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A NOVEL ASSESSMENT OF THE GROWTH-INEQUALITY NEXUS IN EAST-CENTRAL EUROPE

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This paper investigates the nexus between economic growth and income inequality by exploring a sample of 11 Central and Eastern European (CEE) emerging countries from 2000 to 2019. The existing theory argues for three different situations that may appear: a positive link between economic growth and inequality, a negative association or a non-linear relationship. Generally, by employing a fixed-effects model that is robust to heteroskedasticity, cross-sectional dependence and autocorrelation, our findings reveal a significant non-linear growth-inequality connection, in accordance with Kuznets inverted U-shaped hypothesis. Additionally, we find that several transmission channels considerably influence this relationship in the CEE group, including poverty, educational attainment and trade openness. Our results denote a positive impact of international trade and human capital investment on reducing income inequality, emphasizing that an increase in the share of the population with tertiary education and trade openness will lead to a decrease in the Gini coefficient. Moreover, by improving the correlation between labour market requirements and the educational attainment of the population and adopting efficient poverty-reduction strategies, sustainable economic growth may mitigate the adverse influence of inequality in the long term. Therefore, policymakers should pay attention not only to the general macroeconomic framework of these countries but also to the implications of the socioeconomic dimension of inequality to reduce existing income disparities.

Keywords: **Income inequality; Economic growth; Human capital; Trade; Eastern Europe**

JEL Classification: **O40, O47, D63, I32**

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1. Introduction

The connection between income inequality and economic growth has been well-studied over the past 25 years, with papers reporting various results. The ambiguity in the prediction of the theoretical models is reinforced by the empirical literature, which provides evidence of three different situations that may appear: a positive growth-inequality link (Forbes, 2000; Foellmi and Zweimuller, 2006), a negative connection between concepts (Perotti, 1996; Cingano, 2014; Breunig and Majeed, 2020), and a non-linear or non-statistically significant relationship (Panizza, 2002; Neves and Silva, 2014).

To the best of our knowledge, several reasons can be responsible for the conflicting empirical outcomes, including the time horizon considered, the methods employed, the quality of the data, measurement errors and so on. Also, the heterogeneous effect of inequality on growth may be caused by the specificity of the analyzed countries, such as regime and trends in variables: savings (Kaldor, 1956), credit market imperfections (Galor and Zeira, 1993; Durlauf, 1996), political economy (Alesina and Rodrik, 1994; Persson and Tabellini, 1994), social conflicts (Perotti, 1996), and other socioeconomic factors including human capital accumulation and poverty (Ravallion, 2001; Todaro and Smith, 2015; Edward and Sumner, 2018).

Recent research has focused its attention on emphasizing the negative impact of income inequality on economic growth, manifested through these channels (Berg et al., 2018; Chang et al., 2018). Halter et al. (2014) claim that higher inequality enhances growth in the short run, but this impact tends to become negative in the long run. From another point of view, economic theory has also assumed non-linearity in tackling the relationship between economic growth and income inequality (Kuznets, 1955; Barro, 2000; Banerjee and Duflo, 2003). So, in our study, we will test this potential non-linearity, starting our analysis from the popular Kuznets' (1955) hypothesis.

Therefore, we investigate the connection between economic growth and inequality and, at the same time, assess the effect of some factors belonging to the social dimension of inequality in 11 CEE countries during 2000-2019, for which the literature is scarce (Anghel, 2017; Oancea, Tudorel and Pîrjol, 2017). Moreover, in Europe, the income gap between the rich and the poor has increasingly expanded over time (Darvas, 2019). Given the new increases in the degree of inequality, studying its influence on growth remains a research question interesting to tackle. Empirically, we are interested in evaluating the growth-inequality linkage in the East-Central European states due to the mixed findings regarding the pattern of this connection in emerging countries and the potential impact of other macroeconomic drivers that may influence it. Regarding the methodology, the research methods that are used to test the proposed hypothesis consist of employing consistent fixed-effects estimators. As a robustness check, we will use several indicators as control variables, including absolute poverty, trade openness, and education proxies.

The results show the existence of a potential non-linear growth-inequality nexus in the form of a quadratic equation, supporting Kuznets's approach. As we consider additional control variables, the relationship remains highly significant. Moreover, we draw to attention that an indirect connection exists between poverty, trade, education, and inequality, reflecting that an increase in the poverty degree and the number of individuals with tertiary education will lead to a decrease in the level of income inequality. On the other hand, we observe that higher transactions between foreign partners may reduce the degree of inequality. In this regard, the Heckscher-Ohlin (1933) theory states that higher trade openness can reduce income inequality in less developed countries because it may benefit the low-skilled workforce, while unskilled labour in countries well-endowed with skilled labour will suffer from international trade (i.e. individuals that own capital are favoured). Other studies (Berg et al., 2018; Breunig and Majeed, 2020) support the existence of a negative association between trade and inequality in emerging countries, implying that an increase in trade openness will lead to a reduction in income inequality and may boost economic performance.

The rest of the paper is organized as follows: Section 2 presents an overview of the dedicated literature. Section 3 comprises the methodology. Data is presented in Section 4, while Section 5 shows the results. We conclude in the final section.

2. Literature review

Several empirical studies have tackled the inequality-growth nexus due to the mixed evidence obtained in the past decades (Cingano, 2014; Chang et al., 2018; Hailemariam and Dzhumashev, 2019). In this regard, the outcomes of the empirical studies can be divided into three categories: positive, negative and non-linear or non-statistically significant relationships between economic growth and income inequality.

2.1. Empirical evidence of a positive relationship between income inequality and economic growth

In arguing his hypothesis, Kuznets (1955) uses time-series data relative to the United Kingdom, the United States and France and finds a non-linear (i.e. quadratic) relationship between economic growth and income inequality in the form of an inverted-''U''. In this analysis, Kuznets uses as inequality proxy the participation in income earning by the percentiles of a population.

Moreover, some further studies support Kuznets' findings regarding a positive association between concepts (Forbes, 2000; Li and Zou, 2002; Foellmi and Zweimuller, 2006; Rodriguez-Pose and Tselios (2010); Halter et al., 2014). Li and Zou (2002) extend Alesina and Rodrik's (1994) work and use panel data techniques with fixed and random effects spanning 1960-1990. The authors obtained a positive value of the coefficient relative to the inequality measure considered, namely the Gini coefficient. However, these results are in striking contrast with those obtained by Alesina and Rodrik (1994) and those of Persson and Tabellini (1994). Their theoretical explanation of this finding may lay in the fact that a higher level of income inequality could encourage greater savings for rich individuals and, as a consequence, stimulate higher GDP growth rates.

Furthermore, Forbes (2000) employs a model with fixed and random effects and also approaches the Generalized Method of Moments (GMM) system developed by Arellano and Bond (1991), in which economic growth depends on the initial inequality level, individuals' degree of education and market distortion. Employing dynamic panel methods, Lee and Son (2016) contradict Forbes (2000) outcomes. In summary, the existing empirical evidence on the inequality–growth linkage tends to confirm a positive connection driven by various factors in the short run, as shown by the previous works.

2.2. Empirical evidence of a negative relationship between income inequality and economic growth

Since the launch of Kuznets' inverted U-shaped hypothesis, most empirical studies pointed to a significant negative impact of inequality on the growth process (Cingano, 2014; Berg et al., 2018; Breunig and Majeed, 2020). In line with the theory of credit market imperfections and human capital accumulation, a second bulk of literature establishes a negative link between income inequality and economic growth (Persson and Tabellini, 1994; Alesina and Rodrik, 1996; Perotti, 1996).

Several studies reinforce the findings obtained by previous scholars (Cingano, 2014; Berg et al., 2018; Madsen et al., 2018). Cingano (2014) argues that increased inequality hampers economic growth by controlling for initial income, investment and education. He also finds that inequality interacts with human capital to hinder growth by focusing only on the OECD countries. On the other hand, Berg et al. (2018) use more available data regarding the income inequality level and show that lower inequality is correlated with durable economic growth. In their baseline regressions, the authors consider initial income, inequality and redistribution and add as control variables investment, population growth and education to verify the stability of the relationship between the dependent and the regressors.

Other recent works (Grundler and Scheuermeyer, 2018; Royuela, Veneri and Ramos, 2018; Breunig and Majeed, 2020) also focus on the adverse influence of income inequality on growth. The pattern of the relationship between inequality, urban size and economic growth was investigated using a panel of 15 OECD countries observed from 2003 to 2013 by Royuela, Veneri and Ramos (2018). Their results support an inverse relationship by employing country-fixed effects and a dynamic panel approach based on the GMM estimator. On the other hand, Breunig and Majeed (2020) find that when poverty (i.e. daily income below 1.90 USD measured by the World Bank) is less than 30%, the connection seems to be statistically insignificant, but the negative impact increases as the poverty degree increases. Their findings are similar to those of Ravallion (2001) and Grundler and Scheuermeyer (2018), who emphasize the negative effect of income inequality on growth, especially in poor countries.

2.3. Empirical evidence of a non-linear or non-statistically significant relationship between inequality and economic growth

Another strand of literature emphasizes a non-linear association between income inequality and economic growth (Barro, 2000; Panizza, 2002; Chen, 2003; Brueckner and Lederman, 2018). Accounting for non-linearity, Barro (2000) highlights the non-existence of a linear relationship between the variables, where inequality tends to promote growth at high levels of income but retard growth at lower levels. These findings are consistent with those obtained by Chen (2003), who found an inverted U-shaped nexus between inequality and growth. In contrast, Panizza (2002) observes the evolution of income inequality and growth in the United States and does not find statistically significant estimates for the coefficients related to the inequality measures (i.e. the Gini coefficient and the share of income earned by the third quantile). Given that these outcomes are in contrast with those of Forbes (2000), the author argues that the cross-state connection "is not robust to small changes in the data or econometric specification" (Panizza, 2002).

3. Methodology

Although a pooled OLS model may fit the data well, we suspect that each unit or year considered may have a different initial level of income inequality. Each country may have its own initial Gini coefficient, its Y-intercept, significantly different from those of the other countries. Furthermore, we may believe the error terms vary across country and/or year. The former question suspects fixed effects, whereas the latter asks if there is any random effect.

First, we assume that something within the entity (economy) may impact or bias the predictor or outcome variables, and we need to control for this influence. Each entity has its characteristics that may or may not affect the predictor variables. In this case, the fixed effects model is the best approach when we are interested in analysing the impact of variables that vary over time by assessing the predictors' net impact. Another assumption of the fixed-effects model is that those time-invariant characteristics are unique to the individual and should not be correlated with other particular characteristics. This means that the entity's error term and constant should not be correlated with the others. If the error terms are correlated, then this approach would not be suitable, and we should probably model the relationship using random effects. In this regard, we draw upon the Hausman (1978) test to reinforce our economic reasoning, namely the applicability of a fixed effects specification.

Therefore, by adapting Kuznets' expression to account for fixed-effects, our final model becomes:

$$INEQ_{it} = \alpha_i + \beta_1 GROWTH_{it} + \beta_2 GROWTH^2_{it} + \theta X_{it} + \varepsilon_{it} \tag{1}$$

Which assumes a second-order polynomial relationship between economic growth *(GROWTH)* and income inequality *(INEQ).* X represents the vector of control variables that have been added to avoid omitted variable bias *(POV, TERT.ED, TRADE),* α_i is the unknown intercept for each country, implying n country-specific intercepts, and ε the error term with i = 1,..., N and t = 1,..., T. Furthermore, when we suspect that unexpected variations or special events may affect the outcome variable, we should also control for time-fixed effects.

Second, to validate our fixed effects estimations, we employ post-estimation tests to control for the presence of cross-sectional dependence, heteroskedasticity and serial correlation. According to Baltagi (2021), cross-sectional dependence and serial correlation are a problem in macro panels with long time series. The cross-sectional dependence in our sample may be related to the fact that the Gini coefficient in one country could depend on the Gini coefficient of another country, as well as potential common dynamics of GDP, given that these countries belonged to a common system until 1990. To test for this dependence, we use various tests, namely the Breusch-Pagan (1980) LM test, Baltagi et al. (2012) Bias-Corrected scaled LM, Pesaran (2004) CD, and Pesaran (2004) scaled LM. Regarding heteroskedasticity and serial correlation, we employ the modified Wald test for groupwise heteroskedasticity in the fixed effects regression model and the Wooldridge test for autocorrelation in panel data.

If these hypotheses are confirmed, we should apply an estimation method that appropriately adjusts the standard errors in a fixed effects model. Probably the most popular of these alternative covariance matrix estimators have been developed by Eicker (1967), Huber (1967), and White (1980), but they assume that the residuals are independently distributed. Another approach to obtaining heteroskedasticity and autocorrelation-consistent standard errors was developed by Newey and West (1987) using a GMM-based covariance matrix estimator. However, all these techniques do not consider cross-sectional correlation, but in many cases, it would be more natural to assume that the residuals are correlated both within and between groups.

Estimation methods that account for cross-sectional dependence include Parks (1967), who proposes a feasible generalized least squares (FGLS) based algorithm, and Beck and Katz (1995), who suggest relying on OLS estimates with panel corrected standard errors (PCSE). Nevertheless, some sample properties of the PCSE estimator are relatively weak when the panel's cross-sectional dimension (N) is large compared to the time dimension (T). Thus, the cross-sectional covariance matrix's estimate will be rather imprecise if the ratio T/N is small.

By relying on large T asymptotics, Driscoll and Kraay (1998) demonstrate that the standard covariance matrix estimator can be modified such that it is robust to general forms of cross-sectional and temporal dependence. Therefore, Driscoll and Kraay's technique eliminates the deficiencies of large T consistent covariance matrix estimators such as Parks' (1967) method or the PCSE approach. In this case, the error structure is assumed to be heteroskedastic, autocorrelated up to some lag, and possibly correlated between groups.

4. Data

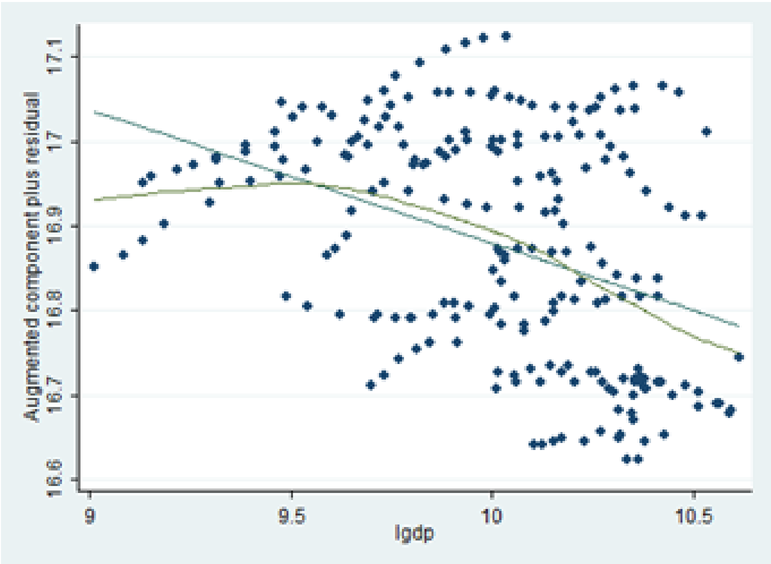
Our full sample of countries for which we have collected the real GDP per capita and other socioeconomic indicators consists of 11 emerging states from East-Central Europe. These countries were selected to better assess this connection in the former communist Bloc by illustrating the overall development trend of these economies.

For the present study, we consider the period 2000-2019 and draw data from different sources. Our income variable is taken from Penn World Tables 10.1 (PWT) and is based on the real GDP per capita expressed in chained PPPs (in mil. 2017 USD). Further, we use an inequality dataset from Solt (2019) using the Standardized World Income Inequality Database (SWIID) v9. To the best of our knowledge, this database covers the largest number of countries and spans the most extensive period for available income inequality data. To capture the real degree of inequality in the income distribution, we use the Gini coefficient based on net inequality, which is calculated after taxes and transfers.

To reflect the socioeconomic dimension of the countries considered, we render specific indicators that highlight the level of poverty, trade openness and human capital. According to the existing literature, countries with higher economic growth rates and productive trade have lower income inequality and poverty levels. In contrast, economies with less investments and trade openness do not succeed in narrowing the disparity in income distribution, emphasizing a higher degree of poverty. The Headcount index measured at 1.90 USD/day and trade as %GDP are taken from the World Development Indicators (WDI) and the Poverty and Inequality Platform (PIP), respectively. For human capital, we use as an explanatory variable the share of the population aged 25 and older with tertiary education, which is collected from Eurostat. All the variables are brought to their logarithmic forms to normalize the data, except the poverty indicator. Descriptive statistics for the above variables are provided in Table 1A from the Appendix.

5. Results

By employing a simple scatterplot to explore the relationship between economic growth and income inequality, we observe a quadratic pattern that claims the need for a squared version of the regressor in the model to efficiently deal with U-shaped curves (Figure 1).



Source: Author's calculations using STATA 17

Figure 1. Gini and GDP relationship

First, we employ the Hausman (1978) test, which examines whether individual effects are uncorrelated with other regressors. So, the random effects model is preferred under the null hypothesis due to higher efficiency, while the alternative (i.e. the fixed effects specification) is at least as consistent and thus preferred. In our case, we failed to accept the null hypothesis with a prob > chi2 of 0.000 and conclude that the fixed effects model is more appropriate. Then, by employing country-fixed effects, we find a non-linear and highly significant GDP-Gini link (Table 1). Furthermore, when we suspect that unexpected variations or special events may affect the outcome variable, we should control for time-fixed effects. Indeed, such events happened in the last decades and must be taken into account if we consider the majority of the CEE countries joining the European Union in the period 2004-2007 and the global financial crisis from 2008-2009. When testing for time-fixed effects, the outcomes confirm their relevance (column 2 of Table 1). Considering both country- and time-fixed effects, education and trade coefficients changed their sign, implying that an increase in the share of the population with tertiary education and trade openness will lead, on average, to a decrease in the Gini index by 0.023 and 0.033%, respectively. Nevertheless, both results are insignificant in this case.

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Table 1. Country- and time-fixed effects estimations

VARIABLES	(1) FE robust	(2) Country and Time FE robust
LGROWTH	3.037***	3.854***
	(0.715)	(1.056)
$LGROWTH^2$	-0.154***	-0.201***
	(0.038)	(0.057)
POV	-0.004**	-0.005***
	(0.002)	(0.002)
LTERT.ED	0.043**	-0.023
	(0.045)	(0.037)
LTRADE	0.020	-0.033
	(0.046)	(0.069)
Constant	-11.76***	-14.87**
	(3.415)	(4.973)
Turning point	19.148, 89 PPP	14.588,66 PPP
Observations	220	220
R-squared	0.957	0.965
Adj. R-squared	0.954	0.959

*Notes: Standard errors in brackets. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.*

Source: Author's calculations using STATA 17

Second, we further proceed to some post-estimation tests to support our main findings. These results show that the null hypothesis of cross-sectional independence is strongly rejected in all cases in favour of the presence of cross-sectional dependence (Figure 2).

Residual Cross-Section Dependence Test
Null hypothesis: No cross-section dependence (correlation) in residuals
Equation: EQ01
Periods included: 20
Cross-sections included: 11
Total panel observations: 220
Cross-section effects were removed during estimation

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	230.1594	55	0.0000
Pesaran scaled LM	16.70079		0.0000
Bias-corrected scaled LM	16.41132		0.0000
Pesaran CD	-2.825335		0.0047

Source: Author's calculations using Eviews 13

Figure 2. Cross-sectional dependence analysis

Regarding the heteroskedasticity and serial correlation tests, we employed the modified Wald test for groupwise heteroskedasticity that rejected the null hypothesis of homoskedasticity or constant variance. These outcomes confirm our main idea that although CEE countries are part of a common framework (i.e. the European Union), they differ across several dimensions.

Moreover, we have to consider the differences in the socio-political environment of these countries, including the year of accession to the EU (Romania and Bulgaria joined in 2007 and Croatia, the latest, in 2013). In conclusion, these features suggest the existence of a certain degree of heterogeneity among CEE economies, consistent with the previously emphasized differences in Gini dynamics. On the other hand, we used the Wooldridge test for autocorrelation in panel data models, and again, we failed to reject the null hypothesis of no serial correlation. Thus, we conclude that our fixed effects specification patterns heteroskedasticity, cross-sectional dependence and serial correlation.

In this case, we should apply an estimation method that systematically overcomes these characteristics. The results are comparatively shown in Table 2. In columns 1 and 2, we illustrate, on the one hand, the estimates obtained by employing the FGLS to account for heteroskedasticity, cross-sectional dependence and autocorrelation of type AR(1) with a common coefficient for all panels, and on the other hand, the outcomes for a panel-specific AR(1) model. This approach requires that N < T be feasible but tends to produce optimistic standard error estimates. The results are quite similar in terms of coefficients and signs for the two methods using generalized least squares coefficients. However, the standard errors obtained seem to be small, as confirmed by Beck and Katz (1995). In this regard, the outcomes obtained using the Driscoll-Kraay method are shown in the last column.

This method allows for autocorrelation with moving average type with a lag length q (MA(q)), even more, if we deal with high-order autocorrelation. The coefficients shown in column 3 depict identical coefficients and significance levels as in the country and time-fixed effects model (excepting the Headcount index's significance that turned at the 5% significance level), but the standard errors are smaller and correctly adjusted to account for heteroskedasticity, cross-sectional dependence and serial correlation, contrary to the simple fixed effects model.

Therefore, we conclude that the relationship between economic growth and income inequality patterns a second-order polynomial form (i.e. inverted U-shape) at the 1% significance level. In contrast, a higher level of poverty, educational attainment and trade openness tend to diminish the degree of inequality in the income distribution by 0.5%, 0.023% and 0.033%.

Table 2. FGLS and, Driscoll and Kraay estimates

VARIABLES	(1) FGLS common AR1	(2) FGLS panel-specific AR1	(3) Driscoll-Kraay SE
LGROWTH	2.880***	2.796***	3.854***
	(0.178)	(0.162)	(0.321)
$LGROWTH^2$	-0.148***	-0.143***	-0.201***
	(0.009)	(0.009)	(0.017)
POV	-0.00002	-0.0002	-0.005**
	(0.0003)	(0.0003)	(0.002)
LTERT.ED	-0.010	-0.019**	-0.023
	(0.010)	(0.007)	(0.028)
LTRADE	-0.033***	-0.032***	-0.033
	(0.012)	(0.009)	(0.048)
Constant	-10.39***	-10.02***	-14.87***
	(0.842)	(0.751)	(1.509)
Turning point	16.814,55 PPP	17.606,09 PPP	14.588,66 PPP
Observations	220	220	220

*Notes: Dependent variable: Gini coefficient in logarithmic form. Standard errors in brackets. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.*

Source: Author's calculations using STATA 17

6. Conclusion

Over the years, there has been a bulk of studies that attempt to shed light on the question of whether inequality is detrimental to long-run aggregate economic productivity or whether it stimulates economic growth. The existing literature has spanned the full set of possible links between economic growth and income inequality: positive, negative, non-linear or non-significant, but the debate has not been concluded yet.

Our study starts from Kuznets' (1955) hypothesis and follows the first approach (i.e. positive relationship in the first stages of development), testing for a potential non-linear association between economic growth and income inequality. This research is in line with the previous works of Siami-Namini and Hudson (2018), arguing for the existence of an inverted U-shaped curve in emerging and less developed countries.

Consequently, we regress the Gini measure of income inequality on economic growth in a panel of 11 CEE countries from 2000-2019. Following Perotti (1996), Cingano (2014) and Berg et al. (2018), among others, we include education measures as a proxy for human capital accumulation, the Headcount index to capture the absolute poverty level, and trade as % of the GDP to reflect the countries' international openness, with the purpose of assessing the influence of some relevant socioeconomic drivers on this connection. Nevertheless, the main limitation of this study represents the lack of recent data availability for poverty and higher education proxies.

Conducting specific panel data techniques robust to heteroskedasticity, cross-sectional dependence and autocorrelation, we find a quadratic growth-inequality linkage corroborated with a beneficial influence of foreign trade and human capital investment, highlighting that an increase in the share of the population with tertiary education and trade openness will lead to a decrease in the Gini index.

Concerning further research, our analysis could advance in various directions that may delimit from the existing literature: 1) considering, on one hand, the full sample of East-Central European countries, including those that are not in the Eurozone, and on the other hand, investigating this connection in a broader sample of developed and emerging economies; 2) testing alternative theories on transmission channels that may influence this relationship by adding other control variables less studied in the literature such as inflation, unemployment, the Human Development Index, etc.

As policy implications, according to the empirical findings, we argue that a method to improve long-run economic growth implies controlling absolute poverty, fostering international trade and higher investments in human capital, especially by expanding the population's access to health and higher education, but also by offering more qualitative job opportunities that are better correlated with individuals' educational attainment. In this manner, growth can sustainably contribute to lessening income inequality in the future.

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Appendix

Table 1A. Summary statistics

Country / Variable	Statistic	GROWTH	INEQ	TERT.ED	POV	TRADE
Bulgaria	Mean	15427.38	34.62	20.37	2.94	109.86
	Std. Dev	4129.25	2.06	3.03	2.17	20.341
	Min	9252.00	31.90	15.10	0.90	75.27
	Max	22773.89	38.00	24.80	8.80	130.59
Croatia	Mean	21085.95	28.38	16.38	0.47	85.07
	Std. Dev	4103.44	0.946	3.07	0.34	8.92
	Min	13183.89	27.20	13.10	0.00	70.94
	Max	27512.02	29.50	22.00	1.20	104.17
Czech Republic	Mean	30977.64	25.25	14.95	0.08	128.75
	Std. Dev	5598.19	0.36	4.56	0.27	21.40
	Min	22238.33	24.40	9.50	0.00	91.33
	Max	40731.74	25.96	21.70	1.20	157.58
Estonia	Mean	25218.17	32.81	29.88	0.76	141.22
	Std. Dev	7464.66	1.34	4.01	0.46	15.38
	Min	13031.79	30.70	24.10	0.20	116.11
	Max	37120.74	35.10	36.50	2.30	169.49
Hungary	Mean	24449.24	27.50	17.07	0.33	150.21
	Std. Dev	4705.50	0.35	3.51	0.42	17.93
	Min	16567.90	26.80	11.70	0.00	116.61
	Max	33265.40	27.90	22.50	1.40	168.24
Latvia	Mean	20786.17	34.87	22.33	0.99	106.08
	Std. Dev	6144.41	0.73	5.85	0.62	17.10
	Min	11103.81	32.80	14.90	0.30	81.63
	Max	31423.22	35.60	31.40	2.40	127.53
Lithuania	Mean	23615.91	33.94	27.73	1.79	125.99
	Std. Dev	7647.01	1.20	6.11	1.33	22.45
	Min	12092.73	32.00	19.00	0.70	83.38
	Max	37497.89	35.80	37.90	5.80	155.89
Poland	Mean	22608.45	30.34	18.57	0.96	83.12
	Std. Dev	6050.13	1.12	6.19	2.44	15.28
	Min	14619.49	28.50	9.20	0.04	58.16
	Max	33248.03	31.90	28.20	11.00	107.42
Romania	Mean	17402.09	32.30	11.69	3.93	70.078
	Std. Dev	6384.68	1.54	2.98	1.50	13.37
	Min	8204.02	28.90	7.50	1.45	48.52

Country / Variable	Statistic	GROWTH	INEQ	TERT.ED	POV	TRADE
	Max	28828.94	33.80	16.00	6.50	87.14
Slovakia	Mean	25569.48	25.03	14.76	0.83	159.05
	Std. Dev	5653.77	0.98	4.72	2.18	25.73
	Min	16290.59	23.00	8.20	0.10	108.79
	Max	32350.58	26.40	23.10	10.00	190.54
Slovenia	Mean	31340.94	24.29	20.67	0.03	131.49
	Std. Dev	4248.63	0.75	5.76	0.40	19.61
	Min	24453.45	23.40	11.60	0.00	102.32
	Max	39716.33	25.60	29.30	0.10	161.10

Source: Author's own calculations using STATA 17