THESIS / THÈSE

SPECIALISED MASTER IN INTERNATIONAL AND DEVELOPMENT ECONOMICS

Trade Openness and Within-Country Income Distribution
A Meta-Regression Analysis

Shifaw, Sirage

Award date:
2019

Awarding institution:
University of Namur

Trade Openness and Within – Country Income Distribution: A Meta-Regression Analysis

Thesis presented by

Sirage Shifaw

Supervisor

Arastou Khatibi (UCL)

Tutor

Marie Seleck (UNamur)

Academic year 2018-19

Project presented as part of the requirements for the award of the Specialized Master in International and Development Economics

Département des Sciences économiques/UNamur • Rempart de la Vierge 8 • 5000 Namur
Ecole d'économie de Louvain/UCL • Place Montesquieu 3 • 1348 Louvain-la-Neuve

Abstract

The within-country income inequality effect from increasing trade openness has long been studied but remains disputed. This paper's meta-regression analysis of 124 estimated within-country income inequality coefficients from twenty-five developing countries studies finds no overall economically meaningful significant inequality effect after controlling for publication bias. The result remains robust when controlling for 15 other characteristics of the estimates and using mixed-effects multilevel meta-regression to account for within-study variations. One possible explanation is that the effects of trade openness on inequality have been offset by other variables.

Keywords: Trade openness, income inequality, meta-regression analysis, publication bias

Table of Contents

Contents

List of Tables and Figures

List of Tables

List of Figures

1. Introduction

Over the past four decades, the world economy experienced two noticeable phenomena: rapidly increasing economic integration and a dramatic rise in within country income inequality. Trade integration and income inequality depicted parallel growth patterns both in developed and developing countries alike (Pol Antr`as et al, 2017). For instance, while the global top one percent income share increased from 16.2 percent in 1980 to 20.6 percent in 2015, the bottom 50% income share only increased from 7.9 percent to 9.7 percent (Alvaredo et al, 2018).

In a chronological coincidence with the rise in within country income inequality in the global economy since the 1980s, this same economy is experiencing an unprecedented increase in world trade integration. For instance, the world trade openness index grew dramatically from a level of 38.7 in 1980 all the way to 56 in 2015 (World Bank, 2018). On the other hand, the share of developing economies in world merchandise export raise from 28 percent in 1980 to 43 percent in 2015 (WTO, 2018). These figures signals how fast the world economy is integrating.

What one can deduce from the last four decades' experience of the world economy is that trade integration and inequality grew very much together since 1980s. Whether such a process of trade integration is associated with widening income inequality within countries is a matter of controversy in the economic literature. This issue has also been prominent in policy debate and political arena. The view that establishes a causal link between the trade dimension of globalization and income disparity is considered as an important driver of growing support for populism (Florian Dorn et al, 2018). Such perception has fuelled the current backlash against international trade in the United States and parts of Europe (Pavcnik, 2017). After all, inequality is one of today's widely discussed issue and seems to remain controversial (Piketty, 2014).

This paralleled growth of inequality and liberalization, in one hand, and its contentious effect on the other, motivated researchers to empirically examine causality between trade openness and inequality. The unprecedented trade liberalization implemented by developing countries and by their trader partners since the 1980s served this purpose as a natural experiment. Guided by the workhorse of neoclassical trade model, the Heckscher-Ohlin-Samuelson model, over the past three decades', economists' accumulated evidence in a large set of developed and developing countries in explaining the actual forces at work. The causality

between trade liberalization and inequality has been examined during the 1990s (H. Beyer, 1999 and Robbins, 1996), in the 2000s (Axel Dreher, 2008; Goldberg and Pavcnik, 2007a; and Daniel Chiquiar, 2004) and in 2010s (Pol Antr`as et al, 2017; Florian Dorn et al, 2018; Shujiro Urata et al 2017; and Kang Kook, 2014) to mention but a few.

Despite the substantial accumulation of evidence on the link between trade and inequality, the impact of trade openness on within-country income inequalities are inconclusive and mixed (Shujiro Urata, 2017; Goldberg and Pavcnik, 2007; and Pavcnik 2017). Thus, there are fundamental questions left addressing: Are the empirical evidences consistent with trade theories and, if not, why? Is the empirical difference induced by selection bias? Or is there a genuine empirical effect beyond publication selection? It is these and other related questions that this paper intends to address.

For the purposes of government policy concerning optimal taxation, social welfare and trade liberalization, conclusive and precise estimates of the income inequality effect of trade openness are of principal importance. Unfortunately, neither empirical investigations nor conventional narrative literature reviews conducted before serves this purpose because they ended up with inconclusive results. An alternative way-out and a systematic method how to make use of these empirical literatures of mixed results is to collect those diversified estimates and summarize them quantitatively. The method is called meta-analysis and has long been used in economics after a pioneering work of Stanley and Jarrel (1989). To the study's knowledge, there is no study that used a meta-analysis method to review the literature on this topic before. Thus, this paper contributes to the discussion by presenting in-depth meta-analysis of the empirical literature on the relationship between income inequality and trade openness.

To give a sneak preview of findings that this study produced, all methods employed detected no evidence of publication bias. On the other hand, when 126 estimates from twenty five studies are combined and statistically analyzed, an inequality effect of -0.031[1] is found as a genuine effect size for developing countries trade-income inequality literature. But, this effect size is not economically meaningful and practically significant. Nevertheless, specification heterogeneity is found to be the main source of estimate variations across the primary studies.

[1] Computed as $(\gamma_1 + \sum \delta_k Z_{ki})$*Se. See section 4.3 for more explanation.

The remainder of the paper is structured as follows. Section 2 explains the procedures followed in selecting primary studies for examination and the properties of the data set. Section 3 discusses the meta-analysis method employed in an effort to answer the research questions raised. Section 4 discusses the results and section 5 concludes. Two points have to be noted at the outset. First, the paper focuses purely on the effects of increased trade openness on income inequality within countries, and ignores any effects on inequality between countries. Second, it focuses purely on the effects of increased trade openness on aggregate income inequality within countries, and not wage inequality between skilled and unskilled workers.

2. The inequality estimates data set

Studies on effects of trade liberalization on income inequality usually examine the correlation between trade openness and its linkages with inequality[2]. Many researchers use data from panel of countries and estimate a variant of the following model:

$$\boldsymbol{Gini_{jt} = \beta_0 + \beta_1 Openness_{jt} + \beta * Controls_{jt} + \mu_{jt}} \qquad (\mathbf{1})$$

Where j and t represent country and time subscripts; and control denote a vector of either theoretically intuitive or country specific control variables. The variable Gini is a measure of income inequality in country j at time t and its value ranges from 0 to 100. A Gini value of zero represents perfect equality while value of 100 represents perfect inequality. A vast majority of studies on within-country determinants of income inequality use Gini coefficient in measuring inequality because of data availability and ease of cross-country comparison. For example, Barro R, 1999; Milanovic, 2005; and Dollar and Kraay, 2002 employed different variant of equation (1) in analysing determinants of income inequality. The variable Openness is a proxy variable used to measure trade liberalization of country j at time t and it is a sum of exports and imports as a percentage of GDP. This paper uses all appropriate studies that have employed equation (1) and its variants in estimating the determinants of within-country inequality.

The first step in meta-analysis begins with collecting all potentially appropriate published and unpublished empirical investigations as a solution for reducing any selection bias (Stanley, 2001). After reviewing the references of literature surveys (Goldberg K. and Pavcnik N, 2006;Shujiro U. and Dionisius A. ,2017; and Pavcnik N, 2017) and a couple of empirical studies,

[2]See Shujiro U. and Dionisius A. (2017) and Goldberg K. and Pavcnik N (2007) for surveys of the broader literature on trade openness and inequality.

electronic database baseline query was accomplished in an effort to capture most of the relevant studies. In effect, this study included many empirical studies that attempted to establish causality between trade openness and inequality. The baseline search in Scopus, EconLit and Science Direct yielded 979 hits. Next, a snowballing method was used and added studies that were missing from electronic database search. All potential studies provided with the two steps were examined in detail to be included in the final list of this study.

The main purpose of meta-analysis is integrating and explaining empirical literature about some specific important parameters (Stanley and Jarrell, 1989). This indicates that the studies have to be comparable to be integrated. This in turn demands pre-set study exclusion and inclusion criteria. This study used the following six criteria and any study that failed to satisfy one or more of them were excluded from the meta-analysis. First, the study must report an empirical estimate of the effect of trade openness on the measure of within-country income inequality. Second, the study must define inequality as Gini coefficient and trade openness as the sum of exports and imports as a percentage of GDP. Third, the study must report information on inferential statistic that use to measure precision of estimates (t-statistics or standard errors). Fourth, the study must be a country level study and not regions, states or sectors within a country. Fifth, the empirical investigation has to be conducted on developing countries. Sixth, the study must be written in English language. Unfortunately, most of the studies identified, although related to trade-inequality literature, did not satisfy the above mentioned inclusion criteria, especially the second, fourth and fifth. The criterion for inclusion of any study is that the study had to employ empirical regression analysis to explore the link between trade and inequality. A few studies were also excluded they did not report the minimum inferential statistics required for analysis (for example, Barro R, 1999; Lim G.C. and McNelis D., 2014).

Following Stanley (2001), no study was excluded on the basis of form or place of publication and therefore dissertations, working papers and articles from local journals were included; and study quality of the primary papers is accounted for using different quality indicators. There is two ways of selecting estimates in meta-analysis, ‘best’ and ‘all’ estimate. This study, following recent trend in meta-regression analysis (Disdier and Head, 2008; Doucouliagos and Stanley, 2009; Cipollina and Salvatici, 2010; T. Havranek and Z. Irsova, 2011), preferred to use all estimates reported in the studies. Selection of ‘best’ estimates from each study could introduce additional bias and averaging all estimates to end up with one

estimate for each study also leads to discard a lot of important information which enable one to control studies heterogeneities.

A few procedures followed to make the studies more comparable and capture heterogeneity between them while coding are worth discussing. To begin with, some studies (24% of the sample studies; for instance, Sato and Fukushige, 2009) are a single country study while the remaining are panel of countries. This study included both study types in the analysis, since they deal with the same issue, but created a dummy variable to control for this aspect of studies. Next, some researchers use foreign direct investment (FDI) as additional control variable in their regression. Based on economic intuition and FDI's potential effect on inequality, a dummy variable is created to control for the effect of such inclusion in a regression.

The final data set includes 124 estimates of inequality taken from 25 studies. The median number of estimates taken from one study is 6, and 15 variables have been codified for each estimate reflecting study design. Nelson and Kennedy (2009) reviewed 140 meta-regression analyses conducted in economics and hence it is an important reference in putting such numbers into perspective. They indicate that a median meta-analysis includes 92 estimates taken from 33 studies and uses 12 explanatory variables.

The list of all studies included in this meta-analysis is presented in table 1. The oldest study in this sample was published in 2001, the median in 2012 and the most recent in 2019: in other words, half of the studies were published in the last six years. This clearly suggests that trade-inequality topic is a lively area of research. The average time horizon of the data used by the primary studies is 29 years, and in total the studies used at least 37,465 observations from 25 studies.

Table 1

List of primary studies used.

Adeel Ali (2015)	M. Majeed& G. Zhang (2014)
Abdul Jalil (2012)	M. Zakaria & B. A. Fida (2016)
Bukhari and Munir (2016)	Nasfi & Malek (2014)
Cesar C.&Alberto C. (2000)	Sadullah &Ulkem (2010)
Christophe Ehrhart (2005)	Samuel Adams (2008)
Djoulassi K. Oloufade (2012)	Sarah Polpibulaya (2015)
ELENA & Marco (2009)	SatheeshAradhyula et al (2007)
Giray G. &Priya R. (2015)	Simplice A. & Michael E. (2012)
H. C. Cho &M. D. Ramirez (2016)	Sumie Sato & M. Fukushige (2009)
Inmee B.&Qichao S. (2016)	Tamer ElGindi (2017)
John C. et al (2016)	Timon Forster et al (2019)
Kimberly Beaton et al (2017)	ZebaAmjad (2015)
Lestari A. & Fanny P. (2018)	

3. Meta-analysis methodology

3.1.The importance of publication bias

Narrative review of literature reports an arithmetic average of the primary studies result and potentially it will be a biased estimate of the true effect if some results are more likely than others to be selected for publication. In fact, this is in line with one of the strongest intuitions in economics: humans react to priors and incentives. Of course, publication selection (file drawer problem) is not strange but has long been identified as a serious issue in empirical economics research (DeLong and Lang, 1992; Card and Krueger, 1995; Ashenfelter and Greenstone, 2004; Stanley, 2005). The bias emanates both from publishers' side and authors themselves. Card and Krueger (1995a) pinpoint the three sources of file drawer problem in economics; first, reviewers and editors may be prone to accept papers consistent with the conventionally well-established view; Second, authors may use the presence of a conventionally expected result as a model selection test and standard; Third, everyone may have presumption of treating statistically significant estimates as more accurate and favourable.

If the trade-inequality literature is free of publication selection, reported estimates of inequality effect are expected to be distributed randomly around the true effect. In contrast, if

some studies fall into the file drawer because of their unexpected and unusual level of significance or sign, standard errors and reported estimates in the primary studies will be correlated. In effect, such an empirical literature becomes quite skewed, distorting any assessment of the typical empirical finding. For example, an author who has a small data set with a presumption of statistically significant estimate may run a specification search that gives large enough estimate size that offset the corresponding high standard errors. In other words, studies with smaller sample size are at an absolute disadvantage of finding statistical significance and in effect they are prone to query nearly infinite model specifications like estimators, techniques and data sets in order to come up with the needed estimate size. That is why publication selection manifests as a systematic correlation between estimates and corresponding standard errors (Card and Krueger, 1995; Ashenfelter et al., 1999).

Thus, with publication bias, arithmetic averages of effect sizes across primary studies will be biased and leans to one direction, or the other, following theories and conventionally established views. The main purpose of meta-regression analysis (MRA) is therefore to identify existence of such publication bias and to lessen its effects as much as possible. Following several authors (Stanley 2005; Rose and Stanley 2005; Doucouliagos 2005; Disdier and Head 2008; Stanley 2008; Doucouliagos and Stanley 2009), publication bias is usually modelled by a meta-regression of a study's reported effects on its standard error. Thus, the benchmark MRA model is specified in equation (2).

$$\boldsymbol{Y_{ij} = \gamma_1 + \gamma_0 Se_{ij} + \varepsilon_{ij}} \; j = 1, 2, 3, \ldots, M \qquad (2)$$

Here, Y_{ij} is the reported estimate of β of the jth study in literature comprised of M studies,$\gamma_1$is the true value of the parameter of interest, Se_i is the standard error of the parameter of interest, γ_0 measures the strength of publication bias, and $\varepsilon_i$is, as usual, the meta-regression disturbance term. The true inequality effect (γ_1)in this specification is already corrected for publication bias: the bias is 'filtered out' and can be thought of as the genuine average inequality effect size. Stanley (2007) indicates that, in the absence of publication bias, the estimated effect will vary randomly around γ_1.

In a standard model like equation (2) above, meta-regression errors are obviously heteroscedastic (Stanley and Jarrell, 1989 and Peach E.K. and Stanley T.D., 2009). Thus, weighted least squares (WLS) is the common method of obtaining efficient estimates. Therefore, heteroscedasticity can be corrected by dividing (2) by the standard error of Y_i, Se_i.

$$t_{ij} = {Y_{ij}}/{Se_{ij}} = \gamma_0 + \gamma_1(1/Se_{ij}) + \mu_{ij} \qquad (3)$$

Equation (3) now can be estimated using Ordinary Least Squares (OLS) method and enables to test for existence of publication selection and other genuine effects. In this case, the dependent variable changes to the t-statistic of the estimate of the parameter of interest, the intercept measures publication bias, and the slope parameter measures the true inequality effect size. Stanley (2008) asserts that equation (3) can effectively filter out publication bias and estimate the true effect size.

As a result of taking all estimates of inequality from each primary study in this analysis, it is important to take into consideration that estimates within one study are likely to be dependent (Disdier and Head, 2008). This means that equation (3) is likely to be miss-specified. As indicated by (Doucouliagos and Laroche, 2009; Doucouliagos and Stanley, 2009), the mixed-effects multilevel model is a common remedy for such problems since it accounts for unobserved within-study heterogeneity. The mixed-effects multilevel model version of equation (3) is:

$$t_{ij} = {Y_{ij}}/{Se_{ij}} = \gamma_0 + \gamma_1(1/Se_{ij}) + \varepsilon_j + \mu_{ij} \qquad (4)$$

Where i and j denote estimate and study subscripts respectively. The overall error term now consists of study-level random effects (ε_j) and the usual estimate level disturbances (μ_{ij}).

As a non-parametric approach, the funnel plot is a common method of examining publication bias (Stanley and Doucouliagos, 2010; Sutton et al., 2000; Sterne and Egger, 2001). The funnel plot represents the estimated inequality effect size on the horizontal axis and a measure of study precision on the vertical axis. In the absence of publication bias the funnel plot resembles a symmetrically distributed inverted funnel (i.e. the estimates of inequality are randomly distributed around the true mean effect size, γ_1). In sharp contrast, if there is publication bias because smaller studies fell into file drawer since they show no statistically significant estimate or expected sign, then the funnel graph will appear asymmetrical. Since asymmetry could potentially result from specification problem not only from publication bias, it is not interpreted as proof of publication bias in meta-analysis (Sterne and Egger, 2001). Formal econometric methods, like the one specified in equation (3) and (4) above, are the appropriate techniques to detect existence or absence of publication bias and beyond in

meta-analysis literature. But, the funnel plot remains a useful device and use of it is made in this analysis.

3.2. What explains differences in inequality estimates

Models specified in equation (3) and (4) can identify both pattern of publication bias and the underlying true empirical effect. But, that is not the end of the story. Primary study's reported statistics may not only reflect publication selection but also patterns of model selection and misspecification bias. As indicated by Stanley (2005), almost all meta-regression analysis done so far in economics identified systematic correlation between selections of models, data and econometric estimation techniques and a study's findings. Of course, heterogeneity is much more common in economic research than psychology and epidemiology, where the meta-analysis was born. Thus, in economics, meta-analysis is used not only to filter publication selection but also to account for and assign a pattern to heterogeneity. In this subsection, this study develops a more general MRA models that explain the reported variations in the inequality estimate results.

To examine the existence of a systematic pattern of heterogeneity in the trade-inequality literature, equation (4) is augmented with additional explanatory variables (moderators) that may potentially affect the reported effect size or publication selection. After correcting for heteroscedasticity and accounting for within-study heterogeneity, the explanatory MRA model then takes the following form (Doucouliagos and Stanley, 2009; Cipollina and Salvatici, 2010; Havranek & Irsova, 2011):

$$t_{ij} = {Y_{ij}}/{Se_{ij}} = \gamma_0 + \sum_{j=1}^{J} \theta_j S_{ij} + \gamma_1 (1/Se_{ij}) + \sum_{k=1}^{K} \delta_k \frac{Z_{ki}}{Se_i} + \varepsilon_j + \mu_{ij} \qquad (5)$$

Where S_j is a set of variables influencing publication bias and Z_k is a set of control variables assumed to affect the estimates of Y directly. Dropping ε_j from equation (5) makes it a fixed effect model while keeping it makes it a random effect specification.

Since meta-regression analyses in economics mostly find systematic relation between study design and reported estimate results, this study explore how the use of different methods affects inequality estimates. Following Havranek & Irsova(2011), this study label this source of systematic correlation in reported estimates with study design *method heterogeneity*. Method heterogeneity emanates from different sources and can be categorized into four blocks: data characteristic heterogeneity, specification or design characteristics, estimation

technique characteristics and publication related characteristics. Thus, it would be prudent to augment publication bias and true empirical effect tests with more general MRA models in an effort to explain the reported variation in the trade openness -inequality literature results.

3.2.1. Data Characteristics

Here, data characteristics are intended to capture properties of the data used by the primary studies. Following Stanley (2005) and Havranek & Irsova (2011), dummy variables for panel data and time series data are included. Since the data sets used by the primary studies vary substantially in size, this study control for the number of years and countries to find out whether smaller studies report systematically different outcomes. Moreover, a large part of the studies included in the analysis use data from the international databases (e.g. World Bank and WIID), and so, a corresponding dummy variable to account for this differences is included.

3.2.2. Specification characteristics

The basic design heterogeneity of different tested models in the primary studies can be represented by specification characteristics. In this respect, dummies for the inclusion of important control variables like FDI and GDP are constructed. Even if most studies included in this analysis use panel of countries in their specification, few of them worked on country level modelling. A dummy variable is introduced to control for such differences. Finally, a dummy variable is included to capture regional effects.

3.2.3. Estimation characteristics

Estimation characteristics represent the econometric strategy employed by the primary studies. In this respect, authors of studies included in this analysis use a variety of econometric estimation techniques ranging from ordinary least square (OLS) to generalized method of moments (GMM). Thus, dummy variables to capture such estimation heterogeneity across studies have been created. For instance, approximately 45 and 22 percent of the regressions employed OLS – 2SLS and GMM respectively.

3.2.4. Publication characteristics

Publication characteristics represent the differences in income inequality estimate not captured by any of the above mentioned three characteristics. In order to control for the quality of studies, this study include a dummy variable for studies published in journals and

the number of Google Scholar citations of the primary study. This study also include a dummy variable for studies where at least one of the author is affiliated with one institution based in the examined country or developing countries in general; this study assume affiliated authors to developing countries based institutions are more familiar with the data used and, on the other hand, they may have vested interests in the results. Finally, study's publication year is included to capture the publication trend and possibly enables to capture the effects of the advances in methodology that are difficult in any other way otherwise. As indicated by Stanley et al (2008), inclusion of this dummy enables to test the economics-research-cycle hypothesis is proposed by Goldfarb (1995). The main point of the hypothesis is that studies conducted in newly emerging research area produce large and significant estimates at first but declines as the time passes.

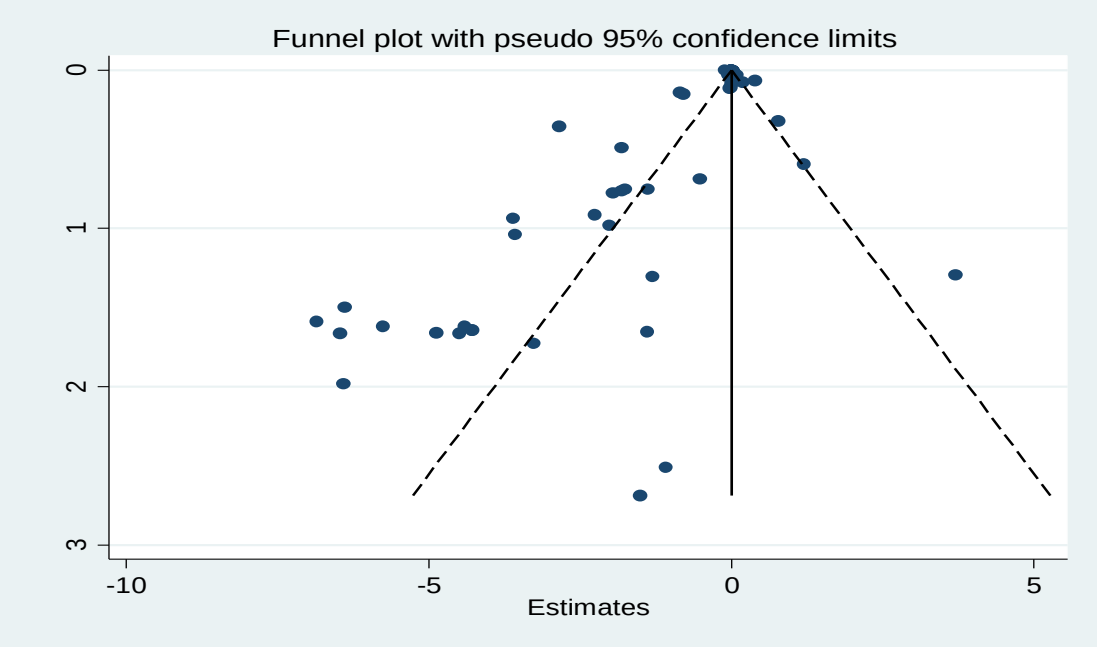
4. Results

This section presents and discusses the main results of the meta-analysis in three subsections. First, non-parametric visual inspection of a funnel plot is presented in subsection 4.1. Second, subsection 4.2 scrutinize whether the observed inequality effect is authentic (genuine) or an artefact of publication selection: separating the wheat from the chaff. Finally, the final subsection is intended to investigate the extent to which the choice of estimation methods, design and data affect reported estimates.

4.1. Non-parametric inspection

Non-parametric (informal) inspection of funnel plots is the usual starting point and common method of publication bias detection in meta-analysis. Actually, Light and Pillemer (1984) were the first to introduce and use funnel graphs to detect publication selection bias and summarize tones of heterogeneous research findings in a single graph. There are multiple choices and alternatives on what to represent on the vertical axis while plotting funnel graphs. The common ones are: standard error, precision (inverse of standard error), variance, inverse of variance, sample size and log of sample size. Following Sterne and Egger (2001), and as depicted in figure 1, each point of all estimates and their corresponding standard error are used to plot the funnel graph. Estimates of the primary studies are represented on the horizontal axis while the vertical axis represents their standard errors. The vertical line at the centre of the funnel plot shows a summary estimate of the effect size from the 25 trade-inequality studies examined in this paper.

Figure 1. Funnel plot of the inequality estimates[3]



Note: the horizontal axis represents inequality effects estimated from individual studies while the vertical axis represents the standard error of the estimates and use to measure precision of the primary studies.

In principle, in the absence of publication bias, the distribution of the funnel graph should be symmetrical around the precise inequality estimate. Looking at figure 1, the right hand side of the funnel depicts few numbers of estimates while the majority of them are located in the left side. This means, the funnel is skewed to the left and is asymmetrical. Hence, there is a good reason to suspect that publication selection bias presents in this literature (trade-inequality literature) and that the examined primary studies shows tendency of favouring negative estimates. This is not surprising and strange as most meta-analysis done so far in economics finds existence of publication bias (Stanley and Doucouliagos, 2009). Furthermore, the estimates with the highest precisions (lower standard error) are both negative and positive but very small in magnitude. This means, inequality effect size in the trade-inequality literature is neither strong and nor unidirectional. In other word, trade may have both positive and negative effect on inequality based on the examined country's context but remains very weak. This is in line with what Goldberg and Pavcnik, 2007 and Pavcnik, 2017 concluded in their narrative review on this topic. In fact, to be sure about the existence of publication bias, a

[3] Here, meta-funnel plotting command rather than simple scatter graph is used. All other appropriate methods have been tested but the result remains the same, method changes did not change the result.

formal test is indispensable because asymmetry emerges not only out of publication bias but also as a result of misspecification. Hence the next section deals with this issue in detail.

4.2.Funnel asymmetry test: separating the wheat from the chaff

Asymmetry occurs due to censoring of results that are labelled 'wrong' by theory, sponsor, author, referee or editors. As a rational agent, all of them dislike 'wrong' results. Funnel asymmetry test and precision estimate test (FAT-PET, hereafter) are the common estimation techniques used to test empirically the existence of such censoring bias.

Table 2 summarizes the publication bias and true effect test results of the regressions based on equation (3) and (4) and their different versions with slight difference.

Table 2

Test of publication bias and inequality true effect

	Dependent variable: t-statistic of the inequality estimate		
	FAT-PET	IRLS	Mixed-effects
Publication bias			
Constant	-0.0868289	-0.0868289	-2.252471
	(1.27487)	(1.274871)	(3.821761)
Inequality effect corrected for bias			
1/(standard error)	-0.003825***	-0.003825***	-0.0029455***
	(0.0007811)	(0.0007811)	(0.0005671)
Observations	126	126	126
Studies	25	25	25

***p< 0.01. Standard errors in parentheses (adjusted for data clustering in column 2 and 3).
Notes: The three specifications used each empirical result reported in the primary studies- that is, each regression is taken as a data point. FAT: is a test for publication selection bias. PET: is a test for the existence of inequality effect corrected for selection bias. Mixed – effects: is mixed effects multilevel model (known as 'Random effect' in MRA literature).

Table 2 depicts the results of all estimates collected from all studies, published and unpublished. A simple t-test on the intercept of equation (3) is employed to test for publication bias: funnel asymmetry test (FAT). In the same fashion, t-test is conducted on the slope of the same regression equation to test for genuine inequality effect: precision estimate test (PET). For both tests, FAT_PET, ordinary least squares estimation technique was

employed in the first column. In the second specification, Due to the vulnerability of meta-analysis to data contamination and as a robustness check to the basic fixed-effect meta-regression (FAT-PET), iteratively re-weighted least squares (IRLS) method which does not assume normality for hypothesis testing following Bowland & Beghin (2001) and Peach & Stanley (2009) is employed. In the third specification, this study use the mixed – effects multilevel model which is analogous to the random effect model used in panel-data econometrics. This preference is made because the multilevel framework allows a within study dependence and takes into account data unbalance (the maximum likelihood estimator is sued instead of generalized least squares).

As depicted in table 2, the constant term, which is used to measure publication bias, is insignificant irrespective of the employed specifications. This suggests that the inequality effect reported by the studies under examination is free of publication bias. This is quite surprising result because publication bias has been commonly found in most economics literatures examined so far by meta-analysis (Doucouliagos and Stanley, 2008). Nevertheless, Havranek and Irsova (2012) found the same result while examining publication bias in the literature on foreign direct investment spillovers when considering published and unpublished studies all together.

The more important question is whether a genuine inequality effect exists after accommodating and filtering publication bias. The slope coefficient, which is used to measure the genuine inequality effect is negative and statistically significant at less than one percent level in all specifications. The study prefers the mixed-effects model, which allows for within-study heterogeneity. Based on the mixed-effects model, as depicted in column 4 of table 2, the true effect is significant at one percent level and it reaches almost about -0.001[4]. In other words, a 1000 percentage points increase in trade openness is on average associated with a decrease in overall aggregate income inequality in developing countries by 1 percent, an economically insignificant effect and so entirely negligible. Nevertheless, this finding is in line with the prediction of the workhorse model of international trade: the Heckscher-Ohlin model. Leonard et al (2014) come up with the same finding while examining adverse employment effect from raising the minimum wage in the United Kingdom and they reported it as negligible: (adverse effect of -0.005).

[4] Since the dependent variable in equation (4) is in terms of t-value, its slope is multiplied by the average standard error of the primary estimates to get the genuine effect size ($\gamma_1 * Se = -0.001$).

The importance of meta-analysis for inference concerning the magnitude of inequality effect is best demonstrated by comparing the corrected and genuine effect size (generated by meta-analysis) and the uncorrected effect size generated by simple arithmetic average (the case of narrative literature review). The arithmetic average of all studies estimate of inequality is -0.645. In contrast, the corrected and genuine effect size of estimates from all studies (resulting from the meta-regression reported in Column 3 of Table 2) is only -0.001. In other words, the average estimate of inequality reported in examined studies is exaggerated 645 fold. This simple example shows how misleading and dangerous it is to make inference based on narrative analysis (taking the simple arithmetic average). This is not the first strange outcome of this type. Of course, this result is averaged across all included developing countries and methods employed in the primary studies. Therefore, this study needs a multivariate meta-analysis to explain the vast differences in the reported estimates. The reported primary studies reports may systematically depend on model misspecifications on the one hand and heterogeneous quality elements of primary studies on the other hand. Section 4.3 of the result analysis deals with this issue in detail and filters the true effect in a more precise manner. The next section looks into the robustness of what we have seen in the publication bias tests.

4.2.1. Robustness

Table 3 reports other subsamples and slight different estimation methods to ensure the robustness of the simple meta-regression findings. Column 1 presents the meta-regression estimates for published studies and fixed-effects method of estimation is employed. Column 2 reports clustered OLS regression results. Finally, columns 3 and 4 report fixed – effects and random – effects for the best set data base (i.e. one estimate is taken from every primary study based on either the author's preference, when mentioned, or based on the specifications goodness of fit in the other cases). Here, fixed – effects and random – effects are another way of naming FAT-PET and mixed-effects respectively and it is common terminology in meta-analysis.

Again, just like that of simple meta-analysis result reported in table 2, there is no evidence of a practically significant inequality effect for any of these samples, even though there is slight difference between the best set result in column 4 and 5 of table 3 and all set results of table 2. But, economically speaking no significant inequality effect is found neither in the basic regression result nor in robustness checks. Just like any conventional econometrics, meta-regression coefficient estimates are sensitive to changes in data (sample size) and methods

(Leonard et al, 2014). To check further how the difference between the best set and all set result is sensitive to changes in method, weighted least squares (WLS) technique is employed. The WLS result is quite similar with the one reported in column 4 and 5 of table 3 in terms of significance status (see table 7 in appendix C of this paper). Regarding the change in data, study with low statistical power (small sample size) has a reduced chance of detecting a weak true effect. As witnessed in different studies, for example Goldberg and Pavcnik, 2007 and Pavcnik, 2017, trade openness has weak effect on inequality. Combining these two reasons, the difference observed between the best set and all set in terms of significance status is attributed to sample size differences. This means, it may not be because of absence of effect that the best set result turned insignificant, but the weak effect coupled with a small sample made it undetected. Thus, the observed slight difference is negligible and does not make any meaningful change. In sum, among 126 estimates of the trade-inequality effect coded from 25 studies, there is no evidence of a genuine nonzero inequality effect and the result is robust.

Table 3

Robustness checks for the simple meta-regression models

	All Set		Best Set	
	Published	Both	Both	
	FAT-PET	Clustered OLS	Fixed-effcets	Random-effects
Constant	-1.593807	-0.0868289	-1.149149	-1.149149
	(2.776771)	(1.382783)	(2.148357)	(2.060632)
1/Se	-0.0037206***	-0.003825	-0.0031954	-0.0031954
	(0.0011275)	(0.0044993)	(0.0045362)	(0.0043509)
Observations	55	126	25	25
Studies	15	25	25	25

*** $p < 0.01$. Standard errors in parentheses.

Notes: Meta-response variable: t-stat. All Set: each empirical result reported in the primary studies- that is, each regression – is taken as a data point. Best Set: each model provides one estimate or data point, the empirical result preferred by the author or with higher goodness of fit- that is, from each study – one estimate is taken. Published: only published studies are included in the regression. Both: both published and unpublished studies are included. FAT-PET: Funnel asymmetry test-precision effect test (fixed-effects).

4.3. What explains differences in inequality estimates

To accommodate a potentially complex inequality effect, misspecification biases, heterogeneity and differential predispositions to report inequality effect, the simple meta-regression model can be greatly expanded as specified in equation (5).

$$t_{ij} = {Y_{ij}}/{Se_{ij}} = \gamma_0 + \sum_{j=1}^{J} \theta_j S_{ij} + \gamma_1 (1/Se_{ij}) + \sum_{k=1}^{K} \delta_k \frac{Z_{ki}}{Se_i} + \varepsilon_j + \mu_{ij}$$

In effect, γ_0 is replaced by $\gamma_0 + \sum_{j=1}^{J} \theta_j S_{ij}$.The Z – variables allow for study heterogeneity and misspecification biases, and the S – variables may represent editors decision to accept and researchers' decision to report a statistically significant inequality effect. See Table 4 for a list of coded moderator variables (family of S and Z – variables).

Table 4

Moderator variables

Moderator variable	Definition	Mean (Standard deviation)
Se	is the standard error of the reported inequality estimate.	0.31 (0.60)
Panel	=1, if estimate relates to panel data with time series as a base.	0.67 (0.47)
Pooled	=1, if estimate relates to cross – country analysis.	0.83 (0.38)
Asia	=1, if estimate relates to Asian countries specific data.	0.21 (0.41)
All	=1, if estimate relates to all developing countries data.	0.63 (0.50)
Africa	=1, if estimate relates to African countries specific data.	0.13 (0.33)
Country	is number of countries in the data set.	50 (40)
Years	is number of years covered by the data set.	29 (10)
Pubyear	is study publication year.	
Omit-FDI	=1, if a study omitted FDI from its explanatory variable.	0.42 (0.50)
Database	=1, if estimate relates to international database.	0.76 (0.43)
GDP	=1, if a study included GDP as control variable.	1.2 (1.6)
OLS-2SLS	=1, if estimate relates to OLS and 2SLS.	0.45 (0.50)
GMM	=1, if estimate relates to GMM method.	0.22 (0.42)
Deving	=1, if the author is from developing country.	0.54 (0.50)
Publication	=1, if the estimate comes from published study	0.87 (1.70)
Citation	Number of citation the study has	14 (25.34)

Table 4 lists the moderator variables with their means and standard deviations, calculated from the trade – inequality data (All data set).But which moderator variables should I use for these S and Z-variables? First, the study begins with all those S and Z variables that appeared across multiple meta-analysis literature and found to be relevant, to avoid problem of picking up variables randomly. Second, the study added two important income inequality related variables upon those common used moderator variables: gross domestic product (GDP) and foreign direct investment (FDI). It is necessary to take in to account the inclusion of a

variable that control for the level of economic development of the country under examination because stage of development per se affects income inequality. On the other hand, FDI being an important element of globalization, its inclusion or exclusion by the primary study may potentially affect the inequality estimate.

Thus, this study begin the multivariate analysis by including all explanatory variables introduced in Section 3.2 and listed in table 4 into the multivariate MRA regression model specified in equation (5).

In total, fourteen explanatory variables, eleven Z - variables and three S – variables, are added to the multivariate specification: the results for method heterogeneity variables are reported in table 5. The importance of the multivariate MRA approach is that it can explicitly model the influence of publication selection and effect size related variables (Z and S variables) and in effect each impact may be separately accounted for, identified and estimated. Furthermore, estimation of equation (5) is useful in identifying the source of heterogeneity among the reported primary studies estimates.

Table 5 presents the multivariate MRA results of the all – set of 124 estimates. That is, all Z and S – variables listed in table 4 were included in the Meta – regression model of equation (5). Column 1 reports the MRA results using OLS approach. Column 2 presents the MRA results using clustered data analysis which is one way to account for dependence within the same study since all estimates were included in the analysis. More genuine and preferred approach to modelling this intra – study dependence is reported in column 3 – mixed effects.

As presented in table 5, there is some slight variation among the estimated multivariate MRA coefficients across the three specifications with only one sign reversal. In this estimation framework, the interpretation of both true effect and publication bias are not straightforward but are more complicated. The models true effects are no more represented by parameter $\boldsymbol{\gamma_1}$only but captured by the combination of all the Z – variables (i.e. those divided by standard error). On the other hand, publication selection is captured by the combination of all the K – variables (i.e. those not divided by standard error) along with the constant term. With such multivariate MRA approach, many method heterogeneity dimensions can be revealed as statistically significant, irrespective of their practical importance and intuition.

Table 5

Method heterogeneity in trade – inequality effects[5]

	Dependent variable: t – statistic of the inequality estimate		
	OLS	Clustered – OLS	Mixed - effects
Constant	-0.1314352	-0.1314352	-0.0917832
	(0.5506646)	(1.176556)	(1.270632)
1/se	0.0835682***	0.0835682***	0.082791***
	(0.0062261)	(0.0169939)	(0.0090653)
Data characteristics			
Panel data	-0.0114111	-0.0114111	0.0030494
	(0.013416)	(0.0170318)	(0.0188579)
Database	0.0266476***	-0.0266476	0.0349183***
	(0.0080964)	(0.0195381)	(0.0088157)
Specification characteristics			
Africa	-0.0591447***	-0.0591447***	-0.0116688
	(0.0131336)	(0.0131155)	(0.0135297)
Asia	-0.1185629***	-0.1185629***	-0.1164196***
	(0.0052935)	(0.01104)	(0.007806)
Latin America	-0.0580481	-0.0580481	-0.0496367
	(0.0253178)	(0.0494325)	(0.0472264)
Number of country	-0.0004521***	-0.0004521***	-0.0003128***
	(0.0000867)	(0.0001352)	(0.000083)
GDP	0.0334468***	0.0334468*	0.0343008***
	(0.005785)	(0.0170926)	(0.0071774)
FDI	-0.024717***	-0.024717	-0.0353255***
	(0.0080671)	(0.0196398)	(0.0087625)
Pooled	-0.0667205***	-0.0667205**	-0.099969***
	(0.0175159)	(0.0284631)	(0.0217361)
Estimation characteristics			
OLS – 2SLS	-0.0096104**	-0.0096104	0.0004173
	(0.0040457)	(0.0084154)	(0.0024394)
GMM	-0.0098896*	-0.0098896	-0.002015
	(0.0052288)	(0.0066216)	(0.0029526)
Publication characteristics			
Deving	3.861423***	3.861423***	3.195757**
	(0.7491228)	(1.18462)	(1.471042)
Citation	-0.0226804*	-0.0226804	-0.0208507
	(0.013051)	(0.0224317)	(0.0233766)
Published	-1.970566***	-1.970566*	-1.994135***
	(0.4161536)	(1.067925)	(0.4632606)
Adj R-squared	0.9794	0.9822	
Observations	124	124	124
Studies	25	25	25

***p < 0.01, **p< 0.05 and *p< 0.10 . Standard errors and robust standard error in parentheses.

Notes: The table contains the results of regression equation (5). All estimates of the primary studies are included in all specifications. OLS: Ordinary least squares. Clustered – OLS: Ordinary least squares with standard errors clustered at each study level. Mixed – effects: Mixed effects multilevel model.

Source: Author's estimates

[5] As a robustness check, weighted least squares is used for all set data base in place of OLS and mixed – effects is used for cross country studies separately. Their overall result remains the same. See table 8 in appendix C.

In this analysis, what truly matters is whether the central findings of the absence of publication selection and a genuine inequality effect detected in the simple MRA remains after method heterogeneity across the primary studies is accounted for. Nevertheless, in isolation, Z variables parameters explain why estimates differ across studies.

Publication selection

Column 3 of table 5 shows that two variables reflecting the characteristics of the publication are significant, suggesting that publication selection may depend on the publication characteristics in a systematic way. Neither the intercept nor K – variables by itself in isolation measure the magnitude of the average publication bias. Rather, it is the combination of the constant term and all the K – variables (Developing, citation and published). Thus, joint significance test of these variables all together is what commands existence or absence of publication bias. Based on the joint significance test (prob >=0.2964) these multivariate MRA results clearly indicate the absence of publication bias and confirm the simple MRA outputs. Nonetheless, as expected, the preferred model reveals that studies conducted by native authors to developing countries are associated with more selection bias. The results are in line with the intuition described in section 3.2, and imply that, other things being constant, selection bias in studies carried out by native authors are larger by 3 compared to non native authors. On the other hand, other things being equal, selection bias in published studies is lower by about 2 relative to unpublished studies.

Effects on inequality estimates

Now, the study turns to identifying variations in the actual responsiveness of income inequality to trade integration enhancement, irrespective of publication selection. In contrast to the simple MRA, in the multivariate version of MRA rather than some single overall genuine effect, trade effects on income inequality are the combination of several factors (1/Se, paneldata/Se, database/Se, Africa/Se, asia/Se, latinamerica/Se, country/Se, GDP/Se, FDI/Se, pooled/Se, OLS – 2SLS/Se and GMM/Se). Before discussing how method heterogeneity affects the primary studies estimates, it is better to know the magnitude of the genuine inequality effect and whether it survives the inclusion of controls for data and method heterogeneity. The average genuine effect in terms of the inequality estimate is calculated from the average estimated value of $(\gamma_1 + \sum \delta_k Z_{ki})$Se or $\gamma_1 Se$ for the simple MRA, using the coefficients estimated by the preferred specification, mixed – effects. Clear statistical evidence of genuine inequality effect holds in this multivariate MRA specification (Chi2 = 21.17; Prob < 0.000). Based on the estimated MRA coefficients of Z – variables

along side with 1/Se, the average genuine inequality effect for the trade – inequality literature under examination is -0.031 compared with -0.001 for the simple MRA, column 3 of table 2. Which means a one percent increase in trade volume reduces overall aggregate income inequality in developing countries, measured in Gini coefficient, by about 0.031 percentage point. This is a practically and economically insignificant effect and so it is negligible. Nonetheless, this result is in line with the prediction of the Heckscher-Ohlin model, at least in terms of its sign. Let's see now how the introduction of Z – variables (data and method heterogeneity) affects the estimates produced by the primary studies.

Data characteristics

Outputs in column 3 of table 5 reveals an upward trend in the results: other things being equal, the use of international data bases increases the reported inequality estimates by 0.035 percentage points. Panel data, which combine both cross – sectional and time information, however, do not produce any substantial variation in estimates.

Specification characteristics

Column 3 of Table 5 shows that among the seven variables reflecting the specification characteristics of the primary studies, five of them are statistically significant. This suggests that results of trade inequality regressions depend on primary studies specification characteristics in a systematic way. The results are affected by regional difference, number of countries examined, inclusion and omission of standard control variables (GDP and FDI respectively) and pooling countries together.

Estimation characteristics

Concerning estimation characteristics, 45 percent of the primary studies estimates examined in this paper were produced by OLS and 2SLS estimation techniques, 22 percent produced by GMM and the rest (33 percent) by other estimation techniques like FEM, REM, LSDV, SUR, etc. As column 3 of table 5 reveals, difference in estimates of the primary studies examined in this paper do not emanate from estimation method heterogeneity employed in producing them. In other words, estimation characteristics did not affect trade inequality regression estimates in a systematic way.

Discussion and directions for future research

How can it be that there is no economically meaningful income inequality effect from a substantial trade openness developing countries experienced in the last four decades? Every

economics and especially international trade student has been taught for many decades that trade openness affects income distribution in developing countries. This is a puzzle, because we would expect a decrease in aggregate income inequality in developing countries following trade openness as predicted by the Heckscher – Ohlin model.

Here are, broadly speaking, four plausible explanations for this puzzle. One is the heterogeneity of sample countries pooled together by the primary studies examined in this paper. They pooled lower income countries with their middle income counterpart. For instance, Sub-Saharan African with Latin-American or Asian countries. About 63 percent of estimates examined in this paper were produced from such pooled cross – country empirical investigation. The Heckscher – Ohlin proposition predicts that trade openness increases the relative demand for skilled labour in middle income countries compared to their lower income countries counterpart. It is possible therefore that in the pooled cross – country empirical analysis, the positive effect of openness on income inequality in middle income countries would be offset by a negative effect in lower income countries.

The second plausible explanation is the fact that trade openness is not the only force at play in affecting income inequality: financial integration or openness, foreign direct investment and domestic fiscal policy are among the top list. These candidate workforces may move in opposite direction in their impact on income inequality. Since they offset each other's effect, the overall aggregate impact will be economically insignificant. The third plausible explanation is another form of offsetting effects: sectoral and regional differences within a country. Trade openness raises wages of workers engaged in export oriented sectors while it deteriorates wages of those working in import competing sectors. On the other hand, particular regions within a country may be more exposed to trade openness and in effect more integrated to the world economy relative to other regions. For instance, Hong Kong and Shanghai in China and regions bordering USA in Mexico. These sectoral and regional differences within a country channels income inequality in opposing directions. In effect, at the aggregate level, the inequality effects of trade openness may offset each other and remain negligible. Finally, trade openness may simply have no economically meaningful and strong effect on overall income inequality in developing countries. If this interpretation is plausible, it implies that the conventional Heckscher – Ohlin model is not an adequate characterization of the developing countries goods and labour markets. In fact, these explanations remain hypotheses, and their verification will require further empirical investigation.

Regarding the directions of future research, in my view, the most important avenue in this field is twofold. Even if a large number of studies have examined the impact of trade openness on within – country income inequality, most of these studies are related to wage inequality at country level rather than overall income inequality. This gives opportunity to collect more estimates from the wage inequality literature at individual country level, in turn provides high degree of freedom to review the studies by meta – analysis method. Finally, the meta – analysis in this paper suggests that study specification may affect results in a systematic way. Given the limited number of studies on income inequality at individual country level, it is still an untapped area to test the impact of trade openness on income inequality at country level by filtering out the effects of misspecifications.

An attempt is made to include large number of trade-inequality literature related to developing countries in this analysis but it is not exhaustive. Exhaustive inclusion of related literature could have generated more accurate results. This is the limitation of the study.

5. Conclusion

In about the last four decades, developing economies experienced a substantial trade liberalization (openness) coupled with raise in aggregate income inequality. On the other hand Hecksher – Ohlin's proposition, the workhorse model of international trade, predicts that trade openness decreases income inequality in labour abundant economies. Following this experience and HO's distributional effect prediction, a vast body of empirical literature has attempted to verify whether and eventually to quantify to what extent trade openness affects within – country income inequality. Nevertheless, the results of individual studies vary significantly and are inconclusive, making it difficult for policy-makers to draw conclusions from those literatures. Hence, it warrants more careful quantitative investigations of the related literature in order to separate the wheat from the chaff. Meta – regression analysis is the ultimate toolkit to accomplish this purpose. This is the ultimate aim of this paper.

A systematic and comprehensive meta – analysis of 124 estimates of the effect of trade openness on within – country aggregate income inequality reported in 25 primary studies focusing on developing countries has been synthesised in this paper. Simple meta – regression analysis (MRA) and more nuanced multivariate MRA approach has been employed with mixed – effects multilevel meta – regression being the preferred estimation

technique. The merit of the multilevel approach is that it accounts for potential study – level and estimate – level variations.

Neither the simple MRA nor the multivariate detected significant publication bias. On the other hand, the multiple MRA results show that the genuine inequality effect of trade openness from the 25 studies examined is negative and statistically significant with a magnitude of -0.031. Even though this finding is robust to the research sample examined and the meta – regression model employed, its small size makes it policy – irrelevant and practically insignificant. This means that no economically meaningful income inequality effect is t found in the examined trade openness – inequality literature.

The following scenarios may explain this empirical research record. First, trade openness may simply have no economically meaningful and strong effect on overall income inequality in developing countries. If this interpretation is plausible, it implies that the conventional Heckscher – Ohlin model is not an adequate characterization of the developing countries goods and labour markets. Next, aggregate income inequality is in fact affected by multiple factors and they may offset each other's effect. Finally, it may be related to pooling countries of heterogeneous income level together by the primary studies. Of course, these explanations need empirical verification.

References

Abreu, Maria; de Groot, Henri L.F.; Florax, Raymond J.G.M. 2005. "A Meta-Analysis of Beta-Convergence: The Legendary Two-Percent." Tinbergen Institute Discussion Paper, No. 05-001/3, Tinbergen Institute, Amsterdam and Rotterdam.

Alvaredo, Chancel, Piketty, Saez, and Zucman. 2018. World Inequality Report 2018. retrieved fromhttps://wir2018.wid.world/files/download/wir2018-full-report-english.pdf.

Ashenfelter, O., Greenstone, M. 2004. "Estimating the value of a statistical life: the importance of omitted variables and publication bias." The American Economic Review 94 (2).

Ashenfelter, O., Harmon, C., Oosterbeek, H.1999. "A review of estimates of the schooling/ earnings relationship, with tests for publication bias." Labour Economics 6 (4).

Barro, R. 1999. "Inequality and growth in a panel of countries." Journal of Economic Growth, vol. 5.

Bowland J. and Beghin C. 2001. "Robust estimates of value of a statistical life for developing economies." Journal of Policy Modelling 23.

Card, D., and A.B. Krueger. 1995. "Time-series minimum-wage studies: A meta-analysis." American EconomicReview 85 (2).

Cipollina, M., Salvatici, L. 2010. "Reciprocal trade agreements in gravity models: a meta analysis." Review of International Economics 18 (1).

Daniel Chiquiar . 2004. "Globalization, Regional Wage Differentials and the Stolper-Samuelson Theorem: Evidence from Mexico." Working Papers, Banco de M´exico.

David Card; Alan B. Krueg. 1995."Time-Series Minimum-Wage Studies: A Meta-Analysis." The American Economic Review, Vol. 85, No. 2.

DeLong, J.B., Lang, K. 1992. "Are all economic hypotheses false?" Journal of Political Economy 100 (6).

Disdier, A.-C. and Head, K. 2008."The puzzling persistence of the distance effect on bilateral trade." Review of Economicsand Statistics, 90(1).

Dollar, D. and A. Kraay. 2002. "Growth is Good for the Poor." Journal of Economic Growth, vol. 7.

Doucouliagos, H., Stanley, T.D., 2009. "Publication selection bias in minimum-wage research? A meta-regression analysis." British Journal of Industrial Relations 47 (2).

Doucouliagos, C., Laroche, P. 2009. "Unions and profits: a meta-regression analysis." Industrial Relations 48 (1).

Edward Anderson. 2005. "Openness and Inequality in Developing Countries: A Review of Theory and Recent Evidence."World Development Vol. 33, No. 7.

Egger, M., Smith, G.D., Scheider, M., Minder, C. 1997. "Bias in meta-analysis detected by a simple, graphical test." British Medical Journal 315 (7109).

Goldberg, and Pavcnik Nina. 2007. "Distributional Effects of Globalization in Developing Countries." Journal of Economic Literature,Vol. XLV.

Goldfarb, R.S. 1995. "The economist–as–audience needs a methodology of plausible inference." Journal of Economic Methodology, 2(2).

Harald Beyer, Patricio Rojas, and Rodrigo Vergara. 1999. "Trade liberalization and wage inequality." Journal of Development Economics, Vol. 59.

Havranek, T., 2010. "Rose effect and the Euro: is the magic gone?" Review of World Economics 146 (2).

Havranek, T., Irsova, Z., 2010. "Which foreigners are worth wooing? A meta-analysis of vertical spillovers from FDI." Working Papers 2010/03 Czech National Bank, Research Department.

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

Havranek, T., Irsova, Z. and Janda, K. 2012."Demand for gasoline is more price-inelastic than commonly thought."Energy Economics, 34(1).

Leonard, Stanley and Doucouliagos.2014."Does the UK Minimum Wage Reduce Employment? A Meta-Regression Analysis."British Journal of Industrial Relations.

Light, R.J. and Pillemer, D.B. 1984. "Summing Up: The Science of Reviewing Research.Cambridge." MA: Harvard University Press.

Lim G.C. and McNelis D. 2014. "Income Inequality, Trade and Financial Openness."

Marta Castilho, Marta Menendez, and Aude Sztulman. 2010. "Trade Liberalization, Inequality and Poverty in Brazilian States."

Milanovic, B. 2005. "Can we discern the effect of globalization on income distribution: evidence from household surveys." World Bank Economic Review, vol.19.

Nelson, J., Kennedy, P. 2009. "The use (and abuse) of meta-analysis in environmental and natural resource economics: an assessment." Environmental and Resource Economics 42 (3).

Pavcnik Nina. 2011. "Globalization and within-country income inequality." International Labour Organization and World Trade Organization, Making Globalization Socially Sustainable, pp. 233 – 259.

Pavcnik Nina. 2017. "The Impact of Trade on Inequality in Developing Countries." Dartmouth College and NBER.

Peach E. K. & Stanley T. D. 2009. "Efficiency Wages, Productivity and Simultaneity: A Meta-Regression Analysis." Journal of Labor Research, Springer, vol. 30(3).

Revenga, A. 1997: "Employment and wage effects of trade liberalization: The Case of Mexican Manufacturing." Journal of Labor Economics, Vol. 15, pp. S20-43.

Robbins, D. 1996: "Evidence on Trade and Wages in the Developing World." OECD Technical Paper No. 119.

Rose, A. K. and Stanley, T. D. 2005. "A meta-analysis of the effect of common currencies on international trade." Journal of Economic Surveys, 19(3).

Thomas Piketty. 2014. "Capital in the Twenty-First Century." The Belknap Press of Harvard University Press.

Sebastian Galiani and Pablo Sanguinetti . 2003. "The impact of trade liberalization on wage inequality: Evidence from Argentina."

Stanley T.D. and Stephen B. Jarrell. 1989. "Meta-regression analysis: a quantitative method of literature surveys." Journal of economic surveys vol. 19, no. 3.

Stanley, T.D., 2005. "Beyond Publication Bias." Journal of Economic Surveys19 (3).

Stanley, T.D., 2008."Meta-regression methods for detecting and estimating empirical effects in the presence of publication selection." Oxford Bulletin of Economics and Statistics 70 (1).

Stanley, T.D, Doucouliagos, H., 2010. "Picture this: a simple graph that reveals much ado about research." Journal of Economic Surveys 24 (1).

Stanley, T.D., Doucouliagos, H., Jarrell, S.B., 2008. "Meta-regression analysis as the

socioeconomics of economics research." The Journal of Socio-Economics 37 (1).
Sterne J. A. and Egger M. 2001."Funnel plots for detecting bias in meta-analysis: Guidelines on choice of axis."Journal of Clinical Epidemiology 54.
Sutton, A.J., Abrams, K.R., Jones, D.R., Sheldon, T.A., Song, F. 2000. "Methods for Meta analysis in Medical Research." Wiley, Chichester.

Appendices

Appendix A: Studies Included in the Meta – Analysis

Table 6. List of Studies Included in the Meta – Analysis

Study Code	Study Details
001	Hyungsun C. & Miguel D. R., 2016.Foreign Direct Investment and Income Inequalityin Southeast Asia: a Panel Unit Root and PanelCointegration Analysis, 1990–2013.
002	Inmee B. and Qichao S. 2016. Impact of Economic Globalization on Income Inequality: Developed Economies vs Emerging Economies. Global Economy Journal 16(1).
003	Lestari A. and Fanny S.P. 2018.Trade Openness Effect on Income Inequality: Empirical Evidence from Indonesia. Jurnal Ilmu Ekonomi, Volume 7(1).
004	Sumie S. and Mototsugu F. 20 Globalization and economic inequality in the short and long run: The case of South Korea 1975–1995. Journal of Asian Economics 20.
005	Zeba Amjad.2015. Trade and Income Distribution in Pakistan. Global Journal of Management and Business Research: Economics and Commerce Volume 15 Issue 8 Version 1.0.
006	Adeel A., Syed F., Ambreen F. and Lubna N. 2015. Income Inequality, Redistribution Of Incomeand Trade Openness. Applied Economics Research Centre, University of Karachi.
007	Muhammad Z. and Bashir A.F. 2016.Trade openness and income inequality in China and the SAARC Region. Asian Specific Economic Literature.
008	Cesar C. and Alberto C. 2001. External sector and income inequality in interdependent economies using a dynamic panel data approach. Economics Letters 71.
009	Giray G. and Priya R. 2015. Globalization, Inequality, and Redistribution: Theory and Evidence. CESIFO WORKING PAPER NO. 5522.
010	Djoulassi K. O. 2012. Trade Openness, Conflict Risk and Income Inequality. Working Paper, Department of Economics, University of Ottawa.
011	Satheesh A., Tauhidur R. and Kumaran S. 2007. Impact of International Trade on Income and Income Inequality.
012	M. T.M. and Guangfeng Z. 2014. INEQUALITY, TRADE AND ECONOMIC DEVELOPMENT: Evidence from Developing Countries. Pakistan Journal of Applied Economics, Vol. 24 No. 1.
013	Tamer ElGindi. 2017. Natural resource dependency, neoliberal globalization, and income inequality: Are they related? A longitudinal study of developing countries (1980–2010). Current Sociology 2017, Vol. 65(1).
014	Elena M. And Marco V. 2009. Trade And Income Inequality In Developing Countries. World Development Vol. 37, No. 2.
015	Sarah Polpibulaya. 2015. Trade Openness and Income Inequality.Theses, Clemson University.
016	John C. A., Andrew E. O. and Emeka O. 2016. Empirical Analysis of the Key Drivers of Income Inequality in West Africa. African Development Review, Vol. 28, No. 1.

017 Sadullah Ç. and Ulkem B. 2010. How Does Globalization Affect Income Inequality? A Panel Data Analysis. International Atlantic Economic Society.

018 Simplice A. and Michael E. 2012. The Impact of Liberalisation Policies on Inequality in Africa. Working Paper, African Governance and Development Institute, WP/12/038.

019 Abdul Jalil. 2012. Modeling income inequality and openness in the framework of Kuznets curve: New evidence from China. Economic Modelling 29.

020 Christophe EHRHART . 2005. Openness to international trade and investment and income inequality: evidence from a panel of Latin American and East Asian countries.

021 Nasfi F. and Malek El W. 2014. The Relationship Between Economic Growth and Income Inequality. International Journal of Economics and Financial Issues Vol. 4, No. 1.

022 Kimberly B., Aliona C., and Andras K. 2017. Revisiting the Link between Trade, Growth and Inequality: Lessons for Latin America and the Caribbean. International Monetary Fund Working Paper, WP/17/46.

023 Samuel A. 2008. Globalization and income inequality: Implications for intellectual property rights. Journal of Policy Modeling 30.

024 Timon Forster, Alexander E. K., Bernhard R., Thomas H. S., Lawrence P. K. 2019. How structural adjustment programs affect inequality: A disaggregated analysis of IMF conditionality, 1980–2014. Social Science Research.

025 Mahnoor B. and Kashif M. 2016. Impact of Globalization on Income Inequality in Selected Asian Countries. Working Paper, University of Central Punjab.

Appendix B: Funnel Plots

Figure 2. Funnel plot of the inequality estimates (Best Set)

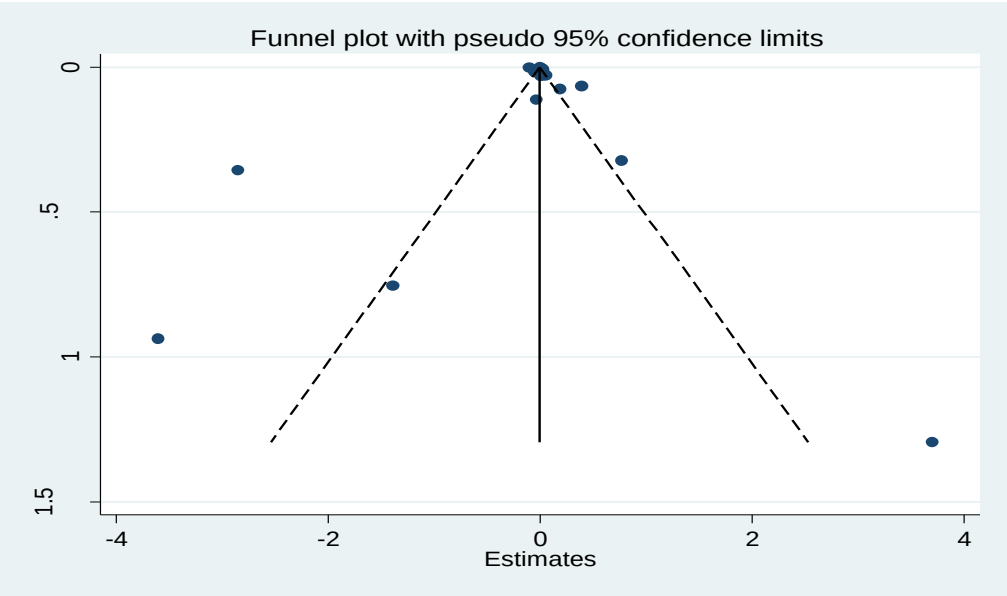


Figure 3. Funnel plot of the inequality estimates (Published studies)

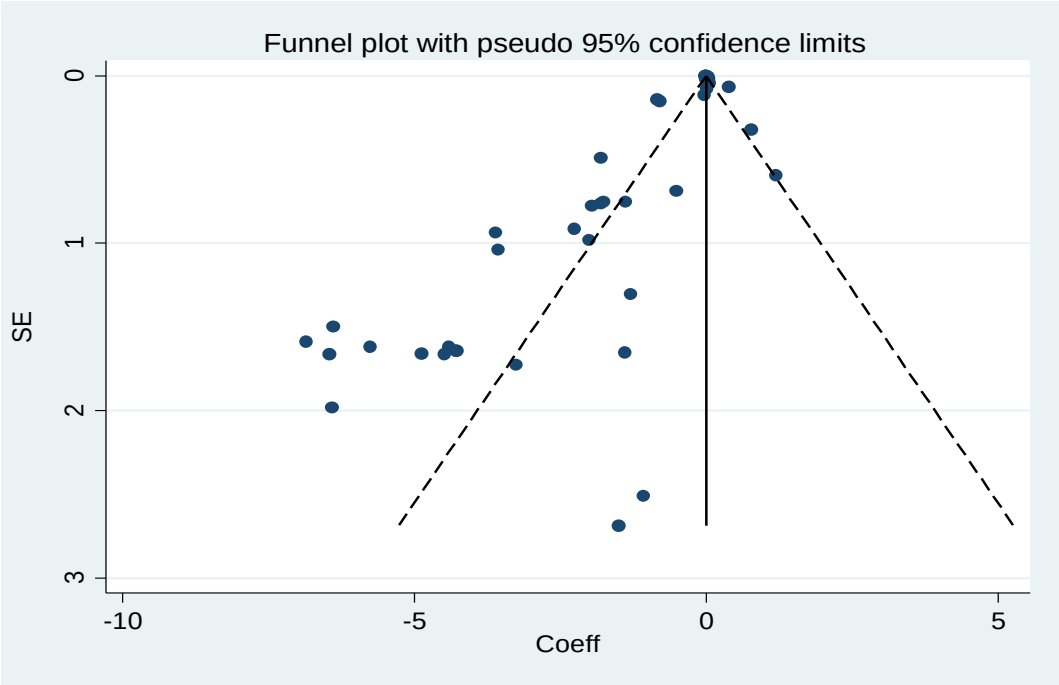
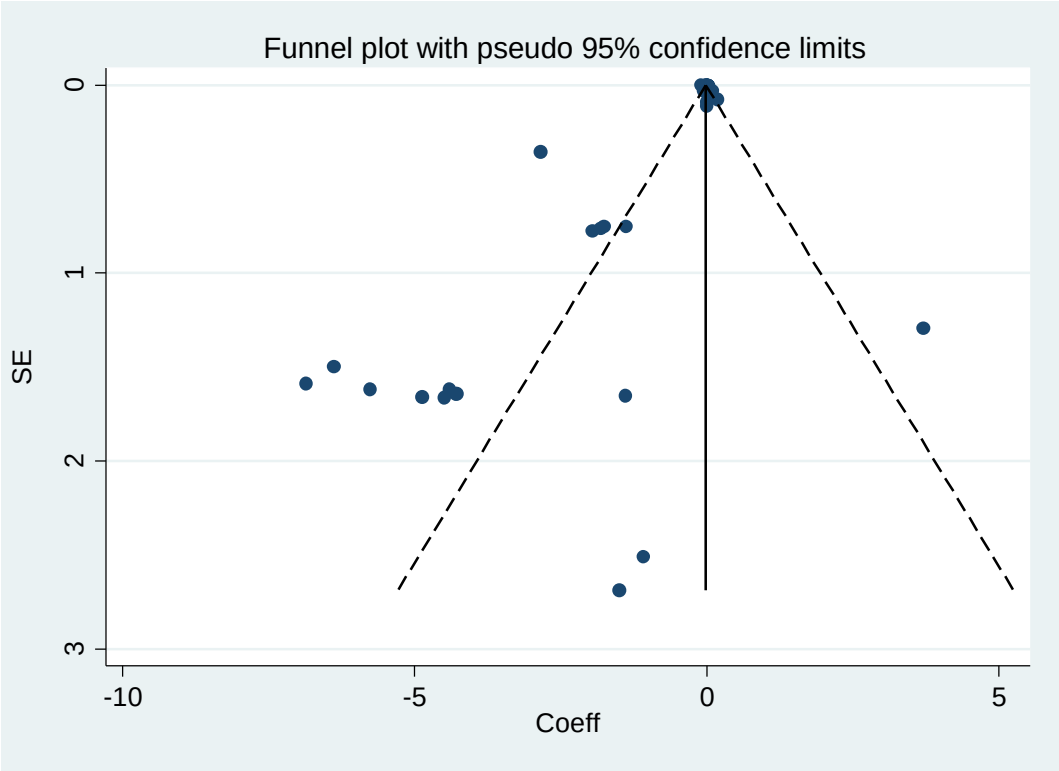


Figure 4. Funnel plot of the inequality estimates (Cross-country studies)



Appendix C: **Robustness check**

Table 7: Further robustness checks for the simple meta-regression models

	Best Set
	Weighted least squares (WLS)
Constant	0.0077414
	(0.0277238)
1/Se	-0.0058627
	(0.00901953)
Observations	25
Studies	25

Standard errors in parentheses.

Notes: Meta-response variable: t-stat. Best Set: each model provides one estimate or data point, the empirical result preferred by the author or with higher goodness of fit- that is, from each study – one estimate is taken.

Table 8

Robustness checks for the multivariate meta-regression models

	Dependent variable: t – statistic of the inequality estimate	
	WLS (All set)	Mixed – effects (Panel Countries)
Constant	-0.6180594	-0.3527711
	(0 .481071)	(1.472711)
1/se	0.0851874***	0.0005954
	(0 .0062337)	(0.0268375)
Data characteristics		
Panel data	-0.0204718*	0.028218
	(0.0120075)	(0.0253238)
Database	0.0252801***	-0.0075389
	(0.0073594)	(0.033064)
Specification characteristics		
Africa	-0.0623768***	-0.0078757
	(0.0132503)	(0.0132405)
Asia	-0.117588***	-0.1163822***
	(0.0053533)	(0.008753)
Latin America	-0.0460752*	-0.0545244
	(0.0250644)	(0.0508222)
Number of country	-0.0004373***	-0.0002897***
	(0.0000821)	(0.0000801)
GDP	0.0306922***	0.0335791***
	(0.005609)	(0.0073613)
FDI	-0.0232215***	-0.0380099***
	(0.0073422)	(0.0088592)
Pooled	-0.0607546***	-
	(0.0148313)	
Estimation characteristics		
OLS – 2SLS	-0.0068131*	0.0009963
	(0.0038719)	(0.0022914)
GMM	-0.0076346	-0.001692
	(0.0050776)	(0.002761)
Publication characteristics		
Deving	4.464187***	3.46669*
	(0.7021756)	(1.833757)
Citation	-0.014926	-0.0355604
	(0.0123217)	(0.0270561)
Published	-1.811512***	-1.969259***
	(0.4015019)	(0.4750942)
Adj R-squared	0.9751	
Observations	124	102
Studies	25	25

***p < 0.01, **p< 0.05 and *p< 0.10 . Standard errors and robust standard error in parentheses.

Notes: The table contains the results of regression equation (5). WLS: Weighted least squares (analytical weight is used). All set: All estimates of the primary studies are included in the estimation. Mixed – effects: Mixed effects multilevel model. Panel countries: Only cross – country studies are included in the estimation.