A Meta-Analysis of FDI and Productivity Spillovers in Developing Countries

PhD Candidate:
Binyam Afewerk Demena

International Institute of Social Studies of Erasmus University of Rotterdam
Department of Economics of Development and Emerging Markets

The Hague, The Netherlands
August, 2014

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List of Acronyms

CRSE	Clustered Robust Standard Error
EDEM	Economics of Development and Emerging Markets
FDI	Foreign Direct Investment
FAT	Funnel Asymmetry Test
G-to-S	General-to-Specific
LP	Levinsohn and Petrin
MLM	Multi-Level Model
MRA	Meta Regression Analysis
MRM	Meta-Regression Model
PET	Precision Effect Test
OLS	Ordinary Least Square
OP	Olley and Pakes, OP
SSA	Sub-Saharan African
UNCTD	United Nations Conference on Trade and Development
WB WDI	World Bank's World Development Indicators
WLS	Weighted Least Squares

Abstract

Empirical results of Foreign direct investment on domestic firms productivity spillovers are clearly mixed. This study reviews the intra-sectoral heterogeneity of productivity spillovers from FDI in a large sample of developing countries. I investigate publication selection bias, and estimate the true underlying empirical FDI-spillover effects. I collect 1,450 spillover estimates conducted by 93 researchers from 69 empirical studies dealing with 31 developing countries for the period of 1986 to 2013. My results suggest that FDI-spillover effects are tainted with moderate to substantial publication bias. In combination with model misspecifications of the primary studies, the bias overstates the true underlying Meta-effect by about 48 per cent of the actual magnitude of the effect size. Once the biases have been corrected, the Meta-effect in the context of developing countries is economically significant. Most importantly, I find that spillovers and their sign depend systematically on the heterogeneity of method and publication characteristics. Furthermore, empirical work disregarded the argument that spillovers requires analysis of the transmission channels through which they actually occur. It does allow to narrow the heterogeneity nature of spillover estimates. Results are robust for different methods.

Keywords

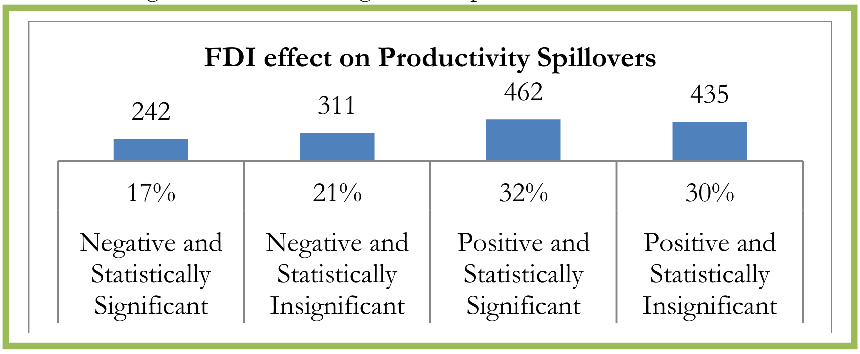
Meta-analysis, Foreign direct investment, Spillover, Publication bias, Meta-effect, Developing countries.

1. Introduction

Starting in the early 1980s, developing countries have been increasingly able to set policies in order to attract and facilitate FDI. To attract FDI, they often provide substantial investment incentives. For instance, conditions favourable for FDI underlie more than 88% of 2,963 national regulatory changes in investment regime introduced in more than 100 countries between 1992 and 2012 (UNCTAD 2013). One main driver to support for the FDI friendly regimes has been policymakers' expectation that these FDI inflows indirectly boost productivity of domestic firms. In other words, FDI assumed to transfer productivity gains (henceforth productivity spillovers), which may regard as enhancing technological capability of domestic firms (e.g., see Blomström 1989, Wooster and Diebel 2010).

An important question to review is whether this enthusiasm of attracting FDI creates productivity spillovers in the context of developing countries. In order to explore the available productivity spillover findings, I review 69 primary studies published in the period of 1986 – 2013, carried out by 93 researchers[1], dealing with 31 developing countries. These empirical studies provide 1,450 estimates of productivity spillovers from 43 peer-reviewed journal articles and 26 working papers, dissertations, and unpublished studies or reports[2]. Figure 1 presents a simple vote counting of the studies under review. The figure provides a rough distribution of estimated spillovers. As can been seen, approximately one out of three empirical studies validate a positive spillovers effect. About half of the studies do not confirm any spillover effects, either negative or positive but are statistically not significant. While some studies (17%) find a significant negative effect. Hence, there is no conclusive FDI spillovers effect: the result on the existence of productivity spillovers greatly differ, and thereby the evidence is far from conclusive.

Figure 1: Vote counting of FDI-spillover effects



Source: Author's own computation from collected empirical studies

Clearly, there is a stock of rich empirical studies with mixed results. The first question is that the combined average spillovers effect is adequately

[1] I thank to all authors, I benefit from the extensive empirical works of 93 researchers,.

[2] A template of data extraction was designed in excel. Using this template, I have coded more than forty potential theoretical and empirical research dimensions, and four categories of the quality of the studies and the journals. This yields 131,325 cells to be manually filled. This data coding required for a second reviewer to check the consistency of the data. I would like to thank the EDEM research program for the financial support and the research assistant.

represent the true empirical effect size. The second question is why do the studies result in different answer of spillovers effect. Furthermore, it is recognized that at least since De Long and Land (1992) "… there may be a tendency among editors of academic journals to publish papers preferably if they reject their null hypothesis, i.e. if they produce statistically significant results" (Görg and Strobl 2001:733). So, it is also important to investigate whether the literature suffers from publication bias, and if so, to what extent. Most importantly, this will help to establish a genuine Meta-effect corrected for this bias.

In what follows I use a Meta-analysis to combine, summarize and investigate the empirical results found in the reported spillover estimates. A Meta-analysis is a useful tool to investigate the mixed results routinely found in empirical studies. Meta-analysis is a statistical approach to investigate previously reported empirical findings for a given hypothesis, research questions, empirical effect or phenomena (Stanley and Doucouliagos 2012). In particular, in the words of Mebratie and van Bergeijk (2013:56) "Meta-analysis helps to identify how the characteristics of a study may influence the possibility of observing spillover from FDI and gives some ideas about how carefully the research methodology of spillover effect analysis should be planned". Further to this, a Meta-analysis can provide the opportunity to model and estimate publication bias, and thereby establish corrected empirical effect. Moreover, the use of this methodology allows to correct misspecification of primary studies. Therefore, a Meta-analysis approach goes beyond a literature review.

My contribution differs from the existing Meta-analysis in several dimensions in the context of developing countries. First, there is clear evidence of publication bias in the FDI-spillovers literature which is initially detected by the funnel plots and then corroborated by the simple MRA and finally by the multivariate MRA (I also add the extent of the bias). Second, the spillover effects found in the empirical studies greatly overstate the magnitude of the true underlying Meta-effect by about 48 per cent. After correcting the publication bias and omitted variable bias, the underlying effect is still economically important which is about 0.084. Third, an important lesson for future research derives from the fact that the analysis has identified a set of moderator variables that are causing the heterogeneity of the spillover estimates. Fourth, existing theories suggest that spillovers are understood to occur via the channels of demonstration, export, labour mobility and competition effects - arguments largely disregarded by the existing primary studies. Instead the empirical work simply focuses to measure the overall spillovers effect, i.e. whether spillovers exist or not. Furthermore, in most of the existing studies, spillover effects are assumed to arise irrespective of the existing specific characteristics of domestic firms. The nature and occurrence of spillovers, therefore, can depend upon the interaction of the transmission channels through which the effects work and the specific firm characteristics. Not only from academic point of view, but also from policy perspectives this would be vital to fine-tune the transmission channels by which spillovers effect actually occur.

Finally, the study also has important lessons related to measurement error of previous Meta-analyses. If multiple estimates are the bases of the Meta-data, the within-study dependence should be considered. If this dependence is not taken into account, for e.g. the OLS estimation may lead to unintentional downward bias of the standard errors (e.g., see Görg and Strobl 2001, Wooster and Diebel 2010, Mebratie and van Bergeijk 2013). This may result in inconsistent findings as estimates may receive false appearance of statistical significance.

The rest of the paper is structured as follows: Section 2 provides an overview of the empirical studies as well as a discussion of a Meta-analysis as a method of systematic synthesis of primary studies. Section 3 discusses the dataset construction, explains publication bias, source of heterogeneity, and introduce the empirical approach. Section 4 delves into a simple model of publication bias, genuine Meta-effect, and provides a multivariate Meta-regression analysis. Section 5 discusses arguments disregarded by the existing primary empirical studies. Lastly, section 6 concludes and suggests lessons for future research.

2. A review of the literature

In this section, I start with an overview of the existing FDI spillovers empirical studies. This follows a Meta-analysis as a method of systematic review as well as a brief assessment of the Mata-analysis of FDI and spillovers studies.

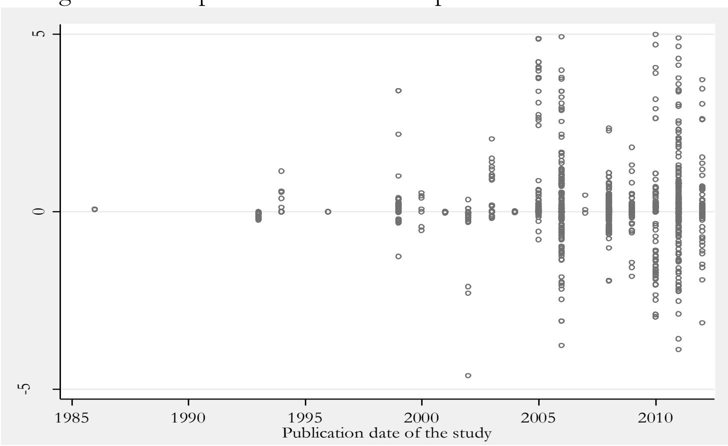
2.1. Overview of the empirical literature

There is a wide range of empirical literatures on the effect of productivity spillovers for domestic firms from FDI. In light of this review, I organize the literature by a period of ten years in order to illustrate changes over time in data, empirical approach, spillover findings among others. For developing countries, the first set of empirical study is by Blomström and Persson in the 1983. This early contribution is for Mexican plants and reported that FDI has a significant positive effect on productivity of domestic-owned firms. In a similar vein, Blomström (1986), for Mexican manufacturing industries has also found a positive spillover effect. All studies in the 1980s use a cross-sectional data and industry-level spillover analysis. These studies, therefore, face an identification problem, mainly the potential endogeneity of FDI inflow. In other words, if FDI gravitates to most productive industries, then the observed result of productivity spillovers will overstate the positive impact of foreign firms (Aitken and Harrison 1999). Consequently, it is not clear whether this evidence of productivity spillover is due to either the presence of FDI or the own-productivity of domestic firms.

An important study in the 1990s is for Moroccan domestic firms by Haddad and Harrison (1993). This study was the first to use panel firm-level data. Their findings suggest a negative productivity spillovers from the presence of FDI. Similarly, using firm-level panel data from Venezuela, Aitken and Harrison (1999) find a negative productivity spillovers. In the former case, the absence of spillovers attributed to the technological gap between domestic and foreign firms. The latter conclude that the positive effect reported in the previous studies has been due to the tendency of foreign firms to invest in more productive industries.

In contrast, Blomström and Wolff (1994), Kokko (1994, 1996), for Mexico, Blomström and Sjöholm (1999), Sjöholm (1999a, 1999b) for Indonesia, Kokko et al. (1996) for Uruguay, and Chuang and Lin (1999) for Taiwan report a positive productivity spillovers. These large body of empirical studies also relied on cross-sectional data as opposed to panel data. This would imply that the use of panel data is a better method to test the validity of FDI-spillovers in order to control the behaviour of firms or industries over time. Note that the studies discussed so far are based on the theory of pipeline model. The pipeline model presumes a potential spillover effects from FDI which is independent of domestic firms' capabilities, i.e. irrespective of the nature of firm heterogeneity.

Figure 2: FDI-spillover effects for the publication data of the studies



Source: Author's own computation from collected empirical studies

Unlike the first and the second set of empirical studies, recent body of studies have shown a shift from the pipeline model towards domestic capability model. The domestic capability model seems to presume a generation of potential spillovers is not automatic, but also depends on the moderating effect of domestic firms' capabilities. As presented in Figure 2, the third set of studies, i.e. in the 2000s, has extensively investigated the spillover effects. This large number of studies is mainly because of the growing obtainability of data. To mention a few, Marin and Bell (2006) and Chudnovsky et al. (2008) in Argentina, Blyde et al. (2004) in Venezuela, Bwalya (2006) in Zambia, Mebratie and Bedi (2013) in South Africa did not find any spillover effects. While Jordaan (2008a) in Mexico and Waldkirch and Ofosu (2010) in Ghana, tend to validate negative FDI effects. In contrast to these recent empirical studies from Latin America and SSA countries, a number of Asian countries report a positive spillovers effect. This may include, Khalifah and Adam (2009) in Malaysia, Taymaz and Yilmaz (2008) in Turkey, Takii (2009) in Indonesia, Nguyen (2008) and Van Thanh and Hoang (2010) in Vietnam among others. Figure 2 provides an alternative way to shed light on the estimated spillovers effect over-time. This visual inspection shows that there are variations in the reported spillover estimates over-time. In fact, the variation among the reported spillover estimates has shown an increasing trend, in particular since mid-2000s.

Again, the empirical evidence is far from conclusive. Over the past three decades, spillover estimates of FDI effect has continuously increasing, in the 1980s from just less than one per cent, in the 1990s to eight per cent and in the 2000s to about 59 per cent (Figure 2). As pointed out, positive productivity spillovers from foreign investment has been reported in Mexico, Indonesia, Taiwan, Uruguay Kenya, Zimbabwe, Turkey and Malaysia. In contrast, in Morocco, Venezuela, Argentina, South Africa, Ghana, India, Thailand, and Tanzania report either the absence or a negative FDI-spillovers effect. Moreover, the seminal positive findings of cross-sectional data studies have been challenged by the growing availability of panel-data studies. It seems that there is a link between cross-sectional studies and positive findings. While negative or insignificant findings are associated with panel-data studies. Studies of panel-data like Haddad and Harrison (1993), Aitken and Harrison (1999) present negative evidence of spillover effects. While Blyde et al. (2004), Blalock and Gertler (2008), and Mebratie and Arjun (2013) report evidence of insignificant effects. Nonetheless, other recent panel-data studies (e.g., see Kee 2005, Taki 2011, Van Thanh and Hoang 2010) find evidence of positive effects. It appears likely, therefore, that the dichotomy of cross-sectional and panel-data findings looks to be no longer present, a point also noted by Jordaan (2012).

Overall, there is a growing number of studies with mixed results. Besides, it is only the most recent body of the literature has been addressed the importance of domestic firms' capabilities. However, studies from the SSA countries instead emphasis on spillover effects regardless of domestic firms' capabilities. Generally, the recent spillover findings seem to suggest that the generation of spillover is not automatic, rather it depends on the existing specific firm characteristics (Marine and Bell 2006, Kohpaiboon 2006). Most importantly, the approach adopted in the literature of 69 studies largely avoids to investigate the transmission mechanisms by which FDI-spillovers effect actually take place. Instead, they simply focus on whether or not spillovers occur. This would be an important aspect to narrow the heterogeneity nature of spillover estimates.

2.2. FDI Productivity Spillover and Meta-Analysis

The term Meta-analysis was first coined in 1976 by Gene Glass. He defined the term as "(t)he statistical analysis of large collection of results from individual studies for the purpose of integrating the findings. It connotes a rigorous alternative to the causal, narrative discussion of research studies that typify our attempt to make sense of the rapidly expanding research literature" (Glass 1976:3).

Nowadays, this approach enjoys widespread application in several fields of the social sciences. In the field of economics since the 1980s several hundreds of studies used a Meta-analysis approach. Even specialized in the field of FDI-spillovers, the number of Meta-analysis studies is impressive: Görg and Strobl (2001), Meyer and Sinani (2009), Wooster and Diebel (2010), Iršová and Havránek (2013), and Mebratie and van Bergeijk (2013). In the following section, I will review the empirical approach and results of these studies.

The earliest Meta-analysis by Görg and Strobl (2001) highlights the impact of study design on the FDI-spillover estimates. Görg and Strobl collect a sample of 25 observations from 21 empirical studies on developing and developed countries. The authors argue that spillover effects are likely to be affected by the definition of the variable that indicates FDI presence. Moreover, analyses that use cross-sectional data are more likely to report higher spillover estimates than panel data studies. Finally, they find some evidence of publication bias. This implies that studies have a better chance to be published if they report statistically significant findings.

Using a sample of 124 observations from 66 empirical studies regarding transition economies, developing countries, and developed countries, Meyer and Sinani (2009) analyse the reasons for the variation of FDI-spillover results. They conclude that cross-country variations in spillovers are determined by the availability of cross-sectional versus panel data analysis and firm-level versus industry-level data. This implies that the design of primary studies matter for the heterogeneity of the spillover results. Wooster and Diebel (2010) investigate aspects of research design associated with spillover results. They use a sample of 141 observations from 32 empirical studies in developing countries. They report that spillover results appear to vary partly with the use of different FDI proxy variables. Moreover, they indicate that the mixed spillover effects may be driven by omitted variable bias. They also point out that spillover effects are more likely to be noticeable in Asian countries.

The two most recent Meta-analyses are by Iršová and Havránek (2013) and Mebratie and van Bergeijk (2013). The former study collects relatively homogeneous post-2000 empirical studies. Iršová and Havránek review 52 empirical studies in 45 developing and developed countries. In contrast to the previous Meta-analyses, Iršová and Havránek do not consider any empirical studies published pre-2000, because they argue that these studies are two heterogeneous in terms of methodology to compare altogether. However, this decision implies that there is a selection bias introduced by the Meta-analysts themselves. In fact, Wooster and Diebel (2010) argue against the two earlier Meta-analyses that studies become more heterogeneous when we pool developing and advanced countries, thereby making it more difficult to draw more reliable results from[3]. Evidence from Iršová and Havránek suggest that even though spillovers sign and magnitude depend on characteristics of foreign investors and domestic economy, on average, intra-industry spillovers are zero.

Using OLS and a panel-data method, Mebratie and van Bergeijk (2013) reviews a sample of 156 observations from 30 empirical studies in developing and emerging economies. To do so, a selection of studies was applied under

[3]Wooster and Diebel (2010) point out that a Meta-analysis in this approach may make it very difficult to discern whether the findings support the likelihood of spillovers in both developing and developed countries. In a similar way, Havránek and Iršová (2010) recognize that pooling results of inter-industry and intra-industry studies together is inappropriate as samples become too dissimilar and less reliable to draw results from.

the condition of one study per country. They conclude that the type and level of data aggregation as well as the definition of foreign presence matters for the variation of the reported spillover results. They also suggest some evidence of higher spillovers in studies that use labour productivity instead of TFP as the dependent variable. Consistent with the findings of Wooster and Diebel (2010), they also find strong statistical effect of spillovers in studies from Asian countries. In accordance with the study by Iršová and Havránek (2013) and contrary to the earliest study by Görg and Strobl (2001), no evidence of publication bias was detected.

To sum up, the absence of clear underlying justification for a Meta-analysis framework is disregarded. It is important to notice that methodological approach should not be simply adopted by authors' choices. Moreover, none of these studies examine the true underlying spillovers effect size (Exception is Iršová and Havránek 2013). Furthermore, except in one case, all previous studies face critical measurement errors: if multiple estimates are reported, then within-study dependence should be identified. For example, the use of OLS model overstates the statistical significance level as the standard errors are biased downward. This may result in the lack of robust analyses. Therefore, Meta-analysis should best identify the predictability pattern of the report in order to draw more reliable inference through thorough and robust analysis (Stanley et al. 2013).

3. Data and Methodology

3.1. Methods, Protocols and Data Construction

I review existing Meta-analyses and primary empirical studies[4] and use this as the basis to begin the literature search. The search commenced with the Economic Literature Index (EconLit) database and was supplemented with Google Scholar and Scopus. The updated database of the World Bank (dated August 20, 2012) that provides empirical studies conducted mainly using the enterprise survey data was also visited. The focus of the search was published and unpublished empirical studies for the 30 years period from 1983 to 2013 dealing with developing countries.

I searched using one or more combination of the keywords: 'productivity spillover + FDI', 'productivity spillover + FDI + developing countries', 'FDI presence effect on host economy', and 'technology transfer + foreign firms'. The search captured a large body of empirical studies. For instance, the keyword 'productivity spillover + FDI + Developing countries' using the Scopus search engine hits 1026 records to review. Examinations of titles, abstracts, and keywords were followed by the inspection of the introduction and conclusion. The approach yielded a gross list of 233 prospective studies.

[4]In this case, the literature review and the reference list section were carefully checked.

Studies that satisfy the following criteria: English language[5] empirical micro econometrics that study intra-industry[6] spillover effects that report regression[7] based coefficients, sample size, t-stats or standard errors are included for a detailed review. The imposition of these criteria has led to 74 empirical studies dealing with 31 developing countries for coding. Before transferring the data to a stata file for analysis, a template for data extraction was designed in excel format. Data on various characteristics of the empirical studies such as spillover measures, FDI proxies and effects, data type, estimation techniques, and study control variables were collected. The search process and data coding took about five months from May – September 2013.

It is worthwhile to describe few critical aspects encountered during the review and data coding. Multiple estimates are a common standard in economics. This is partly due to the demand from editors and reviewers that applied econometric studies should report multiple models, methods and estimates to ensure authors' main findings are robust (Stanley and Doucouliagos 2012). This may lead to a best-set, average-set or all-set Meta-data[8]. Following the advice of Stanley (2001), mainly to evade giving undo weight to a single study, many Meta-analysts chose either one best estimate or the average estimate. It is, however, not possible to average different estimation techniques and models. Moreover, we may lose important within study information if we use average estimates (Disdier and Head 2008). Most importantly, choosing the best estimate is completely flawed. First, in most cases, authors do not explicitly indicate their best estimate. Second, if they do, author's preference may introduce potential selection bias. Third, estimates in a comprehensive single paper can be underweighted relative to estimates of researchers who publish a large number of closely related literatures as each would count as an individual study to be included as a best-set (Stanley 2001). On the basis of these reasons, I adopt the all-set estimates.

Majority, about 86% of the models are estimated in log-linear functional form, with productivity proxies expressed in logs and FDI linearly. In this case, the regression coefficients are semi-elasticities, and the standard errors are directly derived from the regression coefficients. In contrast, when models estimate using the double-log or linear functional form, I had to re-

[5]Getting the minimum estimation report from non-English translation may not be enough for a clear understanding of the studies which is the crucial aspect of a Meta-analysis (Stanley and Doucouliagos 2012). In fact, I have found one non-English paper by Murra (2006) entitled 'Revaluando La Transmisión De Spillovers De La IED: Un Estudio De Productividad Para Colombia Channels for Foreign Direct Investment Spillovers: A Productivity Study for Colombia'. Even though the author provide the abstract in English, the information in the abstract found to be far from enough to complete the data extraction template which compels to understand the literature from inside out.

[6]Inter-industry studies are presumed to be dissimilar to pool with intra-industry studies, leading to a general conclusion that this category of studies should be separately investigated (Havránek and Iršová 2010, Wooster and Diebel 2010).

[7]Studies that examine determinants, descriptive and qualitative studies as well as papers that could not be downloaded are excluded. But first I tried to contact authors for inaccessible papers if contact address was found. For instance, except the abstract, the article by Sasidharan & Ramanathan (2007) is not accessible online. The study was included after communicating with the authors. Conversely, a working paper by Demmel et al. (2013) "Innovation and productivity: evidence for 4 Latin American countries manufacturing industry (No. 1307)" was found to be inaccessible with no contact address, resulting in the exclusion of the article.

[8]The best-set consists of one estimate that the author believes to be the best (key) regression of the study often labelled "preferred equation". While the all-set is constructed from all relevant study estimates. This may offer more observations to explain the heterogeneity of the results. The average-set is constructed from the all-set estimates.

compute the effect size by using sample means (see Gujarati and Porter 2009)[9]. Instead of omitting, I wrote to authors when sample means, observation size, t-values or standard errors are not reported. Moreover, I have contacted the authors when a clarification of the models, methods, and estimates provided were required[10]. Similarly, I have also collected estimates from interaction variables. Finally, five studies are excluded due to functional form and authors are not willing to support missing sample means[11].

3.2. Meta dataset

The dataset constitutes of 1,450 observations from 69 empirical studies regarding 31 developing countries[12]. The median number of parameter estimates taken from a primary study is 11. The mean and maximum are 21 and 100, respectively. For each empirical study, I have coded more than 40 potential research dimensions, and 4 categories of journal and study qualities. To put this figure into comparison, Nelson and Kennedy (2009) summarize and assess 140 Meta-analysis in economics conducted since 1989 report that the average number of parameter estimates included was 191, the median was 92, and the largest number of parameter was 1592. The average and the median of primary studies reviewed were 42 and 33, respectively. The mean and median of explanatory variables included were 14 and 12, respectively, while the maximum control variables used was 41. Therefore, comparing with conventional Meta-analysis in economics, the current dataset can be regarded as large enough and apt to explain robust evidence of the underlying true effect size and heterogeneities nature of spillover estimates.

My study includes 43 peer-reviewed journal articles and 26 working papers, dissertation, book chapters, unpublished studies or reports. The oldest study was published in 1986, and the median study appeared in 2008. In other words, half of the research in question was published in the last five years. This implies that this topic is very lively and that many new investigations of productivity spillovers from FDI appear.

Out of the 1,450 spillover estimates, 16 are found to be larger than 10 in absolute value. Some Meta-analysts (e.g., see Iršová and Havránek (2013) and Mebratie and van Bergeijk (2013) consider that these large estimates are outliers, leading to exclude these estimates from the main analysis. Other researchers, like Stanley and Doucouliagos (2012), however, argue that unusual large estimates may be due to coding errors. Nonetheless, also after a suspicious double check and the review of the research assistant, reported spillover estimates remain to differ largely. To account for the detection of outliers, I applied the multivariate outlier method proposed by Hadi (1994).

[9] Initially, I owe this point to Havránek, Tomas for sending brief procedure and explanation on computing effect size using sample means.

[10] All data sent by the authors are reported in the dataset. In total 37 e-mails (requests) has been sent to the authors of the primary studies. Doing so, 334 (about 23 per cent) observations are included. I would like to thank all authors who responded to my request.

[11] A list of excluded studies and reasons for exclusion are provided in the Appendix Table A. 4.

[12] A brief summary of the studies used in the Meta-analysis is shown in Appendix Table A.1.

Applying Hadi's method, 14 per cent of the observations are identified as outliers. If we consider the assumption that better-ranked journals publish more reliable findings (Havránek and Iršová 2011), these outliers are identified as lower quality as compared to the non-outliers. Even though in the rest of the study I report the findings without outliers, the inclusion of outliers report similar results.

3.3. Empirical Approach

The empirical approach involves three stages. The first stage starts with the computation of the weighted average spillovers effect size. In the second stage, I deal with funnel plots and Funnel-Asymmetry Test (FAT) in order to test whether the weighted average effect size is affected by the presence of publication bias. Publication bias seems to be inevitable and poses a serious empirical studies problem, thereby Meta-analysts need to be aware and correct research findings for this bias (Doucouliagos and Stanley 2011, Stanley and Doucouliagos 2012). So, an important concern of this stage is not only to detect the existence of publication bias but also to remove the bias and establish a corrected summary of the empirical findings. Thus, the genuine magnitude of the Meta-effect is examined through the Precision-Effect Testing (PET). The third stage investigates the heterogeneity nature of reported spillover estimates that can be attributed to method heterogeneity and quality characteristics.

3.3.1. Weighted mean: Meta-effect

The simple weighted average of the reported estimates, say ε_w, can be derived as:

$$\varepsilon_w = \frac{\sum \varepsilon_i N_i}{\sum N_i} \qquad \text{(3.3.1)}$$

where ε_i is the measure of estimates of spillover from the i^{th} study and N_i is the weights used, in this case the number of observations of the i^{th} study. According to Hedges et al (1985) and Copper and Hedges (1995) the inverse of the variance has been suggested as the optimal weights. However, Adams et al. (1997) indicate that those with large sample size which are more precise studies should have more heavy weight than those with small sample size that are less precise. Consequently, in the absence of the variance of the estimates, Hunter and Schmidt (2004) and Schulze (2004) recommend the use of a sample size to weight the effect size as a standard practice of Meta-analysis. The weighted average of the spillover estimates is 0.16, which is statistically different from zero at a 95% confidence interval implying that FDI has a significant positive effect on productivity spillovers. In deed the simple average across all studies, i.e. without using any weights, reveals not much different result, 0.172. Even though this average offers insightful summary, it is quite basic. As indicated above, the major problem of this mean is the issue of publication bias. In absence of publication bias, this mean can be trusted. However, in its presence, it provides wrong inference.

3.3.2. Publication bias and Genuine effect

The simplest and most common method used to detect the presence of publication bias is a funnel plot (Sutton et al. 2000). Light and Pillemer (1984) were the first to use the funnel plots to assess and detect whether empirical researches suffer from the presence of publication bias. A funnel plot is a scatter diagram of the estimated spillovers on the horizontal axis and its precision on the vertical axis, usually the reciprocal of the standard error (e.g., see Stanley 2005, 2008, Stanley and Doucouliagos 2010, 2012, Iršová and Havránek 2013). In the absences of publication bias, a funnel plot should be symmetrical (Roberts and Stanley 2005). It should be symmetrical, because small sample size with typically imprecise spillover estimates or large standard errors are widely dispersed at the bottom of the funnel (Stanley 2005). In contrast, large sample studies with usually most precise estimates should be more compactly distributed at the top of the funnel (Stanley and Doucouliagos 2010). As a result, the plots should be symmetrical and resemble an inverted funnel (Stanley and Doucouliagos 2012). In contrast, when there is a bias, a funnel plot will be asymmetrical. Asymmetrical plots may indicate that some parameter estimates are discarded or unreported. In other words, publication bias is indicated when the funnel plot is overweighed on either side of the plot.

However, this method of publication bias detection is only based on visual inspection which is a subjective interpretation, and therefore may remain unconvincing. Hence, I resort to a more formal statistical method. Modelling publication bias starts with switching the axes of the funnel plot, so that the estimated spillovers effect is the dependent variable on the vertical axis and its estimated standard error is the explanatory variable on the horizontal axis. This transformation of the funnel plot provides the intuition of the Meta-regression model (henceforth MRM) (Card and Krueger 1995, Ashenfelter et al. 1999, Roberts and Stanley 2005, Stanley and Doucouliagos 2010). To see the graphical derivation of MRM, first take the funnel plot described above. Second, invert the funnel by plotting Se_i on the vertical axis. Third, revers the axes and interpret the funnel plot as:

$$\varepsilon_i = \beta_0 + \beta_1 Se_i + u_i \quad \text{……………………..} \; (3.3.2)$$

where ε_i is the measure of estimated spillovers effect from the i^{th} study, Se_i its standard error, β_0 the true magnitude of estimated spillovers effect and β_1 is the magnitude of publication bias. This regression relation shows that as sample size increases and thus the quantity of available information increases, Se_i will approach zero (Stanley 2005). In other words, with large sample size, (ε_i) will approach β_0, the true magnitude of the spillovers effect untainted by publication bias (Roberts and Stanley 2005). It follows that, in the absence of a bias, the spillovers effect should vary randomly around β_0 and should be independent of their standard errors (Card and Krueger 1995, Roberts and Stanley 2005, Doucouliagos and Stanley 2009). Likewise, the presence of a bias can be detected if the spillover estimates correlate with their standard errors (Stanley and Doucouliagos 2010). In other words, as suggested by Card and Krueger's (1995), researchers may be predisposed to select expected estimates through searching across specifications, econometric techniques or data. If this is the case, then the estimated spillovers effect and its standard error should be correlated.

As empirical studies can use different econometric techniques, sample sizes and specifications, equation (3.3.2) is likely to be measured with a well-known heteroscedastic problem. Hence, this should be measured with weighted least squares (WLS). Recall that WLS is dividing equation (3.3.2) by individual standard error, Se_i. Adjusted for heteroscedasticity furnishes:

$$t_i \equiv \varepsilon_i/Se_i = \beta_1 + \beta_0(1/Se_i) + e_i \text{ ……………. (3.3.3)}$$

Here t_i is the t-statistic of the FDI-spillover effect (ε_i/Se_i)[13]. Through testing β_1=0 and β_0=0, the FAT and PET respectively investigate the issue of publication bias and the underlying true effect size.

Following Stanley and Doucouliagos (2014), if PET indicates a true effect (i.e., if β_0≠0), the Precision Effect Estimates with Standard Error (PEESE) is shown to give a better estimates of the true underlying effect. Accordingly, they propose the PEESE as follows:

$$\varepsilon_i = \beta_0 + \beta_1 Se_i^2 + u_i \text{ …………………………... (3.3.4)}$$

Dividing model (3.3.4) by standard error, Se_i to account for heteroscedasticity:

$$t_i = \beta_0(1/Se_i) + \beta_1 Se_i + e_i \text{ ………….……... (3.3.5)}$$

If PET presents a true effect, equation (3.3.5) will helps better to determine the effect size, since it accounts for any non-linear relationship that may exist between the standard error and the reported effect size (Stanley and Doucouliagos 2012). In regression (3.3.3) and (3.3.5), when more than one estimate from each study is collected, within-study dependence could be an important source of potential estimation bias (Rosenberger and Loomis 2000, Bateman and Jones 2003, Disdier and Head 2008, Doucouliagos and Stanley 2009). So that, multiple estimates from the same studies are likely to be correlated as they share the same characteristics[14]. In order to account for within-study dependence, Rosenberger and Loomis (2000) and Bateman and Jones (2003) recommend the use of a multi-level model (MLM). Furthermore, I use clustered-robust standard error (CRSE) at the study level for robustness

[13] Note that the coefficients of the intercept and the explanatory variable are interchanged and the independent variables are the inverse of its standard error which can be now estimated by OLS.

[14] To test for the existence of significant study-level effects, I adopt the Breusch-Pagan Langrange multiplier (BP-LM) test. This BP-LM which is a chi-squared with one degree of freedom revealed the study-level effect to be 47.95 with p<0.001, significant at any statistical level. The procedure reports similar results when outliers estimates are included: $\chi^2_{(1)}$ = 57.26, p<0.001. Thus, there are study-level effects.

check[15]. Moreover, both in order to eliminate the issue of within-study dependence and to further check robustness, I also use the average-dataset across each study.

3.3.3. Explaining Heterogeneity

The potential sources of heterogeneity listed in the Appendix Table A.2 are derived from the debates in the literature as well as the Meta-data at hand. Following the debates in the empirical studies and the approach presented by previous Meta-analyses (e.g., see Havránek and Iršová 2011), I report four categories of potential sources of heterogeneity: data characteristics, estimation characteristics, specification characteristics and publication characteristics.

Data characteristics: Slightly more than 70 per cent of the primary studies that use panel data report either insignificant effects or negative significant effects. Nevertheless, about 29 per cent of recent panel-data studies also find positive effects. Over two out of five of the cross sectional data find positive and statistically significant effects. Firm-level versus industry-level analysis is also another source of variation. Various studies, about 92 per cent use firm-level data, of which 30 per cent and 17 per cent respectively report evidence of positive and negative significant effect. Approximately one out of two of the studies that use industry-level data, report significant positive spillover effects. Combining the data type and the level of data aggregation, 67 per cent of the estimates come from firm-level panel data analyses. I have also considered the number of observations and the time span of the data used to observe if there is systematic variation between small and large studies. Lastly, because developing countries date come from either the World Bank enterprise survey or the national statistics bureaus, I have included a dummy variable to observe systematic difference as a result of data source.

Estimation characteristics: More than two out of five of the studies estimate productivity spillovers using total factor productivity (TFP) as the dependent variable. Others employ a one-step estimation technique using the labour productivity, output or value added. When TFP is computed in the first-step, some authors use OLS while others consider the endogeneity of inputs and employ either the OP (1996) or the LP (2003) estimation techniques. While in the second-step, I include dummies of the estimation techniques performed to report a given estimate and the functional form of the models used. Moreover, dummies for the inclusion of year and sector fixed effects are also created. It should, however, be noted that most primary studies report estimates related to contemporaneous FDI spillover effects for domestic firms while only a few estimates relate to lagged effects of spillovers.

Specification characteristics: Significant heterogeneity also exists with respect to the measurement of foreign presence. Empirical studies use proxy measures in terms of employment, capital, or output share. For instance,

[15] Not correctly removing the issue of dependence in one's MRA can result in a standard error and t-statistics to be calculated incorrectly and this can give a false appearance of the statistical significance level (Stanley and Doucouliagos 2012). Consequently, whether we use clustered data analysis or conventional regression procedure (i.e. OLS), results of the estimated MRA coefficients should be identical.

Wei and Liu (2003) claim that it is better to use employment because many of the spillovers from foreign presence occur through human interaction. The recent Meta-analysis by Mebratie and van Bergeijk (2013), suggests that the use of capital share of foreign investment is more likely to result in a significant spillovers effect than primary studies that use the employment share. In the Meta-data, majority of the studies use the output and employment specification, 45 per cent and 33 per cent respectively. Finally, to observe any systematic difference between the theory of the pipeline model and the domestic capability model, I construct dummies for the inclusion of control variables like absorptive capacity, technological gap, and firm size.

Publication characteristics: I also control for study and journal qualities to find out whether publishing in a peer-reviewed journal systematically results in different outcomes of spillover estimates. To do so, I construct dummies for the inclusion of publication in a peer-reviewed journal, but I also use author's citations in Google Scholar, and journal's rank[16]. Finally, I control the publication year of the study, that is, I try to uncover a publication trend.

To explain the variation in the spillover estimates, I have expanded the FAT and PET of model (3.3.2) to include the moderator variables:

$$\varepsilon_{ji} = \beta_0 + \beta_1 Se_{ji} + \alpha_k X_{kji} + u_i \quad \ldots\ldots\ldots. \text{(3.3.6)}$$

where ε_{ji} is the spillover estimate of j of the i^{th} study, Se_i its standard error, β_0 the true magnitude of spillovers[17], β_1 the magnitude of publication bias and X is a vector of the moderator variables listed in the Appendix Table A.2. Correcting equation (3.3.6) for heteroscedastic with WLS we have:

$$t_i \equiv \varepsilon_{ji}/Se_{ji} = \beta_1 + \beta_0\left(\frac{1}{Se_{ji}}\right) + \alpha_k X_{kji}/Se_{ji} + e_i \ \ldots \text{(3.3.7)}$$

Regression (3.3.7) estimated using the General-to-Specific (G-to-S) modelling approach developed by Charemza and Deadman (1997). The G-to-S modelling starts with a specification in which all potential moderator variables are included in the general equation (3.3.7). Then the most statistically insignificant variables are removed, one at a time, up to the specification in which only significant variables remain (Charemza and Deadman 1997, Doucouliagos and Laroche 2003, Doucouliagos and Stanley 2009, Cipollina and Salvatici 2010, Doucouliagos and Stanley 2011, Stanley and Doucouliagos 2012). In the words of Charemza and Deadman (1997:78), "the strength of G-to-S modelling is that model construction proceeds from a very general model

[16] The national Dutch research school for development studies CERES, for which I involved in providing journals rank in 2013, present journal quality classification through the impact factor of the Institute of Scientific Information (ISI). Based on ISI impact factor, A (high quality) journals ranked from the top one-third cited outlets in the ISI journal category. Thus, I create a dummy for high quality (A ranked journals) and use other classifications as reference.

[17] However, the spillover estimates corrected for selection bias shouldn't be now interpreted only from the single constant term but rather together with vector of X variables. This is because, the moderator variables might affect the decision to present a given estimate (Stanley and Doucouliagos 2012).

in a more structured, ordered fashion, and in this way avoids the worst of data mining”. Then, the specific model is re-estimated using the CRSE data analysis and the MLM to account for the study level dependence.

4. Findings

4.1. Funneling to detect publication bias

Figure 3 shows the funnel plots of the estimated spillovers of FDI. Inspection of the plots seems to reveal a slight heavier midsection on the right-hand side of the plot, implying that many positive results are reported in the literature. The top of the funnel plots are usually a good approximate of the true empirical effect after due allowance for publication bias (Stanley and Doucouliagos 2010). Consequently, in the words of Roberts and Stanley (2005:27) “… for areas of research that contain many studies, the simplest remedy for publication bias is to average the findings from only the largest studies (say, the top 10%),” which is the top portion of the plots. In light of this, Stanley et al. (2010) also argue that giving the most precise 10 per cent a weight of one and the rest a weight of zero can greatly reduce publication bias. Averaging the top 233 (i.e. the top 10%) spillover estimates provide an average of 0.004.

In the absence of publication bias and provided that the most top portion of the plots are more precise, estimated spillovers are expected to vary evenly and randomly around this average. However, the average of all 1233 spillover estimates is 0.172, so that publication bias would seem to be 43 times larger than the average of the most precise estimates. In other words, 97 per cent of the weighted average of reported spillover estimates presented in section 3 is due to publication bias. This kind of publication bias has clear policy implications. For instance, policymakers may expect 1.6 per cent increase in domestic firms’ productivity from a 10 percentage points increase in FDI. However, the top 10 per cent estimates suggest that only 0.04 per cent increases in productivity of domestic firms will occur.

Figure 3 pools published and unpublished study estimates, and Figure 4 provides funnel of published studies only that may indicate a possible additional publication bias from reviewers and editors of journals. If publishing in a peer reviewed journal is characterized by additional publication bias, the funnel plots would move more to right for published studies as compared to the funnel plots of all studies (Havránek and Iršová 2011). In this regard, except the plots being heavier and thinner (all studies and published studies respectively), the shape of the funnel plots seem to remain similar.

All-in-all, close examinations of the funnel plots reveals a somewhat lopsided to the right midsection of published as well as all (published and unpublished) studies. It appears that there is an upward bias, indicating a possible preference for reporting and publishing positive spillover estimates. However, the funnel cannot tell what would be adequate symmetry and also where the top of the plot is located exactly (Stanley 2005). Consequently, a formal, objective statistical method is compulsory. That being said, we can already feel the fog of publication bias.

4.2. FAT and PET results

The formal statistical method for publication bias and genuine effect are reported in Table 1. When all studies are included in the specification, The MLM of regression 2 of Table 1 shows evidence of publication bias. Also only spillover effects from published studies in peer-reviewed journals are considered, I detect publication bias. Further, as a robustness check, the clustered data analysis shows evidence of publication bias. Lastly, to accommodate the potential dependence of estimates within-studies and also as a further robustness check, I report the average studies estimates. In this case, I am left with small number of observations (53 versus 1233, Table 1 and 69 versus 1450, Table A.5).

It is true that "weighting studies equally reduces the influence of researcher discretion in selecting which estimates to include or exclude in the analysis" Krueger (2003:60). Nevertheless, as pointed out, since it is inevitable to lose essential within-study information, this approach is potentially flawed. Having said this, the average-set also uncovers evidence of publication bias when outliers are included (see Table A.5), implying that outliers are important in small sample size. The evidence of publication bias is consistently significant and positive in all specifications reported. So, the funnel diagrams are corroborated and confirmed through the formal MRA. The spillover effects are, therefore, significantly overstated in the estimate. The estimates are likely to be polished as well as the spillover literature, on average, have reported and published many positive spillover effects.

The FAT also serves to investigate whether journal reviewers and editors have been likely to predispose selection pressure in accepting papers. In column 3 of Table 1, the magnitude of publication bias is reported. This column provides evidence of more publication bias for studies published in a peer-reviewed journal. However, this publication bias is not statistically different from the publication bias of all studies. In other words, except through self-censorship, empirical studies have not been probably affected by journal reviewers' and editors' tendency to prefer positive and significant findings of spillovers effect. In light of this, note that the magnitude of publication bias ranges from 0.505 to 1.34. Following the review of Doucouliagos and Stanley (2011), the value of publication bias found in this study is modest to substantial (specifically, the use of MLM as the preferred model since it accounts for both within and between study variations, the bias is substantial). To put this result into perspective, based on the 87 quantitative survey of economics research by Doucouliagos and Stanley (2011), the value of publication bias is 1.58. In contrast, the impact of unionization on worker productivity literature, for instance, has 0.65 coefficient of publication bias, little to modest selectivity bias (Doucouliagos and Laroche 2003). In the current study, I note that the signal of the bias remains unchanged and robust to different methods.

Concerning the true magnitude of spillovers estimate versus the weighted uncorrected average spillovers effect, the inference from the publication bias is important. The slope of model (3.3.3) also provides what Table 1 reports the true magnitude of the effect. In all the specifications, no evidence of genuine spillovers effect from FDI is found. The PET across all specifications is consistently insignificant. Most exciting, putting the within-study information in to consideration the most important empirical effect in question, the overall weighted spillovers effect is a publication bias. Nonetheless, it is worth to mention that these findings are average across all methods. In this regard, I need a multivariate MRA as my inferences may largely depend on other potential sources of heterogeneity like the quality of the primary studies, misspecifications or other characteristics of the primary studies.

4.3. Meta-Regression Analysis

Table 2 presents the results of multivariate MRA using G-to-S modelling approach. The G-to-S procedure in column 1 of Table 2 reveals 12 variables that remain statistical significant. Then, this specific model is re-estimated using the CRSE data analysis and the MLM.

Columns 2 and 3 of Table 2 using the MLM and clustered data analysis respectively report 11 moderator variables that potentially explain the heterogeneity in the reported spillover estimates. The number of years of the data used, the definition of the dependent variable, the estimation techniques, the publication year of the study, the journal rank, and the inclusion of sector fixed effect and technological difference systematically matter to report a given spillover estimate. For instance, a one-step estimation of spillover using output, labour productivity, or value added is likely to find a 0.019 higher adverse spillover effect than the two-step TFP estimation method. At the same time if a random effects, GMM or other spillover estimator is adopted, the estimation result in an upward shift of 0.028, creating on average a more positive estimate compared with the fixed effect regression.

In reference to the specification characteristics, the inclusion of existing technological levels of domestic firms and estimates of lagged spillovers appear to affect the estimates. A specification that controls for the exiting technological difference between domestically-owned firms and foreign-owned firms are likely to find lower spillovers effect (on average 0.054). In light of this, recent researchers that presume the outcome of spillover is not automatic rather depends on the nature of firm heterogeneity (such as, the technological levels) are likely to be valid.

The conceptual debate over how the domestic firms' technological levels influence the outcome of a given spillover estimate offers a significant opportunity for future research. For instance, it would be interesting to investigate how the size of the technological gap between domestic and foreign firms influences potential spillovers. Majority of the studies either associate high (low) absorptive capacity with low (high) technological difference or exclude these important moderator variables from the specification. Furthermore, several researchers report positive spillover effects associated with a large technological gap (e.g., include Castellani and Zanfei 2003, Jordaan 2005, 2008a, 2008b). This relationship and finding may challenge the direct but inverse substitute or the association of low (high) technological gap with high (low) absorptive capacity. Moreover, this study shows that these variables produce opposite signs (although absorptive capacity is not statistically significant) but should be included together and analysed independently. In this regard, either equating the absorptive capacity as the inverse of the technological gap or excluding these moderators from the analysis is potentially flawed, causing a misspecification error.

Lastly on quality characteristics, published studies report spillover estimates that are larger (on average higher by 0.035) than unpublished studies. I also find that publication year of the study affects reported estimates, in that, new studies tend to find a downward trend in spillovers estimate (on average lower by 0.003). Furthermore, high-ranked journals (the impact factor of the journals) is likely to reduce estimated spillover estimates.

4.3.1. Estimating the corrected Meta-effect via a multivariate MRA

The underlying true Meta-effect can be estimated from the result of multivariate MRA conditional on method heterogeneity. This underlying effect is labelled the 'best practice' method (e.g., see Doucouliagos and Stanley 2009, Havránek and Iršová 2011, Stanley and Doucouliagos 2012). There are many potential genuine heterogeneity effects of spillover estimates than suggested by the single in the earlier presented PET[18]. To avoid a subjective judgment, I start from the condition that all the moderator variables are set to be zero. In other words, for unpublished papers that use cross-sectional data aggregated at industry-level among others , the underlying Meta-effect is predicted to have a statistically significant positive effect of 0.124 (t=5.04, using the MLM) and 0.127 (t=5.11, when CRSE analysis used). Note that this Meta-effect is 23 per cent less than the weighted uncorrected average Meta-effect. When I allow for the use of a series snapshot of the data (as opposed to a single snapshot), the MRA model predicts the Meta-effect to reduce to 0.121, but statistically significant at any conventional levels.

Next, I extend the 'best practice' equation by allowing to follow the study by Aitken and Harrison (1999). I chose this study: first, it is published in the American Economic Review journal. Second, it has the highest study citation of all studies in my dataset. Third, the authors use firm-level panel data (as opposed to industry-level cross-section data), estimate a one-step regression and their specification controls for productivity differences across industries. All-in-all, this study seems to be free from model misspecification errors and published in a peer reviewed most rated journal. I further extend such 'best practice' via the recent publication by Mebratie and Bedi (2013) to consider advances in methodology that possibly improve spillover estimations. The authors estimate spillovers in a one-step procedure using labour productivity (as opposed to TFP) and control for firm size effects. The combination of these 'best practice' by Aitken and Harrison (1999) and Mebratie and Bedi (2013), model (3.3.7) predicts a Meta-effect of 0.084 and statistically significant at any conventional levels. The procedure reports similar result when CRSE analysis used, 0.083 with t=3.08. After correcting for publication bias and

[18]In fact the joint test of the significant variables from the MRA revealed that the null hypothesis of zero joint effect has been rejected, $F_{(12, 1220)} = 19.70$ with a p value of less than 0.0001.

misspecification, the true magnitude of the Meta-effect is about 0.084. This implies that the weighted uncorrected average Meta-effect reported in section 3 is greatly exaggerated by about 48 per cent than the actual magnitude of the effect.

A third case would be a study that computes TFP into two-step estimation procedure, specification that controls for technological levels of domestic firms, and fixed effects are used for the estimation of spillovers. Doing these extensions, the best practice estimate results in 0.076 Meta-effect and significant at any conventional levels, which is not much different from the above best practice estimate. Therefore, the magnitude of the Meta-effect after correcting for publication bias and misspecification errors remains economically important.

Having said that, the "worst practice" can be considered as "… (a) mirror image of the best practice estimate" (Havránek and Iršová 2011:240). In light of this, studies that use industry level aggregated cross-sectional data, endogenous TFP estimation, OLS spillover estimation, and specifications that don't control productivity difference across industries among others would be labelled as the worst practice. This worst practice estimation finds a positive statistically significant estimate, 0.151. The procedure finds similar result when the MLM is used, 0.159. In this regard, the positive estimates are partly the result of misspecifications.

4.3.2. Further account for publication bias

After the inclusion of reasonable moderator variables, the presence of publication bias remains valid. Further to this, recall that published studies are more likely to find larger spillover estimates compared to unpublished studies. Most noticeably, my central finding of the presence of publication bias based on funnel plots and simple MRA are corroborated by the multivariate MRA. Apparently, positive spillover effects are associated with publication bias. Consequently, in the context of developing countries, the evidence suggests that the FDI-spillover effects are contaminated with bias towards reporting positive results of spillover estimates.

Following the above discussion of ideal research practice, however, the question is whether the publication bias occurs as a result of everyone's prior interest to follow best practice. It is a fact of life that researchers may prefer to follow conventionally expected results (good practices) to polish their products in order to attract customers (Doucouliagos and Paldam 2009). If authors' or reviewers' prior interest is to estimate or select best practice and not to prefer positive statistically significant results, then the funnel graphs would be symmetrical. To do so, I recall the above best practice research design, that is, studies that use panel data, firm-level analysis, and controlling for sectoral fixed effects[19]. Doing so, as can be seen in Figure 5 and Figure 6, the funnel plots seem to reveal that they are not distributed randomly, in that, slightly skewed to the right portion in both published and all studies. Therefore, they are not

[19]Note that the full design of the best practice is not feasible to follow as very few estimation will left for analysis.

less asymmetrical than plots of section 4.1 and then I conclude that the 'best practise' is not causing the publication bias.

In addition to this method which is a subjective interpretation and based on visual inspection, a more formal statistical method is required. Stanley et al. (2008) demonstrate that for variables that are defined best practice method, the interaction with the standard error should be statistically significant if the method is the source of publication bias[20]. When doing such formal test via equation (3.3.5), none of these aspects of the best practice find statistically significant value[21]. The reported spillovers effect from FDI are, therefore, biased towards positive results. In light of this, a very interesting result is that the best practice approach is not causing the publication bias.

5. The neglected role of transmission channels

Spillover is divided into technological and pecuniary. The former described as the lack of compensation that is caused by the absence of market mechanism to capture the flow of knowledge from one firm to another firm (Smeets 2008, Jordaan 2012). In contrast, the latter considered as occurring indirectly through market mechanism, i.e., external to the production activities of involved firms (Gehringer 2011). These spillovers are assumed to occur through four transmission channels (viz. demonstration, labor mobility, competition and export).

Over the past three decades, an impressive number of empirical studies has investigated these kinds of spillovers. However, the transmission channels through which the presence of foreign-owned firms affect domestically-owned firms have been considerably less frequently investigated. In light of this, the empirical work considerably avoids to discern the channels underlying the spillovers and instead focuses on whether or not the presence of foreign-owned firms influences the productivity of domestically-owned firms. Thus, there is a wide gap between theoretical level and empirical analyses.

Moreover, the studies that investigated spillovers effect are assumed to occur regardless of the nature of firm heterogeneity. More specifically, for instance, from Table 3 they largely ignore the heterogeneity related to the R&D expenditure and the technological levels of domestic firms (as only 10 per cent of the studies control these kinds of heterogeneities), a point also stressed by Mebratie and van Bergeijk (2013) for R&D expenditure. Clearly, universal spillover effects can not exactly indicate how spillover occurs and which domestic firms are gaining. Some may experience positive impacts, others nothing or even negative. For instance, firms with relatively higher level of technology can possibly benefit from spillovers via the competition and/or demonstration effects, while firms with lower level of technology may not be

[20] It is useful to note that the full best practice definition is feasible to use via the formal statistical method. Consequently, I have interacted with and tested the time span of the data, publication status, specification for sector fixed effect, one-step estimations and accounts for misspecification aspects of good practice.

[21] Indeed the joint test of these interactions reveals that the null hypothesis of zero effect has not been rejected (p value of 0.3631).

in a position to compete or imitate (Hamida 2013). Instead the latter kinds of firms may benefit from labor mobility channel.

Thus, the relative importance of the spillover channels varies with the existing firm specific characteristics of domestic firms. I strongly believe that the investigation of overall spillover effects needs to discern the transmission channels through employing various control variables that represent each of the spillovers channels. This would be an important aspect to accurately describe and exactly identify the impact of spillover process, and hence narrowing the heterogeneity nature of spillover estimates. Furthermore, not only from the viewpoint of the academic interest, but also from the viewpoint of policymakers this would be vital to fine-tune the transmission channels by which spillovers effect actually occur. Given the nature of the different spillover transmission channels and firm heterogeneity, therefore, it is tenuous to interpret universal spillover effects. Accordingly, the nature and occurrence of spillovers investigation can gain a great deal from the interaction of the transmission channels under which spillovers effect work and the specific firm characteristics.

6. Conclusion

The study offers a Meta-analysis of intra-sectoral FDI-productivity spillovers effect. I use 1450 reported spillover effects from 69 empirical studies in a large sample of 31 developing countries for the period of 1986 to 2013. In spite of the fact that the oldest study in the dataset was published in 1986, the median study appeared in 2008. The mean and the maximum of spillover estimates taken from a study are 21 and 100, respectively. The median parameter of the spillovers estimate is 11. For each empirical study, I have coded more than 40 potential research dimensions and 4 categories of study and journal qualities. Using different methods, the study investigates, firstly, whether or not the literature suffers from publication bias, and if so, to what extent, and secondly, examines whether or not the empirical evidence supports the existence of a true effect size. Thirdly, the study identifies variables that can explain the variation found in the spillover estimates.

The study presents the following evidence of FDI-spillovers in the context of developing countries. First, in accordance with the seminal findings by Görg and Strobl (2001) and contrary to the Iršová and Havránek (2013) and Mebratie and van Bergeijk (2013), the study uncovers the existence of publication bias (and I add the extent of the publication bias). Reported spillover estimates are significantly overstated, and on average too many positive results have been reported and published. The evidence also shows that the publication bias is not driven by the researcher's prior interest to use the best practice. Second, the spillovers effect found in the empirical studies greatly overstate the true magnitude. Unlike the Iršová and Havránek (2013) that intra-industry spillovers are zero, after correcting for publication bias and misspecification of the primary studies, the underlying Meta-effect is about

0.084 and still economically important[22]. Note that none of the other existing Meta-analyses attempt to establish the underlying true spillovers effect.

Third, using the G-to-S modelling approach, the variation in the spillovers magnitude and its sign were shown to largely depend on study design, that is, method heterogeneity. Spillover estimates are largely affected by the number of years of the data used, the choice of productivity indicators, specification of the model, and spillover estimation techniques. For instance, a one-step estimation of spillovers is likely to find a higher adverse spillovers effect than the two-step TFP approach. Primary studies that use the fixed effects estimators are likely to find a lower spillover than studies that use other estimation models. In reference to study quality, more positive spillovers are likely to be reported in published studies. Excluding sector fixed effect and existing technological levels in the specification of the model may lead to omitted variable bias, in that, researchers may result in a false generalization of the spillovers effect. It is worth noting that the estimation techniques of the G-to-S modelling approach purified the study dependence through the MLM as well as the CRSE approach.

Finally, the study also has crucial lesson with regard to measurement error of previous Meta-analyses. If multiple estimates are collected, the within-study dependence should be identified. As described, misspecification of the primary studies also found to be an important lesson for future researches that partly causing the variation in spillovers effect. Another lesson for future research is the conceptual debate over how domestic firms' existing technological levels influence spillover estimates. Furthermore, not only from academic point of view, but also from policy perspective, it would be more important to separate the different transmission mechanisms under which spillovers actually take place. My review of literature of 69 studies shows that emphasis is given to whether or not spillovers occur. How this spillover actually occur is considered as a black box. In general these offer an interesting future research opportunities and in particular it draws important lessons on how the nature and occurrence of spillovers should be scrutinized.

[22]In other words, the spillover effects found in the empirical studies via the weighted uncorrected average effect overstate the actual magnitude of the Meta-effect by about 48 per cent.

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Tables

Table 1: Meta-Regression Analysis of publication bias and a true effect of estimated spillover

Estimation Method	Variables		
	1/SE (beyond bias, true effect)	*Intercept (publication bias)*	*N*
Weighted Least Square (1)			
All studies	0.0004 (0.10)	**0.505**** (2.22)	1233
Published	-0.0005 (-0.05)	0.572 (1.49)	694
Multilevel mixed-effects (2)			
All studies	-0.006 (-1.16)	**1.06**** (2.19)	1233
Published	-0.012 (-1.14)	**1.34*** (1.76)	694
Clustered data analysis (3)			
All studies	0.0004 (0.06)	**0.505**** (2.07)	1233
Published	-0.0005 (-0.02)	**0.572*** (1.77)	694
Average (40			
All studies	0.026 (1.16)	0.380 (0.81)	53
Published	0.024 (0.99)	0.384 (0.59)	34
Weighted average effect	**0.16****		

Source: Author's own computation from collected empirical studies

Notes: *dependent variable is the t-statistics of the FDI-spillover effect. (t-values in parentheses). ***p<0.01, **p<0.05 and *p<0.10. N denotes the number of FDI-spillover estimates and the weighted average uncorrected spillover effect is using sample size as weights which is reported in section 3.2.*

Table 2: Multivariate MRA model using the General-to-Specific approach

Moderator Variables	Column 1: WLS	Column 2: MLM	Column 3: CRSE
1/se ($\boldsymbol{\beta_0}$)	0.127***	0.124***	0.127***
	(0.023)	(0.025)	(0.025)
Intercept ($\boldsymbol{\beta_1}$)	0.407*	0.472*	0.407*
	(0.215)	(0.265)	(0.226)
Data characteristics			
Time span	-0.003***	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)
No. of firms	0.000004**	0.000003	0.000004
	(0.000002)	(0.000002)	(0.000003)
Estimation Characteristics			
One step estimations	-0.019**	-0.018**	-0.019*
	(0.008)	(0.008)	(0.009)
Fixed effects estimators	-0.028***	-0.028***	-0.028*
	(0.007)	(0.008)	(0.015)
Difference	-0.026**	0.026**	0.026**
	(0.011)	(0.012)	(0.011)
Sector fixed effects	-0.024***	-0.022***	-0.024***
	(0.008)	(0.008)	(0.006)
Specification characteristics			
Technological gap	-0.054***	-0.053***	-0.054***
	(0.014)	(0.015)	(0.016)
Lagged spillover	-0.167***	-0.163***	-0.167***
	(0.018)	(0.019)	(0.019)
Publication characteristics			
Published	0.035**	0.035**	0.035*
	(0.016)	(0.017)	(0.021)
Publication date	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)
Journal rank	-0.035**	-0.035**	-0.035*
	(0.016)	(0.017)	(0.019)
Observations	1233	1233	1233

Source: Author's own computation from collected empirical studies

Notes: *dependent variable is the t-statistics of estimated spillover*; *standard errors are reported in parenthesis*
** significant at 10%; ** significant at 5%; *** significant at 1%*

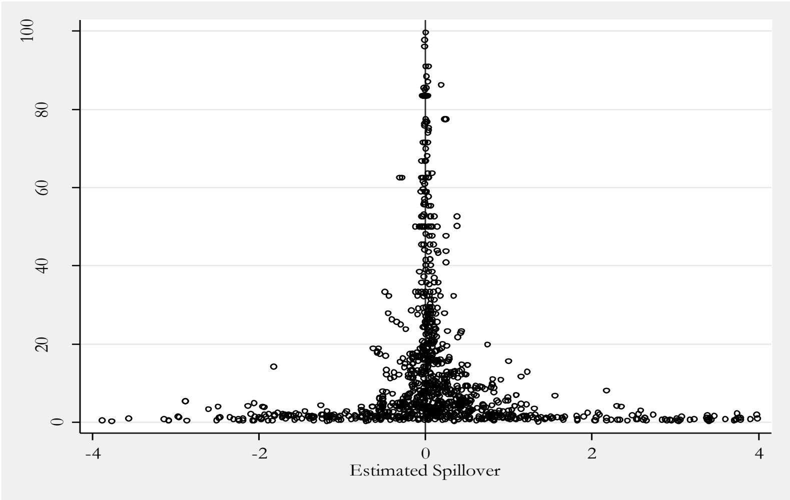
Table 3: Firm heterogeneity and FDI spillovers effect

Variable	Positive & Significant at 10%		Insignificant at 10%		Negative & significant at 10%		Total No.
	No.	%	No.	%	No.	%	
Export	110	38	159	55	21	7	290
R&D	41	28	84	56	24	16	149
Firm size	160	29	269	50	112	21	541
Technological gap	57	36	59	39	40	25	156

Source: Author's own computation from collected empirical studies

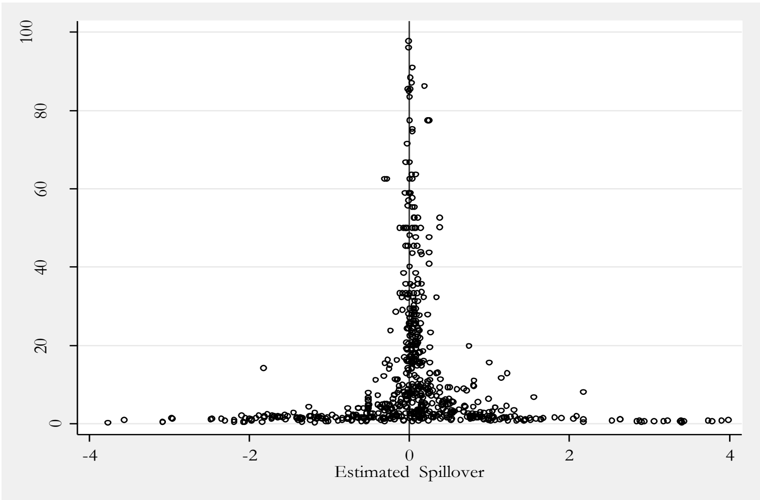
Figures

Figure 3: Funnel plots of estimated FDI-spillover effects: All studies



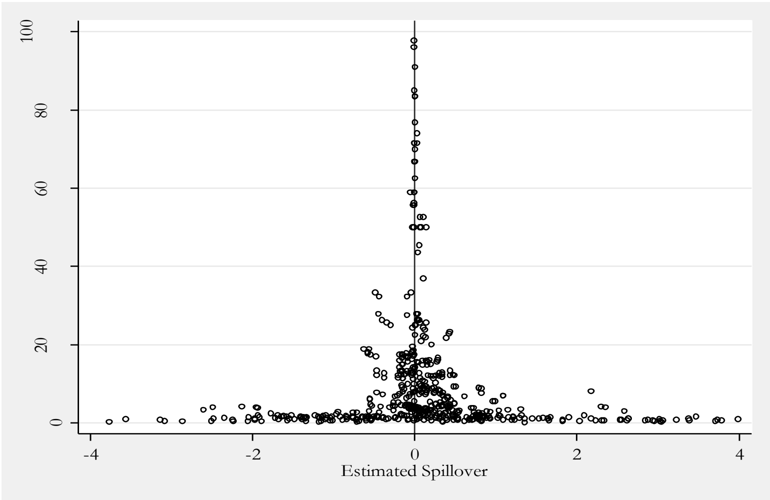
Source: Author's own computation from collected empirical studies

Figure 4: Funnel plots of estimated FDI-spillover effects: Published studies



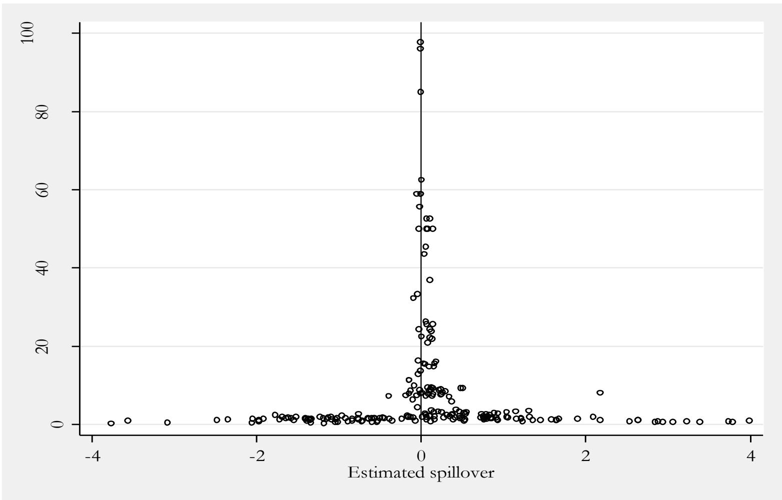
Source: Author's own computation from collected empirical studies

Figure 5: Funnel plots of estimated FDI-spillover effects: best practice, all studies



Source: Author's own computation from collected empirical studies

Figure 6: Funnel plots of estimated FDI-spillover effects: best practice, published studies



Source: Author's own computation from collected empirical studies

Appendices

Table A. 1: FDI-spillover studies used in the Meta-Analysis

Authors (year)	Host Country	Data Aggregation	Data Timespan
Aitken & Harrison (1999)	Venezuela	Firm level	1976-89
Albornoz & Kugler (2008)	Argentina	Firm level	1992-2001
Aldaba & Aldaba (2012)	Philippine	Industry level	1988-98
Aslanoğlu (2000)	Turkey	Industry level	1993
Björk (2005)	Chile	Firm level	2000
Blalock & Gertler (2008)	Indonesia	Firm level	1988-96
Blalock & Gertler (2009)	Indonesia	Firm level	1988-96
Blalock & Simon (2009)	Indonesia	Firm level	1988-96
Blomström (1986)	Mexico	Industry level	1970
Blomström & Sjöholm (1999)	Indonesia	Firm level	1991
Blomstrom & Wolff (1994)	Mexico	Industry level	1970/75
Blyde et al. (2004)	Venezuela	Firm level	1995-2000
Bouoiyour & Akhawayn (2003)	Morocco	Industry level	1987-96
Bwalya (2006)	Zambia	Firm level	1993-95
Castro (2012)	Chile	Firm level	2001-07
Cheng (2011)	Cambodia	Firm level	2005-06
Chuang & Lin (1999)	Taiwan	Firm level	1991
Chudnovsky et al. (2008)	Argentina	Firm level	1992-2001
Cuyvers et al. (2008)	Cambodia	Firm level	2000
Erdogan (2011)	Turkey	Firm level	2004-08
Feinberg & Majumdar (200	India	Firm level	1980-94
Gachino (2010)	Kenya	Firm level	1994-2001
Haddad & Harrison (1993)	Morocco	Firm level	1985-89
Henning (2013)	Ten Latin America	Firm level	2006-10
Jordaan (2005)	Mexico	Firm level	1993
Jordaan (2008a)	Mexico	Firm level	1994
Jordaan (2008b)	Mexico	Firm level	1994
Jordaan (2011)	Mexico	Industry level	1994
Kathuria (2000)	India	Firm level	1975-89
Kathuria (2001)	India	Firm level	1975-89
Kathuria (2002)	India	Firm level	1989-97
Kee (2005)	Bangladesh	Firm level	1999-2003
Kee (2013)	Bangladesh	Firm level	1999-2003
Khalifah & Adam (2009)	Malaysia	Firm level	2000-2004
Khawar (2003)	Mexico	Firm level	1990
Kinuthia (2013)	Kenya & Malaysia	Firm level	2000-05
Kohpaiboon (2006)	Thailand	Firm level	1996
Kokko (1994)	Mexico	Industry level	1970
Kokko (1996)	Mexico	Industry level	1970
Kosteas (2008)	Mexico	Firm level	1990

Köymen (2009)	Turkey	Firm level	1990-2001
Le & Pomfret (2011)	Viet Nam	Firm level	2000-06
López (2002)	Mexico	Firm level	1993-99
Managi & Bwalya (2010)	Kenya, Tanzania & Zimbabwe	Firm level	1993-95
Marin & Bell (2006)	Argentina	Firm level	1992-96
Marin & Sasidharan (2010	India	Firm level	1994-2002
Mebratie & Arjun (2013)	South Africa	Firm level	2003-07
Melese & Waldkirch (2011)	Ethiopia	Firm level	2002-09
Na-Allah & Muchie (2009)	South Africa	Industry level	2004
Narula & Marin (2005)	Argentina	Firm level	1992-2001
Nguyen (2008)	Viet Nam	Firm level	2000-05
Nguyen C. D. et al. (2008)	Viet Nam	Firm level	2000-04
Nguyen A. N. et al. (2008)	Viet Nam	Firm level	2000-05
Nicholas Okot (2013)	Uganda	Firm level	2005-2011
Rattsø & Stokke (2003)	Thailand	Industry level	1975-96
Rutaihwa (2013)	Tanzania	Firm level	2007
Salim & Bloch (2009)	Indonesia	Firm level	1988-2000
Sarkar & Lai (2009)	India	Firm level	2002-05
Sasidharan & Ramanathan (2007)	India	Firm level	1994-2002
Sjöholm (1999a)	Indonesia	Firm level	1980/1991
Sjöholm (1999b)	Indonesia	Firm level	1980/1991
Takii (2009)	Indonesia	Firm level	1990-95
Takii (2011)	Indonesia	Firm level	1990-95
Taymaz & Yłlmaz (2008)	Turkey	Firm level	1990-96
Todo & Miyamoto (2006)	Indonesia	Firm level	1994-97
Thuy (2005)	Viet Nam	Industry level	1992-99, 2000-02
Van Thanh & Hoang (2010)	Viet Nam	Firm level	2003-07
Villegas-Sanchez (2009)	Mexico	Firm level	1992-2001
Waldkirch & Ofosu (2010)	Ghana	Firm level	1992-98

Source: Author's own computation from collected empirical studies

Note: extended information such as, the choice of dependent variable, definition of foreign proxy, pages, volumes, issue, and outlet of the empirical studies can be provided up on request.

Table A. 2: Definition of variables and descriptive statistics

Moderator Variable	Definition	Mean (standard deviation)
1/se	The precision of estimated spillover semi-elasticity	30.49 (56.28)
Data Characteristics		
Panel data	=1 if panel-data are used	0.726 (0.446)
Firm level	=1 if firm-level data are used	0.929 (0.256)
Data source	=1 if the data come from World Bank data (national data base source as a base)	0.816 (0.388)
Time span	The number of years of the data used	5.96 (3.70)
No. of firms	The (the number of observations used)/(time span)	2130.6 (3246.7)
Balanced data	=1 if balanced data set is used	0.178 (0.383)
Estimation Characteristics		
Linear/ Log-log	=1 if the coefficient is taken from a specification different from log-level	0.120 (0.239)
Differences	=1 if the regression is estimated in differences	0.131 (0.338)
Lagged spillover	=1 if the coefficient represents lagged foreign presence	0.105 (0.306)
Year fixed effects	=1 if year fixed effects are included	0.564 (0.496)
Sector fixed effects	=1 if sector fixed effects are included	0.580 (0.494)
OLS	=1 if OLS used for the estimation of spillovers (random effect, GMM, WLS and others as a base)	0.398 (0.490)
Fixed effects	=1 if fixed effects used for the estimation of spillovers (random effect, GMM, WLS and others as a base)	0.269 (0.444)
One step estimations	=1 if spillovers are estimated in one step using output, value added, or labour productivity as the dependent variable	0.547 (0.498)
OLS first TFP	=1 if OLS is used in the first phase of TFP estimation	0.036 (0.188)
Olley-Pakes or Levinsohn-Petrin	=1 if the Olley–Pakes method is used in the first phase of TFP estimation	0.499 (0.500)
Specification Characteristics		
Foreign presence in employment	=1 if proxy for foreign presence is employment (base output and others)	0.352 (0.478)
Foreign presence in equity	=1 if proxy for foreign presence is equity (base output and others)	0.178 (0.383)
Response variable is labour productivity	=1 if response variable is labour productivity (TFP or other efficiency measures as a base)	0.295 (0.456)
Response variable is output	=1 if response variable is output (TFP or other efficiency measures as a base)	0.118 (0.322)
Technological gap	=1 if specification controls for technology gap.	0.097 (0.295)
Absorptive Capacity	=1 if the specification controls for absorption capacity using R&D expenditure or percentage of a firm's workers with college or higher degrees.	0.202 (0.402)
Firm size (sector competition)	=1 if the specification controls for firm size (sector competition)	0.333 (0.472)
All firms	=1 if both domestic and foreign firms are included in the regression	0.337 (0.473)
Publication Characteristics		
Publication date	The publication year of the study (1986 as a base).	21.88 (3.99)
Published	=1 if the study was published in a peer-reviewed journal	0.563 (0.496)
Study citations Google Scholar	Study citations in Google Scholar per age of the study. collected in August 2013.	8.174 (25.026)
Journal rank	=1 if the study published in high journal rank, collected in August 2013.	0.325 (0.467)

Source: Author's own computation from collected empirical studies

Table A. 4: List of studies not included in the Meta-Analysis

Reasons for Exclusion	List of Studies					
No empirical estimates; no econometric analysis	Adams (2009a)	Adams (2009b)	Akinlo (2004)	Alfaro (2003)	Alfaro et al. (2006)	Alfaro et al. (2009)	Alfaro et al.(2010)
	Asiedu (2002)	Blomström (2002a)	Blomström (2002b)	Bouoiyour (2007)	Chidiak (2008)	Cleeve (2009)	Cotton & Ramachandran (2001)
	Crespo & Fontoura (2007)	Dupasquier & Osakwe (2006)	Gelb & Black (2004)	Görg & Greenaway (2004)	Görg & Strobl (2005)	Goldberg (2004)	Hanson (2009)
	Herzer (2011)	Jenkins & Thomas (2002)	Keller (2001)	Kien (2008)	Kim & Hwang (2000)	Krugell (2005)	Laborda Castillo et al. (2011)
	Lipsey & Sjöholm (2011)	Mengistae & Pattillo (2004)	Moran (2005)	Morisset (2000)	Mühlen (2012)	Narula & Portelli (2004)	Naudé & Krugell (2007).
	Navaretti & Tarr (2000)	Ng (2006)	Ng (2007)	Ndikumana & Verick (2008)	Onyeiwu & Shrestha (2004)	Osada (1994)	Pradhan (2006)
	Rojas-Romagosa (2006)	Sadik & Bolbol (2001)	Saggi (2002)	Sawada (2010)	Seetanah & Khadaroo (2007)	Temenggung (2007)	Thuy (2005)
	Tondl & Fornero (2010)	Tybout (2000)	Uttama & Peridy (2010)	Vu et al. (2008)			
Duplicate studies (similar version included)	Aitken & Harrison (1994)	Narula & Marin (2003).	Sasidharan (2006)				
Not productivity spillovers	Diao et al. (2005)	Elu & Price (2010)	Enisan (2005)	Evenson (2000)	Farole & Winkler (2012)	Fons-Rosen et al. (2012)	Fortanier (2007)
	Matthias & Javorcik (2009)						
Not horizontal spillovers	Fernandes & Paunov (2012)	Iyer (2008)	Jordaan (2013)	Kugler (2006)	Vacek (2010)		
Not from Developing countries	Altomonte & Pennings (2005)	Altomonte & Pennings (2009)	Akimova & Schwodiauer (2004)	Akulava (2008)	Ang & Madsen (2012)	Bijsterbosch & Kolasa (2010)	Bosco (2001)
	Cipollina et al. (2012).	Crespo et al. (2009)	Damijan et al. (2003a)	Damijan et al. (2003b)	Damijan et al. (2008)	Damijan et al. (2012).	De Propris & Driffield (2006).
	Djankov and Hoekman (2000)	Driffield & Taylor (2000).	Fons-Rosen et al. (2013).	Frydman et al. (1999)	Geršl (2008)	Geršl et al. (2007)	Glozer (2006)

Not from Developing countries	Görg & Strobl (2005).	Görg et al. (2006).	Gorodnichenko et al. (2007)	Hagemejer and Kolasa (2008)	Hagemejer & Kolasa (2011).	Halpern & Murakozy (2007).	Haskel et al. (2007).
	Jabbour, and Mucchielli (2007)	Javorcik (2004)	Javorcik (2008)	Javorcik. and Spatareanu (2005)	Javorcik. and Spatareanu (2008)	Javorcik et al. (2004)	Javorcik & Spatareanu (2009).
	Javorcik & Spatareanu (2011).	Jensen (2004).	Kejûar (2006).	Keller (2009).	Kejžar & Kumar (2006).	Kinoshita (2001).	Kolasa (2008)
	Konings (2001)	Lipsey (2006).	Lutz & Talavera (2004)	Lutz et al. (2006).	Marcin (2008).	Merlevede & Schoors (2005).	Merlevede & Schoors (2007).
	Merlevede & Schoors (2009).	Nicolini & Resmini (2007)	Rybalka (2001).	Sabirianova et al. (2005).	Schoors & Merlevede (2007)	Sgard (2001)	Slaughter. (2002)
	Sica & Reganati (2007)	Sinani & Meyer (2004)	Slaughter (2002).	Stancik (2007)	Stančík (2009)	Takechi (2011).	Terlak (2004).
	Tian et al. (2004)	Torlak (2004).	Vahter (2004)	Vahter & Masso (2006)	Vahter (2010).	Yudaeva et al. (2003)	Zajc Kejžar & Kumar (2006)
	Zemplinerova & Jarolim (2001)	Zukowska-Gagelmann (2001).					
Non-English studies	Murra (2006)						
Not accessible for download	Batra et al. (2003)	Demmel et al. (2013)	Keini (2008)	Kien (2008).	Vacek (2007).		
Sample means are missing or/and authors are not willing to support	Blomström & Persson (1983)	Kathuria (2010)	Kokko et al. (1996)	Kokko et al. (2001)	Takii (2005)		

Table A. 5: Meta-Regression Analysis of publication bias and a true effect of estimated spillover. Sensitivity analysis with the inclusion of outliers (full data-set both for all-set and average-dataset).

Estimation Method	Variables		
	1/SE (beyond bias true effect)	*Intercept (publication bias)*	*N*
Weighted Least Square (1)			
All studies	0.000 (0.19)	**0.525*** (3.03)	1450
Published	-0.000 (-0.23)	**0.565*** (1.84)	778
Multilevel mixed-effects (2)			
All studies	-0.000 (-0.28)	**0.88**** (2.17)	1450
Published	-0.000 (-0.61)	**1.03*** (1.66)	778
Clustered data analysis (3)			
All studies	0.000 (0.35)	**0.523*** (1.76)	1450
Published	-0.000 (-1.23)	0.565 (1.10)	778
Average (4)			
All studies	-0.000 (-1.41)	**1.07** ** (2.54)	69
Published	-0.000 (-1.22)	**1.23** * (1.89)	43
Weighted average effect	0.16		

Source: Author's own computation from collected empirical studies

Notes: *dependent variable is the t-statistics of the FDI-spillover effect. (t-values in parentheses). ***p<0.01, **p<0.05 and *p<0.10. N denotes the number of FDI-spillover estimates and the weighted average uncorrected spillover effect is using sample size as weights.*