided by the standard errors reported in the primary studies. Estimation by maximum likelihood. Standard errors for coefficient estimators are in parentheses (). 95% confidence intervals for random effects variances are in brackets []. Level of significance: *** for p-value < 0.01; **for p-value < 0.05;* for p-value < 0.01. Wald Test is for global significance and always rejects with high significance. LR Test is HM vs. OLS and always rejects with high significance. Var() means Random Effects variances. Number of observations is 293 in columns (1) and (3) and 221 in columns (2) and (4), for 19 primary studies.

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