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Trade Openness and Income Inequality: Fresh Evidence Based on Different Inequality Measures

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Abstract

Theoretical and empirical literature on the impact of trade openness on income inequality is inconclusive. The inconsistent findings may be partly the result of biased measures of income inequality and divergent data sources. This paper improves upon the previous literature by examining the impact of trade openness on income inequality, using data from three major data sources: the Standardized World Income Inequality Database (SWIID), including disposable and market income; World Development Indicators (WDI); and the University of Texas Inequality Project (UTIP); as well as four Gini coefficients as measures of inequality. We apply a two-step system GMM estimation technique and the findings suggest a negative relationship between trade openness and income inequality. Based on the empirical results, we conclude that changing the

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measure of inequality from different data sources does not affect the empirical results related to the trade-inequality relationship.

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JEL Classification: D63, F14, F15, F63

1. Introduction

Economic theory related to international trade argues that trade openness increases a society's overall welfare by driving economic growth. Like many newly-industrialized nations (NICs), South Korea, Singapore, Taiwan, and Hong Kong have managed to sustain their economic growth rates, using trade openness as a major driving force for encouraging economic growth (Todaro & Smith, 2015). Similarly, after the 1980s, trade openness increased among nations throughout the world. In the process, new, growing economies, such as those of India, Indonesia, and others throughout Latin America started to appear, all of whom substantially increased their trade activity. China's economy stands as yet another leading example of this, having opened after the 1980s and sustaining its growth rates to date. Assuming that trade openness stimulates economic growth, however, the benefits of trade openness may not be equally distributed among the members of society. That is, it may affect different segments of society differently. Heckcher Ohlin (H-O) theory, one of the prominent theories of international trade, shows that when a given country has a comparative advantage in the provision of a service or production of certain good in which it is relatively well endowed, it will export that good or service. As explained by the Stolper Samuelson theorem, trade openness causes an increase in the price of a good that is produced using relatively abundant factors.

Since the 1970s, income inequality has increased in the United States (US). This has spurred recent anti-income-inequality movements in US and could be one of the factors contributing the US' recent imposition of tariffs on Chinese imports. However, Ravallion (2018) argues that inequality within nations depends on an initial set of conditions present in the economy. Just as China no doubt increased its growth through globalization, lower inequality in China was the result of simultaneous reforms. Similarly, South Korea has made simultaneous investments in improving its infrastructure, including institutions of health and education.

Because the above debate is never-ending, empirical evidence may provide the only definitive answers regarding the extent to which trade openness increases inequality. Sadly, empirical evidence also remains inconclusive on this issue. Empirical results vary with changes in measures of inequality, different econometric techniques yield different results when they rely on different data sources, and the use of different proxies for openness can also have an impact on empirical results. In this study, we attempt to see the empirical relationship between trade and inequality by looking into one of the above aspects that causes changes in empirical results. We try to see whether changing the measure of inequality from different data sources affects the trade-inequality relationship. The following sections discuss the contribution of the study.

As highlighted above, the empirical evidence shows contradictory results regarding the relationship between trade openness and income inequality. Some studies show positive results, some negative, and some show an insignificant relationship. There are various possibilities that empirical studies yield contradictory results. Among them, one is that the change in income inequality datasets may affect the results. In addition to this, different data sources reach one specific measure of inequality, which is the Gini coefficient, but the different datasets may not be comparable because they measure income inequality (Gini coefficient) using different income concepts and equivalence scales. Even if two datasets use similar income concepts and equivalence scales, they may not be comparable because they may vary in their data collection methodology. Hence, using different data sources and measures of inequality may affect empirical results.

The current study estimates the relationship between trade openness and income inequality using income inequality (Gini coefficient) data from three major sources; namely, World Development Indicators (WDI), University of Texas Inequality Project (UTIP), and Standardized World Income Inequality Database (SWIID), and four measures of inequality to determine whether the results are altered by changing the measure of inequality from different datasets. To the best of our knowledge, past studies have not compared results using different data sources to examine the relationship between trade openness and inequality. This study also uses updated data for an increased number of country-year observations. This is possible due to the recent availability of inequality data from a larger set of countries and time periods.

The objective of this paper is to investigate the relationship between trade openness and income inequality by using income inequality data from three major data sources (SWIID, UTIP, and WDI) and four measures of inequality. In doing so, we analyze whether the results are data-driven, meaning that numerous measurement errors could possibly provide biased results, or whether the data provides estimates that show the true relationship between trade openness and income inequality.

The remainder of this paper is organized as follows. In section 2 the literature is reviewed, and in section 3 we discuss the data. Our results are discussed and analyzed in section 4, and we provide our conclusion in section 5.

2. Literature Review

This section reviews theoretical and empirical literature on how trade openness is related to income inequality. Despite its limitations, Heckcher Ohlin (H-O) can help demonstrate the effect of trade openness on inequality within a given country (O'Rourke, 2002). Assuming costless mobility of factors of production from one industry to another, the H-O theory argues that a country will export that good which is produced using relatively abundant (cheaper) factors of production (Krugman & Obstfeld, 2009). Consequently, inequality increases in a country exporting a good using abundant factor of production (O'Rourke, 2002).

In contrast to the H-O theory, the Specific Factors Model assumes that factors of production cannot move from one industry to another. As a result, trade openness reduces the price of import-competing factors and increases the price of export-competing factors of production. Hence, if wages of workers in the export sector are higher, trade openness increases income inequality.

Harrison, McLaren and McMillan (2010) show that it is not always necessary for countries to be involved in the export of finished products as both of the aforementioned theories assume. For practical reasons, it is possible that firms in a home country may assign production tasks to workers from foreign countries (Feenstra & Hanson, 1996). Countries with relatively skilled labor have relatively expensive labor and countries with relatively unskilled labor have relatively cheap labor. If there are no trade barriers, meaning that both countries can move capital to other countries, firms from the home country, where labor is skilled, will offshore their lower-skilled tasks to foreign countries. In this way, firms can reduce their production costs. This reallocation of relatively lower-skilled tasks from our “home” country to a “foreign” country will reduce the demand for low skilled labor at home, hence the wages, while the opposite is true for relatively high-skilled labor. Unlike the H-O theory, this theory assumes that this kind of trade openness will increase income inequality in both countries. As a result, the production tasks may be less skill-intensive for the home country while becoming more skill-intensive for the foreign country. Therefore, trade openness will increase the demand for skilled labor in both countries, thus generating inequality.

The Stolper Samuelson theorem assumes that capital and labor are immobile across international borders. However, if we relax this assumption, we come across an important implication of the theorem. Jaumotte, Lall, and Papageorgiou (2013) argue that if we assume that capital is mobile across countries, then the Stolper Samuelson theorem is weakened. Such mobility would lead to foreign direct investment (FDI) inflows into high-skilled sectors in the country that is the beneficiary of the investment. However, the FDI outflows may be less skill-intensive for the sending countries. The distribution of income of the recipient country would depend on financial institutions. If the financial institutions are strong, it would lead to opportunities for the majority of the population. If the financial instructions are weaker, only a limited number of individuals would benefit from the FDI inflows. This, then, would increase income inequality.

Theoretical literature establishes the ambiguous impact of trade openness on income inequality. O'Rourke (2002) argues that this relationship can be confirmed using empirical evidence, yet the empirical evidence yields inconclusive results (Heimberger, 2020).

One of the earlier studies (Spilimbergo, Londono & Szekely, 1999) investigates the link among factor endowments, trade, and inequality using data on personal income distribution, Gini coefficients from (Deininger & Squire, 1996), and different measures of trade openness from 320 country-year observations for 34 countries. They argued that between trade openness and income inequality depends on factor endowments, pointing to a positive relation between their measure of trade openness and income inequality. These findings run counter to the claims of the H-O theory. Further, they used quantile shares as a measure of inequality and show that trade openness seems to affect different distributions of quantiles differently through the effects of factor endowment. As a result, we see that the findings are sensitive to the change measures of openness.

In contrast, Lundberg and Squire (2003) use a similar dataset of Gini coefficients from Deininger and Squire (1996) with 757 country-year data points from 125 countries. They use the Sachs-Warner openness index as an indicator of trade openness. Their results show that trade openness increases income inequality. Similarly, Barro (2000) identifies a positive relationship between trade openness and income inequality. He uses a dataset developed by Deininger and

Squire (1996) on Gini coefficients from 1965 to 1995 and measured trade openness in terms of trade, i.e., the growth rate of the ratio of prices of exports to imports. Barro (2008) shows that trade openness (measured in terms of trade share) leads to higher income inequality, though the effect is modest.

Contrary to the above evidence, Zhou, Biswas, Bowles, and Saunders (2011) used the United Nations University World Institute for Development Economics Research (UNU-WIDER) dataset (World Income Inequality Database or WIID2 version) on Gini coefficient data from 1950 to 2001 for 60 countries and used the Kearney Index to measure globalization. They concluded that globalization tends to decrease inequality within countries. However, they do not show which component of globalization has contributed more, nor do they specify whether the reduction in inequality within a country occurs in developed or developing countries. Jaumotte et al. (2013). separate the effect of three different components of globalization-- trade openness, financial globalization, and technology--using Gini coefficient data from the World Bank Povcal database from 1983 to 2003 for 51 countries. Their results show that trade openness measured in terms of tariff reduction tends to reduce income inequality while financial globalization tends to increase income inequality. Their results show that technological progress has a greater impact on income inequality than globalization. Both trade openness and financial openness have offsetting impacts. Similarly, Asteriou, Dimelis, and Moudatsou (2014). separately tested the impact of trade openness and financial globalization on income inequality for 27 European Union countries from 1995 to 2009 by exploiting the Generalized Methods of Moments (GMM) econometric technique. They used trade share as a measure of trade openness and Gini coefficients from EUROSTAT-SILC.

3. Data

Table 1 provides coverage details of all major available datasets on inequality from original sources while Table 2 provides the summary statistics of select datasets from original sources. In Table 1, one can see that the largest number of country-year observations is provided by the UNU-WIDER with 11,054 while SWIID provides the second-greatest total in terms of countries covered and observations with 176 and 5,093, respectively. The lowest number of observations comes from the European Union Statistics on Income and Living Conditions (EURO-SILC) with just 103, while the lowest number of countries is covered by Socio-Economic Database for Latin America and the Caribbean (SEDLAC) with 23.

Table 1: Data coverage of different datasets on inequality

Data Source	Number of Observations	Countries covered	Time period covered
SWIID	5,093	176	1960-2019
UNU-WIDER	11054	187	1867-2017
WDI	1,456	153	1979-2017
UTIP-UNIDO	4277	143	1963-2015
WID	1463	60	1960-2014
LIS	345	42	1967-2017
EURO-SILC	103	28	2005-2008
SEDLAC	319	23	1974-2014

Source: Authors' compilation from various data sources

Table 2: Summary statistics of five-year average Gini coefficients from selected data sources

Variable	Obs	Mean	Std. Dev.	Min	Max
UTIP Gini	768	43.357	6.454	27.509	62.032
WDI Gini	581	39.768	9.039	24.38	65.8
SWIID Disposable Gini	945	37.921	8.504	18.94	62.35
SWIID Market Gini	945	46.084	6.503	21.9	70.7
WIIDER Gross Income Equiv. Gini	152	39.673	10.115	22.367	71.2
WIIDER Gross Income per capita Gini	152	39.671	10.113	22.367	71.2
WIIDER Net Income Equiv. Gini	282	32.386	7.932	18.9	65.7
WIIDER Net Income Per capita. Gini	296	39.381	11.728	19.1	70.8

Source: Authors' calculation

Considering the UNU-WIDER dataset, it is important to separate the Gini coefficients based on their income concepts and equivalence scales. Finally, almost every study in the past has used the five-year average of inequality data because of the gaps in inequality data. As was argued earlier, those gaps could play a role in diminished comparability among the data. Additionally, we should note that countries that had three observations or less were excluded from this review. Above, Table 2 shows the five-year average of the Gini coefficients from all data sources. It indicates which datasets can be used practically for our regression analysis. From the five-year average we removed consumption data that already had a lower number of observations.

We can see that in all income categories, the UNU-WIDER's observations are substantially reduced, meaning that we may not be able to use this particular data in our analysis.

3.1 Justification for Selection of Datasets

We selected three datasets based on their availability and comparability. These datasets were: WDI, SWIID, and UTIP. This selection will likely reduce the biases of estimates as well as any sample selection bias. The UTIP was shortlisted because it provided the highest number of country-year observations compared to other datasets. Galbraith, Choi, Halbach, Malinowska and Zhang (2016) argue that the UTIP dataset is comparable because it has adjusted the Gini coefficients from disposable income and gross income while also adjusting for equivalence scales. Similarly, SWIID also provides the highest number of country-year observations. Solt (2016) argues that these inequality indices are highly comparable owing to their imputations being based on the quality standards of LIS. These Gini coefficients were then equalized using the equalized scale and adjusted for purchasing power parity exchange rates. As argued earlier WDI does not provide consistent Gini coefficient estimates since they are calculated using different income concepts, and comparability is lost due this problem. Despite this, Gini coefficients from WDI were still selected because of the elevated number of observations it provides as well as the fact that many past studies also used this dataset.

In using four measures of income inequality from three different data sources, the sample size changes with changes in inequality data. Therefore, country-year observations vary by data source. We have selected the data for our study from 1965 to 2019 based on the availability of the data. We used the five-year average of the data that reduced the time period by to 11 periods in total. As explained earlier, because the Gini observations are not consistent over this period of time, we used the five-year average of the time period to avoid the sample selection biases.

Trade openness is our main variable. We use the trade share as proxy for trade openness that is the sum of the absolute value of exports and imports divided by the GDP per capita in percentage terms. Barro (2008) also used the trade share as proxy for trade openness.

3.2 Controlled Variables

We also included controlled variables to capture the impact of the political economy argument. Argued by Knutsen (2015), it is possible that democracy may affect inequality.

Therefore, we employ a polity2 index from Polity data which ranges from -10 for full autocracies to +10 full democracies in order to assess the political circumstances associated with a given economy. Finally, the demography of a society can't be overlooked with respect to its impact on income inequality. Acar and Dogruel (2012) argue that larger families lead to higher income inequality in a society. To include the demographic characteristics of a society as controlled variable, we use the age dependency ratio as proxy variable. WDI calculate the age dependency ratio of the dependent population lower than age 15 and higher than age 64 from the total working age population. The data on all of the independent variables are taken from the WDI except for those otherwise specified. Table 3 and Table 4 report the descriptive statistics and correlation matrix of trade share and controlled variables.

Table 3: Descriptive statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Trade share	1084	72.547	47.338	4.297	414.562
GDP per capita	1084	11957.89	16951.25	226.384	107119.5
Polity2	1084	3.506	6.614	-10	10
Labor force with advanced education	346	78.948	6.751	56.32	100
Age dependency ratio	1081	67.694	19.491	16.847	112.846

Source: Authors' calculations using STATA 13 software.

Table 4: Correlation matrix

Variables	WDI Gini	UTIP Gini	SWIID disp. Inc. Gini	SWIID mkt. Gini	Trade share	GDP per capita	Polity2	Labor force with adv. edu	Age dep. ratio
Trade share	-0.428	-0.388	-0.469	-0.173	1				
GDP per capita	-0.413	-0.610	-0.572	0.030	0.334	1			
Polity2	-0.211	-0.440	-0.355	0.265	0.170	0.429	1		
Labor force with adv. edu	0.169	-0.051	0.091	0.211	-0.075	0.161	0.123	1	
Age dep. Ratio	0.273	0.494	0.370	0.046	-0.309	-0.179	-0.379	0.154	1

Source: Authors' calculations.

4. Empirical Results and Discussion

Fixed and random effects may not provide consistent estimates if the dependent variable is endogenous. If the regressor depends on its past values and its accumulative process, which can cause problems of endogeneity, then it is important to control for endogeneity to get consistent estimates (Labra & Torrecillas, 2018). GMM allow us to control for these endogenous effects by using lags of the dependent variable as a regressor that is instrumented by its lag values.

These internal moment conditions can be used in difference and levels. If the internal instruments are applied using the difference they are referred to as “difference GMM,” and if they use internal moment conditions in difference or levels they are known as “system GMM.” Both difference and system GMM can be used in one or two steps. The one-step estimation uses the homoscedastic weighted matrix for estimation, while the two-step estimation uses the heteroscedastic weight matrix (Labra & Torrecillas, 2018). Therefore, we shall use the two-step approach.

Further, considering the nature of our panel where we have limited time and numerous cross-sectional units, the GMM is ideal. Given that our panel is unbalanced, we adhere to the recommendations of Roodman (2009) as they relate to the use of orthogonal deviations. Orthogonal deviations use internal moment conditions in a way that subtracts the average of all future observations of a variable to help avoid the loss of data.

In using GMM, it is important to choose between two estimators. Bond, Hoeffler, and Temple (2001) argue that in autoregressive models pooled OLS estimates of lag-dependent variables are biased upward while fixed effects estimates are biased downward. Therefore, pooled OLS estimates should be considered as upper bound while fixed effects estimates should be considered as lower bound. Difference GMM estimates should be between the pooled OLS and fixed effects. If difference GMM estimates of a lag-dependent variable are below or close to fixed effects, they are downward biased, likely due to weak instruments. In this case, it is preferable to use the system GMM.

Equation 1 shows the dynamic panel data model for estimation. Where $Gini_{i,t-1}$ shows the lag of dependent variables, which will be treated as an endogenous instrument by its lag values and the rest of the other variables will be treated as strictly exogenous. In this case, we have four dependent variables. Therefore, equation 3 will be estimated four times.

$$Gini = \alpha_i + \theta Gini_{i,t-1} + \beta_1 TS_{it} + \beta_2 GDP_{it} + \beta_3 dem_{it} + \beta_4 HC_{it} + \beta_5 dep_{it} + \gamma_t + \mu_{it} \quad (1)$$

As was the case with our static models for robustness, we first employ the lag of a dependent variable to estimate equation 1 and later add the set of other controls one-by-one.

4.1 Results

Before we discuss the results of the estimators, it is important to choose between the difference and system GMM options, using the work of Bond et al. (2001) as a reference. First, we run the regression with pooled OLS with a lag of dependent variables as an additional controlled variable, subsequently running the regression for fixed effects. We then run regressions with the difference GMM using one- and two-step estimators. Finally, we run regressions with the one step and two-step system GMM estimators. The estimation results show that the difference GMM estimates are below the fixed effects for UTIP, SWIID disposable income, and SWIID market income, respectively whereas in the case of WDI, the two-step difference GMM estimates are close to fixed effects. Since the difference GMM estimates are biased and inconsistent as argued by (Bond et al., 2001). the system GMM is more appropriate. In addition, we apply Im-Pesaran-Shin (IPS) test, following Im, Pesaran, and Shin (2003) and found all variables employed in the model stationary.

Tables 5 through 8 show the estimation results of the two-step system GMM using all four Gini coefficients (WDI, UTIP, SWIID disposable income and SWIID market income) as dependent variables. Across three measures of inequality from Tables 5 through 7 and columns 4 and 5, the estimation results show that the coefficient of trade share remained negative and very low, ranging from 0.006 to 0.009. This implies that a 1% increase in trade share will reduce the Gini coefficient by 0.006 to 0.007. Looking at columns 1 through 3 in Tables 5 through 7, the coefficient of trade share remained insignificant. This probably shows the importance of other determinants of inequality that are not included in the models, which lead to omitted variable biases. Looking at Table 8, which used SWIID market Gini as dependent variables across all five specifications from column 1 to 5, the trade share remained insignificant. Here, one thing to be noted is that trade share remained negative across all the specifications.

Examining the other explanatory variables, the log of GDP per capita remained insignificant with WDI Gini coefficient as a dependent variable. The coefficient estimates of dependent variables remained highly significant but with different signs. With the UTIP Gini coefficient and SWIID disposable income Gini coefficient, we see a negative relationship. However, with SWIID market income Gini coefficient we see a positive relationship. Polity2 remained insignificant when WDI and UTIP Gini coefficients were used as dependent variables. This only remained significant and negative at the 5% level for SWIID disposable income in column 3. However, polity2 remained significant and positive for all the three specifications of SWIID market income Gini with a positive sign. This implies that democracy tends to increase market income inequality. Looking into the labor force, advanced education remained insignificant only in the context of the UTIP Gini coefficient. It is significant at the 5% level with a positive sign for the rest of the three Gini coefficients. Finally, looking at the dependency ratio, which only remained significant for the SWIID market income Gini, the results show that an increase in the dependency ratio tends to correspond with an increase in inequality, other factors held constant.

Moving toward the diagnostics test results from Tables 5 through 8 across different specifications; all variables remained jointly significant at the 1% level as shown by the F-test results. The most common problem in dynamic panel data models is instrument proliferation. We don't have this problem, given that the Hansen test probability results vary from 0.133 to 0.774 across all tables and specifications. Also, we can see that in all of the cases, the number of moment conditions is less than the number of groups. Hence, we cannot accept the Hansen test null hypothesis that over identification restriction applies. Looking into AR(2), the null hypothesis for the Arellano and Bond test for autocorrelation is that there exists no autocorrelation. For AR(2), prob>z should be greater than 0.05 and for AR(1) it should be less than 0.05. In Tables 5 and 6, the AR(2) results show that there exists no second order serial correlation. However, in Tables 7 and 8, which used the SWIID disposable income Gini coefficient and SWIID market Gini coefficient, respectively, the test results show that there exists second order serial correlation, but not first order.

Table 5: Two-step system GMM regression results with WDI income Gini coefficients as dependent variables

Variables	(1)	(2)	(3)	(4)	(5)
Leg of dependent variable	0.928***	0.896***	0.856***	0.851***	0.841***
	(0.074)	(0.083)	(0.087)	(0.027)	(0.027)
Trade share	-0.004	-0.006	-0.008	-0.009**	-0.009**
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Log of GDP per capita		-0.042	-0.252	-0.014	-0.023
		(0.170)	(0.247)	(0.140)	(0.136)
Polity2			0.065	-0.042	-0.032
			(0.045)	(0.040)	(0.041)

Labor force with advance education				0.065***	0.062**
				(0.024)	(0.025)
Age dependency ratio					0.011
					(0.016)
Constant	2.742	4.506	7.695	1.193	1.333
	(3.271)	(4.800)	(5.459)	(2.000)	(2.040)
No. of observations	426	426	426	241	239
No. of countries	112	112	112	94	93
No. of instruments	27	28	29	30	31
F-value	190.813	141.140	127.502	558.601	468.525
Prob>F	0.000	0.000	0.000	0.000	0.000
Diagnostic test results					
Ar(1) prob>z	0.005	0.006	0.944	0.069	0.069
Ar(2) prob>z	0.106	0.098	0.540	0.087	0.090
Hansen test prob>chi2	0.485	0.487	0.442	0.654	0.656
Difference in Hansen test Prob>chi2	0.432	0.439	0.442	0.614	0.630

Note: Standard errors in parentheses. *, ** and *** show the significance level at $p < 0.10$, $p < 0.05$ and $p < 0.01$ respectively.

Here we may conclude that the results from both of the tables are inconsistent due to this problem. Finally, from Tables 5 to 8 and across all specifications, F-test results show that all models are significant at the 1% level.

Table 6: Two-step system GMM regression results with UTIP income Gini coefficients as dependent variables

Variables	(1)	(2)	(3)	(4)	(5)
Lag of dependent variable	0.911***	0.916***	0.920***	0.785***	0.782***
	(0.031)	(0.028)	(0.028)	(0.024)	(0.031)
Trade share	-0.006***	-0.005**	-0.005**	-0.009***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log of GDP per capita		-0.226**	-0.197**	-0.480***	-0.545***
		(0.087)	(0.099)	(0.104)	(0.132)
Polity2			-0.007	-0.035	-0.039
			(0.013)	(0.072)	(0.069)
Labor force with advance education				0.028	0.034
				(0.020)	(0.021)

Age dependency ratio					-0.011
					(0.011)
Constant	4.702***	6.402***	5.986***	12.641***	13.527***
	(1.410)	(1.891)	(1.953)	(3.148)	(3.493)
No. of observations	646	646	646	238	238
No. of countries	111	111	111	71	71
No. of instruments	37	38	39	36	37
F-value	680.451	1266.533	1000.732	601.730	444.787
Prob>F	0.000	0.000	0.000	0.000	0.000
Diagnostic test results					
Ar(1) prob>z	0.000	0.000	0.000	0.001	0.001
Ar(2) prob>z	0.874	0.879	0.889	0.443	0.401
Hansen test prob>chi2	0.290	0.273	0.273	0.240	0.221
Difference in Hansen test Prob>chi2	0.209	0.223	0.245	0.150	0.152

Note: Standard errors in parentheses. *, ** and *** show the significance level at $p < 0.10$, $p < 0.05$ and $p < 0.01$ respectively.

Table 7: Two-step system GMM regression results with SWIID disposable income Gini coefficients as dependent variables

Variable names	(1)	(2)	(3)	(4)	(5)
Lag of dependent variable	1.033***	0.989***	0.994***	0.864***	0.862***
	(0.009)	(0.012)	(0.012)	(0.013)	(0.013)
Trade share	0.000	-0.001	-0.001	-0.006***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Log of GDP per capita		-0.019	0.023	-0.252***	-0.234***
		(0.034)	(0.039)	(0.073)	(0.087)
Polity2			-0.014**	-0.007	-0.005
			(0.006)	(0.017)	(0.017)
Labor force with advance education				0.029***	0.027***
				(0.007)	(0.007)
Age dependency ratio					0.004
					(0.007)
Constant	-1.188***	0.695	0.258	5.395***	5.276***
	(0.349)	(0.732)	(0.761)	(1.056)	(1.302)
No. of observations	815	815	815	336	334
No. of countries	130	130	130	110	109

No. of instruments	56	57	58	46	47
F-Value	9407.302	8076.539	6086.384	3015.629	2475.319
Prob>F	0.000	0.000	0.000	0.000	0.000
Diagnostic test results					
Ar(1) prob>z	0.769	0.758	0.772	0.268	0.259
Ar(2) prob>z	0.000	0.000	0.000	0.001	0.001
Hansen test prob>chi2	0.205	0.174	0.159	0.357	0.351
Difference in Hansen test Prob>chi2	0.135	0.185	0.198	0.474	0.480

Note: Standard errors in parentheses. *, ** and *** show the significance level at p < 0.10, p < 0.05 and p < 0.01 respectively.

Table 8: Two-step system GMM results with SWIID market income Gini coefficient as dependent variables

Variable names	(1)	(2)	(3)	(4)	(5)
Lag of dependent variable	0.918^{***}	0.916^{***}	0.918^{***}	0.790^{***}	0.775^{***}
	(0.011)	(0.010)	(0.011)	(0.022)	(0.025)
Trade share	-0.000	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Log of GDP per capita		0.127^{***}	0.113^{***}	0.224^{***}	0.391^{***}
		(0.024)	(0.034)	(0.067)	(0.102)
Polity2			0.007	0.050^{**}	0.059^{**}
			(0.009)	(0.023)	(0.023)
Labor force with advance				0.033^{***}	0.034^{***}
Education				(0.009)	(0.009)
Age dependency ratio					0.027^{**}
					(0.010)
Constant	3.904^{***}	3.028^{***}	3.005^{***}	4.952^{***}	2.508
	(0.505)	(0.572)	(0.670)	(1.239)	(1.554)
No. of observations	815	815	815	336	334
No. of countries		130	130	110	109
No. of instruments		47	48	41	42
F-value	3557.946	3300.169	2483.881	317.272	326.407
Prob>F	0.000	0.000	0.000	0.000	0.000
Diagnostic test results					
Ar(1) prob>z	0.489	0.452	0.448	0.101	0.087
Ar(2) prob>z	0.001	0.001	0.001	0.005	0.007

Hansen test prob>chi2	0.182	0.160	0.133	0.694	0.744
Difference in Hansen test Prob>chi2	0.140	0.109	0.112	0.723	0.743

Note: Standard errors in parentheses. *, ** and *** show the significance level at $p < 0.10$, $p < 0.05$ and $p < 0.01$ respectively.

4.2 Analysis of the Results

Looking into the fixed effects, the estimation results are similar to those noted in Barro (2008), who used data from UNU-WIDER, where the magnitude of the coefficient of trade openness remained very small and positive.

We used the two-step system GMM as our final estimation technique. With three dependent variables, our estimation results show that trade openness reduces income inequality though the magnitude of the coefficient remains very low. Our main explanatory variable only remained insignificant in the context of the SWIID market income Gini coefficient. Our results are consistent with recent literature, such as that of Jaumotte et al. (2013)., who used data on inequality from World Bank Povcal, and Asteriou et al. (2014), who used inequality data from EUROSTAT-SILC to glean similar results. Similarly, Bergh and Nilsson (2010) used SWIID data, Lin and Fu (2016) used WDI data, and Zhou et al. (2011). used UNU-WIDER inequality data to show that globalization tends to reduce income inequality.

Finally, our results were not impacted by a change to the set of controlled variables, and remained significant throughout most of the specifications and estimation techniques. Thus, we conclude that change in inequality measures from different data sources does not affect the relationship between trade openness and inequality. Our rationale for not changing the results can been seen in the correlation matrix between the dependent variables in part 3, section 3.6.2, where the correlation remained moderately-to-very high and positive.

With this in mind, it's important to reiterate that changes in estimation techniques can affect estimation results. In our case, the fixed effects estimation results show that trade openness tends to increase income inequality, results which are similar to those gleaned from the work of Barro (2008), who also used fixed effects. Likewise, Asteriou et al. (2014). also used GMM, and their results produced evidence in support of a negative trade-inequality relationship. Our results are also consistent with economic theory, in that if trade increases economic growth, then trade openness tends to reduce income inequality.

5. Conclusion and Recommendation

This paper investigates how changing measures of inequality from three data sources (WDI Gini coefficients, UTIP Gini coefficients, and SWIID Gini coefficients) and four measures of inequality can affect the relationship between trade and inequality. Consistent with previous literature (Bergh & Nilsson, 2010; Zhou et al. 2011; Jaumotte et al. 2013; Asteriou et al. 2014; Lin & Fu, 2016). we conclude that trade openness reduces income inequality, and changes in the measure of inequality do not affect the relationship between the two variables. Our research shows these results are robust in most of the specifications.

Based on these findings, it is recommended that the countries should open their economies in the interest of the trade of goods and services, and focus on the other determinants of inequality. Importantly, they should invest in the curbing of population growth as a means of reducing the age dependency ratio, given that, as demonstrated by our findings, an increase in dependency increases inequality. There are a few limitations of this study, such as the use of one proxy of trade openness, employing a five-year average rather than using annual data, and exploring the direct relationship between trade openness and income inequality instead of utilizing channels that could affect the relationship between these two variables. Further, the sample used in this study could also be skewed based on income levels. By addressing these limitations, future research can help policymakers better understand these issues in the interest of providing appropriate solutions to them.

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