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Spillovers and Exports: A Meta-Analysis

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Abstract: This study uses meta-analysis to analyze the empirical literature on spillovers and exports. It collects 3,291 estimated spillover effects from 99 studies. The estimated spillover effects in the literature span a large number of types and measures of both exports and spillovers. As a result, we transform estimates to partial correlation coefficients. We analyze these transformed effects using four different versions of Weighted Least Squares (WLS) estimators, incorporating both meta-analytic "Fixed Effects" and "Random Effects". Our analysis produces three main findings. First, while we estimate a overall mean effect of spillovers on exports that is statistically significant, the size of the effect is economically negligible. Second, we find modest evidence for the existence of publication bias in the empirical literature. Publication bias can arise when researchers and journals have a preference to publish articles that find positive and significant results. While some of our tests indicate the presence of publication bias, in every case the size of the effect is small. Third, using both Bayesian Model Averaging and frequentist meta-regression analysis, we find that some data, estimation, and study characteristics are significant in some regressions. However, only a few of the characteristics are robust, and none are large in size.

Keywords: Spillovers, Exports, Meta-analysis; Meta-Regression Analysis; Bayesian Model Averaging, Partial Correlation Coefficient

JEL Classifications: D62; F10; F20; O30; C80

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1. INTRODUCTION

Many academics and policymakers believe that accessing foreign markets through exports leads to enhanced firm performance. They argue that participation in export markets can be an important source of knowledge acquisition, information assimilation, technological knowhow, and other benefits, leading to improvements in economic performance (Krugman 1980; Bernard et al. 2003). Through comparisons with advanced foreign competitors in global markets, this "learning-by-exporting" channel helps firms improve the quality of their products and production processes (Bernard and Jensen 1999; Falvey et al. 2004). Correspondingly, the World Bank, in its policy recommendations for national governments, suggests that "Improving the policy and business environments to create conditions favorable to trade, especially exports, is one of the most important ways for countries to obtain knowledge from abroad." (World Bank 1998, p18).

Promoting FDI is widely considered an effective means for encouraging trade. This belief has led to significant competition among governments to attract foreign capital using different investment incentives and tax allowances. Almost 90% of the national regulatory investment regime changes introduced in more than 100 countries in 1991–2012 offered more favourable conditions for foreign direct investment in those countries (UNCTAD 2013). The incentives provided by governments for foreign investment are consistent with a belief on their part in the existence of spillover benefits.

One type of spillover benefit that has received attention in the literature is the stimulatory effect that exporters can have on other firms' export performance. If exporting begets more exporting via spillovers, and exporting produces beneficial outcomes for the economy, then there may be a role for public policy to incentivize export behavior by firms. This spillover effect is the focus of our study.

The empirical literature provides mixed evidence on this subject. On the one hand there is a large body of empirical literature that finds evidence for exports creating spillover effects that stimulate increased exporting behavior in other firms (Aitken et al. 1997; Rodríguez-Pose et al. 2013; Bannò et al. 2015; Dumont et al. 2010; Cieślik and Hagemejer 2014; Choquette and Meinen 2015; Malmberg et al. 2000; Harasztosi 2016; and De Rosa 2006). On the other hand, there is a somewhat smaller body of literature that does not find evidence of spillover effects (Bernard and Jensen 2004; Alvarez 2007; Barrios et al. 2003; Silvente and Giménez 2007; Kemme et al. 2014). Some studies even report finding evidence of negative spillover effects (Ruane and Sutherland 2005).

There may be good explanations for this ambiguous state of affairs. It could be that studies are testing the effects of different kinds of spillover, and that some types of spillovers affect exports and others do not. Alternatively, it could be that there are contextual factors that encourage or inhibit spillover effects, such as country or regional differences or differences in time periods or types of industries. There may also be differences in the estimation methodologies employed by researchers, whereby some estimation procedures are better able to detect spillover effects than others. Studies may also differ in the control variables they include in their specifications, and these may affect the magnitude, significance and direction of spillovers.

To investigate this further, we use the method of "meta-analysis" (Stanley and Doucouliagos 2012). Meta-analysis is a statistical method for analyzing estimates from multiple studies that estimate the same or a similar effect. The method both enables the estimation of an "overall" average effect and provides a procedure for identifying factors that explain why different studies obtain different estimates (Wooster and Diebel 2010, pp. 646).

While there are other meta-analyses associated with spillovers, ours is the first to investigate the relationship between spillovers and exports.[1] We analyze 3,291 estimated

[1] Other meta-analyses studying the effects of spillovers include Görg and Strobl (2001); Meyer and Sinani (2009); Havranek and Irsova (2010); Mebratie and van Bergeijk (2013); Irsova and Havranek (2013); Iwasaki and Tokunaga (2016); Demena and van Bergeijk (2017); and Bruno and Cipollina (2018).

spillover effects gleaned from 99 studies. Our main findings are as follows. First, we find a positive and statistically significant, overall effect of spillovers on exports. However, the size of the effect is economically negligible. This suggests that there is little evidence to support the subsidization of exports because of spillovers. Second, we find modest evidence for the existence of publication bias in the empirical literature. Publication bias can arise when researchers and journals have a preference to publish articles that find positive and significant results. While some of our tests indicate the presence of publication bias, in every case the size of the effect is small. Finally, we find that estimates systematically vary according to a number of data, estimation, and study characteristics. For example, our analysis identifies larger spillover effects for studies on Chinese firms. We also estimate that R&D spillovers are larger than spillovers associated with export value or size of employment. Again, however, the size of these effects is small.

The rest of the paper is organized as follows. Section 2 discusses possible ways by which spillovers affect exports. Section 3 describes the data and variable measurements used in our analysis. Section 4 explains the different empirical procedures we employ to estimate the overall mean effect. It then presents the correspoinding estimates, including the results of tests for publication bias. Section 5 reconciles our findings on spillovers and exports with other meta-analyses that have examined the effect of spillovers on firm performance. Section 6 reports the use of Bayesian Model Averaging to identify factors that can explain why different studies obtain different estimates of spillover effects. Section 7 complements that analysis by using meta-regression analysis (MRA) to relate estimated spillover effects to data, estimation, and study characteristics. Section 8 concludes.

2. THE RELATIONSHIP BETWEEN SPILLOVERS AND EXPORTS

Many channels have been hypothesized for spillovers to affect exports. Pioneering work by Melitz (2003) suggests that spillovers can affect a firm’s export performance in two ways. First, they can have a direct effect by extending the information set available to domestic firms, lowering the perceived level of sunk costs of exporting and thereby inducing non-exporters to export. These informational spillovers can take many forms, including information about the characteristics of trading partners and knowledge about foreign consumers' tastes and preferences. This insight builds on earlier work about the importance of information, such as Clerides et al. (1998) who note that entry costs to penetrate foreign markets are often knowledge intensive. Second, spillovers can indirectly affect exports by improving firms' productivity, which, by the Melitz model, leads to greater exports.

Kneller and Pisu (2007) suggest another channel. Competition from foreign firms can cause domestic firms to improve their productivity. By the Melitz model, this can lead to greater export behaviour. Spillover effects can also affect exports via economies of agglomeration as firms take advantage of shared local labour markets (Duranton and Puga 2004) and local infrastructure facilities (Greenstone et al. 2010). Similarly, firms can reduce transportation costs due to proximity to local suppliers and/or buyers (Krugman 1991). Intra-industry and supplier-buyer linkages can generate spillovers via sector-specific technological knowledge (Choquette and Meinen 2015; Kneller and Pisu 2007).

Another key mode is foreign direct investment (FDI). FDI can promote the transfer of advanced technology, superior managerial skills, and innovative product designs. Region-specific external economies associated with FDI can facilitate access to transportation infrastructure and information about foreign consumers (Kemme et al. 2014). Additionally, FDI makes domestic firms more easily aware of potential innovations taking place abroad. This knowledge can be used to improve their position both in domestic and foreign markets.

As spillovers take a variety of forms, we identify several measures that help us evaluate whether spillovers have a significant role in promoting exports. These variables are described in the next section.

3. DESCRIPTION OF DATA AND VARIABLES[2]

3.1 Selection of Studies

Our search for estimated effects followed the procedure outlined in Stanley et al. (2013) that is widely considered as best-practice in the meta-analysis literature. To be included in our meta-analysis, a study had to estimate a regression equation that takes the general form of

$$(1) \qquad Exports = \alpha + \beta Spillovers + \sum_{k=1}^{K} \gamma_k Z_k + error,$$

where β is the effect of spillovers on exports and the Z_k is a set of control variables.

We employed two categories of keywords, "Export" keywords and "Spillover" keywords, and used the search engines Web of Science, Google Scholar, Scopus, JSTOR, EBSCO, ProQuest and RePEc to identify studies that investigate the link between exports and spillovers. The "Export" keywords consisted of "export", "trade", "export decision", "export propensity", "export intensity", "export share", "export performance" and "firm performance". The "Spillover" keywords consisted of "agglomeration", "urbanization", "localization", "external economies", "externality", "spillovers", "export spillovers", "FDI spillovers", "spatial spillovers", "geographical spillovers", "sectoral spillovers" and "industrial spillovers". We combined keywords from both categories when using the respective search engines. Our initial search yielded over 350 studies, including peer-reviewed journal articles, working papers, conference proceedings, doctoral dissertations and master's theses.

To refine our search, we eliminated any papers that did not satisfy the following inclusion criteria: (i) the study must be empirical, (ii) the dependent variable must measure export performance and (iii) the explanatory variables must include one or more spillover measures. This reduced the sample to 115 studies.

To avoid double counting of multiple versions of the same study, such as working

[2] All the data and code necessary to reproduce the results in this paper are publicly available at Harvard's Dataverse: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910%2FDVN%2FSJ5HP1

papers, we only included the published version, which reduced the sample to 106 studies. We further reduced the sample by eliminating studies where a spillover variable was specified in quadratic form or where it appeared as both a main and interaction effect. To calculate the marginal effects needed for our study, these specifications required information not available to us, such as the covariance of the respective coefficient estimates. This reduced the sample to 99 studies and 3,359 estimated effects.

3.2 Variables

In addition to estimating the overall mean effect, we also want to identify data, estimation and study characteristics that may explain why different studies estimate different effects. TABLE 1 describes the information that we record for each estimate in our study.[3] Note that not all of these variables were actually used in our analysis, either because there were insufficient observations in a category or because the variable belonged to a set of indicator variables and was held out as the benchmark. Omitted variables are indicated in the table with an asterisk. We generally do not have expectations about the signs of the respective variable coefficients. As a result, the associated analysis should be viewed as exploratory.

3.2.1 Main Variables of Interest – Spillover Measures

3.2.1.1 Spillover Types

Researchers have posited many channels by which firms' activities can spill over and affect the export performance of other firms. Spillovers are generally considered to be either from firms that are located near the exporter and/or from firms in the same industry. Some spillovers are specifically associated with foreign-owned firms and/or directly related to other exporters. We created dummy variables to correspond to the respective spillover types – whether it was from *Exporters*, from firms in the same *Region* and/or the same *Industry,* and whether the

[3] Once the final sample was determined, a team of researchers coded various data, estimation and study characteristics that could affect the size of the estimated spillover effects. Two coders independently recorded the respective characteristics. Discrepancies were then noted and reconciled.

spillovers were measured as coming from *FDI*.[4] These categories are not mutually exclusive. A study could estimate a spillover effect that simultaneously belonged to all four categories.

3.2.1.2 Spillover Measures

The spillover variables in the 99 studies used in our sample also differed in their units of measurement. We created six mutually exclusive dummy variables to indicate the spillover measures used in the primary studies – if the study used the *Number* of exporting firms, the *Value* of exports, the *Employment* of the firms, the *Output* of the firms, the *R&D* of the firms or *Other* measures[5]. Because the categories *Output* and *R&D* seldom appear in our sample, these, along with *Other*, are held out as benchmark categories.

3.2.2. Dependent Variable - Measures of Export Performance

Among the measures that have been used by studies of export performance, some focus on the firm's decision to export, while others focus on what market, products or quantity was exported. We created a dummy variable *Categorical* to indicate that the export measure used in the prim study was based on a discrete number of categories, as opposed to being continuous[6].

3.2.3. Other Data, Estimation, and Study Characteristics

We collected information on a number of other variables. *Firm-level* indicates that the estimated spillover effect comes from a regression that used firm-level data. The alternative is aggregated data, where the unit of analysis is a geographical jurisdiction, such as a state or region, or an industry aggregate. Almost all of our estimated spillover effects (92.3%) come from firm-level data. *Domestic* indicates that the estimated spillover effect focuses on domestic firms, as opposed to foreign, or a mix of foreign and domestic firms.

SampleYear measures the age of the dataset that was used to estimate the spillover

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[4] See Appendix 2 for further details of the spillover type categories used.
[5] See Appendix 3 for further details of the spillover measure categories used.
[6] See Appendix 1 for further details of the export performance measure categories used.

effect. Country and regional variables (*OECD, EU, Developing, China*) were created to indicate the geographical source of the estimated effects. The categories are not mutually exclusive. For example, a study that used data from the EU would also be categorized as using data from the OECD. For this reason, and in order to focus on differences between OECD countries, China and the rest of the world, the empirical analysis drops *EU* and *Developing.*

We created five categories to indicate industry-specific spillover effects: *Manufacturing, Service, IT, Food* and *Other Industry*, where *OtherIndustry* includes studies that spanned multiple industries. The categories are mutually exclusive. We omit *Service, IT,* and *Food* because they occur infrequently. Accordingly, our study only includes an industry variable for manufacturing, with all other industries constituting the omitted category. Estimation methods were categorized in three mutually exclusive categories: *Probit/Logit/Tobit*, *OLS/GLS* and *OtherEstimation,* with the latter two combined to form the comparison group.

A further advantage of our data analysis is that it allows us explore the extent to which endogeneity affects estimates of spillover effects. Endogeneity can arise from simultaneity, sample selection and omitted variables. Accordingly, we created dummy variables if the estimated effect used an estimation procedure that addressed these: *IV, SampleSelection* and *FixedEffects*, respectively.

If we are willing to argue that simultaneity and sample selection generate a positive bias – that is, if firms that export more are also likely to be located in areas with greater spillovers - then correcting this bias should result in smaller estimates. In the case of panel fixed effects correcting for omitted variables, it is not possible to sign the bias without further knowledge about the omitted, time-constant variables.

We also created variables to indicate commonly-included control variables, as these could also affect the spillover effects estimated by studies. We have dummy variables that indicate that a study controlled for firm size, firm productivity, labor quality, capital/assets and R&D expenditures. Lastly, we have variables that indicate various facets of study quality: whether the study was published in a peer-reviewed journal (*Journal*), the impact factor of the journal where the study was published (*Impact*) and the number of Google Scholar citations the study received (*Citations*).

4. META-ANALYSIS: METHODOLOGY AND ESTIMATES OF OVERALL MEAN EFFECT[7]

4.1 Transformation of Estimated Effects into Partial Correlation Coefficients (*PCCs*)

In a meta-analysis, the dependent variable is the estimated effects, $\hat{\beta}s$, from primary studies (cf. Equation 1). However, in our analysis the estimated effects are not directly comparable even though they are all estimating the "same thing", because the measures used for spillovers and exports are so diverse. Appendices 1-3 give a flavor of the diversity of variables that researchers have used to measure spillovers and exports.

How to aggregate and compare diverse estimates is a common problem in meta-analyses. There is a widely employed solution - transforming estimated coefficients to partial correlation coefficients (*PCCs*):

(2.a) $$PCC_i = \frac{t_i}{\sqrt{t_i^2 + df_i}},$$

where t_i and df_i are the t-statistic and degrees of freedom associated with the respective estimated effect.[8] The corresponding standard error is given by:

(2.b) $$SE(PCC_i) = \sqrt{\frac{1 - PCC_i^2}{df_i}}.$$

The *PCC* belongs to the family of "r-based" effect sizes (Borenstein et al. 2009; Ellis

[7] All the data and code necessary to replicate the empirical analysis in this study are publicly available at Dataverse: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/SJ5HP1.

[8] For other studies using the *PCC* transformation, see for example Bruno and Cipollina (2018); Valickova et al. (2015); Arestis et al. (2015); Wang and Shailer (2015); Nataraj et al. (2014); Iwasaki and Mizobata (2018); Cohen and Tubb (2018); Bijlsma et al. (2018); Churchill and Mishra (2018); Merkle and Phillips (2018); and Churchill and Yew (2017).

2010). It has three main advantages. First, it is directly related to the size of the estimated coefficient in the primary study, since *PCC* is increasing in *t*, and *t* is increasing in $\hat{\beta}$. Second, it has the advantage, like an elasticity, that it does not depend on the particular units used to measure the dependent and independent variables. And lastly, as a correlation, it takes values over a well-defined range (-1 to 1) for which there are guidelines to interpret the respective effect sizes in terms of "small", "medium", and "large" effects (Doucouliagos 2011).

4.2 Eliminating Outliers

TABLE 2 provides descriptive statistics for the *PCC* variable in our sample. As the calculation of *PCC* is based on *t*-values and *df*, we report these as well. There are two columns of data for each variable. The left column reports statistics for the full sample of 99 studies and 3,359 estimates.

While the mean and median *t*-values for the full sample are relatively low at 2.86 and 1.41, respectively, the minimum and maximum *t*-values are -669.8 and 279.1. These are extraordinarily large and raise concern about outliers. A similar concern applies to the *df* variable that has mean and median values of 241,063 and 18,930, with minimum and maximum values of 50 and 5,776,129. The *PCC* values have a mean and median values of 0.016 and 0.008, but range from -0.984 to 0.994.

Given these extraordinary outliers, we proceed by truncating the top and bottom 1% of *PCC* values. This elimination of outliers resulted in our final sample of 99 studies and 3,291 estimated effects.[9] The truncated distributions of *t*-statistic, *df*, and *PCC* values are reported immediately to the right of the full sample statistics. Corresponding histograms for the *t*-statistics and *PCC* values are presented in FIGURE 1.

4.3 How to Estimate the Overall Mean Effect

[9] Bibliographic information for the 99 studies included in this meta-analysis is provided in a document entitled "Studies" that is posted at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/SJ5HP1.

A simple approach to estimating the overall mean effect of spillovers on export performance is to average the sample of PCC values (see TABLE 2). This is equivalent to using OLS to regress $\widehat{PCC_i}$ on a constant:

(3) $\widehat{PCC_i} = \mu + \varepsilon_i, \quad i = 1,2,\dots,N,$

where N is the number of estimated spillover effects in the meta-analysis sample, and μ is the mean, true effect of spillovers on export behavior measured as a partial correlation. Ignoring publication bias and endogeneity for the moment, if our sample of estimated effects is a representative draw from a population of estimated effects, then the estimate of μ in Equation (3) will be unbiased and consistent. However, while unbiased and consistent, simple averaging of the estimated effects will not be efficient.

Let $SE(PCC_i)$ be the standard error of the *i*th estimated effect in the study sample. If all estimates come from a population with a single, true effect, so that the only source of variation in ε_i is proportional to sampling error -- i.e., $\text{var}(\varepsilon_i) = SE(PCC_i)^2\sigma^2$ -- then Weighted Least Squares (WLS) estimation of Equation (3) will produce an asymptotically unbiased, consistent, and efficient estimate of μ, with the appropriate weight being the inverse of $(SE_i)^2$.[10] This model is known as the inverse variance or "Fixed Effects" model in the meta-analysis literature (Borenstein et al. 2010).[11]

The assumption of a single, true effect of the Fixed Effects model can be unrealistic, however, because spillovers have a range of effects on export performance, depending on any number of conditions and variables. Let τ^2 represent the component of the variance of ε_i that is due to differences in mean true effects. If we can assume that sampling error and variation in true effects are independent, and that the variance of ε_i is proportional to these two

[10] Strictly speaking, WLS will be unbiased only if the estimates of $\text{var}(\varepsilon_i)$ are equal to their population values.
[11] This nomenclature is unfortunate, given the association of these same terms with panel data estimation. Nevertheless, given their ubiquitousness in the meta-analysis literature, we will perpetuate the practice of using "Fixed" and "Random Effects" to refer to models of homogeneous and heterogeneous effects, respectively.

components, then $\mathrm{var}(\varepsilon_i) = [SE(PCC_i)^2 + \tau^2]\sigma^2$.

This leads to an alternative version of WLS, known in the meta-analysis literature as the "Random Effects" model, with the appropriate weight now being the inverse of $[SE(PCC_i)^2 + \tau^2]$ (Borenstein et al. 2010).[12] We thus have two WLS estimators that we can use, depending on whether the assumptions of the "Fixed Effects" or the "Random Effects" model is appropriate.

The two WLS models can be easily related to Equation (3) by multiplying each term by the square root of the respective weight, $\frac{1}{\omega_i}$:

$$\text{(4.a)} \quad \frac{\widehat{PCC_i}}{\omega_i} = \mu\left(\frac{1}{\omega_i}\right) + \frac{\varepsilon_i}{\omega_i}, \ \ i \ = \ 1,2, \dots, N,$$

where

$$\text{(4.b)} \quad \omega_i = \begin{cases} SE(PCC_i), & \textit{(FixedEffects1)} \\ \sqrt{SE(PCC_i)^2 + \tau^2}. & \textit{(RandomEffects1)} \end{cases}$$

OLS estimation of this transformed equation produces estimates equivalent to WLS. Additionally, when the meta-analysis sample consists of multiple estimates from the same study, it is standard practice to correct for non-independence of the error terms by using cluster robust standard errors (Stanley and Doucouliagos 2012).

Note that the "Random Effects" WLS estimator produces a more uniform distribution of weights than "Fixed Effects", since the weighting terms include a common constant, τ^2. Further, when τ^2 is large relative to $SE(PCC_i)^2$, the weights will be approximately equal across observations, so that WLS will produce estimates close to OLS. While researchers generally agree that the "Random Effects" model most closely matches reality, there is some debate about which works best in practice (Doucouliagos and Paldam 2013; Reed 2015). Accordingly, our analysis uses both.

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[12] Borenstein et al. (2010) discuss two main procedures for estimating τ^2: DerSimonian and Laird's method of moments, and restricted maximum likelihood. The Stata program that we employ ("metareg") allows both methods. The default is D&L and that is the method we use in our analysis.

A related issue concerns the weighting of estimates versus studies. The number of estimates per study can vary widely. In our sample, the number of estimates per study ranges from 1 to 204, with a mean of 31.[13] The WLS estimators discussed above implicitly give greater weight, sometimes dramatically so, to studies with more estimates. Accordingly, we employ an alternative weighting system that, ceteris paribus, gives equal weight to studies rather than individual estimates:

$$\text{(4.c)} \quad \omega_i = \begin{cases} SE(PCC_i) \cdot \sqrt{n_{i \in S}} & \textit{(FixedEffects2)} \\ \sqrt{SE(PCC_i)^2 + \tau^2} \cdot \sqrt{n_{i \in S}}, & \textit{(RandomEffects2)} \end{cases}$$

where $n_{i \in S}$ is the number of estimates in study S from which estimate *i* was taken and SE_i and τ^2 are defined as above.

While we are aware of no study that compares how frequently researchers use "Fixed Effects" versus "Random Effects" estimators in their meta-analyses, our sense is that "Fixed Effects" is generally preferred by economists. However, we have some concerns with the "Fixed Effects" estimator.

TABLE 3 presents a "study weight" for each study in our sample, weighting the individual estimates of that study by the respective weighting scheme ("Fixed Effects"/"Random Effects") and then aggregating the weights at the study level. In this way, each study receives a weight, the sum of which equals 100%.[14] If the 100% weight was divided equally across studies, given 99 studies, each study would receive a weight of 1.01%.

Against this benchmark, "Fixed Effects" weights are highly skewed. The median weight is 0.03%, and the maximum weight for a single study is 42.6%.[15] The top 3 studies account for 62.9% of the total weight, and the top 10 studies comprise 90.0%. Thus "Fixed Effects" estimates

[13] This is partly explained by the fact that studies commonly use multiple spillover measures in the same regression.

[14] Study weights were calculated by $w_i / \sum w_i$, where $w_i = 1/(SE_i)^2$ or $w_i = 1/[(SE_i)^2 + \tau^2]$ depending on whether Fixed Effects or Random Effects were being used (cf. Ringquist 2013, page 128).

[15] The ID for this study is 3. Its large weight is a function of its exceptionally large sample size (over 4,000,000 observations) and small *t*-values (cf. Equations 2.a and 2.b).

will be disproportionately influenced by a very small number of studies that have large *PCC* values and/or use a large number of observations (*df*). This is particularly concerning if the export and spillovers measures used by this small set of studies is not representative of the literature.

In contrast, as noted above, the "Random Effects" estimator weighs estimates more uniformly - the median value is 1.14% compared to a mean value of 1.01%. The maximum weight any single study receives is 1.31%, and the top 10 studies account for 13.0%. This arguably overcompensates the extreme skewness of the "Fixed Effects" estimator. In what follows, we report both "Fixed Effects" and "Random Effects" estimates, with a mild preference for the latter because it is not so heavily dependent on a small number of studies. As a practical matter, all of our key findings are robust across estimators.

4.4 Estimates of Overall Mean Effect without Correction for Publication Bias

Panel A of TABLE 4 reports our estimates of the overall mean effect. The estimates are all positive, and are statistically significant at the 1-percent level. This is evidence that spillovers, on average, have a positive and statistically significant effect on exports. The estimates range from 0.006 to 0.026. Before considering the economic significance of these estimates, we first consider the impact of publication bias, for which these estimates do not correct.

4.5 Estimates of Overall Mean Effect with Correction for Publication Bias

Publication bias arises when the estimates reported by researchers and/or the studies published by journals comprise a biased sample of the population of all estimates. This can happen when researchers/journals have preferences for estimates that are statistically significant and/or whose signs accord with expectations (Christensen and Miguel 2018). "Publication bias" can occur even in working papers that are not published in journals. This can happen if researchers choose not to write up results because the initial analyses did not produce interesting/promising results.[16] In that case, even unpublished working papers can be characterized by publication

[16] Franco et al. (2014) report that the main source of publication bias is failure of researchers to write up results that are not significant or interesting.

bias.

Publication bias represents a serious challenge to the validity of meta-analysis. If the estimates in the literature are disproportionately large and significant, then averaging them will preserve this bias, producing a distorted estimate of the mean true effect. Thus, it is important to test for the presence of publication bias.

The most common test for publication bias in the economics literature is the Funnel Asymmetry Test (FAT) . The FAT is carried out by adding the standard error variable, *SE*, to the constant-only specification of Equation (3) (Card and Krueger 1995; Egger et al. 1997; Stanley 2008). Evidence of publication bias is given by statistical significance of the *SE* variable. The addition of the *SE* variable to Equation (3) has a further benefit. It adjusts the estimate of μ for the presence of publication bias (Stanley and Doucouliagos 2014).

Panel B of TABLE 4 reports our estimates of the overall mean effect accounting for publication bias. The first row reports the estimated coefficient on the publication bias term, *SE*. Across all four columns, we reject $H_0: \beta_{SE} = 0$ at the 5 percent level of significance, indicating the existence of publication bias. The sign of the estimate indicates positive publication bias, suggesting sample selection that favors the publication of positive spillover effects on exports.

The second row of Panel B reports estimates of μ, the overall mean effect of spillovers on exports, corrected for publication bias. In three of the four cases, the estimates of μ are significant at the 5 percent level. The exception is the *FixedEffects1* estimate of Column (1), which is significant at the 10 percent level. These results provide confirmatory evidence that spillovers exist and they positively impact exports.

To see how much publication bias affects the effect size estimates, we can compare the "Constant" estimates in Panel B with those in Panel A. We see that correcting for (positive) publication bias reduces the estimates of overall mean effect. For example, in Column (1) the uncorrected estimate of the overall mean effect of spillovers on exports is 0.006. This falls to

0.004 when adjustment is made for publication bias.

4.6 Economic Significance of the Overall Mean Estimates

While the transformation of estimated coefficients to *PCCs* solves the noncomparability problem, it raises the question of how one should interpret $\hat{\mu}$. In particular, what values of $\hat{\mu}$ constitute a large effect? A small effect?

To investigate partial correlation sizes, Doucouliagos (2011) collected over 22,000 estimates in empirical economics and transformed them to *PCCs*. He then ranked them from smallest to largest in absolute value. He defined the 25th, 50th, and 75th percentile values as "small", "medium", and "large" effects. While there was some difference across subfields of economics, *PCC* values of 0.07, 0.17, and 0.33 corresponded to "small", "medium" and "large" effect sizes in the full sample.

Our estimates of the overall mean effect from Panel B of TABLE 4 range from 0.004 to 0.021. These fall well below the threshold for a "small" effect using the Doucouliagos guidelines. This suggests that spillovers have, at best, a positive but negligibly small effect on exports.

The reasons for the small *PCC* values are easy to identify. First, a large number of estimates in our study sample are statistically insignificant. The table immediately below the histogram in the top panel of FIGURE 1 reports that 53.0% of all *t*-values lie between -2 and 2. Compounding these relatively low *t*-values are very large sample sizes - the distribution of *df* values for the truncated sample ranges from 57 to 5,776,129, with a median value of 18,933. The combination of very large samples with many statistically insignificant estimates is strong evidence that spillovers do not have large effects on firms' export behavior.

5. COMPARISON WITH OTHER META-ANALYSES OF SPILLOVER EFFECTS

While this study is the only meta-analysis to investigate the relationship between spillovers and exports, no less than eight other meta-analyses have studied various aspects of the relationship between FDI and productivity spillovers (Bruno and Cipollina 2018; Demena and van Bergeijk 2017; Iwasaki and Tokunaga 2016; Mebratie and van Bergeijk 2013; Irsova and Havranek 2013; Havranek and Irsova 2010; Meyer and Sinani 2009; and Görg and Strobl 2001). For the most part, these studies have emphasized the influence of data and study characteristics on estimated spillover effects. For example, a common finding is that cross-sectional data produce larger spillover estimates than panel data. This emphasis on significant data and study characteristics has tended to obscure the fact that almost all of the studies find very small spillover effects.[17]

TABLE 5 summarizes the estimates of mean, estimated spillover effects of FDI on productivity. With one exception, all the economic effects can be characterized as negligible, whether measured by *t*-stats, *PCC* values, or something else.[18] Thus , our finding that spillovers do not have an important economic effect on exports is in line with what most other studies have found with respect to productivity spillovers from FDI.

6. INVESTIGATING DIFFERENCES IN ESTIMATES ACROSS STUDIES: BAYESIAN MODEL AVERAGING

In this section, we investigate the extent to which various data, estimation and study characteristics are correlated with the estimated spillover effects in our sample. This enables an understanding of why different studies report different estimated effects. A straightforward approach is to include all the respective variables in Equation (3) and estimate the corresponding "meta-regression" equation. We will do this. However, the problem with this approach is that multicollinearity among the variables can mask important relationships. Accordingly, we use two additional approaches.

The first approach is Bayesian Model Averaging, or BMA (Zeugner 2011).

[17] Havranek and Irsova (2010), Iwasaki and Tokunaga (2016), and Irsova and Havranek (2013) are exceptions in that they make it clear that the estimated spillover effects are small in economic significance.
[18] The one exception is Görg & Strobl (2001), who find sizeable mean t-statistics in their sample of studies.

Conceptually, BMA consists of estimating all possible regressions and averaging the associated coefficient and standard error estimates with weights determined by the likelihood values of the respective specifications. In our case, there are a total of 27 variables (the 26 variables plus *SE*), producing 2^{27} possible regressions. Rather than estimating all of these, BMA samples from the set of all possible specifications using Monte Carlo Markov Chain (MCMC) sampling. True to its Bayesian nature, BMA requires the user to specify a prior distribution. This typically specifies prior beliefs about the number of variables that belong in the "true" regression equation.

The advantage of BMA is that it provides a global assessment of the relationship between the explanatory variables and the dependent variable (the estimated spillover effect). The disadvantage is that the results do not represent any single specification. This can be a problem when interpreting coefficients for dummy variables. For example, we use three variables to represent spillover measures, *Number, Value* and *Employment*, with the omitted category being *Other*. The interpretation for *Number* when *Value* and *Employment* are included in the specification is different than when *Value* and *Employment* are omitted from the specification, because the comparison group changes. This is concerning given that so many of the data, estimation and study characteristics are dummy variables. Accordingly, the next section adopts a frequentist approach to estimate a "best" variable specification as an alternative method for identifying factors that affect spillover effect estimates.

TABLE 6 reports the results of two BMA analyses. The left half of the table presents results for regressions using the *FixedEffects1* weights, while the right hand side shows results using the *RandomEffects1* weights. Four outputs for each BMA analysis are reported: *PIP, Cond. Mean, Cond. SD,* and *Cond Pos Sign. PIP* can be roughly interpreted as the weighted probability that the given variable belongs in the "true" specification. A *PIP* value of 1.000 suggests that the probability the variable belongs in the "true" specification is approximately

100%. Another way to look at the *PIP* is to note that each variable appears in half of the 2^{27} total possible specifications. If each regression had an equal probability of being true (i.e., equal likelihood values), then the *PIP* would be 0.50. Thus, values greater than 0.50 indicate that the regressions including the respective variable have a higher probability of being "true" than the regressions that do not include the variable.

Cond Mean reports a weighted average of that variable's estimated coefficients, with weights calculated as the posterior probability that a given specification is true. Similarly, *Cond SD* is the weighted average of that variable's estimated standard errors. *Cond Pos Sign* is the weighted average of indicator variables that take the value 1 if the variable's coefficient in a given regression is positive. A *Cond Pos Sign* value of 1.000 suggests that the probability the given variable has a positive coefficient in the "true" specification is virtually 100%.

Variables having *PIP* and *Cond Pos Sign* values both equal to 1.000 are yellow-highlighted for each set of weighted regressions. Variables having *PIP* values equal to 1.000 and *Cond Pos Sign* values equal to 0.000 are highlighted in rose. A compelling result would be one where (i) *PIP* was equal to 1.000 in both the *FixedEffects1* and *RandomEffects1* regressions, (ii) the signs were consistently positive or negative (*Cond Pos Sign* either 1.000 or 0.000), (iii) the *Cond Mean* values were at least twice as large as the *Cond SD* values and (iv) the *Cond Mean* value was economically meaningful using the Doucouliagos (2011) guidelines.

TABLE 6 shows that there are no variables that satisfy all four criteria. Variables that satisfy the first three criteria are *SampleYear, China, Fixed Effects,* and *R&D.* The *Cond Mean* estimate for *SampleYear* (-0.001 for both *FixedEffects1* and *RandomEffects1*) indicates that a dataset the mid-sample "age" of which was 10 years older than another dataset would have, on average, an estimated spillover effect that was approximately 0.01 correlation points lower. This is very small in absolute size, but is roughly comparable in size to the bias-adjusted estimate of the overall mean spillover effect (cf. Columns 1-4 in Panel B, TABLE 4).

The only other variable that has a consistently negative effect is *FixedEffects,* indicating that the associated spillover effect was estimated using panel fixed effects. The negative sign means that studies that used panel fixed effects generally had smaller estimates of spillover effects than other studies (cross-sectional studies and panel studies without fixed effects). This matches with what meta-analyses on FDI and productivity spillovers have reported.

Studies that used Chinese data or that measured spillover effects from R&D expenditures generally estimated larger spillover effects. In the case of China, the associated partial correlations are 0.010 (*Fixed Effects1*) and 0.013 (*RandomEffects1*) larger than for studies with non-Chinese data. For studies focusing on R&D, the corresponding estimates are 0.022 (*FixedEffects1*) and 0.012 (*RandomEffects1*) larger.

Information for the remaining variables is reported in the table. We note that weighting makes a difference. The variable *Employment*, indicating that the measure of spillovers was based on labor, has a *PIP* of 1.000 and a *Cond Pos Sign* of 1.000 in the *FixedEffects1* regressions. In contrast, it has a consistently negative sign in the *RandomEffects1* BMA regressions (*Cond Pos Sign* equals 0.000 with a *PIP* of 1.000).

As these results are exploratory, they should be viewed as suggestive. If there is one main conclusion to be drawn from the BMA analysis, it is that no data, estimation or study characteristics achieves even a small effect on estimates of spillover effects, where we define small using the Doucouliagos (2011) guideline of 0.07.

7. INVESTIGATING DIFFERENCES IN ESTIMATES ACROSS STUDIES: META-REGRESSION ANALYSIS (MRA)

This section complements the BMA analysis above by performing a variety of meta-regression analyses estimating alternative variable specifications. One of the variable specifications includes all variables in the same specification. We supplement this with another specification that uses stepwise regression to select the "best" set of additional variables to accompany the spillover type and measure variables. In particular, we lock in the spillover type and/or spillover measure variables and then use a backwards stepwise regression procedure that sequentially chooses the control variables that result in the lowest BIC/SIC value. BIC/SIC is an information criterion measure that balances goodness of fit against model parsimony. It has the property that it is asymptotically consistent. Thus, our backwards stepwise algorithm is designed to select the additional variables that are most likely to belong in the true equation along with the different spillover variables.

TABLE 7 locks in the four spillover type variables, *Exporters, Region, Industry,* and *FDI*. TABLE 8 locks in the three spillover measure variables, *Number, Value* and *Employment*. TABLE 9 combines both spillover type and spillover measure variables. In addition, we also lock in the publication bias term, *SE*, in all specifications. We do this to investigate whether evidence of publication bias is sustained after other variables are added to the specification.

The results from TABLES 7-9 were largely foreshadowed by the BMA analysis of TABLE 6. Of the seven spillover variables, none are consistently signed and significant across all estimation procedures and variable specifications. *Employment* is generally significant, but it switches signs from positive (*FixedEffects*) to negative (*RandomEffects*), depending on the WLS weights. In addition, none of the estimated coefficients achieves economic significance, as the estimated coefficients are all less than 0.07.

Finally, we note that our previous finding of publication bias becomes suspect in light of the estimates from TABLES 7-9. The *SE* coefficient is never significant in the *RandomEffects* regressions in TABLES 7-9, though it is in the *FixedEffects* regressions. The mixed results here, in combination with the small biases identified in TABLE 4, indicates that publication bias is, at best, weakly present in the empirical literature on spillover and exports.

8. CONCLUSION

This study uses meta-analysis to investigate the effect of spillovers on export performance. Exports have been linked to many positive economic outcomes, such as growth, employment, technology improvements and consumer welfare. Spillovers have likewise received considerable attention. Despite the very large literature on spillovers, including no less than eight meta-analyses, this study represents the first meta-analysis to investigate the relationship between spillovers and exports.

Our final sample consists of 3,291 estimated spillover effects from 99 studies, making it substantially larger than any previous meta-analysis of spillover effects. Our main finding is that spillovers have an economically negligible impact on exports. This conclusion follows directly from the fact that approximately half of the estimated spillover effects in the literature are statistically insignificant. This insignificance is particularly noteworthy given that the sample sizes of the underlying studies are generally very large. The mean and median sample sizes for the estimated effects in our sample are 245,911 and 18,933, respectively. The combination of insignificant estimates with very large sample sizes is indicative that spillovers do not have much effect on exports.

Two other findings from our study are noteworthy: While we find evidence of publication bias using the standard funnel asymmetry test (FAT), the statistical evidence becomes weaker when we include additional variables in our regresion specifications. This suggests that the results of the FAT may, at least somewhat, reflect omitted variable bias. In any case, the size of the estimated publication bias has a very small effect on the overall estimate of mean spillover effects.

Our last finding is that we are unable to obtain compelling evidence that data, estimation and study characteristics affect estimated spillover effects. In particular, there is no robust evidence that estimated spillover effects are affected by how exports are measured, nor that some spillover types have larger effects than others. While some of the respective variables are statistically significant in some of the regressions, neither the Bayesian Model Averaging analysis nor the frequentist regression results produce robust results linking data, estimation and study characteristics to spillover effects.

It turns out that our results should not be surprising. Reviewing previous meta-analyses of spillover effects reveals that they also find economically insignificant effects from spillovers. This is somewhat obscured by the fact that, in many cases, previous studies have focused on statistical, rather than economic, significance. That is, they report that the overall mean effect of spillover effects is statistically significant, or that various data, estimation and study characteristics are significant, without commenting or discussing on the size of the effects. Low partial correlation coefficients and large numbers of insignificant effect estimates are, in fact, characteristic of the spillover literature.

Finally, we might ask why it is that the empirical literature has not been able to estimate economically meaningful effects of spillovers on exports. Of course, it may simply be that the effects are negligible. Alternatively, the problem may reflect data difficulties. Spillovers are inherently challenging to measure. Crude proxies, such as number of exporters in the same region or industry, may only poorly measure the amount of spillover activity taking place. In addition, there may be lagged temporal effects that are not being properly captured in the existing regression specifications. Or it may be that there are non-linear, threshold effects that are missed by conventional linear specifications. However, until evidence in support of these alternative explanations appears, we can only conclude that there is no evidence in the existing empirical literature that spillovers have much influence on firms' export behavior.

REFERENCES

Aitken, B., Hanson, G. H., & Harrison, A. E. (1997). Spillovers, foreign investment, and export behavior. *Journal of International Economics*, 43(1–2): 103–132.

Alvarez, R. (2007). Explaining export success: Firm characteristics and spillover effects. *World Development*, 35(3): 377-393.

Arestis, P., Chortareas, G., & Magkonis, G. (2015). The financial development and growth nexus: A meta-analysis. *Journal of Economic Surveys*, 29(3): 549-565.

Barrios, S., Görg, H., & Strobl, E. (2003). Explaining firms' export behaviour: R&D, spillovers and destination market. *Oxford Bulletin of Economics and Statistics*, 65(4): 475-496.

Bernard, A. B., Eaton, J., Jensen, J. B., & Kortum, S. S. (2003). Plants and productivity in international trade. *American Economic Review*, 93(4): 1268–1290.

Bernard, A. B. & Jensen, J. B. (1999). Exceptional exporter performance: cause, effect, or both? *Journal of International Economics,* 47: 1-25.

Bernard, A. B. & Jensen, J. B. (2004). Why Some Firms Export. *The Review of Economics and Statistics*, 86(2): 561–569.

Bruno, R. & Cipollina, M. (2018). A meta-analysis of the indirect impact of foreign direct investment in old and new EU member states: Understanding productivity spillovers. *World Economy*, 41(5): 1342-1377.

Bijlsma, M., Kool, C., & Non, M. (2018). The effect of financial development on economic growth: a meta-analysis. *Applied Economics*, 50(57): 6128-6148.

Borenstein, M., Hedges, L. V., Higgins, J. P., & Rothstein, H. R. (2009). *Introduction to meta-analysis*. John Wiley & Sons.

Borenstein, M., Hedges, L. V., Higgins, J. P., & Rothstein, H. R. (2010). A basic introduction to fixed-effect and random-effects models for meta-analysis. *Research Synthesis Methods*, 1(2), 97-111.

Card, D. & Krueger, A.B. (1995). Time-series minimum-wage studies: A meta-analysis. American Economic Review, 85(2): 238–243.

Choquette, E. & Meinen, P. (2015). Export spillovers: opening the black box. *The World Economy*, 38(12): 1912-1946.

Christensen, G. & Miguel, E. (2018). Transparency, reproducibility, and the credibility of economics research. *Journal of Economic Literature*, 56(3): 920-80.

Churchill, S.A. & Mishra, V. (2018). Returns to education in China: a meta-analysis. *Applied Economics*, 50(54): 5903-5919.

Churchill, S.A. & Yew, S.L. (2017). Are government transfers harmful to economic growth? A meta-analysis. *Economic Modelling*, 64: 270-287.

Cieślik, A. & Hagemejer, J. (2014). Multinational enterprises, absorptive capacity and export spillovers: Evidence from Polish firm-level data. *Review of Development Economics*, 18(4): 709-726.

Clerides, S. K., Lach, S., & Tybout, J. R. (1998). Is learning by exporting important? Micro-dynamic evidence from Colombia, Mexico and Morocco. *The Quarterly Journal of Economics*, 113: 903-947.

Cohen, M. A. & Tubb, A. (2018). The impact of environmental regulation on firm and country competitiveness: A meta-analysis of the porter hypothesis. *Journal of the Association of Environmental and Resource Economists*, 5(2): 371-399.

De Rosa, D. (2006). Explaining Russian manufacturing exports: Firm characteristics and external conditions. PSE Working Papers, 2006-22.

Demena, B. & van Bergeijk, P. A. G. (2017). A meta-analysis of FDI and productivity spillovers in developing countries. *Journal of Economic Surveys*, 31(2): 546-571.

Doucouliagos, H. (2011). How large is large? Preliminary and relative guidelines for interpreting partial correlations in economics. Economics Series Working Paper 05, Deakin University.

Doucouliagos, H. & Paldam, M. (2013). The robust result in meta-analysis of aid effectiveness: A response to Mekasha and Tarp. *The Journal of Development Studies*, 49(4): 584-587.

Dumont, M., Merlevede, B., Piette, C., & Rayp, G. (2010). The productivity and export spillovers of the internationalisation behaviour of Belgian firms. *National Bank of Belgium Working Paper*, No. 201. Available at: https://ssrn.com/abstract=1692592 or http://dx.doi.org/10.2139/ssrn.1692592

Duranton, G. & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In J. V. Henderson & J. F. Thisse (Eds.), Handbook of Regional and Urban Economics, edition 1, 4(48): 2063-2117. Elsevier.

Egger, M., Smith, G.D., Schneider, M., & Minder, C. (1997). Bias in meta-analysis detected by a simple, graphical test. BMJ, 315(7109): 629–634.

Ellis, P. D. (2010). *The essential guide to effect sizes: Statistical power, meta-analysis, and the interpretation of research results*. Cambridge University Press.

Falvey, R., Foster, N., & Greenaway, D. (2004). Imports, exports, knowledge, spillovers and growth. *Economics Letters*, 85(2): 209-213.

Franco, A., Malhotra, N., & Simonovits, G. (2014). Publication bias in the social sciences: Unlocking the file drawer. *Science*, 345(6203): 1502-1505.

Greenstone, M., Hornbeck, R., & Moretti, E. (2010). Identifying agglomeration spillovers: Evidence from winners and losers of large plant openings. *Journal of Political Economy*, 118(3):536-598.

Görg, H. & Strobl, E. (2001). Multinational companies and productivity spillovers: A meta-analysis. *Economic Journal*, 111(475): F723-F739.

Harasztosi, P. (2016). Export spillovers in Hungary. *Empirical Economics*, 50(3): 801-830.

Havranek, T. & Irsova, Z. (2010). Meta-analysis of intra-industry FDI spillovers: Updated evidence. *Finance a Uver-Czech Journal of Economics and Finance*, 60(2): 151-174.

Havranek, T. & Irsova, Z. (2011). Estimating vertical spillovers from FDI: Why results vary and what the true effect is. *Journal of International Economics*, 85*:* 234-244.

Havranek, T. & Irsova, Z. (2012). Survey article: Publication bias in the literature on foreign direct investment spillovers. The Journal of Development Studies, 48(10): 1375-1396.

Irsova, Z. & Havranek, T. (2013). Determinants of Horizontal Spillovers from FDI: Evidence from a Large Meta-Analysis. *World Development*, 42: 1-15.

Iwasaki, I. & Mizobata, S. (2018). Post-Privatization Ownership and Firm Performance: A Large Meta-Analysis of the Transition Literature. *Annals of Public and Cooperative Economics*, 89(2): 263-322.

Iwasaki, I. & Tokunaga, M. (2016). Technology transfer and spillovers from FDI in transition economies: A meta-analysis. *Journal of Comparative Economics,* 44(4): 1086-1114.

Kemme, D., Mukherjee, D., & Nikolsko-Rzhevskyy, A. (2014). Multinational Enterprises and Export Performance in Emerging Economies: Evidences from Indian IT firms. *Review of Development Economics*, 18(4): 681-692.

Kneller, R. & Pisu, M. (2007). Industrial linkages and export spillovers from FDI. *The World Economy*, 30(1): 105–134.

Krugman, P. (1980). Scale economies, product differentiation and the pattern of trade. *American Economic Review*, 70: 950-959.

Krugman, P. (1991). *Geography and Trade*. Cambridge: MIT Press.

Malmberg, A., Malmberg, B., & Lundequist, P. (2000). Agglomeration and firm performance: Economies of scale, localisation and urbanisation among Swedish export firms. *Environment and Planning A: Economy and Space*, 32(2): 305-321.

Mebratie, A. D. & van Bergeijk, P. A. G. (2013). Firm heterogeneity and development: A meta-analysis of FDI productivity spillovers. *Journal of International Trade and Economic Development*, 22(1): 52-70.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6): 1695-1725.

Merkle, J. S. & Phillips, M. A. (2018). The Wage Impact of Teachers Unions: A Meta-Analysis. *Contemporary Economic Policy*, 36(1): 93-115.

Meyer, K. & Sinani, E. (2009). When and where does foreign direct investment generate positive spillovers? A meta-analysis. *Journal of International Business Studies,* 40(7): 1075-1094.

Nataraj, S., Perez-Arce, F., Kumar, K. B., & Srinivasan, S. V. (2014). The impact of labor market regulation on employment in low-income countries: A meta-analysis. *Journal of Economic Surveys*, 28(3): 551-572.

Reed, W. R. (2015). A Monte Carlo analysis of alternative meta-analysis estimators in the presence of publication bias. *Economics: The Open-Access, Open-Assessment E-Journal*, 9 (2015-30): 1-40. http://dx.doi.org/10.5018/economics-ejournal.ja.2015-30.

Ringquist, E. (2013). *Meta-analysis for public management and policy*. San Francisco: John Wiley & Sons.

Rodríguez-Pose, A., Tselios, V., Winkler, D., & Farole, T. (2013). Geography and the determinants of firm exports in Indonesia. *World Development*, 44: 225-240.

Ruane, F. & Sutherland, J. (2005). Export performance and destiantion characteristics of Irish manufacturing industry. *Review of World Economics*, 141(3): 442-459.

Silvente, F. R. & Giménez, J. C. (2007). Information spillovers and the choice of export destination: A multinomial logit analysis of Spanish young SMEs. *Small Business Economics*, 28(1): 689-86.

Stanley, T. D. (2008). Meta-regression methods for detecting and estimating empirical effects in the presence of publication selection. *Oxford Bulletin of Economics and Statistics*, 70: 103-127.

Stanley, T. D. & Doucouliagos, H. (2012). *Meta-regression analysis in economics and business*. Oxford: Routledge.

Stanley, T. D. & Doucouliagos, H. (2014). Meta-regression approximations to reduce publication selection bias. *Research Synthesis Methods*, 5(1): 60-78.

Stanley, T. D., Doucouliagos, H., Giles, M., Heckemeyer, J. H., Johnston, R. J., Laroche, P., Nelson, J. P., Paldam, M., Poot, J., Pugh, G., & Rosenberger, R. S. (2013). Meta-analysis of economics research reporting guidelines. *Journal of Economic Surveys*, 27(2): 390-394.

UNCTAD (2013). World Investment Report 2013 - Global value chains: Investment and trade for development. New York: United Nations.

Valickova, P., Havranek, T., & Horvath, R. (2015). Financial development and economic growth: A meta-analysis. *Journal of Economic Surveys*, 29(3): 506-526.

Wang, K. & Shailer, G. (2015). Ownership concentration and firm performance in emerging markets: a meta-analysis. *Journal of Economic Surveys*, 29(2): 199-229.

Wooster, R. B. & Diebel, D. S. (2010). Productivity spillovers from foreign direct investment in developing countries: A meta-regression analysis. *Review of Development Economics*, 14(3): 640-655.

World Bank (1998). World development report: Knowedge for development. New York: Oxford University Press.

Zeugner, S. (2011). Bayesian model averaging with BMS. [pdf] Available at http://bms.zeugner.eu/

TABLE 1
Description of Variables

Variable	*Description*	*Mean*	*Min*	*Max*
	SPILLOVER TYPE			
Exporters	=1, if spillovers are from exporters	0.544	0	1
Region	=1, if spillovers are from same region	0.524	0	1
Industry	=1, if spillovers are from same industry	0.521	0	1
FDI	=1, if spillovers are from FDI	0.394	0	1
	SPILLOVER MEASURES			
Number	=1, if spillovers are measured by number of firms	0.349	0	1
Value	=1, if spillovers are measured by export value	0.250	0	1
Employment	=1, if spillovers are measured by employment	0.092	0	1
*Output**	=1, if spillovers are measured by output	0.050	0	1
*R&D**	=1, if spillovers are measured by R&D expenditures	0.018	0	1
*OtherMeasures**	=1, if spillovers are measured by other variables	0.245	0	1
	DEPENDENT VARIABLE			
Categorical	=1, if dependent variable used a discrete number of categories (as opposed to being continuous)	0.680	0	1
	DATA CHARACTERISTICS			
Firm-level	=1, if data are firm-level	0.923	0	1
Domestic	=1, if spillover effects focus on domestic firms	0.468	0	1
SampleYear	Mid-point of sample period	2001.4	1988	2011
	COUNTRIES			
OECD	=1, if sample consists of data from OECD	0.467	0	1
*EU**	=1, if sample consists of data from EU	0.380	0	1
*Developing**	=1, if sample consists of data from developing countries	0.526	0	1
China	=1, if sample consists of data from China	0.230	0	1
	INDUSTRY			
Manufacturing	=1, if data are from manufacturing industry	0.762	0	1
*Service**	=1, if data are from service industry	0.028	0	1
*IT**	=1, if data are from IT industry	0.026	0	1
*Food**	=1, if data are from food industry	0.022	0	1
*OtherIndustry**	=1, if data are from other industries	0.162	0	1
	ESTIMATION METHOD			
Probit/Logit/Tobit	=1, if estimation method is probit, logit, or tobit	0.724	0	1
*OLS/GLS**	=1, if estimation method is OLS or GLS	0.261	0	1

Variable	*Description*	*Mean*	*Min*	*Max*
*OtherEstimation**	=1, if estimation method is none of the above	0.015	0	1
IV	=1, if estimation method uses instrumental variables	0.122	0	1
SampleSelection	=1, if estimation method corrects for sample selection	0.067	0	1
Fixed Effects	=1, if estimation method uses fixed effects	0.356	0	1
	CONTROL VARIABLES			
Size	=1, if specification controls for firm size	0.822	0	1
Productivity	=1, if specification controls for firm productivity	0.648	0	1
LaborQuality	=1, if specification controls for firm labor quality	0.428	0	1
Capital	=1, if specification controls firm capital/assets	0.303	0	1
R&D	=1, if specification controls for R&D expenditures	0.221	0	1
	STUDY QUALITY			
Journal	=1, if study published in a peer-reviewed journal	0.839	0	1
Impact	RePEc impact factor of journal (April 2018)	0.150	0	4.93
Citations	Number of Google Scholar citations (April 2018)	67.8	0	2861

NOTE*:* When the grouped variables include all possible categories, the categories omitted in the subsequent analysis (the benchmark categories) are indicated by an asterisk. Sample statistics are for the final (truncated) sample used in the subsequent analysis.

TABLE 2
Descriptive Statistics for Effect Size Variables

	t-Statistics		***df***		***PCC Values***	
	Full	***Truncated***	***Full***	***Truncated***	***Full***	***Truncated***
Mean	2.86	3.00	241,063	245,911	0.016	0.016
Median	1.41	1.41	18,930	18,933	0.008	0.008
Minimum	-669.8	-51.0	50	57	-0.984	-0.140
Maximum	279.1	147.4	5,776,129	5,776,129	0.994	0.199
Std. Dev.	16.5	9.0	657065	662,943	0.063	0.040
1%	-14.24	-12.61	115	119	-0.148	-0.083
5%	-3.01	-2.81	527	610	-0.040	-0.030
10%	-1.78	-1.71	1011	1137	-0.018	-0.016
90%	10.00	9.51	583,432	631,056	0.073	0.067
95%	18.04	17.00	1,683,178	1,685,285	0.109	0.101
99%	40.42	36.44	3,323,304	3,323,304	0.203	0.158
Obs	3,359	3,291	3,359	3,291	3,359	3,291

NOTE: The truncated sample is obtained from the Full Sample by deleting observations having the top and bottom 1% of *PCC* values.

TABLE 3
Study Weights

	Fixed Effects	*Random Effects*
Mean	1.01%	1.01%
Median	0.03%	1.14%
5%	0.00%	0.39%
10%	0.00%	0.42%
90%	1.78%	1.28%
95%	5.39%	1.30%
Maximum	42.6%	1.31%
Top 3	62.9%	3.9%
Top 10	90.0%	13.0%
Studies	99	99

NOTE: The methodology for calculating "study weights" is described in Footnote #14 in the text.

TABLE 4
Estimate of Overall Mean Effect and Test for Publication Bias

Variable	***FixedEffects1* *(1)***	***FixedEffects2* *(2)***	***RandomEffects1* *(3)***	***RandomEffects2* *(4)***
A. Without Correction for Publication Bias				
Constant	0.006*** (2.66)	0.008*** (3.73)	0.015*** (5.68)	0.026*** (7.42)
B. With Correction for Publication Bias				
SE	1.724*** (2.73)	2.462*** (4.40)	0.348** (2.01)	0.397** (2.00)
Constant	0.004* (1.78)	0.004** (2.20)	0.012*** (3.59)	0.021*** (4.86)

NOTE: The estimates in Panel A are obtained by estimating Equation (3) in the text using Weighted Least Squared (WLS). The four WLS estimators (*FixedEffects1, FixedEffects2, RandomEffects1,* and *RandomEffects2*) are described in Section 4 in the text. The estimates in Panel B are obtained similarly, except they add the publication bias term, *SE,* to Equation (3). All of the estimation procedures calculate cluster robust standard errors. *, **, and *** indicate statistical significance at the 10-, 5-, and 1-percent level, respectively.

TABLE 5
Summary of Meta-Analyses on FDI and Productivity Spillovers

Meta-analysis	*#Studies / #Estimates*	*Measure of Effect Size*	*Evidence of Economic Insignificance*
Görg and Strobl (2001)	21 / 25	*t*-stat	Mean t-stat is 2.8, Mean abs(t-stat) is 4.4 (Table 1)
Meyer and Sinani (2009)	66 / 121	*t*-stat	Predicted t-stats range from -1.5 to 1.5 (cf. Figure 4) Mean t-stat is 1.79 (Table 2)
Havranek and Irsova (2010)	67 / 97	*t*-stat and *PCC*	Median *t*-stat is 0.4 (cf. Table 1). Publication-bias corrected PCCs range from -0.007 to -0.002 (Table 6)
Havranek and Irsova (2011)	57 / 3626	*t*-stat and *PCC*	Mean t-stat is 0.8 (Table A1). Publication-bias corrected semi-elasticity: a 10-percentage point increase in FDI is associated with an increase in productivity of between 0.05%-1.7%, depending on the type of spillover (Table 1).
Havranek and Irsova (2012)	57 / 3626	*t*-stat and *PCC*	Publication-bias corrected semi-elasticity: the change in productivity associated with a 10-percentage point increase in FDI ranges between a 0.4% decrease and a 1.2% increase, depending on the type of spillover (Table 3).
Irsova and Havranek (2013)	52 / 1205	Semi-elasticity	Mean semi-elasticity is -0.002 = 10 percentage point increase in FDI is associated with a 0.02% decrease in productivity (Table 1)
Mebratie and van Bergeijk (2013)	30/ 130	Absolute *t*-stat	Large percentage of insignificant estimates, ranging from 24% to 71%, depending on the type of spillover (cf. Table 2)

Meta-analysis	*#Studies / #Estimates*	*Measure of Effect Size*	*Evidence of Economic Insignificance*
Iwasaki and Tokunaga (2016)	30 / 625	*PCC* and *t*-stat	Mean *PCC* = 0.0006, Mean *t*-stat = 0.28 (Figure 2)
Demena and van Bergeijk (2017)	69 / 1,450	*t*-stat and semi-elasticity	51% of the t-values are insignificant (cf. Figure 2). Publication bias-corrected estimate: 10 percentage point increase in FDI associated with a 0.6% increase in productivity (Table 4).
Bruno and Cipollina (2018)	52 / 1,133	*PCC*	Mean *PCC* is 0.024 (Table 3)

NOTE: Authors' summary. Table and figure numbers refer to the tables and figures in the respective meta-analyses.

TABLE 6
BMA Analysis

Variable	*FixedEffects1*				*RandomEffects1*			
	PIP	*Cond Mean*	*Cond SD*	*Cond Pos Sign*	*PIP*	*Cond Mean*	*Cond SD*	*Cond Pos Sign*
FirmLevel	0.700	-0.003	0.003	0.001	0.848	-0.004	0.004	0.000
Domestic	0.860	0.002	0.001	1.000	0.997	-0.005	0.002	0.000
SampleYear	1.000	-0.001	0.000	0.000	1.000	-0.001	0.000	0.000
OECD	0.478	0.000	0.002	0.938	0.900	0.003	0.002	1.000
China	1.000	0.010	0.002	1.000	1.000	0.013	0.002	1.000
Categorical	1.000	0.009	0.001	1.000	0.691	0.000	0.002	0.957
Exporters	1.000	0.009	0.002	1.000	0.987	0.004	0.002	1.000
Region	0.877	0.002	0.001	1.000	0.998	0.005	0.002	1.000
Industry	0.998	0.003	0.001	1.000	0.986	0.004	0.001	1.000
FDI	1.000	-0.013	0.001	0.000	0.700	0.000	0.001	0.001
Number	0.994	0.005	0.002	1.000	0.924	-0.004	0.002	0.000
Value	0.985	-0.004	0.001	0.000	1.000	-0.012	0.002	0.000

Variable	*FixedEffects1*				*RandomEffects1*			
	PIP	*Cond Mean*	*Cond SD*	*Cond Pos Sign*	*PIP*	*Cond Mean*	*Cond SD*	*Cond Pos Sign*
Employment	1.000	0.020	0.001	1.000	1.000	-0.014	0.003	0.000
Manufacturing	0.623	-0.001	0.001	0.000	0.939	-0.004	0.002	0.000
ProbitLogitTobit	0.981	-0.003	0.001	0.000	1.000	-0.007	0.002	0.000
IV	1.000	-0.007	0.002	0.000	0.851	-0.003	0.002	0.000
SampleSelection	0.583	-0.002	0.003	0.000	1.000	-0.015	0.003	0.000
FixedEffects	1.000	-0.006	0.001	0.000	1.000	-0.011	0.002	0.000
Size	0.715	-0.001	0.001	0.000	0.942	0.004	0.002	1.000
Productivity	0.516	0.000	0.001	0.006	0.715	0.001	0.002	0.989
LaborQuality	0.568	0.001	0.001	0.999	1.000	-0.015	0.001	0.000
Capital	0.994	0.007	0.002	1.000	0.997	0.006	0.002	1.000
R&D	1.000	0.022	0.003	1.000	1.000	0.012	0.002	1.000
Journal	1.000	0.015	0.002	1.000	0.999	0.007	0.002	1.000
Impact	0.595	0.002	0.003	0.950	0.999	-0.013	0.004	0.000
Citations	0.928	0.000	0.000	0.000	0.735	0.000	0.000	0.991

NOTE: The column headings *PIP, Post Mean, Post SD* and *Cond Pos Sign* stand for Posterior Inclusion Probability, Posterior Mean, Posterior Standard Deviation and the likelihood-weighted probability that the respective coefficient takes a positive sign. These are described in Section 6 in the text. The Bayesian Model Averaging (BMA) analysis was done using the R package BMS, described in Zeugner (2011). The WLS estimators *FixedEffects1* and *RandomEffects1* are described in Section 4. The table yellow-highlights variables that (i) have a *PIP* equal to 100%; and (ii) have a *Conditional Positive Sign* of 1.000 (i.e., are consistently positive). Variables that (i) have a *PIP* equal to 100% and (ii) have a *Conditional Positive Sign* of 0.000 (i.e., are consistently negative) are highlighted in rose.

TABLE 7
Meta-Regression Analysis
(*Omitting Spillover Measures*)

Variable	*FixedEffects1 (1)*	*FixedEffects2 (2)*	*RandomEffects1 (3)*	*RandomEffects2 (4)*
All Control Variables Included				
SE	1.611*** *(3.89)*	1.918*** *(4.47)*	0.176 *(0.90)*	0.294 *(1.57)*
Exporters	0.009** *(2.36)*	0.012*** *(2.65)*	0.005 *(1.08)*	0.005 *(0.75)*
Region	0.003 *(1.07)*	0.010*** *(2.69)*	0.006 *(1.37)*	0.015** *(2.16)*
Industry	0.003 *(0.72)*	0.001 *(0.18)*	0.004 *(1.20)*	0.004 *(0.72)*
FDI	-0.014 *(-1.29)*	-0.009 *(-0.85)*	-0.001 *(-0.12)*	-0.003 *(-0.50)*
Control Variables Selected Via Backwards Stepwise Regression				
SE	1.606*** *(4.31)*	1.761*** *(4.21)*	0.197 *(1.02)*	0.302 *(1.59)*
Exporters	0.009** *(2.49)*	0.012** *(2.58)*	0.004 *(1.05)*	0.005 *(0.70)*
Region	0.002 *(0.81)*	0.010** *(2.55)*	0.005 *(1.18)*	0.014** *(2.18)*
Industry	0.003 *(0.67)*	0.001 *(0.30)*	0.003 *(1.00)*	0.005 *(0.79)*
FDI	-0.013 *(-1.37)*	-0.010 *(-1.09)*	-0.000 *(-0.03)*	-0.002 *(-0.30)*

NOTE: The top panel reports the results of estimating a regression specification that adds the full set of data, estimation, and study characteristic variables to Equation (3) (the 26 variables of TABLE 7 plus the publication bias variable SE). The bottom panel begins with this specification, locks in the spillover type variables *Exporters*, *Region*, *Industry* and *FDI*, along with *SE*, and then uses a backwards stepwise regression algorithm to select the control variables that minimize the BIC/SIC information criterion. The top value in each cell is the coefficient estimate, and the bottom value in parentheses is the associated *t*-statistic. The four WLS estimators (*FixedEffects1, FixedEffects2, RandomEffects1,* and *RandomEffects2*) are described in Section 4 in the text. All four estimation procedures calculate cluster robust standard errors. *, **, and *** indicate statistical significance at the 10-, 5-, and 1-percent level, respectively.

TABLE 8
Meta-Regression Analysis
(*Omitting Spillover Types)*

Variable	*FixedEffects1* (1)	*FixedEffects2* (2)	*RandomEffects1* (3)	*RandomEffects2* (4)
All Control Variables Included				
SE	1.611*** *(3.89)*	1.918*** *(4.47)*	0.176 *(0.90)*	0.294 *(1.57)*
Number	0.005 *(1.62)*	0.003 *(0.55)*	-0.004 *(-0.80)*	-0.008 *(-0.91)*
Value	-0.004 *(-1.24)*	-0.010 *(-1.59)*	-0.013** *(-2.23)*	-0.014 *(-1.53)*
Employment	0.021*** *(4.02)*	0.014 *(1.57)*	-0.014** *(-2.33)*	-0.021*** *(-3.02)*
Control Variables Selected Via Backwards Stepwise Regression				
SE	1.621*** *(4.35)*	1.800*** *(4.25)*	0.230 *(1.21)*	0.302 *(1.58)*
Number	0.006* *(1.77)*	0.002 *(0.42)*	-0.006 *(-1.01)*	-0.007 *(-0.88)*
Value	-0.003 *(-1.12)*	-0.010* *(-1.68)*	-0.013** *(-2.23)*	-0.014 *(-1.44)*
Employment	0.020*** *(4.17)*	0.015* *(1.68)*	-0.016** *(-2.52)*	-0.021*** *(-2.97)*

NOTE: The top panel reports the results of estimating a regression specification that adds the full set of data, estimation, and study characteristic variables to Equation (3) (the 26 variables of TABLE 7 plus the publication bias variable *SE*). The bottom panel begins with this specification, locks in the spillover measure variables *Number*, *Value* and *Employment*, along with *SE*, and then uses a backwards stepwise regression algorithm to select the control variables that minimize the BIC/SIC information criterion. The top value in each cell is the coefficient estimate, and the bottom value in parentheses is the associated *t*-statistic. The four WLS estimators (*FixedEffects1, FixedEffects2, RandomEffects1,* and *RandomEffects2*) are described in Section 4 in the text. All four estimation procedures calculate cluster robust standard errors. *, **, and *** indicate statistical significance at the 10-, 5-, and 1-percent level, respectively.

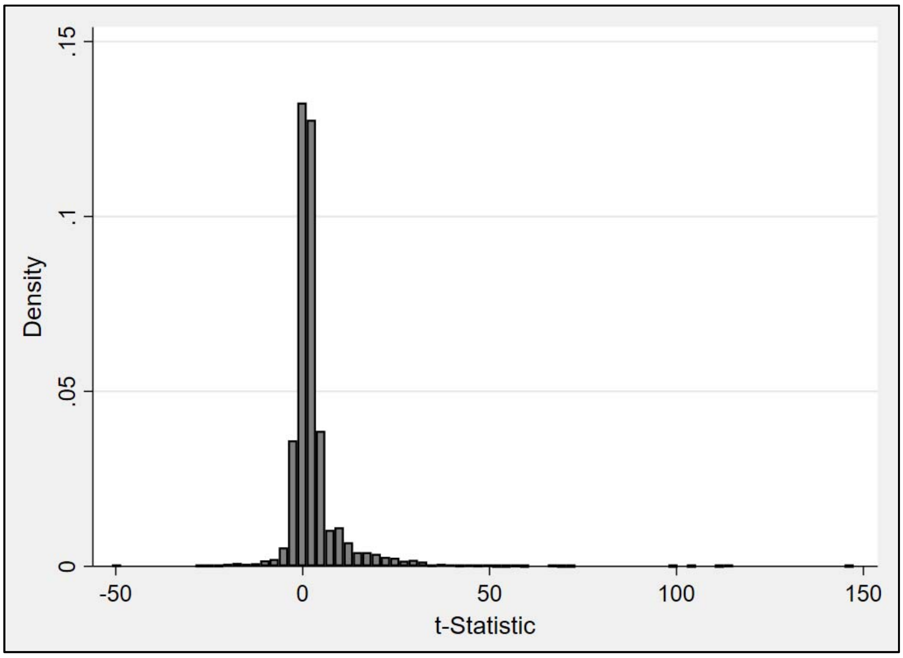
TABLE 9
Meta-Regression Analysis
(*Spillover Types and Measures Included)*

Variable	*FixedEffects1* (1)	*FixedEffects2* (2)	*RandomEffects1* (3)	*RandomEffects2* (4)
Control Variables Selected Via Backwards Stepwise Regression				
SE	1.606*** *(4.31)*	1.794*** *(4.23)*	0.231 *(1.20)*	0.303 *(1.59)*
Exporters	0.009** *(2.49)*	0.012*** *(2.83)*	0.006 *(1.33)*	0.005 *(0.70)*
Region	0.002 *(0.81)*	0.010** *(2.57)*	0.006 *(1.60)*	0.014** *(2.18)*
Industry	0.003 *(0.67)*	0.001 *(0.25)*	0.004 *(1.22)*	0.005 *(0.79)*
FDI	-0.013 *(-1.37)*	-0.010 *(-1.09)*	0.000 *(0.07)*	-0.002 *(-0.30)*
Number	0.005 *(1.58)*	0.002 *(0.39)*	-0.006 *(-0.97)*	-0.008 *(-0.89)*
Value	-0.004 *(-1.16)*	-0.010 *(-1.65)*	-0.013** *(-2.25)*	-0.013 *(-1.42)*
Employment	0.020*** *(4.10)*	0.014 *(1.66)*	-0.016** *(-2.50)*	-0.021*** *(-3.01)*

NOTE: The table reports the results of estimating a regression specification that begins by adding the full set of data, estimation, and study characteristic variables to Equation (3) (the 26 variables of TABLE 7 plus the publication bias variable *SE*). It locks in both spillover type and spillover measure variables *Exporters, Region, Industry, FDI, Number, Value* and *Employment*, along with *SE*, and then uses a backwards stepwise regression algorithm to select the control variables that minimize the BIC/SIC information criterion. The top value in each cell is the coefficient estimate, and the bottom value in parentheses is the associated *t*-statistic. The four WLS estimators (*FixedEffects1, FixedEffects2, RandomEffects1,* and *RandomEffects2*) are described in Section 4 in the text. All four estimation procedures calculate cluster robust standard errors. *, **, and *** indicate statistical significance at the 10-, 5-, and 1-percent level, respectively.

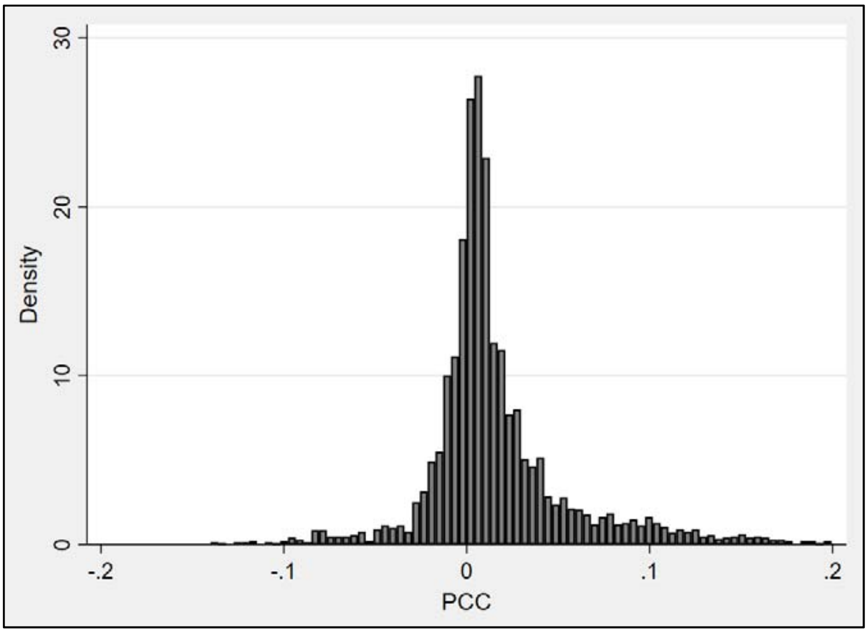
FIGURE 1
Distribution of t-and PCC Values

A. *t*-Statistics



Distribution of t-statistics	*Percent*
t < -2.00	7.7
-2.00 ≤ t ≤ 2.00	53.0
t > 2.00	39.3

B. PCC Values



APPENDIX 1:

Selected Measures of Export Performance

Categorical
• The decision whether firm exports or not in year t • The decision to start exporting to country j • Dummy = 1 if domestic firms in province i begin exporting product k to country j • Export status: permanent exporter, sporadic exporter, new exporter, non-exporter • Internationalisation modes: non-exporter, exporters, firm that exports and engages in horizontal FDI • Status: continue non-exporting, start exporting, continue exporting, exit from exporting • Export dummy = 1 if a firm's export share (direct exports over sales) ≥ 10%
Continuous
• The export scale of firm i for product k to country j at time t • Firm's export value • The ratio of export value to total sales • The share of firm i's exports in industry j • Firm's export volume • Export intensity – the number of macro areas that the firm has served through its exporting activity • Export intensity – the percentage of a firm's exports in output • Growth of exports • Export value / export quantity / export price / export quality • Export variety – the number of HS8 products exported by firm i at time t • Unit value of product j exported by firm i at time t • Export per worker • The share of state i's aggregate exports to country j in GDP

APPENDIX 2:
Examples of Spillover Types

Regional
• Localization – spillovers from spatial agglomeration of related firms • Urbanization – spillovers from urban concentration that apply to all firms and industries in a specific region
Industry
• Horizontal intra-industry – spillovers from firms within the same group of companies within industry • Horizontal inter-interindustry – spillovers from other firms within industry • Backward – spillovers from other firms in industry *j* purchasing intermediate goods from industry *k* where firm *i* is located • Forward - spillovers from other firms in industry *j* supplying intermediate goods to industry *k* where firm *i* is located
FDI / Exporter
• Spillovers that flow from foreign-owned firms / other exporter firms
Examples
• The total number of manufacturing firms in the region • R&D expenditure by domestic firms in sector *j* / sales by domestic firms in *j* • The number of exporting firms outside region that are exporting to market *j* belonging to a different 2-digit industry than firm *i* • The number of other firms in the region operating in the same industry • Regional output of MNEs to domestic markets • The total number of export firms in the region (outside the industry of the firm in focus) • The ratio of foreign-owned firms over total number of firms in the same industry • The number of exporting firms within the same industry but outside region • The share of FDI investment in a certain region-industry • The share of exporters in area, same industry – same destination • The share of exports by foreign firms in total exports in an industry • The share of exports by foreign firms in total exports in a province • The share of exports by foreign firms in total exports in an industry within a province • (Exports by MNEs in sector j / total exports in j) / (total exports by MNEs / total exports) • Exports value / total shipments from plants in the state and in the SIC4 industry • The share of exporting employment in area, all industries – same destination

APPENDIX 3:
Selected Spillover Measures

Value
• Exports value / total shipments from plants in the state and outside the SIC4 industry • The province-industry-firm-type share of national industry exports / the province share of national manufacturing exports • Foreign exports from province *i* of product *k* to country *j* • The ratio of the export volume to total production value
Number
• The number of other firms in the region operating in the same industry • The number of exporting plants / total plants for plants in the state and in the SIC4 industry • The province-firm-type share of national establishments / the province share of national establishments • The number of exporters in area, all industries – same destination • A region's number of firms within the same industry as percentage of a country's total number of firms within the same industry • A region's number of direct and indirect exporters as percentage of a region's total number of firms
Employment
• Exporting employment in area, all industries – same destination • The share of exporting employment in area, all industries – same destination • The number of total employment in the same region and industry (all plants / exporting plants / foreign-owned but non-exporting plants) • The number of skilled workers in the same region and industry (all plants / exporting plants / foreign-owned but non-exporting plants)
Output
• $Horizontal\_FDI_{jt} = \frac{Y_{jt}^{f}}{Y_{jt}}$, Y_{jt}^{f} is the output of foreign firms in industry j, Y_{jt} is the total output of industry j. • $Backward\_FDI_{jt} = \sum_{\forall k \neq j} \alpha_{kjt} Horizontal\_FDI_{kt}$, $\alpha_{kj} = \frac{Y_{kj}}{Y_k}$ where Y_{kj} is the output provided from industry j to industry k. • $Forward\_FDI_{jt} = \sum_{\forall h \neq j} \beta_{hjt} Horizontal\_FDI_{ht}$, $\beta_{hj} = \frac{Y_{hj}}{Y_j}$ where Y_{hj} is the output provided from industry h to industry j. • The sum of squares of an industry's output share by region
R&D

• R&D expenditure by domestic firms in sector j / sales by domestic firms in j • R&D expenditure by MNEs in sector j / sales by MNEs in j • Patent applications per capita in a particular region • The number of patent applications in the region
Other
• If at least one other large exporting firm is present in the region • The presence of foreign-owned firms' capital stock in the total capital stock of an industry, a province and an industry within a province • The share of intangible assets held by foreign firms in fixed assets in an industry, in a province and in an industry within a province • Horizontal spillovers$_{jt}$ = $(\sum_{i\in j} Foreign\ share_{it} * Y_{it})/(\sum_{i\in j} Y_{it})$, $Foreign\ share_{it}$ is the share of foreign fixed capital stock in a foreign-invested enterprise (FIE) i at time t, Y_{it} is the total output of the same FIE at time t. • Backward spillovers$_{jt}$ = $\sum_{k\neq j} \alpha_{jk} Horizontal_{kt}$, α_{jk} is the proportion of industry j's output supplied to industry k. • Forward spillovers$_{jt}$ = $\sum_{m\neq j} \varphi_{jm}[[\sum_{i\in m} Foreign\ share_{it} * (Y_{it} - EX_{it})] / [\sum_{i\in m}(Y_{it} - EX_{it})]]$, φ_{jm} is the share of inputs purchased by industry j from industry m in total inputs sourced by industry j, EX_{it} is the export value of FIE i at time t. • Aggregate shipping weight of exports from each region to each country • Related variety = $\sum_{g=1}^{G} P_g(\frac{1}{H_g})$, H_g is the Herfindahl concentration index calculated at the five-digit level within each two-digit level, P_g is the employment share of sector g. Sector g is located in the same region and related to sector s where firm i is located. • Urbanization = $\frac{LU_p}{Area_p}$, LU_p is the population in province p and $Area_p$ is the number of local units of the province area. • The average number of addresses per square kilometer within a circle of a one-kilometre ray to measure agglomeration • Share of MNEs' expenditures on wages and salaries on total expenditures on wages and salaries of the sector. • The ratio of foreign equity invested to total equity invested in the industry.