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Does income inequality impact economic growth?

Evidence from Eastern European economies

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Abstract

Eastern Europe's post-socialist economies still experience both relatively high inequality and the need for faster growth, when compared to Western Europe. Using annual data for 16 such countries between 1995 and 2019, this paper examines the effect income inequality has on growth. Random-effects panel regressions relate GDP-per-capita growth to the Gini index and three additional measures of inequality. While the Gini index regression is insignificant and suggests that inequality has no impact on growth, some additional tail-focused measures show marginally significant, but very small effects. Therefore, the results suggest that inequality-targeting reforms, such as progressive taxation or broader access to education, are unlikely to decrease growth.

Declaration

I hereby declare that this thesis represents my own work.

I have read and applied the current research ethics guidelines concerning the use of artificial intelligence (AI) tools in this work, as outlined in the General Course Information. In the preparation of this work, the author utilised the following AI tools, specifying the purpose for their use:
Deepseek and ChatGPT were used for research ideas, correcting grammatical mistakes and helping with errors in STATA codes.
As author, I have reviewed and edited the content as needed and take full responsibility for the content of the thesis.

Signature:

Date: 17.5.2025.

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1. Introduction

The relationship between income inequality and economic growth has long been a subject of debate in economics. Early cross-country studies in the 1990s often found that higher inequality is associated with slower growth, suggesting that a more equitable income distribution can lead to faster development (Alesina & Rodrik, 1994; Perotti, 1996; Persson & Tabellini, 1994). However, as more data has become available and new methods applied, the relationship between the two variables has become less clear. A number of studies argue against the idea of a general negative relationship, leading to a diverse literature and no clear agreement on the overall effect. For instance, Barro (2000) argues that the effect of inequality differs depending on the country's stage of development, with higher inequality tending to decrease growth in low-income countries but increase growth in high-income countries. The mixed empirical findings in the literature indicate that the relationship might be complex and depend on the context.

In the specific context of Eastern Europe, studying the inequality-growth relationship is particularly important. Post-socialist Eastern European countries underwent a significant transition in the late 1980s and early 1990s, moving from a socialist to a capitalist socio-economic system. Under socialism, these countries generally had relatively low levels of income inequality, but in the early 1990s saw one of the fastest increases in inequality ever recorded (Brzezinski, 2022). Over the past two decades, inequality in Eastern European countries has stabilised, but remains quite significant and higher than in Western Europe (Brzezinski, 2022). Such levels of inequality, together with the region's ongoing efforts to achieve high economic growth, make it very important to understand how income distribution can influence growth in this region.

Despite extensive research on the inequality-growth relationship, much of the literature has focused either on global cross-country samples or on high-income Western nations, often overlooking Eastern Europe at least partially (Castelló-Climent & Doménech 2002; Cingano, 2014; Herzer & Vollmer, 2012; Thewissen, 2014). As a result, the specific dynamics of inequality and growth in Eastern Europe have not been explored in depth. Recently, Dorjnyambuu (2025) conducted a review of inequality research in Central and Eastern Europe

and found that the phenomenon of income inequality is understudied in these countries, although this region should be studied more than the West, as it exhibits higher inequality.

Therefore, this work attempts to study income inequality in an understudied region, filling a gap in the literature by concentrating on post-socialist Eastern Europe. In doing so, a set of Eastern European countries (beyond just the EU's older or newer members) is included. These are typically left out of Western Europe-centric analyses. The novelty of this research, therefore, consists in its regional focus. By analysing Eastern European economies, the study examines whether the inequality-growth relationship observed in other countries holds under the unique institutional and historical conditions of post-socialist countries.

Considering the motivation for the study, the research question posed is: Does higher income inequality influence economic growth in Eastern Europe? By focusing on Eastern Europe, the study aims to determine if the findings from other regions (such as Western Europe or developing countries) apply here, or if the inequality-growth relationship is different in Eastern Europe due to unique conditions.

This research is highly relevant for economic policy in Eastern Europe. If high inequality is found to decrease growth, it would strengthen the case for policies that promote a more equitable distribution, such as progressive taxation, social safety nets, or investment in inclusive education. These measures could then not only be justified by social justice concerns, but also by the necessity to increase economic performance. On the other hand, if inequality is found to have a positive effect on growth, policymakers might prefer growth-promoting strategies first while addressing inequality through gradual redistributive measures. For a region where inequality remains higher than in the West and where economic growth is needed, this study provides an important analysis.

To study the relationship between inequality and growth, an unbalanced panel is created with annual observations for sixteen post-socialist Eastern European economies between 1995 and 2019. The growth rate of real GDP per capita is the dependent variable, while the Gini index is the independent variable. A random effects model with 3 control variables is employed – human capital, population growth rate, and urbanisation rate. To test the robustness of the results, three additional measures of income inequality are employed: the Palma ratio, the Top20/Bottom20 ratio, and the income share of the Bottom 40. The results of this work suggest

that no consistent relationship between income inequality and economic growth exists in Eastern Europe, though the results might be sensitive to the measure of inequality employed.

The rest of this work is organised as follows: Section 2 (Literature review) discusses the empirical findings from prior studies on income inequality and economic growth, Section 3 (Theoretical framework) presents the theoretical works justifying the analysis, Section 4 (Data and Methodology) describes the data and variables used and details the methods applied, Section 5 (Results) reports the results of the analysis and discusses their significance and sensitivity, Section 6 (Discussion) interprets the results in light of the theoretical framework and empirical literature, Section 7 (Conclusion) summarises the findings and contributions of the work.

2. Empirical literature review

2.1 General findings of previous empirical work

The relationship between income inequality and economic growth has been a subject of academic debate for a long time. Early cross-country studies in the 1990s often found evidence that higher inequality decreased growth rates, supporting the view that a more equal income distribution leads to faster development. For example, Persson and Tabellini (1994) find a negative relationship between inequality and growth, arguing that inequality leads to policies that do not protect property rights and do not allow full private appropriation of returns from investment. Alesina and Rodrik (1994) also found that the relationship is negative, arguing that inequality increases social unrest and political uncertainty, thereby driving away investors.

Empirical analyses by Perotti (1996) also support this negative association. Perotti (1996) argues that channels such as lower human-capital accumulation and political instability are important ways through which inequality slows growth. Neves et al. (2016) conduct a meta-analysis of studies from 1994 to 2014, concluding that inequality's effect on growth is often negative on average, especially in developing economies. In particular, Neves et al. (2016) find that the negative impact of inequality on growth is more significant in developing countries than in developed countries (though the evidence is not unanimous). This suggests that context matters.

However, as more data becomes available and new methods are applied, a number of studies is challenging the notion of a negative inequality-growth relationship. This has resulted in a diverse empirical literature with conflicting evidence and no clear conclusion (Ferreira et al., 2022). Some researchers have found little overall correlation between inequality and growth when examining broad panels of countries. Barro (2000) observes "little overall relation" between income inequality and growth rates. Instead, he found that inequality tended to slow growth in low-income countries but to encourage growth in high-income countries. Specifically, Barro (2000) noted that when a country's per capita GDP is below a certain threshold (approximately $2000 in 1985 US dollars), higher inequality is associated with significantly lower subsequent growth, whereas in economies above that income level, higher inequality correlates with faster growth. This result suggests that the effect of inequality may change sign depending on a country's stage of development, potentially due to differences in mechanisms like credit access or political dynamics between rich and poor nations (Barro, 2000). It also aligns with earlier predictions by Kuznets (1955), the so-called inverted-U Kuznets curve, which predicts inequality rises and then falls with development, although the Kuznets curve does not fully explain growth differences across countries. Barro's (2000) finding also implies that policy implications might differ for developing versus advanced economies. Specifically, in very poor countries, reducing inequality might directly foster growth, whereas in richer nations active income redistribution appears to involve a trade-off between the benefits of greater equality and a reduction in overall economic growth (Barro, 2000). This view is supported by Castello (2010), Chambers and Krause (2010), Herzer and Vollmer (2012), and Khalifa and El Hag (2010).

Adding to the complexity, Forbes (2000) presented evidence of a positive short-run relationship between inequality and growth. Using inequality data and panel estimation to control for country-specific factors, Forbes found that "in the short and medium term, an increase in a country's level of income inequality has a significant positive relationship with subsequent economic growth" (Forbes, 2000). In other words, over five to ten-year periods, countries that experienced rising inequality tended to grow faster. Such a result, which was robust across different specifications, directly challenged the notion that inequality is always detrimental to growth. Forbes's analysis suggested that when looking at shorter horizons and differenced data, the effect of inequality may be positive, possibly because of incentive-related channels where

inequality increases investment or innovation in the short-run. However, it is important to note that this positive effect was identified only for the short and medium run and the long-run was not examined.

In fact, Halter et al. (2014) find exactly this by examining the differences between the short-run and the long-run. They (Halter et al., 2014) find that higher inequality might provide a short-run boost to growth but undermine growth in the long-run. Their panel analysis shows that, while greater inequality can increase growth rates in the short-run, it tends to reduce growth over longer time horizons, so that the total long-run effect of inequality is negative. This time dimension could explain why both positive and negative correlations are observed in the data – they are finding effects at different time horizons. Therefore, it is arguable that empirical findings might suggest a positive impact of inequality on growth in the short-run,[1] but a negative impact in the long-run.[2]

Before making conclusions on the relationship, however, one must acknowledge the problems with the literature as well. Neves et al. (2016), for example, document a significant publication bias in the literature, finding that studies have been more likely to be published when finding statistically significant effects (both positive and negative) than null results. After correcting for such biases, Neves et al. (2016) find that much of the remaining variation is explained by study conditions such as the estimation technique, choice of country (or countries), and the measure of inequality.

In sum, the empirical literature does not point to a single answer. Instead, it shows that the inequality-growth relationship is context-dependent and influenced by several factors. Factors such as time horizons, political environment, the measure of inequality and the level of development might all influence the relationship and the results of regressions. Therefore, the present study does not claim to discuss the relationship between economic growth and inequality. Rather, what is discussed is the relationship between economic growth and

[1] This could be explained by higher savings rates or incentives for effort.
[2] This, on the other hand, could be explained by barriers to education, socio-political instability, or policy distortions. If, in the long-run, the negative correlation prevails, it can be argued that these factors are taking over and eroding away inequality's positive effects on growth.

inequality in post-socialist Eastern Europe, using various measures of inequality. I now turn the reader's attention to the various measures of inequality employed in the literature.

2.2 Different inequality measures and their importance

Different studies have employed different measures of inequality, and these choices can affect the observed relationship with economic growth. The Gini index of income distribution, which summarises income inequality on a 0 to 100 scale, is the most commonly used measure of inequality (Barro, 2000; Das & Parikh, 1982; Deininger & Squire, 1996; Forbes, 2000).

Apart from the Gini index, scholars have examined other indicators, such as income shares of different income groups or the ratios between them. The Palma ratio[3] is also a popular measure of inequality used in the literature (Cingano, 2014; Clarke, 1995). Another way to measure inequality is to simply examine the shares of total income held by different income groups (Persson & Tabellini, 1994; Barro, 2000). Barro (2000), for example, uses the five quintiles (Q1 to Q5) of the income distribution as different measures of inequality.

Apart from the Gini index, Voitchovsky (2005) uses the ratio between the 90th and 75th percentile, as well as the ratio between 50th and 10th percentile of the income distribution, finding that inequality among the rich (upper tail inequality) appeared to spur economic growth, while inequality among the poor (lower tail inequality) tended to impede growth. In other words, a widening gap between the middle class and the very rich might increase growth (possibly by encouraging investment or entrepreneurship by the wealthy), whereas a widening gap between the poor and the middle class can reduce growth (possibly by limiting educational advancement and opportunities for the poor). Such a result implies that a single measure of inequality like the Gini index can hide these offsetting effects. A society with the same Gini index can have very different distributions of inequality, one where disparities are primarily top-to-middle and another where they are bottom-to-middle. And these different distributions could have different effects on growth.

Considering this, the present work includes additional measures of inequality, apart from the Gini index, to test the robustness of the relationship between inequality and growth and examine whether growth is differently impacted by different sides of the income distribution.

[3] This is the ratio between the top 10% and the bottom 40% in the income distribution (Cingano, 2014)

2.3 Political and educational factors

Empirical research has also revealed that the relationship between growth and inequality can depend on a country's political system and educational context. Persson and Tabellini (1994), for example, find a negative relationship between growth and inequality for democracies, but no significant relationship for autocracies. The present study, however, does not include a dummy variable for democracies in the model employed. The reason for this is that deciding which country is a democracy is quite difficult for Eastern Europe, especially when considering the whole time period from 1995 to 2019. While the governments of some Eastern European countries like Hungary, Croatia, Poland, Serbia or Russia might be accused of undertaking undemocratic measures or having autocratic leaders in some moments during the period under consideration, it is very hard to determine the cases and time periods for which this is true. To prevent arbitrary decision-making, such a variable is excluded from the model in this study.

Furthermore, measures of human capital inequality (such as the variance of education levels in the population) have been studied, with some evidence that unequal education attainment harms growth by lowering the average human capital available to the economy (Castello & Domenech, 2002; Deininger and Olinto, 2000; Deininger & Squire, 1998). The present study does not include human capital inequality as a separate measure for inequality, as it is only concerned with income inequality. However, human capital is considered as a control variable to control for growth caused by it and to differentiate it from the growth caused purely by income inequality.

3. Theoretical framework

Over the years, economists have developed several theories to explain why inequality might affect both the sustainability and speed of economic growth, with different theories predicting different relationships between the two variables. In general, the mechanisms by which inequality affects growth can be categorised into a few channels. This section discusses the main channels through which inequality could influence growth: 1) savings and investment, 2) barriers to investment and education, 3) redistributive policies, and 4) socio-political unrest. Each of these channels provides an explanation as to how inequality can influence growth, showing that the debate on this issue is not only unresolved empirically, but also theoretically.

3.1 Savings and investment

One of the oldest theoretical arguments connecting inequality to growth is the theory that savings and capital accumulation, which are caused by inequality, increase growth. Kaldor (1956) suggested that inequality affects growth through savings because of the assumption that the higher the level of income of an individual, the higher would be the saving rate (Aghion et al. 1999). According to Barro (2000), this view dates back to Keynes (1936), who first introduced the concept of the marginal propensity to save,[4] which he believed increased with the income of an individual.

Thorbecke and Charumilind (2002) explain that this assumption that the rich have a higher marginal propensity to save relative to the poor can be explained by two assumptions: 1) an individual does not save until he achieves a certain level of consumption, which means that the poor cannot save, and 2) the possibility to save is conditioned by the previous generations, which leads to a concentration of savings in rich households.

In an economy where investment (and, therefore, growth) is constrained by savings, shifting more income to high-saving, wealthy households can increase the total savings available for investment in the economy, consequently increasing growth. Kaldor (1956) formalises this by assuming that the saving rate rises with income. Under this assumption, inequality has a positive effect on growth through higher aggregate savings. Stiglitz (1969) also provides a formal model in line with this argument. Importantly, both Stiglitz (1969) and Kaldor (1956) assume that the additional savings are actually reinvested into the domestic economy (which might depend on having a sufficiently developed financial system and investment opportunities). However, if the rich mostly save by investing abroad or in unproductive assets, there will be no more growth than if these resources were given to the poor. Nonetheless, the savings channel provides a theoretical explanation for findings showing inequality promotes growth.

A variant of this theory eventually came to be known as "trickle-down economics" or "Reaganomics" and was used to justify tax cuts and deregulation for corporations and high-income earners under Ronald Reagan's economic policies in the 1980s (Brownlee, 2016).

[4] The marginal propensity to save, according to Keynes (1936), is the proportion of an additional unit of income that is saved rather than spent on consumption.

Supporters of the president argued that wealth generated at the top would “trickle down” through increased business spending and wages.

3.2 Barriers to investment and education

A possible explanation offered by Barro (2000) for why inequality could slow growth are barriers to productive investment which could benefit the economy. With the existence of imperfections on the credit market in a highly unequal society, relatively poor individuals may not be able to acquire credit. In such cases, the initial distribution of income and wealth matters for who can invest and improve his economic situation. If capital (in the form of credit) is required to make these investments and credit markets are imperfect, then poorer individuals will be unable to invest in their education or start a business even if they are competent. If wealth is very unequally distributed, only the rich can afford these costs, and potentially high-return investments by the non-rich go unrealised. This results in a lower aggregate growth rate than in a more equal society where a wealthier middle class can invest.

This theory was further developed by researchers like Banerjee and Newman (1993) and Aghion and Bolton (1997), who examined how wealth distribution affects occupational choices and growth when external finance is limited. Their models show multiple equilibria with different levels of inequality, education, and growth, suggesting that persistent inequality can keep an economy stuck on a lower growth path. Therefore, this theory provides an explanation for why inequality has been found to hurt growth, especially in poorer countries. Aghion and Bolton (1997) find that government intervention may be required to redistribute wealth from rich lenders to poor and middle-class borrowers. They argue that this can improve productivity in an economy because it leads to increased equality of opportunity and because it accelerates the trickle-down process.

Galor and Zeira (1993) support this view, finding that the initial distribution of wealth affects aggregate output and investment both in the short and in the long-run. They further develop the theory by arguing that credit market imperfections lead to different investments, not only in the economy, but also in education. Because of fixed costs of education and an inability to borrow, economies with concentrated wealth end up with fewer people investing in human capital than would be optimal. Their model showed that inequality can lead to under-investment in human capital by the poor, which lowers overall growth both in the short-run

and long-run. In an unequal society, many talented but poor individuals cannot afford education, so the working masses fail to fully develop their potential for productivity (Galor & Zeira, 1993). This leads to a negative relationship between inequality and growth in the presence of credit constraints.

The human capital channel of inequality and growth might also be connected with demographics. Some authors (Galor & Moav, 2004; De la Croix & Doepke, 2003) argue that inequality can lead to differences in fertility rates between rich and poor, which in turn affect human capital accumulation. The poor might have more children, lowering their possibility to invest in each child's education. On the other hand, the rich invest a lot in a few children. This can reinforce the negative impact of inequality on the human capital of the next generation, thereby slowing growth.

3.3 Redistributive policies

A third major theoretical explanation for the relationship between growth and inequality states that inequality might influence political decision-making. This theory deals with how inequality influences government policies and how those policies in turn affect growth. The government policies in question are redistributive, such as taxation and public spending, and they are claimed to influence growth negatively (Barro, 2000).

Meltzer and Richard (1981) argue that greater inequality leads the median voter to demand higher taxes on the rich to redistribute income. While redistribution can reduce inequality, the taxes used to fund it (especially if they are imposed on income or capital) may discourage work, saving, or investment, thereby slowing economic growth. Building on this, Alesina and Rodrik (1994) and Persson and Tabellini (1994) each developed models where high inequality in a democracy results in policies (like high taxation) that lower the return on investment and hence reduce growth. Alesina and Rodrik (1994) argue that the median voter's preferred tax rate increases with inequality, and a higher tax leads to a lower growth rate in a standard growth model. Therefore, more unequal societies choose policies that are less growth-incentivising. Persson and Tabellini (1994) similarly argued that inequality leads to "too much" redistribution which, through reduced incentives for private investment, harms growth. The empirical evidence that they (Persson & Tabellini, 1994) present also confirms that inequality was linked with lower growth in democracies. On the other hand, Milanović's (2000) empirical work on

24 democracies questions whether the median-voter hypothesis adequately describes the collective-choice mechanism. Although, he does find that countries with greater inequality of factor income redistribute more to the poor, even when controlling for other factors.

3.4 Socio-political unrest

A closely related concept to democratic redistribution is socio-political unrest, which can be seen as a consequence of how policy fails to address inequality. According to some researchers, high inequality, especially without democratic institutions, might create resentment and violence, leading to insecurity of property and conflict (Alesina & Perotti, 1996; Hibbs, 1973; Venieris & Gupta, 1986).

Social unrest and violence can be viewed as a way to redistribution or expression of discontent by the working masses. Alesina and Perotti (1996) argue that inequality could cause political instability, which then discourages investment. The reasoning is that investors might be afraid to, for example, build infrastructure if riots are common and might destroy what they built. Therefore, inequality could lead to unrest of the working masses, which could make earning returns on investments riskier because of riots, sabotage, strikes, coups, and other forms of unrest.

The relationship between income inequality and economic growth has been examined in various empirical studies. Venieris and Gupta (1986) analyse how socio-political instability influences savings rates, showing that factors such as public demonstrations, regime changes, and politically motivated killings contribute to a decline in savings.

Expanding on this, Alesina and Perotti (1996) employ an index of socio-political instability, incorporating an extended range of variables. Their findings indicate that income inequality worsens socio-political instability, which negatively affects investment. This negative impact might materialise through weakened institutional order or diminished security of property rights (Alesina & Perotti, 1996).

This channel provides another reason why inequality might be bad for growth, regardless of the fact whether redistribution through fiscal policy is present or not. In essence, inequality can generate pressures (either through democratic means or through instability) that change the economic environment in growth-discouraging ways.

3.5 Summary of theoretical expectations

It is clear that the mechanisms listed above work in opposite directions and counteract each other. The savings and incentives channel predicts a positive effect of inequality on growth (the rich invest more, possibly generating faster capital accumulation and innovation incentives), whereas the barriers to investment and education channel and many aspects of the socio-political unrest and redistributive policies channels predict a negative effect (inequality excludes too many from contributing to growth and leads to growth-reducing policies or instability). In total, one must theoretically accept the unclear net effect of inequality.

4. Methodology and data

4.1 Data sources and variables

This study uses an unbalanced panel dataset of 16 post-socialist Eastern European countries observed annually from 1995 to 2019. The countries in consideration are Albania, Bulgaria, Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, Moldova, Poland, Romania, Russia, Serbia, Slovakia, Slovenia, and Ukraine. These countries all transitioned from socialist to capitalist economies in the late 1980s and early 1990s. Due to data limitations, a few Eastern European countries were excluded entirely from the study. These are: Bosnia and Herzegovina, North Macedonia, Montenegro, and Belarus. Each of the 16 included countries has at least 10 yearly observations, with most having over 20. There are a total of 333 country-year observations (20,75 country-year observations per country on average). The panel is unbalanced, as some country-years are missing due to inconsistent statistical practices. Despite the smaller regional focus and incomplete data for some years, the sample is sufficiently large for panel estimation, according to econometric assumptions (Wooldridge, 2010).

The dependent variable of the model is economic growth, measured as the annual growth rate of real GDP per capita. Specifically, the growth rate is calculated using the Penn World Table series for expenditure-side real GDP at chained PPP (2017 US$) and population (Feenstra et al., 2015).

The independent variable in consideration is income inequality: The main measure of income inequality used is the Gini index, as it is the most commonly used measure in the literature (Neves et al., 2016; Sen, 1997). It is an index calculated using the Lorenz curve and ranges

from 0 (perfect equality) to 100 (perfect inequality) (Cowell, 2011). Intuitively, a higher Gini indicates a less equal distribution of income. Gini index data is sourced from the World Income Inequality Database (UNU-WIDER, 2025) for most countries. However, due to WIID data being unavailable or incomplete for Albania, Moldova, Russia and Ukraine, the Gini indices of these 4 countries were sourced from the World Health Organisation (World Health Organization, 2023).

However, Voitchovsky (2005) shows that including only one measure of inequality might not be enough and that results might change depending on the measure of inequality. Specifically, Voitchovsky (2005) argues that different parts of the distribution can affect growth differently, and that's why multiple indicators improve robustness.

To evaluate the robustness of the results across different measures of inequality, three more measures are included, apart from the Gini index. These are:

(1) The Palma ratio: The Palma ratio is defined as the income share of the top 10% divided by the share of the bottom 40% (Feenstra, Inklaar, & Timmer, 2015). Unlike the Gini index, it focuses on the tails of the distribution. This measure has begun to be used as an alternative to Gini because using the Palma ratio helps show distributional changes that the Gini might mask – for example, whether inequality is driven primarily by the very rich against the very poor gap.

(2) The Top 20% / Bottom 20% ratio: In addition to the Palma, a ratio of the income share of the top 20% divided by that of the bottom 20% is included. This is conceptually similar to the Palma but uses the top and bottom quintiles instead of top decile and the bottom 40%. This measure provides another perspective on upper-tail inequality using a bigger wealthy group and a smaller poor group. While not as common as the Palma, it serves further as a robustness check to see if using a slightly different specification gives similar results about inequality.

(3) The income share of the bottom 40%: Finally, the income share of the bottom 40% of the population is used as a measure of inequality. A higher bottom 40% share implies lower inequality, i.e. more income going to the (relatively) poor. This share is expressed in percentage points. This measure specifically examines the lower tail of the distribution. It complements the ratio measures by directly focusing on how much of the total income the poorer population

receives. Notably, if this share rises, the Palma and Top20/Bottom40 ratios would fall, so an inverse relationship is expected between this measure and the other inequality indicators. Using the bottom 40% share allows testing whether improvements in the income of the poor have an association with growth, disregarding the middle-class and the wealthy.

All of the data on the additional inequality measures was sourced from the World Income Inequality Database (UNU-WIDER, 2025). However, it is important to note two things:

(1) Data on the three additional measures of inequality had to be excluded for Moldova, Albania, and Ukraine. This is because of data unavailability.

(2) The dataset for these additional measures of inequality is smaller and more unbalanced than the one used for testing the relationship between growth and the Gini index. It includes 13 countries and 244 country-year observations per measure of inequality, which is 18,77 years per country on average. However, all of the countries have observations for at least 10 years and, therefore, the same conditions for econometric analysis are satisfied as when the Gini index is the inequality measure employed.

Despite these issues, the additional measures of inequality are included to check the robustness of the relationship between economic growth and inequality. Therefore, the usage of a slightly different dataset is assumed to be acceptable and should not interfere with the results if the relationship is robust. However, one must acknowledge that different dimensions of inequality might have different effects on growth. For example, Voitchovsky (2005) finds that inequality at the top of the distribution can have opposite growth effects to inequality at the bottom. The approach employed in the present study helps show whether the growth relationship is sensitive to how inequality is measured.

The panels used in this study are unbalanced, both for the Gini index model specification, and for the other measures of inequality. Years where a country lacked data for any variable (growth or inequality or controls) were dropped from the analysis. According to Verbeek (2017), one can rely on the unbalanced panel estimation under the assumption that data are missing at random. The dataset was inspected for any systemic pattern in missingness, i.e. only low-growth years missing. No concerning trends were found, and it was determined that the gaps

are likely caused only by data collection issues. Therefore, the missing data is unlikely to bias the coefficients, aside from a slight loss of efficiency from fewer observations (Verbeek, 2017).

Apart from the independent variables, three control variables are included:

(1) Human capital: the index of human capital per person from PWT, which is based on years of schooling and returns to education (Feenstra et al., 2015). Human capital is generally assumed to have a positive impact on growth and various measures of human capital have been employed in the literature. For example, Perotti (1996) and Voitchovsky (2005) used the number of schooling years, with minor differences between the two studies. Furthermore, research which examines the direct relationship between human capital and economic growth finds that there is a correlation between the two (Barro, 1991; Bils & Klenow, 2000).

(2) Population growth rate: the annual population growth rate, which is computed from PWT population data. (Feenstra et al., 2015). This variable is used as a control in the literature (Barro, 2000; Forbes, 2000; Li and Zou, 1998) and has a strong theoretical justification. In the Solow-Swan growth model, output per capita depends on the capital/labour ratio, which is determined by the savings rate, depreciation, technological progress, and the population growth rate (Solow, 1956). When the population growth rate rises, a larger number of new workers must be equipped with capital in order to produce, diluting the existing capital. Therefore, the old investment rate is spread more thinly across the labour force, lowering the steady state capital per worker (Mankiw, Romer, & Weil, 1992). Because output per worker is an increasing function of capital per worker under diminishing returns, the decline in the capital/labour ratio translates into a lower steady state level of income per head (Barro & Sala-i-Martin, 2004). During the transition to this new steady state, the economy experiences slower per capita growth (Weil, 2013).

(3) Urbanisation: the percentage of population living in urban areas, from the World Bank's World Development Indicators (World Bank, 2023). As noted by Kuznets (1955), the extent of urbanisation impacts how income is distributed, given that cities typically have greater inequality compared to rural regions, but with higher income per capita. Kuznets (1955) argues that urbanisation initially increases inequality during earlier phases of development but may later contribute to its reduction as a nation becomes wealthier. Jedwab and Vollrath (2015) examine the relationship between growth and inequality and find that the two are related. This

variable is also used as a control when examining the inequality-growth relationship, for example by Perotti (1996).

These controls account for differences in education, demographic trends, and structural urban development, which might influence growth (for example, higher human capital is expected to improve economic growth, while a fast increase in population could dilute capital and slow per capita growth in Solow-type models).

4.2 Determining the appropriate model

In the previous literature, the most commonly used model for estimating the relationship between growth and inequality is the simple OLS model (Knowles, 2005; Sarkar, 2007; Tanninen, 1999; Woo, 2011). However, the usage of this model is limited to cross-sectional data and pooled OLS is not employed in the literature on panel data (Neves et al., 2016). Such models are therefore, not considered, as this study uses panel data.

In panel data analysis, both the fixed effects or random effects models are common (Neves et al., 2016) and it is common to use both, like Li and Zou (1998) or Banerjee and Duflo (2003).[5] However, some researchers also use a random effects model to test this relationship (Banerjee & Duflo, 2003; Davis & Hopkins, 2011; Li & Zou, 1998). Barro (2000) uses a variant of the random effects model and argues against using a fixed effects model in his specific case, as it removes cross-sectional information in the panel. Banerjee and Duflo (2003), on the other hand, use it as just one of the models that they employ to test this relationship.

To determine which one of these is appropriate, the Hausman test is used (Hausman, 1978), the null hypothesis of which states that the random effects model is appropriate. It was determined that the test is not significant at the 5% significance level[6] and the null hypothesis holds. Therefore, the random effects model is appropriate, and the dataset includes no fixed effects. Though it is common and many argue that the fixed effects model is appropriate (Arjona et al., 2002; Castelló-Climent, 2004; Forbes, 2000; Thewissen, 2014), it is possible

[5] According to Neves et al. (2016), many researchers also use more complex methods of estimation, like the system GMM or three-stage LS. Since there is no definite answer on which should be used, these were not considered, and simplicity was preferred in the present study.

[6] I have also estimated the Hausman test for the models specified with the additional measures of inequality, finding that they are all insignificant at the 5% significance level and that RE models are appropriate for all of them.

that unobserved heterogeneity is controlled for in the dataset because of the inclusion of control variables and because of the similarity of the Eastern European economies. Furthermore, the efficiency gains of RE are valuable given the moderate sample size. The random-effects estimator uses both within and between-country variation, whereas fixed effects would discard all between-country information (Nguyen, 2020). Since a sample of 16 countries is not very large, it is preferable to use all available variation, further supporting the use of a random effects model. However, the p-value of the Hausman test for the main model was equal to 0,1074.[7] Though the 10% significance level is not high, the fixed effects model was employed to test the robustness of the relationship between growth and inequality because of its use in previous literature.

4.3 The model

Following Nguyen's (2020) notation, the random effects model used can be written in the following way:

$$Growth_{it} = \beta_0 + \beta_1 Inq_{it} + \beta_2 HC_{it} + \beta_3 PGR_{it} + \beta_4 Urb_{it} + c_i + u_{it} \quad (1)$$

Where: $Growth_{it}$ is the the growth rate of the real GDP per capita for country i at time t, Inq_{it} is the Gini index for country i at time t,[8] HC_{it} is human capital, and PGR_{it} is the population growth rate, Urb_{it} is the urbanisation rate. $\beta_1$represents the coefficient of interest, as it shows the strength and direction of the correlation between growth and inequality. Therefore, the hypothesis of inequality having no effect on growth can be disproven if $\beta_1 \neq 0$ at a certain significance level. Furthermore, c_i is the unobserved individual-specific effect, and u_{it} is the idiosyncratic error. In a fixed effects model, the c_i is removed because of the demeaning of the data, but the random effects model considers it a random variable and includes it in the error structure.

Before presenting the main regression results, preliminary regressions are run on the dataset in order to conduct the diagnostic checks necessary for the present work.

[7] The p-values for the other inequality measures, on the other hand, were much higher, further bringing into question the applicability of the FEM.

[8] Or one of the 3 additional measures of inequality, when conducting robustness checks.

4.4 Diagnostic checks

Upon running preliminary regressions, it was concluded that the dataset contains some undesirable phenomena. This subsection explains how each of them was dealt with.

All of the diagnostic checks were conducted on the main regression, which uses Gini index as the independent variable, and on the three additional specifications, using the three additional measures of inequality, which are used to test the robustness of the relationship between inequality and growth.

Normality of residuals: Skewness-kurtosis tests reject normality for all specifications of the model. However, upon visual inspection, it was determined that the residuals follow an approximately normal distribution for all model specifications, though they have a few outliers (see Appendices 1, 2, 3, 4). Ghasemi and Zahediasl (2012) note that normality tests are often too sensitive to mild outliers and with over 200 observations per regression the central limit theorem ensures that coefficient estimators remain normal. Therefore, deviations from normality do not invalidate statistical inference.

Stationarity: All of the variables employed were tested for stationarity using a Fisher-type unit-root test based on the Phillips-Perron tests (Phillips & Perron, 1988). All of the variables were determined to be stationary at the 5% significance level, except for the Palma ratio, for which only some of the 4 statistics provided by the test were insignificant at the 5% significance level (see Appendix 5). However, the Palma ratio is calculated according to the same income data as the rest of the inequality measures, and it was determined that all of the other inequality variables are stationary at the 5% significance level, with most of their statistics being significant at the 1% significance level even. It is also important to mention that, though some of the test statistics are not significant at the 5% level for the Palma ratio variable, they are all still significant at the 10% significance level. Because of this, the Palma ratio variable is very likely stationary, despite the mixed test results. Therefore, I treat it as stationary.

Serial Autocorrelation and Heteroskedasticity: Using Wooldridge's (2002) test, it was determined that all of the model specifications exhibit serial autocorrelation in the residuals, though at different significance levels. To test for groupwise heteroskedasticity, the modified Wald test was used, the null hypothesis of which is that there is no heteroskedasticity. In the

Gini model specification, heteroskedasticity was found at the 1% significance level, but the other model specifications exhibit no significant heteroskedasticity (see Appendix 6). To make sure inference is consistent under these conditions, cluster-robust standard errors at the country level are employed. It can, therefore, be argued that the calculated estimators are robust to serial autocorrelation and heteroskedasticity (Nguyen, 2020).

5. Results

5.1 Gini index and economic growth

Table 1: The random effects regression, Gini index, all control variables.

Variable	Coefficient	Cluster-robust standard errors
Gini index	0,0007	(0,0007)
Human capital	0,0014	(0,0113)
Population growth rate	-0,6840***	(0,1179)
Urbanisation rate	-0,0001	(0,0002)
Constant	0,0235	(0,0411)
R^2 (within)	0,0136	
Nr of observations	332	

*Note: 16 countries are included in the regression. Observations per country: minimum = 10, maximum = 25, average = 20,8. Standard errors are clustered by country. Significance levels: *** for p<0,01, ** for p<0,05, * for p<0,10.*

Table 1 presents the results for the regression using the Gini index as the independent variable to test the relationship between inequality and economic growth. The main regression results (Table 1) indicate that income inequality, as measured by the Gini index, has no statistically significant impact on economic growth in the 16 Eastern European countries studied. The Gini index in the random-effects model estimation has a statistically insignificant coefficient of approximately 0,0007, which is statistically indistinguishable from zero. Even if it was statistically significant, it would imply that a 1-point increase in the Gini index (on a 0-100 scale) increases the real GDP per capita growth rate by only 0,0007, which is an economically

negligible effect. Even a large change in inequality would correspond to a small change in growth. For example, a 10-point rise in the Gini would produce only a 0,7% change in annual growth, ceteris paribus.

The only control variable which is significant is the population growth rate, while the human capital index and the urbanisation rate are insignificant and have negligibly small coefficients.

To further test the robustness of the relationship between the Gini index and economic growth, the model was altered slightly. Firstly, a regression was run with no insignificant control variables, leaving only population growth as a dependent variable (see Appendix 7). The produced result remained the same. The coefficient of interest is insignificant, while the population growth rate is still significant at the 1% significance level. Secondly, the regression was run without any control variables (see Appendix 8) and again showed that the coefficient of interest is insignificant and negligibly small.

As was stated in the Methodology and data section, the fixed effects model was also considered (see Appendix 9). Considering the assumptions of REM and FEM, it is unsurprising that the coefficient of interest is negligible and insignificant in this specification also. It is, however, interesting to note that the sign of the coefficient becomes negative when the fixed effects model is employed. But since neither approach finds a significant effect, one should not overinterpret the sign change. The absence of significance in both cases means that the null hypothesis of inequality having no effect on growth cannot be rejected.

The overall explanatory power of the model is also very low. The within-country R^2 in the random effects regression is approximately 1%, meaning that almost none of the year-to-year variation in growth is explained by changes in inequality or the included controls. This reinforces the conclusion that the Gini index and the other regressors have little to no explanatory power for growth in this dataset.

In short, there is no evidence that the Gini index either promotes or hinders economic growth in post-socialist Eastern Europe over the period 1995–2019. Considering this measure of inequality alone, one could strongly argue that the null hypothesis cannot be rejected, and that inequality has no effect on growth.

5.2 Additional measures of inequality

Although the Gini index is not able to explain economic growth in the dataset employed, this result might not be very robust across different measures of inequality. To test this, the Palma ratio, the Top20/Bottom20 ratio and the income share held by the Bottom 40% are employed as additional measures of inequality. Table 2 presents the results of the random effects regressions using these additional measures of inequality. It is important to note that the data used for these regressions includes a slightly smaller sample of countries and observations, with the panel being more unbalanced than the one used in the Gini index regression. Considering that a robust result would be obtained even when the data is altered slightly, this is not considered problematic for a robustness check.

However, using these additional measures shows some weak evidence of an inequality-growth relationship, although it is a very small one. In two out of the three alternative specifications, the inequality coefficient is significant at the 10% level. This differs from the Gini index regression where inequality was entirely insignificant. It appears that when focusing on specific parts of the income distribution, a relationship with growth is found that the Gini index regression failed to detect.

Firstly, the Palma ratio shows a positive and marginally significant coefficient. The Palma ratio is defined as the share of income of the top 10% divided by the share of the bottom 40%. Therefore, it focuses on inequality driven by the ends of the distribution. In the results, the Palma ratio coefficient is 0,0247, and significant at the 10% significance level. This suggests that a higher Palma ratio (a greater concentration of income at the top relative to the bottom) is associated with slightly higher economic growth, holding other factors constant. The magnitude is small and an increase of 1,0 in the Palma ratio (which is quite large) corresponds approximately to a 0,0246 increase in annual growth rate, according to the estimated parameter. Most countries' Palma ratios vary in a much narrower range than 1, so smaller changes in inequality would have even smaller effects on economic growth. Thus, even though the coefficient is positive, it implies only a minor potential impact of inequality on growth. The fact that it is only significant at the 10% significance level also suggests caution when interpreting the results. The relationship is statistically weak, and the coefficient of interest is quite small.

Table 2: The random effects regressions for (1) Palma ratio, (2) Top20/Bottom20, and (3) Bottom 40.

Variable	(1)	(2)	(3)
Palma ratio	0,0247*		
	(0,0140)		
Top20/Bottom20		0,0043	
		(0,0028)	
Bottom 40			-0,0024*
			(0,0013)
Human capital	-0,0035	-0,0054	-0,0053
	(0,0122)	(0,0122)	(0,0117)
Population growth rate	-0,6521***	-0,6501***	-0,6508***
	(0,0428)	(0,0434)	(0,0410)
Urbanisation rate	0,0003	0,0004	0,0004
	(0,0004)	(0,0004)	(0,0004)
Constant	0,0024	0,0075	0,0814**
	(0,0348)	(0,0359)	(0,0390)
R^2 (within)	0,0571	0,0604	0,0528
Nr. of observations	244	244	244

*Note: 13 countries are included in the regression. Observations per country: minimum = 10, maximum = 24, average = 18,8. Standard errors are clustered by country and noted in brackets. Significance levels: *** for p<0,01, ** for p<0,05, * for p<0,10.*

Secondly, the income share of the bottom 40% has a negative coefficient that is likewise significant at the 10% level. In this regression, the coefficient of the bottom 40% share is approximately –0,0024. A higher bottom 40% share means a more equal distribution (the poor getting more of the total income). Therefore, a negative coefficient implies that more equality is associated with slightly lower growth. Conversely, a lower bottom 40% share (greater income concentration at the top) correlates with mildly higher growth. This finding is,

essentially, just confirming the Palma ratio regression result. Both indicate that inequality at the extremes might have a small growth-promoting effect in this sample. However, the bottom 40% share's coefficient is negligibly small, being even lower than the Palma ratio coefficient. And, as with the Palma ratio, the result is only marginally significant. It is likely that these findings are an error and, in reality, the relationship is insignificant. However, it is also possible that the two significant measures of inequality just have a small effect on growth.

In contrast, the Top20/Bottom20 ratio does not show a significant relationship with growth in the results. This is a measure which is very similar to the Palma ratio but compares the top quintile's income share to the bottom quintile's. As shown in Table 2, it has a coefficient that is not statistically different from zero. This finding further casts doubt on the significance of the relationship between inequality and growth. Alternatively, the lack of significance for the Top20/Bottom20 ratio, despite the Palma ratio being weakly significant, could also be explained by the fact that the bottom 40% share (which overlaps with Palma's denominator) has a slightly clearer effect on growth.

Taken together, the additional inequality measures provide very limited evidence of a relationship between inequality and growth, with the direction of the effect showing that higher inequality might be associated with slightly higher growth. However, it must be noted that these effects are sensitive to how inequality is defined and small in magnitude. Furthermore, the 10% significance level is relatively weak evidence, and the economic significance is minor. Inequality changes of realistic size would appear as marginal changes in growth rates. Given the marginal significance and small coefficients, one could argue that the results suggest that in post-socialist Eastern Europe, inequality has no effect on growth or that its effect is so small that it is negligible. The effect of inequality, if it exists, is very slight and not robust and clear.

6. Discussion

6.1 Alignment of results with previous literature

Our main regression shows no significant link between the Gini index and per-capita growth, aligning with other research that finds an insignificant or questionable relationship between the two, such as Deininger and Olinto (1999) and Thewissen (2014). Persson and Tabellini (1994) find that the relationship is insignificant once dummy variables for democracies are included.

Though it is unclear whether and which Eastern European countries are undemocratic, the results fit into the literature which says that different countries could have different relationships between inequality and growth. Perotti (1996) finds that the relationship becomes insignificant once regional dummies are included. Following this logic, since post-socialist Eastern Europe is a region with its own specific traits, one could argue that inside of this specific region there would be no correlation between growth and inequality. Panizza (2002) finds similar results and shows that the relationship between these two variables is not robust and that small differences in the way inequality is measured can change the results. The obtained findings, therefore, align with some of the previous literature.

As was mentioned in the Empirical literature review section, an important reason for why the literature generally looks like it supports the notion that inequality does impact growth is publication bias. Neves et al. (2016) show that studies reporting significant coefficients, positive or negative, are more likely to reach journals than studies that find no significant relationship. After correcting for that bias, they conclude that the average effect of inequality on growth is unclear. The acceptance of the null hypothesis, therefore, is not an oddity in the published literature, though it is a less common result.

6.2 The uniqueness of Eastern Europe in the world

Barro (2000) argues that inequality can harm growth in poor countries because of many reasons but can help growth in rich countries if high-income groups save and invest more. Other researchers (Castelló, 2010, Chambers & Krause, 2010, Herzer & Vollmer, 2012, Khalifa & El Hag, 2010) also confirm this finding. Post-socialist Eastern Europe is between those two groups. In the second half of the nineties, the region's real GDP per capita was well above the low-income threshold yet still below OECD levels (Feenstra et al., 2015). While the negative effects of inequality on growth dominate in underdeveloped countries, the positive effects dominate in wealthy countries. Since Eastern Europe is economically between the rich West and the underdeveloped countries, it is possible that the positive and negative effects of inequality on growth balance out in this region. This then appears as inequality having no effect on economic growth, as the findings suggest.

6.3 Sensitivity of results across inequality measures

Another thing to note from the analysis is that the relationship between inequality and growth might be sensitive to how inequality is measured. The found pattern suggests that different distributions of inequality may have different influences on economic growth. This finding would align with Voitchovsky (2005), for example, who showed that inequality in different parts of the income distribution can have opposite effects on growth. In her study, inequality in the upper tail of the distribution (among the rich) appeared to speed up economic growth, while inequality in the lower tail (among the poor) tended to slow down growth. In other words, a widening gap between the very top and the middle class might encourage growth, but a widening gap between the poorest and the middle class can discourage growth.

Considering the results from Table 2, there is a possibility that the different measures of inequality have a different impact on growth (though the results are unclear). The Palma ratio has a positive coefficient (at the 10% significance level), suggesting that greater income concentration in the top 10% (relative to the bottom 40%) was associated with slightly higher growth in the employed dataset. Consistent with that, the bottom 40% income share has a negative coefficient (at the 10% level), indicating that higher inequality at the lower end correlates with marginally higher growth. Both measures essentially suggest the same – in this dataset, inequality at the extremes of the distribution might have a small growth-encouraging effect. This result is like a mirrored variant of Voitchovsky's (2005) finding that lower-tail inequality harms growth.

The Top20/Bottom20 ratio, a very similar measure, was also tested. Its coefficient is completely insignificant. This warns that results depend on how the tails are defined, meaning that the relationship is sensitive to small changes. Changing the inequality measure can create or erase (marginal) statistical significance in the used dataset. And even when the significance exists, the coefficients are negligible, and one could argue that this is an error and not proof of a robust relationship.

Even though the other measures are also likely irrelevant, the findings do suggest that Voitchovsky's (2005) work might be important and that using a single summary measure like Gini can mask opposing effects happening at different ends of the income distribution. This is

true just because the null result becomes less robust across different measures of inequality, though it is still very likely that inequality has no effect on growth.

6.4 The significance of the population growth rate

In every specification of the model, the population growth coefficient is large, negative, and significant at the 1% significance level. This is exactly what the Solow-Swan model predicts, as was discussed in the Methodology and data section. When the population growth rate rises, the steady-state capital per worker is lowered, and therefore economic growth as well (Mankiw, Romer, & Weil, 1992). The findings suggest that these effects on economic growth are strong and significant.

6.5 Limitations

Like in every study, one must address the potential limitations of the work. This study employs the random-effects model because the Hausman test cannot reject the use of a REM at the 10% significance level and because exploiting both cross-country and within-country variation raises efficiency. However, the results might be sensitive to the model choice, as argued by Neves et al. (2016). Previous literature also uses models like system-GMM (Bengoa, 2005; Castelló-Climent, 2010; Halter et al., 2014), which are more complex were not tested in this study. Future research might test the data from Eastern Europe using these and find different results than the ones in this study. Statistical power is another concern. With 16 countries observed up to 25 years, reasonable within variation is obtained, but limited cross-sectional variation. Detecting very small effects, therefore, may simply be beyond the confidence bands of this study. Furthermore, the panel is unbalanced, and missing observations might have an effect on the final results. Finally, the studied period (1995–2019) and data unavailability limit the study further. By ending in 2019, the impacts of recent shocks such as the COVID-19 pandemic cannot be analysed. Data quality is another concern, according to the WIID (UNU-WIDER, 2025), as some of the observations are reported to have low quality estimates for income inequality and may contain measurement errors. The present study attempts to mitigate this by excluding countries with insufficient data and using reputable sources listed in the WIID as much as possible. Some measurement error likely remains, but considering that it is random, one could argue that it does not pose a serious threat to this study.

As was discussed earlier, post-socialist Eastern European economies share some factors which set them apart from the rest of the world, such as the consequences of rapid privatisation and social-safety-net reforms. Therefore, the present study does not claim that income inequality has no or just a negligible effect on economic growth in all countries. Considering the fact that previous research finds different groups of countries have different relationships between inequality and growth (Barro, 2000; Castelló, 2010, Chambers & Krause, 2010, Herzer & Vollmer, 2012, Khalifa & El Hag, 2010), one can only claim that the relationship obtained in the present study holds in Eastern Europe. Therefore, the results of this study are not and are not supposed to be generalisable to other countries or groups of countries.

Despite these constraints, the results do suggest that, in Eastern Europe from 1995-2019, income inequality had no important effect on growth.

6.6 Policy implications

For Eastern European governments wishing to reduce inequality for social or political reasons, this study suggest that they can do so without fearing large growth losses. Distributional policy should, therefore, be judged primarily based on how it influences social-justice, political-stability, or poverty. In suggesting this, the implications of the present study agree with papers showing that there is a negative effect of inequality on growth, like Alesina and Perotti's (1996) work. However, even if it was proved that inequality did impact growth, this would still not be the end of the discussion. While economic growth is important, a government cannot pursue it as its only goal and must take into account other forms of well-being of its citizens.

7. Conclusion

The present study analyses the inequality-growth relationship in a region that has received little attention – post-socialist Eastern Europe. Using the data on sixteen countries from 1995 to 2019, income inequality was regressed on economic growth using a random effects model. The relationship was tested statistically by replicating the common Gini specification and three additional measures (Palma, Top20/Bottom20, and the Bottom 40 share), as suggested by previous literature (Voitchovsky, 2005)

Several conclusions emerge. First, standard, whole-distribution inequality appears irrelevant for growth in this region. For the Gini index specifications, the coefficient is statistically

indistinguishable from zero. The result survives when insignificant controls are removed, when all controls are dropped, and when fixed-effects estimation replaces random effects. This aligns with earlier work that fails to find a robust inequality-growth relationship once regional dummies or country fixed effects are included (Persson & Tabellini, 1994; Panizza, 2002).

Second, some tail-focused indicators deliver only weak evidence, though others further confirm the insignificance of the relationship. The Palma ratio enters with a positive sign at the 10% significance level, whereas the income share of the bottom 40% is negative and marginally significant. The top-20/bottom-20 ratio is insignificant. Coefficient magnitudes are small. Realistically plausible changes in inequality translate into growth differences measured in hundredths of a percentage point, so even the statistically "significant" effects are arguably irrelevant.

Third, among the controls, only population growth is statistically significant. Its large negative coefficient reaffirms the Solow-type prediction that faster labour-force expansion dilutes the capital stock and slows income growth. Human capital and urbanisation, on the other hand, show no significant effect on economic growth.

These findings carry three implications: 1) Policy makers do not need to fear a large economic growth decrease when pursuing equity goals. 2) Aggregate inequality indicators may mask distinct distributional patterns, the growth effects of which cancel out. However, the extent to which this holds is unclear from the data. Therefore, researchers might want to avoid relying on a single metric and should, where possible, separate inequality measures by income deciles or quintiles. 3) Eastern Europe's middle-income position might explain the muted effects observed. Previous literature predicts that inequality decreases growth in very poor countries but can increase it in rich ones (Barro, 2000). The used sample is in between the very wealthy nations and the poor ones, so offsetting effects could be rendering the total impact negligible.

Several econometric limitations must be acknowledged. The reliance on a random-effects model, while justified by the Hausman test and efficiency gains, raises potential sensitivity concerns, as alternative specifications (e.g., system-GMM, used in prior literature) might show different results. Statistical power is limited by cross-sectional variation (16 countries over 25 years), making it difficult to detect very small effects. The unbalanced panel structure and missing observations could also influence the findings. Additionally, the study period (1995–

2019) excludes recent shocks like the COVID-19 pandemic, which may alter the inequality-growth relationship. Data quality for early inequality measures is another limitation, as some estimates, particularly from the 1990s and early 2000s, may contain measurement errors. While efforts were made to mitigate this by excluding unreliable data and relying on reputable sources, some random measurement error likely persists, though it may not critically bias the results.

Future research could expand upon the findings of this study in three ways. First, using dynamic panel or system-GMM techniques might help address problems of simpler methods used in the present work. Second, sub-national data, where available, would allow examination of within-country disparities, arguably more relevant for social tension than national averages. Third, including data after 2019 would enable analysis of how recent shocks, such as the COVID-19 pandemic and the conflict on the Ukraine, influence the relationship in consideration.

To conclude, the present work contributes to the literature by demonstrating that, for Eastern Europe's post-socialist economies, income inequality has been largely unimportant for growth over the past quarter-century. This null or negligible result contrasts with findings for other regions and underscores the importance of context and measure of inequality used. While egalitarian policies could be pursued for social-justice reasons, they need to be justified with theoretical and empirical findings. The evidence presented here suggests that equity and efficiency are not meaningfully related in this context.

8. References

Aghion, P., & Bolton, P. (1997). A theory of trickle-down growth and development. *The Review of Economic Studies*, 64(2), 151–172.

Aghion, P., Caroli, E., & García-Peñalosa, C. (1999). Inequality and economic growth: The perspective of the new growth theories. *Journal of Economic Literature*, 37(4), 1615–1660.

Alesina, A., & Perotti, R. (1996). Income distribution, political instability, and investment. *European Economic Review*, 40(6), 1203–1228.

Alesina, A., & Rodrik, D. (1994). Distributive politics and economic growth. *Quarterly Journal of Economics*, 109(2), 465–490.

Arjona, R., Ladaique, M., & Pearson, M. (2002). Social protection and growth. *OECD Economic Studies*, 35(2), 7–45.

Banerjee, A. V., & Duflo, E. (2003). Inequality and growth: What can the data say? *Journal of Economic Growth*, 8(3), 267–299.

Banerjee, A. V., & Newman, A. F. (1993). Occupational choice and the process of development. *Journal of Political Economy*, 101(2), 274–298.

Barro, R. J. (1991). Economic growth in a cross section of countries. *Quarterly Journal of Economics*, 106(2), 407–443.

Barro, R. J. (2000). Inequality and growth in a panel of countries. *Journal of Economic Growth*, 5(1), 5–32.

Barro, R. J., & Sala-i-Martin, X. (2004). *Economic Growth* (2nd ed.). MIT Press.

Bengoa, M., & Sánchez-Robles, B. (2005). Does equality reduce growth? Some empirical evidence. *Applied Economics Letters*, 12(8), 479–483.

Bils, M., & Klenow, P. J. (2000). Does schooling cause growth? *American Economic Review*, 90(5), 1160–1183.

Brzezinski, M. S. (2022). Determinants of inequality in transition countries. *IZA World of Labor*.

Brownlee, W. E. (2016). *Federal Taxation in America: A History* (3rd ed.). Cambridge University Press.

Castelló, A., & Doménech, R. (2002). Human capital inequality and economic growth: Some new evidence. *The Economic Journal*, 112(478), C187–C200.

Castelló-Climent, A. (2004). A reassessment of the relationship between inequality and growth: What human capital inequality data say? *Valencia Working Papers*, 15.

Castelló-Climent, A. (2010). Inequality and growth in advanced economies: An empirical investigation. *The Journal of Economic Inequality*, 8(3), 293–321.

Chambers, D., & Krause, A. (2010). Is the relationship between inequality and growth affected by physical and human capital accumulation? *The Journal of Economic Inequality*, 8(2), 153–172.

Cingano, F. (2014). Trends in income inequality and its impact on economic growth. *OECD Social, Employment and Migration Working Papers*, 163.

Clarke, G. R. G. (1995). More evidence on income distribution and growth. *Journal of Development Economics*, 47(2), 403–427.

Cowell, F. A. (2011). *Measuring Inequality* (3rd ed.). Oxford University Press.

Das, T., & Parikh, A. (1982). Decomposition of inequality measures and a comparative analysis. *Empirical Economics*, 7(1–2), 23–48.

Davis, L., & Hopkins, M. (2011). The institutional foundations of inequality and growth. *Journal of Development Studies*, 47(7), 977–995.

De La Croix, D., & Doepke, M. (2003). Inequality and growth: Why differential fertility matters. *American Economic Review*, 93(4), 1091–1113.

Deininger, K., & Olinto, P. (1999). Asset distribution, inequality, and growth. *World Bank Policy Research Working Paper*, 2375.

Deininger, K., & Squire, L. (1996). A new data set measuring income inequality. *The World Bank Economic Review*, 10(3), 565–591.

Deininger, K., & Squire, L. (1998). New ways of looking at old issues: Inequality and growth. *Journal of Development Economics*, 57(2), 259–287.

Dorjnyambuu, B. (2025). A systematic literature review of income inequality in Central–Eastern European countries. *Comparative Economic Studies*, 67(1), 1–49.

Feenstra, R. C., Inklaar, R., & Timmer, M. P. (2015). The next generation of the Penn World Table. *American Economic Review*, 105(10), 3150–3182, available for download at www.ggdc.net/pwt

Ferreira, I. A., Gisselquist, R. M., & Tarp, F. (2022). On the impact of inequality on growth, human development, and governance. *International Studies Review*, 24(1), viab058.

Forbes, K. J. (2000). A reassessment of the relationship between inequality and growth. *American Economic Review*, 90(4), 869–887.

Galor, O., & Moav, O. (2004). From physical to human capital accumulation: Inequality and the process of development. *The Review of Economic Studies*, 71(4), 1001–1026.

Galor, O., & Zeira, J. (1993). Income distribution and macroeconomics. *The Review of Economic Studies*, 60(1), 35–52.

Ghasemi, A., & Zahediasl, S. (2012). Normality tests for statistical analysis: a guide for non-statisticians. *International journal of endocrinology and metabolism*, 10(2), 486.

Gujarati, D. N., & Porter, D. C. (2009). *Basic Econometrics* (5th ed.). McGraw-Hill.

Halter, D., Oechslin, M., & Zweimüller, J. (2014). Inequality and growth: The neglected time dimension. *Journal of Economic Growth*, 19(1), 81–104.

Hausman, J. A. (1978) Specification tests in econometrics. *Econometrica*, 46(6), 1251-1271.

Henderson, J. V. (2003). The urbanization process and economic growth: The so-what question. *Journal of Economic Growth*, 8(1), 47–71.

Herzer, D., & Vollmer, S. (2012). Inequality and growth: Evidence from panel cointegration. *The Journal of Economic Inequality*, 10(4), 489–503.

Hibbs, D. A. (1973). *Mass Political Violence: A Cross-Sectional Analysis*. Wiley.

Jedwab, R., & Vollrath, D. (2015). Urbanization without growth in historical perspective. *Explorations in Economic History*, 58, 1–21.

Kaldor, N. (1956). Alternative theories of distribution. *The Review of Economic Studies*, 23(2), 83–100.

Keynes, J. M. (1936). *The General Theory of Employment, Interest, and Money*. Harcourt Brace & World.

Khalifa, S., & El Hag, S. (2010). Income disparities, economic growth, and development as a threshold. *Journal of Economic Development*, 35(2), 23–45.

Knowles, S. (2005). Inequality and economic growth: The empirical relationship reconsidered in the light of comparable data. *The Journal of Development Studies*, 41(1), 135–159.

Kuznets, S. (1955). Economic growth and income inequality. *American Economic Review*, 45(1), 1–28.

Li, H., & Zou, H. (1998). Income inequality is not harmful for growth: Theory and evidence. *Review of Development Economics*, 2(3), 318–334.

Mankiw, N. G., Romer, D., & Weil, D. N. (1992). A contribution to the empirics of economic growth. *Quarterly Journal of Economics*, 107(2), 407–437.

Meltzer, A. H., & Richard, S. F. (1981). A rational theory of the size of government. *Journal of Political Economy*, 89(5), 914–927.

Milanović, B. (2000). The median-voter hypothesis, income inequality, and income redistribution: An empirical test with the required data. *European Journal of Political Economy*, 16(3), 367–410.

Neves, P. C., Afonso, Ó., & Silva, S. T. (2016). A meta-analytic reassessment of the effects of inequality on growth. *World Development*, 78, 386–400.

Nguyen, M. (2020). *A Guide on Data Analysis*. Bookdown.

Panizza, U. (2002). Income inequality and economic growth: Evidence from American data. *Journal of Economic Growth*, 7(1), 25–41.

Persson, T., & Tabellini, G. (1994). Is inequality harmful for growth? *American Economic Review*, 84(3), 600–621.

Perotti, R. (1996). Growth, income distribution, and democracy: What the data say. *Journal of Economic Growth*, 1(2), 149–187.

Phillips, P. C. B., & Perron, P. (1988) Testing for a unit root in time series regression. *Biometrika*, 75(2), 335-346.

Sarkar, D. (2007). The role of human capital in economic growth revisited. *Applied Economics Letters*, 14(6), 419–423.

Sen, A. (1997). *On Economic Inequality* (Expanded ed.). Oxford University Press.

Solow, R. M. (1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*, 70(1), 65–94.

Stiglitz, J. E. (1969). Distribution of income and wealth among individuals. *Econometrica*, 37(3), 382–397.

Tanninen, H. (1999). Income inequality, government expenditures, and growth. *Applied Economics*, 31(9), 1109–1117.

Thewissen, S. (2014). Is it the income distribution or redistribution that affects growth? *Socio-Economic Review*, 12(3), 545–571.

Thorbecke, E., & Charumilind, C. (2002). Economic inequality and its socioeconomic impact. *World Development*, 30(9), 1477–1495.

UNU-WIDER. (2025, April 29). *World Income Inequality Database (WIID)* (Version 29 April 2025) [Data set]. https://doi.org/10.35188/UNU-WIDER/WIID-290425

Venieris, Y. P., & Gupta, D. K. (1986). Income distribution and sociopolitical instability as determinants of savings: A cross-sectional model. *Journal of Political Economy*, 94(4), 873–883.

Verbeek, M. (2017). *A Guide to Modern Econometrics* (5th ed.). Wiley.

Voitchovsky, S. (2005). Does the profile of income inequality matter for economic growth? *Journal of Economic Growth*, 10(3), 273–296.

Weil, D. N. (2013). *Economic Growth* (3rd ed.). Pearson.

Woo, J. (2011). Growth, income distribution, and fiscal policy volatility. *Journal of Development Economics*, 96(2), 289–313.

Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. MIT Press.

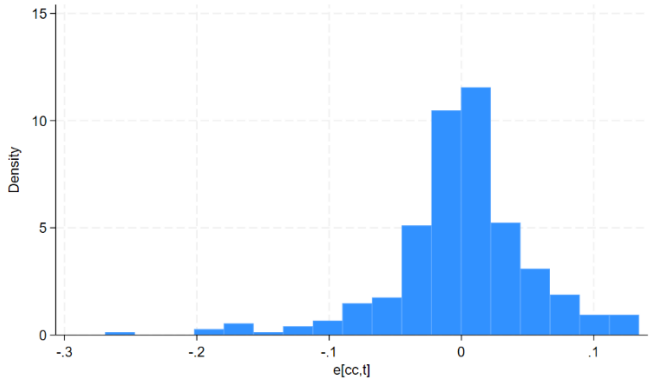
Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data* (2nd ed.). MIT Press.

World Bank. (2023). Urban population (% of total population) [Data set]. *World Bank Open Data*. Retrieved May 10, 2025, from https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS

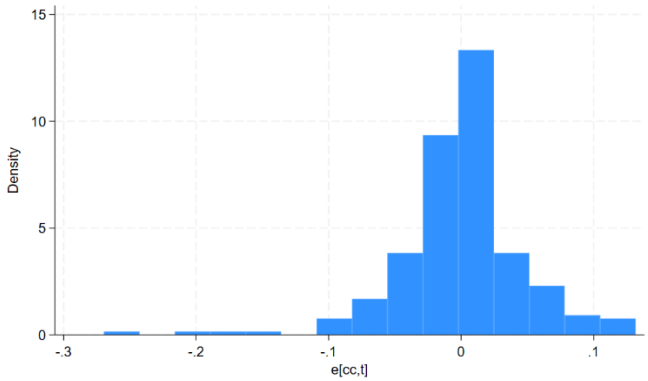
World Health Organization Regional Office for Europe. (2023). *Health for All (HFA) database* [Data set]. Retrieved May 10, 2025, from https://gateway.euro.who.int/en/hfa-explorer/#rNIgvJk47D

9. Appendix

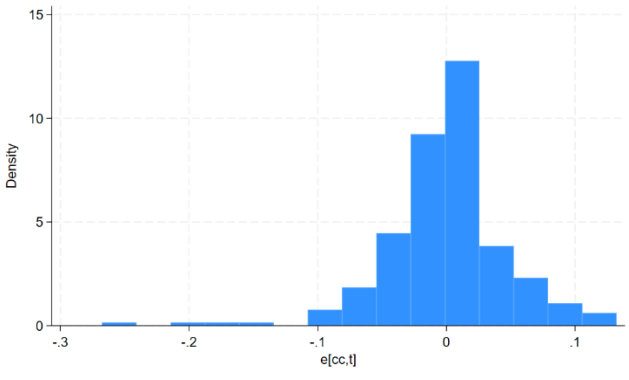
Appendix 1: The distribution of residuals, Gini index specification.



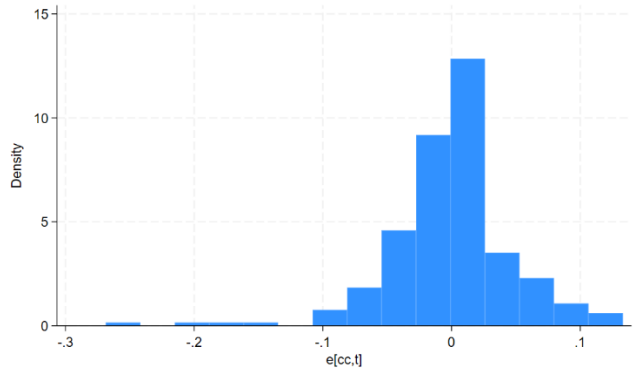
Appendix 2: The distribution of residuals, Palma ratio specification.



Appendix 3: The distribution of residuals, Top20/Bottom20 ratio specification.



Appendix 4: The distribution of residuals, Bottom 40 share specification.



Appendix 5: The Fisher-type unit-root test (based on Phillips–Perron tests) for Palma ratio.

	Statistic	p-value
Inverse chi-squared(26)	43,9465	0,0153
Inverse normal	-1,4871	0,0685
Inverse logit t(69)	-1,4545	0,0752
Modified inv. chi-squared	2,4887	0,0064

Appendix 6: p-values of the modified Wald test for each model specification

	Gini	Palma	Top20/Bottom20	Bottom40
p-value	0,0070	0,1889	0,1955	0,1806

Appendix 7: The random effects regression, Gini index, no insignificant control variables.

Variable	Coefficient
Gini index	0,0006
Population growth rate	-0,6790***
Constant	0,0219
R^2 (within)	0,0134
Nr of observations	332

*Note: 16 countries are included in the regression. Observations per country: minimum = 10, maximum = 25, average = 20,8. Standard errors are clustered by country. Significance levels: *** for p<0,01, ** for p<0,05, * for p<0,10.*

Appendix 8: The random effects regression, Gini index, no control variables.

Variable	Coefficient
Gini index	0,0008
Constant	0,0187
R^2 (within)	0,0105
Nr of observations	332

*Note: 16 countries are included in the regression. Observations per country: minimum = 10, maximum = 25, average = 20,8. Standard errors are clustered by country. Significance levels: *** for p<0,01, ** for p<0,05, * for p<0,10.*

Appendix 9: The fixed effects regression, Gini index.

Variable	Coefficient
Gini index	-0,0011
Human capital	0,0213
Population growth rate	-0,5704***
Urbanisation rate	-0,0022
Constant	0,1435
R^2 (within)	0,0312
Number of observations	332

*Note: 16 countries are included in the regression. Observations per country: minimum = 10, maximum = 25, average = 20,8. Standard errors are clustered by country. Significance levels: *** for p<0,01, ** for p<0,05, * for p<0,10.*