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The Effect of FDI on Environmental Emissions: Evidence from a Meta-Analysis

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Abstract

One important and frequently-raised issue about foreign direct investment (FDI) is the potentially negative consequences for the environment. The potential environmental cost due to increased emissions may undermine the economic gains associated with increases in FDI inflow. Although the literature is dominated with this adverse view of FDI on the environment, there is also a possibility that FDI can contribute to a cleaner environment, especially, if FDI comes with green technologies and this creates spillovers for domestic industries. Theoretically, the effect of FDI on the environment can be negative or positive. To deal with the theoretical ambiguity about the FDI-environment nexus, many empirical studies have been conducted but their results only reinforce the controversy as they produce contrasting results. We* conduct a meta-analysis of the effect of FDI on environmental emissions using 65 primary studies that produce 1006 elasticities. Our results show that the underlying effect of FDI on environmental emissions is close to zero, however, after accounting for heterogeneity in the studies, we find that FDI significantly reduces environmental emissions. Results remain robust after disaggregating the effect for countries at different levels of development as well as for different pollutants.

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Keywords

FDI; pollution haven hypothesis; pollution halo hypothesis; environment; emissions; meta-analysis.

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1 Introduction

Foreign direct investment (FDI) has been identified as one of the main engines of economic growth, a potential source of employment, as well as a channel through which advanced technologies can be transferred to host countries (Sapkota and Bastola (2017), Demena and van Bergeijk (2019)). In recent years, the flow of FDI has become even more important than international trade as the rate of growth of manufacturing investments has outpaced that of international trade flow of merchandise (Chen and Moore, 2010). As trade protectionism increases at the global level, FDI becomes an avenue for firms to gain entry to protected markets by producing directly in those countries. There is also evidence that FDI contributes to productivity spillover (see, e.g., Zhao and Zhang (2010), Demena and van Bergeijk (2017), Demena and Murshed (2018)).[1] As a result, many countries are resorting to intense promotional strategies to attract FDI (Narula and Dunning, 2000). These promotional strategies are commonly implemented through government-controlled investment promotion agencies (IPAs) and are ubiquitous in many countries. These IPAs have proven effective in attracting foreign capital and technical knowledge to many countries (Harding and Javorcik, 2011).

However, one important and frequently-raised issue about FDI is its potentially deleterious consequences for the environment (Zhu et al. (2016), Cole et al. (2011), Pao and Tsai (2011)). It is possible that the economic gains associated with increase in FDI could be negated by potential environmental costs as FDI may occur simultaneously with increased environmental emissions (Cole et al., 2011). Pao and Tsai (2011), for instance, indicate that environmental emissions associated with FDI could easily be ignored because of the growth-promoting tendency of FDI. Realizing the potential environmental costs associated with FDI , most countries are now selective in the type of FDI that comes into their country. Many countries are now promoting the so-called "green" FDI that focuses on FDI that can promote economic growth and also internalizes the adverse environmental externalities associated with industrial production (Golub et al., 2011).

With increased competition for FDI, polluting industries in developed countries would tend to move to developing countries due to strict regulations and the rising cost of pollution abatement in developed countries. This phenomenon is known in the environmental literature as the pollution haven hypothesis (PHH). This hypothesis supports the argument that emissions reductions in many developed countries are partly due to the shifting of polluting activities to developing countries (Kearsley and Riddel, 2010). Anecdotal evidence give credence to the PHH as developing countries simultaneously account for the largest shares of FDI inflow and global emissions. Even though the World Investment Report of UNCTAD (2018) indicates that FDI flows worldwide have been on a declining trajectory, FDI flows to developing countries remain stable and have grown from 36% in 2016 to 47% in 2017.

China is commonly cited as an example of the linkage between FDI inflow and emissions. China is ranked the topmost destination for FDI in the world and it has experienced economic growth consistently at or above 8% over the last three decades. However, this increase in FDI and the subsequent high economic growth were accompanied by high industrial emissions. While China has experienced a boom in FDI and economic growth, it has also become the world largest emitter of greenhouse gases and has the most polluted cities in the world (Cole et al., 2011). Specifically, Cole et al. (2011) indicate that China accounts for 17 out of the 25 most polluted cities in the world. Because of this plausible adverse linkage between FDI and the environment, China has rolled out a myriad of green investment incentives, including reduced

[1] Through a comprehensive meta-analysis involving 69 studies, Demena and van Bergeijk (2017) find that FDI has economically and statistically significant productivity gain for domestic firms.

corporate tax for foreign-invested firms operating in the green belt, and investment allowances and tax credits for investing in environmental protection assets (Golub et al. (2011)).

Although the literature is dominated with this adverse view of FDI on the environment, it is also possible that FDI can contribute to a cleaner environment. Especially if foreign investments come with greener or cleaner technologies. There is also evidence that foreign firms in developing countries are more protective of the environment compared to domestic firms (Eskeland and Harrison, 2003). Eskeland and Harrison (2003) show that US-owned plants in developing countries are not only energy-efficient, they also use cleaner energy. The possibility that FDI reduces pollution intensity is also attested in studies such as Zarsky (1999); Zhu et al. (2016) and Zeng and Eastin (2012). In particular, Zhu et al. (2016) argue that foreign companies are more sensitive to the environment as they use better management practices and advanced technologies that are conducive to the environment compared to their domestic counterparts.

In order to deal with the theoretical ambiguity surrounding the FDI-environment nexus, a myriad number of studies have conducted empirical analyses on how FDI affects environmental emissions. However, the empirical studies on this subject have only reinforced this ambiguity, as they have produce contrasting results (Zhu et al., 2016). Eskeland and Harrison (2003) highlight that the existing literature is predominantly based on scattered case studies. These cases studies use different countries and environmental indicators or pollutants. Different pollutants include for example: carbon dioxide (CO_2), sulfur dioxide (SO_2), nitrous oxides ($N0_x$), volatile organic compounds and suspended particulate matter (dust, fumes, smoke). Specifically, studies such as Zhu et al. (2016) use CO_2 as a measure of pollution while Eskeland and Harrison (2003) also use total particulates, biological oxygen demand (BOD), and total toxic releases. Studies such as Cole et al. (2011) ascertain how the variation in Chinese-sourced and foreign-sourced FDI affect industrial water and air pollution indicators consisting of wastewater, petroleum, waste gas, SO_2, soot and dust. Similarly, Sapkota and Bastola (2017) and He and Richard (2010) use industrial CO_2 and SO_2 emissions respectively.

In terms of heterogeneity, studies have also used different countries or groups of countries. For instance, Zhu et al. (2016) consider five members of the Association of South East Asian Nations (ASEAN): Indonesia, Malaysia, the Philippines, Singapore, and Thailand. Cole et al. (2011) focus on 112 Chinese cities while He and Richard (2010) look at 29 provinces in China. In addition, Eskeland and Harrison (2003) focus on US specific outbound investment in four developing countries: Ivory Coast, Morocco, Mexico and Venezuela. Other studies include, Sapkota and Bastola (2017) that focus on 14 Latin America countries, as well as Pao and Tsai (2011), who explore the relationship between FDI and emissions for the Gulf Cooperation Council countries, and Sapkota and Bastola (2017) focus on Ghana. All these countries are at different levels of development and have varying environmental regulations and investment promotion strategies. Copeland and Taylor (2003) argue that developed and developing countries differ widely in terms of the stringency of their environmental regulations. The stringency of a country's environmental regulations can influence the impact of FDI on the environment.

Apart from these differences, these studies have also relied on different econometric methods to estimate the impact of FDI on the environment. Basically, their econometric models are shaped by the type of data being used. Studies such as Eskeland and Harrison (2003), He (2006), Cole et al. (2011), and Sapkota and Bastola (2017) use panel data compared to Solarin et al. (2017), Abbasi and Riaz (2016), and Kaya et al. (2017) that use time series data. The use of different types of data sets poses different econometric challenges as these require different estimation methods. For instance, studies that use panel data can adequately control for time-invariant heterogeneity that are unobserved to the econometrician. With the challenge of distributional heterogeneity due to countries having different levels of emissions intensity, a quantile regression technique can be employed with panel data (Zhu et al., 2016). Furthermore, in the specification of the econometric models, studies specify different functional forms such as log-linear against double-log model. These differences determine whether the estimated coefficients are elasticities or semi-elasticities. In addition, some studies such as Zhu et al. (2016) and Jalil and Feridun (2011) employ non-linear (quadratic) models by including GDP per capita and its square term in an attempt to account for the environmental Kuznets curve (EKC).

There are also differences in the econometric approaches used to solve for the possible endogeneity in the FDI-environment regressions. There are two endogeneity concerns in the FDI-environment relationship. The first is the concern of omitted variable bias where environmental decisions of a country could also be determined by other factors that are unobserved. To control for the omitted variables, country fixed effects can be used to capture time-invariant heterogeneity. The second is the possibility of reverse causality between FDI and the environment. Copeland and Taylor (2003) indicate that pollution policies in countries response to rising income and changing prices that are brought about by increased global activities such as trade and FDI. This could be a potential source of simultaneity bias. This therefore makes it relevant whether a study includes fixed effects, employs an IV, or uses an approach that minimizes the potential endogeneity bias.

[Insert Figure 1 here]

The heterogeneity in data and empirical methods used in these studies may in part, explain the diverse results and conflicting positions in the literature. The diversity may depend on a myriad of factors ranging from different countries selected into the sample, econometric techniques, environmental indicators and a set of different control variables. Not surprising, these studies report varying effects of FDI on the environmental indicators. Figure 1 confirms diversity in the FDI-environmental literature. 54% of the studies report a negative effect of FDI on the environment compared to 46% of the studies reporting a positive effect. These conflicting results are not limited to the sign of the FDI elasticity of emissions, but also the statistical significance of the elasticities. For the studies that report a negative effect, 29% of them find an effect that is statistically significant while 25% find no statistically significant effect. This similarly applies to the positive elasticities.

This paper contributes to the debate by synthesizing the literature of whether FDI is good or bad for the environment. Through this paper, we provide the first empirical evidence using the tool of meta-analysis. Apart from the main objective of deciphering whether there is any genuine effect of FDI on the environment, this paper also provides an additional contribution as it examines whether the effect of FDI on emissions differs for groups of countries at different levels of development. This disaggregation is in line with the assertion of Copeland and Taylor (2003) that country's income level influences the stringency of their environmental policies. Lastly, our paper also differentiates between the effect of FDI on different pollutants.

We conduct a meta-analysis to identify whether there is any genuine effect of FDI on the environment, as well as explain the diversity in the results. Using this meta-analysis helps to ascertain whether there is any genuine effect of FDI on environmental emissions. Thus, we estimate the combined effect size of FDI on the environment after controlling for heterogeneity in the previous studies. To pre-empt our results, we find that the underlying effect of FDI on emissions is close to zero, however, after accounting for heterogeneity in the studies, we find an inverse relationship between FDI and emissions. In other words, FDI significantly reduces environmental emissions. Our results remain robust even after disaggregating the effect for countries at different levels of development, as well as for different pollutants.

The rest of the paper proceeds as follows: Section 2 provides possible theoretical perspectives on how FDI affects the environment by looking at the different economic conditions under which FDI would increase or decrease emissions. Section 3 presents the empirical strategy, econometric methods, and data. Section 4 provides the empirical results with discussions and robustness checks. Section 5 concludes the study and provides some policy implications.

2 The environment and FDI relationship

Theoretically, the effect of FDI on the environment could have two possible effects. The effect could be negative, in the sense that increased FDI inflows could lead to increased environmental emissions. This is in line with the PHH that argues that "dirty" production could accompany foreign capital that is invested especially in developing countries. There are two main rationales behind the PHH. First, the intense competition among developing countries to attract FDI may lead to relaxing of environmental standards for foreign firms, thus encouraging firms in developed countries to move their pollution-intensive production to developing countries (Golub et al., 2011). Beladi and Oladi (2005) confirm that capital mobility from the North to the South depletes the environmental resources in the South thereby adversely affecting southern agricultural productivity. Second, the increasing costs of pollution abatement in certain sectors in developed countries make pollution-intensive activities costly in developed countries (Eskeland and Harrison, 2003). For example, Eskeland and Harrison cite the case of US FDI being skewed towards industries that face high pollution abatement cost at home.

This supposed adverse effect of FDI on the environment is supported the race-to-the-bottom hypothesis which argues that increased gains from globalization are achieved at the expense of the environment because more open economies adopt looser environmental standards. The pressure on firms to remain competitive forces them to adopt cost-saving production techniques that can be environmentally harmful. There are a number of studies that have provided empirical evidence to support this line of argument. For example, Cole et al. (2011) find that foreign–owned firms that signify the presence of FDI contributed significantly to an increase in the emissions of petroleum pollutants, waste gas, and SO_2 in China. For a group of Latin American countries, Sapkota and Bastola (2017) similarly show evidence of this deleterious impact of FDI on the environment. They estimate that a 1% increase in FDI contributes to a 0.04% increase in pollution.

Conversely, the effect of FDI on the environment could also be positive; in that, an increase in FDI results in a decrease in environmental emissions. In theory, this is referred to as the pollution halo hypothesis. The halo effect is underpinned by the assumption that foreign–owned companies are more energy–efficient and they use cleaner production processes compared to domestic firms. Even if FDI does not use the cleanest technology, it is more likely to use a cleaner technology than the existing technologies used by domestic firms in developing countries. In addition, through technology spillovers, it is likely that foreign firms would transfer their green technologies to local firms thereby leading to an overall reduction in emissions. Through FDI, there is a possibility that environmentally-friendly or green technologies and practices would be transferred to developing countries (Golub et al., 2011). Empirically, this hypothesis has been supported by many studies. Eskeland and Harrison (2003), for example, find that the US outbound investment in developing countries are more energy-efficient and use significantly more clean energy compared to their local counterparts.

In line with the opposing theories of the effect of FDI on the environment, we revisit the literature by synthesizing the previous studies in order to identify the genuine effect. Thus, our first hypothesis is aligned with the two possible effects of FDI on the environment emissions as follows:

Hypothesis 1: An increase in FDI inflows leads to a significant change (increase or decrease) in environmental emissions.

How effective FDI is in reducing environmental emissions in the host country depends to a large extent on the characteristics of the domestic economy (Iršová and Havránek, 2013). Iršová and Havránek (2013), for instance, identify that technology gap between countries can influence the effect of FDI on the environment. Importantly, for FDI to positively affect emissions in the host country, then there must be adequate technology spillovers to domestic firms. For example, if green FDI is transferred to a country, this can only help reduce emissions if green technology is adopted by domestic firms. More technically, the developed-developing country divide can lead to differential impact of FDI. Copeland and Taylor (2003), for instance, argue that exogenous North-South income differences can lead to different pollution policies. Thus, our second hypothesis focuses on whether the effect of FDI differs for groups of countries at different levels of development.

Hypothesis 2: The effect of FDI on environmental emissions differs significantly between developed and developing countries.

3 Data and empirical strategy

3.1 Meta-data

We follow the Meta-Analysis of Economics Research Network (MAER-Net) guidelines for conducting meta-analysis by Stanley et al. (2013) to identify the relevant studies for coding, and analysis. The extensive search for the literature started with Google Scholar to include all accessible empirical studies published until May 2018. We searched using the combination of keywords with the help of Boolean connectors: *FDI (OR foreign direct investment, foreign firms) AND Environment (OR pollution, emissions,* CO_2*,* SO_2*,* NO_2*, energy consumption, environmental quality, and carbon emissions)*. Using the keywords, *FDI and environment*, Google Scholar produces 214,000 studies which we review on the basis of their titles and abstracts. We also use this electronic database to conduct a forward search by looking at references that cited a particular study. In addition, we use the backward search by employing the snowballing technique which relies on the reference list of recent primary studies to find additional related studies. To be sure of capturing all the studies, we also complement our search using the Web of Science (WoS) database by using the same keywords as used in Google Scholar.

The multiple search process and data coding were conducted from September 2017 - May 2018 using a template designed in Microsoft Excel before transferring to a Stata for further analysis. Screening decisions for the search process were made by the two authors. Data extraction was personally done by one author and this was double-checked by the other author. In order to ensure that our data coding has the highest scientific rigor, we later had the data cross-validated with another meta-analysis data of ours which focuses on trade and the environment.[2] In this respect, the evaluation of the screening decisions were taken by the two researchers, while coding was made by three researchers.

The screening process identified a sample of 149 studies which were evaluated on the basis of full-text information. We limit the studies to English language empirical studies that estimate regression-based coefficients of FDI effect on environmental emissions. Following these criteria, at the end of the full-text evaluation we identified 83 empirical studies (1296 observations) that met our selection criteria. Of these, 76 studies are peer-reviewed journal articles and the other 7 are working papers, dissertations, unpublished studies, or reports. From the full-text evaluation, one common reason to exclude studies although they adopt econometric approach was the use of only Granger causality test rather than estimated elasticities to determine the relationship between FDI and emissions (e.g., Lau et al. (2014); Pao and Tsai (2011); Zhang (2011)). Another reason for excluding some studies is that they use different outcome variables. For instance, energy consumption or GDP instead of pollutant indicators (e.g., Acaravcı et al. (2015); Azam et al. (2015); Sbia et al. (2014)).

Focusing on the selected studies, approximately 87% of the studies reported coefficients using the double log functional form, where both FDI and the pollutants are expressed in logs. This makes the estimated coefficients to be interpreted as elasticities and thus the elasticities and their standard errors are directly collected from the regressions. Further evaluation during the coding stage also shows that some of the studies reported estimates using the log-linear or linear form. For this, we had to re-compute the elasticities using sample means. However, 9 of these studies (68 observations) did not report descriptive statistics so it was not possible to re-calculate and standardized the effect size (e.g., Zheng and Sheng (2017); Ren et al. (2014); Talukdar and Meisner (2001)). In addition, there were 9 primary studies (105 observations) that did not provide information on standard errors or t-values (e.g., Abid (2017); Abdouli and Hammami (2017); Abbasi and Riaz (2016). We exclude such studies because the authors were unable to provide missing data in terms of descriptive statistics, standard errors or t-values.

To account for outliers, we apply the Hadi (1994) multivariate outlier method in order to filter out both the effect sizes and their standard errors jointly. The procedure is known for its appropriateness in robustly identifying outliers in a multivariate data sets (e.g., Havranek and Irsova (2011); Demena and van Bergeijk (2017)).[3] By this procedure, we exclude 10.4% reported estimates (117 observations) from the analysis as outliers, resulting in 1006 observations available for the meta-analysis. Nearly one third of the identified outliers were derived from studies published in journals with an approximately zero impact factor as reported by the Institute of Scientific Information (ISI) as of May 2018. Including the number of parameter estimates with an impact factor less than the average represents 87% of the outliers identified by this procedure (the mean impact factor is 2.59 and maximum is 9.12). According to Havranek and Irsova (2011), the better the rank of the journal, the better the reliability of the findings. In this respect, we would assume that these outliers do represent lower quality research as compared to the included parameter estimates ((Demena, 2015), (Demena, 2017)). Finally, we obtain a sample of 65 studies (1006 observations) for our meta-analysis. Table 1A in the Appendix A provides detailed information on the list of studies included in this paper.

[2] The trade-environment data was collected by an independent research assistant that was employed. The two data sets are about 70% overlapping. In addition, the research assistant also checked the remaining 30% to validate it. We have actually compared the data entered by the research assistant and our data and there no significant differences. Based on this data validation, we are strongly convinced that the data used in this analysis is of the highest standard.

[3] The method works first through ordering the observations in ascending order to split it into two subsets: basic and non-basic subsets of the observations and then continues until appropriate basic subset is met. In this regard, the non-basic subset is considered as an outlying subset.

$$ln(Emissions_{jt}) = \beta_0 + \beta_1 ln(GDPpc)_{jt} + \beta_2 lnGDPpc^2_{jt} + \beta_3 ln(X)_{jt} + \delta lnFDI_{jt} + \alpha_j + \alpha_t + \epsilon_{jt} \quad (1)$$

A typical model examining the effect of FDI on the environment has the form of Eqn.(1), where $Emissions_{jt}$ is the outcome variable that measures the environmental emissions of a specific pollutant for country j at time t. The variable of interest is FDI_{jt} and this measures the amount of FDI inflow to country j at time t. In Eqn. (1), some studies include GDP and its square term as a test of Kuznets environmental hypothesis and also a vector of control variables (X_{jt}) that could possibly confound the effect of FDI on the environment. The main parameter of interest, δ, measures the FDI elasticity of emissions. We extract all reported effect sizes (ESs) measured by δ_i from all studies (i) that have estimated a variant of the Eqn. (1).

The majority of the studies (87%) in our sample estimated δ in a double-log functional form. Therefore, we can refer to the regression coefficients as elasticities, and use the standard errors of the regression coefficients directly. In addition, there were studies that report semi-elasticities from log-linear functional form instead of elasticities. To make the latter estimates comparable to elasticities, we employ the Delta method. In this procedure, we follow the approach in Gujarati (2009). This method has also recently been used in meta-analyses of FDI studies by Iršová and Havránek (2013) and Demena and van Bergeijk (2017). We employ sample means of FDI variable to convert semi-elasticity into full elasticity, when the independent FDI variable is in level and the dependent pollution variable is in log form.

3.2 Funnel asymmetric test (FAT) and precision effect test(PET)

Our main empirical strategy is meta-analysis. According to Stanley and Doucouliagos (2012), meta-analysis involves a systematic review of relevant scientific knowledge in previously published, or reported empirical findings on a given hypothesis. Meta-analysis is suitable for an empirical investigation that has produced large variations in reported regression estimates. For an evidenced-based decision-making process in environmental policy, practice, and research, Haddaway et al. (2018) advocate for the use of systematic reviews or meta-analyses. The use of meta-analysis is less susceptible to bias especially if there is strict adherence to the guidelines (Haddaway and Pullin, 2014).

Historically, meta-analysis has been widely-used in medical research (Stanley, 2001). For example, Glass (1976) uses meta-analysis to study the effectiveness of psychotherapy. More recently, the application of meta-analysis is rapidly growing within economics and some of its contemporary applications can be seen in studies such as Rose and Stanley (2005), Oczkowski and Doucouliagos (2015), Demena and van Bergeijk (2017), Afesorgbor (2017), Wehkamp et al. (2018), Havranek and Irsova (2011), and Iršová and Havránek (2013). We have also seen a surge in the use of meta-analysis in environmental and resource economics. For instance, Nelson and Kennedy (2009) identify 140 meta-studies that were conducted within the environmental literature. The empirical estimates of the effect of FDI on the environment has produced extreme variation and this makes the tool of meta-analysis methodologically relevant for the purposes of summarizing, integrating, and synthesizing the overall effect of FDI on environmental emissions.

$$\delta_i = \beta_0 + \beta_1 SE_i + \epsilon_i \quad (2)$$

In line with the meta-analysis guidelines as enshrined in Stanley et al. (2013), we employ two specific steps. The first step involves conducting bivariate FAT-PET. The FAT-PET is captured by Eqn. (2), where δ_i is the estimated FDI elasticity of emissions from study i and SE_i is the standard error of the effect size, δ_i. FAT is the funnel asymmetric test which is used to test the presence or absence of publication bias. Stanley and Doucouliagos (2012) defines publication bias as the preference of accepting research papers in journals for their statistical significance. Econometrically, the FAT is equivalent to testing whether coefficient (β_1) is statistically different from zero. Without publication bias, it is expected that the effect sizes (δ_i) would be independent of the standard errors, thus a significant β_1 indicates the presence of publication bias. PET is the precision effect test that examines whether or not there is a genuine underlying effect beyond publication bias. The estimated coefficient, β_0, is therefore the corrected estimate of the genuine empirical effect after accounting for the publication bias.

A necessary condition to obtain an efficient estimator in a classical regression analysis is that the error term must be independent and identically distributed. However, in estimating Eqn. (2), Stanley (2005) concurs that since the multiple effect sizes are obtained from the same studies, there is the likelihood of dependence in error terms. This therefore makes the variances of the effect sizes and error term correlated with individual heterogeneity in the studies. This makes the error term (ϵ_i) to be plausibly heteroscedastic; hence Stanley (2005) suggested the use of weighted least squares (WLS) in which we divide both sides of the equations by the standard error. Using the WLS, we transform the FAT-PET model (2) into (3), where t_i is t-value obtained when we divide the effect sizes by their standard errors ($t_i = \frac{\delta_i}{SE}$) .

$$t_i = \frac{1}{SE}\beta_0 + \beta_1 + \epsilon_i \tag{3}$$

3.3 Moderator analysis

To explain the heterogeneity in the results, a multivariate meta-regression, or moderator analysis, is employed to determine how the differences in the study designs, publication qualities, or individual heterogeneities in the studies affect the estimated elasticities. In eqn.(4), we augment the FAT-PET equation with all the variables (X_k) in Table 1. This represents a vector of regressors that captures the individual heterogeneity in the studies. The study characteristics differ in many dimensions such as data (data type, data set time period, data source), model (OLS, fixed effects, double-log, log-lin, instrumental variable (IV)), pollution indicators (CO_2, SO_2, other pollutants), macroeconomic variables used as control variables (GDP, institution, energy consumption, trade openness), measurement of FDI (FDI stock, FDI flow, FDI per capita), and quality dimension or publication quality (publication year, published, working paper, journal impact factor, number of citations). Stanley and Doucouliagos (2012) confirm the presence of excess heterogeneity in economic research, and they assert that the observed variation in economics research far outweighs the random sampling error. Furthermore, they indicate that the problem of heterogeneity in studies makes expected values of estimates unstable and they tend to depend on many factors such as country or region, time period, dependent variable measure, functional form used and econometric technique employed.

$$\delta_i = \beta_0 + \beta_1 SE_i + \beta_k \sum_{i=1}^{n} X_{ki} \tag{4}$$

Table 1 provides an overview on the different characteristics of the original studies, including their definitions, means, and standard deviations. Following the heterogeneity in the primary studies, we distinguish four types of characteristics that we can use to explain the heterogeneity in the result of the primary studies: study, model, effect and publication characteristics. The study characteristics differ from one study to another and these attributes remain constant within each study. The model characteristics differ within one study depending on the model, hence are at a finer level than the study characteristics. The effect characteristics are directly related to the effect sizes being coded, and might differ within the same study and model. Finally, the publication characteristics are related to the publication outlet of the original studies. We provide descriptions of the various variables that fall under these four categories in Appendix B.

[Insert Table 1 here]

3.4 Econometric concerns

Estimating Eqn. (4) in its general form poses multicollinearity problems because of the large number of moderator variables (which are dummy variables) Apart from multicollinearity, including all these dummy variables may have negative degrees of freedom. Stanley and Doucouliagos (2012) recommend the use of general-to-specific (G-to-S) technique which is in line with the MAER-Net reporting guidelines. This technique starts with a general specification that includes all the moderator variables and then reduces to a specific model by systematically removing the insignificant variables from the general model, one at a time, until only significant variables remain. We observed that most of the moderator variables included in the general model are not statistically significant. To be specific, we exclude half of the moderator variables which are not statistically significant at least at 10 per cent significance. Empirically, the joint test of the included 14 moderator variables rejects the null hypothesis of a zero joint effect F(14, 990) = 8.90, supporting the specific/reduced model. Moreover, applying the G-to-S has proven to provide better estimation as it can reduce potential multicollinearity and the loss of degrees of freedom.

Using the reduced model, we use three different econometric approaches to explain the heterogeneity in the reported estimates. First, we use the clustered ordinary least squares (OLS) after WLS transforming the variables using their standard errors. However, using OLS does not control for individual prejudices (i) of the authors. This is important as Stanley and Doucouliagos (2012) argue that researchers who self-select findings that are statistically significant, can also experiment with econometric model specifications and techniques to achieve their goal. They therefore suggest the use of fixed effect estimation in the meta-analysis to cater for the individual within-variation. When multiple reported estimates are extracted from the same study, it is vital to control for within-study dependence in order to avoid potential estimation bias.[4]

Beyond the within-study dependence, there is also an econometric concern about between-study dependence. This is important in our case because multiple studies are published by the same authors (and thus unlikely to be statistically independent). Indeed, we check for the existence of statistical dependency between studies using the Breusch-Pagan Lagrange multiplier (BP-LM) test. The result suggests the presence of statistical dependence between the studies.[5] Accordingly, our preferred model is the multi-level mixed model (MEM) that accounts for both between-study dependence and the within-study correlation unlike the clustered OLS and fixed effects that mainly account for only within-study correlation. The importance of controlling for between-study dependence via the multi–level model was also recommended by Bateman and Jones (2003) and Doucouliagos and Laroche (2009). In addition, this procedure is widely applied in recent meta-regression analysis (MRA) (e.g., Havranek and Irsova (2011); Demena (2015); Havranek et al. (2016); and Demena and van Bergeijk (2017)).

[4]Thus, we use the OLS and fixed effect estimators only as our baseline estimations. Our interpretation of the results are not based on these estimators but rather the mixed-level effect.

[5]This BP-LM which is a chi-squared with one degree of freedom revealed the study-level effect to be 167.01 with $p < 0.001$ at any statistical level. The procedure reports similar results when outliers estimates are included: $\chi^2 = 104.02$, $p < 0.001$, indicating the existence of study-level effects.

4 Results and discussion

4.1 Genuine effect and publication bias

To derive a combined effect size from all the previous studies that estimated the effect of FDI on emissions, we first use the naive approach that involves a simple weighted and unweighted average of the effect sizes. Table 2 shows the unweighted (simple) and weighted average of the effect sizes. Although these results do not capture the heterogeneity and the possible publication bias in the empirical studies, they nevertheless provide an indication that generally the average effect of FDI on emissions is negative. Making inference of the overall effect based on this (un) weighted averages would not be valid in the presence of publication bias and heterogeneity in the studies (Stanley and Doucouliagos, 2012).

[Insert Table 2 here]

A conventional approach used within the meta-analysis literature to graphically identify the presence or absence of publication bias is the funnel plot. The funnel plot is a scatter diagram that depicts the relationship between precision (inverse of the standard errors) and the effect sizes of the individual studies. Stanley and Doucouliagos (2012) and Rose and Stanley (2005) pinpoint that the asymmetry of the funnel plot is the antecedent of publication bias. That is, if the pictorial view of the funnel plot does not have a perfectly symmetric shape, then it indicates the presence of publication bias. Figure 2 shows the funnel plot, and it has a perfect shape of a funnel and it also looks symmetric, an indication of the absence of publication bias.

Table 3 reports the bivariate meta-regression analysis (MRA) results for the FAT-PET. The FAT confirms the funnel plot of no publication bias under OLS and mixed effect multilevel (MEM), but this is inconsistent under fixed effect (FE) estimation.[6] For the genuine empirical effect, the analyses under PET find no statistically significant results, which means that the underlying effect of FDI on emissions is near zero. The lack of a significant effect could possibly be due to many reasons that FAT-PET cannot adequately address, ranging from endemic heterogeneity in the study designs, combining studies that use countries at different levels of development, and using different pollutants. Stanley and Doucouliagos (2012), for instance, indicate that FAT-PET model can produce an inflated type 1 error if the model fails to control for the excess unexplained heterogeneity.

[Insert Table 3 here]

Following the argument of Copeland and Taylor (2003) that the effect of FDI on the environment depends on the level of development in the country, we estimate the FAT-PET and disaggregate the results for different countries used in the studies. We classify the studies into developing and developed countries depending on whether the FDI-environment elasticity was estimated for a developing or developed country. However some studies employ crossed-countries analyses that included both developed and developing countries in their sample, thus we add an additional category (both countries) that captures studies that mixed these countries.[7] Table 4 presents the results for the FAT-PET for different group of countries. This shows there is a differential impact for the different group of countries. We find a negative effect that is statistically significant at conventional level only for developed countries. We find an elasticity which indicates that a 10% increase in FDI leads to a 0.16% reduction in emissions. However, the endemic heterogeneity in the previous studies makes it necessary to use multivariate analysis to account for the individual heterogeneity. Specifically, the next sections address this issue in an adequate manner.

[6] Since, our preferred model is MEM, we base our main results on the MEM.

[7] In classifying the countries as developed or developing countries, we use the UN (2014) World Economic Situation and Prospect Report.

[Insert Table 4 here]

4.2 Explaining the heterogeneity

To cater for the heterogeneity that characterized previous studies, we employ a multivariate meta-regression as specified in model (4). In essence, this model helps to assess how the specific study characteristics affect the economic and statistical significance of the estimated effect of FDI on emissions. Stanley and Doucouliagos (2012) emphasize that in applied econometrics, estimating a stable parameter is still predominately influenced by econometric technique, control variables, sample, and data characteristics. Therefore, omitting one relevant variable could change the size, sign, and significance of the estimated coefficients. Table 5 reports our results for the multivariate MRA using the G-to-S technique. Testing our first hypothesis, we consistently find across the different estimators (FE and MEM) that the effect of FDI on emissions is negative and significant. This means that an increase in FDI flow has beneficial effects for the environment of the host country. Essentially, a 10% increase in FDI results in a 2% decrease in emissions in our preferred estimation technique (MEM). Consistent with our previous results, we do not find any evidence of publication bias after controlling for study heterogeneity. Importantly, controlling for individual study characteristics improves the economic and statistical significance of the effect.

[Insert Table 5 here]

Focusing on the study characteristics, our results (based on the MEM estimator,) in column (3) show that the number of countries, the number of observations, the number of years of the data, and the source of data significantly affect the sign and size of the reported estimates. Specifically, we find that, the number of countries included by the primary studies results in a lower effect of FDI on emissions, in that, on average, the magnitude of the estimated size decreases by 0.012 as the number of countries increases by one. We also find a significant negative effect for the span of years of the data set. This may imply that the use of a data set with wider time coverage (as opposed to shorter/single-period data) can significantly lower the FDI-pollution effect. Similarly, we find that larger sample size as measured by the number of observations also has a positive and statistically significant effect on the effect sizes. If the number of observations increases by 10%, this increases the magnitude of the reported estimate by 0.06%. Whether the data is a panel or time series does not have any statistically significant effect.

Additionally, we see that the source of data has a significant effect on the estimated elasticities in contrast to the assertion of Stanley and Doucouliagos (2012) that different data sources do not have any noticeable effect on the reported estimates. Studies that obtained data from international sources tend to have lower elasticities compared to studies that obtained data from local sources. Because of international pressure due to intergovernmental nature of emissions problems (Pao and Tsai, 2011), data on emissions could be sensitive and it is likely that data sourced internationally would be more transparent and free from specific country manipulations. Kousky (2014) states that trustworthiness and quality of data on environment can be linked to the source of the data.

Turning to the effect characteristics, we find that the magnitude of the estimated elasticities is sensitive to whether the coefficients are short-run or long-run elasticities. If the estimated coefficient is a long-run elasticity, the effect of FDI on emissions is more pronounced. This is expected as a long-run relationship between FDI and emissions means that these variables are co-integrated and that the effect of FDI on emissions is not only contemporaneous, but may also have persistent dependence or a distributed-lag multiplier effect (Seker et al., 2015). Whether a study lags the FDI variable also has no significant effect. This may be pointing to the fact that lagging may not be an adequate approach to controlling for endogeneity.

For the model characteristics,studies that control for any external events or common trends using time fixed effects, their estimated effects of FDI on emissions are lower compared to studies that do not.[8] This could mean that studies that failed to control for external events suffer from an upward bias in their estimated coefficients as factors such as technology and government regulation may affect environmental emissions over time. Whether FDI is measured as a flow or stock is not significant at conventional levels in our G-to-S models, thus the variables were left out in our specific model for Table 5. Surprisingly, our results show that the choice of pollutant in a study has no discernible effect on the estimated elasticities. With regard to pollution indicators, our results show that differences in pollutants have no significant effect on the impact of FDI on environmental emissions.

The original studies also control for a vector of factors related to the macroeconomic conditions of a given country that can influence the effect of FDI on emissions. These control variables are important, especially if a researcher is interested in the exact magnitude of the elasticity. Omitting one important control variable that is correlated with the FDI variable would result in either an upward or downward bias depending on the correlation between the omitted variable and the FDI variable. Most studies include GDP and the square term of GDP in line with the popular EKC hypothesis. Similarly, these studies also include different macroeconomic variables that control for institutional development or quality, energy consumption, urbanization, and trade openness. Among these control variables, the effect of energy consumption is negative, meaning that studies that control for it have less effect of FDI on emissions. From an economic point of view, this make sense as FDI and energy consumption could potentially be positively correlated. Pao and Tsai (2011) suggest that there is a bidirectional causality between energy and FDI.

Our findings also suggest that the control for economic activity measured by GDP is associated with higher positive effect of FDI on emissions, however this is only significant at 10% level. Controlling for other macroeconomic variables such as trade openness has a negative effect but not significant. The negative effect could imply that trade openness is also a potential determinant of emissions, thus including it as an additional variable reduces the variation that is explained by the FDI variable.[9]

Our results suggest that the publication year of the study has a significant effect as more current studies tend to report estimates that have more pronounced impacts (on average higher by 0.099) which may be signaling an increasing awareness about climate change in the world in recent times.[10]

[Insert Table 6 here]

We also run the G-to-S multivariate analysis for different groups of countries. Table 6 shows interesting outcomes when we disaggregate the results for countries at different levels of development. Consistently, the results confirm that the effect of FDI on emissions is negative when we control for heterogeneity in the level of development. However, we find there is a differential effect for studies that used developing, developed countries or both (a mix of developing and developed countries) in terms of the magnitude or size of the coefficients. Figure 3 compares the estimated coefficients and their 95%-confidence intervals for all studies (without differentiating the levels of development as in Table 5) to the results for countries at different levels of development (Table 6).

[Insert Figure 3 here]

[8]Surprising, in the general model, studies that control for endogeneity by employing IVs, include country fixed effects, and (or) include interaction terms do not have any significant effect. In addition, the use of different functional forms of whether a model is specified in log-log or log-linear forms do not have any noticeable influence on the estimated effect of FDI on the emissions.

[9]The inclusion of other macroeconomic variables such as urbanization and institutional quality have no significant effect on the reported results in the general model.

[10]In our general model, all other publication characteristics; whether an article has been published in journal, cited more frequently, or has a higher impact factor does not affect the magnitude of the effect of FDI on the environment. This also collaborates the FAT-PET result of no publication bias.

For developing countries, we see that the effect of FDI on emissions become more pronounced in terms of economic and statistical significance. In column (3), the estimated elasticity indicates that a 1% increase in FDI would result in 0.12% decrease in emissions in developing countries. For developed countries, we see an even more pronounced reduction in emissions when FDI increases. Specifically, a 1% increase in FDI leads to an approximate 4.5% reduction in emissions. This may be justified as we know that developed countries have stricter environmental regulations on pollution and emissions (Copeland and Taylor, 2003). The large reduction in emissions in developed countries could also give credence to the PHH as most firms are shifting their pollution-intensive activities to developing countries to avoid the higher abatement costs in developed countries. In addition, since most developed countries already have advanced technologies, they are more likely to only attract FDIs that come with technology that is greener and more environmentally-friendly. This is also in line with the argument that high-income countries would demand higher green products as the environment is considered as a normal good, corroborating our second hypothesis. For studies that mixed both developing and developed countries, we still find a negative and significant effect of FDI on environmental emissions.

In the exception of the urbanization variable, all the studies that control for institutional and macroeconomic control variables have no significant impact in the case of developing countries. This may be highlighting the lack of strong institutions and unstable macroeconomic conditions in developing countries. Institutions are expected to play an important role in environmental governance which may translate into lower emissions for countries. Frankel and Rose (2005) confirm the beneficial effect of political and democratic institutions in improving environmental quality.

4.3 Further investigations and robustness checks

Supplementary to our main analyses, we also perform further analyses to investigate the robustness of our main findings discussed above. Since we only find significant results in the case of our multivariate meta-analysis, our robustness checks are limited to the case of multivariate analyses.[11] In the first case, we check the consistency of our results excluding the primary study with the highest number of observations. By so doing, we exclude the 272 reported estimates from Zugravu-Soilita (2017) to test whether this study alone determines our results. Next, we run Eq. (3), separating the results for the two predominant pollution indicators used by the primary studies, consisting of CO_2 and SO_2.

[Insert Table 7]

The results of the robustness checks as related to the multivariate MRA are reported in Table 7. In columns 1-3, we present multivariate MRA excluding the 272 reported estimates from Zugravu-Soilita (2017) with the same moderators in the G-to-S modeling . In columns 4-6 and 7-9, we divide our sample into two sub-samples consisting of primary studies that used CO_2 and SO_2, respectively, as pollution indicators. Despite the reduction in the number of primary studies and the sample size, the results remain robust and similar to our main findings when we include the whole sample. This suggests that our findings are not particularly influenced by the inclusion or exclusion of one single study. For pollution indicator choices, our results remain robust confirming that FDI significantly reduces emissions, however the size of the effect is larger for SO_2 as compared to CO_2. One possible reason for this could be the explanation provided by Frankel and Rose (2005) that SO_2 is a local pollutant and governments are more concerned with its health implications for the local populace, so will clamp down on pollution activities of SO_2. With their reasoning, we expect that the reducing effect of FDI on emissions should be more pronounced for the local pollutant (SO_2).

[Insert Table 8]

[11]We also conduct robustness checks in relation to the bivariate MRA for FAT-PET analysis and results do not deviate significantly from the our baseline regressions.

[Insert Table 9]

Our final two robustness checks are in relation to FDI and how it is measured. First, we differentiate the effect of FDI on environmental emissions for the primary studies that either measure FDI as a flow or stock. Table 8 gives the results of this further investigation and the results are largely consistent with the previous results, especially the negative effect of FDI on emissions. The results for the PET in columns 4-6 although negative has a large magnitude but this is not significant under the MEM. As explained earlier, one possible reason for this large coefficients for FDI measured as stock is that it is measured as an accumulated amount of FDI over a period of time compared to FDI flow which is measured in terms of the amount of FDI at a point in time. The second robustness check focuses on the choice of measurement for FDI. We differentiate between when a primary study measures FDI at level (FDI in dollar amount) compared to when FDI measured as a ratio or a percentage in which they divide the FDI amount by the GDP of country. The results for this robustness check are presented in Table 9. Whether FDI is measured in terms of per capita terms or at level, there is no significant difference in terms of the sign of the coefficient of FDI on emissions. However, the size of the effect is slightly larger when FDI is measured at level compared to when it is measured in per capita terms.

5 Conclusion and policy implications

The FDI-environmental emissions linkage continues to be a controversial topic in the globalization-environmental debate. This controversy is centered around whether increased globalization through the movement of international capital from one country to another is good or bad for the environment. This debate has generated opposing hypotheses that support each line of argument. The pollution haven hypothesis posits that increases in FDI would be detrimental for the environment, especially in developing countries. Researchers supporting this side of the argument contend that increased FDI may promote increased production and consumption through the exploitation of the environment and the depletion of natural resources. Conversely, the pollution halo hypothesis argues that FDI could have beneficial environmental effects through the transfer of green or environmentally-friendly or energy efficient technologies that would curb environmental emissions. These opposing hypotheses have also culminated in a myriad number of empirical studies, however, the empirical evidence has only produced conflicting and contrasting results, thereby further confounding the theoretical ambiguity.

This paper conducts a systematic and rigorous review of the existing literature on the effect of FDI on the environment using the quantitative and empirical tool of meta-analysis. Meta-analysis helps in achieving two important objectives with regards to the FDI-environment nexus. First, to derive a combined effect size from the conflicting results of the previous studies. We use the bivariate FAT-PET model in line with the MAER-Net guidelines to determine whether there is a publication bias and also to obtain the genuine effect of FDI on emissions after correcting for publication bias. Second, we use multivariate meta-regression analysis to explain the heterogeneity in the previous studies. This is necessary in order to determine how differences in the study characteristics are sensitive to reported estimates of FDI's impact on the environment. The differences in studies range from different data characteristics, econometric techniques, choice of measurement of the FDI variable, environmental pollutants or indicator, and the set of macroeconomic control variables. Altogether, our meta-analysis uses 65 studies that produced 1006 estimated elasticities of FDI on the environment.

Inferences from our results based on both weighted and unweighted meta-averages show that the underlying effect of FDI on the environment is close to zero. This was also confirmed by the FAT-PET regression as it finds no significant effect of FDI on emissions. In addition, it discounts the presence of any publication bias, in that, the empirical studies have not been influenced by some sort of publication selection pressure in terms of preference for positive or negative statistically significance evidence from journal editors, reviewers or authors.

However, after controlling for publication bias and individual heterogeneity using the multivariate analysis, we find a significant inverse relationship between FDI and emissions. More specifically, an increase in FDI reduces emissions. This result is in favor of the pollution halo hypothesis. Thus, our results indicate that FDI does not only improve economic growth, but could also potentially reduce environmental pollution or emissions. Additionally, disaggregating the results for different country categories, we find that the effect of FDI on emissions differs qualitatively and quantitatively for these country groupings. Under our FAT-PET model, we find that FDI has an inverse and a significant effect on emissions for developed countries. The inverse and significant effect is robust when we account for study heterogeneity using the multivariate meta-regression approach. Controlling for individual study characteristics, we find a pronounced effect for developed countries compared to developing countries. Similarly, for studies that mixed the developing and developed countries in their samples, we still find an inverse and significant result.

Turning to how the inherent heterogeneity in the studies affect the effect of FDI on emissions, our results find that for the study characteristics including the number of countries included in a study reduces the magnitude of the elasticities; the number of observation significantly increases the size of the effect, while data sourced from international databases tend to have less pronounced effect of FDI on emissions. For estimation characteristics, studies that report long-run elasticities have larger effects compared to those that report short-run elasticities, while studies that control for year fixed effects tend to have lower effects. Turning to the choice of measurement of the FDI variable, we find that studies that measure FDI as a flow tend to report lower values of the estimated impact of FDI on emissions. Also, how the FDI variable is measured is important. Studies that measure FDI in per capita terms compared to level or amount of FDI report lower elasticities. Among the macroeconomic control variables, studies that include energy consumption as an additional control variable in the econometric model report lower effect of FDI on emissions. Lastly, for the publication characteristics, only the year of publication has a positive and significant impact on the effect sizes.

The results presented in this paper offer some policy implications. First, how countries can use the rising pace of globalization to help tackle the threats of climate change through the channels of green FDI. The results indicating that FDI can be good for the environment offers an interesting perspective that globalization may not be entirely bad for the environment, as many critics of globalization tend to portray. Globalization is not solely about increased competition, production and consumption, but can also reduce environmental emissions through the transfer of green technologies across borders. Through FDI, we may have foreign firms with the best, efficient, and green technologies transferring their innovations to their domestic counterparts. Multinational corporations with clean state-of-the-art technologies can transfer their green know-how to countries with low environmental-friendly technologies.

Although our results do not differentiate whether FDI inflows to countries are green or not, it will be important that both developing and developed countries ensure that in attracting FDI, they enact policies that will subject all FDI inflows to an environmental impact assessment. FDI campaigns should emphasize green FDI that focuses on FDI that can promote economic growth and also internalizes the adverse environmental externalities associated with industrial production. By so doing, they may not only be promoting economic growth, but simultaneously promoting a significant reduction in environmental emissions.

Second, our results also offer policy implications that countries cannot adopt a one-policy-fits-all environmental policy in combating different types of pollutants. From our results, we found that the emission-reducing impact of FDI was minimal for SO_2 compared to CO_2. These differences in the results for these pollutants could possibly due to the fact that SO_2 is a local pollutant in which the adverse effects and health implications are geographically localized so countries are more proactive in curbing the emissions of local pollutants. Compared to CO_2 which is an international pollutant and less regulated because its adverse effects are global. This therefore calls for mixed strategies in combating different pollutants, especially through co-operative international environmental agreements. These agreements should have mechanisms that can punish countries who do not participate or violate the agreements.

Third, our findings suggest that FDI has a more pronounced effect of reducing emissions for developed countries compared to developing countries. This could mean that the quality of FDI inflow to developing countries is lower compared to FDI that goes to developed countries. Thus, giving credence to pollution haven hypothesis. In the light of that finding, it will be important that developing countries also institute stricter environmental policies that will ensure that FDI inflow to their countries are environmentally-friendly. This may also called for shared responsibility between developed and developing countries of ensuring that FDI moving to developing countries should be similarly of high environmental standards as those moving to developed countries. Thus, firms seeking to move their production activities to developing countries do not move there with any technology which is not acceptable in their developed countries of origin.

In summary, a general policy implication of the study is that environmental policies should not be uniform for all countries. Environmental policies must be country- and pollutant-specific in order to solve the nature of the environmental problem that a country faces. A well-designed environmental policy should reflect the specific needs of a country, taking into consideration the country's level of economic development as well as specific environmental pollutants.

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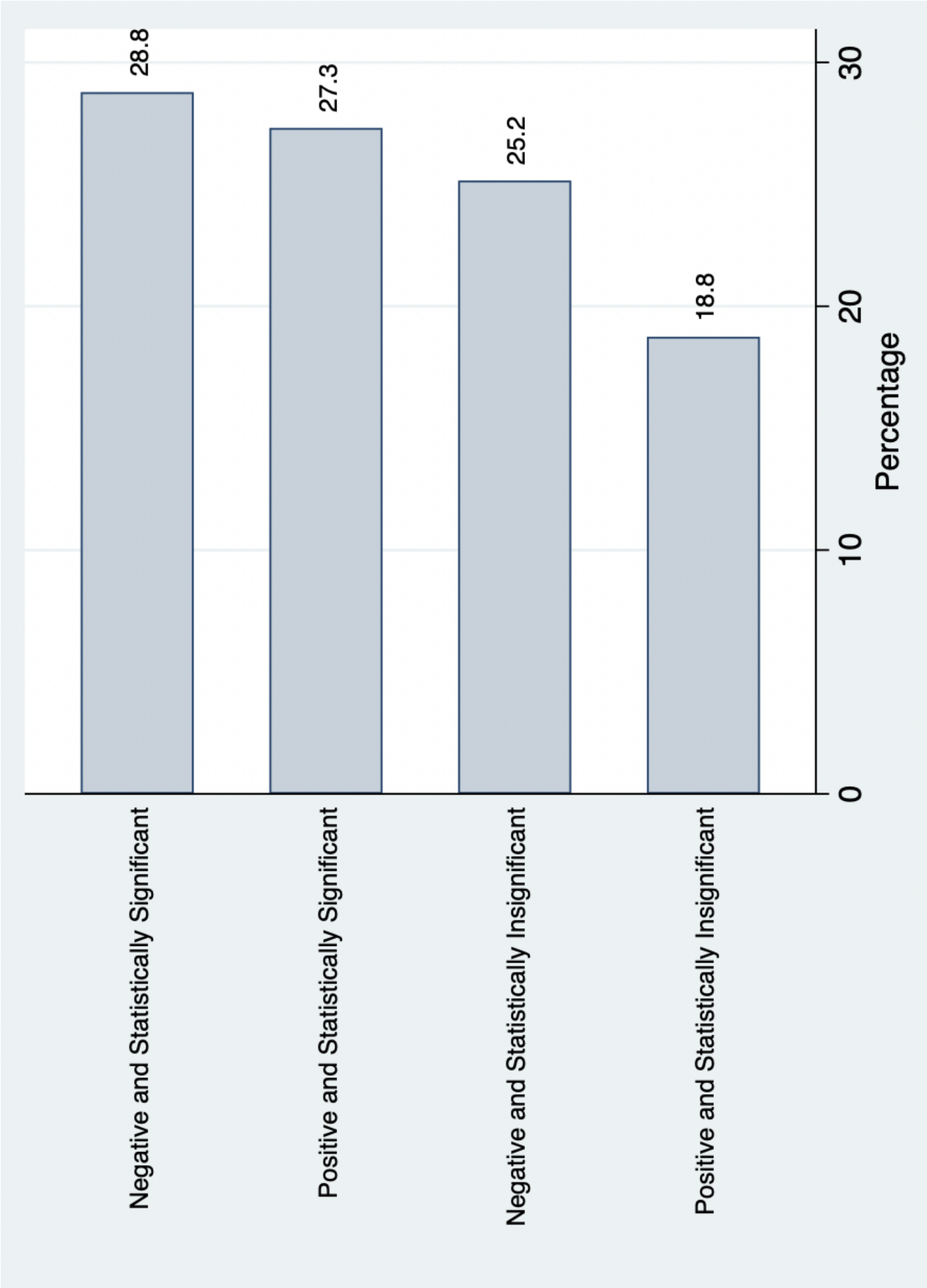
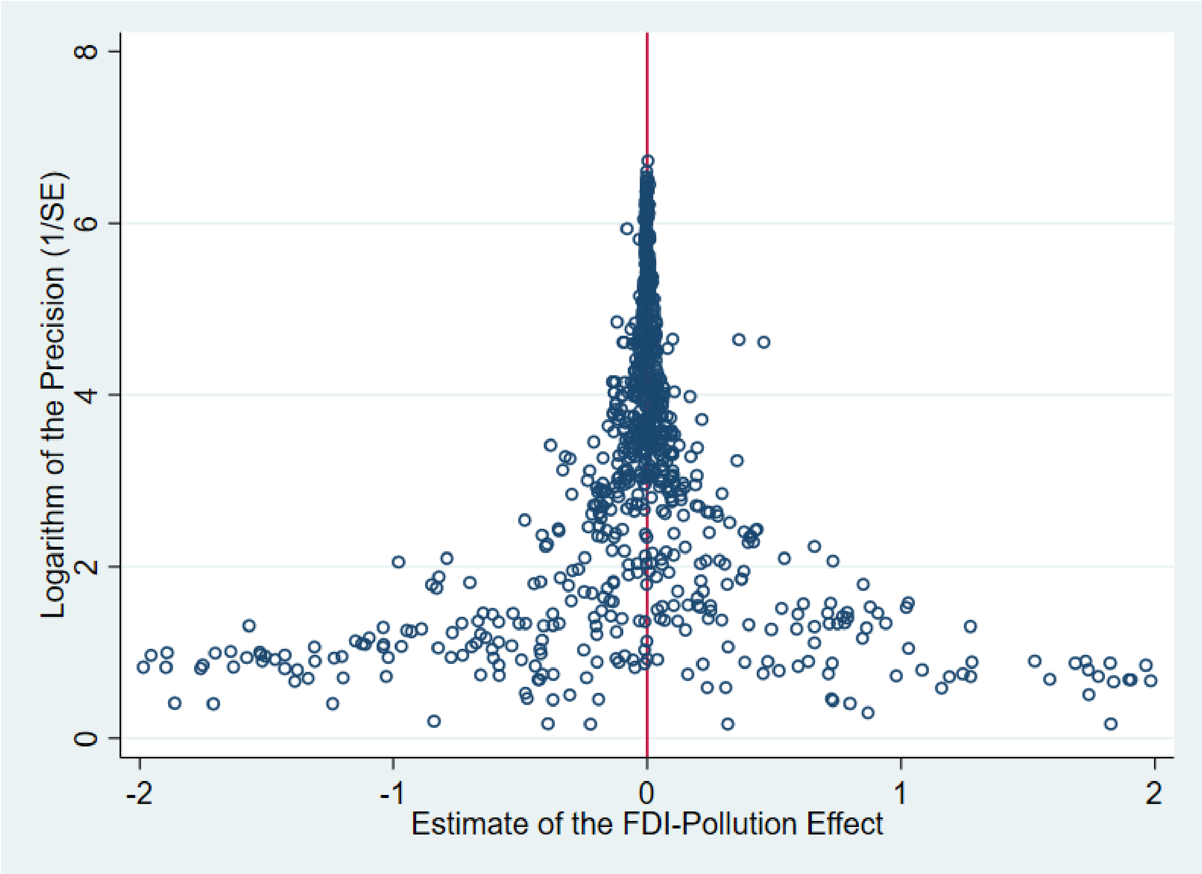


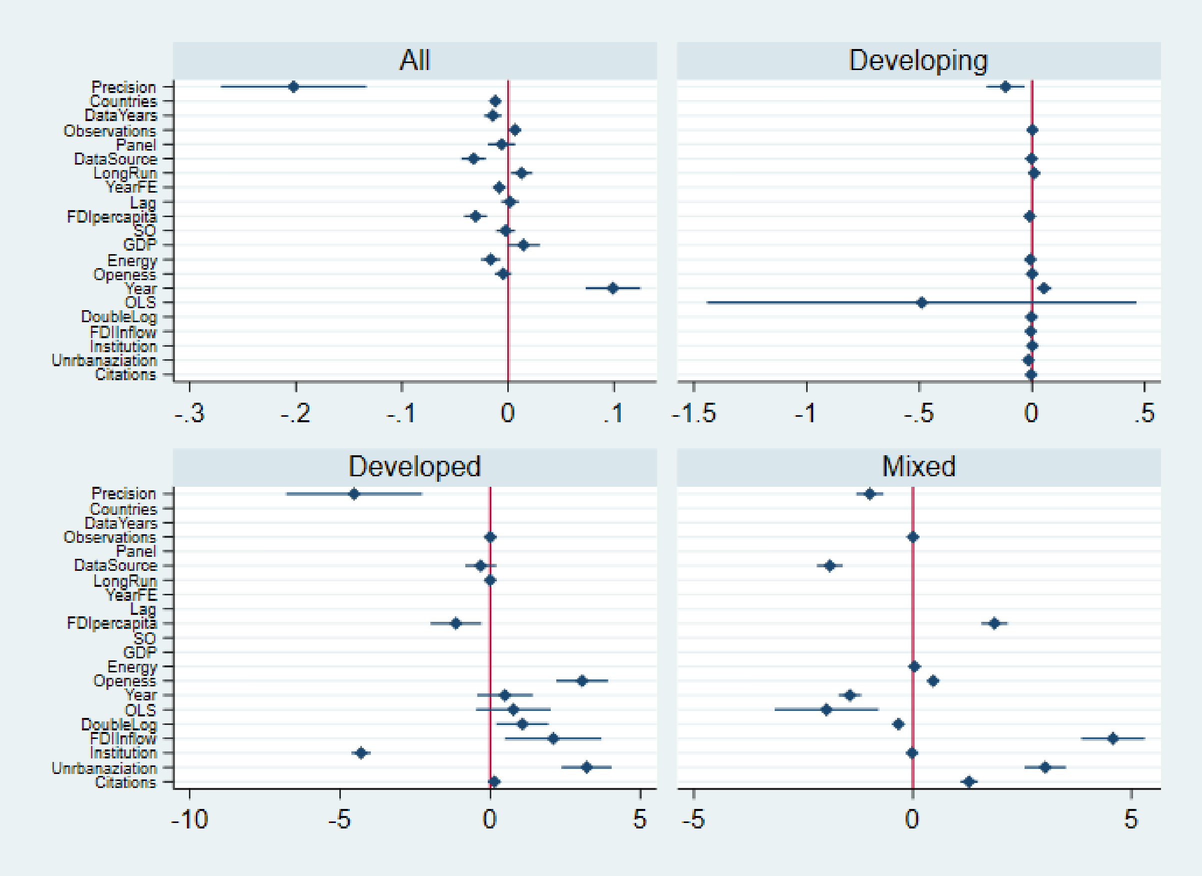
Data Source: Based on studies for the meta-analysis

Figure 1: The effect of FDI on environmental emission reported in 83 studies published in 2001-2018 (N=1296)



Notes: Instead of excluding extremely high precision values, we use the logarithm of the precision derived from the inverse of the standard error of the reported FDI-pollution estimates to allow better visualization of the graphic images illustrating the relationship between the underlying effects size and their measure of precisions.

Figure 2: Funnel plot of the effect of FDI on pollution (N=1006 from 65 Studies)



Notes: This figure shows the results for Table 5 (All) and Table 6 (developing, developed and mixed countries). We restricted the plot to only the MEM results.

Figure 3: Plot of the estimated coefficients and their confidence intervals for multivariate MRA

Table 1: Definition and descriptive statistics of collected variables

Moderator Variables	Definition	Mean	St. Dev.
Outcome Characteristics			
Efect size	FDI effect size	-0.031	1.169
Standard error	Standard error of effect size	0.345	0.889
Study Characteristics			
Number years of data	Logarithm of the number of years of the data used	2.856	0.589
Number of observation	Logarithm of number of observations	5.522	1.208
Number of countries	Logarithm of number of countries	2.523	1.637
Panel	=1 if data set type is panel	0.834	0.0372
Time series	=1 if data set type is time series	0.166	0.372
Data source	=1 if data come from international sources	0.519	0.545
Model Characteristics			
OLS	=1 if estimation method is OLS	0.169	0.375
Fixed effects	=1 if estimation method is fixed effects	0.292	0.455
Endogeneity	=1 if endogeneity is controlled for	0.626	0.484
Log-log	=1 if the coefficient is taken from a log-log form	0.867	0.339
Year FE	=1 if year fixed effects are included	0.562	0.496
Country FE	=1 if country fixed effects are included	0.524	0.499
Pollution Variable Choice			
Carbon dioxide	=1 if dependent is measured with carbon dioxide emission	0.591	0.492
Sulfur dioxide	=1 if dependent is measured with sulphur dioxide emission	0.204	0.403
Other pollutants	=1 if dependent is measured with other pollution measures	0.205	0.404
Macroeconomic controls			
GDP	=1 if GDP is included	0.938	0.241
Institution	=1 if institutional variable is included	0.396	0.489
Energy consumption	=1 if energy consumption is controlled for	0.445	0.497
Urban	=1 if urbanization variable is controlled for	0.378	0.485
Trade openness	=1 if trade openness is included	0.290	0.454
FDI Variable Choice			
FDI inflow	=1 if effect size is measured with the amount of FDI inflow	0.411	0.492
FDI stock	=1 if effect size measured with FDI stock	0.125	0.331
FDI per capita	=1 if effect size is measured with FDI inflow per capita level	0.260	0.439
FDI percentage	=1 if effect size is measured with FDI inflow per capita percentage	0.204	0.403
Effect Characteristics			
Long-run	=1 if estimated elasticity is long-run	0.122	0.28
Short-run	=1 if estimated elasticity is short-run	0.878	0.328
Lag	=1 if effect size represents lagged FDI	0.356	0.479
Interacted	=1 if effect size comes from an interacted term	0.238	0.426
Publication Characteristics			
Publication Year	Logarithm of the publication year of the study (base, 2001)	2.691	0.197
Published	=1 if published in a peer-reviewed journal	0.924	0.264
Study citations	Logarithm of citations in Google Scholar per age of the study, as of June 2018	1.779	0.747
Journal impact	Recursive journal impact factor from RePEc	0.052	0.052

Notes: Not all these variables are included in our multivariate analysis. We use G-S technique, hence variables that are not significant in our first-regressions are dropped in the second stage. In addition, some variables are also used as reference/base variables.

Table 2: Simple and weighted means of the effect sizes

	(1)	(2)	(3)	(4)
Method	Effect size	S.E	95% confidence interval	
Simple average effect[a]	-0.031	0.037	-0.103	0.041
Weighted average effect[b]	-0.004	0.005	-0.013	0.005

Notes: a represents the arithmetic mean of the FDI estimates, and b uses inverse variance as weight. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Bivariate MRA for FAT-PET: publication bias and genuine effect

	(1)	(2)	(3)
	OLS	Fixed	MEM
Genuine effect (PET/Precision)	-0.001	0.001	0.001
	(0.00)	(0.00)	(0.00)
Bias (FAT/Constant)	-0.333	-0.484**	-0.202
	(0.37)	(0.22)	(0.39)
N	1006	1006	1006
Studies	65	65	65

Notes: The dependent variables are the t-values of the associated reported elasticities. Robust standard errors are reported in the parenthesis and all estimates use the inverse variance as weights. Column 1 (OLS) is estimated via the study level clustered robust standard errors; Column 2 (Fixed) is fixed-effect estimation clustered at the study level; and Column 3 (MEM) is mixed-effects multilevel estimated through the restricted maximum likelihood. We apply the Hausman test that indicates that the MEM model is appropriate (a chi-squared with one degree of freedom is 0.03 with a p-value of 0.87). p<0.01***, ** p<0.05, * p<0.1

Table 4: Bivariate MRA for FAT-PET: publication bias and genuine effect for different group of countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Developing Countries			Developed Countries			Both Countries		
	OLS	FE	MEM	OLS	FE	MEM	OLS	FE	MEM
Genuine effect (PET/Precision)	-0.002	0.001	0.001	-0.002	-0.016	-0.016*	0.001	0.004	0.004***
	(0.002)	(0.002)	(0.001)	(0.02)	(0.02)	(0.005)	(0.003)	(0.002)	(0.001)
Bias (FAT/Constant)	0.393	0.035	0.349	-2.541	-1.454	-2.541*	-1.035*	-1.272***	-2.469**
	(0.35)	(0.26)	(0.41)	(3.83)	(1.58)	(2.15)	(0.57)	(0.19)	(0.99)
N	599	599	599	63	63	63	344	344	344
Studies	65	65	65	65	65	65	65	65	65

Notes: The dependent variables are the t-values of the associated reported elasticity estimated using Eq. (4). Robust standard errors are reported in the parenthesis and all estimates use the inverse variance as weights. Columns 1, 4 and 5 (OLS) are estimated via the study level clustered robust standard errors; Columns 2, 5 and 8 (Fixed) are fixed-effects estimation clustered at the study level; and Columns 3, 6 and 9 (MEM) are mixed-effects multilevel estimated through the restricted maximum likelihood. We apply the Hausman test that indicates that the MEM model is appropriate for all the three group of countries (for developing country is 0.09 with a p-value of 0.76; for developed country is 0.14 with a p-value of 0.71; and for mixed country is 0.06 with a p-value of 0.80). Mixed represents when regression specification includes both developing and developed countries. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Explaining Heterogeneity in the Estimates of the Pollution impact of FDI for All Countries

	(1)	(2)	(3)
VARIABLES	OLS	FE	MEM
Genuine effect (PET/Precision)	-0.144***	-0.267***	-0.204***
	(0.05)	(0.10)	(0.04)
Bias (FAT/Constant)	-0.452	-0.416***	-0.194
	(0.38)	(0.15)	(0.39)
Countries	-0.009***	-0.016***	-0.012***
	(0.00)	(0.00)	(0.00)
Data Years	-0.014**	-0.009	-0.014***
	(0.01)	(0.02)	(0.00)
Observations	0.006***	0.007**	0.006***
	(0.00)	(0.00)	(0.00)
Panel	-0.010	0.003	-0.006
	(0.01)	(0.02)	(0.01)
Data Source	-0.033***	-0.029	-0.033***
	(0.01)	(0.02)	(0.01)
Long Run	0.016*	0.018	0.013**
	(0.01)	(0.02)	(0.01)
Year FE	-0.009	-0.006	-0.008***
	(0.01)	(0.00)	(0.00)
Lag	0.008**	0.001	0.002
	(0.00)	(0.00)	(0.00)
FDI per capita	-0.018***	-0.047***	-0.031***
	(0.01)	(0.01)	(0.01)
Sulfur Dioxide	-0.010	-0.004	-0.002
	(0.01)	(0.01)	(0.00)
GDP	0.013	0.029	0.014*
	(0.01)	(0.03)	(0.01)
Energy	-0.010	-0.020**	-0.016***
	(0.01)	(0.01)	(0.00)
Openness	-0.005*	-0.003	-0.005
	(0.00)	(0.01)	(0.00)
Year	0.074***	0.114***	0.099***
	(0.02)	(0.03)	(0.01)
N	1006	1006	1006
R^2	0.112	0.097	

Notes: The dependent variables are the t-values of the associated reported elasticities of Eqn (5): Robust standard errors are reported in the parenthesis. Column 1 (OLS) is estimated via the study level clustered robust standard errors; Column 2 (Fixed) is fixed-effect estimation clustered at the study level; and Column 3 (MEM) is mixed-effects multilevel estimated through the restricted maximum likelihood. In the data category, time series and short-run are used as reference variables for panel and long-run respectively. For the estimation characteristics, all other estimation methods(GMM, random effect, WLS) were used as a reference category and in the pollution variable; all other pollutants (nitrogen dioxide, volatile organic compounds and others) measures are used as reference variables. For the FDI variable, FDI stock is used as reference variable. Insignificant moderator variables excluded from the reduced model as a result of G-S technique are OLS, fixed effect, endogeneity, log-log, country FE, interaction, FDI Inflow, FDI percentage, CO_2, institution, urbanization, reviewed, citations, impact factor. All the covariates have been divided by the standard errors in the MRA. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Explaining Heterogeneity in the Estimates of the Pollution impact of FDI for Different Group of Countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Developing Countries			Developed Countries			Both Countries		
	OLS	FE	MEM	OLS	FE	MEM	OLS	FE	MEM
Genuine effect (PET/Precision)	-0.124*	-0.122*	-0.117***	-4.532***	-16.532***	-4.532***	-0.865***	-1.106***	-0.981***
	(0.07)	(0.07)	(0.04)	(0.25)	(1.49)	(1.15)	(0.03)	(0.10)	(0.16)
Bias (FAT/Constant)	0.413	-0.544	0.035	0.437**	-2.721***	0.437	-0.423***	8.573***	0.123
	(0.35)	(0.60)	(0.45)	(0.18)	(0.16)	(0.33)	(0.13)	(1.50)	(0.41)
Observations	0.003	0.001	0.001	-0.000	0.004	-0.000	0.005***	0.005***	0.005**
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Data Source	-0.013**	0.011	-0.002		-2.763***	-0.322	-1.624***	2.679**	-1.893***
	(0.01)	(0.02)	(0.01)		(0.33)	(0.26)	(0.05)	(0.86)	(0.15)
Long Run	0.009	0.021	0.010	-0.004***	-0.004***	-0.004			
	(0.01)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)			
OLS	-0.769	-0.126	-0.489	0.768	6.812***	0.768	-1.612***	0.698***	-1.972***
	(0.72)	(0.77)	(0.49)	(0.48)	(0.00)	(0.63)	(0.32)	(0.17)	(0.61)
Double Log	-0.002	0.017	-0.003	0.745***	-0.220*	1.066**	-0.272***	-0.034	-0.329***
	(0.01)	(0.02)	(0.01)	(0.18)	(0.12)	(0.44)	(0.02)	(0.50)	(0.04)
FDI Inflow	0.002	-0.018	-0.006	2.098***	2.444***	2.098**	3.897***		4.576***
	(0.01)	(0.02)	(0.01)	(0.46)	(0.26)	(0.82)	(0.10)		(0.37)
FDI per capita	-0.004	-0.033	-0.011	-0.822***	-0.743***	-1.143***	1.589***	1.747**	1.869***
	(0.01)	(0.02)	(0.01)	(0.15)	(0.19)	(0.43)	(0.04)	(0.73)	(0.15)
Institution		0.001	0.001	-4.300***	-3.782***	-4.300***	-0.016***	-0.016***	-0.015**
		(0.00)	(0.00)	(0.05)	(0.10)	(0.16)	(0.00)	(0.00)	(0.01)
Energy	0.000	-0.027**	-0.008	0.322***			0.030*	0.068***	0.039**
	(0.01)	(0.01)	(0.00)	(0.10)			(0.02)	(0.01)	(0.02)
Urbanization	-0.015**	-0.026**	-0.016***	3.210***	2.009***	3.210***	2.578***	3.412***	3.028***
	(0.01)	(0.01)	(0.01)	(0.25)	(0.14)	(0.43)	(0.05)	(0.46)	(0.24)
Openness	0.001	0.006	0.000	3.059***	2.312***	3.059***	0.392***	0.182	0.466***
	(0.01)	(0.01)	(0.01)	(0.26)	(0.17)	(0.44)	(0.02)	(0.51)	(0.05)
Year	0.049*	0.060*	0.053***	0.488**	5.496***	0.488	-1.215***	-1.618***	-1.438***
	(0.03)	(0.03)	(0.02)	(0.16)	(0.62)	(0.47)	(0.02)	(0.24)	(0.13)
Citations	-0.004	-0.007	-0.004	0.134***	0.742***	0.134	1.096***	1.451***	1.285***
	(0.00)	(0.01)	(0.00)	(0.04)	(0.12)	(0.10)	(0.02)	(0.19)	(0.10)
N	599	599	599	63	63	63	344	344	344
R^2	0.108	0.103		0.973	0.884		0.513	0.355	

Notes: The dependent variables are t-values of the associated reported elasticities of Eq. (4). Robust standard errors are reported in the parenthesis. Columns 1, 4 and 7 (OLS) are estimated via the study level clustered robust standard errors; Columns 2, 5 and 8 (Fixed) are fixed-effects estimation clustered at the study level ; and Columns 3, 6 and 9 (MEM) are mixed-effects multilevel estimated through the restricted maximum likelihood. In the FE and MEM estimations, we lose the coefficients for some variables as results of multicollinearity and insufficient observations, hence those coefficients are blanks. Insignificant moderator variables excluded from the reduced model as a result of G-S modeling are countries, data years, panel data, data source, long-run, fixed effect, endogeneity, year FE, country FE, interaction, lag, FDI percentage, Co_2, SO_2, GDP, reviewed, and impact factor. All the covariates have been divided by the standard errors in the MRA. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Robustness Results for the Multivariate Analysis: Excluding a Major Study, and Different Pollutants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Excluding Zugravu-Soilita (2017)			Carbon Dioxide			Sulfur Oxide		
	OLS	FE	MEM	OLS	FE	MEM	OLS	FE	MEM
Genuine effect (PET/Precision)	-0.152***	-0.266***	-0.197***	-0.144**	-0.355**	-0.209***	-12.526***	-11.199***	-18.786**
	(0.05)	(0.10)	(0.04)	(0.07)	(0.15)	(0.05)	(3.07)	(0.89)	(7.30)
Bias (FAT/Constant)	-0.428	-0.535*	-0.314	-0.426	-0.388	-0.304	-0.974**	-1.275***	-1.209
	(0.58)	(0.32)	(0.39)	(0.66)	(0.29)	(0.44)	(0.39)	(0.28)	(0.74)
Countries	-0.008**	-0.014**	-0.010***	-0.011***	-0.012	-0.011***	0.008	0.000	0.000
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Data Years	-0.016***	-0.015	-0.019***	-0.019***	-0.011	-0.016***	0.108	-0.340	-0.267***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.12)	(0.24)	(0.09)
Observations	0.006**	0.005	0.005***	0.005	0.002	0.003		0.004	0.004
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)		(0.00)	(0.00)
Panel	-0.013	-0.003	-0.011	0.002	0.009	0.008	11.399***	11.250***	18.667**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(3.20)	(0.33)	(7.36)
Data Source	-0.031***	-0.024	-0.029***	-0.038***	-0.033	-0.033***	-0.200**	-0.485	-0.370***
	(0.01)	(0.03)	(0.01)	(0.01)	(0.03)	(0.01)	(0.08)	(0.30)	(0.08)
Long Run	0.016	0.017	0.012**	0.019*	0.019	0.015***			
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)			
Year FE	-0.008	-0.005	-0.008**	-0.015*	-0.027**	-0.018***	-0.001	-0.001	-0.001
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Lag	0.009**	0.002	0.003	0.007**	0.008	0.007	-0.113**	-0.189**	-0.168***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.05)	(0.08)	(0.04)
FDI per capita	-0.020**	-0.049***	-0.030***	-0.017**	-0.046**	-0.025***	0.244***	-0.027	-0.018
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.05)	(0.04)	(0.09)
Sulfur Dioxide	-0.014	-0.012	-0.006						
	(0.01)	(0.02)	(0.01)						
GDP	0.013	0.029	0.014	0.016	0.040	0.024**	-0.092	-0.239**	-0.280***
	(0.01)	(0.03)	(0.01)	(0.02)	(0.03)	(0.01)	(0.06)	(0.08)	(0.08)
Energy	-0.012	-0.025***	-0.019***	-0.013	-0.014	-0.012*	-0.022	0.001	-0.034
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.04)
Openness	-0.005	-0.005	-0.006	-0.013**	0.006	-0.006	-0.274***		0.023
	(0.00)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)	(0.08)		(0.10)
Year	0.081***	0.125***	0.106***	0.083***	0.152***	0.102***	0.451***	0.545***	0.518***
	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)	(0.02)	(0.10)	(0.13)	(0.10)
N	756	756	756	595	595	595	205	205	205
R^2	0.123	0.112		0.144	0.114		0.427	0.388	

Notes: The dependent variables are the t-values of the associated reported elasticities of Eq. (4). Robust standard errors are reported in the parenthesis and all estimates use the inverse variance as weights. Columns 1, 4 and 7 (OLS) are estimated via the study level clustered robust standard errors; Columns 2, 5 and 8 (Fixed) are fixed-effects estimation clustered at the study level; and Columns 3, 6 and 9 (MEM) are mixed-effects multilevel estimated through the restricted maximum likelihood. Columns 1-3 are estimated excluding reported estimates from Zugravu-Soilita (2017). Columns 4-6 and 7-9 are reported estimates restricted to primary studies which use FDI effects on carbon dioxide emissions and sulpher oxide emissions, respectively for the choice of pollution variable. All the covariates have been divided by the standard errors in the MRA. Some of coefficients are missing because of multicollinearity or lack of variation under the sub-unit analysis. All the covariates have been divided by the standard errors in the MRA. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Robustness Check for the Multivariate Analysis: FDI Inflow and FDI Stock

	(1)	(2)	(3)	(4)	(5)	(6)
	FDI Inflows			FDI Stocks		
	OLS	FE	MEM	OLS	FE	MEM
Genuine effect (PET/Precision)	-0.099**	-0.124	-0.116***	-18.499***	-14.794***	-11.031
	(0.04)	(0.09)	(0.03)	(5.13)	(3.53)	(22.81)
Bias (FAT/Constant)	-0.327	-0.428**	-0.376	-1.776*	-25.759**	-0.379
	(0.24)	(0.21)	(0.39)	(0.90)	(10.92)	(1.94)
Countries	-0.006**	-0.006	-0.007***	-0.284	-0.195	-0.257**
	(0.00)	(0.00)	(0.00)	(0.26)	(0.13)	(0.10)
Data Years	-0.019***	-0.015	-0.017***	1.095	-0.785	1.096***
	(0.01)	(0.02)	(0.00)	(0.72)	(0.92)	(0.25)
Observations	0.004**	0.005	0.005***	-0.016	0.038*	0.036
	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.04)
Panel	-0.014	-0.013	-0.008	17.880***	26.477***	10.665
	(0.01)	(0.02)	(0.01)	(5.06)	(7.34)	(22.87)
Data Source	-0.033***	-0.023	-0.030***	0.091	1.239	0.091
	(0.01)	(0.03)	(0.01)	(0.80)	(1.14)	(0.44)
Long Run	0.019	0.012	0.015***			
	(0.01)	(0.01)	(0.00)			
YearFE	-0.016	-0.014	-0.015***	0.055	-0.003	0.007
	(0.01)	(0.01)	(0.00)	(0.05)	(0.03)	(0.04)
Lag	0.007**	0.001	0.004	0.382	2.734*	0.560*
	(0.00)	(0.01)	(0.00)	(0.35)	(1.28)	(0.31)
Sulfur Dioxide	0.004	0.014	0.013***	0.024	1.005	0.015
	(0.00)	(0.01)	(0.00)	(0.16)	(0.58)	(0.28)
GDP	0.010	0.003	0.011	-0.203	5.718*	-0.063
	(0.01)	(0.02)	(0.01)	(0.45)	(2.59)	(0.30)
Energy	-0.013	-0.016	-0.016***	-0.045	4.395**	0.148
	(0.01)	(0.01)	(0.00)	(0.39)	(1.84)	(0.17)
Openness	-0.009***	-0.011	-0.015***	0.135	0.005	0.013
	(0.00)	(0.01)	(0.00)	(0.19)	(0.03)	(0.09)
Year	0.065**	0.070*	0.068***	-0.733	-6.629**	-1.065***
	(0.03)	(0.04)	(0.01)	(0.51)	(2.68)	(0.29)
N	880	880	880	126	126	126
R^2	0.141	0.085		0.348	0.543	

Notes: The dependent variables are the t-values of the associated reported elasticities of Eq. (4). Robust standard errors are reported in the parenthesis. Columns 1 and 4 (OLS) are estimated via the study level clustered robust standard errors; Columns 2 and 5 (Fixed) are fixed-effects estimation clustered at the study level; and Columns 3 and 6 (MEM) are mixed-effects multilevel estimated through the restricted maximum likelihood. Columns 1-3 and 4-6 reported estimates are restricted to primary studies which use the measure of FDI inflows and FDI stocks, respectively, for the choice of FDI variable. In the FDI stocks, the coefficient for the long-run is not reported as reported studies that used FDI stocks are all short-run elasticities. All the covariates have been divided by the standard errors in the MRA. *** $p<0.01$, ** $p<0.05$, * <0.1.

Table 9: Robustness Check for the Multivariate Analysis: FDI per capita and FDI percentage

	(1)	(2)	(3)	(4)	(5)	(6)
	FDI at Level			FDI Ratio/Percentage		
	OLS	FE	MEM	OLS	FE	MEM
Genuine effect (PET/Precision)	-0.458***	-1.073***	-0.473***	-0.123**	-0.162	-0.146***
	(0.15)	(0.11)	(0.12)	(0.06)	0.12	(0.04)
Bias (FAT/Constant)	-0.088	-0.015	0.322	-0.395	-0.816	-0.812*
	(0.38)	(0.08)	(0.68)	(0.34)	(0.52)	(0.43)
Countries	0.013	0.011	0.004	-0.003	-0.001	-0.003
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
Data Years	0.003	0.172***	-0.004	-0.022**	-0.028*	-0.027***
	(0.03)	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)
Observations	-0.010	0.012**	-0.002	0.003	0.002	0.002
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Panel	-0.035	-0.053**	-0.034	-0.009	-0.004	-0.003
	(0.03)	(0.02)	(0.03)	(0.02)	(0.01)	(0.01)
Data Source	-0.101***	0.108***	-0.093***	-0.026**	-0.011	-0.020***
	(0.03)	(0.02)	(0.02)	(0.01)	(0.03)	(0.01)
Long Run	0.006***	0.001***	0.002	0.026	0.026	0.025***
	(0.00)	(0.00)	(0.01)	(0.03)	(0.03)	(0.01)
Year FE	-0.025***	-0.021***	-0.026**	-0.012	-0.011	-0.011**
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
Lag	-0.010	-0.010	0.004	0.005	-0.005	0.002
	(0.02)	(0.01)	(0.02)	(0.00)	(0.01)	(0.00)
Sulfur Dioxide	-0.001	-0.001	-0.001	0.004	0.016	0.011*
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
Energy	-0.064***	-0.088***	-0.048**	-0.013	-0.024*	-0.019***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Openness	0.016	0.081**	0.027	-0.009***	-0.016	-0.016***
	(0.06)	(0.03)	(0.04)	(0.00)	(0.01)	(0.00)
Year	0.209***	0.189***	0.210***	0.067**	0.101*	0.084***
	(0.05)	(0.04)	(0.06)	(0.03)	(0.06)	(0.02)
N	413	413	413	467	467	467
R^2	0.240	0.094		0.241	0.190	

Notes: The dependent variables are the t-values of the associated reported elasticities. Robust standard errors are reported in the parenthesis. Columns 1 and 4 (OLS) are estimated via the study level clustered robust standard errors; Columns 2 and 5 (Fixed) are fixed-effects estimation clustered at the study level; and Columns 3 and 6 (MEM) are mixed-effects multilevel estimated through the restricted maximum likelihood. All the covariates have been divided by the standard errors in the MRA. *** p<0.01, ** p<0.05, * p<0.1.

Table 1A: Appendix A, List of Studies

Count	Study (year)	Pub type	Country	Data start	Data end	No of est.	Mean E.S	Std. Dev.	Min	Max
1	Acharyya (2009)	PR	India	1980	2003	1	0.864	0	0.864	0.864
2	Aliyu and Ismail (2015)	PR	Africa	1990	2010	21	0.261	1.386	-1.862	5.631
3	Aller et al. (2015)	PR	Mixed	1996	2010	40	-1.059	3.068	-4.4	5.073
4	Al-Mulali and Tang (2013)	PR	Gulf Cooperation Council	1980	2009	7	-1.489	1.323	-3.108	0.244
5	Al-mulali (2012)	PR	Middle Eastern	1990	2009	8	3.691	1.307	1.029	4.85
6	Atici (2012)	PR	Association of Southeast Asian	1970	2006	8	-0.04	0.04	-0.09	0.01
7	Avazalipour et al. (2013)	PR	Non-OECD	1996	2007	1	0.01	0	0.01	0.01
8	Ayeche et al. (2016)	PR	Europe	1985	2014	1	-0.021	0	-0.021	-0.021
9	Baek and Koo (2009)	PR	China and India	1980	2007	8	0.026	0.087	-0.13	0.19
10	Baek (2016)	PR	Association of Southeast Asian	1981	2010	6	0.043	0.019	0.027	0.07
11	Bakhsh et al. (2017)	PR	Pakistan	1980	2014	3	0.12	0.297	-0.09	0.046
12	Bao et al. (2011)	PR	China	1992	2004	5	-0.258	0.111	-0.381	-0.127
13	Behera and Dash (2017)	PR	South and Southeast Asian	1980	2012	31	0.058	0.225	-0.496	0.789
14	Bernard and Mandal (2016)	PR	Mixed	2002	2012	5	0.002	0.002	0	0.005
15	Blanco et al. (2013)	PR	Latin America	1980	2007	1	0.01	0	0.001	0.001
16	Cheng et al. (2017)	PR	America	1997	2014	8	0.008	0.004	0.003	0.016
17	Cole et al. (2011)	PR	China	2001	2004	12	0.06	0.089	-0.017	0.245
18	de Sousa et al. (2015)	WP	China	2003	2012	27	-0.004	0.019	-0.069	0.028
19	Doytch and Uctum (2016)	WP	Mixed	1984	2011	28	0.004	0.014	-0.017	0.034
20	Gökmenoğlu and Taspinar (2016)	PR	Turkey	1974	2010	5	0.002	0.012	-0.017	0.012
21	Gu and Li (2014)	WP	China	1990	2010	3	-0.042	0.068	-0.119	0.007
22	Hakimi and Hamdi (2016)	PR	Tunisia and Morocco	1971	2013	9	0.032	0.071	-0.042	0.195
23	Hao and Liu (2015)	PR	China	1995	2011	3	0.116	0.137	0.025	0.274
24	He (2006)	PR	China	1994	2011	1	-0.18	0	-0.18	-0.18
25	Hille et al. (2018)	WP	Korea	2000	2011	6	-0.033	0.042	-0.113	0.012
26	Huang et al. (2017)	PR	China	2001	2012	10	-1.334	1.885	-4.322	-0.088
27	Jalil and Feridun (2011)	PR	China	1978	2006	4	-0.098	0.051	-0.157	-0.033
28	Jamel and Maktouf (2017)	PR	Europe	1985	2014	2	-0.019	0.003	-0.021	-0.017
29	Jiang (2015)	PR	China	1997	2012	16	0.222	0.185	0.015	0.433
30	Jorgenson (2007)	PR	Mixed	1975	2000	10	0.095	0.009	0.076	0.108
31	Jorgenson (2009)	PR	Mixed	1980	2000	10	0.038	0.049	-0.047	0.107
32	Kaya et al. (2017)	PR	Turkey	1975	2010	1	-0.012	0	-0.012	-0.012
33	Kim and Adilov (2012)	PR	Mixed	1961	2004	16	-0.4	1.643	-4.021	2.373

Notes: Under publication type, PR denotes peer-reviewed publication while WP denotes working paper. Under country, mixed indicates a mix of countries was used for the study

Table 1A(continuation): List of Studies

Count	Study (year)	Pub type	Country	Data start	Data end	No of est.	Mean E.S	Std. Dev.	Min	Max
34	Kim and Baek (2011)	PR	Mixed	1971	2005	43	0.021	0.074	-0.178	0.306
35	Kirkulak et al. (2011)	PR	China	2001	2007	16	-0.184	0.221	-0.98	0.015
36	Kivyiro and Arminen (2014)	PR	SSA	1971	2009	6	0.087	0.15	-0.03	0.354
37	Kozul-Wright and Fortunato (2012)	PR	Mixed	1990	2004	2	-0.047	0.045	-0.079	-0.015
38	Lan et al. (2012)	PR	China	1996	2006	29	0	2.623	-4.351	4.415
39	Lim et al. (2015)	PR	Mixed	1980	2005	35	-0.009	0.021	-0.048	0.062
40	Lin (2017)	PR	China	2004	2011	3	0.005	0.006	-0.002	0.009
41	Linh et al. (2014)	PR	Vietnam	1980	2010	1	-0.008	0	-0.008	-0.008
42	Long et al. (2018)	PR	China	1997	2014	5	-0.113	0.768	-1.428	0.589
43	Merican (2007)	PR	Asia	1997	2002	5	0.712	1.595	-1.569	2.312
44	Neequaye and Oladi (2015)	PR	Developing	2002	2008	15	1.023	1.532	-0.175	3.938
45	Pazienza (2015)	PR	OECD	1981	2005	3	-0.101	0.027	-0.132	-0.085
46	Rafindadi et al. (2018)	PR	Gulf Cooperation Council	1990	2014	19	-0.268	2.728	-5.8	3.66
47	Salahuddin et al. (2017)	PR	Kuwait	1980	2003	2	0.011	0.014	0.001	0.021
48	Sapkota and Bastola (2017)	PR	Latin America	1980	2010	4	0.043	0.019	0.027	0.07
49	Seker et al. (2015)	PR	Turkey	1974	2010	2	0.027	0.013	0.018	0.036
50	Shaari et al. (2014)	PR	Asia	1992	2015	1	0.061	0	0.061	0.061
51	Shahbaz et al. (2013)	PR	Malaysia	1971	2011	1	0.039	0	0.039	0.039
52	Shao (2018)	PR	Mixed	1990	2013	1	-0.032	0	-0.032	-0.032
53	Solarin et al. (2017)	PR	Ghana	1980	2012	32	0.002	0.018	-0.017	0.06
54	Sun et al. (2017)	PR	China	1980	2012	32	0	0.117	-0.483	0.096
55	Tamazian and Rao (2010)	PR	Mixed	1993	2004	24	-0.006	0.001	-0.008	-0.004
56	Tamazian et al. (2009)	PR	BRIC	1992	2004	6	-0.004	0.026	-0.095	-0.023
57	Tang and Tan (2015)	PR	Vietnam	1976	2009	2	-0.033	0.045	-0.065	-0.001
58	Wang and Chen (2014)	PR	China	2002	2009	19	-0.009	0.034	-0.088	0.021
59	Wang et al. (2013)	PR	China	1995	2005	7	-0.219	0.126	-0.42	-0.074
60	Wu et al. (2016)	PR	China	2002	2011	10	0.003	0.003	-0.001	0.006
61	Yang and Wang (2016)	WP	China	2005	2014	12	-0.128	0.37	-0.83	0.24
62	Zhang and Zhou (2016)	PR	China	1995	2010	20	-0.055	0.051	-0.134	0.013
63	Zheng et al. (2010)	PR	China	1997	2006	4	-0.392	0.219	-0.647	-0.113
64	Zhu et al. (2016)	PR	Asia	1981	2011	78	-0.005	0.007	-0.024	0.004
65	Zugravu-Soilita (2017)	PR	BRICS	1996	2002	250	-0.027	1.06	-4.591	5.697

Notes: Under publication type, PR denotes peered-reviewed publication while WP denotes working paper. Under country, mixed indicates a mix of countries was used for the study

Appendix B:

Study characteristics: We construct dummies for specific characteristics of the studies such as the type of data (panel versus time series), the length (time span) of the data, and the number of countries included in the data. Panel data analyses are more common (83%) and time series are less frequent, whereas the application of cross-sectional data are non-existent in the literature, indicating the empirical studies are less likely to suffer from biases due to time-invariant heterogeneity Gujarati (2009). In order to check for any systematic variation between small and large samples, we consider the number of observations of the data. The mean of number of observations is 479 and the average number of countries included in the regression of the primary studies is 34. Finally, we include a dummy variable for the source of the data, whether the data comes from international sources, national statistics, or other local agencies. Approximately 52% of the data used by the studies were obtained from international sources.

Model characteristics: Different primary studies employ different empirical models in terms of estimation techniques, controls (macroeconomic/institutional variables), pollutants and measures of FDI. Thus, we use a vector of indicator variables to control for this heterogeneity in the primary studies and empirical models. We include dummy variables to capture the different estimation techniques. We control for different econometric estimation techniques such as OLS, fixed-effects, random-effects, or GMM. Controlling for individual heterogeneity using time and fixed effects has an important effect, thus we also control for whether the studies include year or country fixed effects, or both.

Different empirical models use different pollutants as the main outcome or dependent variable. The majority (60%) of the studies used CO_2 as the main pollution indicator, whereas SO_2 is the second most used pollution indicator (about 20%). Other pollutants are sometimes used, such as nitrogen dioxide and other volatile organic compounds. The use of CO_2 as the main pollutant could be due to the availability of internationally publicly available data on CO_2 compared to other pollutants that are local pollutants. In line with this, we use dummy variables to capture the differences in pollutants. However, in our robustness checks, we also restrict our analysis to the two main pollutant (CO_2, SO_2).

The studies also estimate models that controlled for several macroeconomic conditions, such as GDP, institutional quality, energy consumption, urbanization, and trade openness. GDP is mostly included as a control variable to capture the Environmental Kuznets Curve (EKC) hypothesis that postulates environmental pollution as a function of income or economic growth. Almost 95% of the studies included income as one of main determinants of emissions. As a means to circumvent omitted variable bias, a large body of literature includes energy consumption as a control variable (e.g., Ang (2007); Soytas et al. (2007)). About 45% of the studies use this as an additional control variable. The trade effect on emissions was also examined by including trade openness, but only one-third of the primary studies control for trade openness. Following the seminal work of Glaeser and Kahn (2010), a large body of empirical studies focus on urbanization as one of the key factors driving air pollution. Thus, about 38% of the empirical studies control for urbanization as a possible determinant of pollution. Approximately, 40% of the studies control for the quality of domestic institutions. Frankel and Rose (2005) argue that institutions play a relevant role in formulating strong environmental policies.

The empirical studies use several proxies in measuring the variable of interest (FDI). FDI can be measured as a stock or flow variable. Flow is the amount of FDI in a country at a period of time such as annually or monthly, while stock measures the accumulated value of FDI at a given point of time. Overall, about 87% of the empirical studies measure FDI as a flow variable. However, those studies that measure FDI as a flow also use a variant of the flow measurement. More than two in five studies, use total FDI inflow in amount. Approximately, one-quarter of the empirical studies measure FDI in terms of per capita (in level), one-fifth use the measure FDI at per capita in terms of percentage (per capita is in terms of GDP). Only 13% of the primary studies measure FDI as a stock. In order to account for these differences in the FDI measurement, we introduce a dummy variable to capture these different dimensions.

Effect characteristics: We also code variables at the effect level. These include if the effect sizes derived are short-run or long-run elasticities. Short-run elasticities are more common for the effect of FDI on emissions, but this ignores the possibility of persistence dependence in the relationship between FDI and emissions. Primary studies estimate models that control for endogeneity of the regressors using lagged values of the variables, IVs, or some other estimators. Different models estimate different functional forms (log-log or log-linear) of the models. 87% of the estimated coefficients are elasticities directly collected from the log-log regressions while the remaining are log-linear.

Publication characteristics: We measure publication characteristics using conventional variables such as time of publication, whether the article is published in a journal or not, the number of citations in Google Scholar, and the impact factor of the specific journal the article was published from the RePEc database. We use Google Scholar for providing citation counts as it is the richest source. RePEc database also covers almost all journals and working papers for their rankings (Havranek et al., 2016). A break-down of the studies included in our meta-analysis indicates that the oldest study was published in 2001, and the most recent is in 2018, whereas the median study appeared in 2011. Most importantly, the majority of the reported observations (about 85%) were published in the last three years. This may suggest that the FDI-environment linkage debate remains current and relevant. The studies are mostly peer-reviewed journals (92% of the elasticities came from peer-reviewed studies). A larger number of the studies are published in Renewable and Sustainable Energy Reviews (six studies), followed by Energy (five studies). We also control for the quality of the primary studies by including the number of citations in Google Scholar as well as the journal quality by using the recursive impact factor from RePEc. Finally, we control for the publication year of the study in order to ascertain whether the literature points towards a publication trend.