Foreign Direct Investment, Growth, and Publication Bias in Latin America and the Caribbean

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Abstract

Economic literature contains conflicting empirical results and explanations concerning the growth effect of foreign direct investment (FDI). In this study, several numerical estimates of FDI's growth effect in Latin America and the Caribbean were drawn from 33 empirical studies and analysed with meta-analytic techniques. The results show that the true growth effect of FDI is near zero and statistically insignificant at all conventional levels. Tests of publication bias performed on the estimates reveal evidence of publication bias in peer-reviewed journal publications authored by PhD holders, but reveal no evidence of publication bias in the empirical literature as a whole. Furthermore, multivariate meta-regression analysis and Bayesian model averaging both show that publication bias is dependent on type of publication outlet and sample size. More precisely, publishing in peer-reviewed journals leads to publication bias, while sample size enlargement reduces publication bias.

Keywords: Foreign Direct Investment, Economic Growth, Publication Bias, Meta-Analysis, Latin America and the Caribbean.

1. Introduction

How does foreign direct investment (FDI) actually affect growth in Latin America and the Caribbean (LAC)? Is it positively or negatively? Is the effect significant or negligible? For policy sake, answers to these questions are of great importance because policy formulators need to know precisely whether policies aimed at attracting FDI are truly beneficial or merely futile (Mamingi and Martin, 2018). But what does the economic literature say? On the one hand, the literature offers three conflicting explanations about the growth effect of FDI. A fraction of the literature suggests that FDI possibly leads to growth as it facilitates competition, human capital development, technological transfers, and technological imitation (Stancheva-Gigov, 2016). Another fraction of the literature also suggests that FDI ultimately harms growth by crowding out domestic firms and stifling local competition (Susic *et al.*, 2017). Again, some authors argue that FDI might affect growth positively, negligibly, or even negatively, depending on the economic conditions in the host country (Blomstrom *et al.*, 2000; Alfaro *et al.*, 2004).

On the other hand, considering the fact that the literature offers contradictory explanations, many empirical studies have attempted ascertaining FDI's actual growth effect in the countries of LAC. However, obtaining accurate results from previously conducted empirical studies faces two major problems. First of all, one has to deal with publication bias. Publication bias, also called "the file drawer problem", occurs when authors choose to report only premeditated results that agree with widely accepted expectations so as to make them publishable even when they are not factual (Havraranek, 2013). Doucouliagos and Stanley (2013) show that publication bias plagues most of empirical economics, so it can be assumed the same applies for the FDI-growth empirical literature. Secondly, one also has to deal with heterogeneity. Estimates of FDI's growth effect vary so broadly across the empirical literature that one cannot tell what its true effect really is. For example, in the case of Mexico, a study conducted by Oladipo and Galan (2009) found a positive growth effect for FDI, while another study conducted by Mendoza-Velazquez and Cortes (2019) found negative correlations in some states.

To address these problems, Iamsiraroj and Ulubasoglu (2015) recently carried-out a meta-analytic investigation on the growth effect of FDI, focusing broadly on both developed and developing countries, including countries in LAC. By employing meta-analysis, the study sought to resolve conflicting empirical evidence on FDI's growth effect by synthesizing the empirical literature quantitatively and filtering-out publication bias. The study discovered the true growth effect of FDI to be positive and non-negligible with a magnitude of approximately 0.11 units in terms of a partial correlation coefficient. Nevertheless, it is worthy to also note that the study did not attempt identifying what drives publication bias in the empirical literature.

In this study, apart from synthesizing the empirical literature quantitatively and correcting for publication bias in order to ascertain the true growth effect of FDI using meta-analytic techniques, a second goal entails identifying the sources of publication bias. Furthermore, unlike previous meta-analytic investigations that focused broadly on both developed and developing countries, this study is interested in only LAC. To the best of my knowledge, this makes it the first meta-analytic study on FDI focusing solely on the countries in LAC. Overall, the findings show that the true growth effect of FDI is extremely small and statistically insignificant. In terms of a partial correlation coefficient, the true effect amounts to only 0.03 units. Lastly, the findings also reveal that the level of publication bias in the empirical literature is mainly dependent on type of publication outlet (peer-reviewed or non-peer-reviewed) and sample size. More precisely, publications in peer-reviewed journals contribute to publication bias while sample size enlargement reduces the extent of publication bias.

The remaining part of this paper is structured in the following way: section two reviews the relevant literature, section 3 describes the dataset, section four tests and corrects for publication bias, section five ascertains the determinants of publication bias, and section six consists of the conclusion.

2. Literature Review

The literature on FDI's growth effect falls under three main categories. The first category details the positive growth effect, the second category details the negative growth effect, and the third category details the conditional growth effect. In this section, three subsections are set apart for discussing each of the various effects.

2.1 Positive growth effect of FDI

Iamsiraroj and Ulubasoglu (2015) explain the numerous ways through which FDI affects growth positively. To start with, within the context of neoclassical growth theories, FDI leads to economic growth by boosting technological progress. Without FDI and technological progress, the accumulation of capital might increase long-term output but growth would only be transitional. Within the context of endogenous growth theories, FDI accelerates growth both directly and indirectly. In the direct way, FDI might be seen promoting growth as it facilitates the accumulation of capital and the introduction of novel technology. Indirectly, it improves human capital, infrastructural, and institutional development, and also generates positive spill-overs. Also, many empirical studies claim that FDI positively affects growth in both developed and developing regions including LAC countries. Some of the recent notable ones worth mentioning include Kumar (2014) (for 21 LAC countries), Buitrago and Leon (2015) (for Colombia), Shernett (2015) (for Jamaica), Canchari *et al.* (2020) (for Peru), and Hosein *et al.* (2019) (for St. Lucia).

Stancheva-Gigov (2016) equally elucidates the channels through which FDI affects growth positively. First of all, FDI brings about increased competition which leads to productivity gains, efficiency, and accumulation of human and physical capital. Again, the inflow of FDI usually necessitates training for workers and management. Thirdly, as mentioned previously by Iamsiraroj and Ulubasoglu (2015), technological transfers usually accompany FDI. And lastly, with FDI, domestic firms have some propensity to imitate advanced technologies from foreign counterparts.

2.2 Negative growth effect of FDI

Another fraction of the literature is of the opinion that FDI affects growth negatively. Susic *et al.* (2017) for example state that FDI might crowd-out domestic firms. Should this happen eventually, foreign firms would become monopolists and growth would be constrained to fewer firms. Again, growth could also be hampered by payment imbalances owing to outward repatriations of profits to foreign investors. For developing countries, there are issues bordering on environmental degradation that might harm growth in the long-term. To be precise, in a situation where FDI is channelled toward natural resource sectors such as crude oil and coal in developing countries with weak environmental regulatory frameworks, natural resource exploitation over time might pollute the ecosystem and destroy environmental resources needed for growth (Gray, 2002). Furthermore, scarce national resources that would have been otherwise used to foster economic growth might be diverted toward reversing environmental degradation, as often witnessed in Latin America's coastal countries (Donohue *et al.*, 2021). Nevertheless, to date, only few empirical studies claim to have verified the negative growth effects of FDI. Some of these include Musibah *et al.* (2015) and Mendoza-Velazquez and Cortes (2019).

2.3 Conditional growth effects of FDI

A third strand of the literature argues that the growth effect of FDI is dependent on the economic conditions of the host country. To affect growth positively, the host country should have a sufficient supply of human capital (Blomstrom *et al.*, 2000), an environment of macroeconomic stability, open trade, and investment, (Balasubramanyam *et al.*, 1996), financially developed markets, and developed infrastructure (Alfaro *et al.*, 2004). In the absence of the aforementioned economic conditions, FDI might not lead to growth or might even lead to negative growth. The implication of the "conditional" view is that developed countries are more likely to experience growth from FDI than underdeveloped countries. This is because the enabling economic conditions for FDI-led growth are readily available in the developed countries, but barely available in the underdeveloped ones. The positive conditional effects of FDI have been documented in recent empirical studies including Iamsiraroj and Ulubasoglu (2015) and Vedia-Jerez and Chasco (2016).

3. The Dataset

The dataset consists of 33 studies and 94 observations. Many studies reported more than one estimate of the growth effect of FDI. Data was collected electronically from several databases including Google Scholar, RePEc, and Scopus. The oldest study in the dataset was published in 1998 while the latest study was published in 2021. Altogether, the collected studies examined time series data from 1960 to 2019. The examined LAC countries are 35 in number and include Antigua and Barbuda, Argentina, the Bahamas, Barbados, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba, Curacao, Dominica, the Dominican Republic, Ecuador, El Salvador, Grenada, the Grenadines, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Saint Kitts and Nevis, Saint Lucia, Saint Vincent, Suriname, Trinidad and Tobago, Uruguay, and Venezuela. Most of these countries were examined individually as case studies while few were examined in only panel data settings.

In collecting the estimates, consideration was given to only empirical studies that modelled economic growth as a function of FDI and control variables, as depicted in the following equation:

$$G_t = \alpha + \beta FDI_t + \sum_{i=1}^{n} \gamma_i X_{it} + u_t \quad (3.1)$$

where G denotes economic growth, α denotes the intercept, β denotes the coefficient of FDI, FDI denotes a measure of foreign direct investment, γ_i denotes a vector of coefficients for the n control variables, X_i denotes a vector of the n control variables, u denotes a stochastic term, and subscript t denotes time. Here, the estimated growth effects of FDI were captured numerically by making reference to the coefficient β, which is the first derivative of the growth function with respect to the chosen measure of FDI:

$$\frac{\partial G_t}{\partial FDI_t} = \beta, \ |\beta| \geq 0 \quad (3.2)$$

In some of the empirical studies, interaction terms such as "*FDI×Infrastructure*" and "*FDI×Trade*" were included as additional regressors, which made it impossible to calculate the total growth effect of FDI on the basis of equation 3.2. Following Iamsiraroj and Ulubasoglu (2015) such studies were excluded from the dataset and the subsequent meta-regression analysis. Empirical studies that erroneously measured economic growth in terms of GDP and GDP per capita instead of GDP growth and GDP per capita growth were also excluded.

To obtain standardized effect sizes from the estimates, conversions to partial correlation coefficients were performed. The importance of this step emanates from the fact that regression coefficients are not directly comparable and therefore need to be transformed into partial correlation coefficients which are directly comparable (standardized) and at the same time capable of depicting the strength of association between any two variables of interest (Doucouliagos and Laroche, 2009). As with the estimates, all standard errors were also converted to partial correlation coefficient standard errors in order to facilitate comparability. A simple statistical summary of the transformed dataset is presented in Table I.

Table I: Statistical Summary of the Dataset

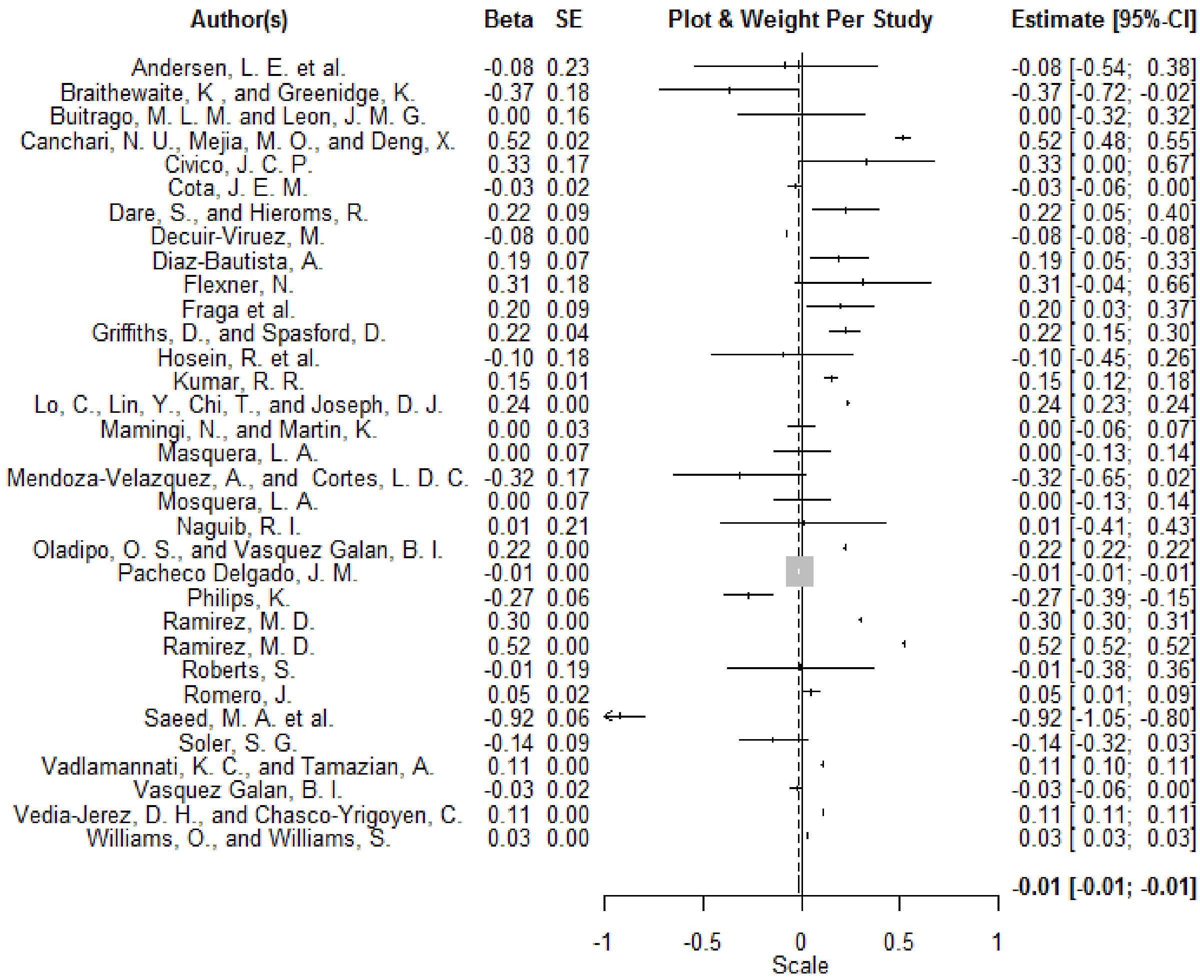
Variable	Mean	S.D.	Min.	Max.
β_{PCC} per study	0.0854	0.2549	-0.9236	0.6138
SE_{PCC} per study	0.1266	0.0604	0.0338	0.3036
Number of observations	94	94	94	94
Number of studies	33	33	33	33

Notes: β_{PCC} denotes partial correlation coefficient of FDI, SE_{PCC} denotes standard error of the partial correlation coefficient, Mean denotes arithmetic mean, S.D. denotes standard deviation, Min. denotes sample minimum, and Max. denotes sample maximum.

On the one hand, the mean partial correlation coefficient carries a small magnitude of only 0.0854 which suggests preliminarily that FDI has no substantial association with growth.

Furthermore, the corresponding standard deviation carries a relatively large magnitude of 0.2549 which implies that the partial correlation coefficients are heterogeneous and widely dispersed from the mean. On the other hand, the mean standard error carries a magnitude of 0.1266 which is approximately 1.48 times bigger than the mean partial correlation coefficient. This suggests preliminarily that the extent of association between FDI and growth might be statistically insignificant. For a pictorial description of the dataset we turn to the forest plot in Figure 1.

Figure 1: Forest Plot of the Dataset



In the forest plot, the black dots represent the partial correlation coefficients (betas) drawn from each study. For studies which had more than one partial correlation coefficient, weighted averages were calculated using inverse-variance as weights. Furthermore, the sizes of the grey squares depict the weights attached to the partial correlation coefficients, the horizontal lines represent the 95% confidence intervals which are also stated numerically at the right, the vertical solid line represents the zero point, and the vertical dashed line represents the average partial correlation coefficient estimated by the fixed effects meta-regression method. Based on the fixed effects method, the average equals only -0.01 units, although it is statistically significant (z-statistic = -4259.22) with an extremely narrow 95%

confidence interval (-0.01, -0.01). Judging by the sizes of the grey squares, the partial correlation coefficient reported by Pacheco-Delgado (2021) carries the greatest weight and therefore exerts the most influence in the sample. When it is excluded, the fixed effects average partial correlation coefficient jumps considerably to 0.04 units with a statistically significant *z*-statistic (298.04) and 95% confidence interval *CI* = (0.04, 0.04). However, at this juncture, it is important to note that all of these statistics cannot be taken seriously owing to the likelihood of publication bias. Testing and correcting for publication bias is the central goal of the next section.

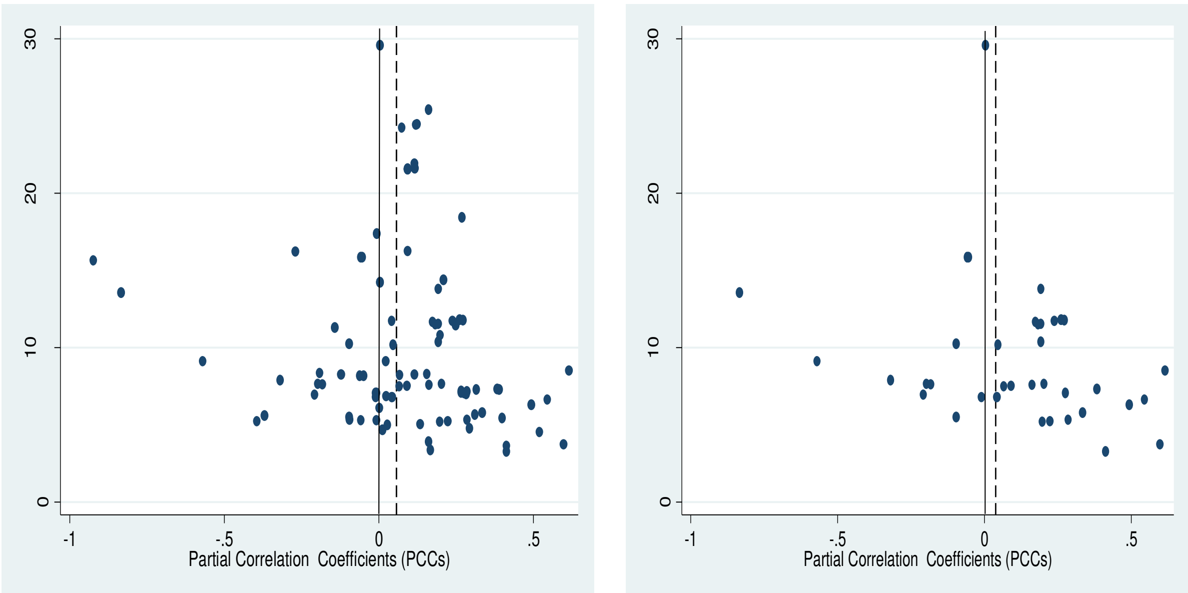
4. Testing and Correcting for Publication Bias

The starting point of the meta-analysis entails visualizing the dataset using funnel plots (Egger *et al.*, 1997) in order to test for publication bias. In simple terms, a funnel plot is a scatter plot which has effect sizes on the horizontal axis and measures of precision on the vertical axis. Evidence of publication bias manifests itself when the funnel plot is asymmetrically distributed around the estimated mean effect size (Havranek, 2013). The funnel plots are presented in Figure 2.

Figure 2: Funnel Plots Reveal Bias in Peer-Reviewed Publications by PhD Holders

(a) All Studies

(b) Peer-Reviewed Publications by PhD Holders



Notes: x-axis: partial correlation coefficients; *y*-axis: precision of partial correlation coefficients (1/SE). Black dashed lines represent the mean partial correlation coefficients obtained by fixed effects; Black solid lines represent zero on the x-axes.

On the one hand, when partial correlation coefficients from all studies are considered as shown in panel (a), there is no clear evidence of publication bias because the funnel plot is almost symmetrically distributed. This is unexpected because Doucouliagos and Stanley (2013) and Ioannidis *et al.* (2017) both reveal that substantial publication bias exists in almost all spheres of empirical economics. On the other hand, when publications by PhD holders in peer-reviewed journals are considered solely as shown in panel (b), there is stronger evidence of publication bias because the funnel plot seems to be denser on the right side. Intuitively, this is not unexpected because peer-reviewed publications and publications by PhD holders are more likely to be polished to suit widely accepted theories. Moreover previous meta-analytic studies such as Havranek and Irsova (2012) have already verified the fact that peer-reviewed publications and publications by PhD holders are prone to publication bias.

Nevertheless, funnel plots are only useful for pictorial analyses. To quantitatively test for publication bias, meta-regression analysis is imperative. Following Havranek (2013), the mixed effects multilevel model which corrects for both heteroskedasticity and intra-study dependence is employed for the meta-regression analysis:

$$t_{i,j} = \alpha_0 + e_0 . \frac{1}{SE_{PCC}} + \zeta_j + \epsilon_{i,j} \quad (4.1).$$

Here, $t_{i,j}$ represents the *t*-statistic of the study-level estimate, α_0 represents the intercept, e_0 represents the 'true' effect in terms of a partial correlation coefficient adjusted for publication bias, SE_{PCC} represents the standard error of the partial correlation coefficient, subscript i and subscript j represent estimate and study subscripts respectively, ζ_j represents the study-level random effects, and $\epsilon_{i,j}$ represents the estimate-level disturbances. A simple *t*-test performed on the intercept (the funnel asymmetry test - FAT) should be statistically significant if there is publication bias, while a simple *t*-test performed on the slope (the precision effect test - PET) should be statistically significant if there is an underlying 'true' effect, e_0. Estimates of the mixed effects model are presented in Table II.

Table II: Test for Publication Bias and the 'True' Effect

	All Studies (ME)	All Studies (OLS Clustered)
Constant (publication bias)	0.3701	0.3701
	(0.3413)	(0.5095)
1/*SE* (true effect)	0.0302	0.0302
	(0.0407)	(0.0541)
Observations	94	94
Studies	33	33
	Peer-Reviewed Publications by PhD Holders (ME)	Peer-Reviewed Publications by PhD Holders (OLS Clustered)
Constant (publication bias)	1.5042**	1.5042**
	(0.6120)	(0.5239)
1/*SE* (true effect)	-0.0941	-0.0941
	(.0816)	(0.0849)
Observations	38	38
Studies	12	12

Notes: Standard errors in parentheses. Dependent variable: *t*-statistic of FDI coefficient. ME denotes mixed-effects multilevel model with robust errors, and OLS Clustered denotes ordinary least squares with errors clustered at the study level. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

By and large, the results of the mixed effects model in Table II agree with the funnel plots. When all of the estimates (partial correlation coefficients) are considered, the intercept is statistically insignificant which implies that there is no evidence of publication bias in the empirical literature. But when estimates from peer-reviewed publications authored by PhD holders are considered solely, the intercept becomes statistically significant which implies that there is some evidence of publication bias in this part of the empirical literature.

Interestingly, similar results are obtained using the ordinary least squares estimator with errors clustered at the study-level as a robustness check.

Apart from testing for publication bias, it is equally important to ascertain the 'true' effect corrected for publication bias. This can be done by examining the estimated slopes of the mixed effects and OLS models in Table II. For the entire sample of estimates, the estimated slopes carry a very small magnitude of only 0.0302 units which is statistically insignificant and implies that FDI has no significant relationship with economic growth. A similar result is obtained from the sample of estimates drawn solely from peer-reviewed publications authored by PhD holders; the estimated slopes are also near zero (-0.0941) and statistically insignificant. Additional robustness checks for the 'true' effect using the Top 10% (Stanley et. al., 2010), the Top 1 (Ioannidis, 2013), and the weighted average of the adequately powered (WAAP) (Ioannidis et. al., 2017) are presented in Table III.

Table III: Robustness Checks for the 'True' Effect

	Top 10%	Top 1	WAAP
'True' Effect	0.1019	0.0025	NA
Observations	9	1	0

Notes: Top 10% denotes top 10% of the most precise estimates; Top 1% denotes the single most precise estimate; and WAAP denotes weighted average of the adequately powered estimates.

Compared to the mixed effects estimate (0.0302), the top 10% (0.1019) is much larger in size while the top 1 (0.0025) is much smaller. The WAAP is not available (NA) because there are no adequately powered partial correlation coefficients. On the one hand, the relatively large magnitude of the top 10% estimate is not surprising. This is because simulations in Stanley *et al.* (2010) reveal that its estimator tends to be biased upward when there is no underlying 'true' effect, as implied by the statistical insignificance of the mixed effects estimate (0.0302). In other words, in the robustness check, the top 10% estimate can be regarded as an upper bound; a value which the estimated 'true' effect (0.0302) should not exceed since it has been found to be statistically insignificant. On the other hand, despite the fact that the top 1 estimate is much smaller, it ultimately reverberates the finding that the 'true' effect is near zero. This enables one to conclude decisively that the 'true' effect is largely negligible.

5. Gauging the Determinants of Publication Bias

> *"Recall that bias is the expected value of the difference between an estimate or estimator and the 'true' effect. We seek to approximate this theoretical magnitude, empirically. Empirically, expected values are approximated by simple averages and bias by the average difference of many estimates from some proxy of 'true' effect"* (Ioannidis *et al.*, 2017, p. F249).

Following the above statement by Ioannidis *et al.* (2017), we can first of all quantify the amount of bias in each study by calculating the absolute difference between each study's reported estimate and the 'true' effect (0.0302) obtained from the mixed effects multi-level model in the topmost section of Table II. Where we have more than one estimate per study, we simply find the average of the absolute differences at the study-level. With 33 studies in our dataset, this yields 33 observations of publication bias.

Having obtained empirical estimates of the response variable, publication bias, the next goal is to explore the sources of its heterogeneity in order to identify its main determinants. For this purpose, drawing heavily on Havranek and Irsova (2012), thirteen possible explanatory variables pertaining to both author and study characteristics are chosen. The statistical summary of these explanatory variables and the response variable is presented in Table IV.

Table IV: Summary Statistics of Explanatory and Dependent Variables

Variable	Type	Mean	S.D.	Min.	Max.
Study-level publication bias	Num.	0.18	0.19	0	0.95
Number of reported estimates (*Ne*)	Num.	2.91	2.38	1	9
Research is a peer-reviewed journal publication (*Peer*)	Dum.	0.45	0.5	0	1
Impact factor of publication outlet (*IF*)	Num.	0.57	0.96	0	3.158
Number of citations received by the study (*Cite*)	Num.	6.88	9.77	0	41
Number of observations in natural log (*N*)	Num.	4.37	1.01	2.89	6.78
A co-author is indigenous to the studied area (*Native*)	Dum.	0.7	0.46	0	1
A co-author works/studies in a US-based institution (*US-based*)	Dum.	0.18	0.39	0	1
A co-author works/studies in an academic institution (*Acad.*)	Dum.	0.88	0.33	0	1
Year the study was officially published or disseminated (*Year*)	Num.	15.33	6.43	1	24
Focus on interpreting significance of FDI (*Signif*)	Dum.	0.76	0.43	0	1
Lead author does not hold a PhD (*Not_PhD*)	Dum.	0.45	0.5	0	1
Lead author had a PhD 1-5 years to publication (*PhD_1-5*)	Dum.	0.15	0.36	0	1
Lead author had a PhD 6+ years to publication (*PhD_6_above*)	Dum.	0.39	0.49	0	1
Observations		94	94	94	94
Number of studies		33	33	33	33

Notes: Num. denotes numerical variable; and Dum. denotes binary dummy variable which equals 1 or 0. Data on *IF*, *Cite*, and all PhD variables obtained using RePEc, Google Scholar, and Google Search, respectively.

The first explanatory variable, *Ne*, measures the number of empirical estimates reported per study. It is expected that studies reporting just one or few estimates will present only those that are polished and possibly biased. Peer-reviewed publications (*peer*) and publications with high impact factors (*IF*) are more selective with regards to the findings they choose to publish. Therefore, publications from these outlets should exhibit some publication bias. Widely cited articles largely conform to widely accepted theories. For this reason one should also expect articles with several citations (*Cite*) to contain some publication bias.

Studies with sufficiently large sample sizes (*N*) have smaller standard errors. Intuitively, an author facing smaller errors will need to put less effort in polishing estimates to make them look statistically significant and covertly biased. Furthermore, three categories of authors are likely to engage in publication bias. These include authors native to the countries under investigation (*Native*), authors affiliated with US-based academic and research institutions (*US-based*), and generally, authors in academia (*Acad.*). Native authors might disseminate biased results to suit their vested interests, while authors in academia and research institutions might disseminate biased results in order to increase the likelihood of penetrating highly-ranked peer-reviewed journals owing to publication pressure from employers.

Stanley *et al.* (2008), as cited in Havranek and Irsova (2012), are of the opinion that as years (*years*) go by, authors become more open to “skeptical” (statistically insignificant) results.

Therefore, publication bias should decrease with time. Authors that focus mainly on interpreting the significance (*Signif.*) of FDI's growth effects are likely to prefer significant estimates. So it is expected that studies published by such authors will have some publication bias. Finally, authors' academic achievements and academic status might affect their publication preferences. More precisely, the desire to occupy and maintain tenured academic positions usually compels PhD holders to publish "publishable" (biased) findings. So it is expected that newly minted PhDs with 1 to 5 years post-PhD experience (*PhD_1-5*) and older PhD holders with more than 5 years post-PhD experience (*PhD_6_above*) will publish more biased results compared to non-PhD holders (*Not_PhD*).

With 13 explanatory variables, there are at least 2^{13} (or 8192) different combinations of the explanatory variables that one can utilize to explain publication bias at the study-level. Therefore, without model averaging methods such as Bayesian model averaging (BMA), one would find it difficult to ascertain the explanatory variables that really ought to be included in the regression. Alternatively, one might choose to include all of the explanatory variables, but this will over-fit the model and limit the degrees of freedom since there are only 33 observations of publication bias. The BMA results are presented in Table V.

Table V: Determinants of Publication Bias

	Robust Least Squares			Bayesian Model Averaging		
Variable	Coef.	SE	Prob.	PM	PSD	PIP
Ne	--	--	--	-0.0011	0.0059	0.1387
Peer	0.1118*	0.0642	0.09	0.0442	0.0714	**0.3620**
IF	--	--	--	-0.0020	0.0127	0.0710
Cite	--	--	--	-0.0251	0.0010	0.0803
N	-0.0625**	0.0243	0.02	-0.0340	0.0368	**0.3933**
Native	--	--	--	0.0191	0.0661	0.2833
US-based	--	--	--	-0.0121	0.0555	0.1727
Acad.	--	--	--	0.0003	0.0505	0.1147
Year	--	--	--	-0.0028	0.0020	0.0760
Signif.	--	--	--	0.0105	0.0213	0.0540
Not_PhD	--	--	--	-0.0206	0.0412	0.1446
PhD_1-5	--	--	--	0.0038	0.0599	0.1653
PhD_6_above	--	--	--	-0.0011	0.0389	0.1273
Constant	0.4005***	0.1133	0.00	1	NA	1
Observations:	33			33		
Studies:	33			33		

Notes: PM denotes posterior mean, PSD denotes posterior standard deviation, PIP denotes posterior inclusion probability, Coef. denotes coefficient, SE denotes robust standard error, and Prob. denotes probability value. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively. PIPs > 0.3 in bold. In the robust least squares check we include only explanatory variables with PIP > 0.3.

In the BMA results, one has to consider the posterior inclusion probabilities (PIPs). Following Polak (2019), only explanatory variables with PIPs greater than 0.3 deserve inclusion in the regression explaining publication bias. Variables with lower PIPs ought to be excluded. *Peer* and *N* are the only variables with PIPs greater than 0.3 and are therefore the only explanatory variables deserving inclusion. Having found the most important explanatory variables, the robust least squares estimator is employed for further estimation. The coefficient for *peer*, 0.1118, turns out to be positive and statistically significant, albeit at the

10% level. This implies that peer-reviewed publications increase the level of publication bias in the empirical literature. On the other hand, the coefficient for *N*, -0.0625, turns out to be negative and statistically significant even at the 5% level. This implies that the larger the sample size or number of observations utilized, the smaller the level of publication bias in a study.

6. Conclusion

This study sought to ascertain the 'true' growth effect accruing from FDI to LAC and what determines publication bias in the empirical literature. 94 estimates of FDI's growth effect were extracted from 33 empirical studies and analysed with several meta-analytical techniques. First of all, the precision effect test (PET) found the growth effect of FDI to be near zero (0.03) and statistically insignificant at all conventional levels. This result appeared to be consistent in the face of multiple robustness checks including the "top 10%" and the "top 1". Furthermore, tests of publication bias found no evidence of publication bias for the whole sample of empirical estimates. But in examining estimates drawn solely from peer-reviewed publications by PhD holders, significant evidence of publication bias was found. This showed that publication bias varies across the empirical literature and created the rational for investigating the determinants of publication bias.

Thirteen variables related to author characteristics and study design were identified as possible determinants of publication bias. To ascertain the variables most relevant in explaining publication bias, Bayesian model averaging was utilized. To econometrically establish the effects of the most relevant variables on publication bias, the robust least squares estimator was utilized. Out of the thirteen variables, Bayesian model averaging revealed that publication bias is mainly dependent on peer-reviewed publications and sample size. On the other hand, estimations with the robust least squares estimator showed that peer-reviewed publications lead to publication bias while sample size enlargement reduces publication bias.

In summary, the absence of a non-zero growth effect for FDI in LAC seems to support the "conditional growth effect" hypothesis. In other words, most of the countries in LAC are still developing countries and therefore lack the economic conditions needed to realize significant growth benefits from FDI inflows. This is important for policy formulators. Policies aimed at attracting FDI inflows can only be beneficial if matched by policies aimed at establishing enabling conditions for growth such as macroeconomic stability, technological advancement, and human capital development. Again, policy relevant empirical results from peer-reviewed journals and small-sample studies must be interpreted with caution. They might be inaccurate and misleading owing to publication bias.

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