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Educational Inequality versus Income Inequality: An Empirical Investigation

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Abstract: Using panel data from 101 countries between 1970 and 2010, this paper explores the dynamic interaction between educational and income inequalities by employing a panel VAR approach with system GMM estimates. The empirical evidence highlights that a more equal distribution of education has contributed significantly to reduce income inequality for low-, middle-, and high-income OECD countries. However, in the higher middle-income and high-income OECD countries, the significance of educational inequality disappears once the level of development, educational attainment and the degree of trade openness are included in the analysis. Further results reveal that an unfair distribution of income acts as a barrier to achieve a better distribution of education in the low- and middle-income economies. Specifically, in the low- and lower middle-income countries, educational inequality and income inequality accentuate each other and generate a vicious cycle of inequalities under all estimation techniques and control variables.

I INTRODUCTION

The persistence of high and rising income inequality with pervasive inequalities in access to quality education, nutrition and healthcare is one of the defining challenges of our time. Even though rapid globalisation and worldwide technological progress have offered many opportunities for the various segments of society, the advantage is still in favour of the rich. In this context, an unfair income distribution has become an obstacle to sustainable economic growth. In addition, the unequal distribution of opportunities has generated unprivileged

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sections of societies, causing social turmoil. Not surprisingly, the extent of inequality, its drivers, and what to do about it have been a growing concern for policymakers and researchers (Dabla-Norris *et al.* 2015; Piketty 2014).

Within this framework, the expansion of education is highlighted as an important policy tool to combat high and persistent income inequality. Although economic theories suggest that the distribution of income is determined by both the level and the distribution of education (Becker and Chiswick, 1966; Coady and Dzioli, 2018; Galor and Tsiddon, 1997; Glomm and Ravikumar, 1992; Saint-Paul and Verdier, 1993), the empirical literature associated with different structural frameworks, country samples, control variables, functional forms, data definitions, estimation techniques and time periods has suffered from inconsistent results. While an extensive array of empirical literature has supported the vital role of educational inequality in income inequality (De Gregorio and Lee, 2002; Lee and Lee, 2018; Castelló-Climent and Doménech, 2017; 2021; Coady and Dzioli, 2018 for emerging developing countries; Park, 1997; Földvári and Leeuwen, 2011 only OECD; Becker and Chiswick, 1966; Ahluwalia, 1976), the contributions by Ram (1989), Földvári and Leeuwen (2011), Dabla-Norris *et al.* (2015) and Bourguignon *et al.* (2004) have questioned these results by finding a negative but insignificant impact of educational inequality on income inequality.

An interesting recent finding by Castelló-Climent and Doménech (2017; 2021) is that a significant proportion of the variation in income inequality remains unexplained in spite of declining educational inequality. In this context, the puzzling persistence of income inequality has been attributed to skill-biased technological progress, globalisation, increasing returns to education, declining labour market institutions and policy failures (Földvári and Leeuwen, 2011; Dabla-Norris *et al.*, 2015; Lee and Lee, 2018; Castelló-Climent and Doménech, 2017; 2021). All these factors are expected to be responsible for shifts in the demand for skilled labour in a way that favours skilled workers and, in turn, increases wage inequality (Acemoğlu, 1998; Goldin and Katz, 2009). Similarly, the World Bank's Global Economic Prospects, published in 2018, points out the important effect of changing skill compositions of workers on the income distribution. Globalisation and technological progress, which are considered the main reasons for the rising skill premium, are likely to be two of the major drivers of high and persistent income inequality. Within this framework, while expansions in educational attainment and reductions in educational inequality act as a social equaliser, income inequality is largely determined by the effects of technology (a determinant of skilled-labour demand) and education (a determinant of skilled-labour supply), exerted on the relative wages (Tinbergen, 1975).

Globalisation, which is generally approximated by the degree of trade openness, has been seen as a reason for the changing demand for skilled workers. However, empirical work on the link between trade liberalisation and inequality are not conclusive. While some studies argue that increasing trade openness may decrease income inequality (Reuveny and Li, 2003; Dollar and Kraay, 2004), another strand of the literature states the opposite and argues that trade openness is actually associated with increasing income inequality (Easterly, 2005; Milanovic and Squire, 2005; Bensidoun *et al.*, 2011; Lin, 2007 for Taiwan; Zakaria and Fida, 2016; Dutt and Mukhopadhyay, 2008). A new trade theory, supporting this second group of empirical studies, suggests that income inequality may rise after trade liberalisation because rising imports of new technology increase the demand for and returns to skilled workers. In addition, Goldberg and Pavcnik (2007) survey the literature on this issue and demonstrate that globalisation worsens the income distribution. To this end, while examining the empirical link between educational and income inequality, one of the aims of this paper is also to incorporate all such factors possibly leading to a rising skill premium.

Furthermore, this paper also aims to address the vicious cycle of inequalities. Even though a fair distribution of education is vital to reduce high and persistent income inequality, it is not always possible for all segments of society to reap the benefits of education as skill development is prohibitively costly for the poor (Aghion *et al.*, 1999; Checchi, 2001; Dabla-Norris *et al.* 2015; Galor and Zeira, 1993). Thus, these two types of inequalities accentuate each other, and the circular causal relationship between the lack of education and the lack of income generates a self-perpetuating inequality trap (Rao, 2006; Bourguignon *et al.*, 2004). However, there is no consensus in the literature on the issue of whether income inequality causes human capital inequality or, alternatively, educational inequality results in income inequality. Against this backdrop, this paper tries to understand the direction of the link between educational and income inequalities.

To address the aims listed above, this paper empirically investigates the interaction between educational and income inequality and uses a panel dataset from 101 different countries between 1975 and 2010. In the empirical analysis, a panel vector autoregression (VAR) approach with system Generalized Method of Moments (GMM) estimates is adopted. Because empirical studies examining the nexus between educational inequality and income inequality are plagued by problems associated with heterogeneity, endogeneity and omitted variable bias, as well as inadequate proxies for education and income inequality and limitations in the econometric techniques, this paper addresses these issues to add new insights to the debate as a supplement to the existing literature. The paper explores the dynamic relationship between income inequality and educational inequality by using a panel VAR approach that incorporates longitudinal and cross-sectional dimensions of the data points. The advantage of using a panel VAR system is that all variables are treated as endogenous, and each variable is expressed as a function of its own lags and the lags of other related variables. In addition, testing the joint significance of the lagged values of one variable permits us to check whether or not that specific variable has any predictive power on the other variables in the system. Specifically, panel VAR models consider both the average level and the dispersion of income as determinants of educational inequality. At the same time, it detects both the average level of schooling and the dispersion of education as determinants of the income distribution. Therefore, this technique is compatible with theoretical models on inequality issues.

The contribution of this paper to the literature is fourfold. First, even though the inevitable role of educational inequality in income inequality is discussed widely, there is yet no consensus on the endogenous interaction between these two types of inequalities. No other study to date performs panel causality tests based on a panel VAR system to assess the dynamic relationship between two types of inequalities. This paper is the first attempt to fill this void in the literature. Second, this paper enriches the existing analysis by applying panel causality tests based on the system GMM estimates, in addition to the panel VAR system. System GMM methodologies allow us to take better care of possible problems associated with small samples, omitted variables, persistence, and endogeneity. Third, the countries in the sample are classified into four income groups: high-income OECD countries (HOCs), higher middle-income countries (HMICs), lower middle-income countries (LMICs), and low-income countries (LICs).[1] This allows us to better understand how the dynamic setting works in different income groups. Fourth, the panel VAR model of this paper is estimated by controlling for educational attainment, the level of development and the degree of trade openness.

The robustness of our findings is explored in three directions. First, the panel VAR framework used in this paper is estimated with fixed effects in addition to the system GMM estimators. Second, robust regression techniques are introduced to control for the influence of outliers. Third, the panel VAR framework is estimated with alternative time lags. The empirical findings are robust to the alternative measures of income inequality, alternative techniques, and alternative control variables.

The main results of the paper can be summarised as follows. First, the association between educational inequality and income inequality is not stable across country groups. The findings suggest that a better distribution of education reduces income inequality for all samples without control variables. However, in the HMICs and HOCs, the econometric estimates start to display negative but insignificant coefficients for educational inequality once the level of development, educational attainment and the degree of trade openness are included into the analysis. In particular, the coefficient on trade openness is positive and significant in the HMICs and HOCs. That is, the race between technological developments through the expansion of trade flows and education reduces the positive effects of educational inequality on income inequality. This important finding not only supports Tinbergen's (1975) arguments on income inequality, but also sheds light

[1] Based on the values of their GNI per capita, the World Bank classifies countries into four categories, namely, low-income, lower middle-income, higher middle-income and higher-income.

on the puzzling link between educational and income inequalities mentioned by Castelló-Climent and Doménech (2017; 2021). Further results reveal that high and persistent income inequality affects the distribution of education in the LICs and LMICs. In these regions, educational inequality and income inequality feed each other and generate a vicious cycle of inequalities under all estimation techniques and control variables.

The roadmap of the rest of the paper is as follows. While the next section introduces the data, Section III explains the empirical methodology. Section IV presents the key results of the panel VAR model. Section V provides policy implications and conclusions.

II DATA

The dataset consists of a panel of annual observations for 1970-2010 and 101 countries, where 32 of them are HMICs, 21 of them are LMICs, 14 of them are LICs and 34 of them are HOCs. We measure income inequality with the net income Gini coefficient taken from the Standardized World Income Inequality Database (SWIID), version SWIID v7.1, which uses a custom missing-data algorithm to standardise the World Income Inequality Database (WIID) from the database of the Luxembourg Income Study (LIS). The SWIID maximises the comparability of income inequality data while maintaining the broad coverage of countries over time. The data on educational inequality are taken from Castelló-Climent and Doménech (2017; 2021). Their study was the first to provide a comprehensive dataset on educational inequality by using educational attainment levels from Barro and Lee (2001) and calculating the Gini coefficient and the distribution of education in quintiles for a large number of countries and for a long period. Since the data on educational inequality and attainment have been constructed for five-year averages, estimations are based on eight five-year periods for 101 countries.[2]

In this paper, additional control variables are introduced to check the sensitivity of the results. In this context, real GDP per capita and trade openness (ratio of exports plus imports to GDP) come from the World Development Indicators Database; and a measure of average years of schooling, as a proxy for educational attainment, is taken from the dataset of Barro and Lee (2013).

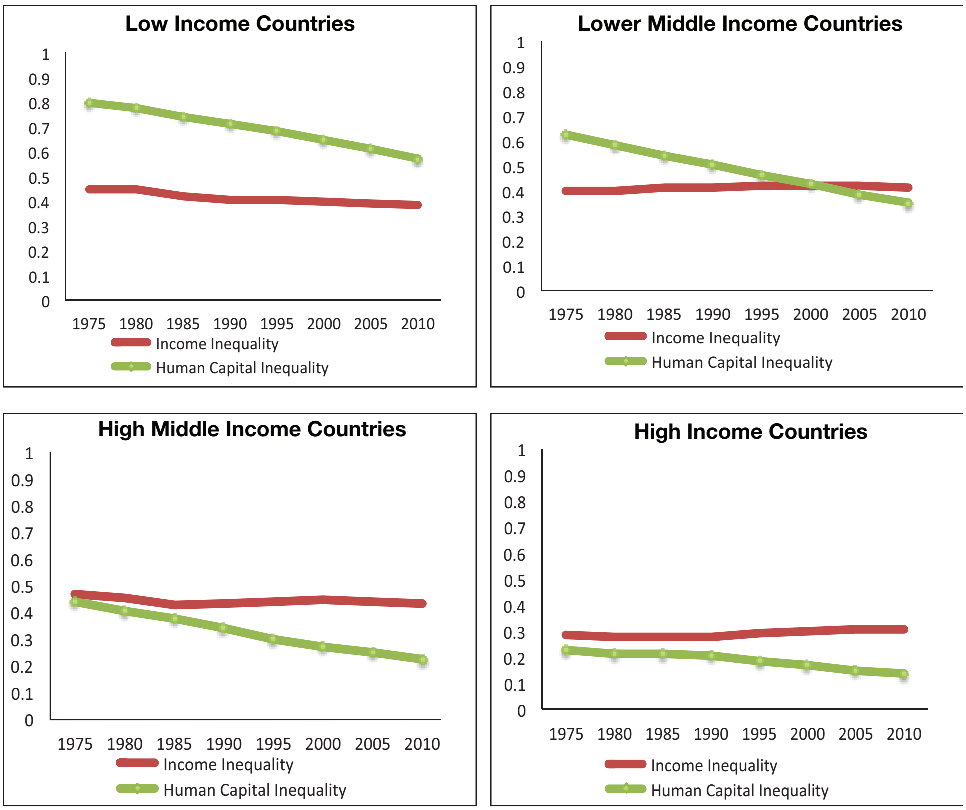
Figure 1 plots the evolution of income inequality and educational inequality for the LICs, LMICs, HMICs and HOCs. Over the past decades there has been a notable reduction in educational inequality in all income groups. Castelló-Climent and Doménech (2017; 2021) reveal that this marked decline in educational inequality is due to a sizeable drop in the illiterate population. According to

[2] This analysis uses five-year averages since no other database reports educational inequality annually.

Figure 1, average educational inequality is higher than income inequality in the LICs and LMICs. Although educational inequality declined, income inequality scarcely changed in the LICs and LMICs. Due to declining educational inequality and stable income inequality, the gap between the average values of these two measures of inequality narrows in both income groups. In the LMICs, it is observed that average income inequality became greater than educational inequality after the 2000s. While income inequality fluctuated around 0.4, educational inequality fell from 0.8 to approximately 0.5 in the LICs. Similarly, in the LMICs, educational inequality fell approximately from 0.6 to 0.3, but income inequality was mostly stable around 0.4.

For the HMICs, Figure 1 illustrates that income inequality fell slightly from 1975 to 1985 but started to increase again after the end of the 1980s. Educational inequality fell approximately from 0.45 to 0.2. This marked decline in educational inequality is not accompanied by reductions in income inequality. In

Figure 1: Development of Educational Inequality and Income Inequality



Source: Own calculation based on SWIID and Castelló-Climent and Doménech (2017; 2021).

addition, the gap between income inequality and educational inequality has widened since the 1990s. On average, the HOCs have the lowest inequality in the distribution of education and income. According to Figure 1, income inequality fluctuated between 0.25 and 0.3, while educational inequality continuously fell from 0.2 to 0.1. However, as in the HMICs, educational and income inequality evolved in a different manner over the last decade in the HOCs.

Overall, two major trends are observed in Figure 1. First, the educational inequality levels have been continuously declining without any significant improvements in the income inequality levels for all samples. Second, the educational inequality and income inequality levels have been diverging in the HMICs and HOCs, while they have been converging in the LICs and LMICs. This different behaviour of educational inequality and income inequality in the last decade across income groups can be explained in part by fast income growth, trade expansions and rapid technological progress (Lee and Lee, 2018). Trade expansions and technological improvements have increased the relative demand for skilled labour and raised the relative earnings of skilled workers. Thus, the expected-to-be close link between education and income has been questioned due to changes in the relative demand for skilled workers.

These observations on Figure 1 support Tinbergen's hypothesis for the HMICs and HOCs. Tinbergen (1975) states that inequality is determined by the race between education and technology. Figure 1 highlights that the gap between educational inequality and income inequality became larger in the HMICs and HOCs. This could be in part explained by the race between education (supply of skill) and technology (demand for skill) which accelerated in the early 1990s. Goldin and Katz (2009) support Tinbergen's hypothesis and demonstrate that, when education races ahead of technology, the relative wages of skilled to unskilled workers fall, and income inequality declines. However, they also state that the relative wages of skilled to unskilled workers and inequality increase if improvements in technology speed up with education falling behind. As this happens, the expansion in education cannot be sufficient to meet the high demands of new technology. That is the reason it is always important to take into consideration the possible factors behind the changing demand for skilled workers, while investigating inequalities. In particular, trade liberalisation, which has played an important role in the distribution of skills across jobs, should be a variable of considerable interest while discussing the vicious cycle of education and income inequality. Empirical results suggest that, in addition to trade liberalisation, skill-biased technological change and the expansion of education are the mechanisms that can boost the skill premium (Acemoğlu, 1998; Autor, 2014; Goldin and Katz, 2009; Xiao, 2019; Wood, 1997; Bourguignon *et al.*, 2004; Lindquist, 2005; Bergh and Nilsson, 2010; Carter, 2007; Berggren, 1999). Therefore, together with the trade liberalisation variable, a variable capturing the expansion in educational attainment is also included as a control variable in the panel VAR model. Furthermore, the level of development, which is proxied by the level of average income, is included as an additional control variable.

III METHODOLOGY

A time stationary VAR model is adopted, following Hartwig (2010) and Holtz-Eakin *et al.* (1988) to examine the endogenous interaction between educational and income inequality. The panel VAR model, which is commonly used in panel-data econometrics, has the following form:

$$y_{it} = \alpha_0 + \sum_{j=1}^{m} \alpha_{1j} y_{it-j} + \sum_{j=1}^{m} \alpha_{2j} x_{it-j} + \sum_{j=1}^{m} \alpha_{3j} z_{it-j} + \mu_i + u_{it} \tag{1}$$

$$x_{it} = \beta_0 + \sum_{j=1}^{m} \beta_{1j} x_{it-j} + \sum_{j=1}^{m} \beta_{2j} y_{it-j} + \sum_{j=1}^{m} \beta_{3j} z_{it-j} + \eta_i + v_{it} \tag{2}$$

where y represents income inequality (giniY), x represents educational inequality (giniHC) and z presents the set of control variables. There are N countries indexed by i and T periods indexed by t. μ_i and η_i are individual fixed effects u_{it} and v_{it} and are white noise errors. m is the number of lags used in the estimation of the VAR model. In this context, the model is estimated by Ordinary Least Squares (OLS), where the choice of the optimal lag length is determined by both Akaike Information Criterion (AIC) and Schwarz Information Criteria (SIC), which reveal 2 as an optimal lag length.

According to the definition of Granger causality, a stationary time series x is said to predict another stationary time series y, if the lagged information on x provides any statistically significant information about y in the presence of lagged values of y. Within this framework, the panel VAR approach, through testing the coefficients on the lagged educational inequality variable, allows us to determine whether the improvements in educational inequality can predict income inequality or whether the lagged effects of income inequality can predict the improvements in educational inequality. Prior to the panel VAR regressions, standard panel unit root tests are performed to check the stationarity of variables.[3]

To address the problems associated with the persistence of the income inequality variable, the endogeneity of the educational inequality variable, serial correlation and heteroskedasticity, the parameters of the dynamic panel model given in Equations (1) and (2) are estimated by a system GMM estimation method (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998).

[3] Due to the lack of space, the panel unit root tests are not reported but they are available upon request. Based on these test results, because all variables are non-stationary, they have to be represented in their first differences in the regressions.

However, the basic weakness in system GMM estimations is the use of too many instruments which may lead to misspecification of a model. In this context, for valid instruments, the methodology suggested by Roodman (2009) has been followed. First, a high p-value of the Hansen test is preferred rather than the conventional level of 0.05. Second, the "collapse" option available in Stata v.12 is used to limit the proliferation of the instruments. The consistency of the system GMM is mainly checked by Hansen and Arellano-Bond (2) tests. While the former test focuses on the correct specification of the instruments, which is robust to heteroscedasticity, the latter test checks the possible existence of a second order serial correlation in residuals. Further, for the validity of additional moment restrictions necessary for a system GMM, the Difference-Hansen test is also reported. The econometric analysis of this paper relies on both Arellano and Bond's one-step and two-step system GMM estimation techniques. In the two-step system GMM estimates, Windmeijer's (2005) method for small sample correction is utilised. Finally, the existence of possible linkages between educational and income inequalities is investigated by running Wald tests on the coefficients on the lagged values of giniY and giniHC to check whether they are jointly statistically different from zero or not.

The robustness of the econometric analysis is explored in four ways. First, fixed effects (FE) are employed to estimate the parameters of Equations (1) and (2). Second, to control for the influence of any outliers, robust regression techniques (RREG) are exploited. Gross outliers are eliminated in cases where Cook's distance measure is greater than one, and by iteratively down-weighting observations with large absolute residuals. Third, the parameters of Equations (1) and (2) are re-estimated by using different lag orders. Since the data are comprised of eight five-year averages, three lags at most are included in the panel VAR regressions. Fourth, a set of control variables – in line with the previous studies – and time dummies are introduced to test the sensitivity of the results.

IV EMPIRICAL FINDINGS

Table 1 presents the empirical results on the interaction between educational inequality and income inequality for 101 countries spanning over eight five-year periods under AB two-step GMM estimates. The first column in Table 1 reports the estimates of Equation (1) for the whole sample. The coefficient on educational inequality is positive and significant. The corresponding Wald test reported at the end of Table 1 highlights that the causality runs from educational inequality to income inequality. The second column in Table 1 reports the estimates of Equation (2) where the dependent variable is educational inequality. The coefficient on income inequality is positive and significant. The Wald test shows that income inequality causes educational inequality. The third and fourth columns repeat the same analysis including a set of control variables. When the control variables are included, neither average years of schooling nor educational inequality has a positive and significant influence on the distribution of income.

Therefore, the causal channel running from educational inequality to income inequality disappears. The third column of Table 1 underlines that expansions in trade and average income affect the distribution of income, given positive and significant coefficients for the degree of trade openness and average income. Further, the last column of Table 1 focuses on the impact of income inequality on educational inequality. Income inequality has a positive and significant influence on the distribution of education. Among the control variables, only average years of schooling has a significant role in reducing educational inequality. Even though the empirical results do not reveal positive and significant coefficients for trade and average income, expansions in trade and income may have negative effects on the distribution of education indirectly by affecting income inequality.

Since the dynamic association between educational and income inequality is expected to be heterogeneous across different income groups, the sample is split into four income groups based on the World Bank classification: LICs, LMICs, HMICs and HOCs, as defined in Introduction. This leads us to derive different policy recommendations for different income groups. In addition, as studies on the relationship between education and income inequality for LICs and LMICs have been very scant, this paper fills the void in the literature by allowing a comparison across different income groups. Tables 2-4 present the regression results for LICs, LMICs, HMICs, and HOCs.

The first column in Table 2 presents the estimates of Equations (1) and (2) for the LICs. The coefficient on educational inequality is positive and significant according to AB two-step GMM estimates. The Wald test, reported at the bottom of panel A in Table 2, reveals that the causality runs from educational inequality to income inequality. Therefore the econometric evidence provided in panel A in Table 2 indicates that educational inequality has predictive power for income inequality under the AB two-step GMM estimates. Panel B in Table 2 focuses on the estimation results investigating the effect of the income inequality on educational inequality (dependent variable) in the LICs. The coefficient on income inequality is positive and significant under AB two-step GMM estimates. The Wald test, reported at the bottom of panel B in Table 2, reveals that income inequality causes educational inequality in the LICs. Thus, panel A and panel B in Table 2 highlight the bi-directional (dual) causality between educational inequality and income inequality: a reduction in educational inequality could be possible with a fairer distribution of income; and, similarly, income inequality could be reduced with a more equal distribution of education. There exists a vicious cycle for these two inequalities in the LICs.

Table 1: Interaction Between Educational Inequality and Income Inequality for all Countries

	(1)	*(2)*	*(3)*	*(4)*
Dependent Variable	*dGiniY*	*dGiniHC*	*dGiniY*	*dGiniHC*
L.dginiY	0.944***	0.060*	0.464**	0.701***
	(0.019)	(0.030)	(0.217)	(0.212)
L2.dginiY	0.171	0.004	–0.253	–0.588
	(0.139)	(0.017)	(0.158)	(0.491)
L.dginiHC	0.082***	0.620**	0.055	0.155**
	(0.030)	(0.268)	(0.129)	(0.0597)
L2.dginiHC	0.174	–0.334	0.084	0.354***
	(0.293)	(0.298)	(0.094)	(0.118)
L.ays			0.002	–0.0191*
			(0.008)	(0.0113)
L2.ays			–0.006	0.00078
			(0.010)	(0.0041)
L.trade			0.0007	0.00053
			(0.0004)	(0.0011)
L2.trade			0.00021*	0.00543
			(0.0001)	(0.0047)
L.gdp			0.0018*	0.00435
			(0.0010)	(0.0033)
L2. gdp			0.0012*	–0.00371
			(0.0007)	(0.0028)
N	101	101	101	101
T	8	8	8	8
Hansen test (p-level)	0.477	0.540	0.315	0.342
Difference Hansen test (p-level)	0.527	0.715	0.522	0.518
AB test (p-level)	0.202	0.765	0.476	0.853
Wald test (p-level)	0.009	0.012	0.535	0.001

Source: Author's analysis.
Note: Arellano Bond two-step system GMM estimates are reported. dginiY – Change in income inequality. dginiHC – Change in educational inequality. ays – Change in average years of schooling. trade – Change in the degree of trade openness. gdp – Change in the real GDP per capita. Standard errors are in parenthesis. Time dummies are included. Estimates for constant terms not shown. AB test = Arellano-Bond test for AR(2) in first differences. L is the first lag of the variable; L2 is the second lag of the variable. * Significance at the 10 per cent level. ** Significance at the 5 per cent level. *** Significance at the 1 per cent level.

The second column in Table 2 conducts the same analysis for the LMICs. According to AB two-step GMM estimates in panel A in Table 2, educational inequality has a significantly positive impact on income inequality. The Wald test statistic reveals that educational inequality has predictive power for income inequality in this group of countries. The coefficient on lagged income inequality is positive and significant, indicating the persistence of income inequality. Panel B in Table 2 reports the estimates of Equation (2) for the LMICs where the dependent variable is educational inequality. The coefficient on income inequality is positive and significant and the corresponding Wald test records that income inequality has predictive power for educational inequality in the LMICs. The AB two-step GMM estimates have identified that there is a bi-directional causality between educational

Table 2: Interaction Between Educational Inequality and Income Inequality for all Subsamples

Panel A	*LICs*	*LMICs*	*HMICs*	*HOCs*
	(1)	*(2)*	*(3)*	*(4)*
Dependent Variable	*dGiniY*	*dGiniY*	*dGiniY*	*dGiniY*
L.dginiY	0.719***	0.591***	0.808***	0.220**
	(0.164)	(0.174)	(0.224)	(0.106)
L2.dginiY	0.299	0.441**	0.329	0.421**
	(0.237)	(0.180)	(0.302)	(0.172)
L.dginiHC	0.556***	0.039	0.066	0.080**
	(0.159)	(0.033)	(0.041)	(0.039)
L2.dginiHC	0.591***	0.064**	0.164***	0.040
	(0.187)	(0.024)	(0.054)	(0.046)
Hansen test (p-level)	0.457	0.454	0.781	0.357
Difference Hansen test (p-level)	0.395	0.826	0.626	0.451
AB test (p-level)	0.357	0.950	0.751	0.871
Wald test (p-level)	0.011	0.047	0.017	0.091
Panel B				
Dependent Variable	*dGiniHC*	*dGiniHC*	*dGiniHC*	*dGiniHC*
L.dginiY	0.653**	0.265	0.482	0.112
	(0.281)	(0.165)	(0.359)	(0.299)
L2.dginiY	0.310	0.749**	0.635*	0.0925
	(0.332)	(0.328)	(0.322)	(0.306)
L.dginiHC	0.885***	0.858***	0.00731	0.995***
	(0.155)	(0.142)	(0.218)	(0.048)
L2.dginiHC	0.0671	0.0201	0.625**	0.0129
	(0.180)	(0.128)	(0.241)	(0.030)
N	14	21	32	34
T	8	8	8	8
Hansen test (p-level)	0.439	0.273	0.822	0.782
Difference Hansen test (p-level)	0.330	0.624	0.731	0.548
AB test (p-level)	0.402	0.705	0.984	0.688
Wald test (p-level)	0.093	0.014	0.001	0.718

Source: Author's analysis.
Note: See the note to Table 1.

inequality and income inequality. This result indicates that a better income distribution is key to a fair distribution of education, and a reduction in educational inequality leads to a fall in income inequality. Thus, these two inequalities are closely linked for this group of countries.

The third column in Table 2 reports the estimation results for HMICs where the dependent variable is income inequality. The positive and significant role of educational inequality in income inequality is supported by the AB two-step GMM estimates. The Wald test, reported at the bottom of panel A in Table 2, reveals that educational inequality predicts income inequality for HMICs. Further, panel B in Table 2 presents the estimates for Equation (2) where the dependent variable is educational inequality. Income inequality has a positive and significant impact on educational inequality, and according to the Wald test statistics, income inequality predicts educational inequality with a positive sign for the HMICs. In this context, it can be concluded that there exists a bi-directional (dual) relationship between educational inequality and income inequality in the HMICs.

The last column in Table 2 focuses on the linkages between educational inequality and income inequality, this time in the HOCs. The estimates of the AB two-step system GMM suggest that educational inequality has a positive and significant impact on income inequality. The corresponding Wald test statistics reveal that educational inequality predicts income inequality for the HOCs. Panel B in Table 2 presents results for the estimation of Equation (2), where the dependent variable is educational inequality. None of the estimation methods shows any significant impact of income inequality on educational inequality, and the corresponding Wald tests report that income inequality has no predictive power for educational inequality in HOCs.

Table 3 and Table 4 conduct the same analysis for each income group, with the addition of a set of control variables. The first column in Table 3 displays the estimates of Equation (1) for the LICs, where the dependent variable is income inequality. According to the results produced by AB two-step system GMM, educational inequality has predictive power for income inequality. Within the set of control variables**,** the coefficient on the change in average years of schooling is negative and significant, indicating that both expansion of education and its distribution significantly improve the distribution of income. The coefficient on the change in the degree of trade openness is not significant, thus the role of trade openness has no significant impact on income inequality for the LICs. According to the Fixed Effects and Robust Regression estimates, the coefficient on average income is positive and significant.[4]

The second column in Table 3 presents the estimates of Equation (1) for the LMICs with control variables and the dependent variable of income inequality.

[4] For the sensitivity of the econometric analysis, Appendix provides additional estimates for Fixed Effects, Robust Regression and AB one step SYS-GMM. Based on fixed effects and robust regression estimates, the coefficient of average income is positive and significant.

According to AB two-step system GMM estimates, educational inequality has predictive power for income inequality. The coefficient on the average years of schooling is not significant, thus rather than the expansion in education, a fair distribution of education is expected to lead to a fairer distribution of income. Further, the coefficient on average income and the coefficient on the degree of trade openness are positive and significant. Thus, trade liberalisation could be responsible for rising income inequality in the last decade in the LMICs.

Table 3: Interaction Between Educational Inequality and Income Inequality with Set of Control Variables: Dependent Variable is Income Inequality

	LICs (1)	*LMICs* (2)	*HMICs* (3)	*HOCs* (4)
Dependent Variable	*dGiniY*	*dGiniY*	*dGiniY*	*dGiniY*
L.dginiY	0.856*	0.408*	0.550**	0.595***
	(0.436)	(0.239)	(0.215)	(0.129)
L2.dginiY	0.676	–0.0562	0.0820	0.291**
	(0.414)	(0.246)	(0.222)	(0.114)
L.dginiHC	0.571**	0.270***	0.0979	–0.0560
	(0.204)	(0.0816)	(0.103)	(0.0742)
L2.dginiHC	0.301	–0.0320	–0.033	–0.0207
	(0.327)	(0.0563)	(0.0829)	(0.0257)
L.ays	–0.107***	0.0451	–0.0810	–0.000489
	(0.031)	(0.0268)	(0.457)	(0.00576)
L2.ays	–0.033**	0.0112	0.0873	–0.00643
	(0.011)	(0.00993)	(0.328)	(0.00428)
L.trade	–0.002	0.00853**	0.0158*	–0.000315
	(0.019)	(0.00409)	(0.0090)	(0.00154)
L2.trade	–0.042	0.00461	0.0171	0.00405**
	(0.041)	(0.00693)	(0.0139)	(0.00175)
L.gdp	–0.004	0.00588**	0.0024*	–0.000524
	(0.004)	(0.00279)	(0.0012)	(0.000413)
L2. gdp	–0.005	0.000329	0.0011	0.00184**
	(0.004)	(0.00217)	(0.0046)	(0.000825)
N	14	21	32	34
T	8	8	8	8
Hansen test (p-level)	0.875	0.457	0.544	0.748
Difference Hansen test (p-level)	0.483	0.442	0.724	0.446
AB test (p-level)	0.201	0.501	0.662	0.544
Wald test (p-level)	0.039	0.000	0.640	0.373

Source: Author's analysis.
Note: See the note to Table 1.

The third column in Table 3 presents the estimates for Equation (1) where the dependent variable is income inequality with a set of controls for the HMICs. Educational inequality has no significant effect on income inequality when the level of development, educational attainment and the degree of openness to trade are controlled for. The corresponding Wald test statistics do not record any causality running from educational inequality to income inequality. Therefore, the findings of the econometric estimates reveal no clear evidence of a predictive pattern moving from educational inequality to income inequality. The coefficient on average years of schooling is not significant with any estimation technique. The third column in Table 3 reveals that both the coefficient on the degree of trade openness and the coefficient on average income are positive and significant with all estimation techniques. In other words, an increase in the degree of trade openness and/or an expansion in average income may lead to a deterioration in the distribution of income. The significance of both educational attainment and educational inequality falls once we include trade openness and average income into the regression specification for the HMICs.

The last column in Table 3 reports the empirical results on the interaction between educational inequality and income inequality for the HOCs when the set of control variables are included in the econometric analysis. The coefficient on educational inequality is not significant with all estimation techniques, and the Wald tests under AB two-step system GMM estimates show that educational inequality does not predict income inequality in the HOCs. Among the control variables, the coefficient on the degree of trade openness and the coefficient on average income are positive and significant while the coefficient on average years of schooling is not significant in any estimation techniques. In contrast to the results reported without any control variables included in the analysis, these new results with the control variables show that in the HOCs a reduction in educational inequality no longer causes any drop in income inequality.

Table 4 displays the econometric evidence to check whether income inequality has predictive power for educational inequality or not when a set of control variables is included into the analysis. The first column in Table 4 repeats the same econometric analysis with the same control variables for the LICs, but this time with educational inequality as dependent variable. The coefficient on the lagged income Gini is positive and significant with all estimation methods, and the corresponding Wald test indicates that income inequality has predictive power for educational inequality. The coefficient on the change in average years of schooling is negative and significant. Thus, the expansion of average years of schooling not only directly reduces income inequality but also indirectly leads to a fall in income inequality by generating a fair distribution of education. After controlling for the level of development, educational attainment and the degree of trade openness, it can be seen that there exists a bi-directional (dual) causality between educational inequality and income inequality.

Table 4: Interaction Between Educational Inequality and Income Inequality with Set of Control Variables: Dependent Variable is Educational Inequality

	LICs (1)	*LMICs* (2)	*HMICs* (3)	*HOCs* (4)
Dependent Variable	*dGiniHC*	*dGiniHC*	*dGiniHC*	*dGiniHC*
L.dginiY	–0.694	0.619**	0.0738	0.188
	(1.088)	(0.281)	(0.286)	(0.193)
L2.dginiY	0.730*	0.548	0.687**	–0.179
	(0.406)	(0.483)	(0.281)	(0.216)
L.dginiHC	0.647***	0.456**	0.204	0.798***
	(0.193)	(0.167)	(0.151)	(0.075)
L2.dginiHC	–0.138	0.0091	0.220	–0.0600
	(0.189)	(0.206)	(0.134)	(0.056)
L.ays	–0.029**	–0.0403*	–0.0259***	–0.0218**
	(0.010)	(0.0224)	(0.0072)	(0.0082)
L2.ays	–0.008	–0.0166	–0.0204	–0.0276***
	(0.026)	(0.0182)	(0.0274)	(0.00875)
L.trade	0.0002	0.0046	0.0075	0.0054***
	(0.000)	(0.0118)	(0.0098)	(0.0013)
L2.trade	–0.0001	–0.0147	0.0089	–0.0015
	(0.0002)	(0.0134)	(0.0121)	(0.0028)
L.gdp	–0.004	0.0001	0.00289	0.0026*
	(0.006)	(0.0004)	(0.0040)	(0.0013)
L2. gdp	0.001	–0.00250	0.00017	0.0055***
	(0.003)	(0.0031)	(0.00299)	(0.0016)
N	14	21	32	34
T	8	8	8	8
Hansen test (p-level)	0.999	0.903	0.623	0.490
Difference Hansen test (p-level)	0.925	0.894	0.514	0.686
AB test (p-level)	0.694	0.287	0.338	0.277
Wald test (p-level)	0.042	0.094	0.007	0.624

Source: Author's analysis.
Note: See the note to Table 1.

For the LMICs, the second column in Table 4 shows that the coefficient on income inequality is positive and significant according to the estimation results based on AB two-step SYS-GMM. The corresponding Wald tests support the predictive pattern running from income inequality to educational inequality. The coefficient on average years of schooling is negative and significant. That is, an increase in educational attainment not only directly lowers educational inequality, but also leads to a fairer income distribution by reducing educational inequality. The coefficient on average income is positive and significant only with FE and RREG methods (see Appendix A). The inclusion of the control variables does not alter the bi-directional causality between educational inequality and income inequality as in the LICs. Thus, both in LICs and LMICs, there exists a bi-directional causality between educational inequality and income inequality.

The third column in Table 4 displays the econometric results of Equation (2) for the HMICs where the dependent variable is educational inequality. Under the umbrella of AB two-step SYS-GMM techniques, income inequality predicts educational inequality with a positive sign when the set of control variables are included in the panel VAR model. Among these control variables, only the coefficient on average years of schooling indicates a negative and significant impact on educational inequality. The coefficients on trade openness and average income indicate that there is no significant impact on educational inequality. However, both trade and income expansions may lead to an unfair distribution of education as they affect the income distribution. The third column in Table 4 reveals that income inequality has significant predictive power for educational inequality even with the set of control variables included in the analysis.

The fourth column in Table 4 presents the econometric results of Equation (2) for the HOCs where the dependent variable is educational inequality. The coefficient on income inequality is not significant, and the corresponding Wald test does not predict any causality running from income inequality to educational inequality when the set of controls are included in the econometric analysis. The coefficients on the degree of trade openness and average income are positive and significant according to AB two-step SYS-GMM. The coefficient on average years of schooling is negative and significant. Thus, the income equalising effect of an educational expansion is not observed when control variables are included in the analysis. In other words, trade liberalisation should have some deteriorating effects on both educational inequality and income inequality in the HOCs. In the HMICs and HOCs, the empirical evidence from Table 2 to Table 4 reveals that an expansion in income and trade leads to an unfair distribution of income, and the findings also highlight that the impact of educational inequality on income inequality disappears once the set of controls is allowed for. This result can be explained by the observation that trade expansions are likely to generate an unfair distribution of income by changing the skill composition of jobs. The pattern of relative wages depends on the rising demand for skilled workers with higher trade flows and the increasing supply of skilled labour through education. In other words, the strength of the demand for skills relative to the supply of skills has played a crucial role on relative wages (Eicher and Garcia-Penalosa, 2001). To absorb new technologies, skill requirements are expanding rapidly, and this race between technology and education is likely to reduce the positive effect of educational inequality on income inequality.

Overall, Table 1 to Table 4 point out the existence of interdependencies between educational inequality and income inequality for different income groups under the umbrella of four different estimation techniques with or without controls for the level of development, educational attainment, and the degree of openness to trade. For all income groups, the common observations are that the estimated coefficient on average years of schooling is negative and significant, indicating that an expansion of educational attainment reduces educational inequality. The results for per capita income show that income expansions contribute to increases in both income inequality and educational inequality in all income groups. The rest of the findings change from one income group to the other. For example, in the LICs and LMICs, there exists a strong bi-directional causality between educational inequality and income inequality. While educational attainment reduces both educational inequality and income inequality, expansions in average income worsen the distribution of both education and income. The degree of trade openness has no significant impact on income inequality or educational inequality. Another interesting observation from the econometric analysis is that an unfair distribution of income acts as a barrier to a better distribution of education. This is plausible since the benefits of education cannot be reaped by large segments of societies as higher-quality education is too costly to be affordable for low-income individuals. Thereby, the vicious cycle of the inequalities still survives even with the set of control variables in the LICs and LMICs.

The major difference observed in the results obtained for the HMICs and HOCs is the existence of a reverse causality. While there exists a bi-directional (dual) relationship between educational inequality and income inequality in the HMICs, the causality runs from educational inequality to income inequality in the HOCs without control variables included. However, in both cases, educational inequality has no significant effect on income inequality when the level of development, educational attainment and trade openness are controlled for. Among the control variables, the coefficients on average income and the degree of openness are positive and significant according to all estimation techniques both in the HMICs and HOCs. This means that a rapid expansion in trade and income outweighs the income equalising effect of education. This is compatible with the results of Lee and Lee (2018). High-quality education and its distribution should be consistent with the changing needs of societies. With a rapid expansion in globalisation and technological progress, educational inequality is not enough to lead to a fair income distribution in the HMICs and HOCs.[5] This result is also in line with the hypothesis of Tinbergen (1975), which indicates that income inequality is determined by the race between education and technology. Because this race is accelerated in the HMICs and HOCs, even though the average skill level of the population has been rising, improvements in trade and technology have started to quickly change the skill requirements of jobs, and this misdistribution of skills over jobs has interrupted the expected-to-be positive link between educational inequality and income inequality.

[5] All results hold when the demand for skills is proxied with the share of high-tech exports in total exports.

V CONCLUSION AND POLICY IMPLICATIONS

The attainment and better distribution of education acts as a social equaliser in terms of income, as it enhances the skills of workers and enables them to engage in high skill activities. Within this context, many countries have experienced massive improvements in the distribution of education, but the interdependency between educational inequality and income inequality has been largely ignored. Since the relationship between educational and income inequality is dynamic and complementary, it is important to determine the linkage between these two inequalities to ensure an effective and targeted policy formulation. However, the empirical evidence on the impact of educational inequality on the distribution of income still remains ambiguous. Furthermore, continuous reductions in educational inequality have not been widely reflected in declining income inequality. This puzzling relationship between educational inequality and income inequality could be partially explained by the rising labour demand for skilled workers due to trade expansions and rapid technological progress, and faster increases in average income. Even though there has been an increase in the supply of highly educated workers, the demand for these workers has been expanding at a faster pace since the 1990s due to new technological improvements. Thus, the crucial role of education in the income distribution is over-shadowed by the quickly rising demand for skilled workers. More importantly, the cost of gaining skills through education has been rising. Therefore, the lack of income and its unfair distribution act as a barrier to acquiring sufficient and high-quality education. In other words, widening income disparities can suppress the development of skills and lead to an unfair distribution of education (Dabla-Norris *et al.*, 2015). Thus, one can argue that the unequal distribution of income may result in educational inequality and vice versa. Within this framework, the circular causal relationship between the lack of education and the lack of income defines the concept of inequality traps (Rao, 2006; Bourguignon *et al.* 2004).

The primary purpose of this paper is to determine the causal relationship between educational inequality and income inequality by employing panel data techniques with an extensive education dataset compiled by Castelló-Climent and Doménech (2017; 2021). In this paper, the endogenous interaction between educational inequality and income inequality is studied by employing panel VAR analysis based on a system GMM for 101 countries between 1975 and 2010 in four income groups: LICs, LMICs, HMICs, and HOCs. To the best of the author's knowledge, no up-to-date study jointly examines the predictive pattern between educational inequality and income inequality with the help of dynamic panel techniques. In addition, the level of development, the degree of openness to trade and average years of schooling are utilised in this paper to check for the robustness of the findings.

The panel VAR estimates provide four important results. First, the country classifications based on their income levels play a crucial role in building up the linkages between educational inequality and income inequality. Significant differences are observed across country groups, and educational inequality does not have the same impact on income inequality in all income groups. Second, income inequality has predictive power for educational inequality in low- and middle-income countries even after the control variables are included in the panel VAR analysis. In LICs and LMICs, educational inequality is associated with the unfair distribution of income and, similarly, income inequality causes the unequal distribution of education. Thus, the findings suggest a bi-directional causality between educational inequality and income inequality in the LICs and LMICs. Third, the significance of educational inequality in explaining income inequality disappears once we control for the degree of openness, the level of development, and educational attainment in HMICs and HOCs. Thus, improvements in educational inequality do not work as a tool to reduce income inequality in these countries. The findings of the paper suggest that an increase in trade openness is likely to affect the income distribution in the HMICS and HOCs and also over-shadows the role of the distribution of education in the fair distribution of income. In the HOCs, the distribution of education will be more uneven when the trade openness of economies increases. In this respect, one can argue that the expansion of educational attainment may not be in line with the rising demand for new technologies due to the rapid expansion of trade flows. The results support Tinbergen's (1975) hypothesis, which underlines that inequality is the outcome of a race between supply and demand for skills. If rising educational attainment had coincided with the higher demand for skills arising from the expansion of trade, increasing income inequality could have been avoided. Thus, the higher competition between the supply and demand for skills is likely to be the main reason behind the weakening link between educational inequality and income inequality in the HMICs and HOCs. Fourth, the results suggest that the coefficients on the lagged values of income inequality continue to be positive and significant, indicating the persistence of income inequality, even after the degree of openness, the level of development, and educational attainment are controlled for, in all income groups.

Overall, even though the results do not suggest a straightforward relationship between educational inequality and income inequality, and the predictive pattern between them is not stable across income groups, policies to improve the skill distribution should still lie at the heart of the policy agenda to reduce income inequality in both low- and middle-income countries. Understanding the impact of education, globalisation, and technological changes on the income distribution is important in order to design and implement deliberate policies towards more inclusive and sustainable economic development. Policy measures to reduce income inequality should also include effective human capital policies, such as inclusive education and training for unskilled workers. In addition, social benefits and redistributive policies should be enhanced to improve the income distribution. For further work, the impact of the financial crisis on the relationship between these two inequalities could be studied if the dataset is extended beyond 2010.

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APPENDIX A

Table A1: Interaction Between Educational Inequality and Income Inequality for all Sample: AB Two-Step SYS-GMM Estimates

	FE	*FE*	*FE*	*FE*	*RREG*	*RREG*	*RREG*	*RREG*	*AB one step SYS-GMM*	*AB one stepSYS-GMM*	*AB one step SYS-GMM*	*AB one step SYS-GMM*
Dependent Variable	*dginiY (1)*	*dginiHC (2)*	*dginiY (3)*	*dginiHC (4)*	*dginiY (5)*	*dginiHC (6)*	*dginiY (7)*	*dginiHC (8)*	*dginiY (9)*	*dginiHC (10)*	*dginiY (11)*	*dginiHC (12)*
L.dginiY	0.282***	0.386***	0.532***	0.169***	0.884***	0.286	0.065**	0.076**	0.950***	0.064***	0.790***	0.709*
	(0.039)	(0.141)	(0.075)	(0.049)	(0.229)	(0.231)	(0.028)	(0.032)	(0.020)	(0.022)	(0.227)	(0.411)
L2.dginiY	0.881***	0.074	0.081	–0.001	0.834***	0.653***	0.971***	0.016	0.137	–0.0009	–0.496***	0.871***
	(0.036)	(0.129)	(0.066)	(0.053)	(0.0384)	(0.065)	(0.010)	(0.032)	(0.087)	(0.014)	(0.189)	(0.241)
L.dginiHC	–0.008	0.143*	0.0603	–0.082***	0.362**	–0.794**	0.049	0.053***	0.199	–0.406	–0.116	0.124*
	(0.018)	(0.084)	(0.052)	(0.025)	(0.140)	(0.334)	(0.042)	(0.016)	(0.266)	(0.248)	(0.133)	(0.0744)
L2.dginiHC	0.022**	0.546***	–0.0260	0.831***	–0.00732	0.367*	–0.042	0.917***	0.075***	0.617**	0.075	0.336**
	(0.010)	(0.082)	(0.035)	(0.031)	(0.0224)	(0.206)	(0.032)	(0.008)	(0.024)	(0.309)	(0.082)	(0.134)
L.ays			–0.0020	–0.008***			0.005	–0.00310***			0.014	–0.0255**
			(0.00255)	(0.001)			(0.002)	(0.0006)			(0.010)	(0.0114)
L2.ays			–0.00352	–0.022***			0.0003	–0.0165***			–0.019**	0.000365
			(0.00286)	(0.002)			(0.002)	(0.0020)			(0.009)	(0.00403)
L.trade			0.000544	0.0003			0.0005**	0.001**			0.0009	0.000787
			(0.000533)	(0.0006)			(0.0002)	(0.0005)			(0.00009)	(0.000676)
L2.trade			0.00151***	–0.0005			0.0008	–0.0005			0.0002	0.00424
			(0.0005)	(0.0008)			(0.0002)	(0.0006)			(0.00002)	(0.00410)
L.gdp			0.002***	–0.001**			–0.00025	–0.0007			0.003**	0.000772
			(0.0006)	(0.0007)			(0.0010)	(0.0004)			(0.001)	(0.00316)
L2. gdp			0.0008	0.0012**			0.0004*	0.0006			0.0009	–0.00162
			(0.0006)	(0.0005)			(0.00024)	(0.0004)			(0.0010)	(0.00283)

Table A1: Interaction Between Educational Inequality and Income Inequality for all Sample: AB Two-Step SYS-GMM Estimates (Contd.)

	FE	*FE*	*FE*	*FE*	*RREG*	*RREG*	*RREG*	*RREG*	*AB one step SYS-GMM*	*AB one stepSYS-GMM*	*AB one step SYS-GMM*	*AB one step SYS-GMM*
Dependent Variable	*dginiY (1)*	*dginiHC (2)*	*dginiY (3)*	*dginiHC (4)*	*dginiY (5)*	*dginiHC (6)*	*dginiY (7)*	*dginiHC (8)*	*dginiY (9)*	*dginiHC (10)*	*dginiY (11)*	*dginiHC (12)*
N	101	101	101	101	101	101	101	101	101	101	101	101
T	8	8	8	8	8	8	8	8	8	8	8	8
Hansen test (p-level)									0.477	0.540	0.315	0.342
Difference Hansen test (p-level)									0.527	0.715	0.522	0.518
AB test (p-level)									0.108	0.534	0.906	0.571
Wald test (p-level)	0.093	0.006	0.513	0.0018	0.018	0.000	0.324	0.000	0.007	0.000	0.103	0.001

Source: Author's analysis.

Note: dginiY – Change in income inequality. dginiHC – Change in educational inequality. ays – Change in average years of schooling. Trade – Change in the degree of trade openness. Gdp – Change in the real GDP per capita. Standard errors are in parenthesis. Time dummies are included. Estimates for constant terms not shown. AB test = Arellano-Bond test for AR(2) in first differences.* Significance at the 10 per cent level. ** Significance at the 5 per cent level.*** Significance at the 1 per cent level. FE – Fixed Effect. RREG – Robust Regression. AB one-step SYS-GMM – Arellano Bond one-step system GMM.

Table A2: Interaction Between Educational Inequality and Income Inequality for all Subsamples: AB two-step SYS-GMM estimates

Panel A	*LICs FE*	*LICs RREG*	*LICs AB one step SS-GMM*	*LMICs FE*	*LMICs RREG*	*LMICs AB one step SYS-GMM*	*HMICs FE*	*HMICs RREG*	*HMICs AB one step SYS-GMM*	*HOCs FE*	*HOCs RREG*	*HOCs AB one step SS-GMM*
Dependent Variable	*dginiY (1)*	*dginiY (2)*	*dginiY (3)*	*dginiY (4)*	*dginiY (5)*	*dginiY (6)*	*dginiY (7)*	*dginiY (8)*	*dginiY (9)*	*dginiY (10)*	*dginiY (11)*	*dginiY (12)*
L.dginiY	0.933***	0.974***	0.856***	0.120	0.995***	0.584***	0.159	0.236***	0.255	0.978***	0.988***	0.173*
	(0.144)	(0.111)	(0.254)	(0.089)	(0.017)	(0.184)	(0.150)	(0.0707)	(0.180)	(0.104)	(0.0363)	(0.0970)
L2.dginiY	0.541*	0.202**	0.169	0.732***	0.550***	0.446**	0.238**	0.106	0.761**	0.377***	0.038	0.542***
	(0.293)	(0.092)	(0.263)	(0.096)	(0.071)	(0.204)	(0.108)	(0.071)	(0.359)	(0.084)	(0.038)	(0.157)
L.dginiHC	0.439	0.450**	0.436**	0.113**	0.0239	0.0434	0.782***	0.700***	0.876***	0.011	0.044**	0.077***
	(0.268)	(0.199)	(0.172)	(0.052)	(0.016)	(0.037)	(0.088)	(0.044)	(0.137)	(0.0209)	(0.0193)	(0.0271)
L2.dginiHC	0.333**	0.413**	0.453*	0.105**	0.0337**	0.0647**	0.0512	0.337***	0.0370	0.031**	0.021*	0.030
	(0.124)	(0.201)	(0.231)	(0.051)	(0.016)	(0.027)	(0.089)	(0.043)	(0.126)	(0.015)	(0.011)	(0.029)
N	14	14	14	21	21	21	32	32	32	34	34	34
T	8	8	8	8	8	8	8	8	8	8	8	8
Hansen test (p-level)			0.457			0.454			0.273			0.357
Difference Hansen test (p-level)			0.395			0.826			0.624			0.451
AB test (p-level)			0.394			0.938			0.637			0.772
Wald test (p-level)	0.0504	0.007	0.034	0.0954	0.083	0.082	0.087	0.000	0.009	0.0866	0.062	0.0215

Table A2: Interaction Between Educational Inequality and Income Inequality for all Subsamples: AB two-step SYS-GMM estimates (Contd.)

Panel B												
Dependent Variable	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*
L.dginiY	0.0667	0.960**	0.642***	0.159	0.236***	0.255	0.092	0.229**	0.448	0.093	0.0047	0.581
	(0.104)	(0.275)	(0.190)	(0.150)	(0.0707)	(0.180)	(0.118)	(0.083)	(0.365)	(0.117)	(0.035)	(0.471)
L2.dginiY	0.306**	0.565	0.474*	0.238**	0.106	0.761**	0.205*	0.0966	0.618*	0.193*	0.0137	0.573
	(0.137)	(0.291)	(0.266)	(0.108)	(0.071)	(0.359)	(0.115)	(0.083)	(0.327)	(0.117)	(0.036)	(0.476)
L.dginiHC	0.765***	0.485***	0.872***	0.782***	0.700***	0.876***	0.990***	0.0775***	0.00597	0.322***	0.985***	0.976***
	(0.156)	(0.096)	(0.121)	(0.088)	(0.044)	(0.137)	(0.084)	(0.023)	(0.195)	(0.070)	(0.020)	(0.051)
L2.dgini HC	0.218	0.564***	0.0943	0.0512	0.337***	0.0370	0.110	0.877***	0.612**	1.174***	0.044***	0.011
	(0.140)	(0.0810)	(0.140)	(0.089)	(0.043)	(0.126)	(0.082)	(0.061)	(0.227)	(0.068)	(0.013)	(0.040)
N	14	14	14	21	21	21	32	32	32	34	34	34
T	8	8	8	8	8	8	8	8	8	8	8	8
Hansen test (p-level)			0.439			0.273			0.822			0.782
Difference Hansen test (p-level)			0.330			0.624			0.731			0.548
AB test (p-level)			0.399			0.637			0.910			0.966
Wald test (p-level)	0.0788	0.019	0.008	0.087	0.000	0.009	0.0822	0.000	0.000	0.182	0.872	0.444

Source: Author's analysis.

Note: dginiY – Change in income inequality. dginiHC – Change in educational inequality. ays – Change in average years of schooling. Trade – Change in the degree of trade openness. gdp – Change in the real GDP per capita. Standard errors are in parenthesis. Time dummies are included. Estimates for constant terms not shown. AB test = Arellano-Bond test for AR(2) in first differences.* Significance at the 10 per cent level. ** Significance at the 5 per cent level.*** Significance at the 1 per cent level. FE – Fixed Effect. RREG – Robust Regression. AB one-step SYS-GMM – Arellano Bond one-step system GMM.

Table A3: The Impact of Educational Inequality on Income Inequality for all Subsamples with Set of Control Variables

Panel A	*LICs FE*	*RREG*	*AB one stepSYS-GMM*	*LMICs FE*	*RREG*	*AB one stepSYS-GMM*	*HMICs FE*	*RREG stepSYS-GMM*	*AB one*	*HOCs FE*	*RREG*	*AB one stepSYS-GMM*
Dependent Variable	*dginiY*	*dginiY*	*dginiY*	*dginiY*	*dginiY*	*dginiY*	*dginiY*	*dginiY*	*dginiY*	*dginiY*	*dginiY*	*dginiY*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
L.dginiY	0.699***	0.972***	0.764**	0.593***	0.566***	0.483***	0.775***	0.845***	0.529***	0.856***	0.965***	0.669***
	(0.200)	(0.112)	(0.341)	(0.125)	(0.050)	(0.166)	(0.115)	(0.212)	(0.181)	(0.069)	(0.038)	(0.175)
L2.dginiY	0.131	0.537***	–0.860**	0.127	0.310***	–0.150	0.233**	0.046	0.087	0.330***	0.0317	0.220
	(0.241)	(0.099)	(0.328)	(0.117)	(0.043)	(0.192)	(0.089)	(0.204)	(0.155)	(0.066)	(0.040)	(0.174)
L.dginiHC	0.551**	0.505**	0.545**	0.052	0.080**	0.274***	0.0878	0.026	0.117	0.048	–0.039	–0.019
	(0.226)	(0.185)	(0.212)	(0.039)	(0.027)	(0.063)	(0.057)	(0.038)	(0.090)	(0.049)	(0.037)	(0.072)
L2.dginiHC	0.270	0.408**	0.321	0.133***	0.023	–0.040	0.0209	–0.109	–0.088	–0.049	–0.001	0.0035
	(0.211)	(0.172)	(0.227)	(0.045)	(0.013)	(0.061)	(0.0586)	(0.069)	(0.074)	(0.043)	(0.030)	(0.039)
L.ays	–0.0342*	–0.316***	–0.103***	–0.015***	–0.018***	0.049	–0.0006	–0.006	–0.099	0.0002	–0.0038	–0.0007
	(0.019)	(0.047)	(0.033)	(0.0047)	(0.002)	(0.033)	(0.004)	(0.006)	(0.300)	(0.0027)	(0.0031)	(0.0052)
L2.ays	–0.0328	–0.257***	–0.036**	–0.009**	–0.023***	0.010	–0.007	0.003	0.0472	0.0009	0.003	–0.0029
	(0.023)	(0.040)	(0.015)	(0.003)	(0.002)	(0.007)	(0.004)	(0.006)	(0.258)	(0.0026)	(0.002)	(0.0059)
L.trade	–0.0007	–0.0002	–0.0050	0.005***	0.008***	0.007	0.006***	0.0104**	0.020*	0.0006	0.001**	–0.00064
	(0.0008)	(0.002)	(0.026)	(0.001)	(0.001)	(0.004)	(0.002)	(0.003)	(0.011)	(0.0006)	(0.0006)	(0.0015)
L2.trade	0.0003	0.010	–0.039	0.003**	0.009***	0.005	0.005***	0.001	0.0274**	0.0016**	–0.0004	0.0047*
	(0.0001)	(0.008)	(0.024)	(0.001)	(0.001)	(0.004)	(0.001)	(0.003)	(0.011)	(0.0007)	(0.0009)	(0.0023)
L.gdp	0.0002	0.001	–0.0029	0.021*	0.041***	0.0046*	0.001	0.030***	0.0034**	0.0013*	0.0062*	–0.0006
	(0.0001)	(0.003)	(0.005)	(0.012)	(0.005)	(0.0026)	(0.001)	(0.011)	(0.0013)	(0.0007)	(0.0032)	(0.00048)
L2. gdp	0.006*	0.011***	–0.002	0.004	0.0201***	0.0007	0.0027**	0.004	0.00058	0.00074	0.0123	0.0013
	(0.003)	(0.002)	(0.002)	(0.009)	(0.003)	(0.002)	(0.001)	(0.010)	(0.0028)	(0.0006)	(0.008)	(0.0012)

Table A3: The Impact of Educational Inequality on Income Inequality for all Subsamples with Set of Control Variables (Contd.)

Panel A	*LICs FE*	*RREG*	*AB one stepSYS-GMM*	*LMICs FE*	*RREG*	*AB one stepSYS-GMM*	*HMICs FE*	*RREG stepSYS-GMM*	*AB one*	*HOCs FE*	*RREG*	*AB one stepSYS-GMM*
Dependent Variable	*dginiY*	*dginiY*	*dginiY*	*dginiY*	*dginiY*	*dginiY*	*dginiY*	*dginiY*	*dginiY*	*dginiY*	*dginiY*	*dginiY*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
N	14	14	14	21	21	21	32	32	32	34	34	34
T	8	8	8	8	8	8	8	8	8	8	8	8
Hansen test (p-level)			0.875			0.457			0.544			0.748
Difference Hansen test (p-level)			0.483			0.442			0.724			0.446
AB test (p-level)			0.149			0.407			0.112			0.943
Wald test (p-level)	0.046	0.025	0.066	0.0131	0.002	0.000	0.022	0.0031	0.378	0.526	0.297	0.964

Source: Author's analysis.

Note: dginiY – Change in income inequality. dginiHC – Change in educational inequality. ays – Change in average years of schooling. Trade – Change in the degree of trade openness. gdp – Change in the real GDP per capita. Standard errors are in parenthesis. Time dummies are included. Estimates for constant terms not shown. AB test = Arellano-Bond test for AR(2) in first differences.* Significance at the 10 per cent level. ** Significance at the 5 per cent level.*** Significance at the 1 per cent level. FE – Fixed Effect. RREG – Robust Regression. AB one-step SYS-GMM – Arellano Bond one-step system GMM.

Table A4: The Impact of Income Inequality on Educational Inequality for all Subsamples with Set of Control Variables

Panel A	*LICs FE*	*RREG*	*AB one stepSYS-GMM*	*LMICs FE*	*RREG*	*AB one stepSYS-GMM*	*HMICs FE*	*RREG*	*AB one stepSYS-GMM*	*HOCs FE*	*RREG*	*AB one stepSYS-GMM*
Dependent Variable	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*
L.dginiY	0.112	0.0340	0.430*	0.0543	0.0822	0.732**	0.160	0.355***	0.132	0.118	–0.0915	0.388
	(0.231)	(0.051)	(0.225)	(0.147)	(0.259)	(0.324)	(0.150)	(0.127)	(0.241)	(0.100)	(0.070)	(0.234)
L2.dginiY	0.755**	0.116**	0.554***	0.231**	0.232***	0.420	0.224*	0.106	0.947**	–0.0154	0.0825	–0.309
	(0.350)	(0.041)	(0.184)	(0.109)	(0.066)	(0.340)	(0.119)	(0.143)	(0.360)	(0.050)	(0.0722)	(0.258)
L.dginiHC	0.0400	0.284**	0.698***	0.147*	0.834***	0.415**	0.890***	0.574***	0.243*	0.115*	0.325***	0.747***
	(0.305)	(0.104)	(0.0837)	(0.076)	(0.077)	(0.152)	(0.089)	(0.155)	(0.133)	(0.0582)	(0.041)	(0.065)
L2.dginiHC	0.589**	0.751***	–0.0575	0.881***	0.155**	0.0631	0.208**	0.245*	0.144	0.886***	0.955***	–0.0275
	(0.280)	(0.104)	(0.147)	(0.078)	(0.068)	(0.171)	(0.082)	(0.141)	(0.108)	(0.058)	(0.021)	(0.067)
L.ays	–0.0646***	–0.0234***	–0.0191	–0.0065	–0.0205***	–0.0411*	–0.0108**	–0.0252***	–0.0284***	–0.00094	–0.0231***	–0.0292***
	(0.018)	(0.0064)	(0.0118)	(0.0046)	(0.0047)	(0.0201)	(0.0041)	(0.0032)	(0.0054)	(0.0107)	(0.0027)	(0.0087)
L2.ays	0.0142	0.0310***	–0.0145	–0.0204***	–0.0179	–0.00682	–0.0283***	0.00401	–0.0202	0.0129	0.0203***	0.0352***
	(0.0227)	(0.0066)	(0.0084)	(0.0064)	(0.0120)	(0.0103)	(0.0050)	(0.0088)	(0.0266)	(0.0092)	(0.0025)	(0.0091)
L.trade	0.0013	0.0016	0.0002**	0.0028	0.0066	0.00667	0.00013	0.0058	0.0002	0.0027*	0.0023**	0.0049***
	(0.0001)	(0.001)	(0.0001)	(0.0019)	(0.0043)	(0.00738)	(0.0022)	(0.0065)	(0.0131)	(0.0016)	(0.0009)	(0.0013)
L2.trade	0.0037	0.0044**	0.00082	0.00042	–0.0034	–0.0210	0.00533	0.0111**	0.0256	–0.0018	–0.0012	–0.0025
	(0.0001)	(0.0017)	(0.0001)	(0.0020)	(0.0044)	(0.0123)	(0.0035)	(0.0048)	(0.0297)	(0.0018)	(0.0008)	(0.0032)
L.gdp	0.009**	0.002*	–0.0035	0.0073***	0.0119	0.00041	0.0158*	0.00465	0.00406	0.0022***	0.0004	0.0038***
	(0.0036)	(0.0014)	(0.0032)	(0.0019)	(0.0104)	(0.00046)	(0.0094)	(0.0243)	(0.0042)	(0.0008)	(0.0006)	(0.0014)
L2. gdp	0.0048	0.0019	0.0027	0.00054	0.0475**	–0.000783	0.0199*	0.0052	0.0019	0.0048***	0.0016**	0.0068***
	(0.0041)	(0.0014)	(0.0022)	(0.0019)	(0.0225)	(0.00280)	(0.0113)	(0.0225)	(0.00455)	(0.0010)	(0.0007)	(0.0018)

Table A4: The Impact of Income Inequality on Educational Inequality for all Subsamples with Set of Control Variables (Contd.)

Panel A	*LICs FE*	*RREG*	*AB one stepSYS-GMM*	*LMICs FE*	*RREG*	*AB one stepSYS-GMM*	*HMICs FE*	*RREG*	*AB one stepSYS-GMM*	*HOCs FE*	*RREG*	*AB one stepSYS-GMM*
Dependent Variable	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*	*dginiHC*
N	14	14	14	21	21	21	32	32	32	34	34	34
T	8	8	8	8	8	8	8	8	8	8	8	8
Hansen test (p-level)			0.999			0.903			0.623			0.490
Difference Hansen test (p-level)			0.925			0.894			0.514			0.686
AB test (p-level)			0.924			0.123			0.560			0.073
Wald test (p-level)	0.029	0.027	0.023	0.0655	0.002	0.096	0.094	0.000	0.011	0.473	0.375	0.232

Source: Author's analysis.

Note: dginiY – Change in income inequality. dginiHC – Change in educational inequality. ays – Change in average years of schooling. Trade – Change in the degree of trade openness. gdp – Change in the real GDP per capita. Standard errors are in parenthesis. Time dummies are included. Estimates for constant terms not shown. AB test = Arellano-Bond test for AR(2) in first differences.* Significance at the 10 per cent level. ** Significance at the 5 per cent level.*** Significance at the 1 per cent level. FE – Fixed Effect. RREG – Robust Regression. AB one-step SYS-GMM – Arellano Bond one-step system GMM.