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The effect of FDI on the host countries' employment: A meta-regression analysis

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Abstract

This study performed a meta-regression analysis (MRA) to reexamine the effect of foreign direct investment (FDI) on the host countries' employment. We detected a publication bias and heterogeneity between studies by employing 61 publications with 477 estimates as the dataset. Studies that do not control for endogeneity suffer an upward publication bias. In contrast, we found a downward publication bias in the studies that control endogeneity. After correcting that bias, we found a small positive effect of FDI on the host countries' employment as the genuine effect. By using the Bayesian Model Averaging (BMA) analysis, we found six moderator variables that could explain heterogeneity. These moderator variables are related to the FDI and employment measurement type, data characteristics, FDI-receiving countries, and estimation methods.

Keywords: employment, employment creation, FDI, labor force, meta-regression.
JEL classification: J20, J21, E22.

1. Introduction

After the COVID-19 pandemic, employment has become a critical issue that has received more global attention. In 2021, the International Labour Organization (ILO) reported a decline in the global employment ratio from 57.6% to 54.9% (ILO, 2021). The global unemployment rate also increased from 5.4% to 6.5% due to COVID-19. However, the global foreign direct investment (FDI) trend has tended to experience uncertainty. Although it rebounded in 2021 and 2022, the United Nations Conference on Trade and Development (UNCTAD) predicts that global FDI will decline in 2023 (O'Farrell, 2022).

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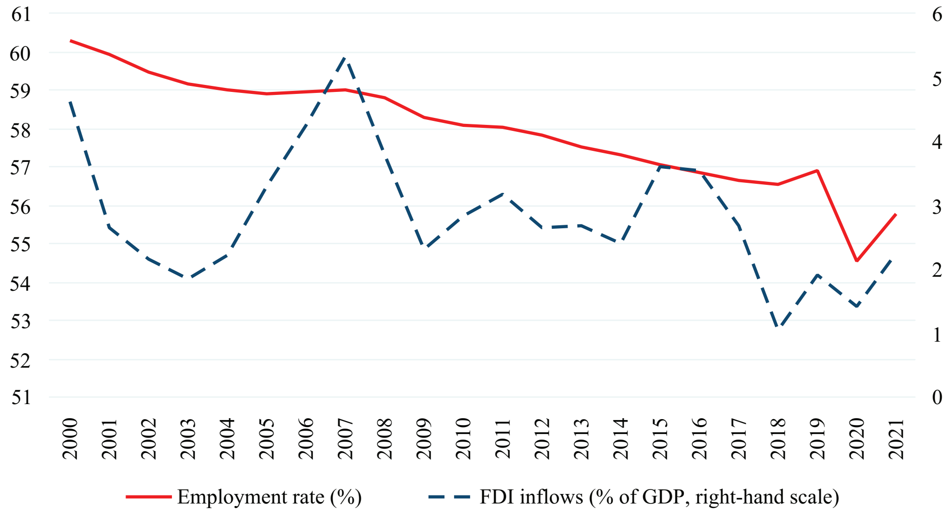

Fig. 1. Global FDI inflows and employment rate (%).

Sources: UNCTAD, ILO.

Fig. 1 indicates a linear relationship between global FDI inflows and the employment rate trend. From 2019 to 2021, for instance, their trends are similar. In 2019, FDI and the employment rate increased, then fell sharply in 2020 due to the COVID-19 pandemic. After that, they rebounded in 2021. It means that, when viewed from a trend perspective, there is a positive relationship between FDI and employment. Because of that, many countries believe that FDI has potential direct and indirect effects on employment.

However, the real effect of FDI on employment is complex and controversial. Several studies revealed contradicting results. For instance, Jula and Jula (2017) and Kharel (2020) found a positive effect of FDI on employment. By way of contrast, Umit and Alkan (2016), and Uddin and Chowdhury (2020) found that FDI harmed employment. Keynes (2018) indicated that investment decisions determined the increase in output and employment. According to that view, FDI triggers employment. Nevertheless, due to labor inefficiency, FDI could reduce it (Jude and Silaghi, 2016).

Consequently, each country should be more selective in determining policies to attract FDI. The heterogeneity among studies regarding the effect of FDI on employment complicates policy implementation. On that basis, a study that can synthesize the literature on the effect of FDI on employment is needed. It is critical to provide an overview of the impact of FDI on employment in certain situations and conditions. Saurav et al. (2020) conducted a literature review of the effect of FDI on employment in developing countries. However, their study still has substantial weaknesses. It neither comprehensively detected a publication bias nor explained heterogeneity. The differences in measurement methods, models, sample size, types of countries sampled, types of data, and types of FDI sectors make heterogeneity challenging to identify. Therefore, our study attempts to fill these gaps by conducting a meta-regression analysis (MRA) to reexamine the effect of FDI on the host countries' employment.

We employ MRA because it can explain heterogeneity in more detail by developing moderator variables. This study has five main objectives: capturing the mean size effect, finding the evidence related to heterogeneity, detecting a publication selection bias, finding the genuine effect (effect beyond bias), and explaining heterogeneity more comprehensively. In this context, the mean effect size measures the average effect of FDI on employment from the literature without controlling the publication selection bias possibility. Meanwhile, the genuine effect is the true effect of FDI on employment after controlling for a publication selection bias from the literature.

Our study could be useful for every country which conducts FDI policies in order to anticipate employment problems. It also might be valuable for subsequent studies that further examine the effect of FDI on the host countries' employment. This paper is organized as follows. We describe our study motivation in Section 1 and provide an overview of the relevant literature in Section 2. Then we describe our methodology in Section 3 and report the main results in Section 4. We conclude in Section 5.

2. Literature review

For the host country, the effect of FDI on employment can be direct or indirect. Those effects could also be positive or negative. Jenkins (2006) stated that FDI could positively affect employment by increasing net capital and creating jobs from industrial expansion. FDI can also increase productivity if it pays higher wages and employment in areas with high unemployment rates. In addition, FDI could have an indirect positive effect if it generated jobs through a multiplier effect on the local economy, encouraging companies to migrate to areas where there is a larger workforce. Referring to Hunya and Geishecker (2005), FDI could positively affect low and high-skilled workers.

Findlay (1978) indicates a change in labor skills due to FDI. The latter could increase employment as well as economic growth through technology transfer. In other words, FDI will increase unskilled workers' demand and then upgrade their skills. However, this view has met a lot of criticism. For example, the study by Jauhari and Mohammed (2021) found no evidence that vertical FDI improved labor skills. FDI could also reduce specific jobs if a foreign company cut off a domestic supplier after acquiring a company in a host country. At the same time, FDI from acquisitions by foreign companies may reduce jobs due to efficiency. They could also become more dependent on imports and potentially reduce the number of workers. McDonald et al. (2002) mentioned that the initial impact of FDI on employment was small and mainly linked to the creation of low-skilled jobs. They also revealed that FDI could reduce employment in host economies due to the displacement of domestic output by increased exports from the parent companies of subsidiaries.

The host country needs to consider the policies on FDI carefully. In such policies, the government of each country certainly needs to be supported by empirical studies. However, empirical studies on the effect of FDI on employment tend to vary and make complex policy recommendations. Several studies, including those conducted by He (2018), Bekhet and Mugableh (2016), Kharel (2020), and Çolak and Alakbarov (2017), found a positive effect of FDI on employment.

Although the conclusions are relatively similar, these studies used different measurements, estimation methods, and samples.

The ordinary least square (OLS) method tends to be widely used by researchers in examining the effect of FDI on employment. Using OLS, Kwan and Tang (2020), Vacaflores et al. (2017), Abor and Harvey (2008), Bakher (2017), and Lee and Park (2020) found a positive effect of FDI on employment. This effect, unfortunately, is not always robust. For instance, Hunya and Geishecker (2005) state that although FDI positively affects employment, the magnitude tends to be small and determined by several other factors. On the contrary, by employing the OLS method, Ngwakwe (2017) and Aswal et al. (2020) found a negative effect of FDI on employment. So it seems there is no guarantee that employing the OLS method would result in a positive effect of FDI on employment.

One of the basic assumptions of the positive effect of FDI on employment lies in the general theory of Keynes (2018). In his book, first published in 1936, he states that investment decisions determine the actual increase in employment. An increase in investment, particularly in FDI, will lead to growing capital inputs which can trigger demand for labor. The relationship between investment, capital, and employment is one of the causes of many studies that have proved the positive effect of FDI on employment.

However, several studies also found a negative effect of FDI on employment, for instance, Mehmood et al. (2018), Uddin and Chowdhury (2020), Aswal et al. (2020), and Wang et al. (2020). Some studies state that the effect of FDI on employment varies depending on several factors, including the skill level of the workforce, the type of jobs, and the FDI target sector. Berman et al. (1998) state that the increasing demand for high-skilled workers is one of the implications of the skill-biased technical change theory. The incoming FDI is considered to increase the workforce with high skills due to the transfer of new technology. Bailey and Driffield (2007), who stated that FDI would only benefit highly skilled workers, proved this theory.

According to Bailey and Driffield (2007), FDI could reduce low-skilled workers, so attracting FDI to reduce unemployment is considered inappropriate. Meanwhile, Akcoraoglu and Acikgoz (2011) explained that FDI inflow negatively impacted employment in the long term. According to the authors, who use Turkey as a sample, the negative effect of FDI on employment occurs because most incoming FDI comes from mergers and acquisitions by foreign companies. On the contrary, Marelli et al. (2014) and Nguyen et al. (2020) state that subsidiary FDI positively affects employment.

3. Method

This study employs MRA to synthesize the empirical literature regarding the effect of FDI on the host countries' employment. As to the data collection, analysis, and conclusion, we adhere to the reporting guidelines for meta-analysis in economics from MAER-Net (see Havranek et al., 2020 for details). The primary purpose of using the MAER-Net recommendations is to produce a standard quality meta-analysis study in economics.

Stanley and Doucouliagos (2011) defined MRA as a multivariate empirical investigation that uses multiple regression analysis related to what factors cause large differences between regression estimates reported by different studies. The MRA method extends basic meta-analysis (Thompson and Higgins, 2002). In MRA, heterogeneity can be explained through one or more study characteristics. The MRA is also able to detect and correct a publication selection bias. Moreover, one could explain heterogeneity more comprehensively by employing multiple MRA.

According to the MAER-Net recommendations, MRA must be carried out using the general to specific (G to S) method or the averaging model. We use a model with Bayesian Model Averaging (BMA) method to fulfill this term. The BMA method is critical for anticipating model uncertainties in meta-analytic studies (Havranek et al., 2017). BMA can select moderator variables most related to the effect size variable. BMA can estimate and simulate millions of models to find moderator variables with the highest explanatory power.

The main purpose of using BMA is to carry out the inclusion model by selecting the best moderator variable. We use the BMA analysis procedure proposed by De Luca and Magnus (2011). It estimates the posterior inclusion probability (PIP) to determine moderator variables with the highest explanatory power. In other words, PIP selects the most effective regressor in the model (Masanjala and Papageorgiou, 2008). If it exceeds 0.5, the regressor variable can explain the dependent variable more effectively. In this study, the regressors are moderator variables (Z-variable), and the dependent one is the effect size.

We have five main questions to be answered. First, what is the mean effect size of FDI on employment that can be explained from the literature? Second, is there evidence that the literature has heterogeneity? Third, is there any publication selection bias in the collected literature? Fourth, how large is the genuine effect of FDI on the host countries' employment? Fifth, what factors determine heterogeneity among studies? In order to answer the first and second questions, we employ a basic meta-analysis. Further, we employ the funnel graph and funnel asymmetry test — precision-effect test (FAT–PET) to answer the third and fourth questions. Moreover, this study employs multiple MRA analyses by applying several moderator variables to answer the fifth question.

We employed the partial correlation coefficient (Pcc) as the effect size. The Pcc is proper because FDI and employment have different units of measure. FDI, for instance, can be measured by FDI projects, total FDI inflows, FDI from foreign firm mergers and acquisitions, and others. Meanwhile, employment can be measured by subsidiary employment, labor force, employment rate, and others. Thus, the Pcc is considered the most appropriate because it is a unitless measure that can be directly compared. According to Stanley and Doucouliagos (2011), the Pcc is readily compared in other studies. It can also be calculated for more significant estimates and studies than any other effect size measure.

The partial correlation was calculated as follows:

$$Pcc = \frac{t}{\sqrt{t^2 + df}}, \tag{1}$$

where Pcc is the partial correlation coefficient, t is the t-statistic of each study, and df is the degree of freedom of the estimated study.

The standard error of the partial correlation can be calculated by dividing the partial correlation value by the *t*-statistic. According to Stanley and Doucouliagos (2011), the formula for calculating the standard error of the partial correlation coefficient is:

$$SEPcc = \sqrt{1 - Pcc^2/df}, \tag{2}$$

where *SEPcc* is the standard error of the Pcc.

3.1. Literature searching, compilation, and coding

The second important part explained in the MAER-Net guidelines is literature searching, compilation, and coding. We used the databases of Google Scholar, JSTOR, Ideas RePEc, Econlit, and NBER. The keywords used in the literature search on these databases are "FDI," "FDI inflow," "employment," "job opportunities," and "labor." In addition, several phrases are also used as keywords, including "FDI on employment," "FDI inflow on employment," "FDI and job opportunities," and "FDI on labor."

This study determined the inclusion criteria for selecting the literature reviewed. First, the literature must use at least one of the FDI proxies as the explanatory variable and one of the employment proxies as the dependent variable. Although the unemployment rate is often used as one of the employment proxies, that proxy was hostile (negative). Therefore, we excluded the literature that used unemployment as the dependent variable. For more details, the econometric model must examine the effect of FDI inflow on employment by using the following equation:

$$Y = \alpha + \beta_1 FDI + \beta_x Z + \varepsilon, \tag{3}$$

where Y is employment; *FDI* is FDI inflow; Z is the vector of other explanatory variables used in the model, and ε is the error term.

The second inclusion criterion is that the literature reviewed must report econometric estimation results. According to Stanley and Doucouliagos (2011), to be used as a meta-analysis dataset the literature must provide the results of the regression coefficients. The third inclusion criterion is that it must examine the direct effect of FDI inflow on employment. Therefore, this study excluded the literature that examined the indirect effect of FDI inflow on employment. Lastly, the literature must be written in English so as not to cause errors in understanding due to language problems.

3.2. Data description

The dataset was collected from February to May 2022. We collected 61 publications with a total of 490 estimates. However, according to Havranek and Irsova (2011), we also attempted to anticipate data outliers. In this context, the estimate is considered an outlier if its *t*-statistic value exceeds 10. From the 490 estimates, we identified 13 estimates that had more than 10 in *t*-statistic. Thus, our final number of estimates employed as the dataset is 477. Furthermore, following the recommendation of MAER-Net, the dataset should be accessible to the public. To fulfill this term, our dataset is available in Supplementary material.

According to the recommendations of MAER-Net, the study dataset and moderator variables also need to be described. In fulfilling this term, the descriptive statistics of the datasets are presented in Table 1.

Table 1 shows that the average effect resulting from each study has heterogeneity. The effect of FDI on employment from these studies was positive and negative. The heterogeneity of the magnitude of the effect is higher than the average value. Although Table 1 shows the average effect of FDI on employment, this is not the actual mean effect size. The average effect in Table 1 is obtained by finding the average value of each estimated regression coefficient produced by the study. Meanwhile, the mean effect size is the average effect which magnitude has been weighted to show the original effect of FDI on employment.

However, the mean effect size does not control the possibility of a publication selection bias. In this context, we employed a basic meta-analysis to ascertain the dataset's mean effect size of FDI's effect on employment and used MRA with the FAT–PET technique to find the genuine effect (effect beyond bias).

Table 1
Descriptive statistics of the datasets.

No.	Authors	No. of coefficient	Mean	Min	Max	Median	Std. dev.
1	Hunya and Geishecker (2005)	6	0.010	–0.136	0.165	0.015	0.107
2	Fu and Balasubramanyam (2005)	2	0.058	0.005	0.110	0.058	0.053
3	Craigwell (2006)	7	0.075	0.016	0.115	0.085	0.035
4	Bailey and Driffield (2007)	4	–0.336	–0.504	–0.177	–0.332	0.148
5	Asiedu and Brepong (2007)	4	0.122	0.070	0.161	0.128	0.035
6	Abor and Harvey (2008)	1	0.282	0.282	0.282	0.282	0.000
7	Massoud (2008)	9	0.030	–0.136	0.302	–0.016	0.152
8	Girma and Gong (2008)	27	–0.036	–0.191	0.147	–0.048	0.090
9	Waldkirch and Nunnenkamp (2009)	18	0.044	–0.001	0.081	0.053	0.024
10	Rizvi and Nishat (2009)	6	0.079	0.023	0.137	0.092	0.040
11	Wang and Wang (2010)	1	–0.599	–0.599	–0.599	–0.599	0.000
12	Vacaflores (2011)	6	0.075	0.001	0.121	0.097	0.047
13	Akcoraoglu and Acikgoz (2011)	4	–0.298	–0.316	–0.279	–0.298	0.013
14	Wong and Tang (2011)	6	–0.102	–0.368	0.361	–0.213	0.275
15	Liu (2012)	1	0.092	0.092	0.092	0.092	0.000
16	Inekwe (2013)	2	0.002	–0.186	0.191	0.002	0.188
17	Nizamuddin (2013)	1	–0.307	–0.307	–0.307	–0.307	0.000
18	Mehra (2013)	2	0.631	0.568	0.694	0.631	0.063
19	Lipsey et al. (2013)	9	0.251	0.000	0.494	0.240	0.173
20	Sarwar and Mubarik (2014)	1	0.324	0.324	0.324	0.324	0.000
21	Marelli et al. (2014)	11	0.056	–0.063	0.148	0.057	0.066
22	Kien (2014)	2	–0.030	–0.269	0.210	–0.030	0.240
23	Said and Jamoussi (2015)	4	0.245	0.122	0.309	0.274	0.075
24	Jude and Silaghi (2016)	11	–0.091	–0.205	0.051	–0.107	0.068
25	Bekhet and Mugableh (2016)	4	–0.053	–0.490	0.282	–0.002	0.286
26	Keorite and Moubarak (2016)	6	0.068	–0.285	0.540	0.088	0.283
27	Sharma (2018)	13	–0.047	–0.176	0.093	–0.070	0.081
28	Mupfawi and Tambudzai (2016)	1	0.457	0.457	0.457	0.457	0.000

(continued on next page)

Table 1 *(continued)*

No.	Authors	No. of coefficient	Mean	Min	Max	Median	Std. dev.
29	Megbowon et al. (2016)	2	0.169	0.111	0.227	0.169	0.058
30	Utouh and Rao (2016)	1	0.730	0.730	0.730	0.730	0.000
31	Umit and Alkan (2016)	2	–0.525	–0.544	–0.507	–0.525	0.018
32	Iuga (2016)	1	–0.435	–0.435	–0.435	–0.435	0.000
33	Vacaflores et al. (2017)	26	0.054	–0.114	0.367	0.033	0.113
34	Bakher (2017)	8	0.047	–0.273	0.374	0.057	0.239
35	Çolak and Alakbarov (2017)	4	0.184	0.026	0.459	0.126	0.164
36	Nikoloski (2017)	14	0.327	0.047	0.480	0.386	0.155
37	Ngwakwe (2017)	1	–0.062	–0.062	–0.062	–0.062	0.000
38	Shinwari and Yongliang (2018)	3	0.313	0.309	0.320	0.309	0.005
39	Mehmood et al. (2018)	1	–0.102	–0.102	–0.102	–0.102	0.000
40	Rafat (2018)	3	0.106	0.058	0.133	0.127	0.034
41	Malik (2019)	9	–0.047	–0.101	0.000	–0.039	0.028
42	Perić (2019)	4	0.234	–0.132	0.500	0.284	0.244
43	Rong et al. (2020)	4	0.074	0.045	0.104	0.073	0.028
44	Saucedo et al. (2020)	16	0.052	–0.085	0.211	0.042	0.087
45	Uddin and Chowdhury (2020)	2	0.102	–0.471	0.675	0.102	0.573
46	Lee and Park (2020)	6	0.057	–0.025	0.186	0.053	0.070
47	Kwan and Tang (2020)	16	0.221	–0.456	0.513	0.344	0.274
48	Nguyen et al. (2020)	19	–0.101	–0.373	0.093	–0.072	0.143
49	Aswal et al. (2020)	1	–0.144	–0.144	–0.144	–0.144	0.000
50	Wang et al. (2020)	21	0.059	0.045	0.076	0.058	0.008
51	Osabohien et al. (2020)	1	0.024	0.024	0.024	0.024	0.000
52	Lee et al. (2020)	28	–0.067	–0.226	0.155	–0.171	0.149
53	Alfalih and Hadj (2021)	3	–0.211	–0.479	0.299	–0.452	0.361
54	Wang and Choi (2021)	18	0.057	–0.087	0.168	0.059	0.070
55	Poumie and Claude (2021)	6	0.058	0.001	0.133	0.041	0.055
56	Deng and Wang (2021)	12	0.213	0.004	0.351	0.217	0.091
57	Solomon et al. (2021)	1	–0.026	–0.026	–0.026	–0.026	0.000
58	Yeboah (2020)	7	0.581	0.427	0.778	0.594	0.124
59	Asravor and Sackey (2022)	7	0.355	–0.557	0.865	0.505	0.495
60	Koerner et al. (2022)	45	–0.017	–0.084	0.047	–0.019	0.036
61	Ni et al. (2022)	16	0.000	–0.174	0.163	0.026	0.106
	Total	477	0.054	-0.599	0.865	0.053	0.120

Source: Authors' calculations.

4. Results

4.1. Dealing with endogeneity

Studies on economic indicators such as supply and demand for labor or the relationships—consumption, investment, imports, exports, and production tend to have an endogeneity bias (Baltagi, 2005). In this context, endogeneity is a condition where explanatory variables are correlated with error terms (Ullah et al., 2018). To anticipate such a bias, Baltagi (2005) suggested an instrumental variable (IV) based analysis or Generalized Method of Moments (GMM). Because of this reason, we identify the literature that employed IV or GMM method as the studies that control endogeneity.

We anticipate an endogeneity bias in the literature in two ways. First, we classify the data into three categories in the FAT–PET analysis. They are the overall sample, ignoring endogeneity and control endogeneity. Thus, differences in the publication bias and genuine effects among samples will be identified. Second, this study includes the *SEPcc* × *NoEndog* as one of the explanatory variables in the multiple MRA in order to examine the difference between the overall standard error coefficients and the standard error coefficient from the literature that does not control endogeneity.

4.2. Basic meta-analysis

We estimated the basic meta-analysis to identify the mean effect size and heterogeneity. We use I^2 and τ^2 (tau square) values to detect heterogeneity. If I^2 exceeds 75%, it indicates great heterogeneity (Higgins and Thompson, 2002). Meanwhile, the value of τ^2 is the variation among studies or the standard deviation distribution that underlies the mean effect size. Therefore, greater τ^2 indicates greater heterogeneity.

The value of τ^2 can be generated by Restricted Maximum Likelihood (REML), Sidik–Jonkman (SJ), Hedges, or Random Effects Empirical Bayes (EB). Meanwhile, I^2 can be generated from a Fixed Effect Estimator (FEE), REML, Maximum Likelihood, or EB. Therefore, we estimate the basic meta-analysis using REML, FEE, and Random Effects EB (see Table 2).

The FEE in Table 2 assumes that all reported estimates come from the same population as the common mean. Therefore, it relatively produces a smaller mean effect size. REML tends to be more relevant because the estimates come from different populations. In this context, although in some literature REML stands for Restricted Maximum Likelihood, it also stands for Multilevel Random Effect (Stanley and Doucouliagos, 2011). Therefore, FEE is a fixed effect, while REML is a random effect. The estimation of EB in the third column resulted from REML estimation with empirical Bayes iterative procedure.

Furthermore, from the three estimates in Table 2, all mean effect sizes are positive. It shows that based on three estimates, the effect of FDI on employment is positive. However, the value tends to be low. Table 2 does not include the Cochran Q-test results, which the meta-analysis often employs to detect heterogeneity (Stanley and Doucouliagos, 2011). This study estimated the Q-test by regressing the *t*-value against the precision (1/*SEPcc*). The value of sum square errors from the regression results is a Q-test distributed as a chi-square

Table 2
Basic meta-analysis results.

Statistics	I	II	III
Mean effect size	0.047	0.026	0.047
95% CI	0.029 to 0.066	0.026 to 0.026	0.028 to 0.066
N of estimates	477	477	477
τ^2	0.043	–	0.044
I^2 (%)	100	99.98	100
K studies	61	61	61

Note: Column I uses REML estimation, column II — FEE, and column III — random effect estimation with iterative empirical Bayes procedure.
Source: Authors' calculations.

with $L-1$ degrees of freedom. The resulting Q-test value is 3,624 with a mean sum square error of 7.614 and a probability lower than 0.05. These results indicate that heterogeneity among studies is significant. Because of this reason, there has been heterogeneity among studies regarding the effect of FDI on the host countries' employment.

4.3. Identifying a publication bias

The basic meta-analysis procedure presented in Table 2 does not control for a possible publication selection bias and heterogeneity. Meanwhile, in the meta-analysis, examining the publication bias is critical. This bias is caused by a publication selection. In this context, one of the motives of researchers conducting such a selection is when they tend to prioritize reporting significant results. The publication selection bias usually arises when editors only publish studies relevant to a particular topic (Stanley and Doucouliagos, 2011). Simply speaking, the publication bias is a condition where negative results are not published (Cleophas and Zwinderman, 2017). The publication selection bias could distort research findings. In this study, we detected it using a funnel graph and FAT–PET.

We perform the funnel using precision ($1/SEPcc$) as the y-axis and the partial correlation coefficient as the x-axis (see Fig. 2). Fig. 2 shows that the distribution of the lower-left area's partial correlation coefficients from the literature tends to be asymmetrical. The studies that report negative results tend to be fewer than those that report positive ones. In other words, some researchers try to report positive results only. However, this funnel plot tends to be subjective (Stanley and Doucouliagos, 2011). Because of that reason, we also performed

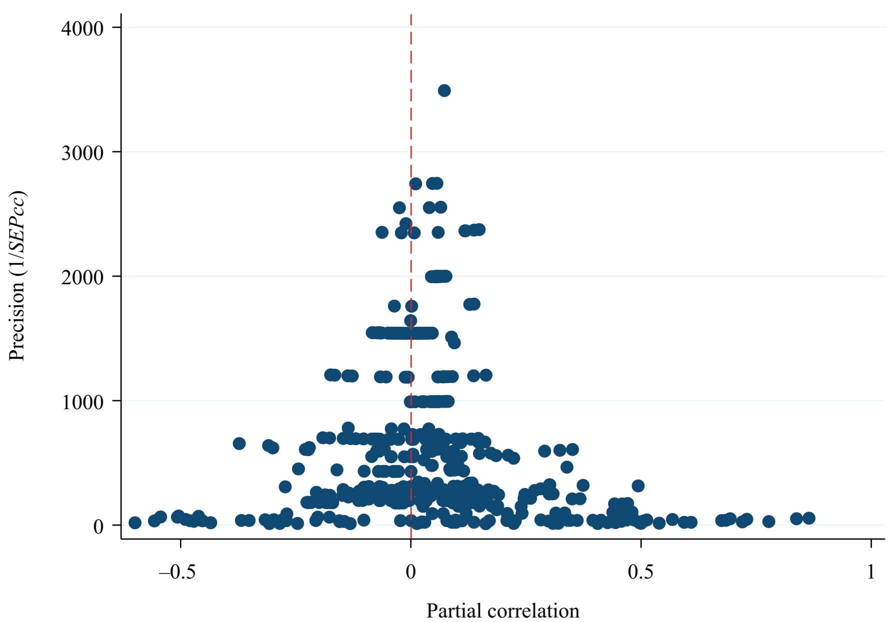

Fig. 2. Funnel plot: The effect of FDI on employment.

Source: Authors' calculations.

FAT–PET to correct the publication bias. This study calculates the FAT–PET by referring to Stanley and Doucouliagos (2011), who employed this formula:

$$Pcc_i = \beta_0 + \beta_1 SEPcc_{ij} + \varepsilon_{ij}, \tag{4}$$

where Pcc_i is the partial correlation coefficient from the i-th study; $SEPcc_{ij}$ is the standard error from the i-th estimate on the j-th study; β_0 is the correction of a publication bias, known as the effect beyond bias or genuine effect; β_1 is a publication bias; ε_{ij} is the error term.

According to Stanley and Doucouliagos (2011), the FAT–PET in the above equation has heteroscedasticity and cannot be estimated by the ordinary least square (OLS) method. The standard error in the above equation comes from the effect size. Because the effect size between studies has different variances, the weighted least squares (WLS) are needed. Therefore, we estimate the FAT–PET with five methods: OLS, Fixed Effect, REML, WLS with 1/*SEPcc* as weight, and WLS with 1/number of estimates per-study as weight (WLS–WS) (see Table 3).

All estimates from Table 3 have a genuine effect. Compared with the mean effect size of 0.047 in Table 2, the value of the effect beyond bias results from the OLS and WLS estimations are the closest. However, because the FAT–PET analysis contains heteroscedasticity, the WLS results are more relevant (Stanley and Doucouliagos, 2011). From the WLS analysis of the overall sample, we found an upward publication bias and the effect beyond bias. The results of

Table 3
The FAT–PET estimation results.

	OLS	FE	REML	WLS	WLS–WS
Panel A: Overall sample					
$\beta_1 SEPcc$	2.287***	–33.122***	–1.959	3.358**	–0.476
(publication bias)	(0.615)	(4.921)	(1.445)	(1.119)	(1.919)
Intercept	0.027**	0.346***	0.088**	0.017**	0.062**
(effect beyond bias)	(0.011)	(0.449)	(0.037)	(0.005)	(0.029)
N of estimates	477	477	477	477	477
K studies	61	61	61	61	61
Panel B: No endogeneity control					
$\beta_1 SEPcc$	1.988**	–34.768***	–2.387	4.539***	–0.853
(publication bias)	(0.722)	(5.511)	(1.687)	(1.153)	(2.092)
Intercept	0.050***	0.486***	0.121**	0.020***	0.086**
(effect beyond bias)	(0.015)	(0.065)	(0.048)	(0.006)	(0.039)
N of estimates	321	321	321	321	321
K studies	48	48	48	48	48
Panel C: Control endogeneity					
$\beta_1 SEPcc$	–19.439***	90.451**	–19.381***	–13.232**	–20.276**
(publication bias)	(5.176)	(30.389)	(4.758)	(4.557)	(7.893)
Intercept	0.055***	–0.296**	0.065**	0.035**	0.079**
(effect beyond bias)	(0.015)	(0.097)	(0.220)	(0.012)	(0.030)
N of estimates	156	156	156	156	156
K studies	18	18	18	18	18

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variable = *Pcc*. Cluster robust standard errors are in parentheses. Column WLS is a WLS method using the inverse standard error as an analytical weight. Meanwhile, WS (within the study) uses the inverse number of estimates as an analytical weight.
Source: Authors' calculations.

the WLS analysis also show that studies that do not control for endogeneity tend to have a higher upward bias. Meanwhile, a downward bias occurs in studies that control endogeneity.

Studies that ignore endogeneity produced a lower genuine effect than those which control it. Furthermore, according to Doucouliagos (2011), if the genuine effect is lower than 0.07, it indicates a small effect. In other words, the genuine effect of FDI on employment in this study is in a low range. This low genuine effect needs to be studied further by using multiple MRA which can explain heterogeneity with moderator variables to get a more comprehensive picture of the factors that cause it. Several meta-regression studies use the term "modeling heterogeneity"' to describe multiple MRA procedures.

4.4. Multiple MRA

In addition to showing the possibility of a publication bias, the funnel plot in Fig. 2 also shows that the analyzed studies have heterogeneity. We employed multiple MRA to explain it more comprehensively. The initial step in the multiple MRA is to model heterogeneity as follows:

$$Pcc_i = \beta_1 + \sum \beta_x Z_{xij} + \beta_0 SEPcc_{ij} + \varepsilon_{ij}, \tag{5}$$

where Pcc_i is the partial correlation from the regression coefficient regarding the effect of FDI on employment from *i*-th to the number of studies (in this study, there were 61 publications with 477 estimates). *SEPcc* is the standard error of the Pcc. *Z* is a vector variable that shows heterogeneity, such as differences in the measurement of FDI and employment, sample country basis, and estimation methods.

Z variables in equation (5) are implemented into moderator variables to explain heterogeneity. We refer to Jarrell and Stanley (1989) in determining *Z* variables. The moderator variables are created in a dummy variable format based on some categories. Therefore, we set six categories for determining *Z* variables. They are the type of FDI and employment measurement, data characteristics, FDI receiving countries, estimation method, publications characteristics, and the type of estimation model. In the category of FDI and employment measurement types, we determine eight moderator variables identified from the literature: inward FDI, FDI growth, merger and acquisition FDI, employment, employment growth, unskilled employment, skilled employment, and other employment. Overall, this study identified 6 *Z* vector groups with 34 moderator variables.

In more detail, following the MAER-Net guidelines on the need to describe variables through descriptive statistics, the definitions of variables are presented in Table 4.

4.5. Multiple MRA results

The moderator variables in Table 4 are *Z* variables identified from the literature. According to the MAER-Net recommendation, the meta-analysis in the economic field needs to simplify a meta-regression model. We employed the Bayesian

Table 4
Variables description.

Variable	Description	Average	Std. dev.
Pcc	The partial correlation coefficient from the *i*-th study	0.048	0.212
SEPcc	The standard error of the Pcc from the *i*-th study	0.009	0.016
SEPcc × NoEndog	The standard error of the Pcc from studies that do not control for endogeneity	0.008	0.016
Type of FDI and employment measurement			
Inward_FDI	=1, if the numbers of inward FDI stock measure FDI	0.423	0.494
FDI_Growth	=1, if the FDI Growth measure FDI	0.170	0.375
Merger_FDI	=1, if the FDI is measured by the form of acquisition of existing assets such as mergers and acquisitions	0.407	0.491
Employment	=1, if the employment is measured by the number of total employment	0.532	0.499
Employment_Growth	=1, if the employment is measured by the percentage of employed persons divided by the labor force	0.279	0.448
Unskilled_Employment	=1, if the employment is measured by the number of unskilled employment	0.082	0.274
Skilled_Employment	=1, if the employment is measured by the number of skilled employment	0.124	0.329
Other_Employment	=1, if the employment is measured by other proxied of employment such as subsidiary employment, employment rate, and others	0.189	0.391
Data characteristic			
Panel_ Data	=1, if the literature employed panel data	0.769	0.421
Time_Series	=1, if the literature employed time series data	0.170	0.375
Cross_Sectional	=1, if the literature employed cross-sectional data	0.061	0.239
Overall	=1, if the literature employed non-sectoral data	0.543	0.498
Manufacturing	=1, if the literature employed FDI and employment data in the manufacturing sector	0.273	0.445
Other_Sectors	=1, if the literature employed FDI and employment data other than manufacturing and services such as mining, agriculture, construction, logistics, and others	0.075	0.264
Services	=1, if the literature employed FDI and employment data in the service sector	0.107	0.309
Across_Countries	=1, if the literature was covered across countries' data	0.306	0.460
Single_Country	=1, if the literature only covered single-country data	0.694	0.461
FDI receiving countries			
Asia	=1, if the literature used Asia countries as bases	0.501	0.500
Latin_America	=1, if the literature used Latin American countries as bases	0.099	0.298
Europe	=1, if the literature used European countries as bases	0.241	0.428
African	=1, if the literature used African countries as bases	0.090	0.286
Developing	=1, if the data was collected from developing countries' category	0.335	0.472
Developed	=1, if the data was collected from developed countries' category	0.348	0.476

(continued on next page)

Table 4 *(continued)*

Variable	Description	Average	Std. dev.
Estimation method			
OLS	=1, if the literature employed the OLS estimation as the basis	0.310	0.463
Other_Estimations	=1, if the literature employed other estimations such as time series analysis, fixed effect, random effect, logistic regression, generalized linear model, Bayesian regression, etc.	0.363	0.481
Control_Endogeneity	=1, if the literature employed the instrumental variable to control endogeneity such as instrumental variable analysis or generalized method of moments (GMM)	0.327	0.469
Type of publications			
Q1	=1, if the literature is published in the first quartile of Scimago's ranked journal	0.358	0.480
Q2	=1, if the literature is published in the second quartile of Scimago's ranked journal	0.105	0.306
Q3_Q4	=1, if the literature is published in the third or fourth quartiles of Scimago's ranked journal	0.130	0.336
Unranked	=1, if the literature is published in the unranked journal	0.407	0.491
Type of model			
Model_1	=1, if the literature adopts the Cobb–Douglas model by including Output, Wages, and Technology as explanatory variables, either only one or all three	0.507	0.500
Model_2	=1, if the literature includes one or more of the following variables: domestic investment, governance, GDP, natural resources, openness, telephone, natural resources, oil rent, and human capital as explanatory variables	0.468	0.499
Other_Model	=1, if the literature includes one or more of the explanatory variables outside of model 1 and model 2	0.308	0.462

Source: Authors' calculations.

Model Averaging (BMA) method to fulfill this term. According to Havranek et al. (2017), the BMA method can anticipate the model uncertainty in meta-analysis. In this context, BMA estimates millions of models generated from the sub-sample to determine the model with greater explanatory power (Havranek et al., 2018). BMA adjusted the linear regression model with the uncertainly explanatory variable model to choose the most appropriate one. BMA estimation in this study refers to the procedure described by De Luca and Magnus (2011). The results are presented in Table 5.

Table 5 shows that the BMA identifies six moderator variables that can explain heterogeneity. The estimation of WLS and REML reinforces the results of the BMA as frequentist checks in this study that still includes *SEPcc* and *SEPcc* × *NoEndog*, even though the BMA does not identify these two variables. They were included to re-identify the publication bias from the studies that did not control for endogeneity. When referring to the results of the WLS analysis, there is a reasonably high upward bias from the studies that do not control for endogeneity. These results strengthen the results of the FAT–PET analysis in Table 3. In addition, the analysis results of BMA, WLS, and REML also confirm that the genuine effect of FDI on the host countries' employment was positive.

Table 5
BMA estimation results for model inclusion and frequentist checks.

Variable	Posterior mean	Posterior std. error	*t*-value	PIP	WLS	REML
Intercept	0.039	0.048	0.82	1.00	0.082***	0.104**
					(0.009)	(0.041)
SEPcc	–0.114	1.304	–0.09	0.07	–14.610***	–7.193
					(3.395)	(8.605)
SEPcc × NoEndog	0.178	1.317	0.13	0.08	17.113***	5.467
					(3.455)	(8.376)
Type of FDI and employment measurement						
Inward_FDI	0.013	0.025	0.51	0.25	–	–
Merger_FDI	–0.032	0.036	–0.88	0.50	–0.055***	–0.014
					(0.011)	(0.058)
Employment	0.006	0.017	0.36	0.15	–	–
Employment_Growth	0.000	0.006	–0.04	0.05	–	–
Data characteristics						
Panel_Data	–0.001	0.011	–0.12	0.07	–	–
Time_Series	0.010	0.026	0.39	0.18	–	–
Overall	0.007	0.028	0.23	0.10	–	–
Manufacturing	0.011	0.033	0.32	0.16	–	–
Other_Sectors	–0.145	0.047	–3.10	0.96	–0.135**	–0.125***
					(0.044)	(0.032)
Services	–0.010	0.032	–0.32	0.23	–	–
Across_Countries	0.001	0.012	0.11	0.05	–	–
Single_Country	–0.001	0.011	–0.05	0.05	–	–
FDI receiving countries						
Asia	0.008	0.024	0.32	0.13	–	–
Latin_America	0.005	0.025	0.18	0.08	–	–
Europe	–0.089	0.034	–2.64	0.93	–0.039**	–0.133**
					(0.014)	(0.045)
African	0.143	0.042	3.41	0.99	0.017	0.103*
					(0.026)	(0.059)
Developed	–0.092	0.025	–3.63	0.98	–0.037***	–0.118**
					(0.009)	(0.045)
Estimation method						
OLS	0.167	0.025	6.60	1.00	0.047**	0.104**
					(0.016)	(0.041)
Other_Estimate	0.002	0.010	0.20	0.07	–	–
Publication characteristics						
Q1	–0.004	0.015	–0.25	0.10	–	–
Q2	0.001	0.009	0.12	0.05	–	–
Unranked	0.003	0.012	0.24	0.09	–	–
Type of model						
Model_1	–0.008	0.020	–0.42	0.19	–	–
Model_2	0.001	0.010	0.13	0.06	–	–
Other_Model	0.015	0.030	0.51	0.26	–	–

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variable = *Pcc*. Cluster robust standard errors are in parentheses. Variables experiencing collinearity are not included. WLS and REML are the frequentist checks. The PIP refers to the posterior inclusion probability, which measures how much the moderator variable relates to the Pcc. In this study, a moderator variable will be chosen to affect the Pcc if it has a PIP value of 0.5 or higher.
Source: Authors' calculations.

4.6. Heterogeneity in the type of FDI and employment measurement

We identified eight moderator variables regarding FDI and employment measurement. However, some of these moderators have a relatively shallow size. In addition, some of the other moderator variables have collinearity problems, so the BMA analysis can only use four moderator variables. They are *Inward_ FDI, Merger_FDI, Employment*, and *Employment_Growth*. Of them, *Merger_FDI* got the highest PIP value.

Based on the results of the BMA analysis, we found that the method of measuring FDI and employment that can explain heterogeneity is *Merger_FDI* (Merger and Acquisition FDI). The negative notation indicated by the *t* value and the posterior mean of *Merger_FDI* shows that FDI originating from mergers and acquisitions of foreign companies will have a lower effect on employment. In other words, *Merger_FDI* reduced the host countries' employment. WLS also captured the negative effect of *Merger_FDI* on the latter.

These results strengthen the arguments of Mcdonald et al. (2002), Jenkins (2006), and Akcoraoglu and Acikgoz (2011), who stated that FDI from mergers and acquisitions reduced employment. Our results also support the findings of Jude and Silaghi (2016) that these FDI might reduce employment because the acquired companies tend to be more efficient. FDI from mergers and acquisitions could also reduce employment if foreign companies cut domestic supply in the host country. Such FDI can also attract high technology to replace employment.

4.7. Heterogeneity in data characteristics

Based on the study dataset, we found nine moderator variables from the characteristic data point of view. Most studies used panel data on FDI and employment from databases such as the World Development Index (WDI) and others. Other studies used time series data in a specific country. Only a few studies used cross-sectional data, so we did not include the data as moderator variables to be tested with BMA. Thus, most studies use non-sectoral data (overall), while others use FDI and employment data in specific sectors. Three sectors are identified as the most widely used: manufacturing, service, and other sectors (mining, agriculture, construction, logistics, and others).

In addition, we add *Across_Countries* and *Single_Country* as moderator variables in the characteristic data category. Thus, eight moderator variables are tested with BMA: Panel Data, Time Series, Overall (non-sectoral), Manufacturing, Services, Other Sectors, Across Countries, and Single Country. These eight moderator variables get different posterior means notation. For example, Panel Data, Other Sectors, Services, and Single Country have a negative posterior mean. Meanwhile, Time Series, Overall, Manufacturing, and Across Countries have a positive posterior mean. However, of the eight moderator variables, only Other Sectors has a PIP value of more than 0.5. Therefore, only it can explain heterogeneity.

The BMA estimation results show that FDI in Other Sectors tends to have a lower effect on employment. The results of the BMA are reinforced by WLS and REML, which also found a significant adverse effect of the Other Sectors variable on the Pcc. In other words, FDI that is included in the Other Sectors category tends to reduce the level of employment in host countries because FDI entering these sectors is relatively less labor intensive. This stands in contrast to the manufacturing sector, which can absorb more labor. Although the BMA does not identify the manufacturing sector as part of the variable that can explain the Pcc, the posterior mean value of the manufacturing variable is positive. Thus, the type of FDI entry sector determines the increase in employment in host countries.

According to Table 4, from the 477 estimates, 331 came from single-country data, while the rest came from across-country datasets. It indicates that most researchers focused on discussing the effect of FDI on employment at the country level. However, based on the results of the BMA analysis, the moderator variables *Across_Country* and *Single_Country* did not have an adequate PIP value. In other words, no empirical evidence exists that using global, regional or country-level data could determine heterogeneity.

4.8. Heterogeneity in FDI-receiving countries

This study identifies six moderating variables based on aspects of FDI recipient countries: Asia, Latin America, Europe, Africa, Developing Countries, and Developed Countries. Developing countries cannot be analyzed using BMA because of collinearity. Meanwhile, from five moderator variables analyzed by BMA, Asia, Latin America, and Africa have a positive posterior mean. In contrast, Europe and developing countries have a negative posterior mean. However, only Europe, Africa, and developed countries have a PIP value more significant than 0.5.

Based on the results of the BMA estimation, FDI entering European countries has a lower Pcc. It was confirmed by WLS and REML, which showed that the European moderator variable negatively affected the Pcc. In other words, FDI entering European countries reduced employment levels. One study examining FDI entering European countries was by Hunya and Geishecker (2005). They mentioned that privatized state-owned companies are among the causes of FDI reducing employment rates in European countries. After the takeover of state-owned companies, foreign firms cut off relations with domestic suppliers.

We confirm that FDI entering developing countries also reduced employment. The analysis of WLS and REML strengthens this finding. Therefore, the results of our study indicated that FDI entering developed countries would only increase high-skilled jobs. FDI into developed countries brings more significant technological changes to replace employment. On the other hand, we found that FDI entering African countries has a relatively more significant influence on employment. To judge by their characteristics, most African countries are developing ones.

Therefore, the positive effect of FDI on employment in African countries was not bringing high-technological changes. However, the BMA results related to the association between African moderator variables and the Pcc were not confirmed by WLS and REML, so these results are weak. However, Asiedu and Brepong (2007), who employed an African sample, found that FDI from multinational companies in African countries increases job opportunities. Moreover, Asiedu and Brepong (2007) suggest that African countries attract more FDI through the liberalization of investment regulations.

4.9. Heterogeneity in the estimation methods

Our study coded the estimation methods employed by the literature into OLS, other estimation, and control endogeneity estimation. The other estimation method contains publications that used methods other than OLS and control endogeneity, such as instrumental variables and GMM. Several items in the other estimation category include those using least squares dummy variable (LSDV) analysis, Heckman estimation, ARDL, and others.

Unfortunately, of these three moderator variables, only OLS and other estimations can be analyzed by BMA because the moderator variable *Control_Endogeneity* has collinearity. Finally, of the remaining two moderator variables, only OLS was shown to have a PIP value greater than 0.5. The posterior mean of the OLS moderator variable is positive, indicating that studies using OLS tend to get a higher Pcc. In other words, studies using the OLS method produce a higher coefficient of FDI influence on employment. WLS and REML corroborate the results of this BMA analysis.

4.10. Heterogeneity in publication characteristics

Based on Table 4, our study identifies four moderator variables from the aspect of publication characteristics, namely Q1, Q2, Q3–Q4, and Unranked. The most widely found literature came from the Unranked category, followed by Q1, Q3–Q4, and Q2. Q3–Q4 experienced collinearity, so it was not included in the BMA analysis. In this case, the results of the BMA analysis show that Q2 and Unranked have a positive posterior mean value, while Q1 is the opposite. However, none of the moderator variables has a PIP value of more than 0.5. Therefore, we found no empirical evidence that publication characteristics explain heterogeneity.

4.11. Heterogeneity in the type of model

Each publication estimates a different model. Most literature used several other explanatory variables accompanying FDI in affecting employment. If they also employed output, wages, and technology as other explanatory variables, we identified them as Model 1. This study sets the model estimation type into three moderator variables (see Table 4 for details). However, none of them was identified by BMA. Therefore, we justified that the type of estimation model cannot explain heterogeneity of the effect of FDI on employment.

4.12. Robustness checks

Our study checks the robustness by excluding estimates from studies not published by the leading journals (indexed by Scopus or Web of Science). Of the 477, only 309 estimates came from them. Furthermore, these estimates were re-analyzed using BMA, WLS, and REML by eliminating all moderator variables in the publication characteristics category. The results are presented in Table 6.

The results of the BMA analysis in Table 6 are slightly different from those in Table 5 because there is a change in the number of datasets. In Table 6, the dataset contains estimates only from the leading journals. The results reveal that six moderator variables have a PIP value more significant than 0.5. They are Manufacturing, Other Sectors, Across Countries, Europe, Africa, and OLS variables. The difference between the BMA results on this robustness checking oc-

Table 6
Robustness checks.

Variable	Posterior mean	Posterior std. error	t-value	PIP	WLS	REML
Intercept	–0.081	0.082	–0.99	1.00	0.009	–0.008
					(0.036)	(0.009)
SEPcc	–0.643	3.260	–0.20	0.08	-14.928^{*}	-9.518^{**}
					(7.773)	(4.167)
SEPcc × NoEndog	0.603	3.124	0.19	0.08	13.295^{*}	12.193^{**}
					(7.491)	(4.322)
Type of FDI and employment measurement						
Inward_FDI	0.000	0.007	0.00	0.05	–	–
Merger_FDI	–0.001	0.009	–0.12	0.05	–	–
Employment	0.028	0.042	0.66	0.41	–	–
Employment_Growth	0.011	0.034	0.31	0.15	–	–
Data characteristics						
Panel_Data	–0.003	0.021	–0.14	0.06	–	–
Time_Series	–0.001	0.023	–0.06	0.06	–	–
Overall	0.015	0.048	0.32	0.15	–	–
Manufacturing	0.126	0.056	2.25	0.98	0.076^{**}	0.056^{***}
					(0.030)	(0.009)
Other_Sectors	–0.138	0.061	–2.28	0.90	-0.155^{***}	-0.212^{***}
					(0.037)	(0.036)
Services	0.012	0.047	0.25	0.13	–	–
Across_Counries	0.097	0.062	1.56	0.83	0.086^{*}	0.065^{***}
					(0.044)	(0.016)
Single_Country	–0.005	0.053	–0.10	0.20	–	–
FDI receiving countries						
Asia	0.006	0.028	0.23	0.09	–	–
Latin_America	0.007	0.033	0.20	0.08	–	–
Europe	–0.109	0.043	–2.53	0.94	-0.117^{**}	-0.123^{***}
					(0.046)	(0.021)
African	0.272	0.054	5.02	1.00	0.204^{**}	0.141^{***}
					(0.062)	(0.034)
Developed	–0.004	0.018	–0.21	0.09	–	–
Estimation method						
OLS	0.123	0.044	2.81	0.97	0.093^{**}	0.089^{***}
					(0.046)	(0.023)
Other_Estimate	0.003	0.013	0.24	0.09	–	–
Type of model						
Model_1	0.000	0.006	–0.05	0.05	–	–
Model_2	–0.001	0.008	–0.13	0.06	–	–
Other_Model	0.001	0.009	0.15	0.06	–	–

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variable = *Pcc*. Cluster robust standard errors are in parentheses. Variables experiencing collinearity are not included. WLS and REML are the frequentist checks. The PIP refers to the posterior inclusion probability, which measures how much the moderator variable relates to the Pcc. In this study, a moderator variable will be chosen to affect the Pcc if it has a PIP value of 0.5 or higher. The moderator variables in the distinct publication category were excluded because all datasets came from the leading journals.
Source: Authors' calculations.

curs in Manufacturing, Across Countries, Merger_FDI, and Developed variables. Meanwhile, Other Sectors, Europe, Africa, and OLS variables did not change. Therefore, the four moderating variables are robust in explaining the effect of FDI on employment heterogeneity.

Table 6 indicates that *Merger_FDI* and the *Developed* variables could not explain heterogeneity in the leading journals dataset because their PIP value is less than 0.5. However, the posterior means notations for the two moderator variables have not changed, which are negative. On the other hand, in this leading journals dataset, Manufacturing and Across Countries variables get a higher PIP value with positive posterior means notation. Therefore, studies in the leading journals that used FDI in the manufacturing sector and data across countries tend to report higher FDI effects on employment.

4.13. Limitations of the study

This study has several limitations. First, we have not employed the year of a study publication as a moderator variable. Consequently, we cannot justify heterogeneity by this parameter. Second, we only categorize heterogeneity based on the estimation method into three moderator variables: OLS, Other Estimate, and Control Endogeneity. These three moderator variables may be too general because the estimation methods used in the literature tend to vary widely. Lastly, the moderator variable's estimation results based on the publication type have a potential bias because we identify the types of publications based on journal rankings in 2022. When the study was published, it was possible that the journal had not been indexed by Scopus or had a different Scimago ranking.

5. Conclusion

We found a publication bias and heterogeneity among studies on the effect of FDI on employment in the host country. After correcting that bias, this study revealed a positive effect of FDI on the host countries' employment. However, that effect is relatively shallow. We also found that heterogeneity among the studies can be explained through differences in FDI and employment measurement type, data characteristics, FDI-receiving countries, and the estimation method. Meanwhile, no evidence that publication characteristics and a model type could explain heterogeneity was found.

From the FDI and employment measurements point of view, this study determined that FDI from mergers and acquisitions could reduce employment. Thus, if the FDI enters into other sectors such as mining, agriculture, construction, and logistics, it relatively reduces employment. We have also found that from the FDI-receiving countries' point of view, FDI entering European and developed countries tends to reduce employment. On the other hand, FDI entering African countries is proven to increase employment. Meanwhile, studies using the OLS method will produce a higher FDI effect on employment.

There are several policy implications resulting from our study. All countries should be more selective in implementing FDI policies from mergers and acquisitions because they reduce employment. Each country also needs to be directing FDI to more labor-intensive sectors. Especially for Europe and developed countries, it is necessary to strengthen the domestic industry to offset the negative effect of FDI on employment in their country. By way of contrast, African countries should soften FDI policies in order to attract more FDI to increase employment.

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Supplementary material

The datasets of FDI effect on employment

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Data type: Table

Explanation note: Based on the Reporting Guidelines for Meta-Analysis in Economics (MAER-NET), a meta-analytic study must disclose its dataset. The datasets in this study are 477 estimates obtained from 61 studies. We choose the partial correlation coefficient (Pcc) as the effect size. That Pcc comes from dividing the *t*-statistic by $t^2 + df$ (degree of freedom). If several studies did not report *t*-statistic, we calculated it by dividing the estimated coefficient's value by the standard error. We gathered this dataset from February to May 2022.

Link: https://doi.org/10.32609/j.ruje.9.98252.suppl